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RESEARCH ARTICLE

Design and Implement Low-Cost Industry 4.0 System Using Hybrid Six Sigma Methodology for CNC Manufacturing Process

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ABSTRACT The mechanical components manufacturing industry is carried out through turning processes using CNC machines. Improving productivity and improving product quality in the CNC process is necessary. Automating operations at the CNC process with Industry 4.0 technology at low cost is a direction in the right direction with the development trend of Industry 4.0 technology. Making decisions to improve CNC processes at operations and implementing continuous improvement is an urgent activity. Industry 4.0 technology helps connect data between customer companies, business sectors, and supply chain partners in a more specific and simple way. Commonly connected data between companies helps decision-makers at each company have a common source of analytical data to make more effective production and business development decisions. Industry 4.0 technologies are the subject of much research, but it is important to consider how to integrate them into the manufacturing world in the most efficient and effective way possible. Manufacturers will benefit from this article's additional insights to solve their problems more effectively. This paper proposes a Hybrid Six Sigma methodology based on Fuzzy TOPSIS and PLS-SEM methods. First, the Fuzzy TOPSIS method helps decision-makers to select problem points for improvement in an unknown environment to implement continuous improvement. Second, the PLS-SEM method evaluates the impact factors of the results of continuous improvement at the mechanical component factory. The Industry 4.0 technology is proposed to be designed, tested, and installed in the CNC manufacturing process. As a result of this study, the product length dimensional error rate decreased from 54.90% per month to zero defects, saving $9593 in annual production costs. Research machines are semi-automatic and cannot increase or digitize their performance because of studies on the application of low-cost Industry 4.0 technology systems to increase the capacity of industrial processes. This study contributes by using Industry 4.0 technology's low-cost way to improve manufacturing processes using the Hybrid DMAIC method in Six Sigma methodology. This hybrid approach is adaptable and can be used with different business process improvement models.

INDEX TERMS Low-cost industry 4.0, productivity, fuzzy TOPSIS, hybrid DMAIC method, PLS-SEM.

NOMENCLATURE

Acronyms	Detail of acronyms
CNC	Computer Numerical Control.
PLS-SEM	Partial Least Squares-Structural Equation Modeling.
IOT	Internet of Thing.
DT	Digital Twin.
MTTR	Mean time to repair.
MTBF	Mean time between failure.

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SMEs	Small and Medium Enterprise.
AHP	Analytical hierarchical process.
DNC	Digital Numerical Control.
SS	Six Sigma.
CEO	Chief Executive Officer.
KPIs	Key Performance Indicators.
SIPOC	Suppliers, inputs, processes, outputs and customers.
RFID	Radio Frequency Identification.
PLC	Programmable Logic Controller.
CBN	Cubic Boron Nitride.
DC	Direct Current.
LabVIEW	Laboratory Virtual Instrumentation Engineering Workbench.
VBA	Visual Basic For Applications.
HMI	Human-Machine-Interface.
SQL	Structured Query Language.
MES	Manufacturing execution system.
ERP	Enterprise resource planning.
QR Code	Quick response code.
HH:MM:SS	Hours Hours:Minutes Minutes: Second Second.
PDF	Probability Density Function.
IT	Information Technology.
CSV	Comma Separated Values.
kHz	Kilohertz.
LED	Light-emitting diode.
THD	Total Harmonic Distortion.
RMS	Root mean square.
AVE	Average Variance Extracted.
CFI	Comparative Fit Index.
HTMT	Heterotrait monotrait ratio.
VIF	Variable Inflation Factor.
CRs	Composite reliabilities.
SMC	System Management Controller.

I. INTRODUCTION

Since 2011, the phrase "Industry 4.0 technology" has been used by businesses from production to business to refer to both production and business activities [1]. It was invented by the German government, is well-known around the world, and enhances the original concepts. The automotive, electronics, metal, mining, and processing industries are among the major ones testing and adopting it, with an acceptance rate of up to 36% [2]. Manufacturing companies in developed countries such as Japan, America, and Europe gradually moved their factories to developing countries such as Vietnam and India to take advantage of cheap labor sources. However, due to the low educational level of the workforce, lack of understanding of the potential for application, and high initial deployment cost, businesses and industries have not thought about testing and installing it [3], [4]. To increase the system's efficiency, researchers must lower investment expenses and further enhance operating functionalities.

For academics and makers of IoT devices, developing solutions to achieve digital transformation (Industry 4.0 technology) for small and medium-sized businesses is a topic worth exploring and funding [5]. Businesses have successfully improved production and business processes by more than 25% thanks to digital transformation, which is the integration of digital technologies into business process improvement. For corporations with large economic resources, investing in the design and implementation of Industry 4.0 technology is not difficult. But for manufacturing companies with low investment capital and companies with low financial potential, designing and implementing Industry 4.0 technology at a reasonable cost is always a top consideration. Multi-criteria decision-making methods for selecting urgent problems for implementing improvements are needed for decision-makers. It is challenging to ask small and medium-sized businesses to make decisions to shift new process operation approaches, especially when the process efficiency of the current business is successful because they lack the qualified employees needed to operate and use Industry 4.0 technology. Researchers need to pay particular attention to this research stage [6].

The digital twin (DT) is a depiction of a production system that uses real-time data elaborations, mathematical models, networked smart devices, and sensory data. It has been used in manufacturing settings to provide a bridge between the offline and online worlds, giving manufacturing businesses a new method for adopting smart production and precise management. The synchronization of virtual and real systems is one of the characteristics of the DT, and its capabilities of conceptualization, comparison, and collaboration liberate us from the physical actual model. The DT can be used in several simulation disciplines (Fig. 1).

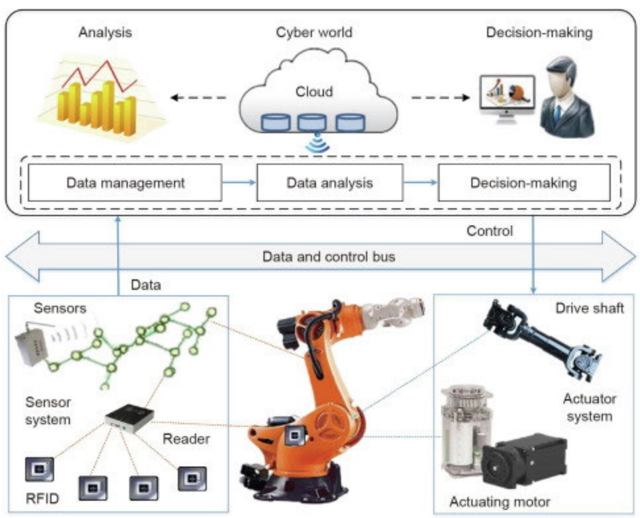

FIGURE 1. Digital twin with a cyber-physical system.

A thorough operational understanding of manufacturing and business processes is required for testing and implementing solutions, and decision-makers should approach Industry 4.0 technology as an intelligent business [7]. The move from Industry 3.0 technology to Industry 4.0 technology is known as industrial digitization. Small and medium-sized businesses should think about integrating digitalization into business process improvement since it provides a chance to boost their company's value, effectiveness, and competitiveness [8], [9]. To achieve high application efficiency, this study suggests a compact digital technology that meets the relevant efficiency for each stage. Even though the data obtained is not a lot or even very much, it is used for data analysis and reaction to produce adequate value for internal or external stakeholders. To be competitive, decision-makers must adhere to Industry 4.0 technology standards.

Cost-effective: Investing in cost-effective business processes will help decision-makers lower the danger of financial wear and tear. Financial risk management is one of their top concerns. Investments in Industry 4.0 technology are being made to raise the level of digitization in business and industrial operations.

The Industry 4.0 technology system is easy to use: While using an Industry 4.0 technology system is easier and more convenient, there are numerous technological difficulties and a still-restricted force level. For small and medium-sized businesses, attacking their business processes is a significant hurdle.

Information-data security: Because it impacts the security of information-user data, information-data security is a major concern in today's digital device business. To guarantee data privacy, researchers and digital device manufacturers should give priority to strengthening security.

Scalability: When implementing Industry 4.0 technology into corporate production processes, decision-makers must consider both the solutions' maturity and the scalability of the devices and systems. To guarantee that the items are prepared for usage, these factors must be considered.

Unobtrusive: To achieve stable efficiency, the operating process requires a minimum value of the MTTR index and a mean time between failure (MTBF). The better it is, the shorter the downtime management time of the production process.

Manufacturing processes using Industry 3.0 technology are designed and implemented individually at each export process. Data at each process is recorded manually depending on the operator's skill and stored separately. Disconnected data makes it difficult for analysts and decision makers in manufacturing business development activities. A DT is a physical item that is made possible by components like simulation software, hardware, data transport, and processing methods, among others. It can be divided into three categories, including phenomenon-based, evacuation and product-related, and social and process-based, based on the simulation's granularity and range of analysis (Fig. 2).

Small and medium-sized businesses frequently adopt Industry 4.0 technology to streamline their production operations. The lack of resources and the requirement for a solution prototype that exemplifies the high responsiveness

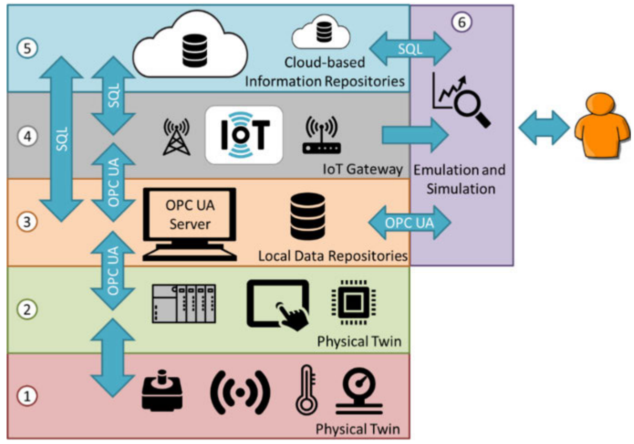

FIGURE 2. The hierarchical structure of digital twins.

and advantages of digitalization, however, place restrictions on them [10]. More than 40% of SMEs have already integrated these solutions and are testing and implementing them in a small portion of their business operations, according to a survey analyzing the preparedness to test and install these solutions. The production process's equipment is closely connected by data, and if the solution is operated correctly, the data information can be enhanced [11].

Decision-making approaches are meant to close this gap since groups of decision-makers frequently assign different priorities to the same evaluation criteria. This problem has a big impact on the final decision-making activity. Multiple fields have adopted the multi-criteria approach for decision support, and numerous researchers have proposed various methods, including the Analytical Hierarchical Process (AHP) [19] and the technique of ranking options based on how closely they resemble the solution ideal law [20]. The most popular method for multi-criteria analysis is the AHP method. Because of its efficiency in handling multi-criteria problems and ease of calculation, the TOPSIS method is also frequently employed to resolve many complicated decision-making situations. Additionally, scholars and professionals can easily understand and AHP method and TOPSIS method due to their seamless construction methods. However, the incapability of the AHP method and TOPSIS method to deal with unclear variables continues to draw harsh criticism. Because a discrete scale from one to nine is used to determine the weights of the various qualities, the AHP method is unable to handle the ambiguity in this decision. Like how the traditional TOPSIS method avoids verbal judgments in favor of clear numerical values, it can encounter difficulties in real-world applications because of imprecise human perception and judgment.

Industry 4.0 technology is a crucial instrument for small and medium-sized businesses to generate consistent financial success. Even though decision-makers do not intend to test and install it into production process improvement, this study assesses the advantages and the immediate effects of doing so. This study focuses on the testing and implementation of Industry 4.0 technology to enhance the production of mechanical goods at a Vietnamese company. With the least additional cost, it offers a digitizing solution for the machining machine operating in Industry 3.0 technology, transforming it into a seamless system between machines in the production process and offering quick and affordable prices [12]. This study serves as a sample for the next installation and testing studies as well as an experimental model. Objectives of the study:

- Integrating the multi-criteria decision-making Fuzzy TOPSIS method and PLS-SEM method into the Six Sigma method creates a continuous improvement model based on the Six Sigma method.
- Design and implement a lower-cost Industry 4.0 technology system to improve CNC manufacturing process operations.
- Improve productivity and product quality to meet customer satisfaction at a mechanical component manufacturing company.
- Measuring user satisfaction with continuous improvement results in CNC processes using the PLS-SEM method.

The structure of this research study is as follows: The status of engaging in testing and implementing industry 4.0 technology (digitization) into production process improvement is examined in Section II together with the internal motivational effects of small and medium-sized businesses in this area. The industry 4.0 technology solution utilized to enhance the production process and utilize Internet of Things (IoT) devices is described in Section III. Section IV focuses specifically on the manufacturing process that was chosen as an Industry 4.0 technology prototype and installation. The operation of an Industry 4.0 technology system and the process for choosing Industry 4.0 technology solutions are described in depth in Section V. Conclusions and suggestions for future research are presented in Section VI.

II. STATE OF ART

Mechanical components are machined from raw steel materials and are processed through many processes (Fig. 3). Each production process is carried out with different production goals and meets different product dimensions and quality parameters. Improve the quality of production processes and improve quality at each production process to meet customer requirements. The Six Sigma method is considered a highly effective tool in implementing continuous improvement activities. The production process is very complex and has many problems that need to be prioritized for improvement. Fuzzy TOPSIS method is an effective tool for decision makers to prioritize problems to make improvements. Industry 4.0 technology designed with low costs is always considered by decision-makers in the company to make continuous improvements.

The lack of enthusiasm among decision-makers in small and medium-sized businesses to test and implement

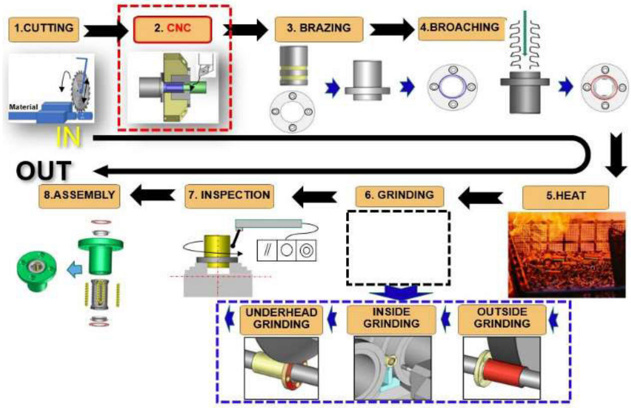

FIGURE 3. Process of products.

Industry 4.0 technology in production process improvement needs to be documented in this study [13]. A study conducted in Germany and China revealed that decision-makers lack the motivation to test and install Industry 4.0 technology because they are unaware of its advantages. However, given that it can result in rapid efficiency, some CEOs think it is appropriate for the production process [14]. The researchers advise decision-makers to experiment with new business processes through testing and installation, but they also need to reserve adequate financial resources to guarantee the security of the sector. It is argued that a better approach is required to the issue of boosting motivation.

Digitalization technology known as ''Industry 4.0 technology'' has the lowest initial investment costs and the quickest business benefits. Through inter-process communication and communication standards, it is used to connect all processes in the supply chain. [15], [16]. By testing and using this technology in production processes, such as by purchasing new machines or retrofitting existing ones with IOT devices, small and medium-sized businesses can gain from it. It is not necessary to purchase numerous devices, and IOT equipment has a cheap investment cost (Fig. 4).

FIGURE 4. Common IOT devices used for Industry 4.0.

Research publications on testing and implementing Industry 4.0 technology into production process optimization,

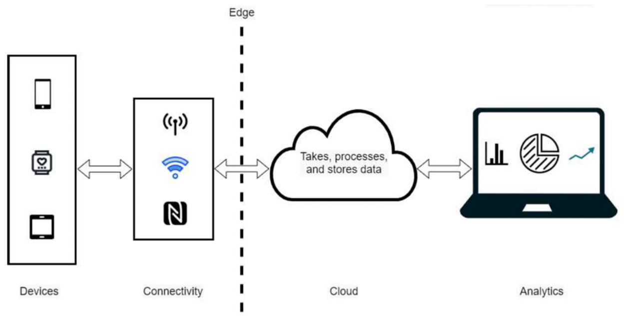

FIGURE 5. The overall architecture of Industry 4.0.

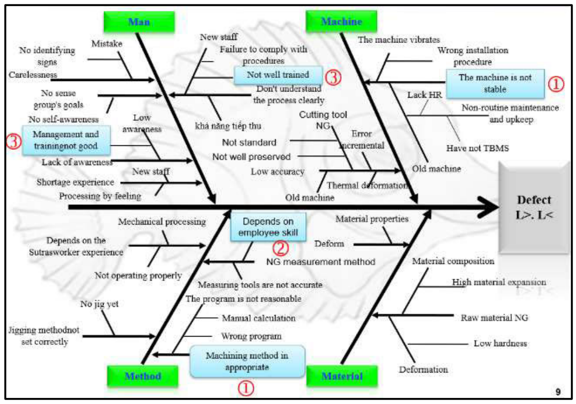

FIGURE 6. Cause-and-Effect Diagram.

as well as research articles using AI and machine learning, because of results of IoT retrofit solutions and studies [17], [18]. IoT sensors are viewed as the perfect instrument for digitizing manufacturing processes since they enable machine operating systems to communicate and exchange data. Automation firms have recognized the advantages of IOT retrofit solutions, which allow the CNC machine to function similarly to new equipment [19]. Examples include Siemens' Siemens IOT2040 gateway and Bosch's XDK sensor. Real-time data collecting capabilities are provided by IOT devices and Arduino boards, which are both digital solutions with cheap initial investment costs (Fig. 5). The Arduino board in the industry 4.0 technology can monitor and measure humidity, temperature, pressure, air, renewable energy systems, keep an eye on the power grid in real-time, and operate motors. The cost of implementing Industry 4.0 technology is a concern for decision-makers.

Using the 5 Whys analysis method combined with the Brainstorm method, analyze the causes of long and short length dimension errors based on the Cause-and-Effect Diagram. The analysis results according to the fishbone diagram show 3 main causes of waste generation. Cause 1 of waste products is due to the machine operator's actions, sewing operations depend entirely on human skills. The second reason is the accuracy in machining, the machining speed is unstable or incorrect, causing waste, and the third reason is that the machine operator chooses the wrong machining program compared to the product code. The product to be machined causes the machined size offset tolerance dimension to be incorrect (Fig. 6).

III. OBJECTIVE, METHODOLOGY, AND DATA OF RESEARCH

A. OBJECTIVE

A company that manufactures mechanical products uses the Six Sigma (SS) methodology to enhance the production process. The Industry 4.0 technology model is implemented using the DMAIC method, which also includes creating instructional materials for using the IOT system, standards for inspection and control of IOT contents, and an overview assessment of operating procedures and management standards on IOT systems [20]. This study aims to increase understanding of the advantages and efficacy of Industrial 4.0 technology when evaluated and implemented in the manufacturing process by decision-makers in small and medium-sized businesses. Additionally, it offers information that can be viewed as supporting evidence for the value of this technology in creating high-quality solutions that satisfy the requirements of low initial investment costs, straightforward and secure operation, avoid upsetting current production processes, and bring high and quick efficiency to boost business value. Although the challenges of testing and implementing Industry 4.0 technology were examined in the preceding portion of this study, the ultimate objective is to improve the digitalization of production processes in processing or manufacturing businesses. According to the operational standards of Industry 4.0 technology, the DMAIC method evaluates the existing state of the business's production processes [21], [22]. To advance process improvement and digitize the entire production process, which brings benefits and the highest level of company efficiency, the production process evaluation stage is tested and installed. The five levels of the automation pyramid—field level, control level, supervisor level, planning level, and management level—each achieve a particular purpose for the digitization of the production process (Fig. 7).

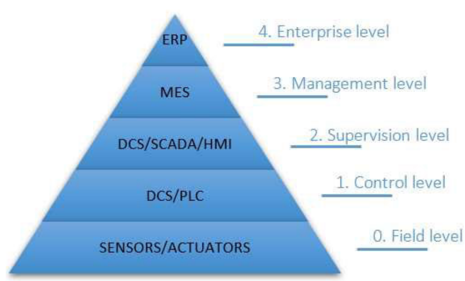

FIGURE 7. The five-layer automation pyramid.

The key distinction between the terms production, process, production process, and define phase is that for issues identified in the define phase, a suitable digitalization plan or model must be proposed to conduct testing and implement

TABLE 1. DMAIC method for Implementing Industry 4.0.

Define phase (D)	Measure phase (M)	Analysis phase (A)	Improve phase (I)	Control phase (C)
Initiative Charter	system evaluation and measurement	flowchart for a process	Brainstorming	SIPOC
Project horizon	Plan for obtaining data	Value stream mapping	**Fishbone Diagram**	Indicator Matrix
economic evaluation	flowchart for a process	examination of cycle times	5W2H	Key Performance Indicator
GRIP evaluation	Reset your income and goals	5 Whys	Indicator Matrix	Poka-Yoke method
customer feedback	Sample	Chart of stratification	Participants' analysis	Checklist
Supply, inputs, processes, outputs and customers (SIPOC)	Key Performance Indicators (KPIs)	Brainstorming	Analysis of investment projects	routine operational processes
	Brainstorm	Fish-bone Diagram	Gantt charts	The meeting
	Ishikawa Diagram	Multi-criteria fuzzy TOPSIS method analysis	routine operational processes	**Digital numerical control**
	Tool for statistical hypothesis testing		Taguchi techniques	**RFID Techniques**
			Sensor signal processing	**Harmonic mitigation measurement**

Industry 4.0 technology into production process improvement [23]. The decision-maker should be the company's CEO, and the solution must be appropriate for production processes and fulfill the needs of each specific organization. Industry 4.0 technology solutions must be able to adapt to the needs of the company's production process as well as to its needs and goals. With the aim of minimizing interruption to the current production process, the digitization system must include additional capabilities to swiftly update and modify algorithms after they are placed in the production process [24]. Customer happiness is a factor in boosting customer satisfaction, and production lead time is vital in the manufacturing process [25]. Factors include enhancing the motivation to implement Industry 4.0 technology to improve the production processes and enhance decision-makers' perceptions of the industry at small and medium-sized businesses.

The synchronization model was developed using stochastic parameters to simulate the synchronization of the IoT's physical environment. It is transformed into deterministic parameters to reconfigure the model and is utilized for experimental mode evaluation for prediction and optimization. The synchronization mode model (Fig. 8) is then fed to the model back.

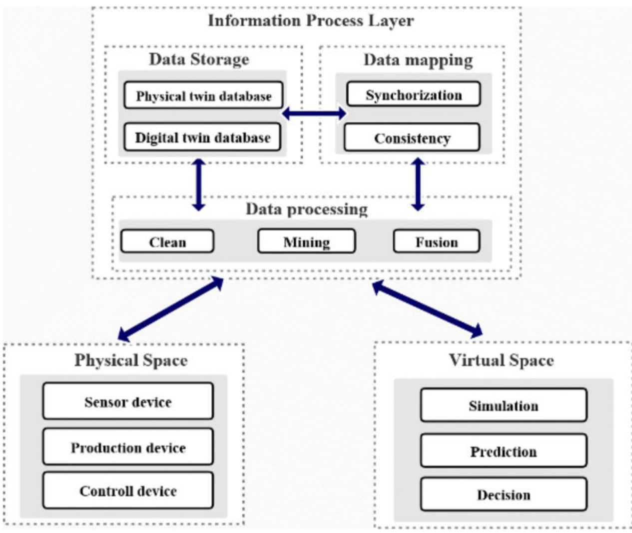

FIGURE 8. Framework for construction of a DT-oriented simulation model.

B. METHODOLOGY

1) SIX SIGMA METHOD BASED ON DMAIC

The DMAIC acronym, which stands for "Define, Measure, Analyse, Improve, and Control," describes the phases of the Six Sigma process and has a defined structure. In many major firms, Six Sigma has been effectively implemented and has grown to be one of the most well-known quality management techniques worldwide. It contributes to efficiency growth, waste reduction, and customer satisfaction enhancement. Data analysis is used to assess the effectiveness of Industry 4.0 technology systems and offers managers information so they may choose whether to update new functionality or include IOT sensors. By performing analysis, improvement, and control, the DMAIC method is utilized to enhance production processes, assisting Industry 4.0 technology solutions in enhancing the production process (Tab. 1).

2) FUZZY TOPSIS METHOD

Fuzzy TOPSIS method, Hwang, and Yoon [26] first presented the TOPSIS method approach, then Chen [27] refined it to consider the usage of Fuzzy numbers and to permit the use of linguistic variables as a means of data collection. A hierarchy of levels is used to distinguish between natural languages and artificial languages as language variables. Specific definitions and assessments of a group of languages are made. When using Fuzzy set theory, managers can gather and incorporate information without verification, missing information, or data that is largely ignored in decision models. A potent method for modeling uncertain systems and obtaining tacit knowledge from professionals in the field is to use Fuzzy sets and Fuzzy logic. The sharp set also includes the fuzzy set as a subset. AHP method is frequently chosen over fuzzy VIKOR method and fuzzy TOPSIS method for picking crucial components in a mechanical manufacturing plant's production department, depending on the situation. Using fuzzy AHP method and TOPSIS method, two have created an evaluation tool for new product development tools for small and medium-sized businesses (SMEs). To classify studies on TOPSIS method, Behzadian et al. [28] carried out a thorough literature review. In the 266 scholarly publications included in the classification method for this evaluation, only one dealt with design improvement, and its emphasis was on process optimization rather than product design. As a result, there isn't much research looking at how to improve the effectiveness and caliber of manufacturing processes utilizing multi-criteria analysis.

Six Sigma methodology is formed because of using the Fuzzy TOPSIS method as a guideline for guidance throughout the decision-making process. Each variable at the grinding stage significantly affects the final product's quality. As a result, it is uncertain whether the priority criterion for product quality improvement action will be met. Our recommendation is to use the Fuzzy TOPSIS method to resolve this unclear situation as a result. On the other hand, there are a lot of myths regarding the Fuzzy TOPSIS method's logical precision of inaccurate inference and approximation inference. First off, Fuzzy TOPSIS method assists in making wise choices in situations when there is ambiguity, insufficient knowledge, conflicting information, partial truth, or partial probability. Second, Fuzzy TOPSIS method may carry out numerous physical and mental tasks without the need for computations or measurements. We apply Taguchi techniques in the Improve phase to improve the state of the option that was prioritized in the Analysis phase. To increase certainty, Fuzzy TOPSIS method specifically prioritizes actions in a hazy environment. In Six Sigma methodology, this is also known as the Taguchi Fuzzy TOPSIS method. We integrate RFID technology into the production process's data collecting and overall information management throughout the Control phase.

Analyze phase: Using Fuzzy TOPSIS method, we decide which option is the best one based on the outcomes of the analysis of the reasons and the results for three potential sources of flaws in the outside diameter. Analyze the problem areas using Fuzzy sets and Fuzzy numbers.

Definition 1: Set Fuzzy set $\tilde{A}$ is a language variable X that is defined as a feature variable in member function variables $\mu\tilde{A}\,(x)$, associated elements x in real number X in the range [1,0], and more. The degrees at which x is a member of $\tilde{A}$ are assumed to be represented by the values of the member function variable $\mu\tilde{A}\,(x)$ [28].

Definition 2: (n_1, n_2, n_3, n_4) is the value of the trapezoidal Fuzzy number $\tilde{n}$ (Fig. 7). and the value of the member function variable $\mu\tilde{A}\,(x)$ is determined in Figure 9 [53]. In terms of trapezoidal Fuzzy, $\tilde{n}$ is equal to (n_1, n_2, n_3, n_4), and in the situation that $n_2 = n_3$, $\tilde{n}$ is referred to as a triangle Fuzzy number. An unfuzzy r is regarded as being expressed as (r, r, r, r). The Fuzzy addition (+) and Fuzzy subtraction (-) of any two trapezoidal Fuzzy numbers are equal to the Fuzzy value of the trapezoid, according to the expansion principle [54]. However, only one trapezoidal Fuzzy number results from multiplying (x) two trapezoidal Fuzzy numbers. The scenario in which any two trapezoidal Fuzzy numbers, such as $\tilde{m} = (m_1, m_2, m_3, m_4)$ and $\tilde{n} = (n_1, n_2, n_3, n_4)$, are formed along with a positive real number r. Form the following main operations on the Fuzzy numbers $\tilde{m}$ and $\tilde{n}$.

$$\tilde{m}\,(+)\,\tilde{n} = [m_1 + n_1, m_2 + n_2, m_3 + n_3, m_4 + n_4] \tag{1}$$

$$\tilde{m}\,(-)\,\tilde{n} = [m_1 - n_4, m_2 - n_3, m_3 - n_2, m_4 - n_1] \tag{2}$$

$$\tilde{m}\,(x)\,r = [m_1 r, m_2 r, m_3 r, m_4 r]\,, r \geq 0 \tag{3}$$

$$\tilde{m}\,(x)\,\tilde{n} = [m_1 n_1, m_2 n_2, m_3 n_3, m_4 n_4] \tag{4}$$

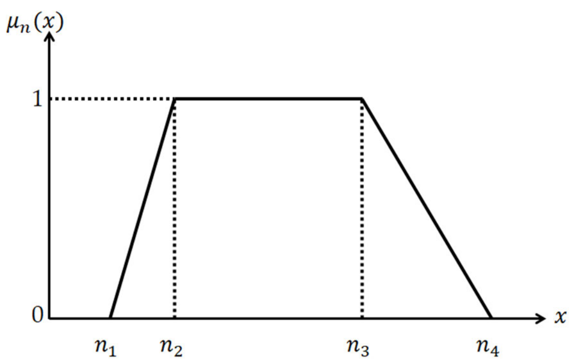

FIGURE 9. The trapezoidal fuzzy number $\tilde{n}$.

Definition 3: A linguistic variable is a variable whose values are expressed in linguistic terms. It is effective in dealing with complex situations or in circumstances where it is not clear enough to be adequately described logically by standard quantitative expressions [29]. The Language Variable Weight, for instance, can be set to very low, low, medium, high, or very high values. This Weight variable can also be used to represent other grave variables.

Definition 4: When there are two trapezoidal Fuzzy numbers, such as $\tilde{m} = (m_1, m_2, m_3, m_4)$ and $\tilde{n} = (n_1, n_2, n_3, n_4)$, formula 5 is used to compute the distance between the two trapezoidal fuzzy numbers.

$$d_v(\tilde{m},\tilde{n}) = \sqrt{\frac{1}{4}\left[(m_1-n_1)^2+(m_2-n_2)^2+(m_3-n_3)^2+(m_4-n_4)^2\right]} \tag{5}$$

The vertex method is a highly effective and straightforward method for calculating the distance between two trapezoidal or triangular fuzzy integers. The case when two trapezoidal fuzzy integers $\tilde{m}$ and $\tilde{n}$ are identical is determined by this vertex approach to be true if and only if $d_v(\tilde{m},\tilde{n}) = 0$. If and only if $d_v(\tilde{m},\tilde{n}) < d_v(\tilde{m},\tilde{p})$, the fuzzy number $\tilde{n}$ is closer to the Fuzzy number $\tilde{p}$ than the Fuzzy number $\tilde{p}$ in a field with three Fuzzy numbers, such as $\tilde{m},\tilde{n},\tilde{p}$ [30].

When using the Fuzzy TOPSIS method to make decisions, the force to select the best options is determined by how far apart they are from a positive ideal solution. This distance value must be greater than that of the negative ideal solution. Problems are organized, classified, have distinct changes, and specific criteria at first. By selecting linguistic variables appropriately, one can assess the significance of the criteria and the actions of the alternatives in relation to the criteria. As part of the model created for the Fuzzy TOPSIS method, we use linguistic variables in this work that are connected to positive trapezoidal Fuzzy numbers [31].

Create a type of Fuzzy ranking and weigh the decision-makers kth accordingly. $\tilde{x}_{ijk} = (a_{ijk}, b_{ijk}, c_{ijk}, d_{ijk})$ and $\tilde{w} = (w_{ij1}, w_{ij2}, w_{ij3}, w_{ij4})$, $i = 1, 2, .., m, j = 1, 2, .., n$. Therefore, the following formulas are used to determine the $\tilde{x}_{ij}$ composite Fuzzy ranking of the options that change depending on each distinct criterion.

$$\tilde{x}_{ij} = (a_{ij}, b_{ij}, c_{ij}, d_{ij}) \tag{6}$$

where:

$$a_{ij} = \min_k \{a_{ijk}\}, b_{ij} = \frac{1}{k}\sum_{k=1}^{k} b_{ijk}, c_{ij} = \frac{1}{k}\sum_{k=1}^{k} c_{ijk}, d_{ij} \min_k \{d_{ijk}\}$$

The following equation can be used to determine the total Fuzzy weight $(\tilde{w}_j)$ of each criterion.

$$\tilde{w}_j = (w_{j1}, w_{j2}, w_{j3}, w_{j4}) \tag{7}$$

where:

$$w_{j1} = \min_k \{w_{jk1}\},$$
$$w_{j2} = \frac{1}{k}\sum_{k=1}^{k} w_{jk2}, w_{j3} = \frac{1}{k}\sum_{k=1}^{k} w_{jk3}, w_{j4} = \min_k \{w_{jk4}\}$$

Below is the composite matrix:

$$\tilde{D} = \begin{array}{c} A_1 \\ A_2 \\ \vdots \\ A_m \end{array} \begin{bmatrix} \tilde{x}_{11} & \tilde{x}_{12} & \cdots & \tilde{x}_{1n} \\ \tilde{x}_{21} & \tilde{x}_{22} & \cdots & \tilde{x}_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ \tilde{x}_{m1} & \tilde{x}_{m2} & \cdots & \tilde{x}_{mn} \end{bmatrix}, \tilde{w} = [\tilde{w}_1, \tilde{w}_2, \ldots, \tilde{w}_n]$$

Positive trapezoidal Fuzzy numbers can be used to approximate the following index values:

$$\tilde{x}_{ij} = (a_{ij}, b_{ij}, c_{ij}, d_{ij}) \text{ and } \tilde{w}_j = (w_{j1}, w_{j2}, w_{j3}, w_{j4}),$$
$$i = 1, 2, .., m, j = 1, 2, .., n$$

To consider the varying importance of each criterion, the normalized fuzzy decision matrix was created as follows:

$$\tilde{V} = [\tilde{v}_{ij}]_{mxn}, i= 1, 2, \ldots, m, j = 1, 2, \ldots, n \tag{8}$$

where: $\tilde{v}_{ij} = \tilde{x}_{ij}(x)\tilde{w}_j$

The value of normalized positive trapezoidal fuzzy numbers for the $\tilde{v}_{ij}, \forall_{ij}$ elements can be approximated using the weighted normalized fuzzy decision matrix. The following are the definitions of Fuzzy positive (A∗) and Fuzzy negative (A^-) ideal solutions.

$$A^* = (\tilde{v}_1^*, \tilde{v}_2^*, \ldots, \tilde{v}_n^*) \tag{9}$$
$$A^- = (\tilde{v}_1^-, \tilde{v}_2^-, \ldots, \tilde{v}_n^-) \tag{10}$$

where,

$$\tilde{v}_j^* = \max_i \{v_{ij4}\} and \tilde{v}_j^- = \min_i \{v_{ij1}\}, i = 1, 2, \ldots, m; \quad j = 1, 2, \ldots, n$$

The following formula is used to compute the distance between the values in each of the A∗ and (A^-) variants.

$$d_i^* = \sum_{j=1}^{n} d_v\left(\tilde{v}_{ij}, \tilde{v}_j^*\right), i = 1, 2, \ldots, m \tag{11}$$
$$d_i^- = \sum_{j=1}^{n} d_v\left(\tilde{v}_{ij}, \tilde{v}_j^-\right), i = 1, 2, \ldots, m \tag{12}$$

where: The distance between two fuzzy integers is referred to as d_v.

For each alternative $A_i, i = 1, 2, \ldots, m$, the coefficients used to establish the rank in the order of one-time alternatives d_i^* and d_i^- have been determined. The ideal solution eliminates the fuzzy (A^-) and the temporality by considering the relative proximity of the opacity, and the coefficient denotes the proximity to the positive fuzzy solution (A∗). The following formula is used to compute the coefficient of closeness to (CC_i).

$$CC_i = \frac{d_i^-}{d_i^- + d_i^*}, i = 1, 2, \ldots, m \tag{13}$$

C. DATA OF RESEARCH

To determine the quality of the best decision, the alternative selection terms are arranged in descending order by the sequential (CC_i) closeness coefficient value calculated from the values of the most significant factor. As a result, it supports the Six Sigma methodology, which involves choosing improvement actions based on the best product quality rankings. Figure 10 provides more information on the Fuzzy TOPSIS method's integration into Six Sigma during the DMAIC method's analysis phase.

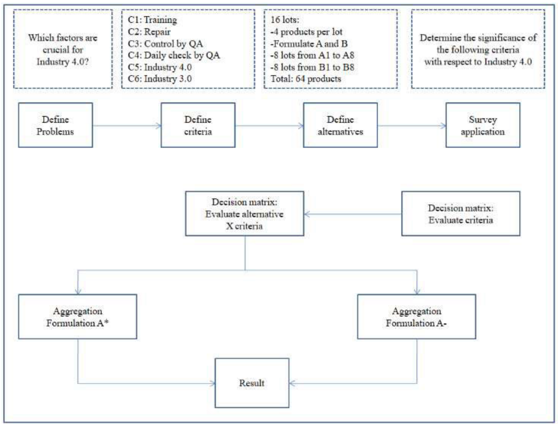

FIGURE 10. **Fuzzy TOPSIS method process for identifying areas for improvement.**

The iteration step establishes the exact criteria for the outer diameter sizing procedure, along with the DMAIC method's relevant Six Sigma methodology requirements based on the information displayed in Figure 8. Six Sigma projects are successful thanks to the ability of its members to work. Their skills and working attitude help the project bring high efficiency. In this Six Sigma project, there are 3 mechanical maintenance staff, 2 electrical system maintenance staff, 5 operators. CNC machine, 2 people supervising 2 off-shift shifts, a production manager (Six Sigma project team leader), 1 data analyst and 2 quality management staff. C1: Training to improve staff capacity, C2: Repairing damaged parts, C3: Controlling the production process by QA staff, C4: Periodic checking by QA staff, C5: Improve production processes according to Industry 4.0 technology and C6 technology: Improve production processes according to Industry 3.0 technology. The operator gathers data when grinding the outside diameter of the blank product while performing alternative identification on the ground. 16 batches of data were gathered at 4 separate time intervals, and 64 products in total were chosen for study based on the criteria C1, C2, C3, C4, C5, and C6. These study samples were representative of various dates, and the researchers described the sampling procedures, giving instructions to the operator performing sampling during the grinding process, and reassessing sample quality. These samples each correspond to 16 different product batches. The lots are subjected to both formulas A and B. Due to a change in the formula, 8 lots were numbered from A1 to A8 for formula A during the study period, and the remaining 8 lots were numbered from A1 to A8 and B1 to B8 for formula B.

The leader educated the operator monthly while recording the outcomes in the skill map, using the operating instructions for grinding processes and materials on grinding process standards. In the subsection labeled "Using scale feedback to adjust size," we employ a scale to determine the separation between the grinding wheel's surface and the product's surface. The tool has been reconstructed to allow for automatic control of the grinding wheel and table. The table is now connected to a servo motor and is controlled by a PLC with digital

TABLE 2. **Language variables give the weight of each criterion.**

Language variable	Fuzzy number trapezoid
None (N)	(0.1, 0.1, 0.2, 0.3)
Very low (VL)	(0.2, 0.3, 0.3, 0.4)
Low (L)	(0.3, 0.4, 0.5, 0.6)
Mean (M)	(0.5, 0.6, 0.6, 0.7)
High (H)	(0.6, 0.7, 0.8, 0.9)
Very High (VH)	(0.8, 0.9, 0.9, 0.9)
Absolute (AB)	(0.9, 0.9, 1.0, 1.0)

numerical control. The instructions on using operation timers are meant to keep track of when each operator's operation is finished. Reducing the number of stone cleaning sessions is advised in the section on using CBN grinding wheels rather than switching to a different kind of wheel. The rock tracing tool has been modified to automatically scan stone surfaces utilizing a DC motor, a digital numerical control program, and an interface for LABVIEW software. During the grinding process, practitioners of the Six Sigma methodology concentrate on improving the quality of the outside diameter of blank products. Members of the SS project team make decisions as well. The criteria for the standard of outer diameter were examined using linguistic considerations by survey respondents who are familiar with the norms and practices of the grinding process. Professional perspectives vary on topics relating to quality outside of the diameter. Table 2 was made using fuzzy integers representing linguistic characteristics that were discovered to be crucial in determining the ranking. Trapezoidal saving functions are used to encode linguistic variables to evaluate them in an uncertain situation [27], [32].

In this study, The samples were valued at a predetermined amount using a certain analytical criterion to compare them to the alternative lot. Each language variable is identified using this outcome. Each sample was related using a range of values that matched the appropriate linguistic variables (Tab. 3).

Analyze the samples for each alternative considering the requirements. The comparable trapezoidal fuzzy number and linguistic factors are used to rate the various alternatives (Tab.4).

Alternatives, decision-makers, language variables, and criteria variables all have definitions. In order to examine the criteria variables, the decision-maker develops a fuzzy decision matrix and gives weights to the criteria variables. Table 5 contains the specifications, and the decision-maker creates the values of the linguistic variable in accordance with each standard connected to the trapezoidal fuzzy number.

The stage 5 results show that C5: Checking the surface automatic grinding Criterion provides outstanding value above all, and decision-makers view it as the most important factor influencing the quality of the outside diameter of the finished blank product after the grinding process. According to the analysis results generated by formulas A and B, decision-makers on the SS project team select the range of measured values. Following that, a value is created for each of the six criteria for each lot of the various formulas using the sample bushels. Using formulas 15 and 16, calculate the

TABLE 3. Range of values for the correlation.

Criteria	Terrible (T)	Very Bad (VB)	Bad (B)	Reasonable (R)	Good (G)	Very Good (VG)	Great (G)
C1	0 – 0.38	0.39 – 0.61	0.59 – 0.81	0.69 – 0.78	0.79 – 1.12	1.21 – 1.32	> 1.5
C2	8 – 9.9	9.5 – 10.4	11.9 – 14.1	14.1 – 15.2	14.99 – 16.04	15.7 – 18.01	> 18.9
C3	0 – 0.38	0.35 – 0.61	0.71 – 0.82	0.69 – 0.79	0.9 – 1.14	1.15 – 1.33	> 1.6
C4	0 – 1.27	1.35 – 2.01	2.0 – 2.48	2.7 – 3.01	3.1 – 3.48	3.6 – 3.98	> 6
C5	< 15.6; > 21	15.5 – 16.01; 19.4 – 20.02	16.2 – 16.6; 19.2 – 19.6	16.7 – 17.01	18.5 – 19.2	17.2 – 17.6; 18.2 – 18.6	17.7 – 18.3
C6	< 6; > 10.6	5.01 – 5.05; 10.02 – 10.5	5.6 – 5.8; 9.5 – 9.8	6.6 – 6.8; 8.7 – 9.1	6.6 – 6.9; 8.7 – 9.2	7.1 – 7.6; 8.2 – 8.6	7.7 – 8.3

TABLE 4. Language variables for evaluating alternatives.

Language variables	Fuzzy number trapezoid
Terrible (T)	(0.1, 0.1, 0.2, 0.3)
Very Bad (VB)	(0.2, 0.3, 0.3, 0.4)
Bad (B)	(0.3, 0.4, 0.5, 0.6)
Reasonable (R)	(0.5, 0.6, 0.6, 0.7)
Good (G)	(0.6, 0.7, 0.8, 0.9)
Very Good (VG)	(0.7, 0.8, 0.8, 0.9)
Great (G)	(0.8, 0.9, 1.0, 1.0)

distances between each alternative and A∗ and A-, as well as the asymptotic coefficient (CC_i) value using formula 17, and then define the values of the replacement options (See Tabs 6 and 7).

The analysis's findings indicate that the A2 index, which is ranked first in Table 6 and has the highest value, has the most noticeable defect value and the most favorable points for exterior diameter quality. As a result, the product quality is steadier and the defect rate is lower, producing a well-analyzed (CC_i) value. A7 and A8 are placed in the second and third positions, respectively, and are distinguished by their similarity of values in Table 7—including the value of the (CC_i) index. Category B3 is ranked first for the analysis results in Table 8 because it produces the best outcomes. The defect rate of the corresponding value, however, is greater than that of formula A, and the value of (CC_i) is greater than the analytical result of formula A.

In this study, we suggest using the Fuzzy TOPSIS method approach to help LSS method project team members make decisions. In an uncertain environment, improvements found during the analysis phase are combined with the analysis results to improve the grinding process. The LSS team received help from fuzzy TOPSIS method in choosing option C5 as the initial improvement.

To assist managers and decision-makers in understanding the operational health of the machine in real-time and the present situation of the business, production process data is collected and evaluated (Fig. 11). To better the digitization of the production process, analytical data is visualized by analysis charts and information is retrieved based on monitoring criteria. The entire process being modeled enhances digitization across the board and lowers expenses for the business.

Instead of using the actual data, random data inputs are employed to create simulation models. The simulation

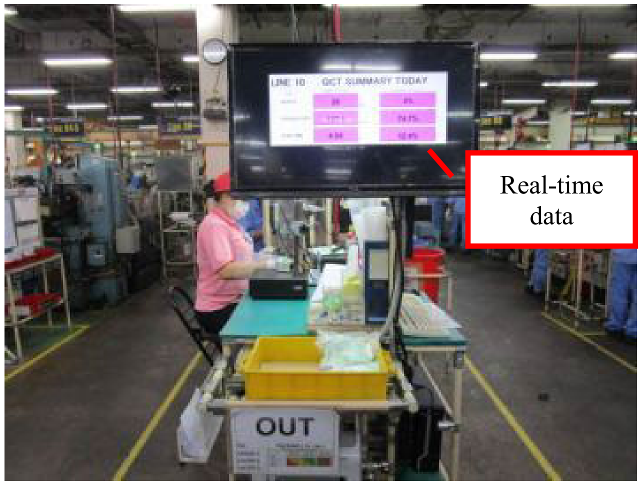

FIGURE 11. Industrial's Real-time visual management.

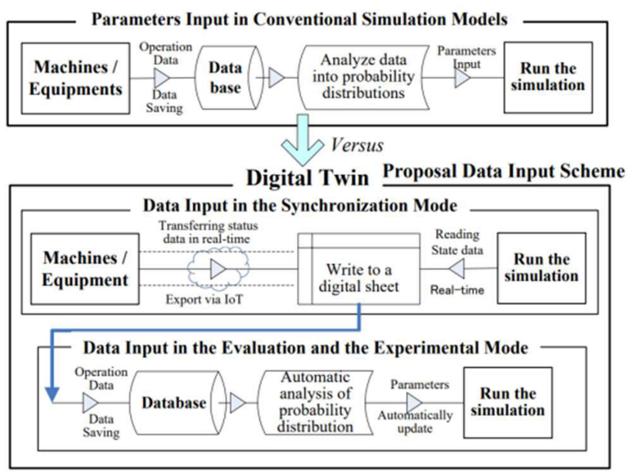

FIGURE 12. Proposal of data input scheme for simulation models in a DT.

model's input is given as distributions, particularly for processing time and interval time, like the triangular distribution and the normal distribution. This causes the execution outcomes (outputs) to be random. Analysis of the model's outputs from repeated execution is important to provide statistically meaningful results. However, when building the synchronization mode (the real-time simulation) in DT, the simulation must be executed at the actual-time advancing speed; as a result, it is crucial to minimize introducing unpredictable parameters into the model. The data input method

TABLE 5. Evaluate the criteria of the decision maker.

Criteria	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10	Fuzzy composite weight ($\widetilde{w}_j$)
C1	VH	M	H	VH	H	M	H	AB	H	AB	(0.39, 0.58, 0.81, 0.99)
C2	H	H	M	VH	M	M	M	H	L	H	(0.41, 0.61, 0.70, 1.00)
C3	M	M	H	VH	M	H	M	AB	M	H	(0.39, 0.59, 0.71, 1.00)
C4	M	H	M	H	M	M	M	M	VL	H	(0.21, 0.71, 0.65, 0.91)
C5	**AB**	**AB**	**AB**	**M**	**M**	**VH**	**H**	**VH**	**VH**	**AB**	**(0.6, 0.74, 0.79, 1.00)**
C6	H	M	M	M	L	VH	VH	VH	H	AB	(0.29, 0.59, 0.71, 0.99)

TABLE 6. The results obtained for the formula A.

Formulation A	d_i^*	d_i^-	CC_i	Ranking	Defects (%)
A1	4.001	3.512	0.432	8	16.6
A2	4.101	2.991	0.487	1	10.5
A3	3.596	3.514	0.501	6	15.1
A4	3.721	2.454	0.510	5	17.12
A5	3.699	2.712	0.401	7	17.02
A6	3.532	3.023	0.521	4	11.99
A7	3.561	3.145	0.524	3	10.98
A8	3.571	3.331	0.501	2	10.17

TABLE 7. The results obtained for the formula B.

Formulation B	d_i^*	d_i^-	CC_i	Ranking	Defects (%)
B1	4.412	3.345	0.512	6	14.6
B2	4.013	3.551	0.534	7	15.1
B3	4.154	4.103	0.535	1	10.2
B4	3.989	3.517	0.528	4	13.3
B5	4.091	3.845	0.581	8	16.2
B6	4.109	3.763	0.521	3	15.7
B7	4.215	4.103	0.591	2	12.9
B8	4.304	3.841	0.535	5	14.6

for simulation models in actual production systems (DT) is suggested in this research. The simulation model aggregates and stores the status data it has extracted from the digital sheet in a database using a numerical sheet, such as an Excel sheet. The historical data kept in the database is then read using the evaluation and experimental modes of the DT, and the fitted probability distribution parameters are then entered into the simulation model. This is a crucial element to consider when building a synchronization mode in DT because it ensures the data isn't too terrible (Fig. 12).

D. INFORMATION OF HARDWARE

Industry 4.0 technology can be implemented in a variety of ways, depending on factors including production process complexity, deployment scope for durability, and production process readiness [33], [34]. The hardware components of the Industry 3.0 technology deployment solution enable quick performance measurement of the production process.

- *Cost-effectiveness:* Because Industry 4.0 technologies are not cost-effective, they cannot satisfy the demands of decision-makers, which has an impact on the efficacy of production processes.
- *Simple-Industry 4.0 technology implementation:* The most crucial idea is that small and medium-sized businesses must have a simple-Industry 4.0 technology implementation strategy to guarantee quick efficiency and simplicity with human resources that are only moderately skilled.
- *Unobtrusive:* The most crucial point is that Industry 4.0 technology doesn't interfere with factory operations, and IOT devices don't alter how production processes, machine operations, and operation processes operate.
- *Scalability* is the process of digitizing the manufacturing cycle from testing to installing to mass production, necessitating the horizontal and vertical deployment of Industry 4.0 technology systems. This necessitates testing all production processes and synchronized data synchronization.
- *Data security* is ensured by Industry 4.0 technology, which offers a data-binding solution for all manufacturing processes. This prevents production from being disrupted by insecure data.

E. INFORMATION OF SOFTWARE

Firmware and cloud applications are the two key parts of Industry 4.0 technology's embedded software, which employs sensors to connect, process, and analyze data. For the user to confirm, it must be able to adjust to the production process and visualize data.

- *Effective at saving money:* The firmware of IoT devices, which is open source and gathers data from enormous memory, often includes Industry 4.0 technologies. To support big data calculations, data must be kept in enormous amounts of memory. Users will need to buy an additional cloud application to accomplish this.
- *Simple deployment of Industry 4.0 technology solutions:* Different testing and implementation are needed for Industry 4.0 *technology* solutions. To fast provide benefits, they improve the production process as well as the deployment process and system operation.
- *Scalability* is a property of IOT devices made possible by the open-source design, which enables simple function additions and extensions as well as firmware embedding. This offers an easy fix for Industry 4.0 *technology* systems, which can react to actions linked to several different devices in various production processes. Data collected from numerous IoT device types is saved using a customizable open-source cloud application.
- *Speed of development:* Hardware used in Industry 4.0 technology solutions is tested and installed in two processes, testing and installation. Hardware can be certified for production use and set up with ease using this deployment method. The commercial market uses IoT devices, and the solutions are created with straightforward operating functions in mind.
- *Security:* As they store data and connect it to IOT devices to execute data collection and saving, cloud applications and data collection are crucial for data security. Future researchers should be particularly concerned about data security since it helps shield data from hackers.

Modern hardware and software are needed for IOT solutions, which are crucial for industrial automation. Companies like Siemens, ABB, and Bosch offer IoT devices. However, using them is challenging for decision-makers due to their high initial investment prices and the length of time needed for their deployment, testing, and installation [26]. This makes using Industrial 4.0 technology to enhance their production process much more challenging for small and medium-sized businesses. Using electronic components like Arduino boards and open-source microcontrollers, an entry-level Industry 4.0 technology prototype solution is taken into consideration. The Raspberry Pi board is a great option for industrial manufacturing, but it must adhere to strict safety standards against circumstances like intense vibration, high temperatures, low humidity, oil vapor, cooling steam, and other harsh conditions. It has a lot of shortcomings and hasn't complied with the current board's safety standards.

To broaden the operational reach of the manufacturing process after testing and deploying it throughout the whole manufacturing process, this study suggests a strategy to produce Industry 4.0 technology primary prototypes utilizing IOT devices on the commercial market with low initial investment costs. With inexpensive IOT equipment, our Industry 4.0 technology prototyping solution satisfies production process operating standards and is simple to install and use. It employs Python, an open-source programming language that supports objects and object-oriented programming and is well-liked for embedded programming. The Arduino board's processing speed is increased when Python programming is used. To analyze data and display it using analytical charts, the system is integrated with SQL programming. To guarantee operational security and data privacy, quality control is essential. When Excel received a signal from the Arduino and immediately recorded the receipt time in a worksheet, the Excel VBA application was created. The program estimated the time difference between the current time and the previous time if the reaction sensor was not Sensor, then it recorded the interval times onto a worksheet. EasyComm, a VBA module, received the signal through serial connection. The Excel processing logic flow is controlled by the VBA application (Fig. 13).

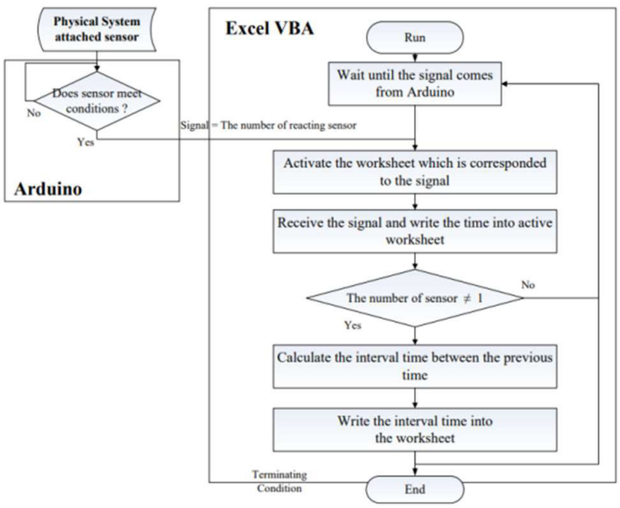

FIGURE 13. The flow of processing logic of the Excel VBA program.

IV. CASE STUDY FOR IMPROVEMENT PRODUCTIVITY IN MECHANICAL FACTORY

The improvement of digital conversion at CNC machines in the manufacturing of cylindrical product dimensions is the main topic of this study. To satisfy the requirements of the IoT device application to collect data such as machining conditions, machining condition parameters, product dimensions, power supply, IOT devices, and control devices, Industry 4.0 technology solutions are tested and deployed. Real-time graphs and graphical visualizations are created from the analysis of the sensor data.

Improvement process goals include enhancing the manufacturing process, cutting waste, preventing workers from selecting the incorrect machining program, and enhancing productivity, efficiency, and product quality. Industry 4.0 technology solutions are required to achieve these goals. Before the heat process, the product length and material hardness are processed using CNC machines. A disruption in output at the CNC stage will have an impact on the output throughout the entire production process. By increasing decision-makers' awareness of their use throughout the whole manufacturing process, these solutions assist boost corporate operations' efficiency.

A description of the CNC machines' production process: The cylindrical product length dimension must have a tolerance of +/-0.010mm, which necessitates accuracy in manufacturing and guarantees the least amount of material removal. The machining software calls the cutting tool, which is fixed to the machine's spindle. Both the employee's hand and memory must be used to choose the order name. Even in severe circumstances, the improper order name or recall of the wrong order name might have an impact on the processing equipment's performance and product quality.

By measuring the first product dimension using a callipers type 0-500mm and comparing it to the standard size given in the CNC process, the employee re-enters parameters for the machining program. Although this is done manually, the operation's flaws have been identified, including the offset amount and parameters, which are crucial information.

Results of the product length (L) measurement indicate that 54% of defective items have L that is above norms and 22.8% have L that is below requirements. Between September 2021 and March 2022 is the timeframe (Fig. 14). Due to a disruption in the production process, scraps were produced at the CNC stage, with an average lead time of 9.1 days, which was longer than desired (less than 7 days). The goal of Industry 4.0 technology is to decrease waste, boost productivity, enhance product quality, and raise customer satisfaction.

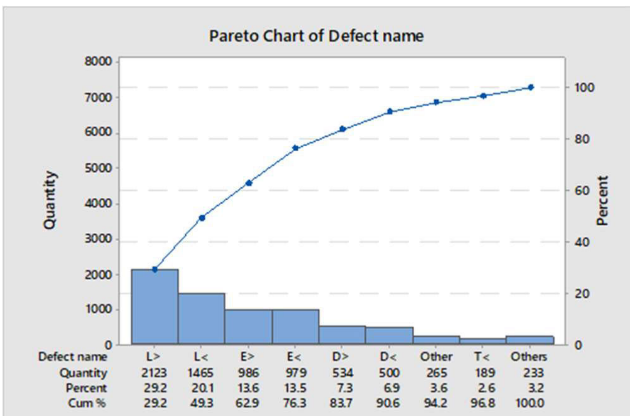

FIGURE 14. Pareto chart of defects at CNC process.

Study of the items in detail before digitization: The primary axis of a CNC machine is the primary axis, where the cutter positions are set in place. The inappropriate machining program is chosen, the knife cutting edge vibrates due to the precision of the spindle, and the machine operator is left with a tolerance standard deviation of +/-0.010mm. When machining the product's length dimension (L), this is the factor that needs to be considered the most.

To control the processing process for the CNC machine, the employee measures the length of a product with a 0-700mm callipers and notes the initial product measurement result in a check sheet. The machine's machining program settings are adjusted using this data, although all three operations run the danger of producing waste: To call the machining program from CNC, employees must enter the product name into a control panel. The staff remembers the length of the first product and how to operate the CNC machine's machining program parameters by entering offset parameters into the control panel screen. They measure the length of the product with a 0-700 mm callipers and memorize measurements, then record the results in a manual production control check sheet.

According to the POKA-YOKE theory, all CNC machine operator operations require a suitable instrument to monitor, assess, and verify processes. This hypothesis states that there is no reaction and that there is a very high chance that waste will be produced during the production process.

Analyse the production process's present state: A cylindrical product line's manufacturing process is not yet using an Industry 4.0 technology solution. To achieve the objective of having a thorough understanding of the complete production process, this study assesses the entire production process in accordance with the automation tower's specifications. Data visualization at the CNC machining process and the goal of a hundred packaged solutions are the foundations of the first three stages of the automation pyramid, while the scaling up of industrial solutions is the objective of the final two layers. When evaluating and implementing these solutions, the production procedure is in-depth.

The primary axis of the CNC machine, the cutting tools, the control screen, the choice of the CNC machining program, the measuring tools, and the areas that need to be checked for operational conditions are all under the control of the field class. A meter and pressure gauge are included in the production process to regulate the power supply and other machinery. All measuring tools and equipment are gathered and listed on a check sheet that will be manually controlled.

Power quality meters, Mitsubishi PLCs, DCs, and IoT devices are examples of devices in the controller class that include memory and programming. They collect real-time data from sensors and relay it to the top levels to support the manufacturing process.

Connecting to the control layer and carrying out the task of seeing the output from the layers, such as the controller class, is the responsibility of the monitoring class. To stay informed about the status of production results in real-time, all firm employees watch the information results displayed on television displays or other monitoring screens placed at the company's production processes. The monitoring layer comprises tools to improve the performance of the above levels, such as HMI control room monitors, the online control panel, and the internal internet.

The production execution system (MES) layer or the planning iteration layer The MES layer carries out the data exchange protocol from the control layer with the MES software at the SQL system, which is updated often and sends precise and detailed production plans to each individual production process. For a production to be successful, real-time monitoring and control of actual performance are required.

The management layer or the iteration layer of enterprise resource planning (ERP) Device configuration for RFID, barcode, and data communication sensors falls within the management layer, commonly referred to as the ERP layer (Fig. 15). Under the direction of the company's information technology department, ERP executes the data exchange protocol between production processes and adjacent departments, as well as with suppliers. This layer quickly and centrally streamlines stakeholder communication and data analysis tasks (Fig. 16).

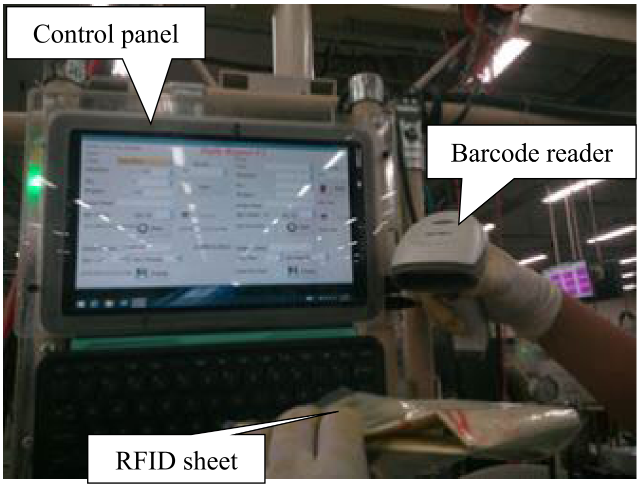

FIGURE 15. RFID input data system.

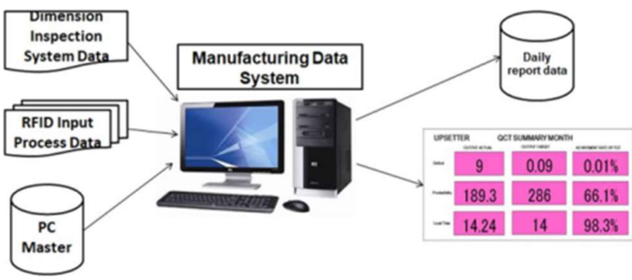

FIGURE 16. Enterprise resource planning (ERP) system.

Three main activities are performed to test the production process at the CNC machine and install the Industry 4.0 technology system: automatically starting the DNC machining program, using the online inspection system to monitor machining conditions and evaluate product quality after processing, and connecting production plan data from the SQL server to the machinery at each production process connected with the inspection system. This aids in real-time manufacturing output control and decision-making on the addition of processing for damaged goods.

Choosing a digitizing toolkit, The CNC manufacturing process uses machining equipment that adheres to Industry 3.0 technology standards. The operator chooses the cutters based on the machining needs and mounts them on the dock. The operator manually examines whether the cutting tools are affixed to the standard mound by vibration. A digital numerical control (DNC) system is utilized to manage the tightening force of the blades attached to the mound, and a QR Code system is proposed to be used to automate the two activities. The system is anticipated to meet the required requirement of 100N–200N.

To choose the incorrect CNC machining program, the CNC machine operator must define several associated factors, which lengthens the handling process and production lead times. For every broken cutting tool, the accuracy of the machine mound deviates by 0.007mm from the precision specified by the factory, according to analysis results of monthly maintenance of CNC machines. Each time the machine breaks the cutting tools, the accuracy rises to 0.012mm, boosting the machine's productivity to 0.005mm. In this study, it is suggested that a digital numerical control system be set up, tested, and used automatically.

Along with Using a caliper to measure the length of the product and record the measurement results, the employee writes the results of the CNC process's machining on the check sheet. The machine operator must do this operation manually, and there are several possible dangers involved, including inaccurate measurement, no measurement, incorrectly recording measurement findings, failing to record measurements, and failing to measure the outcomes. This problem needs to be managed and controlled by managers.

This study suggests testing and installing an automatic test system by connecting measuring devices using IOT technology and connecting all devices since measurement data monitoring product quality during production is not guaranteed. Measurement results are evaluated by the online measurement system using data entered the same SQL database.

Development of an Industry 4.0 technology solution: Manufacturing CNC machines demands cutting-edge power electronics and close coordination between the hardware and the controller. It is advised that the cutting tools' precision be less than 0.005mm. The operator must manually operate on the CNC machine's control panel screen to choose and call a CNC machining program. The data and order names from the linked production system are connected to the SQL server using an algorithm that interfaces with the barcode reader. The consumer then needs to check the information about the order name with the QR code that launches the program from memory.

The system of a CNC machine has advantages like increased durability and efficiency: Reduce reliance on operator emotion and expertise. To increase efficiency and shorten the lead time for production, digitize outsourcing operations. Systems based on Industry 4.0 technology offer machine operators and solution users' significant levels of efficiency and ease. Tools, scraping, and other expenses can all be reduced to lower production costs. Industry 4.0 technology systems need to be simple to maintain and Industry 4.0 technology installations that increase consumer trust and dependability by enhancing customer satisfaction.

IOT-based Industry 4.0 technology systems feature drawbacks such poor data security, a high response rate, and sluggish data transmission. Researchers are researching towards creating an information network that performs better and is superior to 5G information networks to address these problems. The biggest problem with their performance, though, is the information connection loss brought on by faulty communication cables. This can cause delays or even cause IoT devices to crash in Vietnam and other nations.

Using a screw belt and digital torque, measurement data is transmitted to an online measuring system. Except for the SQL system is locked if the torque measurement results are not fulfilled, the online test system detects the tightening force results of cutting tools and saves them in real time. The key information in the terms "safety requirements," "SQL," "measuring," "data," and "safety" is that the CNC machine operator must first ensure that the machine complies with safety standards before calling the appropriate product processing program based on the product's name and kind. It will be locked if the machine operator calls the product's machining program erroneously when compared to the program to check the cutting tools. The operating system's data must also be connected to an online measurement system, and all data must be saved to SQL in real-time.

The machine operator enters data using the barcode analysis protocol into the processing program package utilizing the barcode reader system. It arranges date and time, separates production numbers from production order numbers, and inserts barcodes for each stage of the manufacturing process. It also organizes customer order numbers, company production numbers, date, and time. To start the machining program at the appropriate production process and lock the system in case of machining, the machine operator then reads the bar code on the processing order.

According to the IOT protocol, all measurement devices are connected to a system for sizing products using the same protocol. The operation of the measuring system and the network system's transmission function are assessed by the communication system. The goal of this research is to create knowledge that will help the Industry 4.0 technology system develop. Through C# programming, Arduino control, and connection tools, the client can configure the measurement dimensions from the measuring system to the control screen (Fig. 17). If the data does not match the dimensions, the system screen is locked, and the measuring process is stopped. The route is set up in accordance with the customer's specifications for product size tolerance. Based on the POKA-YOKE hypothesis, IoT solutions are tested and installed to increase manufacturing process efficiency and reduce the risk of issues brought on by operator skills.

Data from IoT devices used in the CNC manufacturing process are processed in real-time to gather and show data on screens for all process operators. Operators of production

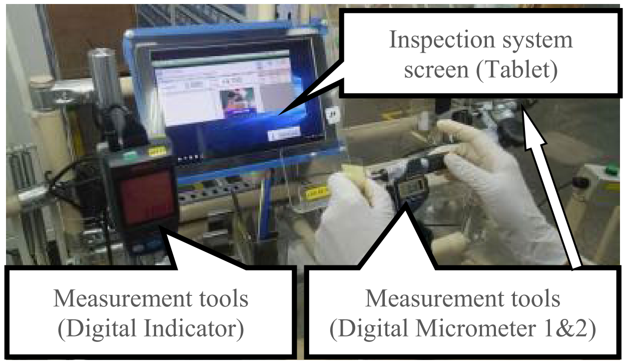

FIGURE 17. Screen measuring system.

lines or production managers can zoom in, out, or slide through time to view historical data or data that is needed later by a data analyst. The data is set to scroll according to the time given for each screen, and it is presented on the screen in the format HH:MM: SS (Fig. 18). Data readers can modify the state of the data table as desired by using the pause or enter buttons on the table. The customer's needed standards, production objectives, and potential anomalies at each stage of the manufacturing process are included in the data and data analysis graphs that are logically organized and transferred on the screen. The key points of the terms "production process," "remote monitoring," "response speed," and "recognition" are that remote monitoring can spot a weakness in Vietnam when the production process is disrupted, but that the internet system must be stable and that the response speed must be quick and reliable, which is a weakness.

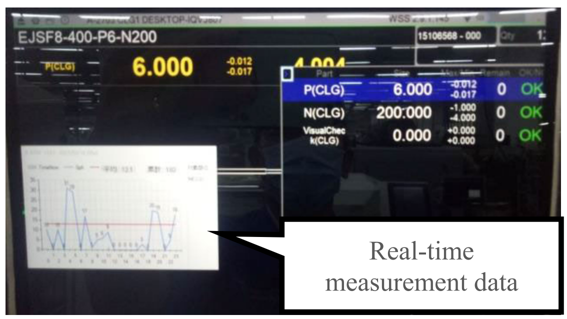

FIGURE 18. Real-time data on the Screen.

Verify the outcomes of continuous improvement initiatives: Industry 4.0 technology solutions are swiftly tested, set up, and completed according to schedule. With the aid of these solutions, businesses can gather and monitor performance data in real-time for each stage of the production process, including successful and damaged goods, and broken cutting tools, and other irregularities. It is not considered in management to prevent machine failures, prevent manufacturing waste, and monitor worker safety. If the product is longer than the normal length, it is anticipated that up to 54% of product length problems and a delivery delay rate of 9.1 days in comparison to the target of 7 days will be corrected. For testing and installing this system, decision-makers should authorize Arduino boards (Fig. 19).

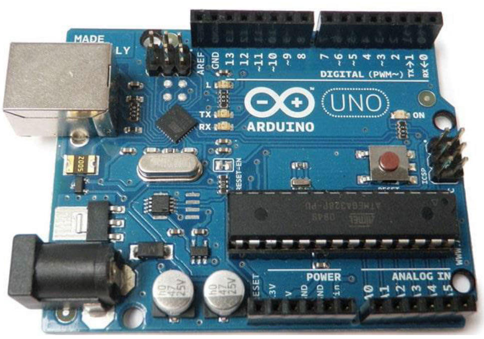

FIGURE 19. Arduino boards for Industry 4.0 system.

Production supervisors can keep a close eye on the CNC production procedures to spot any oddities or potential dangers. By accessing sensor data and reviewing recent analyses of the manufacturing process, Industry 4.0 technology solutions facilitate communication between production managers and decision makers. This technology enhances operator cooperation, communication, and satisfaction, enabling management to identify common patterns and enhance other production procedures. Additionally, it helps decision-makers have more faith in the outcomes of their use of Industry 4.0 technology to remotely monitor work.

Use the Weibull and Beta distribution to model the lifetime of an Industry 4.0 technology system and the uptime of an Industry 4.0 project. The question is for the Industry 4.0 technology system to work for 20 hours without damage and the time it takes to test the Industry 4.0 technology system at the NCL machine is within 20 hours. A Weibull random variable is a continuous random variable used to model the lifetime of an Industry 4.0 technology system given the past operating time of an Industry 4.0 technology system and uses two parameters (alpha and beta) to define a Weibull random variable to estimate the time the Industry 4.0 technology system operates without generating errors.

Beta is a continuous random variable used to iteratively model the duration of an activity, with estimates of the minimum duration, maximum duration, mean duration, and standard deviation of duration.

A Weibull random variable's probability density function (Eq. 14)

$$f(x;\lambda;k) = \begin{cases} \frac{k}{\lambda}\left(\frac{x}{\lambda}\right)^{k-1} e^{-\left(x/\lambda\right)^{k}}, x \geq 0 \\ 0, \quad x < 0, \end{cases} \tag{14}$$

where, k: shape parameter, λ: scale parameter

Alternative parameterizations detected in the Weibull distribution are of two types. The first alternative (Tab. 8) is Applications in economics and medical statistics frequently use distinct parameterizations and the Second alternative (Tab. 9) is the shape parameter k is the same as in the stance shape parameter k is identical to that in the common case.

TABLE 8. Step by Step of the first alternative.

Step	Explain detail step by step
Step 1	Calculate the value of the probability density function (Eq. 15) $f(x;k,b) = bkx^{k-1}e^{-bx^k}$ (15)
Step 2	Calculate the value of the cumulative distribution function (Eq. 16) $F(x;k,b) = 1 - e^{-bx^k}$ (16)
Step 3	Calculate the value of the hazard function (Eq. 17) $h(x;k,b) = bkx^{k-1}$ (17)
Step 4	Calculate the value of the mean (Eq. 18) $b^{-1/k}\Gamma\left(1+1/k\right)$ (18)

TABLE 9. Step by Step of the Second alternative.

Step	Explain detail step by step
Step 1	Calculate the value of the probability density function (Eq. 19) $f(x;k;\beta) = \beta k(\beta x)^{k-1}e^{-(\beta x)^k}$ (19)
Step 2	Calculate the value of the cumulative distribution function (Eq. 20) $F(x;k;\beta) = 1 - e^{-(\beta x)^k}$ (20)
Step 3	Calculate the value of the hazard function (Eq. 21) $h(x;k,\beta) = \beta k(\beta x)^{k-1}$ (21) Where, $\beta = 1/\lambda$

A generalized gamma distribution with both shape parameters equal to k is known as a Weibull distribution. There is an additional parameter in the translated Weibull distribution (or 3-parameter Weibull). The probability density function is present. Before the standard Weibull process starts, value specifies an initial failure-free period. This simplifies to the 2-parameter distribution $\theta = 0$. Evaluation of the operating life of this Industry 4.0 technology system includes 2 parameters, error-free operation time, and on each Industry 4.0 technology system, the Second alternative of Weibull distribution should be selected to calculate the operating time in 20 error-free hours of Industry 4.0 technology systems.

The three-parameter exponentiated Weibull distribution with an additional exponent of one is a specific instance of the Weibull distribution, which is typically sufficient in reliability engineering. Monotone, bathtub-shaped, and unimodal failure rates can all be accommodated by the exponentiated Weibull distribution. The generalized extreme value distribution, which is named after this work and has the probability density function, is a special case of the Weibull distribution (Eq. 22).

$$f_{Weibull}(x; -k, \lambda) = \frac{k}{\lambda}\left(\frac{x}{\lambda}\right)^{-k-1} e^{-(x/\lambda)^{-k}} \tag{22}$$

A poly-Weibull distribution is the distribution of a random variable that is defined as the minimum of many random variables, each of which has a unique Weibull distribution. Rosin and Rammler used the Weibull distribution for the first time to characterize particle size distributions. It is frequently used in the processing of minerals to characterize the distribution of particle sizes during comminution. The cumulative distribution in this instance is represented by Eq. 23.

$$f\left(x; P_{80}, m\right) = \begin{cases} 1 - e^{\ln(0.2)\left(\frac{x}{P_{80}}\right)^m} & x \geq 0, \\ 0 & x < 0 \end{cases} \tag{23}$$

where, x: Particle size, P_{80}: Particle size distribution, m: parameter of the spread of the distribution.

The Gamma distribution exhibits similar geometries for the same values of k, whereas the Weibull distribution is more platykurtic. K can be thought of as Lévy's stability parameter from the perspective of the Stable count distribution. When a Laplace distribution or a Weibull distribution serves as the kernel, a Weibull distribution can be reduced into an integral of kernel density (Eq. 24).

$$F\left(x; k, \lambda\right) = \begin{cases} \int_0^{\infty} \frac{1}{v} F(X; 1, \lambda v)((\frac{1}{k} + 1)\delta_k(v))dv \\ \int_0^{\infty} \frac{1}{\mathrm{s}} \mathrm{F}\left(\mathrm{x}; 2, \sqrt{2}\lambda s\right)\left(\sqrt{\frac{2}{\pi}}\boldsymbol{\Gamma}\left(\frac{\mathbf{1}}{\boldsymbol{k}}+\mathbf{1}\right)\right)\mathrm{V_k(s)} \end{cases} \tag{24}$$

where, $\delta_k(v)$: stable count distribution, $\mathrm{V_k(s)}$: stable vol distribution.

The experimental data table of the Industry 4.0 technology system at 7 NCL machines at the parent company in Japan (Tab. 10), shows that the average operating time of the Industry 4.0 technology system is 18.684 hours, and the standard deviation of the duration of Industry 4.0 technology system operation is 7.400 hours.

TABLE 10. Industry 4.0 system full-time data.

No.	Industry 4.0 system	Time (Hours)
1	Industry 4.0 system 1	8.50
2	Industry 4.0 system 2	12.54
3	Industry 4.0 system 3	13.75
4	Industry 4.0 system 4	19.75
5	Industry 4.0 system 5	21.46
6	Industry 4.0 system 6	26.34
7	Industry 4.0 system 7	28.45
	Maximum	28.45
	Minimum	8.50
	Mean	18.648
	Sigma	7.400

Random variables of the Weibull distribution are used to calculate the operating life of the devices and the author of this study used the Weibull distribution to calculate the operating life of the Industry 4.0 technology system. Weibull random variable determines two parameters alpha and beta. Applying Weibull to the above data table results in an Industry 4.0 technology system operating well over a period of 18.68 hours with a standard deviation of 7.40 hours.

In this case, the Weibull density for 20 hours is twice the Weibull density for 10 hours. This indicates that the Industry 4.0 technology system will experience more failure when operating for 20 hours than a system operating for 10 hours. Applying the formula for calculating the area in the Weibull distribution according to the PDF distribution (Eq. 14) shows the time period for the Industry 4.0 technology system to fail after 15 hours of operation. This proves that the Industry 4.0 technology system will work and there is a possibility of failure from 15 to 20 hours. Experimental research results using the Weibull distribution provide input results for information technology engineers to set up periodic maintenance plans for Industry 4.0 technology systems to help improve efficiency and stability in the operations dynamics of the Industry 4.0 technology system.

The Industry 4.0 technology system maintenance plan is integrated into the online inspection system through digital numerical control (DNC) method and the system automatically locks when it is time for the system to be maintained appears (Fig. 20) and the whole system is locked, only after the system is maintained and unlocked by IT staff, the system can be operated again (Fig. 21). Maintenance data, results of Industry 4.0 technology system operating conditions are saved to the SQL database system and easily retrieved by .CSV files from the system.

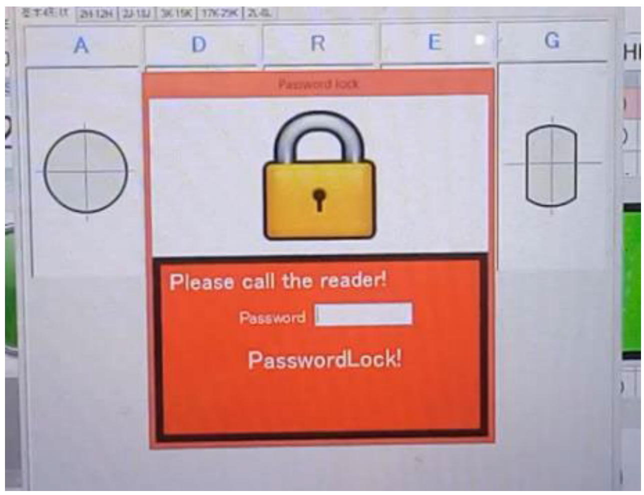

FIGURE 20. System maintenance request screen.

V. RESULT AND DISCUSION

A. RESULT

Due to the diverse working and cultural norms of every country, the production process of Industry 4.0 technologies poses a complex challenge for small and medium-sized businesses in the host nation [36]. Continuous progress is severely hindered by the fact that businesses in poor nations frequently construct industrial facilities using out-

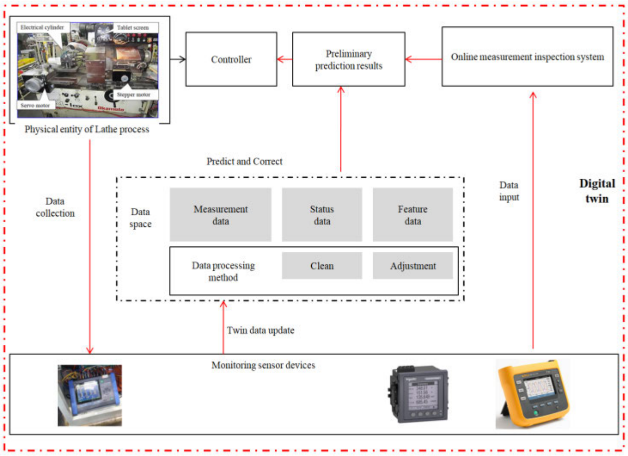

FIGURE 21. Flowchart online measurement system.

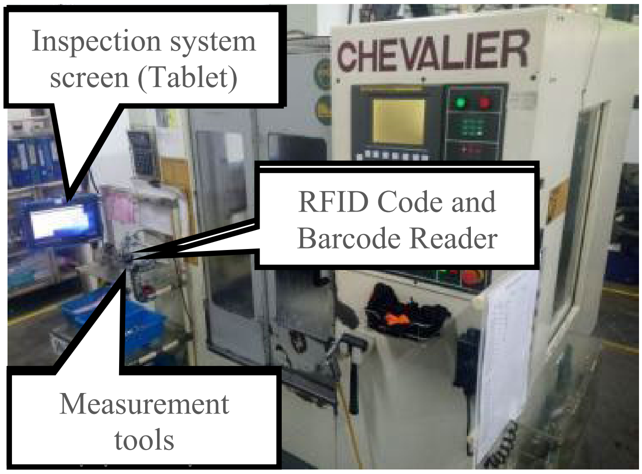

FIGURE 22. Actual Industry 4.0's system in CNC process.

dated technology and inexpensive labor [36]. It is also challenging to address this issue since low-level manufacturing process operators frequently reject the new system and are fired. Industry 4.0 technology solution suppliers must show investors or other decision-makers through empirical data that an Industry 4.0 technology system's initial investment should be within reason when it is tested and installed. Since production managers may track the performance of machines in real time and offer a solution that satisfies delivery standards, the system must satisfy their objectives in the production process. Additionally, it offers a straightforward solution that industrial process operators can employ despite their inadequate credentials. To enhance their business outcomes, performance, and competitiveness, production and business enterprises frequently experiment with and implement Industry 4.0 technology to enhance production processes. Decision-makers in organizations constantly consider and prioritize the requirement for a digitalized environment in manufacturing processes that capture data from IOT devices such as sensors in real-time. This study establishes a foundation for subsequent research on evaluating and implementing Industry 4.0 technology solutions at modest investment levels. With the inclusion of new CNC machines and IoT devices, the manufacturing process for Industry 4.0 technology systems is improved, leading to higher productivity, improved business efficiency, and increased communication and data connection between old and new equipment (Fig. 22).

An Industry 4.0 technology solution prototype with a low initial investment cost, good reaction to manufacturing equipment, and use of Arduino circuits is described. The cost of ongoing improvement is 725 USD; however, expansion connections are required to accommodate the expanding demand for additional connections.

Utilizing IOT devices to swiftly install and assemble hardware for data collecting Industry 4.0 technology systems in the CNC machine production process reduce production downtime to 8:00 hours. The digitized environment's open libraries and online data connections also enable system implementers to work remotely on system design, increasing the complexity and system operation speed.

Industry 4.0 technology systems have successfully undergone rapid testing and installation with great efficiency right away. Data visualization tools have demonstrated their effectiveness, enabling managers to track and assess each production line's progress without having to dive right into the manufacturing procedure. On real-time monitoring displays, anomalies have been represented by graphs and data analysis tables, giving decision-makers confidence in deploying, testing, and implementing the system. In the future, we should think about enhancing IOT devices and expanding connection for the system.

Industry 4.0 technology solutions are low-cost, tried, and true, implemented in the manufacturing of CNC machines, and they have proven to be effective in terms of production process efficiency, initial investment costs, and IOT compatibility [37], [38]. They are visually represented and have no constraints on the types of data they can contain. The constraint of small and medium-sized businesses, however, is in data connection because their production process makes use of antiquated processing hardware and antiquated connection gadgets that are incompatible or compatible with the incorrect protocol. To avoid interference in the power supply, the operation of the solution cannot subsequently interfere with controlling associated factors like power quality.

According to the study's findings, the DT's synchronization mode is used to remotely monitor the factory's operation and condition, but it can also be quantitatively understood by an entity's performance indicators and resource consumption. The DT mode can be used to improve a system similarly to a traditional simulation model, such as by shortening lead time and evaluating scenario comparison analysis. The DT evaluation mode can be used to forecast the behaviors of the system, such as machine failures and entity cycle times.

Industry 4.0 technology system is designed and built from the Internet of things devices, switching devices with different switching frequency levels from 15kHz to 50 kHz such as Barcode readers, DC motors, Motor servo motors, LED warning light systems, fuses and switches to control equipment such as trip switches or contact switches, Tablets use Leb screens to display information for the system. Industry 4.0 technology and many other switches. All the above sources of equipment are sources of harmonics that cause much harm to the power supply system for CNC machines. It is necessary to establish a real-time power quality measurement and control system (Fig. 6) to improve the stable operation quality of CNC machines when the Industry 4.0 technology system is installed.

The amount of harmonic distortion present in power systems is typically measured as total harmonic distortion, or THD (Eq. 25, Eq. 26). THD is defined as the ratio of the RMS value of all harmonics to the RMS value of the fundamental component multiplied by 100%; the DC component is disregarded. THD can be related to either current harmonics or voltage harmonics [39], [40], [41].

$$THD_v = \frac{\sqrt{\mathrm{V}_2^2 + \mathrm{V}_3^3 + \mathrm{V}_4^2 + \ldots + \mathrm{V}_n^2}}{\mathrm{V}_1} \times 100\% \tag{25}$$

$$THD_I = \frac{\sqrt{I_2^2 + I_3^2 + I_4^2 + \ldots + I_n^2}}{I_1} \times 100\% \tag{26}$$

where, V: Value of the kth harmonic's RMS, I: The kth harmonic's RMS current, and The fundamental component's order is k = 1.

The value of the supply voltage for the CNC machine is $200V \pm 0.1$ and the value of the power supply for the CNC machine is $15A \pm 0.1$. The THD value of the voltage source and the THD of the power supply is less than 5%. All the above values are measured directly at the source and saved to the database system in real-time (Fig. 23). In case the value of voltage, power value, and THD value exceeds the required threshold, the Online test system will lock, and the warning screen will appear (Fig. 20) and all systems. Industry 4.0 technology, CNC equipment and machines are shut down to wait for technical staff to check and repair.

FIGURE 23. Power quality parameter online inspection screen.

B. DISCUSSION

Controlling quality, ensuring on-time delivery, standardizing labor procedures, making optimal use of equipment, and eliminating waste are some of the main objectives of continuous improvement in the manufacturing process. The general objective is to implement minor adjustments gradually over time to produce improvements inside the business. The person who operates the system because of continuous improvement is the operator of the manufacturing process. The Industry 4.0 technology system that is tested and implemented in the production process of a CNC machine needs to ensure operator satisfaction. Measuring and evaluating user satisfaction and operating the Industry 4.0 technology system is imperative. This measurement result is used as input for subsequent continuous improvement activities.

TABLE 11. Sample characteristics.

Variables	Items	Frequency	Percentage
	Male	45	90%
Gender	Female	5	10%
Age	21-30	40	80%
	31-40	6	12%
	41-50	4	8%
Academic	High school	48	95%
degree	University	2	5%

Manufacturing businesses have had a lot of promise and opportunity in the last few years because of the integration of Industry 4.0 and Six Sigma methodologies. Industry 4.0 is a new industrial revolution that uses big data, smart automation, artificial intelligence (AI), and the Internet of Things (IoT) to develop more flexible and intelligent production processes. Production process efficiency and effectiveness can be increased for manufacturing organizations when Six Sigma, an advanced quality management system, is used in conjunction with it. The following are some advantages and prospective applications of Industry 4.0 and Six Sigma combined: Activate flexibility and interoperability, reduce waste and errors, improve predictability, boost productivity, and optimize industrial processes. To summarize, industrial businesses can reap numerous advantages and potential gains by integrating Industry 4.0 and Six Sigma. Processes are improved, waste and errors are decreased, predictability, flexibility, and engagement are raised, and performance and productivity are raised. In the age of Industry 4.0, manufacturing organizations may become more competitive and adaptable by implementing cutting-edge technology and management techniques.

There are a few crucial actions you can take to begin using Industry 4.0 with Six Sigma in your manufacturing company: Evaluate the existing circumstances, Establish goals, Determine which Industry 4.0 technology is suitable. Educate staff members, Determine particular projects, Execute and assess, and provide ongoing education and development. Your manufacturing organization can start applying Six Sigma and Industry 4.0 to improve performance, quality, and competitiveness in the current industrial climate by following the above steps.

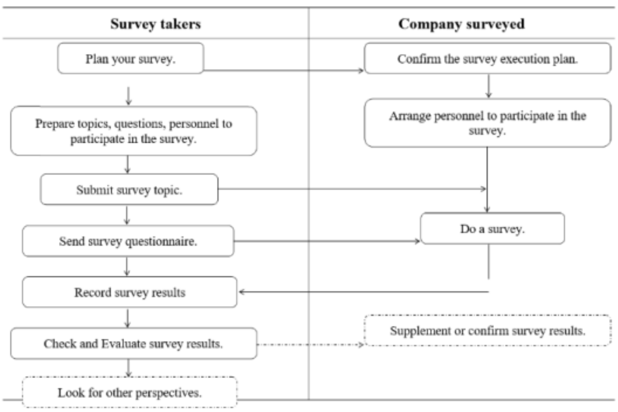

FIGURE 24. **Process to prepare to take a survey.**

In this study, the author proposes to use the PLS-SEM method running on smartPLS 3.3.0 software to measure the satisfaction of Industry 4.0 technology system operators after improving the production process at CNC machines.

Hypotheses development: TRI 2.0, a model for forecasting customer behavioral intentions about technological products, was created by Parasuraman and Colby. It identifies drivers of acceptance, such as perceived ease of use and utility, as well as technological readiness elements (optimism, innovation, discomfort, and insecurity.

Technology acceptance includes both positive and negative features, according to earlier studies. Positive people embrace technology, whilst negative people could be reserved. Users experience technology with optimism, which makes it practical and simple to utilize. IoT and Industry 4.0 technology are examples of new technologies that improve control, flexibility, and efficiency. These innovations promote satisfaction and continued application development. Users of new technology are given fresh concepts and applications, encouraging innovation and user happiness. Users encourage new features in apps like Industry 4.0 technology and IoT, ensuring their use and support. Users of technology feel unsafe because Industry 4.0 technology systems lack personal security. The technology's intended usage does not address user privacy issues, which can have unfavorable consequences and undermine confidence. User satisfaction and willingness to keep utilizing Industry 4.0 technology items are significantly impacted by security. Users' uneasiness with new technology has a detrimental impact on their happiness with Industry 4.0 technology systems and generates shifting feelings, which affects their intention to keep using the system. The following theories were developed considering the investigation, the debate above, and the findings:

- *Hypothesis 1 (H1):* User satisfaction is positively impacted by the ease of use of new technologies (Industry 4.0 *technology*).
- *Hypothesis 2 (H2):* User happiness is positively impacted by the utility of new technologies (Industry 4.0 technology).
- *Hypothesis 3 (H3):* The usefulness and convenience of technology (Industry 4.0 technology) have a beneficial impact on user satisfaction.
- *Hypothesis 4 (H4):* Innovation increases user happiness by enhancing the practicality and convenience of technology (Industry 4.0 technology).
- *Hypothesis 5 (H5):* Lack of security has a detrimental impact on users' satisfaction with the usefulness and convenience of technology (Industry 4.0 technology).
- *Hypothesis 6 (H6):* User satisfaction is negatively impacted by discomfort and the usefulness and ease of technology (Industry 4.0 technology).

Using a non-randomized lottery system, this study gathers information from operator employees, process managers, and post-improvement process management technicians at a mechanical manufacturing company. Participants were surveyed to gauge their level of familiarity with IoT applications in the manufacturing process. The questionnaire was created in Vietnamese using the Likert-5 scale. It was submitted to the leaders of three departments (the technical manager, the quality manager, and the production manager) for their feedback. Based on their responses, the writers modified the questionnaire.

Data collection and description: Descriptive research employs representative techniques like probabilistic and non-probability sampling for efficient and error-controlled sampling in visit studies. The probability sampling method is employed in this investigation. The quality of the sample size (Eq. 27) and the number of samples (Eq. 28) are two factors that are considered while determining the best sampling technique for the study.

$$n = \frac{[q(1-q)]\,Z^2_{\alpha/2}}{D^2} \tag{27}$$

where: q: demonstrates the frequency with which the elements in the sample unit occur in relation to the sampling target $0 \leq q \leq 1$.

$$n = \left(\frac{Z.s}{a.\bar{x}}\right)^2 \tag{28}$$

where: Z: The statistical value corresponds to the reliability. s: Standard deviation of the original sample. $\bar{x}$: Average of the original sample. a: The sample bias rate depends on the sensitivity of the research results. The process of carrying out the survey (Fig. 24).

The survey sample size was 60 questions, and 10 invalid responses were eliminated. This may have happened because the employees did not thoroughly read the questions or choose all the possible answers. For analysis, IBM SPSS 20 and smartPLS 3.3.0 were employed using 50 valid questions. According to the findings, 90% of boys, 10% of girls, and 95% have high school diplomas (Tab. 11).

Measures of scale reliability and validity include Composite Reliability (CR) and Cronbach's Alpha. For the PLS-SEM

TABLE 12. Step by Step of PLS-SEM Methodology.

Step	Explain of Step by Step of PLS-SEM Methodology
Step 1	Calculate the Outer Approximation of the measurement model (Eq. 29) $$Y_j = \sum_{h=1}^{k} x_{jh}\widetilde{w}_{jh} \quad (29)$$ Where, Y_j :Value vector for the j-th latent variable's initial estimation, x_{jh}: a matrix with a column vector of the k-th latent variable's indicator, $\widetilde{w}_{jh}$: (For the first iteration, $\widetilde{w}_{jh}$ was initialized as a column vector with entries of 1) Outer weight estimation value vector of the j-th latent variable with k indication
Step 2	Calculate the value of the Inner Approximation index in the measurement model (Eq. 30) $$Z_j = \sum_{i=1}^{m} Y_i e_{ij} \quad (30)$$ Where, Z_j: initial estimation of the hidden variable's value vector Y_i that is connected to a hidden variable Y_j, e_{ij}: A correlation between related Y_i and Y_j is represented by the inner weight value vector, m: the quantity of Y_i connected to Y_j.
Step 3	Calculate the value of the Updating Outer Weight index in the measurement model (Eq. 31 and Eq. 32) $$\widetilde{w}_{jh} = cor(X_{jh}, Z_j) \quad (31)$$ $$\widetilde{w}_{jh} = \left(X_{jh}^T \times X_{jh}\right)^{-1} \times X_{jh}^T \times Z_j \quad (32)$$
Step 4	Calculate the value of the Convergence Examination index in the measurement model (Eq. 33) $$\left|\widetilde{w}_{jh}^{s} - \widetilde{w}_{jh}^{s-1}\right| < 10^{-7} \quad (33)$$ Where, At the sth and (s-1)th iteration, $\widetilde{w}_{jh}^{s}$ and $\widetilde{w}_{jh}^{s-1}$ represent the outer weight estimation of the h-th indicator on the j-th latent variable.
Step 5	Provides the estimated value of each hidden variable (Eq. 34) $$Y_j = \sum_{h=1}^{k} X_{jh} \times \widetilde{w}_{jh} \quad (34)$$
Step 6	Estimating the outer loading value and the path coefficient (Eq. 35) $$\hat{\delta}_{jh} = cor(Y_j, X_{jh}) \quad (35)$$ Where, $Y_j = Y_i \times \beta + \rho$ and $\beta = (Y_i^T \times Y_i)^{-1} \times Y_i^T \times Y_j$, β: vector of the route coefficient, ρ: the residual vector
Step 7	Using Cronbach's alpha (Eq. 36), the study model's internal consistency is assessed. $$\alpha = \left(\frac{k}{k-1}\right)\left(1 - \frac{\sum_{i=1}^{k} \sigma_y^2}{\sigma_x^2}\right) \quad (36)$$ Where, k: the number of items in the measure, σ_y^2: variance associated with each, σ_x^2: variance associated of the total scores.
Step 8	The average variance extracted (AVE)(Eq..37) method is used to test the construct's convergent validity. $$AVE = \frac{\sum_{i=1}^{k} \partial_i^2}{\sum_{i=1}^{k} \partial_i^2 + \sum_{i=1}^{k} Var(e_i)} \quad (37)$$ Where, k is the number of items, ∂_i: the factor loading of item i, $Var(e_i)$: the variance of the error of item i.
Step 9	The internal VIF (Variable Inflation Factor) value indices (Eq. 38) are examined. $$VIF_i = \frac{1}{1 - R_i^2} \quad (38)$$ Where,R_i^2 is the uncorrected coefficient of determination when the ith independent variable is regressed on the other independent variables. Tolerance is the reciprocal of VIF. Depending on personal taste, multicollinearity can be found using either VIF or tolerance
Step 9	Composite reliabilities (CRs) (Eq. 39) are used to test the convergent validity of the notion. $$CR = \frac{(ld_1 + ld_2 + \cdots + ld_m)^2}{(ld_1 + ld_2 + \cdots + ld_m)^2 + \sigma_1^2 + \sigma_2^2 + \cdots + \sigma_m^2} \quad (39)$$ Where: CR: composite reliability CR of latent variable A, ld_1, ld_2, ld_m: the normalized load coefficient of the observed variable belonging to the latent variable A, m: number of observed variables of latent variable A,

TABLE 12. ***(Continued.)*** **Step by Step of PLS-SEM Methodology.**

	$\sigma_1^2, \sigma_2^2, \sigma_m^2$: variance of the measurement error of the observed variable belonging to the latent variable A with $\sigma_m^2 = 1 - ld_m^2$
Step 10	Both the Comparative Fit Index (CFI) (Eq. 40) should meet certain thresholds. $$GFI = 1 - \frac{F_t}{F_n} = 1 - \frac{x_t^2}{x_n^2} \quad (40)$$ Where: x_t^2: The chi-square of the target model, x_n^2: The chi-square of the null model, F: The corresponding minimum fit function value
Step 11	The study tests direct correlations, the Confident Interval (Eq. 41), and the results of the tests using the structural equation modeling (SEM) technique. $$CI = \left[\bar{x} - \frac{cs}{\sqrt{n}}, \bar{x} + \frac{cs}{\sqrt{n}}\right] \quad (41)$$
Step 12	The heterotrait monotrait ratio (HTMT) (Eq. 42) is used to evaluate the discriminant validity of structural indices. $$HTMT_{ij} = \frac{\overline{Cor_{ij}}}{\sqrt{\overline{Cor_i} \times \overline{Cor_j}}} \quad (42)$$ Where, $HTMT_{ij}$: HTMT value of latent variables i and j, Cor_{ij}: average of correlation coefficients of all pairs of observed variables of latent variables i and j, Cor_i: the average of the correlation coefficients of the pairs of observed variables of the latent variable i, Cor_j: average of the correlation coefficients of the pairs of observed variables of the latent variable j

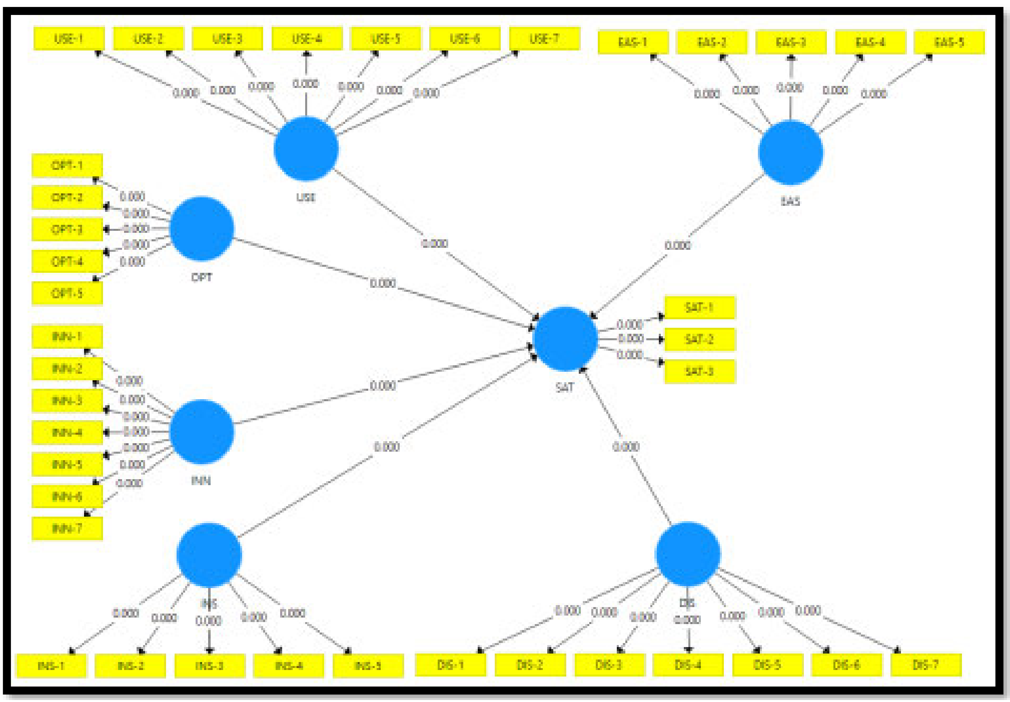

FIGURE 25. **Results of bootstrapping analysis.**

model (Tab. 12), survey results that are plausible and valid are indicated by A CR and Cronbach's Alpha values better than 0.8. The validity of the scale is demonstrated by the AVE square root value, which is higher than the correlation coefficient and values more than 0.5 (Tab. 13) and (Fig. 25).

SmartPLS 3.3.0's Bootstrapping analysis is used to analyze the path coefficient of the model using a T-Test analysis model with a 5% significance level. The R-squared value index is used to gauge how well the Industry 4.0 technology low-cost improvement system is being received by users at the study model's mechanical manufacturing company. The

TABLE 13. Convergent validity and reliability.

Construct	Indicators	Factor Loading	SMC	AVE	CR	Cronbach's Alpha
Ease of use	EAS-1	0.815	0.608	0.517	0.851	0.862
	EAS-2	0.852	0.599			
	EAS-3	0.803	0.618			
	EAS-4	0.876	0.599			
	EAS-5	0.856	0.602			
Usefulness	USE-1	0.792	0.715	0.617	0.857	0.841
	USE-2	0.801	0.692			
	USE-3	0.793	0.718			
	USE-4	0.819	0.699			
	USE-5	0.821	0.689			
	USE-6	0.792	0.701			
	USE-7	0.802	0.609			
Optimization	OPT-1	0.799	0.624	0.617	0.871	0.878
	OPT-2	0.826	0.698			
	OPT-3	0.799	0.692			
	OPT-4	0.799	0.667			
	OPT-5	0.821	0.689			
Innovation	INN-1	0.829	0.608	0.656	0.867	0.825
	INN-2	0.804	0.613			
	INN-3	0.838	0.601			
	INN-4	0.792	0.652			
	INN-5	0.799	0.605			
	INN-6	0.821	0.621			
	INN-7	0.809	0.634			
Insecurity	INS-1	0.813	0.613	0.619	0.853	0.823
	INS-2	0.805	0.694			
	INS-3	0.803	0.629			
	INS-4	0.819	0.593			
	INS-5	0.799	0.601			
Discomfort	DIS-1	0.742	0.706	0.667	0.856	0.838
	DIS-2	0.793	0.691			
	DIS-3	0.696	0.692			
	DIS-4	0.741	0.686			
	DIS-5	0.699	0.701			
	DIS-6	0.723	0.699			
	DIS-7	0.722	0.689			
Satisfaction	SAT-1	0.712	0.604	0.609	0.834	0.867
	SAT-2	0.734	0.623			
	SAT-3	0.767	0.608			

TABLE 14. Results of hypothesis analysis.

Hypothesis	Path	Estimate	t-Value	S. E	p-Value	Result
H1	EAS -> SAT	0.122	3.45	0.032	0.000	Supported
H2	USE -> SAT	0.132	3.06	0.012	0.000	Supported
H3	OPT -> SAT	0.133	2.94	0.032	0.000	Supported
H4	INN -> SAT	0.141	3.01	0.043	0.000	Supported
H5	INS -> SAT	0.132	3.32	0.023	0.000	Supported
H6	DIS -> SAT	0.123	3.04	0.025	0.000	Supported

smartPLS 3.3.0 software evaluated the study data consistency (Tab. 14). Results of empirical research demonstrate that the low-cost Industry 4.0 technology improvement system had a favorable response from every factor used to gauge user satisfaction. A P-Value of less than 0.05 results from every measurement factor. This demonstrates that users and

workers of the system are pleased with the better outcomes following the low-cost Industry 4.0 technology enhancement.

VI. CONCLUSION

Business collaboration and data sharing with customers, partners, suppliers, and other supply chain participants are made easier thanks to Industry 4.0 technologies. It enables the transition to a digital economy, improves competitiveness and productivity, and presents the opportunity to generate sustainable economic growth. This fourth industrial revolution may alter the labor market less favorably than it offers opportunities, leading to greater inequality. The gap between return on investment and return on labor may widen if Industry 4.0 technology is used to automate all human labor and replace employees with machines, as well as create an increasingly divided labor market between ''low-skill/low-wage'' and ''high-skill/high-wage'' segments, worsening social stratification. Enhance the standard of vocational training, build a team of highly skilled workers who are increasingly adept at science and technology, increase their comprehension of Industry 4.0 technology, and possess discipline, work ethic, and labor skills. Building a team that is getting stronger in both quantity and quality while at the same time being constantly prepared to confront the difficulties brought on by the Industry 4.0 technology.

Industry 4.0 technology solutions significantly improve operational effectiveness, productivity, product quality, asset utilization, time to market, agility, worker safety, and environmental sustainability, enabling intelligent, digitally integrated value chains with practically endless potential.

To continuously enhance the production process of a firm that manufactures mechanical products, this study describes the testing and installation stages of a low-cost Industry 4.0 technology solution for small and medium-sized businesses. In order to increase production process productivity, reduce waste, and realize data connection between production processes, Industry 4.0 technology 's solution digitizes the production process using outdated CNC processing machines into a production process with automatic CNC machines in accordance with the Industry 4.0 technology operating method. This allows the monitoring system to visualize all data that has been collected. Provides an Industry 4.0 technology solution implemented through a continuous improvement process in the Six Sigma methodology implementation of the DMAIC method, which aids production managers in the company in identifying anomalies and predicting potential hazards in the future. Small and medium-sized businesses upgrade their processing methods by retrofitting IOT devices to comply with Industry 4.0 technology solutions, and they simultaneously purchase new equipment to satisfy their growing production demands. According to the findings of this study, testing and installing this Industry 4.0 technology system compared to purchasing a new machine is equally efficient. This information will help decision-makers become more aware of the fact that developing Industry 4.0 technology solutions that cover existing production processes will require a much smaller initial investment than purchasing new machines. IOT devices can be added to new machines to increase production and operational efficiency for decision-makers in small and medium-sized businesses as well as production managers who utilize a combination of old machining machines. Realizing continuous improvement of CNC machines through testing and implementing Industry 4.0 technology systems that significantly improve production efficiency and business efficiency and specifically improve production process that production costs are reduced by \$9593 per year and the defect rate of product's length dimensions is reduced from 54.90% per month down to zero defects. The ease of using the production process system at the CNC process and the improved employee satisfaction that results from smooth communication between new and improved processes are just a few of the additional advantages that Industry 4.0 technology solutions bring. Data collected from sensors is saved into the SQL system in real time and data is visualized for everyone in the company to see easily.

Given how rapidly urbanization and industry have advanced, people may soon be unable to forecast social crises and their repercussions on society. The two key problems are cybersecurity and privacy. Because all data is digital and moved to computers, IoT devices are vulnerable, and these vulnerabilities can occasionally be disastrous if important security data is stolen from them. a crucial place. Employee education and training must be updated to reflect Industry 4.0 technology-based procedures. To keep up with and fit in with the astounding developments in science and technology, people must constantly adapt and improve. Even machines have constraints of their own. If businesses rely too heavily on sophisticated gear and equipment, they risk suffering severe harm. Additionally, because relocating and replacing machines would be highly expensive, organizations need to carefully evaluate their financial status.

Researchers will need to continue to advance several areas of the constraints of Industry 4.0 technology solutions in the future. The first is that there are many examples of hackers accessing user data, which law enforcement agencies have not been able to prevent, and the data security system is not sure for users' peace of mind. The second is an information network system that has a slow information response speed and a high latency level, not yet meeting the requirements of the Industry 4.0 technology system. Future researchers will need to build an information network system that has a faster reaction speed. The third step is to set up an environment for training so that users may learn more about the Industry 4.0 technology system or the communication of IOT devices and satisfy the demand for ongoing replacement of experienced labor in the production environment. Anyone at any level can use it straight away. The fourth is that more IOT devices need to be produced by manufacturers to address the demand for continual improvement of outdated equipment for medium-sized and small businesses with the least amount of initial expenditure.

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