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Enhancing business performance by integrating Fuzzy TOPSIS into Six Sigma

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Abstract—The mechanical component manufacturing industry relies on CNC machining processes, where improving productivity and product quality is crucial. Automating CNC processes with affordable Industry 4.0 technology is a viable approach for continuous improvement. Industry 4.0 facilitates data connection across companies, improving decision-making for efficient production and business development. This paper proposes a hybrid Six Sigma method combining Fuzzy TOPSIS and PLS-SEM. Fuzzy TOPSIS helps decision-makers identify improvement areas, while PLS-SEM evaluates factors affecting continuous improvement outcomes. The study shows a reduction in length dimension errors from 54.90% to zero, saving $9,593 annually. This approach, adaptable to different business process models, contributes to enhancing production efficiency using affordable Industry 4.0 technologies.
Keywords—Six sigma, Fuzzy Topsis, CNC, SMEs.

INTRODUCTION

In today's manufacturing environment, waste management is a significant concern, especially with disruptions in product flow. To address this, mechanical manufacturing plants must adopt new production control methods. Information technology is utilized to centralize data requirements, emphasizing the role of production management (PM) [1]. However, challenges remain, such as managing operators with insufficient skills and ensuring safety. Additionally, manual or semi-automatic data collection methods can lead to operator dissatisfaction [2].

This study proposes several key initiatives: (1) Optimize machining processes using Industry 4.0, (2) Automate product measurement with long-term data collection and soft computing, (3) Apply real-time data collection using Industry 4.0 IT techniques, (4) Redesign tools to enhance operator satisfaction and optimize machining, (5) Use IT and barcode systems for automation and remove human intervention, (6) Integrate enterprise resource planning to support production control and decision-making, (7) Improve workplace safety using face recognition and computer vision, (8) Use statistical tools like Minitab, SPSS, and Matlab for data analysis, (9) Break barriers between research and practice by integrating research results into manufacturing processes, and (10) Maintain Total Demand Distortion (TDD) and Total Harmonic Distortion (THD) within international standards, IEEE 519, and IEC 61000 in power grids.

Lean Six Sigma (LSS) is a quality management method that combines Lean Manufacturing and Six Sigma to optimize performance and reduce waste. Lean focuses on eliminating non-value-adding activities, while Six Sigma aims to reduce variability and defects in production processes [3-4]. DMAIC (Define, Measure, Analyze, Improve, Control) is commonly used in LSS for process improvement.

TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) is a multi-criteria decision-making method used to rank options based on proximity to an ideal solution [5]. Fuzzy TOPSIS is an extension of TOPSIS designed to handle decision-making in uncertain environments, using fuzzy sets to represent uncertainty and multi-valued information [6].

This study aims to design and implement a low-cost Industry 4.0 technology system, integrating the Six Sigma method to optimize the CNC machining process, thereby improving productivity, product quality, and minimizing production defects. It contributes to supporting small and medium-sized enterprises (SMEs) in their digital transformation and enhancing their competitive capabilities. A continuous improvement model is built by integrating the Fuzzy TOPSIS and PLS-SEM methods

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into Six Sigma, with the goal of identifying and evaluating factors affecting CNC machining process quality.
The design and implementation of a low-cost Industry 4.0 technology system involves the use of IoT devices and digital technologies to improve monitoring capabilities, control the production process, and support data-driven decision-making. The main research focus is on factors influencing productivity, product quality, and defect rates in the CNC machining process. The analysis process examines the characteristics of IoT, monitoring systems, and the application of Industry 4.0 technology to optimize production. The focus is on integrating low-cost Industry 4.0 technology into CNC production processes, including IoT sensors and real-time data monitoring systems. The production data is analyzed using the Fuzzy TOPSIS and PLS-SEM models. The Six Sigma method is applied for continuous improvement. The impact of the solution on defect rates, product quality, and production costs is evaluated. The structure of the research is as follows: Section 2 discusses Raw Material and Methodology, Section 3 presents the Results, Section 4 covers the Discussion, and Section 5 concludes.

RAW MATERIAL AND METHODOLOGY

The mechanical components are manufactured from raw steel materials and undergo several processes. Each production process is carried out with different production goals and meets different product dimensions and quality parameters. Improving the quality of the production process and enhancing the quality at each manufacturing stage to meet customer requirements is essential. The Six Sigma method is considered an effective tool for implementing continuous improvement activities. The production process is very complex and has many issues that need to be prioritized for improvement. The Fuzzy TOPSIS method is an effective tool for decision-makers to prioritize issues for improvement. Low-cost Industry 4.0 technology is always considered by company managers to implement continuous improvements.
The lack of enthusiasm among managers in small and medium-sized enterprises (SMEs) to experiment with and implement Industry 4.0 technology in production process improvement needs to be addressed in this study [7]. A study conducted in Germany and China revealed that managers lack motivation to experiment with and install Industry 4.0 technology because they are unaware of its benefits. However, since it can bring rapid results, some CEOs believe it is suitable for the production process [8]. Researchers advise managers to experiment with new business processes through trials and installations, but they also need to allocate sufficient financial resources to ensure safety for the industry. There is an opinion that a better approach is needed to enhance motivation. Digital technology, referred to as "Industry 4.0 technology," has the lowest initial investment cost and the fastest business benefits. Through inter-process communication and communication standards, it is used to connect all processes in the supply chain [9], [10]. By experimenting with and using this technology in production processes, such as by purchasing new machinery or retrofitting existing machines with IoT devices, small and medium-sized enterprises can benefit from it. It is not necessary to buy many devices, and IoT devices are low-investment solutions. Research publications on experimenting with and implementing Industry 4.0 technology to optimize the production process, as well as research papers using AI and machine learning, have resulted from IoT retrofitting solutions and studies [11], [12]. IoT sensors are considered ideal tools for digitizing production processes as they allow machine systems to communicate and exchange data. Automation companies have recognized the benefits of IoT retrofitting solutions, enabling CNC machines to operate similarly to new equipment [13]. Examples include Siemens' IOT2040 gateway and Bosch's XDK sensors. The ability to collect real-time data is provided by IoT devices and Arduino boards, both of which are low-cost digital solutions. Arduino boards in Industry 4.0 technology can monitor and measure humidity, temperature, pressure, air, renewable energy systems, power grid monitoring in real-time, and operate motors. The cost of implementing Industry 4.0 technology is a concern for decision-makers. Using the 5 Why analysis method combined with brainstorming, the causes of long and short length dimension defects are analyzed

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based on a cause-and-effect diagram. The analysis results from the fishbone diagram show three main causes of scrap generation. The first cause of scrap products is due to machine operator actions, as sewing operations depend entirely on human skills. The second cause is accuracy in machining, with unstable or inaccurate processing speeds causing waste. The third cause is the operator selecting the wrong machining program compared to the product code. The product to be machined makes the machining dimension tolerance inaccurate (Figure 1).

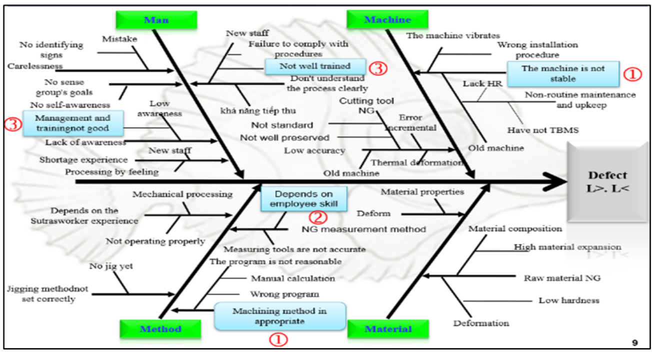

Figure 1: Cause and Effect Diagram

A company manufacturing mechanical products uses the Six Sigma (SS) method to improve the production process. The Industry 4.0 technology model is implemented using the DMAIC method, including creating user manuals for the IoT system, testing and control standards for IoT content, and an overview evaluation of the operational process and management standards on IoT systems [14].

This study aims to enhance understanding of the benefits and effectiveness of Industry 4.0 technology when evaluated and implemented in the production process by managers in small and medium-sized enterprises. Additionally, it provides information that can be seen as evidence supporting the value of this technology in creating high-quality solutions that meet low initial investment cost requirements, simple and safe operation, avoid disrupting the current production process, and provide high and quick effectiveness to increase business value. Although the challenges of experimenting with and implementing Industry 4.0 technology were addressed in the previous section of this study, the ultimate goal is to improve the digitization of production processes in processing or manufacturing companies. According to Industry 4.0 technology operation standards, the DMAIC method assesses the current state of production processes in businesses [15], [16]. To improve the process and fully digitize the production process, bringing the highest benefits and efficiency to businesses, the stage of evaluating the production process is tested and installed. The five levels of the automation pyramid – field level, control level, monitoring level, planning level, and management level – each achieve a specific purpose for the digitization of the production process (Figure 2). The main difference between the production terms, process, production process, and identification phase is that for issues identified in the identification phase, a suitable digitization plan or model must be proposed to test and implement Industry 4.0 technology to improve the production process [17]. The decision-maker should be the company's CEO, and the solution must match the production process and meet the needs of each specific organization. Industry 4.0 technology solutions must be adaptable to the needs of the company's production process as well as its needs and objectives. With the goal of minimizing disruption to the current production process, the digitization system must include additional capabilities to quickly update and adjust the algorithms once they are implemented in the production process [18]. Customer satisfaction is a key factor in increasing customer satisfaction, and lead time in production is crucial in the production process [19]. Factors include enhancing motivation to implement Industry 4.0 technology to improve the production process and increasing managers' awareness of the industry in SMEs.

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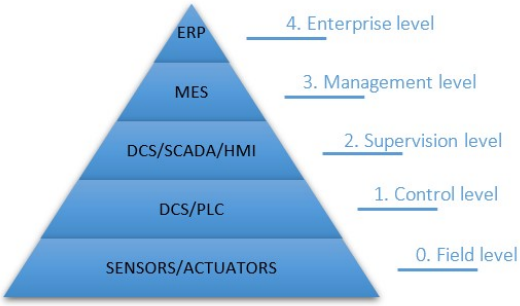

Figure 5: Five-Level Automation Pyramid

A synchronization model is developed using random parameters to simulate the synchronization of the IoT physical environment. It is converted into deterministic parameters to restructure the model and is used to evaluate the test mode model to predict and optimize. The synchronization mode model (Figure 6) is then incorporated into the reverse model.

A. Six Sigma Method based on DMAIC

The acronym DMAIC stands for "Define, Measure, Analyze, Improve, and Control," and it describes the stages of the Six Sigma process with a well-defined structure. In many large companies, Six Sigma has been effectively implemented and has become one of the most recognized quality management techniques worldwide. It contributes to growth efficiency, reduces waste, and enhances customer satisfaction. Data analysis is used to assess the effectiveness of Industry 4.0 technology systems and provides information for managers to decide whether to update functions or integrate IoT sensors. By performing analysis, improvement, and control, the DMAIC method is used to enhance the production process, supporting Industry 4.0 technology solutions in improving manufacturing processes (Table 1).

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**

B. Phương pháp fuzzy topsis

The Fuzzy TOPSIS method, first introduced by Hwang and Yoon [20], was later refined by Chen [21] to incorporate the use of fuzzy numbers and allow the use of linguistic variables as a means of data collection. A hierarchical system of levels is used to distinguish between natural and artificial languages as linguistic variables. Specific definitions and evaluations of a linguistic group are carried out. When using fuzzy set theory, managers can collect and combine information without the need for verification, missing data, or overlooked information in decision models. A powerful method for modeling unclear systems and collecting tacit knowledge from experts in the field is the use of fuzzy sets and fuzzy logic. A crisp set also includes a fuzzy set as a subset.

The AHP method is often preferred over the fuzzy VIKOR and fuzzy TOPSIS methods for selecting important components in the production department of a mechanical manufacturing plant, depending on the situation. By using the fuzzy AHP and TOPSIS methods, two researchers created an evaluation tool for new product development tools for small and medium-sized enterprises (SMEs). To classify studies on the TOPSIS method, Behzadian et al. [22] conducted a thorough

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literature review. Among the 266 academic papers included in the classification for this review, only one paper mentioned design improvement, and it focused more on process optimization rather than product design. Therefore, there is limited research that examines how to improve the efficiency and quality of manufacturing processes using multi-criteria analysis.

The Six Sigma method, when combined with the Fuzzy TOPSIS method, serves as a guide for decision-making. Each variable at the grinding stage significantly affects the final product quality. As a result, there is uncertainty about whether the priority criteria for actions aimed at improving product quality will be met. Your recommendation to use the Fuzzy TOPSIS method to address this ambiguity is valid, as it helps manage situations with uncertainty or incomplete knowledge.

However, I would like to gently ask for further clarification regarding the statement on "many misconceptions about the logical accuracy of the Fuzzy TOPSIS method in imprecise reasoning and approximate inference." Could you elaborate on what specific misconceptions you're referring to? Fuzzy TOPSIS is often praised for handling uncertainty well, but I'm curious if there are particular areas where its logical application might be misunderstood.

Additionally, it seems that you suggest applying Taguchi methods in the Improve phase to enhance prioritized options identified in the Analyze phase. Could you explain a bit more about how you're combining these techniques? It would be helpful to understand how Taguchi methods specifically integrate with Fuzzy TOPSIS in this context.

Lastly, integrating RFID technology into the process for data collection and information management during the Control phase is an interesting approach. How do you see RFID enhancing the feedback and control mechanisms in your Six Sigma process, especially with the added complexity of fuzzy decision-making? I'd love to hear more about how these elements come together to improve the system's performance.

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.

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.

RESULT

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

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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 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. 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. [23-24].
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 2 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.

Table 2. Evaluate the criteria of the decision maker.

Criteria	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10	Fuzzy composite weight ($\tilde{w}_j$)
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)

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 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 (Table 3).

Table 5. 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

Due to the working standards and cultural diversity of each country, the production processes of Industry 4.0 technologies present a complex challenge for small and medium-sized enterprises (SMEs) in the host country. Continuous progress is severely hindered by the fact that companies in poorer countries often build industrial facilities using outdated technologies and cheap labor. Addressing this issue is also challenging because low-level production operators often reject new systems and face layoffs. Industry 4.0 technology solution providers must demonstrate to investors or decision-makers, through experimental data, that the initial investment in Industry 4.0 systems is justified when tested and installed. As production managers can monitor the performance of machinery in real-time and make decisions to meet delivery standards, the system must meet their goals in the production process. Moreover, it provides a simple solution that industrial process operators can use despite their insufficient qualifications.

To improve business results, performance, and competitiveness, manufacturing and business enterprises often experiment with and implement Industry 4.0 technology to enhance their production processes. Decision-makers in organizations constantly consider and prioritize digitalization requirements in production processes, collecting data from IoT devices like real-time sensors. This study lays the foundation for future research on evaluating and deploying Industry 4.0 technology solutions at modest investment levels. By adding new CNC machines and IoT devices, the production process for Industry 4.0 systems is improved, leading to higher productivity, better business performance, and enhanced data connectivity and communication between old and new equipment .

A prototype for a low-cost Industry 4.0 technology solution, responsive to manufacturing equipment and using Arduino boards, is described. The cost of continuous improvement is $725; however, there is a need to expand connectivity to meet the increasing demand for additional connections.

Using IoT devices to install and assemble hardware for Industry 4.0 systems in CNC manufacturing quickly reduces downtime to just 8 hours. Open libraries in the digitalization environment and online data connections also allow system implementers to work remotely on system design, enhancing system complexity and operational speed. Industry 4.0 systems have been quickly tested and installed with immediate high effectiveness. Data visualization tools have proven effective, enabling managers to monitor and assess the progress of each production line without directly participating in the production process. On real-time monitoring screens, abnormalities are represented by charts and data analysis tables, providing confidence to decision-makers in system deployment, testing, and installation. In the future, we should consider enhancing IoT devices and expanding connectivity for the system.

Low-cost, tested, and proven Industry 4.0 technology solutions have been implemented in CNC manufacturing, demonstrating effectiveness in production process performance, initial investment costs, and IoT compatibility. They are visually represented and have no limitations on the types of data they can contain. However, the limitations for SMEs are data connectivity because their production processes use outdated processing hardware and outdated, incompatible devices or devices that are incompatible with the wrong protocols. To avoid interference with power supply, the operation of the solution must not interfere with controlling related factors such as power quality.

According to the study results, the synchronization mode of Digital Twin (DT) is used to remotely monitor the operations and conditions of the factory, but it can also be quantitatively understood through performance indicators and resource consumption of an organization. The DT mode can be used to improve a system similar to a traditional simulation model, for example, by shortening lead times and evaluating comparative scenario analysis. The DT evaluation mode can be used to predict system behavior, such as machinery failures and entity cycle times.

The Industry 4.0 system is designed and built from Internet of Things devices, transforming equipment with switching frequencies ranging from 15 kHz to 50 kHz, such as barcode readers, DC motors, servo motors, LED warning light systems, fuses, and switches to control devices like circuit breakers or contact switches. Tablets using Leb screens display information for the system. Industry 4.0 technology and many other switches. All these device sources are harmonic sources that can cause significant harm to the CNC machine's power supply system. It is essential to establish a real-time power quality measurement and control system to improve the stable operation quality of CNC machines when the Industry 4.0 system is installed.

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Discussion and 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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