DOI: 10.21062/mft.2022.028 http://www.journalmt.com

Application of Lean Six Sigma for Improve Productivity at The Mechanical Plant. A Case Study

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This study focuses on performing the analysis of manipulator operations on the machining line of precision mechanical products using the Human-Machine correlation analysis tool through images collected from the camera, wasteful operations incurred in machining according to Lean Six Sigma (LSS) standards to control fluctuations in the machining line, improving the overall productivity of the line (OEE). Specifically, contributing to improving productivity, quality, and competitiveness of the company in the market, create a good product image for consumers. This paper proposes a 7-step quality control (QC) cycle improvement model, called 10 step QC cycle. In step 5, use Man - Machine correlation analysis tool from video images to identify wasteful activities. In step 6, we propose a Direct Numerical Control (DNC) model to call the machining program for MC machines using a barcode system and a computer vision model for human identification at each processing line according to a controlled fixed layout. The right people have been trained enough to operate the line; the specific result is eliminating the occurrence of accidents in processing from 7 cases to none. A model of a product dimensioning system implemented for fully automated product quality control combined with redesigned machining jig with a vapor sensor system eliminating the reliance on human manipulation Specifically, the result from this improvement activity is the increase in productivity from 115 products per 8 hours to 155 products per 8 hours and the handling time has decreased from 1.3 hours per day to 0.36 hours per day (reduce 0.94 hours per day). The Partial Least Squares Structural Equation Modeling (PLS-SEM) is used to analyze the results of the survey of employees' opinions about the usefulness, convenience, and technical factors after the operation. The results from improvement activities show that user loyalty is highly appreciated in terms of usefulness and convenience. However, in terms of technical factors, it is still necessary to improve the quality of the information network system, the barcode scanning system and the quality of barcodes in the oil environment.

Keywords: Productivity improvement, QC Story; DMAIC; PLS-SEM; Continuous improvement

1 Introduction

The strong rise of precision mechanical processing companies in Asia, especially those from Taiwan and China has created a very competitive environment for companies from Europe, America, and Japan. In order to increase market share as well as attract customers to use the company's products, creating a trust for users of the company's products is the top goal of the manufacturer. In addition to improving the processing output, the improvement of technological processes, the improvement of machining tools, and the improvement of product quality are the goals that need attention and continuous implementation. KTC, a US company, has a factory in Dong An industrial zone, Binh Duong province. Recognizing the fierce competition, the company has established a subcommittee to improve the processing process, where quality is an important factor in all businesses and fine machining always requires high quality for products. The objective of firms in the field is to constantly enhance quality.

Linear Guide has both experience and modern technology and is still looking for methods to improve quality. According to data, sudden faults increase means solutions must be found. In search, sudden increase in faults is related to the wrong position error of Linear Guide. This requires urgent solutions. Bad quality products found in customers complaints increase continuously.

Analyze the cause and output of failures according to the 5 why method and the assembly line and at the component processing stage. The status is that product processing tools depend entirely on human skill in controlling the placement of products in machining tools at automatic machining. Along with that, after the parts are processed, employees use measurement tools to check the dimension, just like in a machine, the dimension measurement, recording, and evaluation of product dimension after machining also depend on operator skill. Applying the hypothesis testing to test the performance results at the stage and get the clear results that the results are skewed and unstable due to human factors.

In order to eliminate dependence on operator skill in machining as well as in metrological inspection as a necessary activity, think and improve the machining tool, develop sensorial control of the tool, therefore tool transformation and automation are essential, and machining productivity is increasing. Moreover, automate the manipulation of measurement results by computer tools and save the measurement data to the database on the system to facilitate the retrieval of measurement data quickly and without taking up space in the warehouse to store paper measurement results, in addition, develop more online data application tools to control machining capacity at each stage and count the lead time of each order by online boned system.

The purpose of this research is to create an improved model in the quality control cycle by analyzing human activities on the machining line at a mechanical company in order to improve the quality of the product and thus improve the company's productivity, quality, and competitiveness, as well as to create a good product image for consumers. Furthermore, this research adds to the creation of continuous improvement activities in the factory, in addition to upgrading machining tools and other indirect component improvement activities such as logistics, buying, and human resources. Concerning initiatives to remove waste and boost value business while assisting employees in understanding the phases of improvement operations.

2 Introduction

Product machining process performance improvement and process innovation are the crossroads of precision machining organizations. The outcome of the improvement process is critical to the organization's competitiveness and survival. F. L. Lizarelli et al [1] used the form of document review, administrative procedures for continuous improvement activities in the organization of precision machining, identification of waste, tasks that do not create value, repetitive and inefficient tasks. J. B. D. C. Junior et al [2] proposed an option to interview 24 experts including mechanical technicians, electrical technicians, leaders at all levels in precision mechanical processing factories, and analyze data against data benchmark data through 6 questions focusing on the benefits of continuous improvement. Continuous quality improvement is of great interest to quality control masters such as Deming and Juran [3]. In the manufacturing industry, it is very important to verify using the proper scales and measurements, continuous improvement failure occurs due to many factors such as strategic planning, change management, knowledge management, measuring the operational efficiency, performance, and sustainability of continuous improvement. Continuous improvement programs / comparisons study about Total Quality Management (TQM), LSS, Define – Measurement – Analysis – Improvement – Control (DMAIC), Plan – Do – Check – Action (PDCA) cycle to create awareness about the production organization and the factors that need to change in continuous improvement [4], [5], [6]. To continuously improve the reliability of the manufacturing process, engineers should strive to identify and measure manufacturing process defects, as well as the analysis of these defects against performance indicators Key Performance Indicator (KPI) process. Engineers can take corrective action and make continuous improvements by performing daily monitoring of the manufacturing process. Zahharov Roman et al [7] integrates different tools and methods such as six sigma, DMAIC, Failure Classifier (FC), Theory of Constraints (TOC), Swim line diagram, Failure Mode and Effect Analysis (FMEA).

Statistical testing is an essential tool for measuring and analyzing quantitative or qualitative data of collected survey data [8]. Multiple nominal quality characteristics of inside or outside diameter dimensions, with asymmetric tolerance, a function of process mean and standard deviation to obtain a 100(1-α) % confidence interval of the index. Chang Hsien Hsu et al [9] applied mathematical models to find confidence intervals as well as used confidence intervals to test hypothesis statistics. Statistical hypothesis testing is one of those quantitative analysis methods that sounds simple, but it has interdependence between components, on the basic logic behind the experimental statistical hypothesis. F. E. Streib et al [10] use statistical hypothesis testing in data science activities. Statistical hypothesis testing is one of those statistical topics that is prone to error [11].

In today's business environment, the trend of product diversification, uninterrupted product supply, with this development, the production system must be fast and the reconfiguration of production processing tools to optimize production [34]. production system as well as selecting optimal products [12], [13], [14]. As products increasingly require high precision, machining and inspection is controllable requirement [15]. Open and innovative design platform, design solutions and optimize machine performance [16], in recent years many methodologies and tools support the redesign of production systems. Continuous production, processing, and data acquisition allow the creation of a useful data repository for the redesign of manufacturing systems [17], [18], [19]. Jun Hong et al [20], Ben Hicks et al [21] apply the soft-optimal growth principle of branching, which provides unique capabilities to improve efficiency and is common to machine development by machining by re-engineering the tool to improve machine efficiency, use the Design of Disassembly (DOD) is a design approach that assists engineers in the product development process, where individual components can be disassembled [22], [23]. Reconfigurable Transportation Systems (RTSs) are based on transport units, basic mechatronic interfaces, and distributed control solutions, tailored to individual configurations and very short timelines suitable for process management production [24].

The main factors driving the digitization industry are higher competitiveness through reducing production costs [32], improving efficiency, shortening time to market [25], [33], designing semi-automatic testing equipment, improving machine performance, and improving quality [26], one of the important transformations in the era of the internet of things (IoT) and the new revolution in the digital twin industry lookup big data [27]. A. Papetti et al [28] propose a cross-engineering approach that supports internet of things technology to complement the redesign of manufacturing and machining processes. The emergence of the IoT brings many benefits and links many devices together and a smart measurement using the system by using the measuring system [29], D. Boehme's author [30] researched and linked measurement data processing with data online. K. Y. Lee's author [31] processing measured data in real-time with high accuracy and at the same time. Nataliia. K's author [32] proposed to connect the measurement data and display it on the tablet screen that can be deployed at the factory site.

In this paper, it is proposed to attach a position sensor to the machining tools of the surface grinding of mechanical products through the dynamic mechanism of steam pressure and control the stability by color of the sensor. At the same time, apply the measurement data connection method to the system and process the data online by entering the standards dimension and dimension tolerances into the data master table on the network, and then compare the data actual measurement with master data on the network to determine whether the dimension results pass or fail automatically though the online data processing system.

3 Case study for improvement

Brand and competitiveness are factors that manufacturing companies pay special attention to. Specifically, product quality control, productivity improvement according to the theory of total quality management in general and LSS method is the model that most mechanical processing companies pay special attention to. Any activity in outsourcing has somewhere wasteful operations, reducing the competitiveness of the business there for detecting waste and eliminating it is imperative. LSS is a useful model for detecting and implementing practical waste-removal improvement actions, the proposed 10-step QC model from improving the 7-step QC model combines the application of the DNC model to call the machining program by the barcode system, the computer vision model with the identification function. List of people according to each position fixed layout control of safety in machining related to operator errors causing labor accidents due to lack of skills in machine operation is used by python programming language. Redesigned the machining jig and simulated it with solid work software before putting it into actual manufacturing. The product dimensioning system model saves measurement data to the database on the Structured Query Language (SQL) system deployed at each processing line according to the process linkage model. PLS-SEM model using smart PLS 3.0 software to analyze the results of the user survey, the results after improvement in terms of usefulness, convenience and technical factors affecting loyalty to use the results. of improvement activities. The research focuses on improving machining line efficiency in terms of productivity, improving quality, reducing handle time, and improving safety in the labor environment with automatic processing machines. The research is carried out in the following order of contents: (1) Inspect, confirm, and evaluate the entire production process of the processing line from the beginning to the end of the process. (2) Detailed assessment at each processing stage at each product processing step by industrial tools. (3) identify waste factors arising in the processing line. Continuous improvement is the activity of identifying waste and eliminating waste, eliminating non-value-added activities, and optimizing value-added activities. Previous studies have linked waste elimination and productivity enhancement by applying LSS tools to control variability in machining. The proposed 10-step QC model combines the application of industrial tools cybernetics such as DNC, computer vision model by human identity recognition model, tool redesign in machining and PLS-SEM model. Analyze user loyalty in the machining line before and after the improvement operation, the results are practical in terms of improving productivity and quality, reducing the lead time. Key stages of improvement activities performed to achieve the above result is done in the following steps: Phase 1 (identify and measure) using Pareto chart and the ability to analyze the processing process by human-machine interaction flowchart from industry tools to identify waste factors. In production line operations. Phase 2 (analysis) applies LSS tools and industry tools to analyze the current state of deployment according to "Best of Best" and "Worse of Worse" theories. Phase 3 (improvement) applies the DNC model, computer vision, jig redesign, PLS-SEM model and finally implements control plans to ensure sustainable profits.

4 Raw material and proposed methodology

4.1 Raw material

Lean or lean management systems do the work of identifying wastes using tools such as workflow diagrams, value flow diagrams, pareto charts, cause-effect diagrams, 5 whys. Next, the analysis to identify the effects of waste is a measure of Lean. Improvement action to eliminate waste is considered through tools like 5S, standardization, visual control, redesign layout, future flow diagrams, continuous improvement and finally implement monitoring and control to determine according to Lean measures. Lean manufacturing or Lean production is a system of tools and methods of continuous improvement that eliminates all the wastes that arise in the production process. Specifically, it is to reduce production costs, increase output and reduce production time. The main point of Lean manufacturing is that everyone is thinking together to implement innovative solutions in a timely manner target, same output but lower input, less time, less space, less labor, less machines, less materials, and less cost. LSS is a team-focused management approach that improves performance by eliminating waste and limiting defects, developing the best internal potential of an organization. A combination of LSS (6 sigma) and lean manufacturing or lean Enterprise methods to try to eliminate waste of physical resources, time, effort, and talent while still ensuring quality in the production process and organization. LSS model focuses on reducing and eliminating eight types of waste in manufacturing which is abbreviated as downtime. The eight types of waste are: (1) Waste due to product defects (defects). (2) Waste due to overproduction. (3) Wasting of useless time (waiting). (4) Waste of human resources (unused talent). (5) Waste of transportation (transport). (6) Waste of inventory (inventory). (7) Waste due to process (excess processing). (8) Waste in operation (motion). The LSS model with a 5-step process abbreviated as DMAIC is also used in the LSS model. The five steps of DMAIC are: (1) Define, (2) Measure, (3) Analyze, (4) Improve, (5) Control. This 5-step process of the 6 Sigma model improves, optimizes, and stabilizes business processes based on available data. The LSS improvement model is a combination of the lean management model and the LSS model showing that the production process tends to change and then limit these variations to ensure continuous process improvement. Continuous improvement is a tool of the LSS method in the process of implementing improvement, eliminating waste, and reducing variability in the manufacturing environment. Continuous improvement focuses on 10 key principles as follows: 1. Customer focus. 2. Always improve. 3. Admit issues candidly. 4. Promote openness. 5. Encourage teamwork. 6. Manage cross-functional projects. 7. Cultivate the right relationship processes. 8. Promote the spirit of self-training. 9. Notice to all employees. 10. Create conditions for all employees. Kaizen activities are performed by tools such as (1) Instruction systems (Suggestion Systems). (2) Quality control cycle. (3) Process oriented management. (4) Visible management. (5) Cross-functional management (cross-functional management). (6) JIT management (just-in-time management). (7) Kanban. (8) Statistics process management (statistics process management). (9) The PDCA cycle (The PDCA cycle). The Kaizen model follows 7 main steps as follows: 1. Make problems visible. 2. Develop countermeasure. 3. Determine the root cause. 4. Hypothesis solution. 5. Test hypothesis. 6. Implement a solution. 7. Standardization work. The model has not yet shown the explanatory content describing the object, production line, or organization that will be the object of Kaizen activities. This is a step that needs to be shown so that the Kaizen implementer and Kaizen performer know about the Kaizen activity. After Kaizen, the results of improvement activities have not been evaluated and identified in terms of strengths and weaknesses of Kaizen results after being implemented in a practical environment survey the opinions of users and operators about Kaizen results. from there, as a premise for shaping future research. found these 3 missing points in the 7-step Kaizen.

There are 8 activities from the safe house as: (1) Establishing safety regulations, (2) Safety implementation plan, (3) Deploying safety awareness training for workers, (4) Carrying out the assessment and checking of safe operations at the site of the processing line, (5) making a plan to assess the risks related to occupational safety at the site, (6) Carrying out investigations, analyze the causes and hazards of unsafe points, (7) make tables showing safety standard requirements in an easy-to-see location, (8) perform re-inspection, assessment, and communication for workers. The main activities are to comply with 5S standards and the safety standards for occupational accident prevention in each country have been revised to be consistent with ISO/IEC standards, ISO 12100: 2010 specifies standards for machine safety such as risk assessment and risk reduction. Safety is that no matter what happens, employees are not harmed. Safety training is good, there must be more design and production of safety machinery, based on safety technology. Safety words in ISO 12100 need to be understood like (1) Hazard means potential source of harm, (2) Protective measure means measure intended to achieve risk reduction, (3) Safeguarding means protective measure using safeguards to protect persons from the hazards which cannot be reasonably be eliminated or risk which cannot be reduced by inherently safe design measures, (4) Safeguard means to guard or protective device, (5) Hazardous situation means context in which a person is exposed to at least one hazard, (6) Hazardous event means an event that can cause to harm propose an action plan to ensure the above 6 factors to create a safe working environment.

Numerical control in automation combines the model of digital signal processing by barcode, which is designed to be integrated into the machining environment. Specifically, redesigning the method of calling the machining program corresponding to each product line with different machining parameters using a numerical control model, to ensure that there is no risk of accidents due to the wrong choice of workers machining program of the automatic lathe. Computer vision analyzing objects from images extracted from cameras is a modern and convenient research model in a production environment. Application of computer vision in facial recognition of human objects in machining line layout redesign, identify the machining line for each specific employee such as the person's name and the identification password of each specific person, ensuring the layout works with the right person, at the right machine, eliminating wasteful movement of the machining in the process, production line, safety in machine operation to avoid errors caused by using the wrong person at the processing machine.

4.2 Proposed methodology for case study

We propose a QC 10-step Kaizen model, see Tab. 1. Model PLS-SEM, Numerical control method and Computer vision represented by human face recognition model combined with LSS method in improving productivity and quality at mechanical product processing lines. Specifically, the QC 10-step Kaizen model is detailed.

Tab. 1 *Propose a QC-10 step Kaizen model*

Define	Measure	Action	Improve	Control
Step 0: Introduction	Step 4: Hypothesis solution	Step 6: Implement solution	Step 7: Standardization work	Step 9: Plan for the future
Step 1: Make problems visible	Step 5: Test hypothesis		Step 8: Reflection / remaining problems	
Step 2: Develop countermeasure				
Step 3: Determine root cause				

In the QC 10-step Kaizen model, step 0, step 8, step 9 are 3 steps added to the standard 7-step improvement model. The purpose of clarifying the object information, the environment for implementing improvement activities, analyzing the results after improvement, and proposing content for future improvements. Specifically, the content follows the improved model 10 for research to improve productivity and quality at precision mechanical processing plants, the software used in the study includes Python, Minitab 18.0 and smart PLS 3.0.

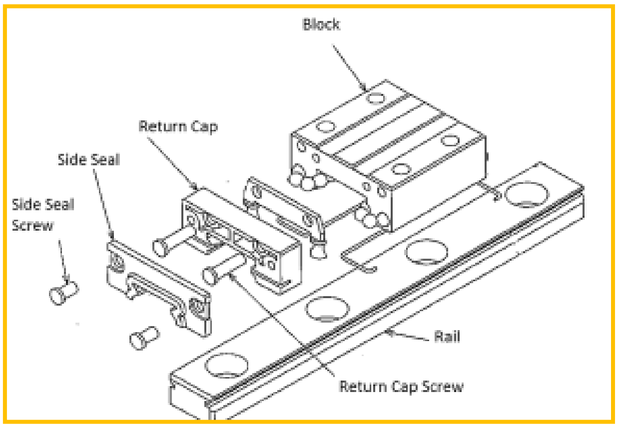

Fig. 1 *Slide guide assembly product*

Step 0: Describe the space, time, and scope of the object to be studied. Specifically, at a mechanical processing factory with investment capital from Japan, the headquarters of the processing company is located in the southern region of Vietnam. Raw materials are imported from China, semi-automatic and automatic processing machines are imported from Japan, America and products are distributed to most markets around the world. The product is called Block, which is a piece that is assembled into a set of products called a slide guide, see Fig. 1.

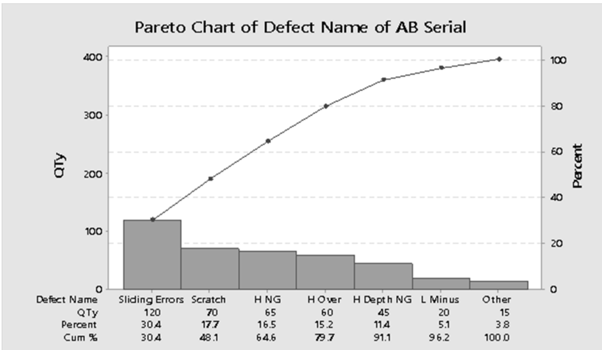

Fig. 2 *Defect type of product AB*

Step 1 (Make problems visible): Collect to analyze past and present data from check sheet, data on SQL system from machine parameters to measurement results of actual machining conditions and product size measurement results are recorded by check sheet at each processing line. Specifically, at the mechanical processing line, the product measurement results are recorded in the check sheet, the measurement results are evaluated as unsuccessful based on the measurement results compared to the standards of the processing staff, the results are analyzed by the Pareto chart shows the most common slip-groove error with 30.4%, see Fig. 2.

Step 2 (Develop countermeasure): the processing of block mechanical products is carried out according to the following steps: Step 1 of raw material turning, Step 2 of heat treatment of products to hardness from 58 to 62 hrs. Next, the finishing stage and final inspection, packing & shipment. slotted waste generated at the finishing stage. Continuing to analyze the data relation to machining parameters about the position of ball movement in the motion region of products AB, see Fig. 3, discovered the errors of ball return hole deviation, see Fig. 4 and ball groove deviation, see Fig. 5, this causes the ball not to move smoothly resulting in arising. The ball moves well around the ball return hole dimension making the mechanism operate smoothly and otherwise, the mechanism will not operate smoothly and cause the ball to jam. Establish a plan to improve the misaligned product implemented according to the Gant chart and Work Breakdown Structure (WBS) with each specific job, the person in charge, and time to complete the work, which is clearly shown in the plan table.

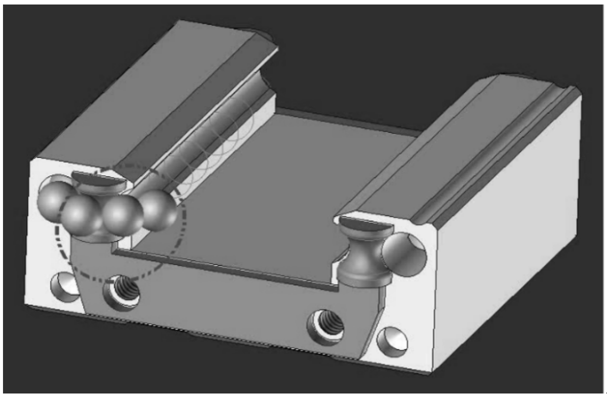

Fig. 3 *The motion region of product AB*

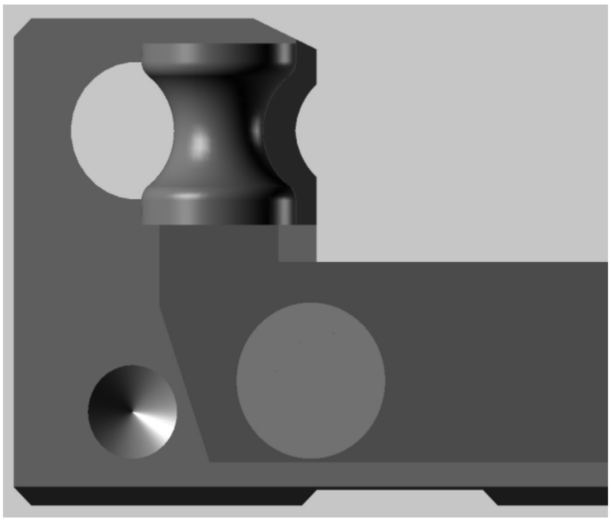

Fig. 4 *Ball return hole deviation*

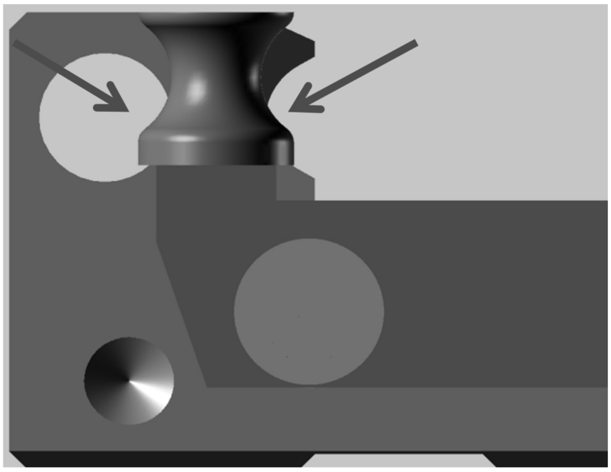

Fig. 5 *Ball groove deviation*

Step 4 (Hypothesis solution): Test hypotheses that may cause problems, the goal is to design optimal parameters in tool improvement for the object that generates the groove deviation error of block AB products. The hypothesis testing model was established to verify actual results at the finishing stage, before and after improvement activities.

Notation for parameters:

X…Random variable,

W…Reject domain,

$z_{0,}t_{qs}, x_0^2$…Test statistics,

s^2…Standards deviation,

μ, σ^2…Expected,

$\bar{X}$…Unbiased estimate,

H_0…Null hypothesis,

H_1…Alternative hypothesis,

$t_{\alpha/2}^{n+m-2}$…Look up value from student distribution table,

$x_{\alpha,n-1}^2$…Look up value from normal distribution table.

Model constrains:

Definition 1: Hypothesis Testing on the Mean, Variance Known (Z-Test):

Suppose that we wish to test the hypothesis where μ_0 is a specified constant. It is usually more convenient to standardize the sample mean and use a test statistic based on the standard normal distribution. That is, the test procedure for H_0:$\mu = \mu_0$ uses the test statistic.

$$H_0 : \mu = \mu_0, H_1 : \mu \neq \mu_0, \tag{1}$$

Test statistic:

$$z_0 = \frac{\bar{X} - \mu_0}{\sigma / \sqrt{n}}, \tag{2}$$

Two-Sided Test reject domain:

$$W = \left(-\infty; -u_{\alpha/2}\right) \cup \left(u_{\alpha/2}; +\propto\right), \tag{3}$$

One-Sided Test reject domain:

$$RightSidedTest: W = \left(u_\alpha; +\infty\right), LeftSidedTest: W = \left(-\infty; -u_\alpha\right), \quad (4)$$

Definition 2: Tests on the Variance and Standards Deviation of a Normal Distribution:

Suppose that we wish to test the hypothesis that the variance of a normal population σ^2 equals a specified value, say σ_0^2, or equivalently, that the standard deviation σ is equal to σ_0. Let $X_1, X_2, \ldots, X_n$ be a random sample of n observations from this population. To test:

$$H_0: \sigma^2 = \sigma_0^2, H_1: \sigma^2 \neq \sigma_0^2, \quad (5)$$

We will use the test statistic:

$$x_0^2 = \frac{(n-1)S^2}{\sigma_0^2}, \quad (6)$$

Two-Sided Test reject domain:

$$W = \left(0; x_{1-\alpha,n-1}^2\right) \cup \left(x_{\frac{\alpha}{2},n-1}^2; +\infty\right), \quad (7)$$

One-Sided Test reject domain:

$$RightSidedTest: W = \left(x_{\alpha,n-1}^2; +\infty\right), LeftSidedTest: W = \left(0; x_{1-\alpha,n-1}^2\right), \quad (8)$$

Definition 3: Hypothesis Testing on a Binomial Proportion

Modeling the occurrence of defectives with the binomial distribution is usually reasonable when the binomial parameter p represents the proportion of defective items produced. Consequently, decision problems involve hypothesis testing about p.

We will consider testing:

$$H_0: P = P_0, H_1: P \neq P_0, \quad (9)$$

Let W be the number of observations in the random sample of size n that belong to the class associated with p. Then if the null hypothesis $H_0: P = P_0$ is true, we have $W \sim n[np_0(1-p_0)]$, approximately. To test $H_0: P = P_0$, calculate the test statistic:

$$z_0 = \frac{X - np_0}{\sqrt{np_0(1-p_0)}}, \quad (10)$$

Two-Sided Test reject domain:

$$W = \left(-\infty; -u_{\alpha/2}\right) \cup \left(u_{\alpha/2}; +\infty\right), with: \theta_0\left(u_{\alpha/2}\right) = 1 - \alpha/2, \quad (11)$$

One-Sided Test reject domain:

$$RightSidedTest: W = \left(u_\alpha; +\infty\right), LeftSidedTest: W = \left(-\infty; u_\alpha\right), with: \theta_0\left(u_\alpha\right) = 1 - \alpha, \quad (12)$$

Definition 4: Compare to the t-test

The t-test is known to have the smallest value of β possible among all test that have significance level α for the one-sided alternative and for tests with symmetric critical region for the two-sided alternative, so it is superior to the sign test in the normal distribution case. Thus, the sign test is usually considered a test procedure for the median rather than as a serious competitor for the t-test.

Null hypothesis:

$$H_0: \mu_1 = \mu_1, \quad (13)$$

Test statistic:

$$t_{qs} = \frac{\bar{X} - \bar{Y}}{\sqrt{\frac{nS_x^{2+mS_y^2}}{n+m-2}} + \sqrt{\frac{n+m}{n \times m}}}, \quad (14)$$

Two-Sided Test reject domain:

$$W = \left(-\infty; -t_{\alpha/2}^{n+m-2}\right) \cup \left(t_{\alpha/2}^{n+m-2}; +\infty\right), \quad (15)$$

One-Sided Test reject domain:

$$RightSidedTest: W = \left(t_{\alpha/2}^{n+m-2}; +\infty\right), LeftSidedTest: W = \left(-\infty; -t_{\alpha/2}^{n+m-2}\right), \quad (16)$$

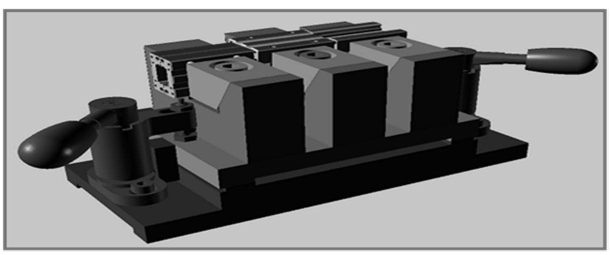

Fig. 6 *Machining tools*

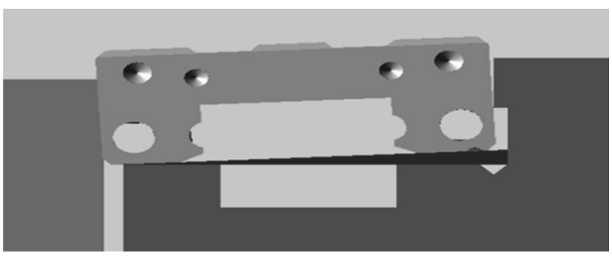

Fig. 7 *Products face is not balance*

The employee attaches the product to the machining tools, see Fig. 6. At the machining stage, if the product is warped relative to the tools plan, see Fig. 7, then machining to make the product face tilted means the dimension of the return hole and the deviation of the ball hole.

Actual data analysis at the machining line for substandard groove sizes due to inadequate machining jigs and waste in the machining process depends on the eye of the processor, results from the analysis of the interaction between the machinist and the machine according to the industrial tool by video recording and the analysis of the operation then evaluate the measurement results according to the hypothesis test. As a standard, the dimension of return ball holes is 6.0mm, by randomly checking 100 samples, the average dimension of return ball holes is 6.4mm. With a significance level of 0.05, it can be assumed that the ball hole dimension is not up to the standards or not, knowing that the ball hole dimension is a random variable with a normal distribution with a standard deviation of 2 mm, apply constraints (1-4) to confirm the problems.

Follow hypothesis of parameter testing of Two-Sided Test:

$$H_0: \mu = 6.4, H_1: \mu \neq 6.4, \tag{17}$$

With significance level $\alpha = 0.05$, look up the standard distribution table:

$$u_{0.025} = 1.96, \tag{18}$$

Reject domain:

$$W = (-\infty; -1.96) \cup (1.96; +\infty), \tag{19}$$

With $\bar{X} = 6.4$, value of the statistical standards:

$$\boldsymbol{u_{qs}} = \frac{\mathbf{6.4-6.0}}{\mathbf{2}} \times \sqrt{\mathbf{100}} = \mathbf{2} \in \boldsymbol{W}, \tag{20}$$

Reject H_0, the dimension of return ball holes is not up to standard. Conclusion, the employee remembered and recorded by hand the wrong measurement results in the check sheet.

Redesigning optimal parameters and implementing machine jig improvements, specifically, eliminating the dependence on the eye of the machine operator, which means eliminating the dependency on the machine operator, automatically optimizing the processing process, overcome the grooved waste for the block. Implementing improvements in automation of collecting and analyzing product dimensioning data at the processing line are the two topics studied in this article.

Step 5 (Test hypothesis): Analyze the operation of employees at the MC processing line by Man - Machine diagram. As a result, at Step 4 of setting up the product into the processing jig, it was shown that employees use their ears to hear, use their hands to touch, and use their eyes to perceive the contact surface between the product and the jig, see Tab. 2. Humans have emotions, therefore manipulations that rely on humans will result in blunders. Similarly, operations in steps 6 and 7 rely on humans, and the outcomes are likely to be erroneous. These are wasteful processes that require improvement actions to remove waste.

Tab. 2 *Man – Machine chart*

Step	Operations	Time (s)	Comments
1	Open the door of MC Machine	5	
2	Air flow around the jig	15	
3	Put semi-product on the jig	10	
4	Check the clearance between the product face and the jig	55	Wasteful, inaccurate
5	Close the door	5	
6	Select the machining program based on the product name by eye	30	Wasteful, inaccurate
7	Press start button	5	
8	Get out products	40	
9	Measure the product dimensions and record the measurement results on the check sheet by hand	65	Wasteful, inaccurate
10	Next cycle	….	

Step 6 (Implement solution): According to Poka-yoke theory, it is necessary to redesign the solution to replace the dependence on people. For Step 4, using a gas sensor system, open the machined jig through a vent hole see Fig. 8. The model is simulated on solid work software to control the clearance between the product surface and the machining tool face to export the drilling tool hole plan and attach the position sensor to the plane clearance control, see Fig. 8.

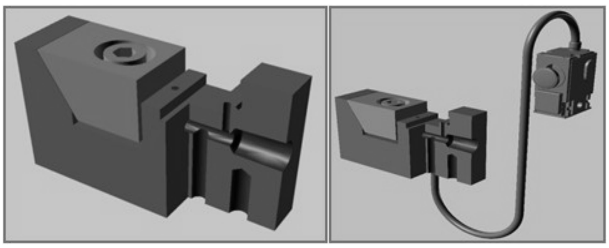

Fig. 8 *Improvement tools and Connect sensor to the tools*

For step 5, eliminate errors caused by wrong selection of machining programs, the risk of tool collisions in the processing machine, and labor accidents. Re-design the corresponding set of processing parameters for each product line and save it to the server system, link the parameter set to the processing order issuance system, the processing order is coded with the product name by barcode, connect the barcode system and the processing parameters to the MC machining program.

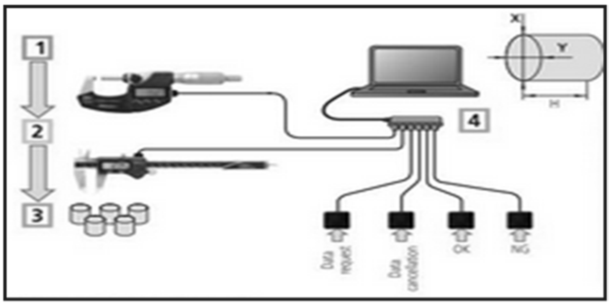

Fig. 9 *Link measurement tools to system by cable*

For step 6, Connect the measuring instrument to the network with a cable, and the link program takes data from the measuring instrument into the system, see Fig. 9.

Step 7 (Standardization work): Correct operation of tool reconstruction results, preventing recurrence of urgent operating errors. Update the sequence of instructions for operating the processing machine, the assembly sequence, the machining setup, the measurement steps need to be clearly standardized. Periodic staff training, capacity check after training, and update the process quality control standard table (control plan) and update the risk analysis table in the production line (FMEA document).

Step 8 (Reflection/remaining problems): Controlling and re-evaluating post-improvement results is essential in continuous improvement activities. The workers are the ones who directly use the results of the improvement activities, tabulate the operator's opinions on the criteria of technical factors, convenience, and usefulness from the reconstruction results. Instrument design, analysis of survey results using smart PLS 3.0 software according to PLS-SEM model, looking for shortcomings that lead to disloyalty, using post-improvement results of users see Tab. 3.

Tab. 3 *Sample for surveying at processing line*

Department	Gender	Quantity	Percent (%)
Operators	Man	69	69
	Women	20	20
Maintenance	Man	4	4
Technique	Man	4	4
Supervisors	Man	3	3

Step 9 (Plan for the future): Looking for future development directions is urgent, the results from the past serve as a basis for future research. From the analysis results from the PLS-SEM model in Step 8 and the results of the current situation analysis using the Man - Machine chart tool from industrial tools through the images obtained from the camera as a guide for future improvement activities in the future. Analyze, determine, and classify problem points according to the flowchart below, see Fig. 10.

Ensuring occupational safety for employees is an essential element in the modern working environment. In particular, the environment using automatic processing machines, ensuring that trained, certified workers are trained when operating automatic processing machines is a must and control employees according to the established layout regulations, see Fig. 11. Ensuring the right people, enough skills to operate automatic machines and applying computer vision models by analyzing human face recognition to control layout is a new step in the application of industrial 4.0 in the production environment.

Improve productivity and quality of machining line operations of mechanical product lines by eliminating waste, optimizing machining capacity (OEE) by applying innovative tools from new technology techniques such as: automatically calling the machining program using DNC model, controlling the layout according to the worker's fixed position by computer vision technology by human face recognition and analyze user opinions, improved performance results from the reconstruction of the machine machining tools using PLS-SEM model as a premise for future studies.

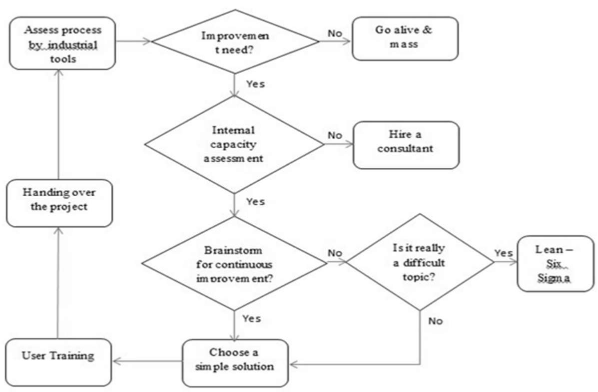

Fig. 10 *How to select a good improvement program*

Fig. 11 *Layout of machining process*

5 Result

5.1 Proposing activities in re-design jig at MC machine program

The control is or does not reach the level of perception through color display on the sensor, see Fig. 12. If a red light is generated an alarm will sound and the machine will stop, tools after adding vent position to control clearance and deploying tools at machining stage. Verify the results after deploying using improved tools to fix the errors of the ball return hole dimension.

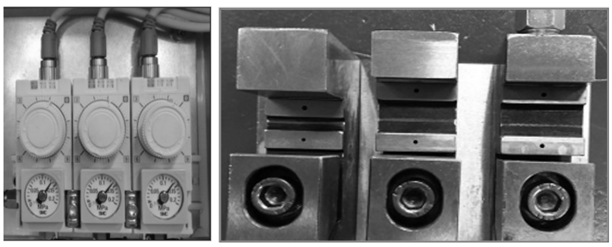

Fig. 12 *Actuak using sensor and Tools after improvement tools*

Verify #1: After improving the tools, randomly take 20 samples about the deviation to get the standards deviation $S'^2 = 0.0153(12)$ and the dispersion does not differ by more than 0.01 (12). At a significance level of 5%, let's check whether the improved tools are successful or not. The position deviation A1, A2, or H1, H2 is a random variable with a normal distribution. Apply constraints (6-8) to verify the problems.

Null hypothesis:

$$H_0: \sigma^2 = 0.01;\ H_1: \sigma^2 > 0.01, \tag{21}$$

With significance level $\alpha = 0.05$, and degress of freedom 19, look up the Chi-square distribution table:

$$x^2_{0.05;19} = 30.144, \tag{22}$$

Reject domain:

$$W = (30.144; +\infty), \tag{23}$$

With $s'^2 = 0.015(1^2)$, the value of the statistical:

$$x_{qs} = \frac{(19-1)\times 0.0153}{0.01} = 29.07 \notin W, \tag{24}$$

Accept hypothesis H_0. Conclusion that after improvement the grinding machine tools to get results are as required.

Verify #2: Continue to verify the stability of the tolls after the improvement by letting 2 employees A and B work on the same improvement tool and check product quality. Employee A processes 8 samples, Employee B also processes the same products as Employee A 8 samples.

Dimension [A1-A2] process by employee A: 91.5; 94.18; 92.18; 95.39; 91.79; 89.07; 94.72; 89.21.

Dimension [A1-A2] process by employee B: 89.19; 90.95; 90.46; 93.21; 97.19; 97.04; 91.07; 92.75.

At a significance level of 5%, it can be assumed that the dimension [A1-A2] of the products processed by Employee A and Employee B are the same, given that the dimension [A1-A2] has a normal distribution. Apply constraints (13-16) to verify.

Null hypothesis:

$$H_0: \mu_1 = \mu_2;\ H_1: \mu_1 \neq \mu_2, \tag{25}$$

With $n = 8; m = 8$, and signification level $\alpha = 0.05$, look up the student distribution table:

$$t^{8+8-2}_{0.025} = t^{14}_{0.025} = 2.14, \tag{26}$$

Reject domain:

$$W = (-\infty; -2.14) \cup (2.14; +\infty), \tag{27}$$

With the given sample, the calculation result:

$$\bar{X} = 92.255;\ S_x^2 = 4.998;\ \bar{Y} = 92.733;\ S_y^2 = 7.77, \tag{28}$$

Statistical standard value:

$$t_{qs} = \frac{92.255-92.733}{\sqrt{\frac{8\times 4.988+8\times 7.77}{8+8-2}}\times\sqrt{\frac{8+8}{8\times 8}}} = -0.353 \notin W, \tag{29}$$

Accept hypothesis H_0. Conclusion that the A-A measurement value of Employee A and Employee B is the same.

Verify #3: Continue, check if the improvement tools are used on 2 different machine stages, the product processing quality is the same or not. Use the improved following tools on Machine A and Machine B to determine if the accuracy is the same. To do this, to get conduct sampling as follows Tab. 4.

Tab. 4 *Result of quality of 2 machine*

Machine	Samples						
Machine A	135	138	136	140	138	135	139
Machine B	140	135	140	138	135	138	140

At significance level 5% and detail dimension is a normally distributed random variable. Apply constrains (5-8) to verify the problem.

Null hypothesis:

$$\boldsymbol{H_0}: \boldsymbol{\sigma_1^2} = \boldsymbol{\sigma_2^2};\ \boldsymbol{H_1}: \boldsymbol{\sigma_1} \neq \boldsymbol{\sigma_2}, \tag{30}$$

At significance level of 5% and sample size $n = 7, m = 7$, look up the distribution table F obtained:

$$\boldsymbol{f_{0.976;6,6}} = \mathbf{0.2};\ \boldsymbol{f_{0.025;6.6}} = \frac{\mathbf{1}}{\mathbf{0.2}} = \mathbf{4.995}, \tag{31}$$

Reject domain:

$$W = (0; 0.2) \cup (4.995; +\infty), \tag{32}$$

With the given sample, calculation to get:

$$s_x'^2 = 3.905;\ s_y'^2 = 5, \tag{33}$$

Statistical standards value:

$$\boldsymbol{f_{qs}} = \frac{\mathbf{3.905}}{\mathbf{5}} = \mathbf{0.781} \notin \boldsymbol{W}, \tag{34}$$

Accept hypothesis H_0. Conclusion that using the improved tool for machine A and machine B has the same quality.

Verify #6: Continue to verify the product quality when using the same improvement tool on 3 machining stages of the same quality or not. Deploying the improved post-processing tool for 3 different machining stages, the product test results are as follows Tab. 5.

Tab. 5 *Result of quality and defect products of 3 machine*

Machine Quality	Machine A	Machine B	Machine C	∑
Defect	12 13,14	16 15,77	18 17,09	46
Products (OK)	88 86,86	104 104,23	112 112,91	304
∑	100	120	130	350

At a significance level of 5%, can it be assumed that the quality rates of the 3 processing machines are the same or not. Apply constraints (9-12) to verify.

At significance level 5%, and $k = 3$, look up the table to get:

$$\boldsymbol{x^2_{0.05;2}} = \mathbf{5.99}, \tag{35}$$

Null hypothesis:

$$\boldsymbol{H_0}: \boldsymbol{p_1} = \boldsymbol{p_2} = \boldsymbol{p_3};\ \boldsymbol{H_2}: \exists \boldsymbol{p_i} \neq \boldsymbol{p_j}, \boldsymbol{i} \neq \boldsymbol{j}, \tag{36}$$

Reject domain: $W = (5.99; +\infty)$, calculating with the given data to get:

$$\boldsymbol{x^2_{qs}} = \frac{\mathbf{(12-13.14)2}}{\mathbf{13.14}} + \frac{\mathbf{(88-86.86)2}}{\mathbf{86.86}} + \frac{\mathbf{(16-15.77)2}}{\mathbf{15.77}} + \frac{\mathbf{(104-104.23)2}}{\mathbf{104.23}} + \frac{\mathbf{(18-17.09)2}}{\mathbf{17.09}} + \frac{\mathbf{(112-112.91)2}}{\mathbf{112.91}} = \mathbf{0.174} \notin \boldsymbol{W}, \tag{37}$$

Accept hypothesis H_0. Conclusion that using the improved tool for 3 machine and all them have the same quality.

5.2 Proposing activities in the calling MC machine program.

Read the barcode containing the product name with a barcode reader to call a machining program with parameters to set the processing amount for each product size from the system and select the correct program that has been pre-set for the MC machine, see Fig. 13. In case the wrong barcode is scanned, or the barcode is damaged, the system cannot call the processing program.

Fig. 13 *DNC system by barcode systém*

5.3 Proposing activities in the measurement

Apply the measuring system to the machining stage and instruct employees to use measuring instruments and save measurement data to the online system. Look at the computer interface screen, see Fig. 14 and sound an alarm when the measurement is out of standards.

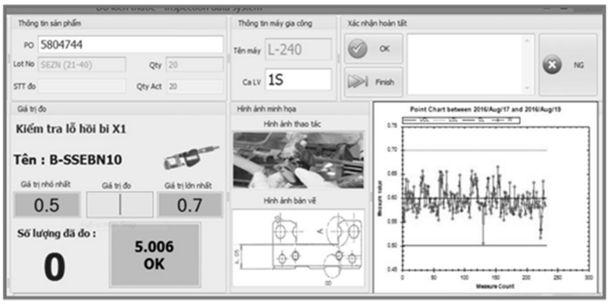

Fig. 14 *Actual measurement system in the machine stage*

After applying the measuring system to a processing stage and verifying the effectiveness of the results between using the measuring system, processing measurement data online, and the operation in which the employee records the measurement results in the check sheet and determines the correct or incorrect results according to judge.

Verify #1: Using method A (measure and record the results on the check sheet) and method B (measure and process measurement data online) for the same dimension and the same products, the result: method A: $n = 64; x = 7.32$, method B: $m = 68;\ y = 7.66$. Know that the measured data of the two methods are normal distribution random variables with standard deviations of $\alpha_1 = 1.09$ and $\alpha_2 = 1.12$, respectively. With a significance level of 1%, it can be said that the result of method B is higher than method A. Apply constraints (13-16) to verify.

Null hypothesis:

$$H_0: \mu_1 = \mu_1;\ H_1: \mu_1 < \mu_2, \tag{38}$$

With significance level of 1%, look up the normal distribution table:

$$\boldsymbol{u_{0.01} = 2.33}, \tag{39}$$

Reject domain:

$$W = (-\infty; -2.33), \tag{40}$$

The value of the statistical:

$$u_{qs} = \frac{7.32-7.66}{\sqrt{\frac{1.09^2}{64}+\frac{1.12^2}{68}}} = -31.43 \in W, \tag{41}$$

Reject hypothesis H_0, Conclusion, asserting that measurement method B is better than method A.

Verify #2: Continue to verify the output after the application checks and process measurement data online at the processing stage. Perform a countermeasure to connect measuring data from the caliper to the measuring system and determine OK/NG results by online data processing. Eliminate employees from mistakenly perceiving a product as a successful product and increase productivity at the stage. Know the average productivity at stage MC1 is 32.5 parts per hour. Investigation over 15 hours of processing and results collection: 33.7; 35.4; 32.7; 36.3; 37.3; 32.4; 30.0; 32.4; 31.7; 34.5; 42.0; 33.9; 38.1; 35.0; 33.8 (parts per hour). With a significance level of 1%, accept that hope or not, knowing that the output is a research variable with a normal distribution with a variance of 10 parts per hour. Apply constraints (1-4) to verify the problem.

Null hypothesis:

$$H_0: \mu = 32.5;\ H_1: \mu > 32.5, \tag{42}$$

With significance level $\alpha = 0.01$, have $\theta_{0(u_{0.01})} = 1 - 0.01 = 0.99$, look up the standard distribution table:

$$u_{0.01} = 2.33, \tag{43}$$

Reject domain:

$$W = (2.33; +\infty), \tag{44}$$

With $\bar{X} = 34.613$, the statistical standard value is:

$$u_{qs} = \frac{\bar{X}-\mu_0}{\sigma} \times \sqrt{n} = \frac{34.613-32.5}{\sqrt{10}} \times \sqrt{15} = 2.587 \in W, \tag{45}$$

Reject hypothesis H_0. Conclusion that processing output at MC stage increase.

5.4 Proposing activities in the control layout by computer vision

The camera system to acquire images of the processor is specified at each processing stage. At each company, there is only one employee with the employee identification code numbered in order. The identification system detects other employees and displays a warning on the screen, the system checks the products and the system to notify the date at the locked stage. In case, the data reported for the previous stage is not available, the system for reporting the next stage date will not work, see Fig. 15. The management staff can only use barcodes to open the system and record the case of skipping the processing stage and implement a recall of all suspicious products.

Fig. 15 *Missing system alarm*

6 Conclusion

Since applying the measurement data link to the system and online data processing, the handling time has decreased from 1.3 hours per day to 0.36 hours per day (reduce 0.94 hours per day). The strength of this improvement is that it eliminates the dependence on human manipulation and judgment to save the measured data on the network (database) and can be used for later data analysis. Improvements are costly to set up initial equipment and time to training resources.

In addition, the improvement of tools in the machining stage from operating by relying on human control to using automatic tool operation control mechanism by the sensor system. The strength of innovation is increasing processing capacity from 115 products per day to 155 products per day (increase 40 products per day), ensuring product quality according to customer requirements, and eliminating dependence on the machining experience of the staff. The limitation of this improvement is that the time to improve the machining tools is long and resources are needed for the design.

The results after used improvement operation in machining stage:

- 1. Material cost decrease: 364 USD per month
- 2. Labor cost decrease: 155 USD per month
- 3. Tool cost decrease: 159 USD per month
- 4. Depreciation expense: 500 USD
- Total cost decrease: 678 USD per month
- Total cost decrease: (1+2+3) *12-(4) = 7,636.00 USD per year

The automatic MC machine program call system and the employee monitoring camera system at each processing line respectively have improved the level of labor safety. Specifically, the level of employee satisfaction with improvement activities in terms of usefulness is very high, the results in labor safety decreased from 5 cases of wrong selection of the machining program and 2 cases of untrained operators operating the machine to no service, the convenience side when applying the improved results is highly appreciated by the operator. Technically, it needs to be further improved such as weak signal reception network system, network flickering, barcodes are damaged due to oil adhesion at processing stages, and reading barcodes is not good or the signal is lost and cannot be read. The results are analyzed from the survey of users at the processing line in the mechanical factory and the maintenance technicians, designers, and factory management staff using the PLS-SEM model by the smart PLS 3.0 software program, see Fig. 16.

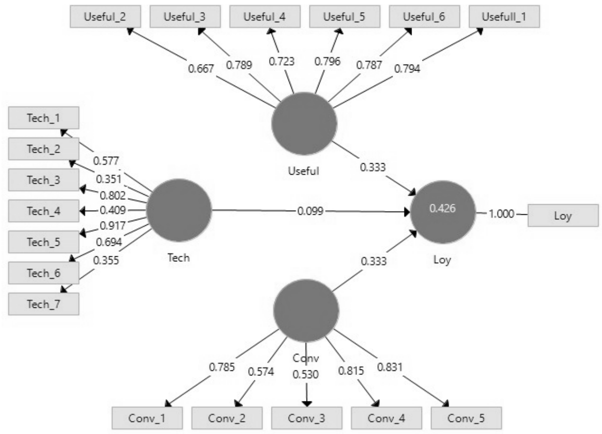

Fig. 16 *PLS-SEM model*

Using smart PLS 3.0 software to analyze user survey results, the results show that the improvement factor affecting loyalty has a strong correlation with the P- value of 0.01, the factor of convenience the advantage in using improved results of stone surface sanding table has a strong impact on loyalty using highly improved results with a P - value of 0.00. However, in terms of technical factors, the interaction on loyalty is unsatisfactory with a P - value of 0.54. This shows that from a technical point of view, the improvement team needs to re-evaluate and consider improving the improvement activities in technical terms for the next improvement activities, the content of the analysis is shown in Tab. 5.

Tab. 6 *Path coefficient, t-value and p-value of PLS estimation*

Path	Path coefficient	t-value	p-value
Useful -> Loyalty	0.33	2.54	0.01
Convenience -> Loyalty	0.33	2.92	0.00
Technology -> Loyalty	0.10	0.61	0.54

7 Discussion and future work

The result of this paper is the premise of another discussion for the next stage. Moreover, this improvement activity increases the tools design skills for employees as well as understanding the 10 steps of improvement activities. Inheriting from the result of database data collected from linked measurement data to the system, computer vision by human recognition database to the system and DNC system to call MC machine program automatics, can continue the work of calculating and controlling the processing lead time of each line at each stage and expressed through the following information daily detail reports and visual control on the status of machining at each machining stage on the job. The activity of improving machining tools to increase productivity at the processing machine creates a good premise for continuous improvement activities in the factory, in addition to improvement machining tools but also for other improvement activities for indirect parts such as logistics, purchasing, human resources. In terms of activities to eliminate wasteful operations and increase valuable operations.

Acknowledgement

Sincere thanks to Van Lang University, 69/68 Dang Thuy Tram, Ward 13, Binh Thanh District, City. HCM has provided time and space support for this research.

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