Design of Industrial System Using Digital Numerical Control

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Minh L. Duc, Petr Bilik, Thuy D. Truong

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ABSTRACT

Purpose: This paper would be based on applying quality 4.0 technology to mechanical factories. The overall purpose of quality 4.0 technology is to transition production lines from semi-automatic production to automatic production.

Methodology/Approach: The lean six-sigma with five phases of Define Measure Analysis Improve Control (DMAIC) would be used to measure the quality of 4.0 integration. Each phase is composed of statistical tools, hypothesis testing, experimental design, industrial tools, etc. to provide less error for precision in manufacturing control.

Findings: Results shows that scrap products decreased by 59.66% per year, the productivity of the production line assembly increased by 7.8%, and the total lead time decreased by 20 minutes. As well as the required payments and the monthly reduction of value cost of 500 USD for jig improvement, and profit is 678 USD per month and 7,636 USD per year.

Research Limitation/Implication: Gaseous hydrocarbons or organic compounds from n-hexane can be a challenge for sensors utilizing signals for researchers. Also, another issue would be the power supply output to the sensor due to external interference.

Originality/Value of paper: This research focuses on applying the usage of sensors from a semi-automatic machine tool to an automatic machine tool.

Category: Case study

Keywords: sensor; signal processing; DMAIC; computer vision; digital numerical control

1 INTRODUCTION

Due to the advancement of precision in mechanical products from the well-known machinery industry in China, Taiwan, Korea, India, and Malaysia has caused Japanese manufacturers to lag behind (Rehman et al., 2018). Quality systems such as ISO 9001:2015 or IATF16949:2015 have been used to improve product quality and production lines which means Japan must apply quality systems in their companies to catch up with the other global manufacturing countries (Gandhi, Sachdeva and Gupta, 2019). Lean Six Sigma is an indispensable technique for manufacturing businesses and has been used in continuous improvement for over 20 years (Garg, Raina and Sharma, 2020; Prabu et al., 2013). The phases of DMAIC in Lean Six Sigma engineering deal with the entire job (Ahmed, 2019; Gupta et al., 2018) and follow the PDCA (Plan-Do-Check-Action) cycle planning. The process of machining mechanical parts always generates abnormal errors in no one direction, it is essential to ensure stable process parameters throughout the machining time (Jamil et al., 2020; Bedi et al., 2015; Karout and Awasthi, 2017). Controlling, limiting or eliminating process variation, improving production productivity, minimizing waste, and eliminating waste is all that is needed to apply DMAIC to operations. continuous improvement activities (Soundararajan and Janardhan, 2019; Alqahtani, 2020).

Applying DMAIC to continuous improvement, providing a systematic view of supply chain operations, strategic planners see problems visually and make decisions easily Specifically. Product quality improvement (Smetkowska and Mrugalska, 2018), machining process quality improvement, and human capacity improvement are essential activities in the continuous improvement process. The continuous improvement method keeps the process perfect and supports the previous and subsequent processes in the best way (Kaoudom Yimtrakarn and Choomrit, 2019; Kaushik and Khanduja, 2009; Kumar, Wolfe and Wolfe, 2008). Previous studies have shown that applying Lean Six Sigma techniques promotes growth in production, motivating people to better understand the quality management system from theory to practice (Marques and Matthé, 2017; Mustaniroh, Widyanantyas and Kamal, 2021; Nandakumar, Saleeshya and Harikumar, 2020; Padmarajan and Selvaraj, 2021). Improve process efficiency, improve productivity, improve product quality stability throughout the machining process, making the company improve its competitive position compared to other companies (Basios and Loucopoulos, 2017). Managers must always be interested in continuous improvement activities, and closely monitor the operation process. The DMAIC phases help managers clearly identify problem points, areas that need to be faced and make improvements, following a specific plan (Barbosa, de Carvalho and de Souza, 2014; Biju and Nair, 2017). Improving customer satisfaction, reducing quality costs, and reducing machining costs are thoroughly solved by Lean six sigma tools. Lean tools eliminate waste and defects that arise in the machining line.

The DMAIC phases carry out continuous improvement activities in the manufacturing process, to process optimization, defect elimination, waste elimination, and multiple benefits (Carnovale et al., 2016). Value chain diagram. Pareto charts and overall yield are used during the DMAIC phase analysis of problem points. SIPOC (Supplier-Input-Process-Output-Customers) cycles, fishbone diagrams and other diagrams are applied for cause analysis (Cunha and Dominguez, 2015; De Mast and Lokkerbol, 2012). Machining process throughput performance is represented on a process capability measure and developed by statistical tools for quality control, DMAIC provides quick and timely analytical tools, Fast implementation of process improvement. DMAIC is methodologically limited and weak in the technical aspects of data aggregation. There are no studies that combine Lean Six Sigma techniques with digital control techniques into digital twin in machining operations, facial recognition computer vision techniques into operator behavior control and measurement systems (digital twin) sets the quality of the product.

Product quality depends on the workmanship of the processor, it is necessary to have a strict control plan. Improving product quality means gradually eliminating human skills in production activities (Rifqi et al., 2021; Kosina, 2015). Optimize tooling in the production process, eliminating the dependency on human skills (Pereira et at., 2019; Pech et al., 2018). In this study, re-design measuring instruments, set up measuring systems at each processing stage, collect product quality measurement data automatically, analyse product quality data one by one following a systematic way. The company’s management is constantly monitoring the quality improvement work of the Bush product line, a linear guide for a ball that rotates around a cylinder, with extremely low friction and precise movement, the ball bearing system is designed with a material with a low coefficient of friction.

The benefits of this study are as follows: (1) Integrating statistical tools, experimental design, industrial tools into Lean six sigma techniques in continuous improvement activities; (2) Computer vision recognizes human faces to control machine operator behaviour; (3) Computer Integrated Manufacturing (CIM) into automation calling machining programs, eliminating the dependency on worker skills; (4)Sensors used in continuous improvement activities to improve production line productivity, eliminate waste, control waste; (5) Product quality measurement system implemented at each processing stage, overall quality management; (6) Create a close connection from the research and academic environment to the actual outsourcing environment. remove barriers in people’s thinking and practice.

In this study, we propose to apply Digital Numerical Control (DNC) technique to call machining machines automatically. Computer Vision technology to recognize human faces to control the position of each employee. Online product quality measurement system at each stage according to total quality management rules, redesigned hole grinding tool with the used of sensors. The paper is organized as follows: Part II presents the raw material and research methodology, Part III presents the results of the case study and discussion, Part IV records the conclusions and research direction.

2 RAW MATERIALS AND RESEARCH METHODOLOGY

Lean Six Sigma consists of 5 phases (De Mast and Lokkerbol, 2012) such as DMAIC. Phase 1 (Define) shows the content of the problem points. Phase 2 (Measure) measures problems arising in the topic to be researched, sets goals according to SMART criteria, and makes action plans. Phase 3 (Analysis) clearly and specifically analyses the content of the problems using statistical methods or tools such as hypothesis testing, QC tools, six sigma tools, industrial tools (Khayrullina, Kislitsyna and Chuvaev, 2015). At each stage, identifying waste points is a necessary requirement. However, the limitation that needs attention is the analysis and measurement of inappropriate factors such as incorrect application of analytical tools, sample analysis is not suitable, this leads to incorrect measurement analysis results. Analysis and measurement of the stage are done in real-time, so the problem is detected wrong leading to the wrong requirements, generating waste products, leading to additional costs in the process of implementing improvements. Phase 4 (Improve) establishes improvement action to eliminate wastes or arising causes just found from phase 3 (Analysis) and implements improvement action in the real environment. Phase 5 (Control) collects data from the results of applying improvement measures using statistical tools such as hypothesis testing, control charts or histograms, as well as process capability assessment.

2.1 Define

The Pareto chart and the pie chart analyse the product line quality data for the past 1 year, and select the objects that need to be improved and increased the productivity of the machining line. The Bayesian formula is used to determine the type of processing line that gives rise to defective products (eq. 1):

$$P(B_i|A) = \frac{P(B_i)\times P(A|B_i)}{\sum_{j=l}^{m} P(B_j)\times P(A|B_j)}, i = l, \ldots, m. \tag{1}$$

Cycle time, lead time, valid time and non-value time on the machining line recorded by value stream mapping.

2.2 Measure

The Bootstrap ANOVA technique in the single variance analysis method analyses and locates the machine that generates the main waste, identifies the problem point in the machining line (eq. 2-5):

$$P\overline{\mathrm{Y}}_{\mathrm{i}} = \frac{1}{\mathrm{n_i}}\sum_{\mathrm{j}}^{\mathrm{n_i}} \mathrm{Y_{ij}}, \mathrm{i} = 1, 2, \dots, \mathrm{t}, \quad (2)$$

$$\mathrm{SSD_i} = \sum_{\mathrm{J}=1}^{\mathrm{n_i}}\left(\mathrm{Y_{ij}} - \overline{\mathrm{Y}}_{\mathrm{i}}\right)^2,\ \mathrm{i} = 1, 2, \dots, \mathrm{t}, \quad (3)$$

$$\sum_{\mathrm{i}=1}^{\mathrm{t}}\sum_{\mathrm{j}=1}^{\mathrm{n_i}}\left(\mathrm{Y_{ij}} - \overline{\overline{\mathrm{Y}}}\right)^2 = \sum_{\mathrm{i}=1}^{\mathrm{t}} \mathrm{SSD_i} + \sum_{\mathrm{i}=1}^{\mathrm{t}} \mathrm{n_i}\left(\overline{\mathrm{Y}}_{\mathrm{i}} - \overline{\overline{\mathrm{Y}}}\right)^2, \quad (4)$$

$$\mathrm{Y_{ij}} - \overline{\overline{\mathrm{Y}}} = \sum_{\mathrm{i'}}\sum_{\mathrm{j'}} \mathrm{c_{i'j'}}\mathrm{Y_{i'j'}}\ . \quad (5)$$

The technique of testing expectations according to student distribution to assess the quality stability of machines in process. The method of testing the expected deviation evaluates two processing machines (Machine A1 has assessed that the quality of the products after processing is unstable and Machine A2 is a new machine with the defective generation rate in the control area) is the product quality consistent? (eq. 6):

$$\left[(\overline{\mathrm{X}}_1 - \overline{\mathrm{X}}_2) < -\mathrm{Z}_{\alpha/2}\sqrt{\frac{\mathrm{S}_1^2}{\mathrm{n}_1} + \frac{\mathrm{S}_2^2}{\mathrm{n}_2}}, (\overline{\mathrm{X}}_1 - \overline{\mathrm{X}}_2) > \mathrm{Z}_{\alpha/2}\sqrt{\frac{\mathrm{S}_1^2}{\mathrm{n}_1} + \frac{\mathrm{S}_2^2}{\mathrm{n}_2}}\right]. \quad (6)$$

Statistical method measures the actual problem arising on the processing line, determines the specific location of the machine that gives rise to the problem point of product quality.

2.3 Analysis

Analysis of variance two factors evaluates the results of machining jigs running on machines, which affect product quality (specifically, jigs on machining center process surface dimensions) (eq. 7-11):

$$\mathrm{Y_{ij}} = \mu_{\mathrm{ij}} + \mathrm{E}, \quad \mathrm{i} = 1 \div \mathrm{a}; \mathrm{j} = 1 \div \mathrm{b}, \quad (7)$$

$$\mu_{ij} = \mu + \tau_i + \beta_j, \quad (8)$$

$$\mathrm{SS_E} = \sum_{\mathrm{i}=1}^{\mathrm{a}}\sum_{\mathrm{j}=1}^{\mathrm{b}}\left(\mathrm{y_{ij}} - \bar{\mathrm{y}}_{\mathrm{i}} - \bar{\mathrm{y}}_{\mathrm{j}} + \bar{\mathrm{y}}\right)^2, \quad (9)$$

$$MS_T = \delta^2 + \frac{b\sum_{i=1}^{a}\tau_i^2}{a-1}, \tag{10}$$

$$MS_B = \delta^2 + \frac{a\sum_{j=1}^{b}\beta_j^2}{b-1}, \tag{11}$$

with μ_{ij} – expectations turn out for experimental treatment i, block j, μ – expectations fade away, τ_i – expected deviation due to the effect of treatment i, *i=1-a*, β_j – expected deviation due to block j, *j=1-b*.

The multivariable experimental design technique for evaluating product jigs when processing and the technique for measuring the quality of product surface dimensions are the two main factors that give rise to surface scraps that do not meet customer requirements (eq. 12-15). Analysis of total sample variation:

$$SS = \sum_{i=1}^{a}\sum_{j=1}^{b}\sum_{k=1}^{n}\left(Y_{ijk} - \overline{Y}\right)^2. \tag{12}$$

The sum of squares of the entire sample was analysed from the sum of squares of each part:

$$ss_E ss_E = \sum_{i=1}^{a}\sum_{j=1}^{b}\sum_{k=1}^{n}\left(Y_{ijk} - \overline{Y}_{ij}\right)^2, \tag{13}$$

$$MS_{AB} = SS_{AB}/[(a-1)(b-1)] \sim x^2_{(a-1)(b-1)}. \tag{14}$$

Expectations of the mean squared of the observed samples:

$$MS_{AB} = \sigma^2 + \frac{n\sum_{i=1}^{a}\sum_{j=1}^{b}(\tau\beta)_{ij}^2}{(a-1)(b-1)}. \tag{15}$$

Hypothesis testing the influencing factors that give rise to unsatisfactory product surface defects based on the distribution of the observed sample mean squares with τ_i, β_j – expected deviation, y_{ijk} – output variable value, e_{ijk} – experimental error, Y – output of experimental variance, μ – expectations of the output variable, i, j – indicator range.

Analysis of variance in univariate experimental technique evaluates the impact of jigs on the output quality of product surface quality (eq. 16-17). Model of output's variable, sum of squared variation of observed data:

$$SS_E = \sum_{i=1}^{a}\sum_{j=1}^{n}\left(y_{ij} - \overline{y}_i\right)^2. \tag{16}$$

Mean squared variation of observed data:

$$MS_T = \sigma^2 + \frac{n\sum_{i=1}^{a}\tau_i^2}{a-1}, \tag{17}$$

with μ, μ_i – expectations of output variable, E_i – experimental error, τ_i – expectation deviation.

Univariate analysis of variance, univariate and multivariate experimental design analysis, measurement of observed patterns and specific identification of the main causes of defective products arising on the machining line.

2.4 Improve

The Monte Carlo analysis technique simulates the improvement options and makes the decision to choose the most feasible improvement option out of the four options. Univariate variance test evaluates the response of jigs after improvement at a machining center machine (eq. 18). Hypothesis rejection domain H_0:

$$\left[S^2 < x^2_{1-\alpha/2,n-1}\sigma_0^2/(n-1),\ S^2 > x^2_{\alpha/2,n-1}\sigma_0^2/(n-1)\right]. \tag{18}$$

The fuzzy set-based decision-making technique evaluates the stability of the system after using improved jigs at the machining center. Fuzzy object techniques and statistical tests perform the selection of the most suitable machining center jigs improvement plan and evaluate the results apply improved jigs to practice with high marks and improve jigs stable operation over time.

2.5 Control

A machining center is an automatic processing machine, untrained operators are at risk of causing labour accidents. A computer vision system that recognizes human faces is proposed to be applied to control workers operating at each processing line. The computer vision system uses artificial intelligence techniques to identify the face of each processor corresponding to the machine position and extract images from the camera system. The machining center operator stands in the wrong position according to the factory layout, the computer vision system detects and the alarm sounds, the machining center operation system locks. The machining center program call system is supported by DNC technology. Operating principle of DNC system according to CIM principle. The barcode reader reads the order barcode at the machining center, the order code is transmitted to the production system and requires the DNC system to select the machining program at the machining center to respond. The combination of computer vision and DNC systems creates a perfect system for occupational safety and operation of automatic processing machines at the factory. A product quality measurement system is also proposed to be applied at each processing line, measuring equipment is connected to the measuring system and measurement data is automatically saved to the production system server.

3 RESULTS OF CASE STUDY AND DISCUSSION

3.1 Define

Analysing scrap data from March 2019 to March 2020 at the machining line, the surface error accounted for 0.33%. Frequency of occurrence of a number of defects on 30 products, Empirical CDF shows that the cumulative frequency of scrap rate in the process tends to increase.

The processing line (B1) has an error probability ratio p1 = 0.01 and B2 is p2 = 0.05, has an order of 20 products and does not know which processing line. Bayes formula gives the results P(B1/A) = 0.7613 and P(B2/A) = 0.2387, (eq. 1), proving that the B1 production line is 3 times more likely to generate unsatisfactory surface defects than B2.

The surface is not up to the standard and is unstable, causing time (35 minutes) to both checks and calibrate so that the product runs smoothly, at the assembly stage, and it takes time to re-check. The roughness of the product after processing, is a wasteful step. The value stream mapping chart of the current state of the processing line shows that the total lead time of a product is 1,190 minutes, the total cycle time is 995 minutes and the value-add time is 443 minutes.

3.2 Measure

Three machining centers (MC) are operating at line B1, Box plots show that MC 3 is the machine with the highest rate of waste generation (eq. 2-5), one-variable ANOVA analysis results in p-value = 0.001 and F-value = 68.86, standard deviation MC 1 is 0.596, standard deviation MC 2 is 1.184 and standard deviation MC 3 is 1.680, the pooled standard deviation is 1.23565, the F-value is quite large, and the p-value is close to 0, the conclusion is to reject the hypothesis H0, the rate of waste generation of the 3 machines is different. The standard deviation value of MC 3 is larger than the pooled standard deviation value indicating that MC 3 is a machining center that produces the scrap.

The mean plane dimension value of 50 machined samples at MC 3 is 34.45 mm (eq. 6) larger than the rejection area value of 33.95729 mm with 95% confidence interval, H0 is rejected, set size quality calculation of the machined surface dimension at MC 3 is unstable.

The mean deviation of the product flatness dimension between 50 samples machined by MC 2 and 50 samples machined by MC 3 is 0.96 mm (eq. 6), the rejection value of H0 with 95% confidence level is less than -0.67786 and greater than 0.67786, the mean deviation between the two samples falling into the rejection region and the rejected H0, the product surface flatness size between the two machines MC 2 and MC 3 is different.

3.3 Analysis

Experimental analysis of variance evaluates that machining jigs have an impact on the quality of product surface flatness, size, and surface flatness, for jigs to run sequentially on 4 MC machines at two processing lines, with a p-value of 0.041 less than 0.05 (eq. 7-11), H0 is rejected, machining jigs have an impact on product surface flatness dimension quality. The MS_B is 12.83 is much larger than the MS_E is 7.54, demonstrating that jigs have a strong influence on the surface flatness dimension quality.

Evaluation of machining jigs interaction conditions on surface flatness quality and surface flatness dimensioning methods have an impact on flatness dimension quality at the machining line (eq. 12-15). Considering the condition that jigs affect the flatness dimension quality, the p-value is $0.002 < 0.05$ and it is concluded that jigs influence the flatness dimension. Considering the method condition, the p-value is $0.0001 < 0.05$, concluding that the measurement method has an impact on the flatness dimension quality. Considering the interaction between jigs conditions and measurement method conditions, the p-value is $0.0186 < 0.05$, with a 95% confidence interval, the jigs and measurement method conditions have an impact on the quality of the flatness dimension and the measurement method. The above two conditions do not affect each other.

Repeat 5 times on the same machining jigs at 1 machine MC 3, p-value is $0.001 < 0.05$, null hypothesis H0 is rejected, F-value is $18.31 > 2.87$ (with 95% confidence interval). In conclusion, the difference between five times of jig experiment influences the plane size. The results of statistical analysis and experimental design show that machining jig is the main cause of unstable surface dimension quality, measurement method is also a factor to consider when implementing process improvement. The Failure Tree Analysis (FTA) model analyses the cause of surface dimensional instability errors, leading to measurement loss of calibration time, checking the smooth operation of the product after assembly. FTA analysis model for dimensional instability error of surface size. The results of the FTA analysis show that the type of product placement in the jigs is the main factor causing the instability of the surface dimensions.

3.4 Improve

Four improvement options are proposed, option 1 (A1) to periodically maintain jigs, option 2 (A2) to purchase new jigs, option 3 (A3) to improve jigs by adding steam sensors and creating a control system and option 4 (A4) combines the DNC system into the system of option 3. Present value (PV), present value probability P(PV), expectation and present value variance E(PV), V(PV). Calculate the above parameters for each option. According to the expected standard E(PV), which option has the highest expected value is considered the best solution, option A4 has the best value E(PV) = 65,000 USD, options A1, A2, A3 have the same expected value and equal to 60,000 USD. According to the probability criterion P(PV < 0), the solution with the lowest probability is considered the best solution, option A3 is the best, with probability value = 0.0, followed by A2 and A4 = 0.1 and A3 = 0.2 is the final. According to the standard of variance V(PV), the option that gives the lowest variance value is considered the best option, the alternative A3 is the best and has the value = 2.5, followed by A2 = 3, ranked second. 3 is A4 = 3.85 and finally A1 = 5. According to the alternative selection criteria, option A3 (improve jigs by adding steam sensors and creating a control system) is considered the best of the four alternatives. Option A4 (combines the DNC system into the system of option 3) is the 2nd priority out of 4 options when making improvements and is followed by options A2, A1.

Option A3, drill a vent hole on the jig at the position where the jig is in contact with the product surface, the steam sensor is connected to the vent position, the signal filtering system is set up by MATLAB software with a low pass filter. Collect and process steam volume control signals. In case, the surface of the product is not adjusted to the jig, steam escapes, the signal processing system recognizes and sends out a red sensor signal, the processing system automatically locks, the machine cannot operate (Figure 1).

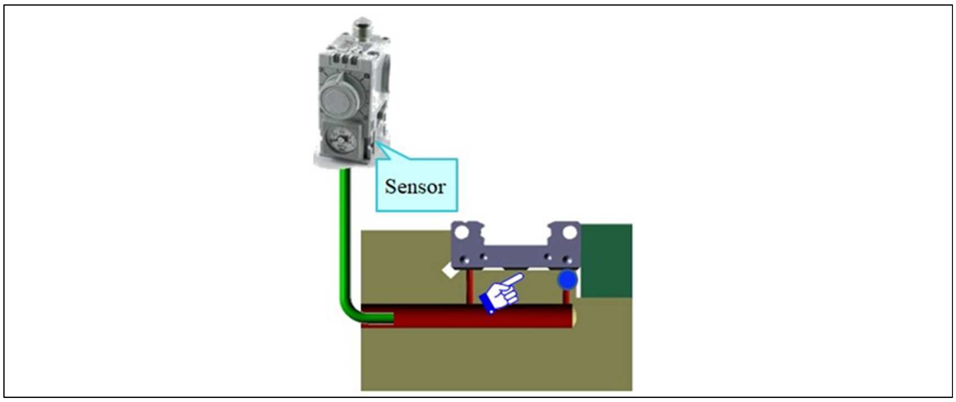

Figure 1 – Air Sensor System

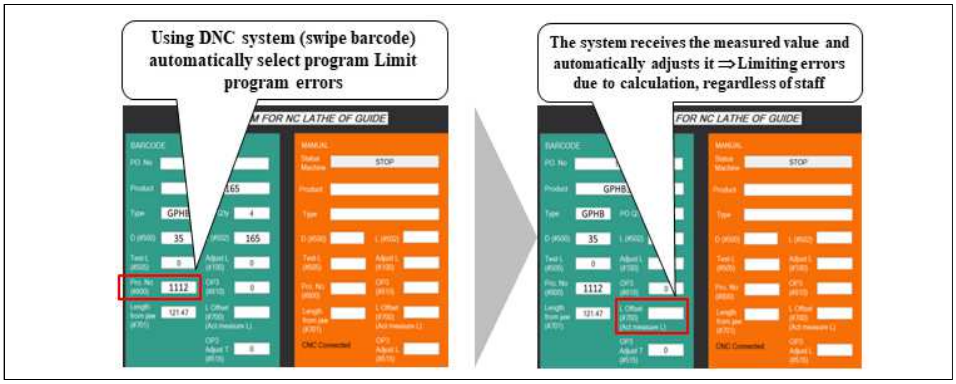

Figure 2 – DNC Program Screen Interface

Option A4 is further developed from the idea of plan A3, establishing a DNC system to automate the process, linking the machining center program to the management system. The barcode system acts as a bridge to call the machining program and update the machining tolerance system, update the product quality measurement results from the measurement system in real-time, the product dimension value is updated in the machining center program tolerance system table, and the DNC system automatically updates the offset table of the machining size tolerance parameter in the machining program according to the machined size of products in real-time (Figure 2). In case, the machining system and the measuring system have inconsistent results, the measuring system will automatically lock, and the machine system will be locked, the alarm will sound.

DNC signal processing and control system receives sensor signals and processes signals, measurement data from the measurement system is updated into the tolerance system, the system updates the machining program to update the dimensions. Quality of products from the system and control the machining program. In case the system does not match the value, the system is locked.

Deploy the DNC system to a machining center, run 30 samples consecutively and the dimensional variance values of 30 samples (eq. 16-17) is 1.44, with a 95% confidence interval of the null hypothesis being less than 0.83 and greater than 2.36. The 30-sample variance does not fall into the rejection region, H0 is accepted, the product quality is guaranteed, proving that the DNC system works stably, gives satisfactory results, and does not generate waste products.

Overall performance evaluation of the entire improved machining system (applying DNC system, automatic measurement system at each machining line and real-time data collection) including operational features (P: Process), operating cost (C: Cost), availability (A) and sensor signal processing system software program (S: Software), Rating scale includes good (E), good (S), average (A) and bad (I). A sample of hitting and establishing a fuzzy matrix is as follows (19).

$$R= \begin{vmatrix} & E & S & A & I \\ P & 0.1 & 0.3 & 0.4 & 0.2 \\ C & 0.0 & 0.1 & 0.8 & 0.1 \\ A & 0.1 & 0.6 & 0.2 & 0.1 \\ S & 0.1 & 0.4 & 0.3 & 0.2 \end{vmatrix} \tag{19}$$

Standard weight vector: W = [0.4 0.3 0.2 0.1], the integrated evaluation fuzzy set is: E = W x R = [0.1 0.3 0.4 0.2]. From the results of the fuzzy set, the performance of the system is assessed as average A. The DNC system and the signal processing measurement system operating for production meet the requirements but need further improvement.

3.5 Control

The post-improvement system has turned the machining line from semi-dynamic to fully automatic operation, requiring operators to be trained with sufficient operating skills, in case the operator is not skilled enough, it can cause problems, because the machine system is fully automatic, the proposed facial gender recognition computer vision system is put into use to control the layout of automatic machine operators. After being trained and qualified to operate automatic machines, employees' faces are taken at different levels and each employee takes 100 pictures, taking 70 training pictures for the system. The computer vision system and the remaining 30 images were used to test the computer vision system. The computer vision system recognizes human faces as an artificial intelligence (AI) system. Each employee is assigned a fixed working position according to the machine layout and trained skills, if the employee arbitrarily moves to another area, the computer vision system will recognize and issue a warning at the same time. The measurement system is locked.

4 CONCLUSION

The DNC system and sensor system are set up at the machining center (Figure 3) and operational in production, improving productivity, reducing waste, and reducing product production time.

Rebuild the future value stream map and as a result total lead time is reduced by 20 minutes compared to pre-improvement in future value stream mapping. Scrap products decreased by 59.66% per year, the production line assembly productivity increased by 7.8%. Calculating all related costs and monthly depreciation cost of 500 USD for jig improvement cost, the profit is 678 USD per month and 7,636 USD per year.

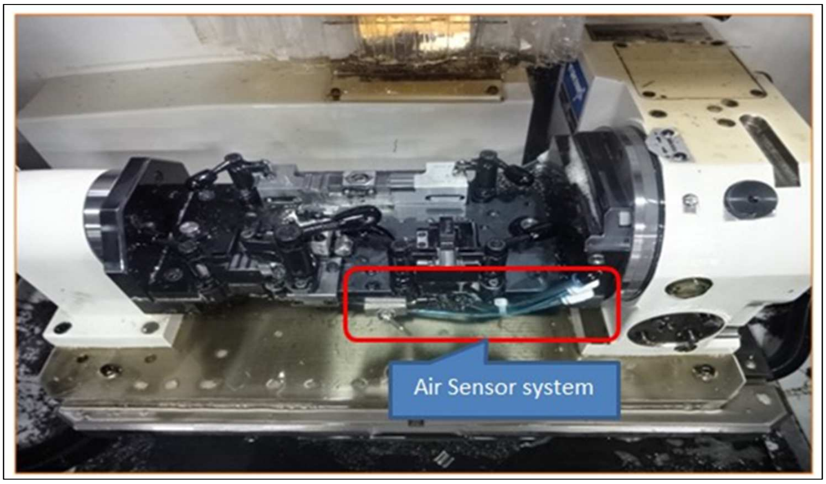

Figure 3 – Actual Improved jig of MC

The sensor signal processing system in the environment is gradually incomplete and still generates many noise signals, the measurement system has not yet developed a system to check external products by computer vision system, signal feedback system. Measuring and updating offset tolerance is not perfect. The above issues are research directions open to researchers.

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ABOUT AUTHORS

Minh Ly Duc0000-0003-0200-7153 (M.L.D.) – M.S degree in Industrial Engineering, Ph.D. Candidate, Technical University of Ostrava, Ostrava, Czech Republic, email: minh.ly.duc.st@vsb.cz.

Petr Bilik0000-0001-8655-778X (P.B.) – Prof., Department of Cybernetics and Biomedical Engineering, VSB—Technical University of Ostrava, Ostrava, Czech Republic, email: petr.bilik@vsb.cz.

Thuy Duy Truong0000-0002-9563-6524 (D.T.T.) – Ph.D. Candidate in Computational and Applied Mathematics, Department of Applied Mathematics, Technical University of Ostrava, Czech Republic, email: thuy.duy.truong.st@vsb.cz.

AUTHOR CONTRIBUTIONS

Conceptualization, M.L.D. and P.B.; Methodology, M.L.D.; software, M.L.D.; Validation, M.L.D., P.B. and D.T.T.; Formal analysis, M.L.D.; Investigation, M.L.D.; Resources, M.L.D.; Data curation, M.L.D.; Original draft preparation, M.L.D.; Review and editing, D.T.T.; Visualization, D.T.T.; Supervision, P.B.; Project administration, P.B.; Funding acquisition, P.B.

CONFLICTS OF INTEREST

The authors declare no conflict of interest. The funders had no role in the design of the study; in the collection, analyses, or interpretation of data; in the writing of the manuscript, or in the decision to publish the results.