APEM journal

Advances in Production Engineering & Management **ISSN 1854-6250**
Volume 18 | Number 1 | March 2023 | pp 32–48 Journal home: apem-journal.org
https://doi.org/10.14743/apem2023.1.455 Research paper

Enhancing manufacturing excellence with Lean Six Sigma and zero defects based on Industry 4.0

Ly Duc, M.[a,b,*], Hlavaty, L.[b], Bilik, P.[b], Martinek, R.[b]

[a]Faculty of Commerce, Van Lang University, Ho Chi Minh City, Vietnam
[b]Department of Cybernetics and Biomedical Engineering, Faculty of Electrical Engineering and Computer Science, VSB–Technical University of Ostrava, Ostrava, Czech Republic

A B S T R A C T

Improving quality, enhancing productivity, redesigning machining tools, eliminating waste in production, and shortening lead time are all objectives aimed at improving customer satisfaction and increasing profitability for manufacturing companies. This study combines lean manufacturing and six sigma techniques to form a technique called Lean Six Sigma (LSS) by using the DMAIC (Define-Measure-Analysis-Improve-Control) model. This study proposes to use statistical test models to analyze real data collected directly from the operator. The study proposes to use the Taguchi optimization technique to determine the optimal conditions for oil dipping tanks of molybdenum materials. In addition, the study also proposes a computer vision technique to recognize objects using color recognition techniques running on the LABVIEW software platform. This study builds a digital numerical control (DNC) model operating on digital signal processing techniques, linking the data of each process together. The results reduced the rate of defective parts in the whole processing stage from 6.5 % to zero defects, the whole processing line production capacity increased by 7.9 %, and the profit of the whole production line was USD 35762 per year. As a valuable external outcome, the conclusion of the LSS project fostered a spirit of continuous improvement. The utilization of research results from the research environment in the actual production setting is significantly enhanced for the operator. The LSS model is deployed with specific tasks and targets for each member of the LSS project team, and the processing conditions for each specific stage are optimized, such as the oil dipping process and hole grinding process. Industry 4.0 techniques, including computer vision, digital numerical control, and commercial software such as LabVIEW and MINITAB, are optimized for use, simplifying machining operations. Some proposed directions for future research are also presented in detail. For example, studying the improvement of the quality of the 220 V power supply through harmonic mitigation in processing factories is an intriguing area of investigation. Additionally, exploring data security for big data in the context of Industry 4.0 would be a valuable study to enhance customer satisfaction with big data technology in the future.

A R T I C L E   I N F O

Keywords:
Lean Six Sigma;
Industry 4.0;
Manufacturing;
Smart manufacturing;
Zero defect manufacturing;
DMAIC (Define-Measure-Analysis-Improve-Control);
Computer vision

**Corresponding author:*
minh.ld@vlu.edu.vn
(Ly Duc, M.)

Article history:
Received 17 November 2022
Revised 4 April 2023
Accepted 6 April 2023

1. Introduction

Industry 4.0 techniques develop strongly in the product factory environment [1]. Specifically, applying computer vision techniques is for object recognition and object classification, artificial intelligence (AI) techniques to create robots that work in place of humans and create high productivity. Using automate manufacturing operations to eliminate waste, shorten lead times, increase productivity, and move towards zero defect production [2-3]. The Six Sigma technique has been implemented and brought to great effect at Motorola since 1980 and is embraced by many other companies as a model of continuous improvement in the manufacturing company. Lean manufacturing tools and models are logically integrated into each phase of Six Sigma implementing a continuous improvement model that delivers efficiency, and that hybrid model is called Lean Six Sigma (LSS) [4-5]. General Electronic Company has implemented the LSS model into its continuous improvement activities since 1998 and has brought high efficiency. Specifically, the company's revenue is more than 1.2 billion USD, which shows to the world the high efficiency in business operations when applying the LSS model to continuous improvement activities.

1.1 Research question

The LSS model is implemented by manufacturing companies in continuous improvement activities to improve quality and productivity, enhance customer satisfaction. Holtskog [6] and Sony *et al*. [7] also highlight the limitations of the LSS model when deployed by manufacturing companies. However, many manufacturing companies implement the LSS model into continuous improvement activities with high efficiency while several companies also implement the LSS model but the results are not as required. The LSS is a project, so it is necessary to plan work specifically, clearly divide work for each member of the project, and describe in detail, specific goals. Completion time for each task is absolutely necessary [8-9]. This study details the process of implementing the DMAIC model of the LSS technique into the product production line at a mechanical company. The specific goals of this research are (1) Optimize production conditions at the oil dipping process, prevent defects and prevent delays for customers. (2) Automatic selection of production tools by Industry 4.0 or computer vision technology at hole grinding process, preventing mistaken selection of production tools caused by careless employees and shortening production time, simply optimize the work performance for operators, improving operator satisfaction on continuous improvement activities. (3) Digital signal technology is deployed to collect data of each individual line by barcode system, call machining programs for automatic machining machines by barcode system and measurement system to collect stored data into the SQL system to form big data in Industry 4.0 [10].

In production activities, there are several questions such as: (1) Determine the specific production conditions for semi-automatic and automatic processing machines such as Oil dipping tanks, and hole grinding machines; (2) Product quality is guaranteed throughout the entire processing stage, which method is appropriate and not too complicated in the operation of employees; (3) The factory is illuminated by LED lights, and the factory is operated by smartphones and computer systems. All of them are sources of harmonics in the power supply to the furnace, the circuitry that controls the semi-automatic and automatic machines, ensuring that harmonic components according to IEEE 519:2022 are essential. The main operating principle of the LSS model is based on manufacturing fundamentals. Lean manufacturing and six sigma techniques are also based on manufacturing fundamentals. The implementation LSS project model is effective in action process planning, operational process analysis, and action process assessment. In addition, the LSS project investigates, analysis, and identifies problems at specific production lines and proposes improvement plans. Werkema [11] detailed evaluation of the results of implementing the LSS model into continuous improvement activities at manufacturing companies and brought high results, enhancing the company's competitiveness. Lean manufacturing technique has not yet clearly formed the detailed structure of each solution corresponding to each specific problem [12]. The Six Sigma technique is highly effective in minimizing process variation but has not really cared about the time and speed completion of production process [13]. These two techniques are deployed in combination to overcome each other's weaknesses and improve efficiency [14].

1.2 Contribution of research

This article details the steps of implementing an LSS model that combines lean manufacturing and six sigma techniques in continuous improvement operations at a manufacturing company [15]. The research results show that the defective rate decreased from 6.5 % to zero defect, the production capacity of the whole production line increased by 7.9 % and the profit increased by 35762 USD per year. This study contributes to improve the working morale of machine operators, the spirit of applying techniques from research to the practical environment, and remove the thinking separating the research environment and the production practices. In this study, it is considered as a model for managers performing each step in the analysis to find out the origin problem. The DMAIC model is used as a guide for members of the continuous improvement project in a variety of companies [16]. The data in this study were collected directly at the production line by the operator at the mechanical product manufacturing company [17-18]. This study proposes the use of statistical tools such as descriptive statistics, statistical hypothesis testing in data analysis, and determination of the current status of the problem on the table of specific analysis results. The Taguchi optimization technique is implemented to specifically determine the optimal condition for the machining condition. Computer vision technology identify and classify objects by color is deployed to redesign production operating conditions at specific production stages. Digital signal processing techniques based on barcodes and QR Codes are developed for real-time data collection at each separate manufacturing process and create a close connection in terms of data between the stages [19].

This study is a big challenge for researchers because its data completely collected from reality at each specific production line. Analytical tools are deployed to analyze data such as PARETO charts, descriptive statistics tools, statistical hypothesis testing tools, fishbone charts, value stream mapping, failure tree analysis, techniques, Taguchi optimization techniques, computer vision techniques, and digital numerical control techniques. This paper details the implementation of the LSS model using DMAIC in continuous improvement and also serves as a reference model for LSS researchers, managers, and project members implemented as a model. The DMAIC model is applicable to many different environments and organizations and serves as a model.

The next structure of the research paper is organized as follows: Section 2 details the content of the literature review. Section 3 presents the research method in detail. Section 4 details the results of the experimental study and discusses the results from the experiment, and Section 5 presents the conclusion of this study.

2. Literature review

The Lean Six Sigma model combines Lean manufacturing and Six Sigma techniques [20-21]. The literature review for both Lean manufacturing and Six Sigma techniques is performed first. Next is the evaluation of the data for statistical techniques applied to actual data analysis techniques and numerical processing techniques in data collection and analysis.

2.1 Lean manufacturing

Key tools used in Lean manufacturing are Value Flow Mapping, Fishbone Diagram, Kanban System, Pareto Diagram, and Failure Tree Analysis [22]. These tools mainly perform analysis to confirm the wastes incurred in production activities and suggest improvement actions to eliminate wastes with the aim of increasing productivity and set goals to improve production methods [23]. Value Stream Mapping (VSM) details valuable and non-valued activities across each activity in the supply chain. The VSM tool identifies valueless activities (waste activities) to help managers easily decide on improvement proposals. The 5 Whys tool and fishbone diagram does the enumeration problem point causes and root cause selection. The system charting tool builds countermeasures based on weighting indicators [24-25]. In addition, Fault Tree Analysis combined with the 5 Whys tool adds extra power to root cause analysis. However, Fault Tree Analysis focuses on detailing the problem points according to the 5 whys method without focusing on finding the root cause and 5 whys analysis only focuses on the starting content of the problem point. A combination of failure tree analysis and 5 whys analysis makes a powerful analyze model and Kanban System is a fundamental tool in Lean manufacturing to control operations.

2.2 Six Sigma

Fluctuations in the production process stem from machining conditions, human factors, unstable machine accuracy, and power sources that generate many harmonic components that exceed IEEE 519:2022 standards. Six Sigma technique helps to eliminate fluctuations in the production process. Improve product quality, and customer satisfaction. Motorola Company pioneered the implementation of Six Sigma technology in the phones production line and achieved great results in controlling volatility and reducing defect rates below 1 Sigma. Six Sigma techniques use DMAIC (Define-Measure-Analysis-Improve-Control) model implemented as a model for performing problem analysis and measurement [26-27], using the actual database at the machining line. Define phase (D) presents an overview of the environment around the problem to be analyzed and analyzed to determine the content of the problem point using statistical charting tools such as Pareto chart, and bar chart. Measure phase (M) deploys statistical testing tools, and statistical hypothesis testing to measure and analyze real data at the production stage and find the root problem point. Analysis phase (A) deploys the Taguchi optimization technique to determine optimal production conditions for production conditions. Conduct experiments and collect experimental data by operators. Improve phase (I) deploy Industry 4.0 tools such as computer vision to identify and classify objects by color running LabVIEW software and digital numerical control techniques in digital signal processing by barcode or QR Code, data collected into the big data system in Industry 4.0 systems [28-30]. Control phase (C) deploys an online measurement system using digital numerical control (DNC) technology to control the system automatically and completely eliminate workers' skill. A comprehensive literature review of the Six Sigma technique is needed.

2.3 Lean Six Sigma (LSS)

The main goal of the Lean Six Sigma model is to eliminate the fluctuations of the production process and improve product quality by manufacturing according to the zero defects model to improve product quality, process quality, people quality, production capacity, and customer satisfaction [31-32]. Ensuring quality meets customer requirements and delivering products on time is a challenge. Pande *et al.* [33] pointed out level problem of responsiveness between providing services to customers and meeting customer requirements is a big challenge. Rathi *et al.* [34] specifically outlined 17 obstacles when implementing LSS projects for enterprises and the main content is data collection. Data is the backbone of the LSS project. The ability monitoring the LSS project to ensure that the projects are completed on schedule and project manager's target met is a challenge. Implementing LSS projects knowledge of team members is also an issue that needs attention. The main tools used in the DMAIC phase such as Process Flowchart, Data Collection Checklist, Fishbone Diagram, Histogram, 5 Whys Analysis, Statistical Hypothesis Test, Experimental Design, Taguchi method, and Statistical analysis are comparing results before and after improvement [35-36]. If the LSS project is not performed well, it can lead to loss of investment, time, and resources, customer trust and the image of the organization implementing the LSS project. Lean Six Sigma technique has been successfully applied in many companies. However, there are still a few companies that still do not give good results when applying Lean Six Sigma. Because of the inconsistent use of statistical techniques, Lean manufacturing techniques. Shokri [37] has implemented LSS technology in a mechanical manufacturing company with the goal of eliminating scrap to zero and achieving a profit of 98 USD per year. Guleria *et al.* [38] proposed to apply the LSS project to the gear component manufacturing process, the tools applied such as SIPOC (Supplier-Input-Process-Output-Customer) diagram, Pareto chart, Fishbone chart, reject results from 10641 to 3193 (PPM). Minh and Thu [39] proposed to apply the LSS project to the manufacturing process of mechanical components, apply tools such as the Pareto diagram, fishbone diagram, scatter plot, histogram, and lifting work of production capacity from 118 products in 8 hours to 155 products in 8 hours.

3. Research methodology

3.1 Research characterization

The company produces condensed products using many automatic processing machines and processing conditions, so the variation in the production process is very large. Controlling product quality means controlling fluctuations in production conditions. This study employs both quantitative and qualitative research methods. The quantitative method is to use statistical charts to analyze the data. De Boer [40] highlights the need for a large enough sample size to meet the requirements of statistical models. Qualitative research is seen as a management tool implemented to understand and find solutions for specific problems in the workplace. De Boer [40] demonstrates that quantitative research provides logical information about reasons without using mathematical equations, observable behaviors or problem-solving solutions. This study specializes in a particular mechanical production line, and conducts a process assessment of the status quo that generates problem points for waste and human skill-dependent operations. Hart [41] highlights the need for direct workers at each stage of the LSS project implementation process. Operators at the machining line understand the need for continuous improvement and implementation. The main goal of the project is to implement the research results into practice, the researcher directly participates in the implementation of the project's work together with the operator. Practice research projects, measure the results of practice directly at the production line, and evaluate their effectiveness. The researchers provide instructions on how to collect and analyze samples for LSS project workers and operators who perform direct sampling. The author directly participates in the implementation of the LSS project at a mechanical processing company from April 2021 to March 2022, participates in all project activities as the manager, and performs the works such as defining research, performing data collection, analyzing data to collect results after implementing the LSS project.

3.2 Scope of Lean Six Sigma application

The slow implementation of the tasks in the Lean Six Sigma project will waste the company's resources, so the LSS project management team needs to focus on controlling the progress of activities [42]. Changing the production process entails changing a lot of other things such as changing standards and technical conditions, changing operating methods and controls. This study presents a step-by-step implementation of Lean Six Sigma techniques with the DMAIC model as Table 1.

Table 1 Activities development in DMAIC phase

Activities / DMAIC phase	Activities 1	Activities 2	Activities 3	Activities 4
Define	Present an overview of the environment surrounding the problem point to be analyzed and describe information about the problem point to be studied.	Using fishbone diagrams, the 5 whys or failure tree analysis details the causes of the problem score according to 4 aspects: Man-Machine-Method-Material.	Gather the opinions of the Lean Six Sigma project team members and identify the root cause of the problem.	The system diagram is implemented in the construction of improvement activities according to the rating scale.
Measure	Make surveys and check sheets to collect data directly from the production line by operators.	Planning, methods, and data collection directly on the line [43-44].	Deploy statistical tools, and test statistical hypotheses to analyze data.	-
Analysis	Set up a specific implementation plan for each trial according to the GANTT and WBS diagrams.	Analyze the current status of each stage by video recording method and analyze the correlation between man and machine using a Man-Machine diagram [45-46].	Set specific goals for each case according to S.M.A.R.T criteria.	-
Improve	Re-optimize production conditions at each soybean production line by the Taguchi method [47-48].	Rebuild management standards, and work instructions according to ISO9001:2015 and IATF16949:2015.	-	-
Control	Build a digital processing system to control the operation of each operation at each corresponding production line, the Industry 4.0 system is built based on the POKA-YOKE theory.	Build an online measurement system using digital numerical control techniques [49-50].	-	-

4. Results and discussion

4.1 Define (D)

This phase outlines the Lean Six Sigma (LSS) project scope clearly and specifically. The fish bone diagram combined with the 5 Whys analysis lists individual causes of defects in 4 aspects as Man-Machine-Method-Material (Fig. 1). Failure tree analysis combined with the 5 Whys analysis are also reviewed and verified the cause of defects.

A survey questionnaire was established and researchers assessed the accuracy of each question, surveying the opinions of direct operators of the production line such as machine operators, chief and deputy shift staff of production, production line managers, machine maintenance technicians, production line design technicians, and factory managers. All comments show the general content is that there are no specific regulations on machine operating conditions, there is no connection of production data between stages, and employees choose production tools by experience, so they often give rise to defects. Evaluating the current state of the machining process by using the control plan sheet tool is easy to spot gaps in the manufacturing process. Managers who lack understanding of the production process and completely depend on the skills of workers. Interviews with workers of LSS project members contribute to enhancing the culture of sharing in the company. The LSS project needs to clearly show two goals: (1) Clearly define the goals of each specific task and (2) Form a plan table according to Gant and WBS (Works Breakdown Structure) diagrams for each specific task. From Fig. 1. This research paper has 3 main projects: Project A (Make sure to use the right tools to process the hole size of the product at the machining center). Project B (Determine the temperature conditions, time of the oil dipping, and the stabilization time based on the expansion of molybdenum) and Project C (Check the quality of power supply for the oil dipping machine).

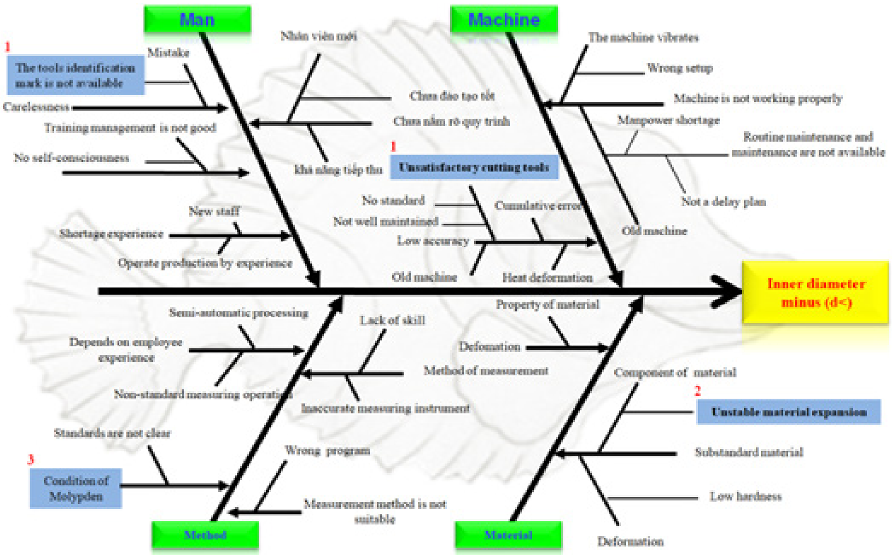

Fig. 1 Fishbone diagram

4.2 Measure (M)

Project A is implemented experimentally at the product hole grinding stage. The product is manufactured with 2 different materials depending on customers' requirements. (1) Material type FC250 and molybdenum has a hardness of 196 HV, and (2) Material type copper and molybdenum has a hardness of 125 HV. The tool for hole grinding also depends on the respective material. Tools employing FC250 materials used blue-labeled tools, while those using SUJ2 materials used red-labeled tools. However, the shapes of the two types of tools are similar (Fig. 2), make their identification and differentiation is a challenge.

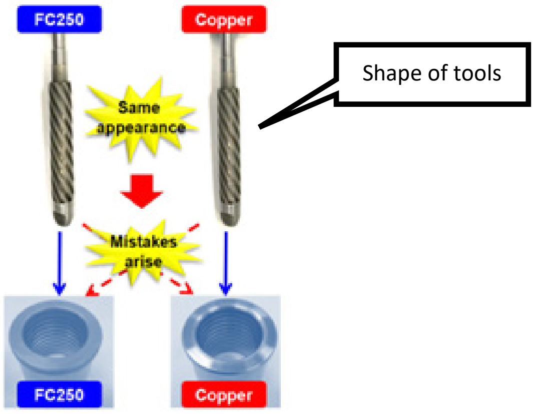

Fig. 2 Shape of hole grinding tools

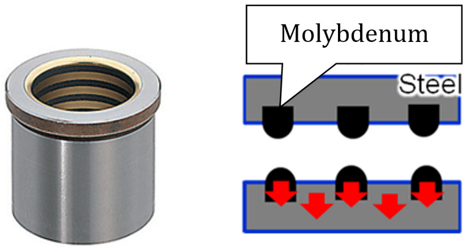

Fig. 3 Molybdenum disulfide inside Bush product

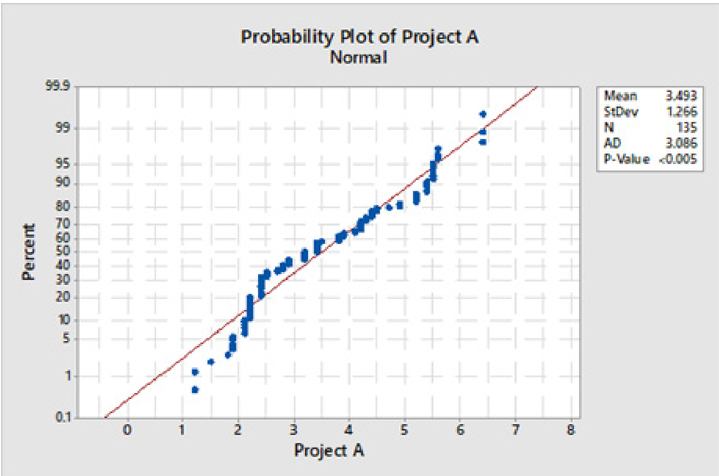

Fig. 4 Probability plot of Project

Project B performs the task of determining the most optimal oil dipping conditions. Bush product line uses molybdenum material inserted into the groove inside the product hole (Fig. 3), the molybdenum material deforms in size according to thermal conditions and heat time. Molybdenum is manufactured by Sumi Steel Co, Ltd. manufacturing, its main ingredient is molybdenum disulfide. It is effective in reducing friction or wear in high-temperature and load-bearing environments, and is effective in grease-restricted environments. Optimizing conditions for oil dipping is a challenge for LSS project team members.

Project C performs quality control of the power supply for electronic boards and thermistor devices at the oil dipping stage. The factory uses a lot of LED lighting systems, computer systems, internal and external telephone systems, all the above devices are harmonic sources in the power supply, and harmonics make the image. The sine waveform of the power supply is distorted, and the system of power boards is unstable. Specifically, the extreme resistance of the oil dipping tank does not guarantee thermal stability and is the cause of defects. Designing systems for harmonic mitigation to ensure that total harmonic distortion (THD) falls within the IEEE 519:2022 standard is a major challenge.

The statistical testing method is applied to data analysis activities of the LSS project to meet the right objectives. The Anderson-Darling normalization method is performed to check the normality of the hole diameter data with an error of fewer than 3 microns using Minitab 18.0 software. The P-value of Project A), the P-Value of Project B), and the P-Value of Project C) are less than 0.005 (Fig. 4). The hypothesis H0 that data are normally distributed is rejected. A non-parametric method was used to analyze this data, as this data set is not normally distributed. The analyze results will be presented in the analysis phase contributing to the implementation of Project A, Project B, and Project C.

4.3 Analysis (A)

Project A (The identification of machine tools by color at the hole grinding process). The product hole grinder has 3 main parts: Mandrel, Nut, and Blade (Fig. 5). The FC250 and the Mandrel Synchronous Material Cutting Kit and the Nut Kit are the same and interchangeable. However, the hardness setting at the blade's cutting surface is different. It should be distinguished when using FC250 and copper materials for machining. Using the chi-square test is for association statistics running on Minitab 18.0 software to evaluate the similarity of the results of correct identification of the cutting tool's blade type H0 or the dissimilarity of the correct identification of the cutting tool blade type H1. Use the difference between the expected number E_i and the actual number of observations O_i to find the chi-square value (called a statistic), according to the Eq. 1.

$$x^2 = \sum_{i=1}^{k} \frac{(O_i - E_i)^2}{E_i} \tag{1}$$

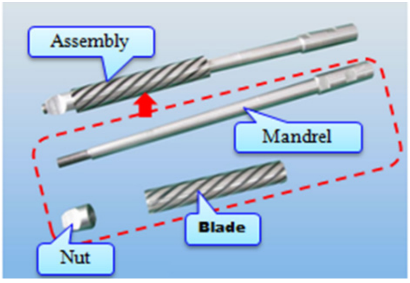

Fig. 5 Structure of cutting tools

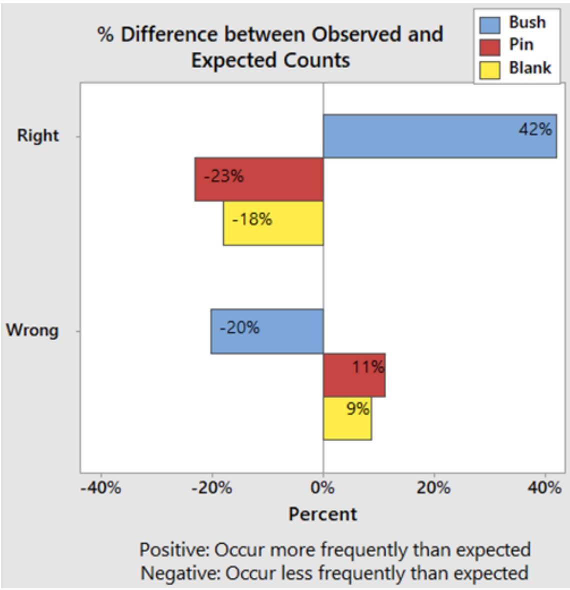

Fig. 6 Difference between observed and expected counts

Randomly select 200 employees of 3 processing lines (65 Bush product line employees, 60 Pin product line employees, and 75 Blank processing line employees) to distinguish between the blade type used for FC250 material and the blade type used for copper material. The P-Value of the Chi-square test is 0.016 less than 0.05, H0 is rejected, and H1 is accepted. Indicating is the results of blade selection of tools cut are not uniform among 3 groups of 200 employees. Line Bush products that the rate of choosing the right type of Blade is 46 % and the rate of choosing the wrong type of Blade is 26 %. In line Pin, the right selection rate reaches 23 % and the wrong selection rate reaches 33 % in Line Blank the right selection rate reaches 31 % and the wrong selection rate reaches 41 %. The percentage difference between Observed and Expected Counts of Line Bush's right choice reaches 42 % and the wrong choice reaches negative 20 %. Line Pin's right choice reached negative 23 % and the wrong choice reaches 11 % and Line Bush correctly pick negative 18 % and the wrong choice reaches 9 %, see Fig. 6.

Project B (Re-designed of oil dipping tank processing condition). The oil dipping process of molybdenum-based products is done through 3 steps: Step 1) The product is neatly lined up and immersed in MG815 oil which is heated to 100°C by the thermistor. Step 2) Store products are in a warehouse environment with a temperature of 70°C. Step 3) Cool the product in a normal temperature environment from 28°C to 32°C for about 7 days. To evaluate the size expansion of molybdenum powder after implementing the 3 above conditions, with 5 factors and 2 levels for initial treatment conditions (Table 2). Taguchi method responds well to many factors in the system simultaneously, ensuring independent research and reliable influence of factors. The L32 (2^5) orthogonal matrix table designed for 5 elements is presented in Table 3. In this study, the quality characteristics of the molybdenum set size extension (E6) in the standard region are less than 3 microns. The test prototype is sampled directly from the production process, the results are converted to signal-to-noise ratio (S/N), according to Eq. 2.

$$S/_{N} = -10 \cdot \log[(\mu - m)^2 + S^2] \quad (2)$$

The molybdenum expansion dimension of 3 microns was measured with a Koshaka 3D profile tensile tester with a profile measuring distance of 80 mm. The results of the S/N analysis (Fig. 7) show that the product response of cooling time after oil immersion and oil immersion time strongly affects the quality of molybdenum size expansion. Next, the oil immersion temperature has a relative response and the drying time as well as the product drying temperature after oil immersion is responsive but not high. The results of the one-way ANOVA analysis (Table 4) show a 95 % confidence interval for the thermal conditions of the molybdenum product.

Project C (Quality control of power supply is for oil dipping tank). A supply voltage of 400V/3 phase/30A provides a thermistor (Fig. 8) to heat the oil bath (Fig. 9). Ensuring a constant and stable power supply to the thermistor is essential. Power meter type PQ3100 manufactured by HIOKI firm is used by the company to measure voltage source, current source for thermistor. Results of document search in the frequency of power quality testing by PQ31000 on Wednesday 7 weekly (shared work area) cleaning day before Sunday off. Measurement results are recorded manually on the test sheet to check the machine's status.

Table 2 Experimental factors and their level for L_{32}

Factor	Level 1	Level 2
E1: Oil dipping time (hours)	1	3
E2: Oil dipping temperature (°C)	90	110
E3: Dry time after oil dipping (hours)	1	3
E4: Dry temperature after oil dipping (°C)	60	80
E5: Cooling time after oil dipping (days)	5	7

Table 3 L_{32} (2^5) orthogonal array experimental parameter

Exp.	E1	E2	E3	E4	E5	E6	S/N
L1	1	90	1	60	5	4.1	-12.26
L2	1	90	1	60	7	3.0	-9.54
L3	1	90	1	80	5	3.7	-11.36
L4	1	90	1	80	7	2.9	-9.25
L5	1	90	3	60	5	3.6	-11.26
L6	1	90	3	60	7	3.1	-9.83
L7	1	90	3	80	5	3.2	-10.10
L8	1	90	3	80	7	2.9	-9.25
L9	1	110	1	60	5	3.5	-10.88
L10	1	110	1	60	7	2.9	-9.25
L11	1	110	1	80	5	3.2	-10.10
L12	1	110	1	80	7	2.6	-8.30
L13	1	110	3	60	5	3.5	-10.88
L14	1	110	3	60	7	2.6	-8.30
L15	1	110	3	80	5	3.5	-10.88
L16	1	110	3	80	7	2.6	-8.30
L17	3	90	1	60	5	3.2	-10.10
L18	3	90	1	60	7	2.1	-6.44
L19	3	90	1	80	5	3.7	-11.36
L20	3	90	1	80	7	2.9	-7.60
L21	3	90	3	60	5	3.1	-9.83
L22	3	90	3	60	7	2.5	-7.96
L23	3	90	3	80	5	3.6	-11.13
L24	3	90	3	80	7	2.6	-8.30
L25	3	110	1	60	5	3.2	-10.10
L26	3	110	1	60	7	2.7	-8.23
L27	3	110	1	80	5	3.5	-10.88
L28	3	110	1	80	7	2.3	-7.24
L29	3	110	3	60	5	3.1	-9.83
L30	3	110	3	60	7	2.3	-7.24
L31	3	110	3	80	5	3.2	-10.10
L32	3	110	3	80	7	2.1	-6.44

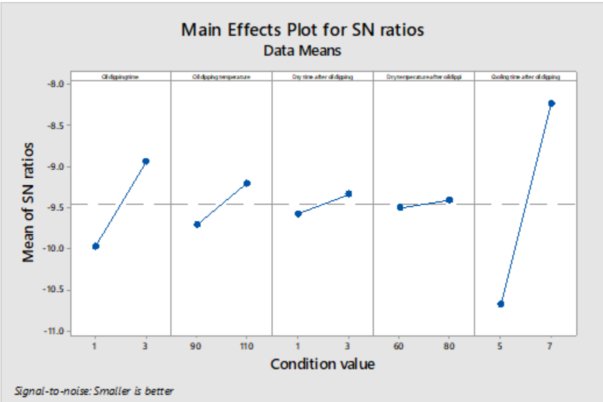

Fig. 7 S/N analysis

Table 4 The mean value of One-way ANOVA analysis

Factor	N	Mean	StDev	95 % CI
E1	32	2.00	1.02	(-0.062, 4.062)
E2	32	100.00	10.16	(97.94, 102.06)
E3	32	2.00	1.02	(-0.062, 4.062)
E4	32	70.00	10.16	(67.94, 72.06)
E5	32	6.00	1.02	(3.938, 8.062)
E6	32	3.01	0.51	(0.953, 5.078)

Pooled StDev = 5.91340

Fig. 8 Thermal resistance 3KW/33cm/380V

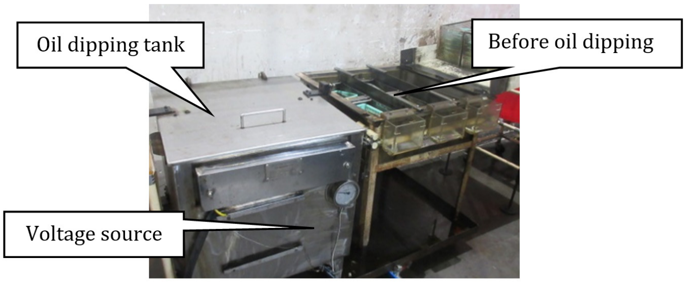

Fig. 9 Oil dipping process

4.4 Improve (I)

Project A (The identification of machine tools by color at the hole grinding process). Propose a method to identify objects by color. The red and blue grading feedback system is much better than commercially available color sensors which have limitations. The camera system is designed and installed in the production process. A basic camera with 720p resolution is used for image acquisition tools. The color system of the tool's image, after being recorded by the camera, is transmitted to LabVIEW software running on PC to process and classify tools according to the system's requirements. The camera system is opened when scanning the barcode of the order on the Order sheet. Image processing tool is written in LabVIEW software (Fig. 10). The real-time database is deployed on the company's server hardware system developed with simple and fast programming applications in simplifying data access. The data connection model is between the server and the clients. The image processing algorithm in LabVIEW is implemented as a closed process (Fig. 11). The camera captures the image and image is processed on PC. The image with 3 RGB color systems (Red, Green, and Blue) is analyzed and converted to HSL color system (Hue, Saturation, and Lightness). The IMAQ Color Learn function learns the HSL color system and divides each cell containing each color system according to the color sensitivity selection. The FC250 material cutters are available in blue and red for copper tools and are divided into 16 color racks arranged from 0 to 15 (blue on the 6th color and red on the 15th color shelf). The reference value used is 0.4 for the purpose of improving accuracy in color selection and discrimination. In case where the return value at the 6th price is greater than 0.4, the evaluation is shown in blue, and the same process for the 15th price is identified in red. This cut-off value of 0.4 is obtained from the experiment during the observation of the value at each of the blue and red shelf boxes (Fig. 12).

Fig. 10 Actual camera system in process

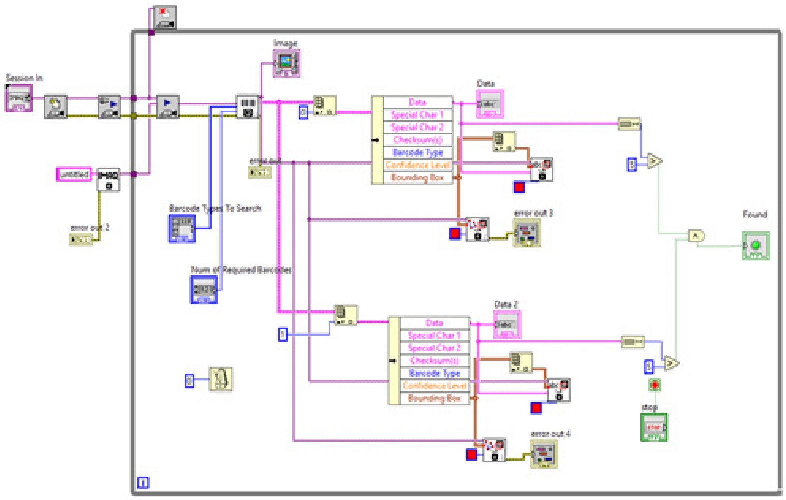

Fig. 11 LabVIEW graphical programming environment

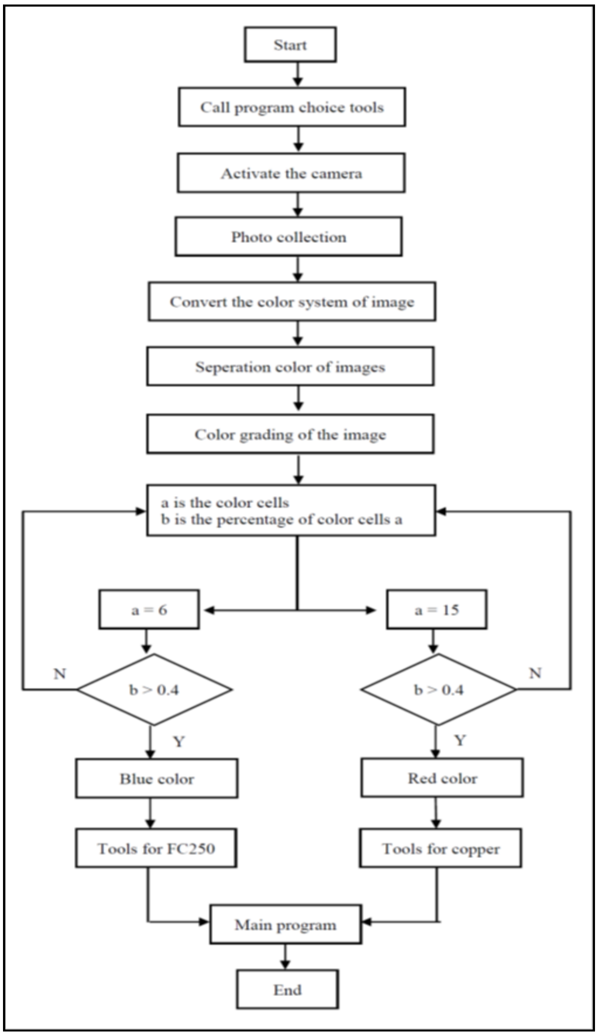

Fig. 12 Image processing in LabVIEW

Project B (re-designed is oil dipping tank processing condition). The response of the oil dipping process includes the dimensional expansion of molybdenum *h*, the hardness of the molybdenum material *c*, the input variables for the oil dipping process including the oil dipping bath temperature *F*, heat temperature of molybdenum drying bath after oil dipping F_1, changing oil immersion time F_2, changing molybdenum drying time F_3, and changing molybdenum powder cooling time F_4. Building the mass balance equation and the composition balance equation in the oil immersion heat accretion process assuming conditions such as the density of MG 815 oil and the motion inertia of MG 815 oil in the tank are ignored. Construct the mass balance equation for oil MG 815 in the oil immersion tank (Eq. 3), and a simulation of the thermal operation of oil dipping (Eq. 4).

$$\rho V \frac{dc}{dt} + \rho c \frac{dV}{dt} = F_1 F_3 + F_2 F_4 - Fc \quad (3)$$

$$\frac{dc}{dt} = \frac{1}{\rho A h}(F_1 F_3 + F_2 F_4 - (F_1 + F_2)c) \quad (4)$$

The system of differential equations describing the thermal oil dipping process is built into, Eq. 5.

$$\frac{dy}{dt} = \frac{d}{dt}\begin{bmatrix} h \\ c \end{bmatrix} = \begin{bmatrix} \frac{1}{\rho A}(F_1 + F_2 - F) \\ \frac{1}{\rho A y_1}(F_1 F_3 + F_2 F_4 - (F_1 + F_2) y_2) \end{bmatrix} \quad (5)$$

The hypothesis at equilibrium working point taken from the mean of Table 4 (One Way ANOVA analysis) with 95 % confidence interval is F_2 = 2 hours, F_3 = 2 hours, F_4 = 6 days, and ρA = 0.001 m/kg. Proceed to solve Eq. 6 to find the optimal condition of oil dipping temperature F, optimum temperature condition F_1, and waiting time for molybdenum cooling after oil dipping F_4.

$$\begin{cases} \overline{F_1} + \overline{F_2} - \overline{F} = 0 \\ \overline{F_1}\,\overline{F_3} + \overline{F_2}\,\overline{F_4} - (\overline{F_1} + \overline{F_2})c \end{cases} \quad (6)$$

The optimal result of oil dipping temperature is that the oil dipping temperature F is 100°C, the bath temperature F_1 is 70°C, the oil dipping time F_2 is equal to the drying time F_3 is 2 hours and the waiting time for molybdenum cooling after oil dipping F_4 is 6 days. Using the above condition in the oil dipping process to produce 110 products continuously, using the histogram to analyze the molybdenum size data measured by the Koshaka profiler. Standard molybdenum size expansion is less than 3 microns, analysis results show that the C_{pk} stage capacity index reaches 1.16. Dimensional stability analysis of 110 continuously produced samples using the I-MR Chart and found the results to be within the norm but with large inter-series variability.

Project C (Quality control of power supply is for oil dipping tank). Connect the voltage measurement results and THD value to the measurement system at the oil dipping stage. The standard THD power supply for the thermistor is 5 % max and the mains voltage is 380 V ± 20 %. For each oil dipping order, the measuring system program is activated and the power supply measurement value is updated in the system, the results are processed by the system online (Fig. 13). If the value of the power supply (THD and Voltage) exceeds the standard, the system generates an alarm. Data is collected in real-time, and connected to the SQL (Structured Query Language) system.

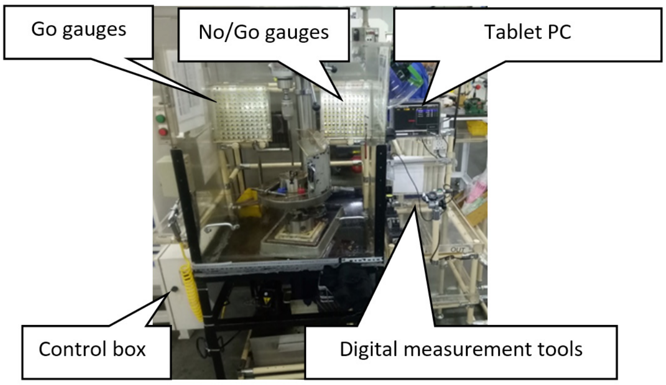

Fig. 13 Actual digital measurement system in process

4.5 Control (C)

This study focuses on controlling the molybdenum size variation in the production line and is a long-term development strategy of the enterprise. Enhancing workers' confidence in tool improvement from the improvement department is a very important step forward. Applying lean tools, statistical tests, and experimental design methods as well as applying quality 4.0 techniques such as computer vision, digital numerical control, and inspection system have contributed to bring great success for Lean Six Sigma projects. The team leader of the Lean Six Sigma project is a member of the company's technical committee (an engineer) and the project members are employees working directly at the product processing line. The lessons learn from failed experiments as well as from successful experiments are valuable that help improve the capacity of engineers as well as research team members. Helps build new knowledge and develops team leadership skills for project members. Engineers become leaders in the future, for machine operators, accumulate experience, and apply quality 4.0 technology to improve process and product quality. Achieves the goals set out from the beginning of the project implementation. This study has relevant contributions to researchers, managers, engineers, and even direct machining machine operators. These key results are presented step-by-step by phase in the DMAC (Table 5).

Table 5 Description of research results through each phase of DMAIC

Phase \ Results	Result 1	Result 2	Result 3
Define	It is necessary to redesign the process of applying Industry 4.0 technology to the operation and controlling production line of products using the special raw material molybdenum.	The Lean Six Sigma (LSS) project specifies a specific target, a specific timeline for each task, and each member according to each specific project.	Enhancing the morale of employees through continuous improvement activities to improve productivity and quality.
Measurement	Using statistical techniques, statistical hypothesis testing to analyze data collected directly at the machining line by the operator		
Analysis	Specify each activity in the LSS project and deploy the corresponding analysis tool for each activity. Namely, the Optimization of machining conditions by the Taguchi optimization technique. Object recognition and classification by computer vision technique with color processing function. Real-time data acquisition by digital signal processing with RFID barcode scanning and digital numerical control technology to control the corresponding object.	Many noise factors in the factory environment affect machining conditions.	Link data of individual stages into a common data block.
Improve	Industry 4.0 techniques and computer vision technology are deployed directly to the production line and operated by workers.	Digital numerical control technology is deployed to the direct processing line to collect data in real-time.	The processes are linked together.
Control	Tasks in each project are completed. Re-engineered the production line from semi-automatic to fully automatic operation. Machining operation is simple.	The research results are that the defect rate decreased from 6.5 % to zero, the productivity increased by 7.9 % per year and the profit increased by 35762 USD per year.	Improve the working spirit of workers and employees in the company. Connecting and implementing research results into practice brings high results.

5. Conclusion

All members of the outsourcing line participate in the Lean Six Sigma (LSS) project, the goal of the LSS project is to improve the internal capabilities of the organization within the company. This study implements the implementation of the LSS project on rebuilding the production process at the mechanical product processing line and redesigning the production conditions at each specific production process. The specific result is optimizing the conditions for the oil dipping process, creating a system that links data from individual processes into a system and processes that can access and recognize each other's data. The measurement and data collection system by barcode scanning tool using Industry 4.0 techniques is deployed at each line, the operation is simplified, and the operation changes from semi-automatic to automatic operation. The Industry 4.0 system follows the principle that if the fieldwork quality is not completed, the next stage will be locked and the industrial system will not work, which means the processing line is stopped by the leader and transferred to the employee card (Fig. 14).

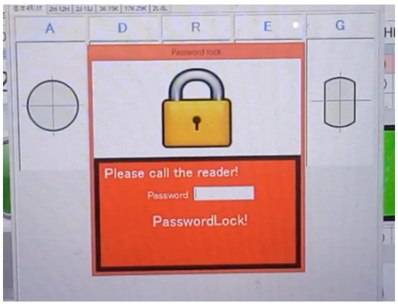

Fig. 14 Lock system screen

This study serves as a project planning and reporting model for activities in companies. However, this study raises the issue of data security systems in Industry 4.0 systems and is a promising research direction for future researchers. This study implements the LSS project implemented directly at the production line at the mechanical manufacturing company and the data is collected at the production site by the operator. This is also considered a promising data set for researchers carrying out new studies on improving productivity and product quality in the future.

The research results are that the defect rate decreased from 6.5 % to zero defect, the total production capacity increased by 7.9 % and the profit was 35762 USD per year, reaching the set target compared to the LSS implementation plan. Another result is to improve the working spirit of employees, and at the same time remove prejudices about the gap between research results and application of research results in practice. Enhance the spirit of implementing continuous improvement activities in the company.

However, it is necessary to reanalysis each specific tool when applying the DMAIC model to each specific process to promote the strongest. Because some companies only define the goal without really paying attention to the empirical research and the research method is not enough. This study establishes a model for the application of statistical tools, statistical hypothesis testing, and optimal experimental design Taguchi in data analysis to meet organizational development goals. This research paper provides a scientific research model for organizations applying directly to their production processes in order to develop and bring good results. It is also worth noting that computer vision technology is applied to the process of continuous improvement to deliver results that exceed expectations. This model is considered as the foundation for research and application of artificial intelligence in improving production processes and production operations.

Some recommendations are for further studies. It is proposed to extend this research model to apply to all departments in the company. Improve power quality by minimizing and controlling harmonics generated in the power supply for the signal processing sensor operating boards, the thermostat power supply, and the actuator circuit power supply in the processing line. Real-time data security is also considered a promising research direction.

Acknowledgement

Sincere thanks to VSB–Technical University of Ostrava, Czech Republic and Van Lang University, Vietnam to support for this research, and This work was supported in part by the Ministry of Education of the Czech Republic under Project SP2023/090

References

[1] Bashar Fakhri, A., Latteef Mohammed, S., Khan, I., Safaa Sadiq, A., Alkazemi, B., Pillai, P., Cho, B.J. (2021). Industry 4.0: Architecture and equipment revolution, *Computers,Materials & Continua*, Vol. 66, No. 2, 1175-1194, doi: 10.32604/cmc.2020.012587.

[2] Rodriguez Delgadillo, R., Medini, K., Wuest, T. (2022). A DMAIC framework to improve quality and sustainability in additive manufacturing – A case study, *Sustainability*, Vol. 14, No. 1, Article No. 581, doi: 10.3390/su14010581.

[3] Zhao, Y., Lu, J., Yan, Q., La, L., Xu, L. (2020). Research on cell manufacturing facility layout problem based on improved NSGA-II, *Computers, Materials & Continua*, Vol. 62, No. 1, 355-364, doi: 10.32604/cmc.2020.06396.

[4] Ly Duc, M., Bilik, P. (2022). Zero defect manufacturing using digital numerical control, *Management and Production Engineering Review*, Vol. 13, No. 3, 61-74, doi: 10.24425/mper.2022.142383.
[5] Kregel, I., Stemann, D., Koch, J., Coners, A. (2021). Process mining for Six Sigma: Utilising digital traces, *Computers & Industrial Engineering*, Vol 153, Article No. 107083, doi: 10.1016/j.cie.2020.107083.
[6] Ringen, G., Holtskog, H. (2013). How enablers for lean product development motivate engineers, *International Journal of Computer Integrated Manufacturing*, Vol. 26, No. 12, 1117-1127, doi: 10.1080/0951192x.2011.593046.
[7] Sony, M., Naik, S., Therisa, K.K. (2019). Why do organizations discontinue Lean Six Sigma initiatives?, *International Journal of Quality & Reliability Management,* Vol. 36, No. 3, 420-436, doi: 10.1108/IJQRM-03-2018-0066.
[8] Elsayed, E.K., Elsayed, A.K., Eldahshan, K.A. (2022). Deep reinforcement learning-based job shop scheduling of smart manufacturing, *Computers, Materials & Continua*, Vol. 73, No. 3, 5103-5120, doi: 10.32604/cmc.2022.030803.
[9] Pang, J.H., Zhao, H., Qin, F.F., Xue, X.B., Yuan, K.Y. (2019). A new approach for product quality prediction of complex equipment by grey system theory: A case study of cutting tools for CNC machine tool, *Advances in Production Engineering & Management*, Vol. 14, No. 4, 461-471, doi: 10.14743/apem2019.4.341.
[10] Bucko, M., Schindlerova, V., Krupova, H. (2022). Application of lean manufacturing methods in the production of ultrasonic sensor, *Tehnički Vjesnik – Technical Gazette,* Vol. 29, No. 5, 1671-1677, doi: 10.17559/TV-20220421141917.
[11] Werkema, C. (2012). *Criando a cultura Lean Seis Sigma,* Elsevier, Rio de Janeiro, Brazil.
[12] Ali Abdallah, A. (2021). How can lean manufacturing lead the manufacturing sector during health pandemics such as Covid 19: A multi-response optimization framework, *Computers, Materials & Continua*, Vol. 66, No. 2, 1397-1410, doi: 10.32604/cmc.2020.013733.
[13] Medic, N., Anisic, Z., Lalic, B., Marjanovic, U., Brezocnik, M. (2019). Hybrid fuzzy multi-attribute decision making model for evaluation of advanced digital technologies in manufacturing: Industry 4.0 perspective, *Advances in Production Engineering & Management*, Vol. 14, No. 4, 483-493, doi: 10.14743/apem2019.4.343.
[14] Straka, M., Khouri, S., Lenort, R., Besta, P. (2020). Improvement of logistics in manufacturing system by the use of simulation modelling: A real industrial case study, *Advances in Production Engineering & Management*, Vol. 15, No. 1, 18-30, doi: 10.14743/apem2020.1.346.
[15] Sarı, T., Güleş, H.K., Yiğitol, B. (2020). Awareness and readiness of Industry 4.0: The case of Turkish manufacturing industry, *Advances in Production Engineering & Management*, Vol. 15, No. 1, 57-68, doi: 10.14743/apem2020.1.349.
[16] Ly Duc, M., Vo, T.H.N., Do, N.H. (2019). Continuous improvement of productivity and quality with Lean Six-Sigma: A case study, *Applied Mechanics and Materials,* Vol. 889, 557-566, doi: 10.4028/www.scientific.net/AMM.889.557.
[17] Al-Refaie, A., Lepkova, N., Abbasi, G., Bani Domi, G. (2020). Optimization of process performance by multiple pentagon fuzzy responses: Case studies of wire-electrical discharge machining and sputtering process, *Advances in Production Engineering & Management*, Vol. 15, No. 3, 307-317, doi: 10.14743/apem2020.3.367.
[18] Zywicki, K., Rewers, P. (2020). A simulation-based approach to study the influence of different production flows on manufacturing of customized products, *Advances in Production Engineering & Management*, Vol. 15, No. 4, 467-480, doi: 10.14743/apem2020.4.379.
[19] Ly Duc, M., Bilik, P., Duy Truong, T. (2022).Design of industrial system using digital numerical control, *Quality Innovation Prosperity,* Vol. 26 No. 3, 135-150, doi: 10.12776/qip.v26i3.1747.
[20] Stanivuk, T., Gvozdenović, T., Žanić Mikuličić, J., Lukovac, V. (2020). Application of Six Sigma model on efficient use of vehicle fleet, *Symmetry*, Vol. 12, No. 5, Article No. 857, doi: 10.3390/sym12050857.
[21] Hakimi, S., Zahraee, S.M., Mohd Rohani, J. (2018). Application of Six-Sigma DMAIC methodology in the plain yogurt production process, *International Journal of Lean Six Sigma*, Vol. 9, No. 4, 562-578, doi: 10.1108/ijlss-11-2016-0069.
[22] De Mast, J., Lokkerbol, J. (2012). An analysis of the Six Sigma DMAIC method from the perspective of problem solving, *International Journal of Production Economics,* Vol. 139, No. 2, 604-614, doi: 10.1016/j.ijpe.2012.05.035.
[23] Yusof, N., Sapuan, S., Sultan, M., Jawaid, M. (2020). Materials selection of "green" natural fibers in polymer composite automotive crash box using DMAIC approach in Six Sigma method, *Journal of Engineered Fibers and Fabrics*, Vol. 15, doi: 10.1177/1558925020920773.
[24] Hrnjica, B., Behrem, S. (2022). A new multi-objective optimization approach for process parameters optimization during numerical simulation of quenching steel parts, *Advances in Production Engineering & Management*, Vol. 17, No. 1, 16-32, doi: 10.14743/apem2022.1.418.
[25] Adrita, M.M., Brem, A., O'Sullivan, D., Allen, E., Bruton, K. (2021). Methodology for data-informed process improvement to enable automated manufacturing in current manual processes, *Applied Sciences*, Vol. 11, No. 9, Article No. 3889, doi: 10.3390/app11093889.
[26] Ly Duc, M., Sang, N.Q., Bilik, P., Martinek, R. (2023). Optimize design of source energy for manufacturing machine by digital numerical control, *International Journal of Automotive and Mechanical Engineering, Vol*. 20, No. 1, 10307-10321, doi: 10.15282/ijame.20.1.2023.12.0797.
[27] Jirasukprasert, P., Arturo Garza-Reyes, J., Kumar, V., Lim, M.K. (2014). A Six Sigma and DMAIC application for the reduction of defects in a rubber gloves manufacturing process, *International Journal of Lean Six Sigma*, Vol. 5, No. 1, 2-21, doi: 10.1108/ijlss-03-2013-0020.

[28] Sin, A.B., Zailani, S., Iranmanesh, M., Ramayah, T. (2015). Structural equation modelling on knowledge creation in Six Sigma DMAIC project and its impact on organizational performance, *International Journal of Production Economics,* Vol. 168, 105-117, doi: 10.1016/j.ijpe.2015.06.007.

[29] Rosin, F., Forget, P., Lamouri, S., Pellerin, R. (2021). Impact of Industry 4.0 on decision-making in an operational context, *Advances in Production Engineering & Management*, Vol. 16, No. 4, 500-514, doi: 10.14743/apem2021.4.416.

[30] Salunkhe, O., Berglund, Å.F. (2022). Industry 4.0 enabling technologies for increasing operational flexibility in final assembly, *International Journal of Industrial Engineering and Management*, Vol. 13, No. 1, 38-48, doi: 10.24867/IJIEM-2022-1-299.

[31] Fırat, S.Ü.O., Akan, M.Ö.A., Ersoy, E., Gök, S., Ünal, U. (2017). A Six Sigma DMAIC process for supplier performance evaluation using AHP and Kano's model, *International Journal of Business Analytics*, Vol. 4, No. 2, 37-61, doi: 10.4018/ijban.2017040103.

[32] Peruchi, R.S., Rotela Junior, P., Brito, T.G., Paiva, A.P., Balestrassi, P.P., Mendes Araujo, L.M. (2020). Integrating multivariate statistical analysis into Six Sigma DMAIC projects: A case study on AISI 52100 hardened steel turning, *IEEE Access*, Vol. 8, 34246-34255, doi: 10.1109/access.2020.2973172.

[33] Pande, P.S, Neuman, R.P., Cavanagh, R.R (2001). *Estratégia seis sigma: Como a GE, a Motorola e outras grandes empresas estão aguçando seu desempenho,* Qualitymark, Rio de Janeiro, Brazil, 472-481.

[34] Rathi, R., Singh, M., Verma, A.K., Gurjar, R.S., Singh, A., Samantha, B. (2022). Identification of Lean Six Sigma barriers in automobile part manufacturing industry, *Materials Today: Proceedings,* Vol. 50, Part 5, 728-735, doi: 10.1016/j.matpr.2021.05.221.

[35] Tomov, M., Gecevska, V., Vasileska, E. (2022). Modelling of multiple surface roughness parameters during hard turning: A comparative study between the kinematical-geometrical copying approach and the design of experiments method (DOE), *Advances in Production Engineering & Management*, Vol. 17, No. 1, 75-88, doi: 10.14743/apem2022.1.422.

[36] Pugna, A., Negrea, R., Miclea, S. (2016). Using six sigma methodology to improve the assembly process in an automotive company, *Procedia - Social and Behavioral Sciences,* Vol. 221, 308-316, doi: 10.1016/j.sbspro.2016.05.120.

[37] Shokri, A. (2019). Reducing the scrap rate in manufacturing SMEs through lean six sigma methodology: An action research, *IEEE Engineering Management Review,* Vol. 47, No. 3, 104-117, doi: 10.1109/EMR.2019.2931184.

[38] Guleria, P., Pathania, A., Shukla, R.K., Sharma, S. (2021). Lean six sigma: Panacea to reduce rejection in the gear manufacturing industry, *Materials Today: Proceedings,* Vol. 46, No. 9, 4040-4046, doi: 10.1016/j.matpr.2021.02.559.

[39] Ly Duc, M., Thu, M.N. (2022). Application of lean six sigma for improve productivity at the mechanical plant. A case study, *Manufacturing Technology*, Vol. 22, No. 2, 124-138, doi: 10.21062/mft.2022.028.

[40] de Boer, T. (2010). Chapter 6 - Global user research methods, In: Schumacher, R.M. (ed.), *Handbook of global user research,* Elsevier, Burlington, USA, 145-201, doi: 10.1016/B978-0-12-374852-2.00006-9.

[41] Hart, E. (1996). Action research as a professionalizing strategy: Issues and dilemmas, *Journal of Advanced Nursing,* Vol. 23, No. 3, 454-461, doi: 10.1111/j.1365-2648.1996.tb00006.x.

[42] Titmarsh, R., Assad, F., Harrison, R. (2020). Contributions of lean six sigma to sustainable manufacturing requirements: An Industry 4.0 perspective, *Procedia CIRP,* Vol. 90, 589-593, doi: 10.1016/j.procir.2020.02.044.

[43] Li, S.-H., Wu, C.-C., Yen, D.C., Lee, M.-C. (2011). Improving the efficiency of IT help-desk service by Six Sigma management methodology (DMAIC) – A case study of C company, *Production Planning & Control*, Vol. 22, No. 7, 612-627, doi: 10.1080/09537287.2010.503321.

[44] Sun, Y., Qiao, F., Wang, W., Xu, B., Zhu, J., Mansour, R.F., Qi, J. (2022). Dynamic intelligent supply-demand adaptation model towards intelligent cloud manufacturing, *Computers, Materials & Continua*, Vol. 72, No. 2, 2825-2843, doi: 10.32604/cmc.2022.026574.

[45] Vukicevic, A., Mladineo, M., Banduka, N., Macuzic, I. (2021). A smart Warehouse 4.0 approach for the pallet management using machine vision and Internet of Things (IoT): A real industrial case study, *Advances in Production Engineering & Management*, Vol. 16, No. 3, 297-306, doi: 10.14743/apem2021.3.401.

[46] Leksic, I., Stefanic, N., Veza, I. (2020). The impact of using different lean manufacturing tools on waste reduction, *Advances in Production Engineering & Management*, Vol. 15, No. 1, 81-92, doi: 10.14743/apem2020.1.351.

[47] Vukelic, D., Prica, M., Ivanov, V., Jovicic, G., Budak, I., Luzanin, O. (2022). Optimization of surface roughness based on turning parameters and insert geometry, *International Journal of Simulation Modelling*, Vol. 21, No. 3, 417-428, doi: 10.2507/IJSIMM21-3-607.

[48] Tanasic, Z., Janjic, G., Sokovic, M., Kusar, J. (2022). Implementation of the lean concept and simulations in SMEs – A case study, *International Journal of Simulation Modelling*, Vol. 21, No. 1, 77-88, doi: 10.2507/IJSIMM21-1-589.

[49] Bajic, B., Suzic, N., Simeunovic, N., Moraca, S., Rikalovic, A. (2020). Real-time data analytics edge computing application for Industry 4.0: The Mahalanobis-Taguchi approach, Vol. 11, No. 3, 146-156, doi: 10.24867/IJIEM-2020-3-260.

[50] Fırat, S.Ü.O., Akan, M.Ö.A., Ersoy, E., Gök, S., Ünal, U. (2017). A Six Sigma DMAIC process for supplier performance evaluation using AHP and Kano's model, *International Journal of Business Analytics*, Vol. 4, No. 2, 37-61, doi: 10.4018/ijban.2017040103.