



Study of the Predictive Mechanism with Big Data-Driven Lean Manufacturing and Six Sigma Methodology

Hong Chen, Jiande Wu, Wei Zhang, Qing Guo, Huifeng Lu

► To cite this version:

Hong Chen, Jiande Wu, Wei Zhang, Qing Guo, Huifeng Lu. Study of the Predictive Mechanism with Big Data-Driven Lean Manufacturing and Six Sigma Methodology. IFIP International Conference on Advances in Production Management Systems (APMS), Sep 2021, Nantes, France. pp.662-672, 10.1007/978-3-030-85910-7_70 . hal-03806514

HAL Id: hal-03806514

<https://inria.hal.science/hal-03806514>

Submitted on 7 Oct 2022

HAL is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.



Distributed under a Creative Commons Attribution 4.0 International License



This document is the original author manuscript of a paper submitted to an IFIP conference proceedings or other IFIP publication by Springer Nature. As such, there may be some differences in the official published version of the paper. Such differences, if any, are usually due to reformatting during preparation for publication or minor corrections made by the author(s) during final proofreading of the publication manuscript.

Study of the Predictive Mechanism with Big Data-Driven Lean Manufacturing and Six Sigma Methodology

Hong Chen¹[0000-0002-1376-9789], JianDe Wu¹[0000-0003-2330-6048], Wei Zhang¹, Qing Guo¹,
HuiFeng Lu¹

¹ College of Electrical Engineering, Zhejiang University, 310027, Hangzhou, People's Republic of China

chenhonghz@zju.edu.cn

Abstract. In order to achieve the sustainable development, the predictive mechanism with big data-driven Lean Manufacturing and Six Sigma methodology is proposed in this paper. The sustainable development for serious competition is often studied, however, the predictive mechanism with big data-driven Lean Manufacturing and Six Sigma methodology is seldom mentioned in publications. This paper reports the predictive mechanism from the perspective of big data-driven Lean Manufacturing. The key techniques including PLC communication, DMAIC roadmap, SPC technique and Hypothesis Testing are utilized to eliminate the waste and obtain continuous improvement. The demonstration of calculator production indicates the predictive mechanism can effectively eliminate the waste and improve the output by 60% with the sufficient capability of $C_p > 1.33$ and $C_{pk} > 1$.

Keywords: Predictive Mechanism, Lean Manufacturing, Six Sigma, DMAIC, Statistical Process Control, Hypothesis Testing

1 Introduction

It is very important for the industrial company to achieve the sustainable development for the increased competition. The increased competition is based on the sustainable development. The sustainable development roots in the forecast and the current capability. The variation in current capability can cause the unacceptable output in technology, management, operation and production. If the variation can be predicted and eliminated at the first occurrence, the remedy cost can be saved. So it is necessary to set up the Predictive Mechanism (PM) to prevent the potential out of control accident from happening. The Big Data and the Internet of Things (IoT) are often studied in Industry 4.0. However, the PM with big data-driven Lean Manufacturing is seldom emphasized in publications.

In the 21st century the industrial revolution starts with the automation and the IoT to bring the new production scheme and the smart products. The big data is the outcome of IoT [1]. Digitalization-based manufacture is often referred to as Industry 4.0 [2]. The data from IoT in manufacturing site is big volume, real-time, variety in operation, pure

and practical digitals, which is called as Big Data. In this research the Big Data is the base of PM with Lean Manufacturing (LM) and Six Sigma methodology.

The LM corresponds to a system that addresses a range of practical management applications [3]. Increased competition means that lean paradigms are increasingly employed to reduce waste and improve productivity: to reduce non-value-added activities and create value for the customer [4]. Lean origins are linked to the Toyota production system, which was a manufacturer's principle, attributed to engineers from Japan [5]. Now LM becomes popular in industry for its reducing waste. The waste are caused by variance in process. One method to analyze process issues and variance is Six Sigma and was developed in the 1980s by Motorola and is analogous to previous improvement techniques, such as, total quality management [4]. From a business point of view, it is used to improve the effectiveness and efficiency of all operations to meet or exceed the customers' needs and expectations [6]. The waste often cause the quality out of control. The Big Data can be analyzed by Six Sigma methodology to find and reduce the variation of process for the quality control and continuous improvement. PM can ensure LM and LM can help to achieve high productivity and sustainable development. In this research, the Echelon company's LonWorks technology is utilized to get the real-time Big Data and the data is analyzed by Six Sigma methodology to find the source of variations, which drive and achieve LM in PM.

The paper is structured as follows. This first section presented the initial considerations and the aim of this research. Section 2 presents the systematic literature review and PM workflow. Section 3 introduces the case study. Section 4 performs a general discussion and then conclude in Section 5.

2 Literature Review and PM Design

2.1 Literature Review

Lean Manufacturing

LM is a business concept and philosophy in management to minimize the amount of time and resources used to get the customer satisfaction. The lean principles provide perfect quality to satisfy the customer's demand and at the same time minimize the non-value-adding activities [7]. The minimum non-value-activities means the maximum customer satisfaction. The LM tools includes JIT, Kanban, Poka-Yoke, VSM, Kaizen and TPM [8]. The LM with eliminating waste is to achieve customer satisfaction, on time delivery, cost reduction and quality assurance. Both Total Productive maintenance (TPM) and Six Sigma are key business process strategies to enhance manufacturing performance [9]. As Six Sigma adopts a data driven philosophy, the opportunities provided by big data environments would be a natural fit [10].

Six Sigma Methodology

Six Sigma is a data-driven approach using specific tools and methodologies that lead to fact-based decision-making. This is a continuous improvement to reduce process variability and eliminate waste [11]. The data-driven nature of Six Sigma applied in a big data environment can provide competitive advantages by implementation of the

problem solving strategy – define, measure, analyze, improve and control (DMAIC) [6]. DMAIC is a systematic and scientific method, based on facts that contribute to the improvement of processes [12].

Since variability is often a major source of poor quality, statistical techniques, including Statistical Process Control (SPC) and designed experiments are the major tools of quality control and improvement [13]. When the quality characteristics of the process distributes with the specification limit at three standard deviation σ either side of the mean, the variability in this process are at least six standard deviation from the mean [13]. The Process Capability Indices of SPC indicates the statistical characteristics of process. The Process Capability Indices include the process potential index C_p and the process performance index C_{pk} . The equation of double-sided distribution is in (1) [14].

$$C_p = \frac{USL - LSL}{6\sigma} \quad (1)$$

$$C_{pk} = \min\left(\frac{USL - \mu}{3\sigma}, \frac{\mu - LSL}{3\sigma}\right)$$

Where USL and LSL are the upper and the lower specification limits, μ and σ are the average value and the standard deviation. The process potential ability is sufficient when $C_p > 1.33$ and the process performance ability is sufficient when $C_{pk} > 1$ [14]. The C_p will increase as the mean of the process measurement center to the target with high potential. The C_{pk} is the distance of the process mean and the specification limit.

A Hypothesis Testing was applied to understand the process performance for the real data [15]. Hypothesis Testing can check either modified input could improve the process outcome or not [15]. The null hypothesis and the alternative hypothesis are set up by checking the P-Value of 0.05.

2.2 PM Design

The research of PM is to eliminate the non-value-activities and keep the process control in supply chain management. The PM is set up based on the big data-driven LM and Six Sigma Methodology (see Fig. 1).

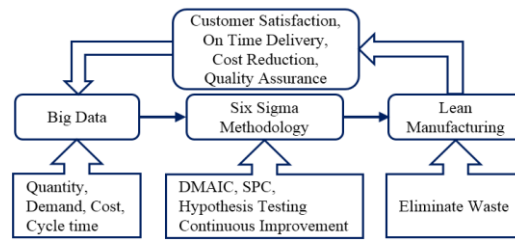


Fig. 1. Predictive Mechanism

The idea of Industry 4.0 pivots around extensive automation, intelligization and digitization of the processes in a data-driven environment [16]. Industry 4.0 is driven by data and the rapid development of Industry 4.0 technologies has led to the explosive growth

of data in almost every industry and business area [17]. The Power Line Carrier Communication (PLC) is suitable for the data acquisition and machine to machine talking in manufacturing site. Narrowband PLC (NB-PLC) technology is a data communication via LV electric power grids which operates in the frequency bandwidth of 0–500 kHz and provides data rates of tens of kb/s [18]. If compared to the broadband PLC (BPL, 1.7–250 MHz), which commonly requires a number of repeaters with a shorter distance among devices, NB-PLC has been considered the technology with best tradeoff among communication distance range, low data rate requirement, and implementation cost [18]. The LonWorks technology of Echelon company is utilized to set up the acquisition of Big Data. Routing is realized by tunneling LonTalk protocol telegrams in IP standard frames [19]. The software in control layer is programmed by C language in LonWorks (see Fig. 2).

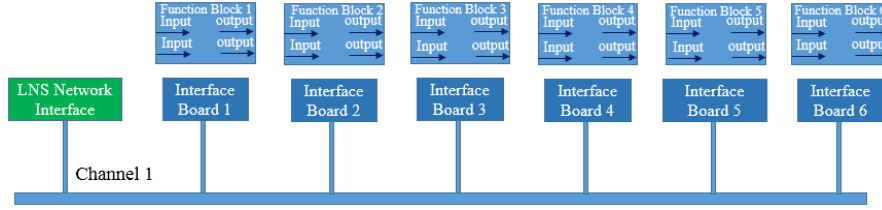


Fig. 2. Software Design for IoT

The Function Block in Fig. 2 is programmed according to the hardware connection in LonWorks field bus with input ports and output ports. The hardware of interface board is designed (see Fig. 3).

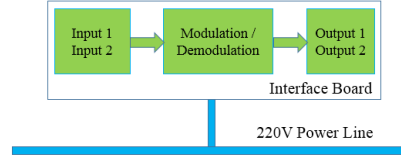


Fig. 3. Structure of Interface Board

The interface board get the data and the power supply by 220V power line in blue color. The signal is modulated and demodulated in the interface board.

3 Case Study

The PM is implemented in the calculator manufacturing. DMAIC roadmap is utilized to implement PM. The manufacturing process includes PCB Printing, PCBA Testing, LCD Assembly, Housing Assembly, Function Testing, Cosmetic Checking, Quality Checking, and then pack to ship out (see Fig. 4).

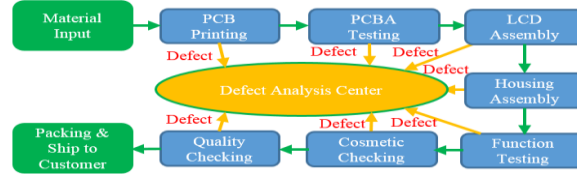


Fig. 4. Manufacturing Process of Calculator

All of the parts in “Pass” status stay on production line to send to next station with green arrows. All of the defects are sent to the Defect Analysis Center (DAC) to be repaired with brown arrows. The data of facility running and material quantity are supervised with the output of production line every day. PM is used in this case study to predict and eliminate the variation with DMAIC roadmap. The target output is 400 pieces of finished goods every day. However, the maximum quantity of the finished goods is 250 pieces.

Define

The material is input and the finished goods is the output of production line. The output quantity has 37.5% less than the target output every day. The data of material quantity and the finished goods within ten days are plotted (see **Fig. 5**).

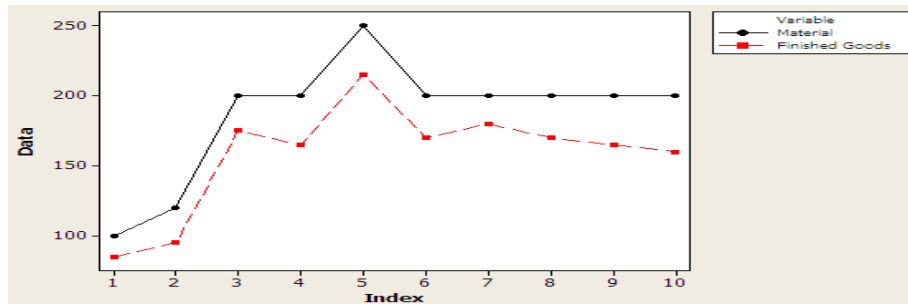


Fig. 5. Ten days' data of material qty. and finished goods qty.

The analysis indicates that the material quantity in black color is much higher than the quantity of the finished goods in red color, which indicates the defects and failure rate are high.

Measure

The quantity of the material and Working-In-Progress (WIP) are accumulated on each station in production line. The working station on production line are listed by number as PCB Printing as 1, PCBA Testing as 2, LCD Assembly as 3, Housing Assembly as 4, Function Testing as 5, Cosmetic Checking as 6, Quality Checking as 7 (see **Fig. 6**).

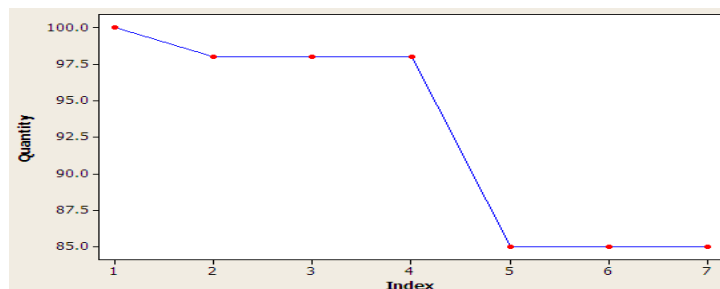


Fig. 6. Material and WIP quantity measurement on production line

The quantity changes on the stations of No.2 and No. 5. The No.2 indicates PCBA Testing and the No.5 indicates Function Testing station. The reduced quantity means that the defect is sent to Defect Analysis Center.

Analyze

The defect from the PCBA Testing station is analyzed that LCD connector on PCBA is skewed. The defect from the Function Testing station is analyzed and the LCD flex cable dropped out of skewed connector so as to cause No Display issue. The flex cable dropped out is caused by the skewed connector. Thus the SMT printing need be checked from the solder, the connector material, the SMT printing machine to the stencil. It is found out that the connector layout and the connector position on stencil are different (see **Fig. 7**).



Fig. 7. Connector layout in green color and connector hole on stencil in black color

The connector hole on the stencil in black color is unfit for the connector layout. The solder on the PCB is less than expectation, which causes the connector skewed and flex cable dropped out. The stencil need get the same size as connector layout. At the same time the repairing of No Display issue causes the housing material scrap in DAC.

Improve

The root causes of the defects are found and the corrective action plan can be considered to set up. Firstly the new stencil same as connector layout need be made. Secondly the LCD Assembly is advised to combine with the PCBA Testing in order to reduce the housing scrap. The new process is analyzed (see **Fig. 8**).

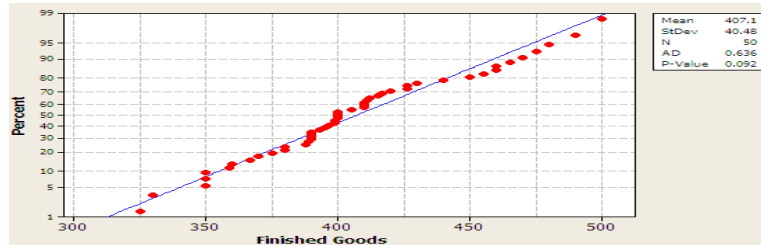


Fig. 8. Probability Plot for Finished Goods in Improved Process

The null hypothesis and the alternative hypothesis in Hypothesis Testing are set up with checking P-Value of 0.05. The P-Value of the finished goods per day is 0.092 in the probability plot, which is larger than the hypothesis checking value 0.05 and the null hypothesis cannot be rejected. Thus the data of finished goods is in normality distribution. The output with new stencil and improved process can reach the maximum 520 pieces and average 407 pieces per day, which meets the target and the non-value-activities are effectively eliminated. The process capability is analyzed (see **Fig. 9**).

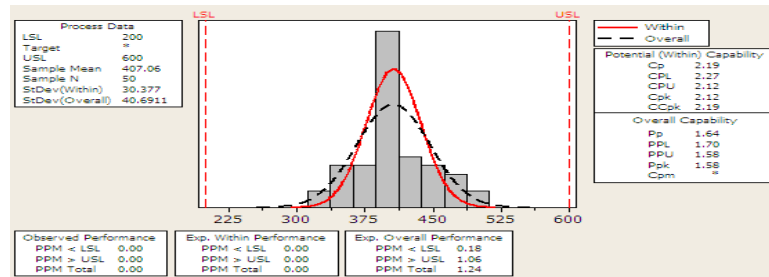


Fig. 9. Capability Analysis of New Process

The Process Capability means the ability of process to produce the output that are centered on the target and a very high percentage of the measurement fall within the specification. The Process Capability is sufficient with $C_p > 1.33$ and $C_{pk} > 1$ in Capability Analysis of new process, which meet the criteria and the corrective action plan is effective. The quantity of input material and output are analyzed to check the quality control with minimum failures (see Fig. 10).

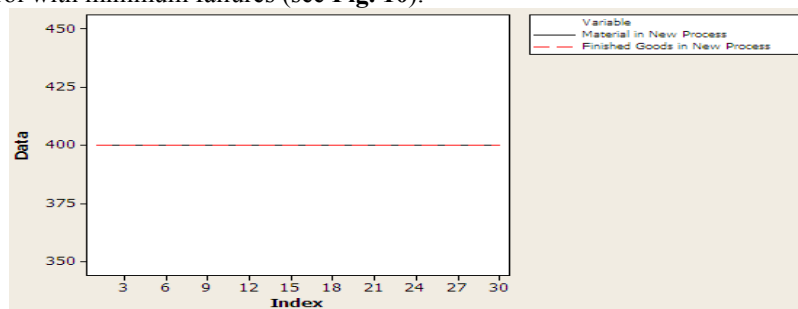


Fig. 10. Material qty. and Finished Goods qty. by Improved Process

The 30 days' input material quantity are same as the data of the finished goods, which shows the defect drops to zero.

Control

The process performance is improved with new stencil and updated process. The improved process become the Working Instruction (see Fig. 11).

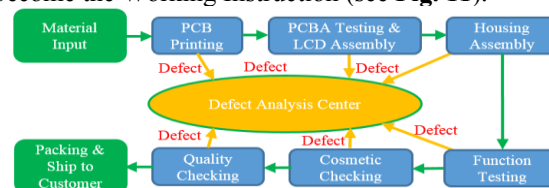


Fig. 11. Improved Process with Big data-driven LM

The PCBA Testing station combines with LCD Assembly to reduce the cycle time. The scrap of housing material is dropped to zero. The non-value-activities of manufacturing process is eliminated and 60% improvement for output with sufficient capability of $C_p > 1.33$ and $C_{pk} > 1$.

4 Discussion

4.1 Practical Contribution

In this research, the research of PM starts from the Big Data, moves to find the waste in production process, then focuses on quality control and ends at LM to achieve sustainable development. The purpose of this research is to set up the PM to maintain the sustainable development and competition enhancement in Industry 4.0.

IoT make the automation in Industry 4.0, which can make the every step in process stable and repeatable with data record. The recorded data can be analyzed by Six Sigma methodology and predict the potential waste. It is the reducing variation that the waste can be eliminated for LM and the continuous improvement can be achieved. Thus PM is very necessary to avoid that the minor variation become the big remedy cost and the loss of productivity in Industry 4.0.

PM implementation is both the continuous improvement and the sustainable development in supply chain management by three contributions. Firstly the research utilizes PLC communication with the LonWorks technology to realize the Big Data real-time acquisition in IoT operation. And the Big Data can be used for variation's real-time monitoring. Secondly the variation is the source of waste on the cost and the productivity. The Six Sigma methodology can find the source of variation by analysis of Big Data in IoT. Thirdly PM that can reduce the variation and maintain the quality control for the continuous improvement and the sustainable development with the Big Data-driven LM and Six Sigma Methodology. The continuous improvement and the sustainable development are ensured by PM with the reduced variation and the achieved LM. The case study demonstrates the effective PM workflow, which can effectively eliminate the waste and improve the output by 60% with the sufficient capability of $C_p > 1.33$ and $C_{pk} > 1$.

4.2 Theoretical Contribution

The research has the following theoretical values. Firstly PM set up the connection between sustainable development and the Big Data in Industry 4.0. IoT provide the automation and the real-time data acquisition, which have been reported widely for Industry 4.0 technologies. However, how to gain the value of Big Data in sustainable development and competition enhancement in Industry 4.0 is seldom discussed. It is PM that can make the Big Data drive LM in Industry 4.0 with Six Sigma Methodology which is effective in setting up the close loop for the sustainable development (see Fig. 12).

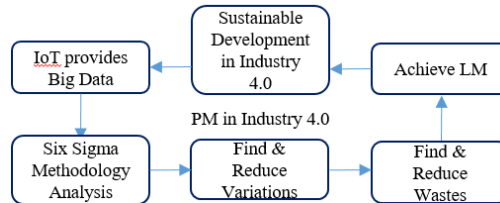


Fig. 12. PM in Industry 4.0

Secondly PM can indicate the trend of development by Big Data-driven LM and Six Sigma Methodology in advance. The business decision is often made for sustainable

development and the competition enhancement by business management level. PM provide the predictive operation status to business management level before their making correct decision, which is very important for industrial operation.

4.3 Limitation and Future Research

The PM is effective in sustainable development and competition enhancement in Industry 4.0. But the research has limitations. Firstly the Big Data come from the PLC network and the power supply is very important for PLC communication. The data will miss when the power supply is cut off. Secondly PM workflow need the manufacturing staff's involvement. The related function team members must be trained with the knowledge of LM and Six Sigma Methodology. The unskilled technicians are not suitable for PM.

The research of the PM is verified to be effective for calculator manufacturing. In future, the research of PM in different industries that provide other products or services may reveal different valuable results.

5 Conclusion

PM with Big Data driven LM and Six Sigma methodology is proposed in this paper to achieve sustainable development and survival in serious competition of Industry 4.0. The automation of IoT provide the data to monitor the process. The Six Sigma methodology provide the analysis to find and reduce the variation and waste to reach LM for the sustainable development in Industry 4.0.

The PM demonstrates that it is effective to improve the output by 60% with the sufficient capability of $C_p > 1.33$ and $C_{pk} > 1$ by Six Sigma methodology. The process output is measured with null hypothesis and alternative hypothesis by checking P-Value of 0.05 on the normality status before SPC analysis. The Process Capability of SPC is utilized to verify the improvement of the process with the acceptance criteria. The LM is obtained by the waste elimination and improved status with Big Data. The research demonstrates that PM has the practical contribution and theoretical value in sustainable development in Industry 4.0.

References

1. Mousumi Roy and Abhijit Roy, F.:Nexus of Internet of Things (IoT) and Big Data: Roadmap for Smart Management Systems (SMgS). IEEE Engineering Management Review 47(2), 104–117 (2019).
2. V. A. Vasilieva, S. V. Aleksandrova, M. N. Aleksandrova, and Yu. V. Velmakina, F.: Possibilities for the Integration of Quality Management Tools and Methods with Digital Technologies. Russian Metallurgy (13), 1649–1652 (2020).
3. Salvador, Rodrigo; Barros, Murillo Vetroni; Tagliaferro dos Santos, Giovani Elias, etc., F.: Towards a green and fast production system: Integrating life cycle assessment and value stream mapping for decision making. Environmental Impact Assessment Review 87, 1–14 (2021).
4. Daniel Lee Hardy, Saikat Kundu and Muhammad Latif, F.: Productivity and process performance in a manual trimming cell exploiting Lean Six Sigma (LSS) DMAIC – a case study

- in laminated panel production. *International Journal of Quality & Reliability Management* 0265-671X, 2(2021).
5. Ibrahim Alhuraish, Christian Robledo, and Abdessamad Kobi, F.: The effective of lean manufacturing and six sigma implementation. In: Editor Framinan JM, Editor Gonzalez PP, Editor Artiba A, *International Conference on Industrial Engineering and Systems Management 2015, IESM*, pp. 1–8. IEEE Publisher, Seville, Spain (2015).
 6. Michael Sony, Jiju Antony, Sung Park, and Michael Mutingi, F.: Key Criticisms of Six Sigma: A Systematic Literature Review. *IEEE Transactions on Engineering Management* 67(3), 950–962 (2020).
 7. Jagdeep Singh, Harwinder Singh, Amandeep Singh, Jashanpreet Singh, F.: Managing industrial operations by lean thinking using value stream mapping and six sigma in manufacturing unit: Case studies. *Management Decision* 5, 1118–1148 (2019).
 8. Luana Sposito Valamede, F.: Lean 4.0: A New Holistic Approach for the Integration of LeanManufacturing Tools and Digital Technologies. *International Journal of Mathematical, Engineering and Management Sciences* 5(5), 851–868 (2020).
 9. Sharma, Rajiv Kumar; Sharma, Rajan Gopal, F.: Integrating Six Sigma Culture and TPM Framework to Improve Manufacturing Performance in SMEs. *Quality and Reliability Engineering International* 30(5), 745–765 (2014).
 10. Siim Koppel and Shing Chang, F.: DMAIC – a Six Sigma implementation strategy in big data environments.: *International Journal of Lean Six Sigma* 2040-4166, 7(2020).
 11. Bucko, Michal, Schindlerova, Vladimira, Hlavaty, and Ivo, F.: Application of six sigma tools in the production of welded chassis frames. *MM Science Journal* 12, 4188–4193 (2020).
 12. Mendes, Fernanda Santos; Soares, Jose Miguel, F.: Financial KPI Analysis in the Implementation of DMAIC in a Pharmaceutical Organization – A case study. *International Journal for Quality Research* 15(1), 189–208 (2021).
 13. Montgomery, Douglas C.; Borror, Connie M., F.: Systems for modern quality and business improvement. *Quality Technology & Quantitative Management*, 14(4), 343-352 (2017)
 14. Kaya Ihsan and Kahraman Cengiz, F.: Process Capability Analyses Based on Fuzzy Measurements and Fuzzy Control Charts. *Expert Systems with Applications* 38(4), 3172–3184 (2011).
 15. Ahammed, Rubel; Hasan, Md. Zahid, F.: Humming noise reduction of ceiling fan in the mass production applying DMAIC-six sigma approach. *World Journal of Engineering* 18(1), 106–121 (2021).
 16. Muhammad Saad Amjad, Muhammad Zeeshan Rafique, Mohammad Aamir Khan, “Modern divulge in production optimization: an implementation framework of LARG manufacturing with Industry 4.0,” *International Journal of Lean Six Sigma*, pp. 1–25(2021).
 17. Mohd Soufhwee, Bin Abd Rahman, Effendi Mohamad and Azrul Azwan Bin Abdul Rahman, “Development of IoT-enabled data analytics enhance decision support system for lean manufacturing process improvement,” *Concurrent Engineering: Research and Application*, pp. 1–13 (2021).
 18. Leonardo de M.B.A.Dib, Victor Fernandes, Mateus de L. Filomeno, and Moises V. Ribeiro, “Hybrid PLC/Wireless Communication for Smart Grids and Internet of Things Application,” *IEEE Internet of Things Journal*, vol.5, No. 2, pp. 655–667 (2018).
 19. Ozadowicz Andrzej and Grela Jakub, “Energy saving in the street lighting control system-a new approach based on the EN-15232 standard,” *Energy Efficiency*, vol.10, No. 3, pp. 563–576 (2017).