PRODUCTION PLANNING AND “DEFINE, MEASURE AND ANALYSIS“ TOOLS IN AUTOMOTIVE INDUSTRY AS PREREQUISITE OF AUTOMATION: A CASE STUDY

Janev Nemanja[1][ORCID 0000-0001-6710-7759], *Spasojević Brkić Vesna*[1][ORCID 0000-0003-4642-3482], *Misita Mirjana*[1][ORCID 0000-0002-7039-0783], *Mihajlović Ivan*[1][ORCID 0000-0002-9489-8207], *Perišić Martina*[1][ORCID 0000-0002-8385-1593], *Papić Neda*[1][ORCID 0000-0002-4454-2464]

[1]*University of Belgrade - Faculty of Mechanical Engineering*

Abstract: *For the production planning process to be successful, an enterprise's internal business processes must be effective and efficient, while the DMAIC cycle is important aspect of practice-based continuous improvement. In accordance to those facts, this preliminary research includes the first part of the DMAIC methodology - “define“ and “measure“ tools, applied to a case study in automotive industry, with the aim of improving production planning processes. Analysis in “define“ phase starts with SIPOC, continues with calculation of critical indicators in “measure“ phase and is followed by Pareto charts. Research shows that the existing method of manual collection of production data is not precise enough, and during two months observation period, between 14 and 52 percent of planned production time on 9 observed machines, passed as unnoticed downtime. Further data analysis showed that this time is 1.5 to 9 times higher than the total reported downtime on individual machines. Results show that the further development of data collection tools is crucial, and the recommendation is to move in the direction of automation of that process in order to make the most of available technical resources, in “improve“ phase and to “control“ it by statistical comparison of previous and new state indicators.*

Key words: *DMAIC, Automotive industry, Production data, Process automation*

1. INTRODUCTION

Production planning in modern systems is very sensitive to changes of different factors, and a good answer to these problems can be found in adequate decision support systems (Graves, 2011). As a required base for support systems, data and information can be considered the primary assets of a firm, and most organizations strive to collect and process as much data as possible (Bendoly, 2016; Demirkan et al., 2013). In order to increase the quality of the collected data as a result of increased business performance, it is necessary to have a desire for constant process improvement (Spasojević et al., 2020). When better quality of data about production elements and processes is available, it should be used to improve the system performance, by a constant cycle of improvement (Lee, 2018). In different branches of industry and different countries, processes improvement can be done using a variety of methods (Brkić et al.; Tomic et al., 2017), but the DMAIC (Define Measure Analyse Improve and Control) method that drives Lean Six Sigma approach proved to be a good universal tool for ensuring the smooth movement in the cycle (Smetkowska et al., 2018). With its structure, DMAIC cycle provides a rigorous approach of results-oriented process management (Sokovic et al., 2010). As numerous case studies show, for resolving performance problems in automotive industry, the most appropriate approach is implementation of DMAIC cycle (Ani et al., 2016; Rifqi et al., 2021; Rozak et al., 2020), and the starting point for all research is the evaluation of data collected from the production process.

This paper contains the first three phases of DMAIC tool, as it aims to explore the necessary elements for the company to successfully implement the automation of its production. After introduction of the topic explored which points out to the interrelation between quality of data about production, automation and performance improvement, the next section describes the methodology used in this research. In the third part the results are presented and later on, after discussion part, is concluded that the recommendation is to move in the direction of automation in order to make the most of available technical resources, in “improve“ phase and to “control“ it by statistical comparison of previous and new state indicators.

2. METHODOLOGY

The first 3 phases of the DMAIC cycle, “define“, “measure“ and “analyse“, were applied to a case study in medium sized company which deals with the production of automotive components. Out of 35 installed machines, 9 of them were selected according to their capabilities for interconnectivity and fulfilling the demands that Rubmann et al., (2015) suggest . Data collection was performed using a manual method, in manner that after removing the cause of the stoppage, the worker on machine recorded the reason for the stoppage and its duration. Such a method was applied for a long period of time in this sector, and the aim of this paper is to examine the effectiveness of this method.

3. RESULTS

The first step towards system improvement is comprehensive analysis of the problems that appear in standard everyday work. Figure 1 shows the SIPOC diagram of the improvement process, where input data and their suppliers, as well as output data and their users are presented. This diagram makes a good starting point for “define“ phase of the DMAIC methodology, as it provides a comprehensive overview of the flow of data through the process.

S	I	P	O	C
Suppliers	**Inputs**	**Processes**	**Outputs**	**Customers**
Production sector	Capacity plan	Data collection	Weekly and monthly machine performance reports	Machine workers
Machine workers	Production plan	Analysis of machine efficiency	Proposal of measures for process optimization	Sector of production
Sector of maintenance	Congestion tables	Data accuracy analysis	Work instructions	Logistics sector
External partners	Information obtained from machine workers	Determining the type and frequency of downtime	Training plan	Sector of maintenace
Sector of quality	Written reports on machine operation	Identification of the cause of the stoppage	Investment justification report	Higer management
	Report on defect products	Ranking of causes by priority for solving		

Figure 1: SIPOC diagram for process of improving production

This paper is focused to the first element of output section of SIPOC, namely monthly machine performance reports. An example of one monthly report is shown in Figure 2, on which it can be seen that 53.3% of planned machine working time, machine was in stoppage. The problem appears in the part where more than half of that period (28.45%) belongs to unnoted downtime, about which no data is recorded.

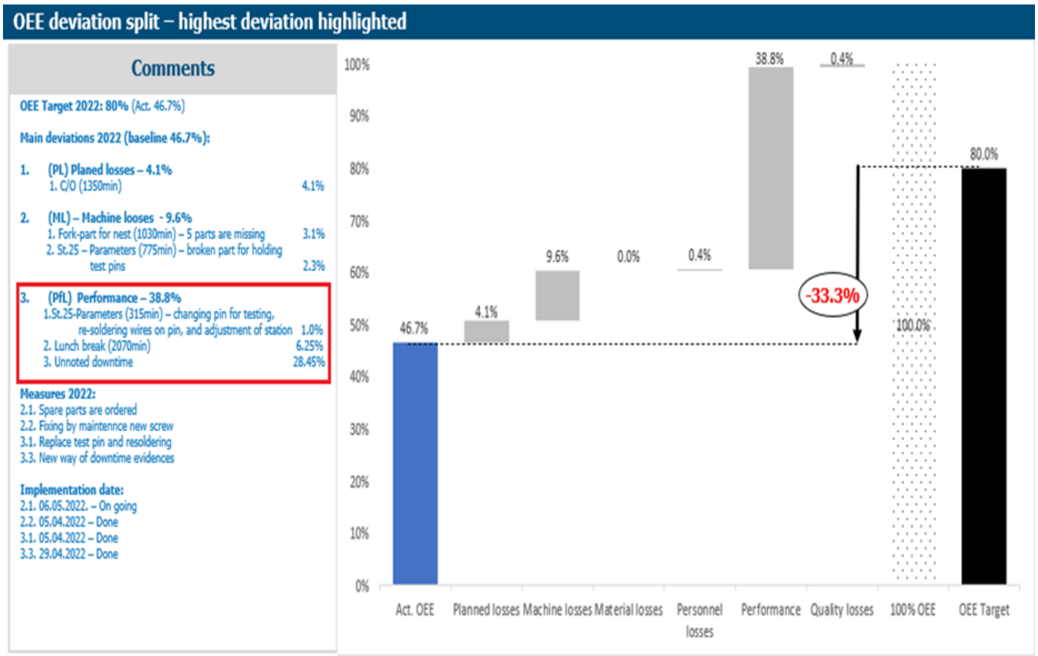

Figure 2: Monthly report for machine no. 2

In order to confirm this deviation, the operation of another 8 machines was monitored in 2 consecutive months, resulting in data collection from 9 machines in total. Obtained results for the first month are shown in Table 1 and for second month in Table 2. Parameters that are recorded are:

- Number of good parts (*OK*)
- Number of bad parts (*NOK*)
- Total planned production time of machine (T_{pl})
- The actual working time of the machine (T_{pr})
- Time out of production (T_{pl} - T_{pr})
- Time of recorded stoppages (T_z)
- Share of undefined time in planned production time (T_u).

Table 1: Recorded parameters for the first month

	OK (pc.)	*NOK* (pc.)	T_{pl} (min)	T_{pr} (min)	T_{pl} - T_{pr} (min)	T_z (min)	T_u (%)
Machine 1	423400	1472	33120	19119	14001	5465	19.5%
Machine 2	367900	3522	33120	15476	17644	5995	28.9%
Machine 3	623000	2072	33120	18752	14368	3490	26.6%
Machine 4	606700	3747	37440	25944	11496	2100	18.8%
Machine 5	197400	1369	29760	9143	20617	8125	35.7%
Machine 6	352700	1639	29760	14174	15586	2700	37.1%
Machine 7	542300	2683	32160	21799	10361	1415	21.6%
Machine 8	532980	3969	32160	21478	10682	2010	20.7%
Machine 9	568000	1407	32160	22776	9384	2140	16.3%

Table 2: Recorded parameters for the second month

	OK (pc.)	*NOK* (pc.)	T_{pl} (min)	T_{pr} (min)	T_{pl} - T_{pr} (min)	T_z (min)	T_u (%)
Machine 1	493600	2692	34560	22333	12227	2450	22.0%
Machine 2	331000	2971	34560	13915	20645	4115	41.6%
Machine 3	562200	1941	34560	16924	17636	3195	35.5%
Machine 4	543800	5667	40320	23352	16968	3280	27.7%
Machine 5	190320	1583	28800	8828	19972	3315	51.6%

Machine 6	238000	1105	19200	9564	9636	2260	32.2%
Machine 7	428600	2790	34560	17256	17304	5045	29.2%
Machine 8	581360	3978	34560	23414	11146	1145	22.7%
Machine 9	618000	1473	34560	24779	9781	2660	14.4%

The parameter of undefined time in planned production time is calculated using a formula:

$$Tu = \frac{(Tpl - Tpr) - Tz}{Tpl} * 100\% \tag{1}$$

The represented collected data shown above mark the end of the “measure“ phase. The data of total machine working time and total downtime recorded per month are presented on Figure 3.

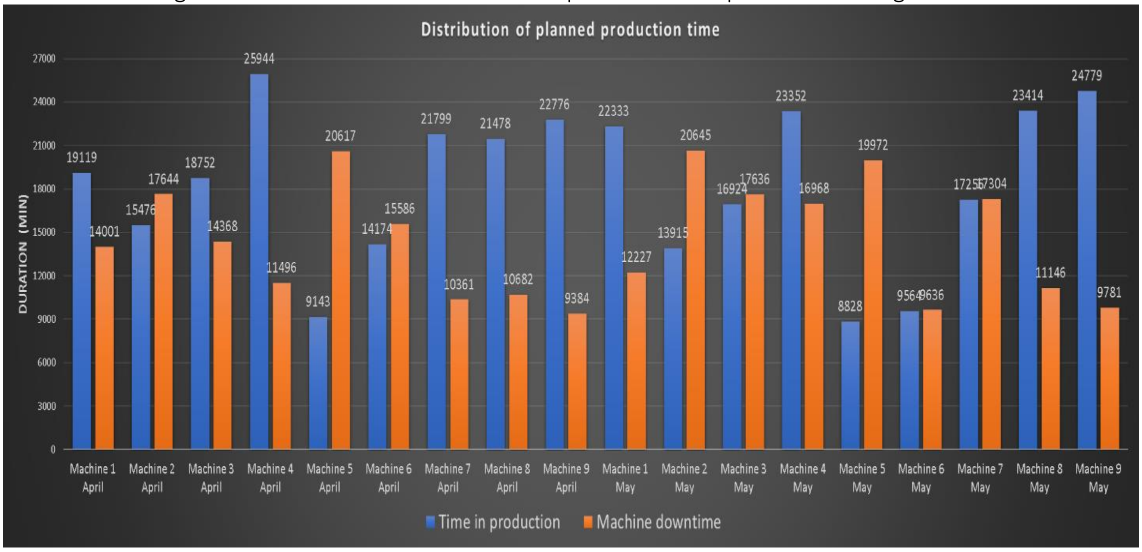

Figure 3: Distribution of planned production time

In order to have better understanding of collected data, the recorded downtimes are grouped by the station on the machine where they occurred and presented by Pareto diagrams. The example of Pareto diagram for downtimes that occurred during the first month on machine no. 7 is shown in Figure 4.

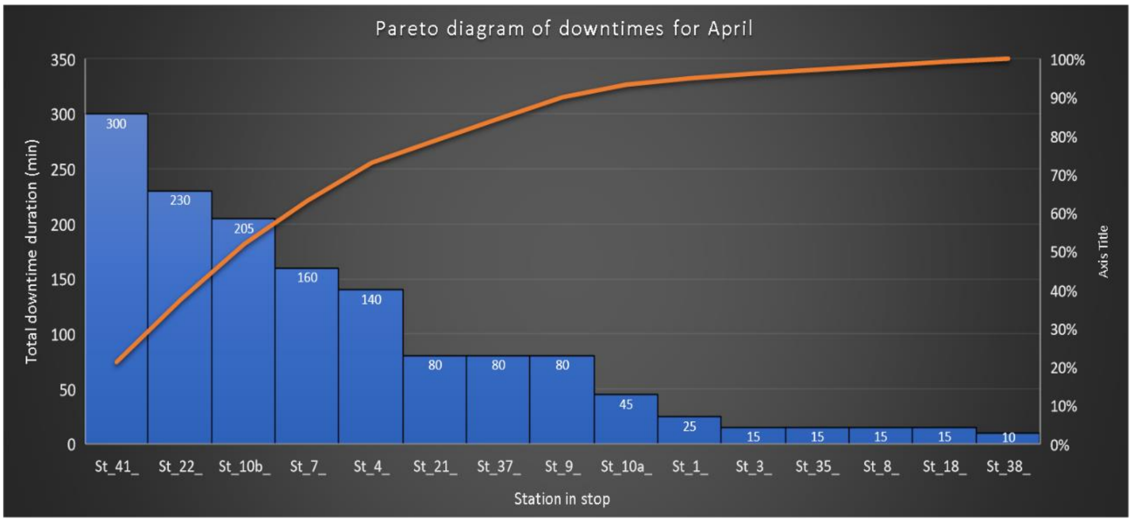

Figure 4: Pareto diagram of downtimes on machine no. 7

The ratio between recorded downtimes and unidentified downtimes in both observed months are shown in Figure 5.

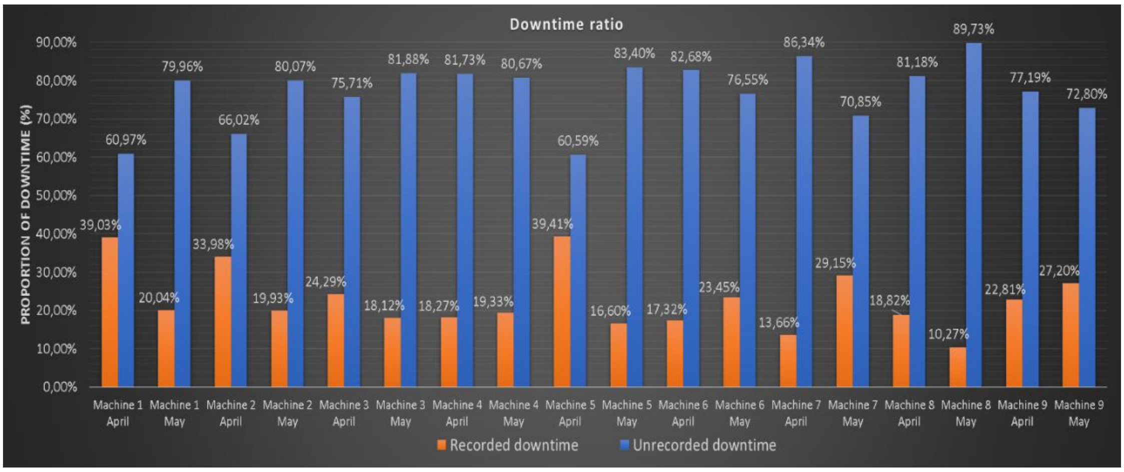

Figure 5: Downtime ratio

4. DISCUSSION

In order to successfully apply the DMAIC cycle, the first and the most demanding step is to define the problem of interest that requires solving. It is done by comprehensively looking at the different parts of the process, its inputs and outputs as well as the suppliers of inputs to the process and users of outputs from process. In this case, according to the process output, monthly reports, it can be seen that data collection, analysis of machine efficiencies, data accuracy analysis, determining type and frequency of downtime and identification of the cause of downtime, have problems with data reliability. The measurement phase that was conducted over the period of two months, confirmed that with manual reporting and recording of downtime, between 14 and 51 percent of planned production time is spent in machine downtime, which is not recorded (Table 1 and Table 2). The whole problem can be better seen when data is displayed on diagram. For example, on Figure 3 it can be seen that during observed period some machines had more downtime than work time, and because decisions for improving elements of production process are made according to Pareto charts, it is of crucial importance, that all causes and durations of downtime are available in the decision-making process. The potential and benefits of the improvement can be seen in Figure 5, which shows that only 10 to 40 percent of total machine downtime is reliably recorded.

5. CONCLUSION

Previous researches that included the application of DMAIC cycle for process improvement has shown significant increase in business performance, pointing out importance of reliable collected data for good quality management (Godina et al., 2021; Karout et al., 2017; Kaushik et al., 2009).
After analysis and presentation of the collected data, which as pointed out in the discussion part of this paper, unequivocally confirm the existence of the deviation in process data, further research was conducted with the company's senior management, and the conclusion was drawn that due to size of the production system and the number of visible problems, there are not enough resources left to carry out a detailed research on data quality, so decisions are made on the basis of available data.
In that aim, the main purpose of this paper is fulfilled. It confirmed the necessity of improving data collection tools and identify the weak points of the current collection process and with elimination of manual downtime recording and the introduction of a more automated system, plant productivity can be drastically increased. This solution can be designed through the remaining stages of "improvement" and "control" of the DMAIC cycle, which would be recommended for further research.

6. ACKNOWLEDGEMENT

This research was funded by Ministry of Science, Technological Development and Innovation of the Republic of Serbia under Contract 451-03-47/2023-01/ 200105 dated February 3, 2023 and RESMOD Safera project.

7. REFERENCES

Ani, M. N. C., Ishak, A. A., & Shahrul, K. (2016). Solving quality issues in automotive component manufacturing environment by utilizing six sigma DMAIC approach and quality tools. *IEOM, Proceedings of the 2016 International Conference on Industrial Engineering and Operations Management. Kuala Lumpur, Malaysia*, 08–10.

Bendoly, E. (2016). Fit, Bias, and Enacted Sensemaking in Data Visualization: Frameworks for Continuous Development in Operations and Supply Chain Management Analytics. *Journal of Business Logistics*, *37*(1), 6–17. doi: 10.1111/jbl.12113

Brkić, V. S., Tomic, B., Perišić, M., & Janev, N. (n.d.). Differences in Kaizen Implementation between Countries and Industry Types in Multinational Supply Chain. *Organization*, *2*(3).

Demirkan, H., & Delen, D. (2013). Leveraging the capabilities of service-oriented decision support systems: Putting analytics and big data in cloud. *Decision Support Systems*, *55*(1), 412–421. doi: 10.1016/j.dss.2012.05.048

Godina, R., Silva, B. G. R., & Espadinha-Cruz, P. (2021). A DMAIC Integrated Fuzzy FMEA Model: A Case Study in the Automotive Industry. *Applied Sciences*, *11*(8), 3726. doi: 10.3390/app11083726

Graves, S. C. (2011). Uncertainty and Production Planning. In K. G. Kempf, P. Keskinocak, & R. Uzsoy (Eds.), Planning Production and Inventories in the Extended Enterprise: A State of the Art Handbook, Volume 1 (pp. 83–101). New York, NY: Springer US. doi: 10.1007/978-1-4419-6485-4_5

Karout, R., & Awasthi, A. (2017). Improving software quality using Six Sigma DMAIC-based approach: a case study. *Business Process Management Journal*, *23*(4), 842–856. doi: 10.1108/BPMJ-02-2017-0028

Kaushik, P., & Khanduja, D. (2009). Application of Six Sigma DMAIC methodology in thermal power plants: A case study. *Total Quality Management & Business Excellence*, *20*(2), 197–207. doi: 10.1080/14783360802622995

Lee, H. L. (2018). Big Data and the Innovation Cycle. *Production and Operations Management*, *27*(9), 1642–1646. doi: 10.1111/poms.12845

Rifqi, H., Zamma, A., Ben Souda, S., & Hansali, M. (2021). Lean Manufacturing Implementation through DMAIC Approach: A Case Study in the Automotive Industry. *Quality Innovation Prosperity*, *25*(2), 54–77. doi: 10.12776/qip.v25i2.1576

Rozak, A., Jaqin, C., & Hasbullah, H. (2020). Increasing Overall Equipment Effectiveness in Automotive Company Using DMAIC and FMEA Method. *Journal Européen Des Systèmes Automatisés*, *53*(1), 55–60. doi: 10.18280/jesa.530107

Rubmann, M., Lorenz, M., Gerbert, P., Waldner, M., Justus, J., Engel, P., & Harnisch, M. (2015). Industry 4.0: The future of productivity and growth in manufacturing industries. *Boston Consulting Group*, *9*(1), 54–89.

Smetkowska, M., & Mrugalska, B. (2018). Using Six Sigma DMAIC to Improve the Quality of the Production Process: A Case Study. *Procedia - Social and Behavioral Sciences*, *238*, 590–596. doi: 10.1016/j.sbspro.2018.04.039

Sokovic, M., Pavletic, D., & Pipan, K. K. (2010). Quality Improvement Methodologies – PDCA Cycle, RADAR Matrix, DMAIC and DFSS. *Journal of Achievements in Materials and Manufacturing Engineering*, *43*(1).

Spasojević, B. V., Tomić, B., Perišić, M., & Brkić, A. (2020). Kaizen implementation context and performance. *Journal of Engineering Management and Competitiveness (JEMC)*, *10*(1), 31–37. doi: 10.5937/jemc2001031S

Tomic, B., Spasojević Brkić, V., Karapetrovic, S., Pokrajac, S., Milanović, D. D., Babić, B., & Djurdjevic, T. (2017). Organizational culture, quality improvement tools and methodologies, and business performance of a supply chain. *Proceedings of the Institution of Mechanical Engineers, Part B: Journal of Engineering Manufacture*, *231*(13), 2430–2442. doi: 10.1177/0954405416629100