Industry 4.0 and Quality Management in Automotive sector

Goran Despinoski

Abstract - The main purpose of this study is to conduct a thorough analysis of existing academic literature related to Industry 4.0 and quality improvements in manufacturing, and to find potential to complement the academic research gap. As a quality improvement methodology Lean Six Sigma is chosen, which is the most efficient one recently recognized in automotive industry. A systematic literature review is carried out to find relevant studies which analyze the contribution of different Industry 4.0 technique to Lean and Six Sigma improvements in terms of quality. Based on findings in this paper, theoretical model is proposed which integrates Industry 4.0 with Lean Six Sigma using Define-Measure-Analyze-Improve-Control (DMAIC) structure. The model aims to provide an innovative set of guidelines to support practitioners and researchers in the design of effective and efficient cyclical process for quality improvement. This model goes into further details about the respective I4.0 technologies used for the specific tasks in quality management, and exact benefits achieved by each of them. The purpose of the proposed model which integrates Industry 4.0, is to achieve rapid quality improvements in automotive sector, reduce expert – dependent activities, reduce implementation time and achieve sustainability of quality improvements.

Index Terms: Artificial Intelligence (AI), Big Data, Cyber-physical system (CPS), Define-Measure-Analyze-Improve-Control (DMAIC), Internet-Of-Things (IoT), Lean Six Sigma (LSS), Industry 4.0 (I4.0), Machine Learning.

1. Introduction of Industry 4.0

Known as the fourth industrial revolution, Industry 4.0 has become one of the most trending topics in the past few years [1]. Industry 4.0 was initiated by German Government in 2011 as the 2020 high-tech strategy [2]. The international equivalent for industry 4.0 is the "Industrial Internet Consortium" in the USA, "Internet plus initiative" in China [3] or "Industry 2025" in Switzerland [4].

The emerging fourth industrial revolution is being shaped by the integration of Cyber-Physical Systems (CPS) and Internet of Things (IoT) in industrial processes [5]. This new industrial paradigm will bring together the digital and physical words by using CPS technology, allowing improvement of productivity, efficiency and quality among the companies that are adapting to this new paradigm [2].

This concept is an umbrella term that embraces a set of future technological developments such as CPS, IoT, Big Data, Cloud Manufacturing, Virtual Reality (VR), Augmented Reality (AR), Artificial Intelligence (AI), Machine Learning, and Robotics [6]. The adaptation of these technologies is crucial to the development of intelligent manufacturing process, including smart devices, machine and products that can autonomously exchange information's, trigger actions, and control each other [7], [8].

2. Quality management in Era of Industry 4.0

Most of the existing academic literature related to Industry 4.0 focus their research field on the technical aspect of Industry 4.0. This paper gives insights about the identified potential of Industry 4.0 related to quality management in the automotive sector. The latest academic studies raise the necessity of integrating these two disciplines [9],[10], [11].

Davies [12] argues that Lean and Six Sigma capabilities can be enhanced by Industry 4.0, through CPS which enables access to real-time operations data. As per Pereira [6] CPS provides real time data that can be used to give instant visual feedback about production performance. This technology is helpful in simplifying the use of Andon System, automatic orders processing through e-Kanban, as well as other production material pull techniques. Combination of CPS and Radio frequency identification technology (RFID) can collect relevant information about inventory, location, identification which can support the creation of value stream mapping (VSM). In relation to Total Productive Maintenance (TPM), CPS can collect data about maintenance needs and automatically send signals to the maintenance staff. The work of Jidoka can be improved with CPS as well. Ma [13] proposed CPS - based Jidoka system which is cost effective on flexibility, standardization, changeability, and modularity. Kukushkin [14] present a new concept for production planning and analyzing production lines using CPS and simulation model.

Xu и Chen [15] proposed a framework with IoT to support dynamic production planning and scheduling in just-in-time (JIT) production system. This system can react to dynamic changes about orders, production, and available resources, allowing the users to adjust schedules during production to maximize productivity.

Witkowski [16] argues that Big Data model will help to be stored and analyzed data which are important to quality. Hohmann [17] discuss that Big Data can be used to analyze big mass of data instead of Six Sigma statistical tools. Lee [18] supported use of industrial Big Data analytics framework for self-awareness and self-maintenance of machines as contribution to TPM. This concept includes CPS and decision support system and can reduce maintenance cost and energy consumption as one of the main targets in TPM. Lugert [19] and Wagner [20] supported the potential of using Big Data technology for improvement of VSM. Most of the academic research considers that the statistic VSM must be further developed to a dynamic VSM through digitalization technologies that include an integrated Big Data model Pereira [6].

According to Muller [21] and his research conducted in 204 industries the biggest influence of Industry 4.0 to Lean Practices is related with production planning, traceability of materials and semi-finished products, logistic and managing customer complains.

Demircioglu [22] presents a model that integrates machine learning techniques and Six Sigma control charts. In this model machine learning will make classification of fault types, identify the cause of the fault, and define the correct value that variable should take. Ramezani and Jassbi [23] propose a model that uses machine learning and artificial neural network to replace SPC, to carry out root cause analyze and trigger corrective actions. This model support knowledge acquisition process as substitution of classic failure mode and effect analysis (FMEA) and define priorities in corrective actions using the same principle of risk priority number in risk assessment. Hohmann [17] discuss that machine learning features as autonomous learning and predicting of process behavior can replace Six Sigma statistical control. According to him high performance computing will take over Design of Experiments (DoE) and reduce to minimum required experiments for identifying influent parameters.

Kuo, Ting, and Chen [24] claim that Industry 4.0 will increase the quality of Industrial production. They propose a prediction model with sensors, Artificial Intelligence techniques and simulation that predict machine health status and diagnose any quality defects resulting from machine failures. According to Foidl [9], quality control could highly benefit from the significant spread of sensor technology on the shop floor, where the quality engineers will be able to collect as much measurement data as possible, opening the possibility to detect defect that otherwise would be undetected. This spread of sensors could also open the possibility to record 100% of measurement data, therefore signifying that the quality control will no longer need Statistical Process Control (SPC) since 100% control could be reality. This is a fundamental change since every single defect could be identified and thus segregated, which is the main postulate of Jidoka.

Krenczyk [25] presented an approach based on simulation models for balancing of mixed and multi model assembly lines. The author argue that this solution is an efficient and effective tool for planning, control, as well as ensuring a correct reconfiguration of manufacturing resources and production flow.

Albers [26] summarized the influence of Industry 4.0 on the industry from the perspective of quality. Studies reported 50 % increase in productivity, and 80% of the companies using the Industry 4.0 indicated its impact on increasing efficiency. Whereas 45% believed that Industry 4.0 improved customer satisfaction, thanks to the elimination of products with defects.

3. MAIN CHALLENGES IN THE EXISTING ACADEMIC LITERATURE

Existing academic literature shows inevitable influence of Industry 4.0 to Lean principles and quality management, but also, they present challenges in the integration of these disciplines. We can categorize the findings of the main issues in existing literature in 3 groups:

1. Several Authors claim that merging on Industry 4.0 with Lean principles and quality management is still seen in its initial stage [27], [28], [29]. The concept of Industry 4.0 to improve quality requires further research for integrating of Industry 4.0 disciplines with Lean and Six Sigma [30], [31], [32]. Pereira [6] claims that despite the numerous studies for integration of Industry 4.0 with Lean, the potential of the integration between these two disciplines is still not clear.

2. Comparably to lean management studies related to Industry 4.0 with respect to quality management is still in its infancy [21]. According to Demartini [33] there is lack of knowledge on the topic related to the integration of quality management and Industry 4.0. Academic researchers mainly focus on how Industry 4.0 can improve quality control which is only one phase of DMAIC structure and TQM.

3. Several Authors pointed to the underestimating manufacturing laws, requirements and the power of Lean Six Sigma when implementing Industry 4.0. Ruttimann and Stockli [4] claim that presently experi-

enced non-focused activism of Industry 4.0 in academic researches is likely to fail to meet high quality management expectations due to unclear understanding of the physical capabilities of manufacturing process. With all its potential, although CPS, wireless sensors, machine learning, IoT, AI algorithms which have tremendously increased in performance, but none of these components can go against physical manufacturing capabilities. Sanders [35] claim that many mistakes have been made over the years with different technologies, creating many problems in different companies.

The findings in the existing academic literature justify the needs of developing widely accepted model that integrates Industry 4.0 with Lean and Six Sigma. The model should be created based on thorough understanding of manufacturing requirements, considering the power of Lean and Six Sigma as methodology which delivered excellent quality results in the past years.

4. GUIDE TO IMPROVE QUALITY SYSTEM

The proposed model in Table 1 aims to provide an innovative set of guidelines to support practitioners and research in the design of effective and efficient cyclical process of quality improvements, achieved with integrating Industry 4.0 and LSS. In this paper is used DMAIC structure as a roadmap for integrating Lean, Six Sigma, and Industry 4.0. This model is upgraded with summary findings from the review of 60 journals and scientific documents related to application of technologies enabled by Industry 4.0 to enhance quality management. The main objectives of the proposed model can be categorized as:

1) Understanding the LSS (DMAIC) as a tool to improve physical manufacturing capabilities.

2) Understanding the relationship between Lean Six Sigma tools and different Industry 4.0 techniques.

3) Assessing how the application of Industry 4.0 can improve Lean Six Sigma in terms of quality.

TABLE 1
Guide to improve quality with Lean Six Sigma (DMAIC) 4.0

LEAN SIX SIGMA DMAIC		ACTIVITIES	INDUSTRY 4.0 TECHNIQUES	IMRPOVEMENTS OF LSS TOOLS WITH INDUSTRY 4.0
DEFINE	Lean Six Sigma Project	• Charter • Define Scope of Project • Cost savings • Team Members • Champion • Any other improvements? (Quick wins)	• Big Data analytics • Cloud Manufacturing • Machine Learning • Internet of Things (IoT) • Wireless Sensors • Cyber physical system (CPS)	• CPS, Wireless sensors, Cloud computing, IoT, Machine learning and Data mining techniques (text mining, video mining and process mining) can collect real time data, record 100% of measured data, make clustering, analyze data, identify area for improvement, and define scope of Lean Six Sigma project.
MEASURE	Six Sigma	• Kickoff Meeting • Collect data • High Level Process Map • Low Level Process Map • Cause & Effect matrix • Measurement system analyze (MSA) • Statistical Process control (SPC): Cpk; 6-Pack; I-MR; Histogram; Normality test • FMEA	• Big Data analytics Machine Learning • Internet of Things (IoT) • Artificial intelligence (AI) • Wireless Sensors • Cyber physical system (CPS)	• CPS (horizontal M2M communication), IoT, sensors and in-process quality control devices can record 100% of measured data and autonomously calculate MSA and SPC, without human involvement. • Machine learning and Artificial Neural networks can deal with control charts and propose smart predictive model instead of passive descriptive model for SPC control. This model support knowledge acquisition in FMEA and define Risk priority number which give priority in implementation of corrective actions. • IoT, sensors and devices for autonomous In-process quality inspection can replace manual quality inspection. This will eliminate appraiser variations (measurement system variations due to human inconsistence) as part of MSA study and will address efforts to actual process variations.
	Lean – VSM	• Collect Real • Value stream mapping • Analyze the current state of VSM, identify waste and propose actions for improvement (new VSD).	• Big Data analytics • Internet of Things (IoT) • Wireless Sensors • Cyber physical system (CPS) • Radio frequency ID (RFID) • Virtual Reality (VR)	• Big data and analytics can enhance data collection, handling, storage, and utilization of information. These systems can autonomously calculate KPI's (OEE%, ppm, scrap) and compare actual vs. planned results. • CPS and RFID with instant localization of objects can surface the problems in VSM: big inventory, material flow distance, batch production, and idle time (due to different reasons: machine downtime, not synchronized processes, lack of material, ect.). • Virtual Reality could be extended to create virtual VSM which will replace understanding for conventional VSM and the interaction of the various VSM symbols. Observing virtual stream of current and future state will speed up creation of new VSD.
ANALYZE	Six Sigma	• Cluster and analyze Data • Subjective root cause analyze: Process mapping; PDCA cycle; 5- why; Cause & Effect diagram; Cause & Effect matrix; FMEA; Correlation matrix • Hypothesis Testing: Ho Vs. Ha; t-test; ANOVA; Regression test; Reject or not reject Ho • Determine X's that have the most impact on Y	• Big Data analytics • Machine Learning • Internet of Things (IoT) • Artificial intelligence (AI) • Simulation	• Big data analytics, clustering, classification, machine learning and prediction can support root cause analyze. • Machine learning techniques (Artificial Neural Networks, Support Vector machine, Naive Bayes-Kernel, decision tree learning technique, Multi-layer perception, Deep learning and hybrid methods) can classify the faults type, identify the variables that cause the fault and define correct value that variable should take. • Camera-based visual inspection which autonomously created failure reports, detailed analytics and correlation models can support root cause analyze. • Machine learning and simulation can make trial-error or DoE tastings to confirm theoretical hypothesis for the identified root causes. Experts-depended and time limited root cause analyzes can be transferred to artificial intelligence.

International Journal of Scientific & Engineering Research Volume 12, Issue 10, October-2021
331
ISSN 2229-5518

LEAN SIX SIGMA DMAIC		ACTIVITIES	INDUSTRY 4.0 TECHNIQUES	IMRPOVEMENTS OF LSS TOOLS WITH INDUSTRY 4.0
IMPROVE	Six Sigma	• Design of Experiment (DoE) • Implementation Plan • Collect data and validate improvement • Finalize FMEA • Change Management	• Machine Learning • Simulation • Internet of Things (IoT) • Artificial intelligence (AI)	• Machine Learning can reduce the number of required experiments in DoE and can isolate influencing parameters. Then autonomously can adjust best set of parameters. • Artificial intelligence, machine learning, predictive analytics and flow diagrams can optimize the problems and improve the process.
	Lean – Value Stream Design (VSD)	• Create product family as per commonly used equipment and processes • Calculate needed equipment for the new defined product families • Define tact time • Create one piece flow and cells to surface the problems • Introduce supermarkets, pull system and standardized work-in- process inventory • Define pacemaker process to which production orders will be send • Relocate equipment as per new defined Layout • Level out production workload by mix and volume (Heijunka) • Prepare the process to function as per future design VSD, implement: SMED; TPM; 5S; Poka Yoke; Jidoka • Optimize and standardize process: 1. Time study with Tack Time/Cycle Time Bar Charts, eliminating waste in Cells. 2. Line balancing and Improve Cell design 3. Consider human factors and work balance 4. Implement Chaku Chaku rotation mode of production 5. Develop new standardized work combination sheet as per implemented improvements 6. Develop standard operating procedures and best practices • Implement visualization to surface future problem (Lean Performance Management system LPMS) • Validate improvements • Finalize FMEA	• Big Data analytics • Machine Learning • Internet of Things (IoT) • Wireless Sensors • Cyber physical system (CPS) • Robotics • Simulation • Optimization algorithms	• Machine learning and data analytics can continuously improve the process and support creation of dinamic VSD. • Cloud computing base application can be used to allow real-time access of information's and based on operation description, sequence, production times, assembly lines and assigned products can create new optimal VSD. With creating documents (WI, SOP) can support standardization of the improved VSD.
	Lean – One piece flow		• Big Data analytics • Internet of Things (IoT) • Cyber physical system (CPS) • Simulation • Optimization algorithms	• Vertical Machine to Machine (M2M) communication between ERP system and machines enables an individual one-piece-flow without manual change overs of production schedule. • Horizontal Machine to Machine (M2M) communication enables dynamic auto-adaptive production plan which will avoid machine breakdowns, capacity constraints and idle waiting time of equipment and people. • Robotics can replace manual operations and support one-piece flow
	Lean – Haijunka		• Big Data analytics • Internet of Things (IoT) • Wireless Sensors • Cyber physical system (CPS) • Radio frequency ID (RFID) • Artificial intelligence (AI) • Automated guided ve-hicles (AGV) • Augmented Reality (AR)	• Vertical M2M communication can be used to enable transition of the information's contained in Kanban through sensors that send signals to ERP. This will reduce production lead time, bullwhip effect, will improve production planning and gain transparent and integrated supply chain. • Horizontal M2M communication can be used for flexible e-Kanban production scheduling, where machines interact between each other and trigger e-Kanban. No more lost Kanban cards. Man-machine communication can provide information's about cycle time to operators via Augmented Reality and trigger material movement. • Simulation methods or a virtual real-time digital twin model can plan new Kanban loops which ensures the identification of ideal Kanban parameter lot size, stock, or delivery frequency. External changes can be included while the system refreshes parameters autonomously. • Auto-ID technology (RFID) can be applied to track material in real-time and to localize objects precisely which will increase transparency in the value chain and reduce stock level to min. This system supported by CPS and e-Kanban can trigger production orders when minimum level of Work-In-Process is reached, and inform Milk Run to refill the raw material when needed. Bar code readers allows identification of incorrect components. • Automated guided vehicles (AGV) can automatically transport objects in material flow and refill materials at the exact moment when needed. This will result in reducing number of containers with same material thus reducing total stock level. Also, empty trips of Milk run will be reduced. Intelligent bins and smart products can pursue self-optimization and can navigate AGV efficiently.
	Lean – Haijunka		• Big Data analytics • Internet of Things (IoT) • Wireless Sensors • Cyber physical system (CPS) • Radio frequency ID (RFID) • Optimization algorithms	• Big Data can analyze real-time information's and improve the quality of forecasting of customer requirements which will result in better leveling of production workload. • Camera system and e-Kanban installed in customer warehouse can autonomously schedule ERP production plan. • Vertical M2M communication between ERP and pacemaker process can control the production by volume and mix and control the pace of production to avoid overproduction. Planning will be automated, and short-dated adjustments can be integrated smoothly, which will improve flexibility and response time to frequent customer requirements shifting's. • Horizontal M2M communication, optimization algorithm and simulation can create dynamic production planning where new value stream can be defined when occurs machine breakdown, quality problem, lack of materials or lack of resources. With
	Lean -SMED		• Radio frequency ID (RFID) • Augmented Reality (AR) • Additive manufacturing	• Augmented reality (AR) with plug and play technology can reduce time for searching, selection and adjustment of tools when making changeover in machines. • Additive manufacturing can produce tools that are easier and faster for changeover. • RFID products, machine automation and software make it possible for machines to automatically identify products and load the appropriate program/parameters and tools without manual intervention. People can focus on value added activities. • Big Data analytics and cloud database can create basic statistical modeling and define actions to reduce changeover time.

LEAN SIX SIGMA DMAIC		ACTIVITIES	INDUSTRY 4.0 TECHNIQUES	IMRPOVEMENTS OF LSS TOOLS WITH INDUSTRY 4.0
IMPROVE	Lean – TPM		• Big Data analytics • Machine Learning • Internet of Things (IoT) • Wireless Sensors • Cyber physical system (CPS) • Radio frequency ID (RFID) • Artificial intelligence (AI) • Virtual Reality (VR) • Augmented Reality (AR) • Additive manufacturing	• Industry 4.0 can make autonomous maintenance performed by operators more spread and accessible. • Big data and cross-linked machine predictive analytics can: collect data about equipment, predict machine defects, define machine priority matrix, create autonomous and preventive maintenance plan as per priority matrix, send plans to operators and maintenance staff and improve maintenance response time. This system can support dynamic schedule of maintenance activities which will result with reduced machines downtime, reduced ppm and scrap due to technical issues, reduced rework, and increased quality. • Systems for full monitoring of machine condition supported by AI, Sensors and Deep learning diagnostics can improve maintenance with detecting abnormalities while machine is operating. Knock sensor detection system can analyze abnormalities based on noise and vibration and support early detection, isolation, and identification of defects. • Big data analytics can be used to identify best practices from previous installations/designs while taking in consideration current machine conditions and support new equipment management. • Systems for monitoring of energy consumption can indicate worn-out parts and support preventive maintenance. • Virtual reality (VR) and Augmented reality (AR) can be used as detailed repair guidelines for autonomous and preventive maintenance. • Mobile devices can provide real-time data on equipment performance, breakdown and causes and immediate remote access to maintenance documents. • Big data analytics and smart maintenance/inventory systems can reduce inventory of spare parts and costs. • Building managements system can reduce energy consumption of equipment. • Additive manufacturing (3D printing) can allow spare parts to be printed on-site and on-demand, which will drastically reduce spare parts inventory/costs, and improve machine downtime with eliminating lead time for ordering spare parts.
	Lean – 5S		• Internet-of-things (IoT) • Wireless sensors • Radio frequency ID (RFID) • Augmented Reality (AR)	• RFID ensures the identification and localization of objects which reduces searching time. RFID tags can store instructions for cleaning tools. • Augmented reality (AR) may replace physical shadow boards and guide operator where to place tools. • Zoning allows marking destinations by using visual means, this includes paths, manufacturing cells and departments.
	Lean - Poka Yoke		• Machine Learning • Internet of Things (IoT) • Wireless Sensors • Cyber physical system (CPS) • RFID • Augmented Reality (AR)	• Machines equipped with smart sensors and machine learning software's can automatically adjust irregularities and ensure optimal product quality. • Condition monitoring measurement technology can be used as end-of-line test for total control of products. • Augmented Reality, head-mounted displays and RFID can be used to achieve zero-error picking.
	Lean – Jidoka		• Big Data analytics • Machine Learning • Internet of Things (IoT) • Wireless Sensors • Cyber physical system (CPS) • Radio frequency ID (RFID)	1. In-station quality control: • CPS and wireless sensors can be used to gain real time data related with quality, can trigger repair action, and reduce delay time. • Wireless sensors can be used as inspection tools for early failure detection. The measurements for quality control no longer will be done in a distinct metrological section, they will be carried out instantaneously in the production line. • Machine learning can be used for self-adaption possibilities to avoid defects. 2. Andon system: • IoT, Sensors, and CPS can be used to instantly inform operators and supporting departments that failure occur, which will reduce response time. 3. Man-Machine separation: • Machine learning and sensors can make capable machines to operate autonomously, which will enable separation of man from machine, and allow operators to rotate which is known as Chaku-Chaku production. 4. Solve the root cause of the problem: • Big data, data mining and analytics techniques can be used for data classification, trial-error testing, defining and rapid implementation of corrective actions.
	Lean – LPMS		• Big Data analytics • Internet of Things (IoT) • Wireless Sensors • Cyber physical system (CPS) • Radio frequency ID (RFID)	• CPS and Big data ensure collecting data at machine level and converting them in relevant information's, select KPI's and analyze plan vs. actual result. • Digital Andon boards/TV's can be used to visualize real-time complex data. Retrieving this information's from mobile devices supports a location-independent access and use. Automatic e-mail can be generated and send to supporting departments.

LEAN SIX SIGMA DMAIC		ACTIVITIES	INDUSTRY 4.0 TECHNIQUES	IMRPOVEMENTS OF LSS TOOLS WITH INDUSTRY 4.0
Control	Six Sigma	• Standardize achieved results as foundation for continuous improvements: update FMEA, working instruction, Standardized work combination sheet and employee empowerment • Update the control plan • Measure and compare actual data vs. control plan • Identify potential for additional improvements • Implement Improvements • Continue monitoring/ Cost avoidance	• Big Data analytics • Cloud Manufacturing • Machine Learning • Internet of Things (IoT) • Wireless Sensors • Cyber physical system (CPS) • Radio frequency ID (RFID) • Augmented Reality (AR)	• In-process control devices, IoT, wireless sensors, RFID and CPS can replace manual quality inspection and avoid human errors, can record 100% of measured data and detect defects that otherwise would not be detected. Every single defective product can be identified, segregated, and locked. With measuring and recording 100 % of products even small shifting's in the process can be detected, which normally would be not detected (with SPC control or sampling method) • Machines upgraded with sensors can gain measurement and quality control capabilities which will support autonomation. Noise and vibration sensors can detect abnormal behavior of machines which causes defective products. This system can drastically reduce response time and can support preventive maintenance. • Data mining algorithms such as adaptive neuro-fuzzy inference system or neural networks can be used for rapid and interactive evaluation of measurement data. Process mining techniques can discover and track information's from event logs that can help in minimizing process variations and wastes.
	Lean - VSD		• Big Data analytics • Cloud Manufacturing • Internet-of-things (IoT) • Cyber physical system (CPS) • Radio frequency ID (RFID)	• Digital twin system (CPS) and IoT can support control of dynamic VSD with collecting real time data, comparing this data with KPI's and virtual model and accelerate actions for VSD optimization. Dynamic VSD based on real-time data are more flexible and quicker to the unexpected changes compared with stochastic VSD. • Cognizant computing which provides real-time database that are mainly supported by cloud computing and IoT can enhance Lean practices through elimination of wastes such as control of transport of goods, control of lead time, control of inventory volumes, and reduction of defects and rework.
	Lean Six Sigma- Standardization		• Cloud Manufacturing • Augmented Reality (AR) • Virtual Reality (VR) • Sensors	• Cloud technology, augmented reality and head-mounted displays can be used to create and display last revision of digital standard operating procedure, working instructions and control plans which will eventually standardize the activities and gain sustainability in the results. With this system distribution of obsolete documents in Production will be eliminate. • CPS can improve OEE % with pushing operators to respect cell balancing (labor distribution as per tack time/cycle time bar chart). CPS can measure machine utilization, how operators are rotating, can control productivity, PPM, and Scrap targets. Analyzing finding can accelerate process and preventive maintenance improvements with eliminating deviations from standard. • Sensors can measure air quality, radiation, temperature, and other environmental conditions which may affect health and performance while the early detection of harmful gases, electrical surges and fire can support safety.

5. The Results and Discussion

Existing academic literature give insight how Industry 4.0 can enhance different Lean or Six Sigma tools, hoping that this will improve total quality management in the organization. For the companies that are facing with big quality or productivity issues this approach is doomed to fail.

In Table 1 is proposed model for rapid improvements in the quality system in automotive sector. This model simultaneously implements Lean, Six Sigma, and Industry 4.0, where Lean and Six Sigma focus to eliminate physical manufacturing constraints, while Industry 4.0 focus to digitalize LSS tools thus to boosting further quality improvements. The main phases of the proposed Lean Six Sigma 4.0 model are:

- Define phase - To define the problem and select/ an opportunity for improvement.
- Measure phase - To identify process variations and non-value-added activities in the current value stream.
- Analyze phase - To analyze the root causes of the problems.
- Improve phase - To identify the best solutions for eliminating the root causes of process variations and non-value-added activities in the value stream.
- Control phase – To standardize improvements, to control process performance and achieve sustainability in results.

In the first 2 columns of this model are presented Lean Six Sigma tools and their activities which focus to improve manufacturing maturity level. Some of the activities, such as Lean in Improve phase of DMAIC shall be implemented prior to Industry 4.0 involvement, to achieve full blast from I4.0 techniques in terms of quality improvements. Next column "Industry 4.0 techniques" gives a summary of techniques that digitalized different Lean or Six Sigma tools. The last column "Improvements of LSS tools with Industry 4.0" is the sum of quality system improvements achieved with Industry 4.0, prepared based on the review of 60 academic journals and scientific documents for Industry 4.0 and quality.

The key techniques of Industry 4.0 that can improve Six Sigma are: Data mining technique (Big Data), Machine Learning and artificial neural networks, IoT, Sensors and CPS. Data mining techniques can support Six Sigma with collecting, clustering, and analyzing real-time data to define area for improvement. Machine Learning and artificial neural networks can replace SPC control charts, define root-causes of problems and trigger corrective actions. This system can support knowledge acquisition and replace classic FMEA methodology. IoT, Sensors and CPS can add measurement capabilities to machines, replace manual quality inspections, rapidly evaluate measured data, and improve visualization of process performances. With the support of these techniques, process can achieve 100 % detection and segregation of defective products.

The key techniques of Industry 4.0 that can improve Lean tools in terms of quality management are IoT, Sensors, CPS, RFID, Data mining technique (Big Data), and Machine Learning and artificial neural networks. In summary they are clustered as per their involvement in Lean implementation phases:

1) Value stream mapping (VSM) – IoT, Sensors, RDIF and CPS can instantly localize objects in production, compare with autonomously created KPI's and surface the problems and area for improvement.

2) Value stream design (VSD) – Vertical Machine to Machine communication (M2M) between ERP system and pacemaker process enables leveling of production mix and volume. Horizontal (M2M) communication between pacemaker processes, digital storages, e-Kanban's, and machines supported by RFID technology enables an individual one-piece-flow without manual change overs which can trigger production orders and material movement when min level is reached. This system upgraded with optimization algorithm and simulation can enable dynamic auto-adaptive production plan and can optimize value stream to avoid machine breakdowns, capacity constraints, idle time, and quality problems. Automated guided vehicles (AGV) can transport objects in material flow automatically, thus eliminating empty trips of milk run and reducing inventory stock level. Machine learning and predictive analytics can support creation of preventive maintenance plan, send the plan to maintenance staff, trigger real-time response to reduce machine downtime, reduce scrap due to machine defects and increase quality. Virtual reality (VR) and Augmented Reality (AR) can support creation of a detailed maintenance plan and can improve 5S and changeover process.

3) Control and continuous improvement - CPS and IoT can support control of dynamic VSD by collecting real time data, comparing this data with virtual model, and triggering actions to optimize VSD. This system can control product lead time, machine cycle time, standardized work in process inventory, transport of goods, bull weep effect, process waste, and quality and rework. Wireless sensors can support in station quality control and Jidoka. Condition monitoring measurement technology can be used as an end-of-line tester for total control of products. Machine learning and simulation can make trial-error or DoE tastings to confirm the theoretical hypothesis for identified root causes of problems and reinforced by data analytics can continuously improve value stream and support the creation of dynamic VSD.

We can summarize the main contributions of Industry 4.0 to quality achieved by the digitalization of Lean Six Sigma tools: eliminate manual activities and associated human errors in LSS project, reduce LSS project implementation time, accuracy and real-time acquisition of data, reduce resources and expert-dependence related with problem identification and defining solutions, autonomous control and optimization of dynamic VSD, reduce response time, achieve sustainability in results, and autonomous continuous improvement of VSD.

6. CONCLUSION

The systematic literature review reported in this article focused on the technologies enabled by Industry 4.0 that can enhance Quality management system. Today, there are many available quality management tools like ISO 9001, Total quality management (TQM), Continuous improvement Kaizen, Plan-Do-Check-Act cycle, Lean, Six Sigma, integrated Lean Six Sigma, and many others. In this research is chosen LSS methodology, acknowledged recently as the most efficient quality improvement tool in automotive industry.

Totally 60 acritical were analyzed, some of them propose how Industry 4.0 can enhance Lean practices, others propose how Industry 4.0 can enhance quality control, a few of them propose Industry 4.0 and Six Sigma solutions, but neither of them provides an answer how Industry 4.0 can be systematically integrated in Lean Six Sigma considering manufacturing maturity level and give a summary of quality benefits achieved with the integration of Lean, Six Sigma and Industry 4.0.

In sum, this paper provides among the first insights regarding potential contribution of Industry 4.0 to Lean Six Sigma in terms of quality. The paper goes into further details of the respective Industry 4.0 technologies used for the specific tasks and the exact benefits achieved with these techniques. The proposed model can help both, Industry 4.0 and LSS experts to achieve their targets. To LSS experts can give insights about the capabilities of Industry 4.0 to improve quality, support them to assess physical manufacturing capabilities, guide them to define LSS implementation plan prior to Industry 4.0 involvement, and help them to define investment priorities when introduce Industry 4.0 in the organization. To Industry 4.0 experts, this model gives insights about the manufacturing constrains that is expected to be solved by Industry 4.0, technical specifications and requirements based on which will be developed Industry 4.0 solutions, and sequence and summary of techniques that need to be implemented to gain quick wins in terms of quality.

As a further research, the suggested guide should be practically implemented in automotive industry and impacts to quality should be evaluated by statistical research where findings will be upgraded in the proposed design framework.

7. References

[1] MacDougall, W.: *Industry 4.0: Smart manufacturing for the future,* Germany Trade & Invest", (2014).

[2] Zhou, K. L.: *Industry 4.0: Towards future industrial opportunities and challenges*, 12th International Conference on Fuzzy Systems and Knowledge Discovery (FSKD) IEEE, pp. 2147-2152, (2016).

[3] Muller, J. O.: *Fortune favors the prepared: How SMEs business model innovations in Industry 4.0,* Technological forecasting and social change, pp. 17, (2018).

[4] Ruttimann. B.G., S. M.: *Lean and Industry 4.0 - Twins, Partners, or Contenders? A due clarification regarding the supposed clash of two production systems,* Journal of service science and management, pp. 486-500 (2016).

[5] Kagermann, H. W.: *Recommendations for implementing the strategic initiative Industry 4.0 - Final report of the Industry 4.0 working group,* Communication promoters group of the industry Munich, pp. 84, (2013).

[6] Pereira, A. D-C.: *How industry 4.0 can enhance Lean Practices,* Algorithm Research center, University of Minho, Portugal, pp.810-822, (2018).

[7] Nunes. M., P. A.: *Smart products development approaches for Industry 4.0,* Procedia manufacturing, vol. 13. No. supplement C, pp. 1215-1222, (2017).

[8] Weyer. S., S. M.: *Towards Industry 4.0 - Standardization as the crucial challenge for highly modular, multivendor production systems,* IFAC-Papers Online, vol. 48, no.3 pp. 579-584, (2015).

[9] Foidl, H. F.: *Research Challenges of Industry 4.0 for Quality Management,* Innovations in Enterprise Information Systems Management and Engineering. Springer, Cham, (2015).

[10] Gunasekaran, A. S.: *Quality management in the 21st century enterprises: Research pathway toward Industry 4.0,* International journal of production economics, pp. 125-129, (2019).

[11] Jayram, A.: *Lean six sigma approach for global supply chain management using industry 4.0 and IIoT,* 2nd International conference on contemporary computing and informatics (IC3I), IEEE, pp. 89-94, (2016).

[12] Davies, R. C.: *Review of Sociotechnical Considerations to Ensure Successful Implementation of Industry 4.0,* Procedia Manufacturing, pp. 1288-1295, (2017).

[13] [13] Ma. J., W. Q.: *Smart lean automation engine enabled by cyber-physical systems technologies*, Sensors (Switzerland), vol 17, no.7, (2017).

[14] Kukushkin, I. Z.: *Model based concept for scheduling analysis of packaging lines,* International DAAAM Symposium, pp. 1149-1157, (2015).

[15] Xu, Y. C.: *An Internet of Things based framework to enhance just-in-time manufacturing,* Proc. Inst. Mech. Eng. Part B J. Eng. Manufacturing, pp.10, (2017).

[16] Witkowski.: *Internet of Things, Big Data, Industry 4.0 – Innovative Solutions in Logistics and Supply Chains Management,* Procedia Engineering, vol. 182, pp. 763-769, (2017).

[17] Hohmann, C.: *Six Sigma and Industry 4.0,* http://christian.hohmann.free.fr/index.php/read-me-in-english/read-me-in-english/333-six-sigma-and-industry-40, (2019).

[18] Lee. J., K. H.: *Service innovation and smart analytics for industry 4.0 and big data environment,* CIRP Conference on Industrial Product - Service Systems. Procedia CIRP 16, pp. 3-8, (2014).

[19] Lugert, A., Völker, K., Winkler, H.: *Dynamization of Value Stream Management by technical and managerial approach,* Procedia CIRP, vol. 72, pp. 701–706, (2018).

[20] Wagner, C. H.: *Identifying target-oriented Industry 4.0 potentials in lean automotive electronics value streams,* Procedia CIRP, pp. 1003-1008, (2018).

[21] Muller, J. M.: *Contribution of Industry 4.0 to quality management,* International federation of automatic control IFAC, pp. 6, (2019).

[22] Demircioglu, D. C.: *Integration of machine learning techniques and control charts,* International journal for Science &Technology Scientia Iranica, pp. 24, (2019).

[23] Ramezani. J., J. J.: *Quality 4.0 in Action: Smart Hybrid Fault Diagnosis System in Plaster Production,* www.mdpi.com/journal/processes, pp. 29, (2020).

[24] Kuo C.J., T. K.: *Automatic Machine Status Prediction in the Era of Industry 4.0: Case Study of Machines in a Spring Factory,* Journal of Systems Architecture, pp. 81, (2017).

[25] Krenczyk. B., S. A.: *A heuristic and simulation hybrid approach for mixed and multi model assembly line balancing,* Advance Intell. System Computer, pp. 88-108, (2018).

[26] Demartini, M. T.: *Quality management in the Industry 4.0 era,* Industrial systems engineering, University of Genova, Italy, pp. 8-14, (2019).

[27] Leyh, C. M.: *Analyzing industry 4.0 models with focus on Lean production aspects,* Information technology for management ongoing research and development, Springer, pp. 16, (2017a).

[28] Leyh, C. M.: *Industry 4.0 and Lean production - a machine relationship,* Proceedings of the institute of electrical and electronics (IEEE), Federated conference of computer science and information systems, (2017b).

[29] Santana, A. A.: *Costing model for capacity optimization in Industry 4.0: trade-off between used capacity and operational efficiency,* Procedia Manufacturing, pp. 1183-1190, (2017).

[30] Lasi, H. K.: *Industry 4.0,* Business and information systems engineering, pp. 239-242, (2014).

[31] Muller, J. K.: *What drives the implementation of industry 4.0,* Sustainability, pp.10, (2018b).

[32] Muller, J.: *Antecedents to digital platform usage in industry 4.0 by established manufacturers,* Sustainability, (2019b).

[33] Demartini, M. T.: *Quality management in the Industry 4.0 era,* Industrial systems engineering, University of Genova, Italy, pp. 8-14, (2019).

[34] Schmitt. J., S. D.: *Enhanced Six Sigma - Integration of Data Mining Techniques into DMAIC cycle,* http://www.researchgate.net/publication/329916208, pp. 7, (2019).

[35] Sanders, A. E.: *Industry 4.0 implies lean manufacturing: Research activities in industry 4.0 function as enablers for lean manufacturing,* Journal of Industrial Engineering and Management, pp. 811-833, (2016).

[36] Six Sigma, Emerald group publishing, pp.250-274 (2018).

[37] Onur Dogan, O. F.: *Data perspective of Lean Six Sigma in industry 4.0 Era: A guide to improve quality,* Proceedings of the International Conference on Industrial Engineering and Operations Management Paris, France, pp. 12, (2018).

[38] Sader. S., D. M.: *Quality management practices in era of Industry 4.0,* https://www.researchgate.net/publication/337012990, pp. 126, (2019).

[39] Mayer. A., W. A. (2018). *Lean 4.0 - A conceptual conjunction of lean management and Industry 4.0,* Science Direct Procedia CIRP72, pp. 622-628, (2018).

[40] Wagner. T., H. C.: *Industry 4.0 impacts on lean production systems,* Science Direct Procedia CIRP63 pp. 125-131, (2017).

[41] Kolberg. D., Z. D.: *Lean automation enabled by Industry 4.0 technologies,* IFAC (International Federation of Automatic Control) https://www.researchgate.net/publication/282465205, pp.7, (2015).

[42] Schumacher. A., E. S.: *A maturity model for assessing Industry 4.0 readiness and maturity of manufacturing enterprises*, Procedia CIRP https://www.researchgate.net/publication/307620022, pp. 161-166, (2016).

[43] Gupta. S., M. S.: *Big data in lean six sigma: review and further research directions,* International Journal of Production Research, pp. 24, (2019).

[44] Prinz. C., K. N.: *Lean meets Industry 4.0 - a practical approach to interlink the method world and cyber physical world,* Science Direct Procedia Manufacturing 23 pp. 21-26, (2018).

[45] Sodhi. H.: *When Industry 4.0 meats Lean Six Sigma: A review,* 2nd International Conference on Contemporary Computing and Informatics (IC3I) IEEE. https://www.researchgate.net/publication/338752017, pp. 89-94, (2020).

[46] Sancez. B., A. R.-d.-R.: *Enhancing process control in Industry 4.0 scenarios using Cyber-physical systems,* Journal of Wireless Mobile Networks, Ubiquitous Computing, and Dependable Applications http//www.researchgate.net/publication/316860583, pp. 41-64, (2016).

[47] Rodrigo, R Mello., Antonelli, M..: *Machine Learning – a practical approach on the statistical learning theories*, (2018).

[48] G. Arcidiacono, A.: *The revolution of Lean Six Sigma,* International Journal Advance science engineering information technology, pp. 141-149, (2018).

[49] Aldag. M., E. B.: *What is Quality 4.0 in the era of Industry 4.0,* 3th International conference on Quality of life http://www.reserachgate.net/publication/329442755, pp. 31-34, (2018).

[50] Sony. M., A. J.: *Essential Ingredients for the implementation of Quality 4.0: A narrative review of literature and future directions for research,* The TQM Journal: ISSN pp. 1754 – 2731, (2020).

[51] Sang M.Lee, D. L.: *The quality management ecosystem for predictive maintenance in the Industry 4.0 era,* International Journal of Quality Innovations, pp.11, (2019).

[52] Dominic, G., Mathias, S., Detlef, Z.: *Human-Machine Interaction in the Industry 4.0 Era*, Innovative Factory Systems, German Research center for Artificial Intelligence (DFKI), Kaiserslautern, Germany, pp. 284-294, (2014).

[53] Bergweiler, S.: Smart *Factory Systems - Fostering Cloud-based manufacturing based on Self-Monitoring Cyber-Physical Systems,* International Journal on Advances in Systems and Measurements, pp. 91-101, (2016).

[54] Breyfogle, F.W.I.: *Beyond troubleshooting",* ASQ Six Sigma Forum Magazine, Vol. 8 No. 1, pp. 27-31, (2008).

[55] Hilton, R.J., Sohal, A.: *A conceptual model for the successful deployment of Lean Six Sigma",* International Journal of Quality & Reliability Management, Vol. 29 No. 1, pp. 54-70, (2012).

[56] Chen, M., Lyu, J.: *A Lean Six-Sigma approach to touch panel quality improvement,* Production Planning & Control, Vol. 20 No. 5, pp. 445-454, (2009).

[57] Albliwi, Saja., Antony, Jiju., Lim, Sarina. : *A systematic review of Lean Six Sigma for the manufacturing industry,* Business Process Management Journal Vol. 21 iss 3 pp. 665 – 691, (2015).

[58] Liker, J. K.: *The Toyota Way: 14 Management Principles from the World's Greatest Manufacturer,* McGraw-Hill, (2004)

- *Author name is currently pursuing PhD degree program in Lean Six Sigma and Industry 4.0, University Ss. Cyril and Methodius, Skopje, North Macedonia. E-mail: goran.despinoski@gmail.com.*