Using Industry 4.0 Concept – Digital Twin – to Improve the Efficiency of Leather Cutting in Automotive Industry

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ABSTRACT

Purpose: The aim of this study is to propose alternatives of increasing the efficiency of material selection and processing in the selected company and reduce costs and leather sustainability as a result.

Methodology/Approach: In this case study, an automotive company processing a natural leather material that enters the process of a large-scale production was explored. For this purpose, the internal documents of the firm selected including its internal database and know-how of its employees were used. The ways of improving the efficiency of the material processing were proposed and tested in a digital environment. In the proposed solutions, Industry 4.0 principles were implemented.

Findings: By the use of Digital twin and other Industry 4.0 principles and solutions in the process of material selection and processing in the company selected, the increased efficiency and cost savings were achieved.

Research Limitation/implication: The solutions proposed in this paper were based on exploration of the chosen data set of the selected company. For the future research, testing of the given proposals in other companies should be conducted.

Originality/Value of paper: Although there is an increasing number of publications describing the concept Industry 4.0, the research providing evidence of its benefits for business entities is still scarce. This paper offers such a research in the enterprise selected.

Category: Case study

Keywords: cloud computing; Internet of Things; efficiency; big data; Industry 4.0; sustainability

1   INTRODUCTION

Meeting specific clients' requirements and needs has become more and more challenging for companies. The reason lies in ever-rising customers' demands on the quality of the purchased goods and services, time needed for processing requests, as well as after-sales service, what results from ever more spreading globalization and fast development in the field of IT. This trend is generally called fourth industrial revolution, also known as Industry 4.0.

According to Kamble, Gunasekaran and Gawankar (2018), the issue of sustainable growth connected with sustainability should be more discussed in accordance with Industry 4.0 literature. They also claim that there is a direct connection since Industry 4.0 concept can significantly reduce the waste during the manufacturing process. This reduction in waste should be weighted to costs connected with the implementation of Industry 4.0 tools. The application of Industry 4.0 tools could result in environmentally sustainable manufacturing (De Sousa Jabbour et al., 2018) but it could be more obvious when connected with UN Sustainable Development Goals (Bonilla et al., 2018). Based on literature review in the field of Industry 4.0 (Oztemel and Gursev, 2018), authors argue that incorporating new methods could bring important sustainable competitive advantage and improve several industrial areas, e.g. monitoring, automation, energy efficiency. From the point of view related to managerial implications (Piccarozzi, Aquilani and Gatti, 2018), the concept and strategy of Industry 4.0 should be implemented regarding to sustainability issues and the application of such strategies could improve sustainable social welfare growth. In another review conducted by Saucedo-Martínez et al. (2018), it was stated that Industry 4.0 environment should be included in company in two areas, both socio-technical area and physical objects virtualization. Industry 4.0 is still emerging in research field, but the results from past research are strongly encouraging the incorporation of selected methods in managerial practice (Schneider, 2018). The main drivers of Industry 4.0 implementation are strategic, operational, as well as environmental and social opportunities as presented in Müller, Kiel and Voigt (2018) and application of cyber physical systems results in more efficient processes which could be connected to increasing of economic sustainability (Nagy et al., 2018).

Industry 4.0 has several tools, which could be implemented in real companies. One of them is Big data analysis, one of the most frequently used method (Sivarajah et al., 2017). There are also other approaches e. g. Internet of Things (IoT), cyber physical system and many others (Tamás and Illés, 2016; Zhong et al., 2017). According to Roblek, Meško and Krapež (2016), cyber physical systems will integrate computation, networking, and physical processes. The aim of this study is to propose a way of improving the efficiency of the material selection and manufacturing process in the selected company in line with the Industry 4.0 concept. This could be done, according to the character of the process researched, by approach called "digital or cyber twin" which is defined in Negri, Fumagalli and Macchi (2017) as the virtual and computerized

part of a physical system, able to simulate it by conducting a real-time data synchronization by the use of Industry 4.0 technologies. This approach could reduce time needed for commissioning of machines but requires a higher level of planning (Ayani, Ganebäck and Ng, 2018), while 74% of time assigned to planning is needed for multimodal data acquisition and evaluation (Uhlemann, Lehmann and Steinhilper, 2017). The benefits of automated data acquisition, such as automated derivation of optimisation measures and capturing of motion data are presented in Uhlemann et al. (2017). The concept of digital twin can be used e. g. in CNC programs designed for punching machines (Moreno et al., 2017) in order to make the process of cutting more efficient (Botkina et al., 2018), into cyber-physical cloud manufacturing (CPCM) systems (Hu et al., 2018; Kunath and Winkler, 2018), into manufacturing cyber-physical system (MCPS) (Leng et al., 2018), in the cloud assisted cyber-physical systems (CPPS) (Nagy et al., 2018; Wan and Xia, 2017; Zhang, Zhang and Yan, 2018) in the smart process planning of the construction of the diesel engine parts (Liu et al., 2018), or could be helpful to support job scheduling in cyber-physical production systems. Many other applications of digital twins are mentioned in Kritzinger et al. (2018), Negri, Fumagalli and Macchi (2017), Padovano et al. (2018).

2   METHODOLOGY

As primary sources, internal documents of the firm selected including its internal database as well as the knowledge of its employees were used. The study was conducted based on the analysis of an automotive company located in Slovakia, processing a natural leather material that enters the process of a large-scale production. Since the material explored is of a natural origin, it contains various defects. Hence, it is used only to a certain extent, i.e. there is always some inefficiency which could be decreased by proper management and change in the way the processes are conducted. Some studies conducted by Pringle, Barwood and Rahimifard (2016), Stepanov et al. (2015) proposed a new point of views connected with leather processing. Some of them are directly connected to leather cutting for the needs of automotive industry (Grieco, Pacella and Blaco, 2017).

Testing the ways of improving the efficiency of a material processing is very costly, if carried on a real production line. Therefore, a solution for the company lay in providing the "offline testing", realized outside the real production process, in our case in a digital environment. The concept of Industry 4.0 – Digital twin was implemented.

The objective of the study was to provide the answer to the following question: Could the efficiency of the material selection and processing in selected company be increased in case of different processes settings? Due to the complexity of this question, three partial objectives were defined.

The first partial objective was to find out if the yield changes in case of changing the order in which the material enters the production process. The efficiency of that process was watched and expressed through the indicator "*yield of the material*" defined as follows:

$$Yield(\%) = \frac{UMA}{TMA} \tag{1}$$

where *UMA* is Usable Material Area, *TMA* is Total Material Area, where the "*usable material area*" represents the material area which is suitable for being used in a given process.

In order to achieve the first partial objective, the sample of 22 material pieces was chosen, which were processed by selected company in specific period in past, using "First In - First Out" (FIFO) order. By each piece, a certain yield was achieved, as recorded from the firm's internal database. In the virtual experiment, the material was arranged in ascending and then in descending order according to the Internal Quality Control Index (IQCI), which represents a quality of the material detected at the entrance check and the value of yield observed.

The second partial objective was to find out if the yield changes in case of changing the strategy used for material processing. In the company, there is a software used for finding out the suitable way of the use of defect-free parts of the material, with the overall aim to reduce waste. The software decides what shapes should be cut from the defect-free parts of the material in order to satisfy customer needs. The software has currently 15 strategies programmed. For the selected material sample, the strategy No. 1 was used. In the virtual experiment, all available strategies were applied for each material piece and the achieved yield was recorded.

The third partial objective was to find out if the efficiency changes in case of providing a significant system change – a transition from online to offline process flow.

During the online process flow, material received from the supplier is registered and it is subject to entrance check. Then, natural material errors are detected and marked manually. Later, the material is scanned and its suitable use is determined by the firm's software. Finally, material proceeds to the process of cutting and other operations. All these processes are running online, i.e. they are a part of a real production process.

In the third experiment, the offline process flow was proposed, during which the material is scanned and its optimal use is determined by the firm's software offline, i.e. outside real production process (even before the production starts). Material scans are saved on cloud since it is commonly used method to process the data (Hu et al., 2018; Thames and Schaefer, 2016; Wan and Xia, 2017; Zhang, Zhang and Yan, 2018; Zhong et al., 2017), while the material is physically placed in warehouse. After the customer order is known, the software explores the scans on the cloud and determines a suitable strategy of further use

of the material, with the aim to select material samples which achieve the highest efficiency if used for that specific order. At the time of their real need, material samples are transferred into the production process, where they undergo other operations, including cutting.

In order to achieve the third partial objective, the sample of 4 customer orders were chosen, and for each of them, 20 material pieces were processed by a company in a specific period in past with a certain level of efficiency achieved. For the third experiment, we proposed to take all those 80 material scans into consideration and proceed the following way: firstly, the first customer order will be managed. Hence, the software explores all 80 digital scans and chooses 20 of them, which will be processed with the highest efficiency if chosen for the first order. Then, from the remaining 60 scans, the software chooses other 20 ones, which will be processed with the highest efficiency if chosen for the second order, etc. In the third experiment, the efficiency of each customer order is measured. The assumption was, that since the material is selected in a more sophisticated way than by using FIFO, the achieved efficiency would be higher. Moreover, that assumption was also driven by the fact, that a variability of the material was higher due to a bigger sample used.

3   RESULTS

The first experiment proved that by changing the order in which the material enters the production process, the yield changes. Obtained results from measurement are stated in the Tab. 1.

Table 1 – Yield by Different Material Pieces Order

Material piece number (M_{No})	Yield FIFO order	Yield IQCI ascending order	Yield IQCI descending order	Material piece number (M_{No})	Yield FIFO order	Yield IQCI ascending order	Yield IQCI descending order
1	41.81	24.29	20.626	13	20.423	26.536	13.877
2	18.27	22.455	21.901	14	21.473	19.02	16.423
3	22.265	21.612	19.473	15	31.931	26.661	26.303
4	33.373	29.535	29.511	16	13.393	18.48	16.862
5	38.34	41.438	56.513	17	19.5	24.07	21.693
6	17.999	15.003	17.181	18	14.708	28.973	15.723
7	26.834	23.659	23.659	19	24.454	21.955	21.414
8	28.108	20.006	23.659	20	28.32	42.314	41.705
9	13.241	13.241	8.672	21	45.2345	37.935	50.935
10	24.771	27.073	23.828	22	19.709	27.616	20.734

Material piece number (M_No)	Yield FIFO order	Yield IQCI ascending order	Yield IQCI descending order	Material piece number (M_No)	Yield FIFO order	Yield IQCI ascending order	Yield IQCI descending order
11	17.583	13.776	18.101	*Weighted average*	24.90	25.101	23.472
12	24.738	19.182	21.915				

If the selected material sample had entered the process in ascending order according to IQCI criterion, there would have been an increase in yield by 0.2012% on average, in comparison with FIFO order. In order to make a conclusion that ascending order tends to affect the efficiency only in a positive way, more experiments with a bigger sample and a higher variety of material and types of customer order, ought to be conducted.

The second experiment exhibited that by changing the strategy used for material processing, the yield changes. If the selected material sample had been processed by the strategy No. 14, there would have been an increase in yield by 0.13% on average, in comparison with strategy No. 1, as depicted in the Tab. 2.

Table 2 – Yield (%) from Selected Material Pieces by Individual Strategies

M_{No}	Strategy														
	X_1	X_2	X_3	X_4	X_5	X_6	X_7	X_8	X_9	X_{10}	X_{11}	X_{12}	X_{13}	X_{14}	X_{15}
1	40.70	44.03	40.73	44.03	44.03	40.73	44.03	44.03	44.68	43.58	44.68	43.58	44.68	43.58	44.03
2	38.16	42.94	36.72	42.94	38.38	36.00	38.38	39.82	29.60	34.73	29.60	34.73	29.60	34.73	42.94
3	21.62	21.11	21.62	21.11	21.07	21.62	21.43	21.43	23.22	21.47	23.22	21.47	23.22	21.47	21.11
4	24.30	25.25	24.30	25.25	25.25	22.22	25.25	25.25	21.90	24.16	21.90	24.16	21.90	24.16	25.25
5	37.05	35.29	37.05	35.29	41.84	41.84	41.84	41.84	42.27	42.27	42.67	42.27	42.67	42.27	35.29
6	19.70	15.40	19.70	18.97	13.61	15.40	13.61	13.61	21.49	19.70	21.49	19.70	21.49	19.70	15.40
7	22.66	17.75	22.66	16.39	18.04	19.64	21.80	20.99	21.51	22.55	21.51	22.90	21.51	22.90	17.75
8	20.99	16.96	20.28	16.96	17.47	18.16	17.47	14.12	19.77	19.41	19.77	19.05	19.77	19.5	16.96
9	10.10	14.63	10.10	14.63	14.63	12.43	14.63	14.63	13.60	10.07	13.60	10.07	13.60	10.07	14.63
10	21.81	19.40	19.40	17.46	21.35	20.69	21.35	17.46	18.60	22.25	18.97	21.89	18.97	22.62	19.40
11	23.62	23.62	23.62	23.62	15.37	17.99	21.00	23.62	18.50	22.43	18.90	22.82	18.90	23.22	23.62
12	23.92	23.51	23.92	23.51	23.51	23.92	23.51	23.51	17.83	22.69	17.83	23.51	17.83	23.51	23.10
13	18.78	13.88	18.78	13.88	13.88	18.78	13.88	13.88	13.88	18.78	13.88	18.78	13.88	18.78	13.88
14	14.73	14.73	14.73	14.73	14.73	14.73	14.73	14.73	14.73	14.30	14.73	14.30	14.73	14.30	14.73
15	32.45	32.05	32.85	32.48	32.05	32.45	32.45	32.45	31.65	32.05	31.65	32.05	31.65	32.45	32.05

M_{No}	Strategy														
	X_1	X_2	X_3	X_4	X_5	X_6	X_7	X_8	X_9	X_{10}	X_{11}	X_{12}	X_{13}	X_{14}	X_{15}
16	18.25	17.48	18.25	17.48	17.48	13.68	17.48	17.48	17.09	17.48	17.09	17.86	17.09	17.86	17.48
17	32.16	31.37	32.16	31.37	27.51	32.16	27.51	27.51	30.98	30.59	30.98	30.59	31.37	30.59	27.12
18	15.72	15.28	15.72	15.28	15.28	15.72	15.28	15.28	15.28	15.72	15.28	15.72	15.72	15.72	15.28
19	27.26	22.98	27.65	22.98	22.98	27.26	22.98	22.98	27.26	26.87	27.26	27.26	27.26	27.26	22.19
20	43.79	38.51	43.79	38.51	47.84	43.79	48.25	48.25	37.70	42.56	37.70	43.38	37.70	43.38	42.56
21	47.63	45.95	47.20	45.95	41.23	49.37	45.08	45.08	45.95	49.37	45.95	48.93	45.95	50.23	45.95
22	19.71	20.92	19.71	20.92	20.92	19.71	19.71	19.71	20.92	20.31	20.92	20.31	20.92	20.31	20.92
Yield (%)	26.16	25.14	25.96	25.16	24.94	25.36	25.56	25.36	24.92	26.07	24.97	26.16	25.01	26.29	25.07

The third experiment confirmed that by providing a significant system change from online to offline process flow, the efficiency changes. If the selected material sample had been processed in a proposed offline way, there would have been an increase in efficiency by 0.55% on average, in comparison with the online way.

Table 3 – Efficiency by Customer Orders O1 – O4

Customer order number	Material number	Efficiency (%) Online process	Efficiency (%) Offline process
O1	1 – 20	54.90	56.46
O2	21 – 40	55.70	56.01
O3	41 – 60	55.60	55.91
O4	61 – 80	55.40	55.41
Average		*55.40*	*55.95*

4   DISCUSSION

The first and the second experiment proved that by changing the order in which the material enters the production process, as well as the strategy used for material processing, a higher yield could be achieved, which would save the company a significant amount of money in the long run, depending on company's specifics. Therefore, it is important to choose the right order and strategy at right time. Due to the natural origin of the material explored, more sophisticated methods have to be used for that purpose. Hence, we suggest the implementation of machine learning in the future.

The third experiment was designed in a simplified way in order to test its functionality in a firm environment. However, since it proved the assumed increase in efficiency, we propose to conduct more extended experiments in the future, by which a bigger material sample will be used. Moreover, we suggest the creation of a consignment stock in the firm's premises, where the supplier will have an online access to the information about the stock level and, thus, will be able to replenish the stock as soon as they leave the warehouse. That way, the software could always choose from 80 digital material scans, which could lead to the increase of the efficiency even more. Furthermore, the software should incorporate a feature alerting the presence of the material pieces in the warehouse, which have not been selected over a longer period to prevent them from expiration.

However, it is necessary to consider, that there should not be big differences in the efficiency achieved by processing the material for single customer orders. The aim is to achieve the highest possible efficiency in the selection and processing process of the material while preserving its sustainability (Wolf, Meier and Lin, 2013/2014; Zgodavová et al., 2019). Therefore, we propose to define the maximum level of efficiency which can be achieved for a specific customer order. In case of a higher efficiency level, material samples with the highest usability should be kept for a different customer order. For this purpose, the software should become familiar with the potential upcoming customer orders for a reasonable period. That step could prevent a high efficiency variability as well as can increase the overall average efficiency achieved.

5   CONCLUSION

All those three experiments were conducted in a virtual environment using computing capacities, since the cost savings linked to the increase in efficiency would be useless if conducting them in a real environment, using the real production capacities. Industry 4.0 brings about solutions which allow finding more efficient ways of conducting processes without blocking the real production capacities. Considering a relatively high price of the input raw material, which is a subject to exploration in this study, as well as more demanding customer requests, the reasonable way for companies to achieve competitive advantage is to focus on decreasing the costs. For this purpose, the use of the Industry 4.0 principles becomes a must.

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