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ORIGINAL PAPER

POTENTIAL CONNECTIONS OF UNIQUE MANUFACTURING AND INDUSTRY 4.0

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ABSTRACT. **Background:** Based on the concept of Industry 4.0, or the fourth industrial revolution, production processes are optimised by machines connected to each other via intelligent communication systems (machines keep track of the process and adjust their own settings accordingly). Our objective was to achieve more reliable processes with shorter production times and, consequently, lower production costs.

Methods: We examined the possibility of incorporating a robot into the panel cutting subprocess of the unique furniture manufacturing process of a timber company.

Results: Currently, using robots in industrial practice is economical only in the case of mass production. Using robots in unique manufacturing calls for higher resource need. In order to examine which part of the furniture manufacturing process a robot can be incorporated into and what problems can be solved with the robotic arm, the first step is to look for any potential failures in the process, as well as causes of failure, by performing a process model-based Failure Mode and Effects Analysis. Following the exploration of potential causes of failure, we examined the possibility of involving a robotic arm as a measure of improvement. Accordingly, the robotic arm was programmed in a computerised environment. The parameters of the robotic arm were set using the software Mitsubishi RV-2AJ Cosimir Educational. As a next step, process simulation was used to examine the total production time and cost of the process with using the robotic arm.

Conclusions: The implementation of robots is a relevant option in unique production systems, as an intelligent system is capable of identifying problems even at the origin of failures and therefore it allows to avoid delay and increase the precision of operation.

Key words: Failure Mode and Effects Analysis, Industry 4.0, cosimir software, sorting robot, automated production.

INTRODUCTION

In order to remain competitive in a globalised environment, manufacturing companies constantly need to evolve their production systems and accommodate the changing demands of markets [Pedersen et al., 2006].

The panel cutting process performed by the unique furniture manufacturing timber company in question is inappropriate. There are numerous failures in the process, resulting in high total process costs and frequent repairs. As a result of re-cutting, the process takes more time than planned. For this reason, we considered it to be necessary to revise the process, as well as to identify and eliminate any possible failures and causes of failure. During the panel cutting process, smaller panels are cut out of large panels of 2800 x 2070 mm in order to fit the furniture to be manufactured. The pieces cut from large panels are placed in bins to be taken out when they are used for the given piece of furniture. According to our observations, most problems appear during the sorting of the cut panel pieces. For this reason, we focused our development on the sorting phase. The panel cutting process was identified with a process model and a Failure Mode and Effects

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Analysis, based on which the improvement measure was determined. As a solution, we used a Mitsubishi robotic arm equipped with sensory support. After determining the improvement measure, its efficiency was examined in Cosimir, a modelling and simulation software. As the last step, we examined the total production time of the process with a Monte-Carlo-based process simulation to determine the process cost.

LITERATURE REVIEW

Industry 4.0

Today, in an Industry 4.0 factory, machines are connected as a collaborative community. Such evolution requires the use of advance prediction tools, so that data can be processed systematically into information to explain uncertainties, and thereby make more informed decisions [Bildstein et al., 2014]. It can be concluded that the term Industry 4.0 describes different – primarily Information Technology (IT) driven – changes in manufacturing systems. These developments do not only have technological but furthermore versatile organisational implications [Lasi et al., 2014]. Future production systems have to be developed considering the need for strong product individualisation and, therefore, the necessity for highly flexible production processes [Schlechtendahl et al., 2015]. To accomplish this challenge, Cyber Physical Production Systems (CPPSs) [5] should be integrated into the production sites in order to create smart factories. Cyber Physical Systems (CPS) are central to this vision and are entitled to be part of smart machines, storage systems and production facilities able to exchange information with autonomy and intelligence [Reinhart et al., 2013]. These CPS monitor the physical processes, make decentralised decisions and trigger actions, communicating and cooperating with each other and with humans in real time. This facilitates fundamental improvements to the industrial processes involved in manufacturing, engineering, material use and supply chain and life cycle management [Toroa et al., 2015].

Kagermann et al. [2013] propose a production model which is capable of establishing inter-machine communication with proper server service and cloud-based data storage. The data generated by machines, robots and sensors during production have to be stored and processed. As a result, it is possible to establish a smart factory which is able to react flexibly to environmental changes.

According to the concept of Industry 4.0, which represents the fourth industrial revolution, each product component plays an important role in the management of manufacturing and logistics processes. Intelligent systems keep track of where and when each component was built and what packaging and transport the given product needs. During production, sensors perform self-checks and the system gives a signal if something differs from the previously set values. Also, the system is capable of intervening and correcting failures.

Smart Factory

The proliferation of cyber-physical systems introduces the fourth stage of industrialisation, commonly known as Industry 4.0. The vertical integration of factory to implement flexible and reconfigurable manufacturing systems, i.e. smart factory, is one of the key features of Industry 4.0. Thus, the smart factory is characterised by the self-organised multi-agent system assisted with big data based feedback and coordination. Based on this model, we propose an intelligent negotiation mechanism for agents to cooperate with each other [Rajenthirakumar et al., 2014].

Smart Factory, which is the fourth revolution in the manufacturing industry and is also considered as a new paradigm, is the collection of cutting-edge technologies that support effective and accurate engineering decision-making in real time through the introduction of various information and communication technologies and the convergence with existing manufacturing technologies [Chen, 2007].

The successful integration of Industry 4.0 and cyber-physical systems provides significant benefits for the entire manufacturing industry. These benefits can be summarised in one term the so-called: Smart Factory [Bowles, Peláez, 1995]. Nowadays, smart factories focus mostly on control-centric optimisation and intelligence. Moreover, greater intelligence can be achieved by interacting with different surrounding systems that have a direct impact on machine performance. Achieving such seamless interaction with surrounding systems turns regular machines into self-aware and self-learning machines, and consequently improves overall performance and maintenance management [Rhee, Ishii, 2003].

Process development

Process development has three interconnected areas: organisation, technology and process. The main purpose of process development is to establish a process which conforms to organisational and technological factors and achieves the desired outcome by involving key players and taking all three areas into consideration. Various quality improvement techniques can be used during process development. Failure Mode and Effect Analysis (FMEA) also has a wide range of industrial uses.

FMEA is used to identify failure modes. Failure modes are the ways, or modes, in which an asset can fail [Sharma et al., 2015]. It is a method that evaluates possible failures in the system, design, process or service. It aims to improve and decrease these kinds of failure modes continuously [Gilchrist et al. 1993, Vandenbrande 1998, Chin et al. 2009, Chang, Cheng 2010,]. In particular, it provides design engineers with quantitative or qualitative measures necessary to guide the implementation of corrective actions by focusing on the main failure modes and its impact on the products [Vliegen, van Mal 1990].

Since its introduction as a support tool for designers, FMEA has been extensively used in a wide range of industries, including aerospace, automotive, nuclear, electronics, chemical, mechanical and medical technologies industries [Puente et al 2002, Kwai-Sang et al. 2009, Guerrero, Bradley 2013, Wenyan et al. 2014, Yeh et al. 2014, Neagoe 2011, Jianpeng et al. 2015]. Moreover, FMEA is now used not only in manufacturing processes, but also in service and administrative processes [Gao et al. 2014]. FMEA is also a good tool to provide support information for making risk management decisions [Sellappan, Sivasubramanian 2008, Hu et al. 2009]. FMEA analyses have been used to enhance the R&D, design, production, testing and maintenance of innovative products [Stamatis 2003]. A good FMEA can help analysts identify known and potential failure modes and their causes and effects, help them prioritise the identified failure modes and can also help them work out corrective actions for the given failure modes [Kwai-Sang et al., 2003]. Neagoe [2011] the FMEA methodology requires a team effort, in-depth knowledge of the various designs and processes, as well as time and financial expenses. The global industry-wide integration of the FMEA as a reliability management process is due to the proved efficiency of the method, as well as the simplicity and transparency of the analysis.

Traditional FMEA has three types: design, concept and process FMEA. The main purpose of FMEA is to reveal and identify failures, as well as to rank them based on their effect. This procedure calls for teamwork and the team should consist of individuals from various professional fields. Parameters are assigned to the causes of failure revealed in the methodology and their respective failure modes [Gao 2014, Jianpeng 2015]. The following parameters are used:

- S=Severity: severity of the effect of the failure mode.
- O=Occurrence: frequency of the occurrence of the failure mode.
- D=Detection: detectability of the failure.

The product of the values assigned to these parameters results in the so-called Risk Priority Number (RPN) which serves the ranking of failures. Values assigned to these parameters are provided on a scale from 1 to 10 [Hu et al., 2009].

The mathematical formula for calculating the conventional RPN is questionable and debatable [Sellappan, Sivasubramanian 2008]. Why S, O, and D should be multiplied to produce the RPN, but not other numerical operations. The simple multiplication in conventional FMEA may produce RPN with exactly the same value from different products of S, O and D, which may lead to confusion for failure modes ranking [Sellappan, Sivasubramanian 2008]. Based on their RPN ranking, it is decided whether an improvement action needs to be implemented in order to reduce the RPN. The issue is to find the threshold that triggers this improvement action. This problem is therefore better solved with a sorting technique, where failures are sorted into predefined priority classes.

$$RPN = S \times O \times D$$

The traditional FMEA procedure consists of the following steps:

- Establishing the team performing the analysis.
- Detecting failures and collecting data: identifying potential failure modes, as well as their causes and effects, followed by their evaluation in terms of severity, occurrence and detectability on a scale from 1 to 10.
- Analysis: determining the Risk Priority Number.
- Confirmation, working out action plans [Stamatis, 2003].

A successful development is based on a process model. For this reason, it is very important to prepare the model of the examined field. Proper planning is indispensable for running a process without any failure. Furthermore, planning is helped by process modelling methods which provide a visual image of the activities, resources and functions that are part of the process, along with the correlations between each other. The main purpose is to describe the currently working system and the requirements of the requested system in an accurate way, as well as to demonstrate the functioning of the system. An event-controlled process chain diagram was used in which the running of the process is provided by the change of events and activities.

METHODS

Raising the problem

The total production time and cost of the panel cutting process of unique furniture manufacturing are higher than planned. The work pieces which were cut off are incorrectly distributed and identified. In many cases, it takes a long time to look for a certain component, as it is put in the wrong place after sorting. For this reason, it is necessary to revise the process and correct the revealed failures.

Objectives

To find any potential failures in the process of unique furniture manufacturing and to redesign the process in order for identification and sorting to be appropriate.

Method of analysis

Following the identification of activities, regular and expert measurements are carried out to determine the time and cost data of activities. As a next step, the prepared process model provides a basis for the FMEA, during which potential causes of failure are identified. Activities eliciting failures are then incorporated into the model. As a result, the running of the process becomes more reliable. During the next step, the time and cost of running the process are determined. A corrective measure is taken on the basis of the FMEA. This measure is converted into an activity and built into the model. Accordingly, the cost and duration of the new process can be determined.

RESULTS

Description of the current process

In the examined company, the base material is transported to the panel cutting area after the order has arrived. In the panel cutting area, an employee cuts out the work pieces in accordance with the cutting list. This employee or another one puts the work piece into the bin in accordance with the given project or it is transported to the edging area and then put into a bin. Three or four projects are being carried out in the plant simultaneously; therefore, the panel cutting department performs the cutting duties of the various projects at the same time. The following failures were revealed during the current process: the work pieces cut out by the employees were not put into their correct places; therefore, once they would need to be used, employees have to look for them or re-cut them. It can be concluded that the examined process is completely linear and failures are not indicated. However, in order to reveal failures, a more thorough analysis is necessary.

Fig. 1. The basic process model
Rys. 1. Model podstawowego procesu

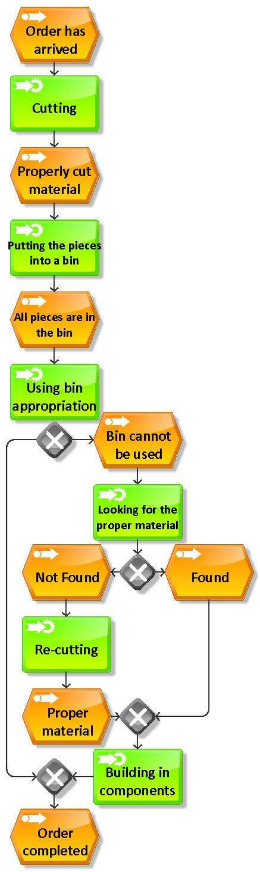

Fig. 2. The failure process model
Rys. 2. Model procesu niepowodzenia

Two failure modes were identified in the process using the FMEA method.

The first identified failure is that the incorrect size is cut out (Table 1). The reason for this failure is either a wrong initial size, wrong cutting list or the slipping of the equipment when the panel is being pushed. Each cause of failure has eight different weights, as wrong sizes either need to be corrected or re-cut. The occurrence factor of this failure was rated to be 3 and 4. During the research, it was concluded that this problem occurred in the case of 10-15% of all work pieces. The second identified failure was observed during the process of building in a work piece. This failure originated in a previous activity. The given work piece cannot be found during the assembly process. This problem originated from the phase of putting work pieces into bins. One of the causes of this failure was that the employee was tired and put the work piece into a different bin. It might also have happened that the bin into which the work piece was put was incorrectly labelled. The most common problem is that the employee at the end of the line who puts the work piece in its place did not properly communicate with the employee performing the cutting; therefore, the work piece is put in the wrong place.

Table 1. FMEA sheet
Tabela 1. Arkusz FMEA

Panel cutting process							
Process step	**Potential failure**	**Potential consequence**	**S**	**Potential cause of failure**	**O**	**D**	**RPN**
Cutting	Inappropriate size	The work piece cannot be used	8	Slipping while pushing	3	4	96
			8	Wrong size is specified	4	4	128
			8	Wrong cutting list	3	8	192
Building in	The work piece cannot be found	The order cannot be completed	7	A tired operator put the work piece to a different place	3	5	105
			7	Improper labelling	4	5	140
			7	Wrong communication	7	5	245

The detected failures and their respective RPN values are shown in Table 1. The RPN limit is 120, values higher than this are considered to be critical failures.

Figure 2 shows the activities causing failure that are built into the process model, as well as the activities which need to be corrected. This is not a linear process anymore. Once there is a failure, an XOR operator divides the process into two.

Describing the correction process

This section aims at the corrective actions in relation to the observed problems. At the end of the panel cutting process, the activities of sorting and putting work pieces into bins were performed by a robot (Mitsubishi RV-2AJ) instead of the employee. With the help of sensors, the robot placed each work piece into its correct bin. Furthermore, the robot uses an image processing diagnostic tool during the process of loading to keep track of each work piece and provide feedback on whether it is of the correct size based on previously set parameters. Also, the robot is able to perform calculations based on the sizes of the panels which were loaded in and determine whether the given furniture can be manufactured using the work pieces of the given size.

The movements performed by the robot were programmed, modelled and simulated using the software Cosimir Educational. The program consisted of the following steps: adding objects, positioning objects, sizing objects, indexing outputs, indexing inputs, assigning inputs to outputs, setting robotic arm positions, programming robotic movement, failure control, running.

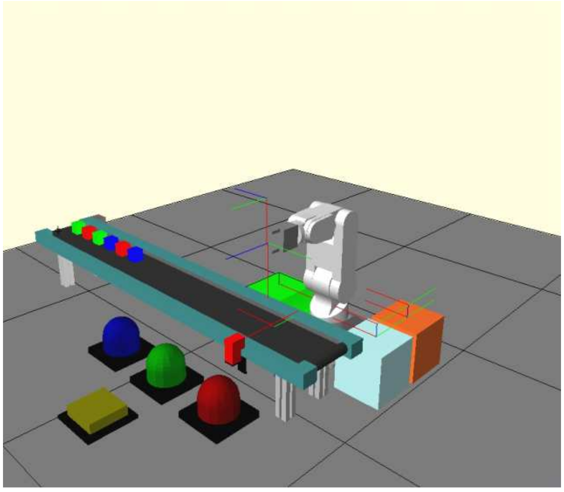

Fig. 3. Basic settings of the 3D model
Rys. 3. Podstawowe założenia modelu 3D

The employee places the work pieces which were cut out on the assembly line at the end of the panel cutting machine. The examined work pieces approach the sensor which identifies them. Based on the sensory data, the robot puts the work piece into the appropriate bin. In the model, this activity is performed using a simple colour sensor. The three bins placed next to the robot represent the project bins of the three active projects. The small bins on the assembly line represent the different work pieces.

In the case of the basic settings, work pieces are correctly lined up and they start to move once the program starts to run. The assembly line stops if a work piece reaches the sensor. The robot takes the given piece and puts it in its correct place in accordance with the program. The assembly line is restarted and runs until the next bin reaches the sensor. This is an endless cycle which stops only when the program is stopped.

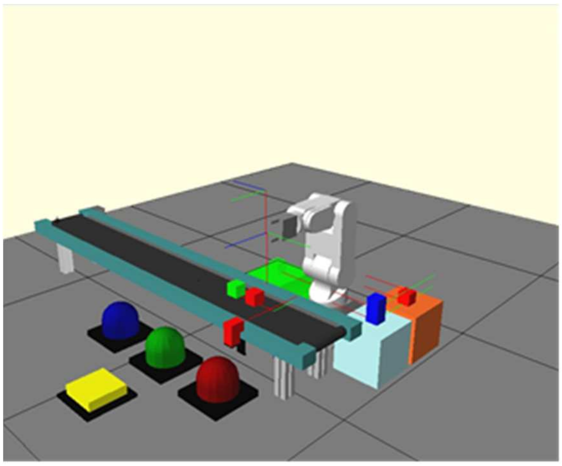

Fig. 4. Process of placing work pieces on top of each other
Rys. 4. Proces ułożenia elementów jeden na drugim

Two solutions were found for the sorting problem. The first is a simple solution: the employee performing the cutting duties labels the work pieces. The sensor detects and reads the label and sends a signal to the robot with the instruction where exactly to put the given work piece. The second solution is more complex, as it is based on programming in the values of the cutting list. The camera mounted on the robot identifies the work pieces once they get there, measures them and compares their size to the pre-programmed cutting list in order to determine which bin the given work piece has to be put into. This research focuses on the first, more simple development.

The program is structured the following way (Figure 4): the colour sensor sends a signal to the respective led based on the colour of the bin being sensed. The led sends a signal to the robot and activates the subroutine (program segment) which places the work piece into the bin. Three projects are running for the purpose of carrying out the sorting duty; therefore, one subroutine is assigned to each of the three leds for the three bin colours. If any of the leds receives the signal, the subroutine starts by moving the robotic arm into the P2 position where the work piece can be found. The robotic arm picks up the work piece and puts it into the correct bin. As a next step, the program returns to the beginning of the routine and restarts. A single bin contains work pieces of the same thickness and, since they have to be placed on top of each other, the robotic arm puts each work piece -50 units above the other in the bin. In order to do this, we introduced variables. Variables are assigned to each project and, consequently, each bin. The value of variables is 0 when the program starts. If the robotic arm already puts a work piece into the bin, +1 is added to the variable of the respective bin. As a result, the robotic arm will put the work piece to a higher position in the subsequent round.

The solution described above makes this part of the production process reliable, while the sorting activity will be accurate, efficient and quick. Therefore, the probability of the second failure in the process is reduced almost to zero. The only problem may arise from the non-compliance of the cutting list. However, the second, more complex version of the robot program provides a solution to this problem, as the robot identifies the work piece using a camera and based on laser sensory measurement. In this case, if any deviation is observed, the robot is able to give a signal immediately; therefore, it is possible to detect the problem in time.

The result of the simulation is shown in Figure 1. If the employee performs the sorting activity in the process, the total process time is 6.15 minutes. An average piece of furniture consists of around 550 components. Seven days are needed for cutting and sorting these components if the employee is responsible for the sorting. However, if a robot is incorporated into the process, the amount of time needed for cutting and sorting a work piece is reduced to 4.41 minutes and the total amount of time to be saved is five days in the case of 550 components.

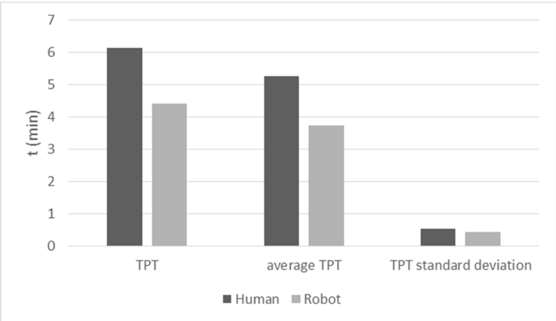

Fig. 5. Total process time in the case of a robot and human operator
Rys. 5. Całkowity czas procesu w przypadku operatora ludzkiego i robota

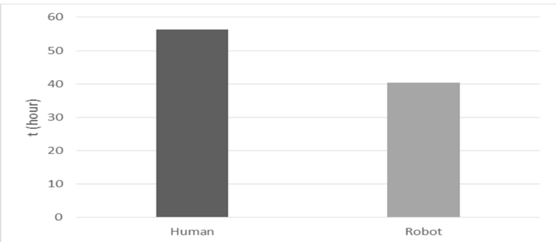

Fig. 6. Amount of time needed for sorting and cutting 550 work pieces
Rys. 6. Czas potrzebny na sortowanie i przycinanie 550 elementów

Therefore, if a robot is used in the process of manufacturing an average piece of furniture (25 m^2 material surface), the necessary components can be prepared and put to their correct places in only five days instead of seven. During the conventional process, two pieces of furniture can be manufactured in 21 days, while the new process makes it possible to manufacture three pieces of furniture within the same period. Consequently, it can be concluded that using robots is a relevant option in unique production, since a proper identification system and sensors make it possible to perform quicker and more efficient processes.

CONCLUSIONS

It was concluded from this research that using robots is a relevant option in unique production systems, as an intelligent system is capable of identifying problems even at the origin of failures. In conventional systems, the production process is not necessarily stopped when a failure occurs and sometimes faulty work pieces are detected only at the assembly stage. In mass production, such problems are solved by simply reaching for another work piece and building them in. However, in the case of unique production, each work piece is different; therefore, they need to be manufactured again. Since time is money, the timely detection of failures is a strategic issue, especially in the case of SMEs.

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POTENCJALNE POŁĄCZENIE PRODUKCJI JEDNOSTKOWEJ ORAZ INDUSTRY 4.0

STRESZCZENIE. **Wstęp:** W oparciu o koncepcję Industry 4.0, nazywaną również czwartą rewolucją przemysłową, procesy produkcyjne są zoptymalizowane przy użyciu maszyn, połączonych ze sobą przez inteligentne systemy komunikacyjne (urządzenia rejestrują przebieg procesu i dostosowują odpowiednio swoje działanie). Celem tego badania było zwiększenie niezawodności procesu w połączeniu ze skróceniem czasu produkcji, a co z tym związane, niższymi kosztami produkcyjnymi.

Metody: Poddano testom możliwość użycia robota w procesie obróbki cięciem produkcji unikatowych mebli drewnianych.

Wyniki: Obecnie zastosowanie robotów w produkcji ma uzasadnienie ekonomiczne tylko w przypadku produkcji masowej. W celu sprawdzenia, w którym etapie obróbki mebla można zastosować robota oraz jaki problemy były by możliwe do rozwiązania przy takim sposobie produkcji, w pierwszym etapie ukształtowano proces w oparciu o analizę błędów i osiągnięć (Failure Mode and Effects Analysis). Analizując potencjalne możliwości niepowodzenia procesu, podjęto próbę użycia ramienia robota jako miernika poprawy. Ramię to zostało zaprogramowane w środowisku komputerowym. Parametry ramienia zostały ustawione przy użyciu oprogramowania Mitsubishi RV-2AJ Cosimir Educational. Następnie przeprowadzono symulację mierząc całkowity czas produkcji oraz koszty produkcji przy użyciu ramienia robota.

Wnioski: Zastosowanie robotów jest uzasadnioną opcją w systemie produkcji jednostkowej, gdyż jako inteligentne urządzenie, jest on w stanie identyfikować problemy nawet u samego źródła ich powstawania.

Słowa kluczowe: Failure Mode and Effects Analysis, Industry 4.0, oprogramowanie cosimir, robot sortujący, zautomatyzowana produkcja

POTENZIELLE VERBINDUNG VON EINZELPRODUKTION MIT DEM INDUSTRY 4.0-KONZEPT

ZUSAMMENFASSUNG. Einleitung: In Anlehnung an das Industry 4.0-Konzept, das auch als die 4. Industrie-Revolution genannt wird, werden Fertigungsprozesse anhand von Maschinen, die mit Hilfe von intelligenten Kommunikationssystemen miteinander verbunden sind (die Einrichtungen verfolgen den jeweiligen Prozessverlauf und passen dementsprechend ihre Einwirkung an), optimiert. Das Ziel der betreffenden Forschung war es, die Zuverlässigkeit des Fertigungsprozesses in Verbindung mit der Verkürzung der Fertigungszeit und den damit verbundenen, niedrigeren Produktionskosten zu erhöhen.

Methoden: Es wurde die Möglichkeit der Inanspruchnahme eines Fertigungsroboters im Sägeverfahren bei der Fertigung von einzigartigen Möbelstücken aus Holz durchgetestet.

Ergebnisse: Die Inanspruchnahme von Fertigungsrobotern ist heutzutage nur im Falle einer Massenproduktion wirtschaftlich begründet. Zwecks der Überprüfung, auf welcher Etappe der Behandlung eines Möbelstückes ein Fertigungsroboter eingesetzt und welche Probleme bei einer solchen Produktionsweise gelöst werden könnten, wurde einleitend der Fertigungsprozess in Anlehnung an die Analyse von Mängeln und Leistungen (Failure Mode and Effects Analysis) ausgestaltet. Anhand der Analyse von potenzialen Gefahren des Scheiterns eines konkreten Fertigungsprozesses wurde ein Versuch der Inanspruchnahme eines Roboterarmes als Maßstab einer Rationalisierung unternommen. Der Fertigungsarm wurde anhand einer Computer-Software einprogrammiert. Die Parameter des Roboterarmes wurden unter Anwendung der Software Mitsubishi RV-2AJ Cosimir Educational installiert. Demzufolge wurde anhand des Roboterarmes eine Simulation mit Auswertung der Gesamtproduktionszeit und der betreffenden Fertigungskosten durchgeführt.

Fazit: Der Einsatz der Fertigungsroboter stellt eine mögliche und begründete Option bei der Einzelfertigung dar, denn sie als intelligente Einrichtungen sind imstande, die Probleme selbst an ihrem Entstehungsursprung zu identifizieren.

Codewörter: Failure Mode and Effects Analysis, Industry 4.0, Software Cosimir, Sortierroboter, Fertigungsroboter, automatisierte Fertigung

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