DOCTORAL THESIS

Development of Intelligent Manufacturing Cell Structure for SME Digital Manufacturing Hub

Tavo Kangru

TALLINNA TEHNIKAÜLIKOOL
TALLINN UNIVERSITY OF TECHNOLOGY
TALLINN 2021

TALLINN UNIVERSITY OF TECHNOLOGY
DOCTORAL THESIS
7/2021

Development of Intelligent Manufacturing Cell Structure for SME Digital Manufacturing Hub

TAVO KANGRU

PRESS

TALLINN UNIVERSITY OF TECHNOLOGY
School of Engineering
Department of Mechanical and Industrial Engineering
This dissertation was accepted for the defence of the degree 21/12/2020

Supervisor:	Prof Tauno Otto School of Engineering Tallinn University of Technology Tallinn, Estonia
Co-supervisor:	Prof Jüri Riives School of Engineering Tallinn University of Technology Tallinn, Estonia
Opponents:	Prof Esko Niemi School of Engineering Department of Mechanical Engineering Aalto University Espoo, Finland
	Prof Andrei Lobov Faculty of Engineering Department of Mechanical and Industrial Engineering Norwegian University of Science and Technology Trondheim, Norway

Defence of the thesis: 29/01/2021, Tallinn

Declaration:
Hereby I declare that this doctoral thesis, my original investigation and achievement, submitted for the doctoral degree at Tallinn University of Technology has not been submitted for doctoral or equivalent academic degree.

Tavo Kangru

----
signature

European Union
European Regional
Development Fund

Investing
in your future

ISSN 2585-6898 (publication)
ISBN 978-9949-83-656-7 (publication)
ISSN 2585-6901 (PDF)
ISBN 978-9949-83-657-4 (PDF)
Printed by Koopia Niini & Rauam

TALLINNA TEHNIKAÜLIKOOL
DOKTORITÖÖ
7/2021

Intelligentse robot-tootmise struktuuri arendus väike- ja keskmise suurusega ettevõtete digitaalsete töökohtade tarbeks

TAVO KANGRU

Contents

List of Publications

The list of author's publications, on the basis of which the thesis has been prepared:

I. 3.1 Vaher, K.; Kangru, T.; Otto, T.; Riives, J. (2019). The Mobility of Robotised Work Cells in Manufacturing. Proceedings of the 30th DAAAM International Symposium pp. 1049–1055, B. Katalinic (Ed.), Published by DAAAM International, Vienna, Austria. DOI: 10.2507/30th.daaam.proceedings.146

II. 3.1 Kangru, T.; Riives, J.; Otto, T.; Pohlak, M.; Mahmood, K. (2018). Intelligent Decision-Making Approach for Performance Evaluation of a Robot-Based Manufacturing Cell. Proceedings of the ASME 2018 International Mechanical Engineering Congress and Exposition. Volume 2: Advanced Manufacturing Pittsburgh, Pennsylvania, USA. November 9–15, 2018. V002T02A092. ASME. https://doi.org/10.1115/IMECE2018-86666

III. 1.1 Kangru, T.; Riives, J.; Otto, T.; Kuts, V. (2020). Optimisation of decision-making process in industrial robot selection. Journal of Machine Engineering 2020; 20(1): 70–81. DOI: https://doi.org/10.36897/jme/117788

IV. 1.1 Kangru, T.; Riives, J.; Mahmood, K.; Otto, T. (2019). Suitability Analysis of Using Industrial Robots in Manufacturing. Proceedings of Estonian Academy of Sciences, 2019, 68, 4, 383–388. https://doi.org/10.3176/proc.2019.4.06

V. 3.1 Mahmood, K.; Otto, T.; Golova, J.; Kangru, T.; Kuts, V. (2020). An Approach to Analyze the Performance of Advanced Manufacturing Environment. Procedia CIRP, 93, 2020, 628–633. doi.org/10.1016/j.procir.2020.04.042

VI. 3.1 Kangru, T.; Riives, J.; Otto, T.; Mahmood, K.; Moor, M. (2020). Knowledge-driven robotic manufacturing performance simulation for cell design improvement. Proceedings of the ASME 2020 International Mechanical Engineering Congress and Exposition: IMECE2020, November 9–15, 2020. Portland, PA, USA: ASME, Paper No. IMECE2020-23541. (accepted to publish 18.08.2020)

Publications appear in the appendix 1.

Author's Contribution to the Publications

Contribution to the articles in this thesis are:

I. Article I: the author composed and conducted the survey on the current state and future prognosis of the utilization of robot-based manufacturing and the following more specific robot-based production cell study. The author compiled and analyzed the data and wrote the conclusion and summary.

II. Article II: the author prepared and wrote part of the literature review. Based on the literature review, he developed the production cell performance evaluation model. The author collected the information for two case studies and tested the developed model. The author wrote the case studies and conclusions. The author presented the publication at the conference.

III. Article III: the author carried out the decision-making process for industrial robot-cell component selection and did the literature review. The author participated in the development of the dual approach model and method for DSS selection. He wrote and formulated conclusions and presented the publication at the conference.

IV. Article IV: the author developed a production cell suitability evaluation system for DSS. He tested the developed system with 20 cases and helped to develop production cell suitability categories. The author presented the publication at the conference.

V. Article V: the author developed a DES model for the case study and analyzed the results. The author presented the publication at the conference.

VI. Article VI: the author prepared and wrote part of the literature review on which the methodology developed was based. The author developed a manufacturing cell model for simulation in a DES environment. He tested the system developed and wrote the case studies and conclusion. The author presented the publication at the conference.

Abbreviations

AA	Advanced Analytics
AHP	Analytic Hierarchy Process
AI	Artificial Intelligence
AMS	Automated Manufacturing System
ANN	Artificial Neural Network
ASME	American Society of Mechanical Engineers
BOM	Bill of Material
BOO	Bill of Operation
CAD	Computer-Aided Design
CAM	Computer-Aided Manufacturing
CAPP	Computer-Aided Process Planning
CH	Cost per Hour
CIRP	The International Academy for Production Engineering
CNC	Computer Numeric Control
CPS	Cyber-Physical Systems
CT	Cycle Time
CTO	Chief Technology Officer
CU	Cell Utilization
DAAAM	Danube Adria Association for Automation & Manufacturing
DEA	Data Envelope Analysis
DES	Discrete Event Simulation
DESI	The Digital Economy and Society Index
DMU	Decision-Making Units
DPP	Discounted Payback Period
DSS	Decision Support System
EF	End-Effector
ERP	Enterprise Resource Planning
GI	Gain of Investment
I4.0	Industry 4.0
IIoT	Industrial Internet of Things
IMECC	Innovative Manufacturing Engineering Systems Competence Centre
IMS	Intelligent Manufacturing System
IoT	Internet of Things
IR	Industrial Robot
KBE	Knowledge-Based Engineering
KPI	Key Performance Indicators
LP	Loading-unloading Positions

M2M	Machine to machine
MAG	Metal Active Gas
MCDM	Multi-Criterion Decision-Making
MES	Manufacturing Execution System
Mfg.	Manufacturing
MIG	Metal Inert Gas
MSD	Manufacturing System Design
MU	Market Uncertainty
NGMS	Next Generation Manufacturing Systems
NI	Net Income
NIST	National Institute of Standards and Technology
NOP	Net Operating Profit
OEE	Overall Equipment Effectiveness
OLE	Overall Labor Effectiveness
OTD	On-Time Delivery
PEM	Performance Evaluation Model
PEM	Performance Evaluation Model
PM	Product Mix
PP	Payback Period
PV	Product Volume
R&D	Research and Development
RCS	Resilience Control System
ROI	Return on Investments
RQ	Research Questions
SM	Smart Manufacturing
SME	Small and Medium-sized Enterprises
TalTech	Tallinn University of Technology
TCO	Total Cost of Ownership
TD	Digital Twin
TE	Transporting Equipment
TH	Throughput
TIG	Tungsten Inert Gas
TOPSIS	A Technique for Order Preference by Similarity to Ideal Situation
TTK UAS	TTK Tallinn University of Applied Sciences
WIP	Work in Progress
WSM	Weighted Sum Model
WT	Working Tables

Explanations of abbreviations used in the thesis.

Introduction

I received an MSc degree in Product Development and Production Engineering from the Tallinn University of Technology (TalTech) in 2012. Since 2014, I have been the chair of mechanical engineering at the TTK Tallinn University of Applied Sciences (TTK UAS) and have been responsible for the development and ensuring of the sustainability of the mechanical engineering study program and relevant laboratories. My doctoral studies in mechanical engineering have helped me improve my knowledge of factories of the future, as I worked closely with the Industry 4.0 research group and combined R&D with my work at the TTK UAS.

One future goal at the TTK UAS is to widen digital manufacturing possibilities by developing flexible manufacturing cells for Small and Medium-sized Enterprises (SME´s). With that goal in mind, my PhD thesis is related to the development of intelligent manufacturing cells for a network of SME's. The main objective is to develop a new model focused on the implementation of CNC robot-based solutions for SMEs. Continuous optimization and preventive action, including remote monitoring and analysis, are critical processes in the robot-based solution.

The work's experimental part will be carried out in the production facilities of privately held companies and the laboratories of the TTK UAS, TalTech, and the Innovative Manufacturing Engineering Systems Competence Centre (IMECC). The introduction of the thesis comprises a discussion of robotization based on Industry 4.0 concepts and future trends in manufacturing. The research gaps and research problems have been defined based on the current state of industry robotization. In the final section, the structure of the dissertation and research process are described.

1.1 Background and Research Gaps

The industrial robot manufacturing sector has been around and growing rather steadily since the 1960s. An industrial robot by definition is an automatically controlled, reprogrammable, multipurpose manipulator, programmable in three or more axes, which can be either fixed in place or mobile for use in industrial automation applications. The industrial robot is assembled from manipulator, actuators, controller, teach pendant and any communication interface, hardware and software (International Organization for Standardization, 2012). The first industrial robots appeared in the automotive industry, where they were used to spot weld vehicle bodies. It was the first growth spurt in the application of industrial robots in automation. The second growth spurt took place in 2010, driven by fundamental changes in the industry and economic environment (Teulieres, Tilley, Bolz, Dehm, & Wägner, 2019). It has been estimated that by 2030 fifty-two percent of transportation and storage jobs and forty-five percent in manufacturing will potentially be highly automated (Hawksworth, Berriman, & Goel, 2018). As transportation and storage are part of the production value chain, the industry's effect is expected to be enormous.

In 2011, the Industry 4.0 philosophy was widely introduced and was followed by systematic and determined development in this field. An architecture related to Industry 4.0 (I4.0) based on eight pillars was developed that describe the modern production system narrowly and the main development trends of production more broadly (Dalmarco, Ramalho, Barros, & Soaresa, 2019).

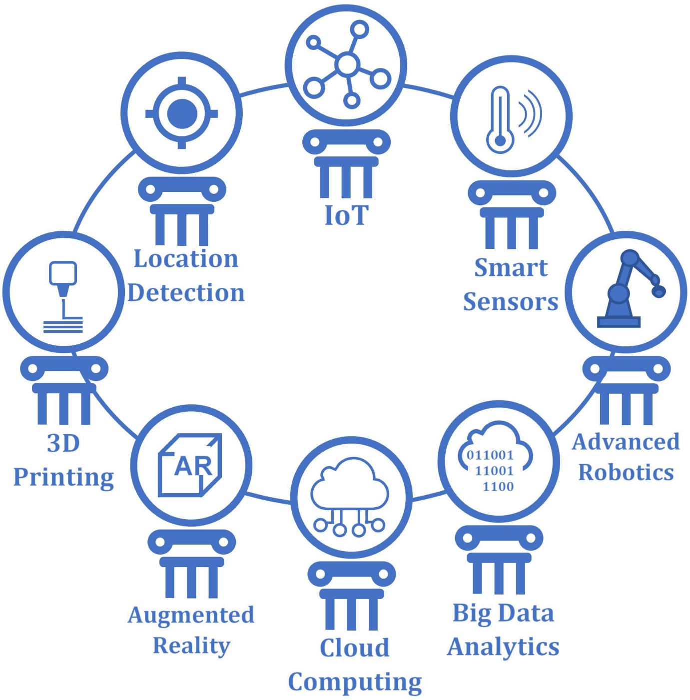


Figure 1. Industry 4.0 Digital Technology Pillars (Dalmarco, Ramalho, Barros, & Soaresa, 2019).

As the manufacturing industry in European countries accounts for a large share (24.7%) of GDP (European Central Bank Eurosystem, 2020), the sector's development significantly impacts all other sectors. At the same time, significant changes have occurred in the population structure due to low birth rates and high life expectancy. The last decade has seen an increase in the proportion of people aged 65 and over in the European Union by more than 2.9 times, leading to a rise in the dependency ratio to over 20,3% (Eurostat, 2020). There are currently just over three working-age people for every person aged 65 or over (Eurostat, 2020). This is having a direct impact on the number of employees in the industrial sector today, and low birth rates will affect the share of employees in the industrial sector in the future.

In addition to labor market problems, the European industry is under constant pressure from cheaper production in developing countries. Over the years, exports to the European Union have been rising continually, growing by 16.2% in 2016–2018 (European Commission, 2020).

The EU is one of the world's leading environmental regulators. Environmental regulations generally require polluting facilities to undertake abatement activities, and this may impose an increase of costs on businesses. Thus, regulatory differences across companies, sectors, or jurisdictions can cause changes in relative production costs. Differences in environmental regulations can, therefore, alter the competition between companies by changing their relative production costs (Dechezleprêtre & Sato, 2018). These difficulties have been driving the development of industrial technologies to reduce the labor force, use resources more efficiently, and shorten product development time.

Trends in digitalization are of great significance to manufacturing (McKinsey Global Institute, 2017). More companies are making footprint decisions using a "total factor performance" approach that considers logistics, lead time, productivity, and risk, as well as proximity to suppliers, the operations of other companies, and final demand. Fundamentally, manufacturers need to identify strategic use cases that are linked to their digital initiatives and business strategy. Furthermore, they need to consider how to begin working alongside machines in a more automated and data-driven way.

Larger companies with more resources are more likely to be able to invest and develop new I4.0 technologies to stay competitive and tackle these challenges. However, SMEs (European Commission, 2017) are certainly not able to adopt similar solutions. This is also one of the reasons why technical solutions for companies of different sizes in the industrial sector should be considered according to the company's investment potential. It is essential to ensure the competitiveness of small and medium-sized enterprises by finding solutions to labor problems, trying to increase productivity with equivalent resources, shortening the time to market, and producing products in compliance with current environmental standards. The biggest challenge for SME's is to fulfil these conditions simultaneously. Those factors are forcing entrepreneurs to automate their processes at an increased rate. As technology advances, there is less need for advanced, expensive outsourced development services. The same goal can be achieved by using the company's own engineering resources or using the help of integrators. Simulation software can further close the gap between design and installation by helping end-users prove their solution before committing to the final investment (Hawksworth, Berriman, & Goel, 2018).

Research gap 1: It is necessary to explore how to automate existing labor intensive production cells in SMEs, making them productive and profitable robot integrated production cells.

The automation of individual processes may not be the most sensible solution here. A systematic and broader approach is needed.

Research gap 2: There is a need to develop a methodology and methods which are based on decision algorithms and simulation systems to assist developers and integrators in the designing of highly automated and intelligent cyber-physical systems.

1.2 New Developments and Trends

Although the prices of industrial robots have been declining in recent years, the cost of an entire integrated robot system is still high, thus extending considerably the expected payback period. The implementation of robots will increase further in the coming years, with the automotive, electronics, and medical industries still leading the way (International Federation of Robotics, 2018). Continuous growth has slowed since 2019 in almost every leading industry, see Figure 2. There are various reasons for this: in the automotive industry, a large investment in electric cars; in the electronics industry, a substantial decrease in the demand for electronic devices. The installation of industrial robots in 2020 will certainly be affected by the global COVID pandemic (International Federation of Robotics, 2020), but robotization is still ongoing.

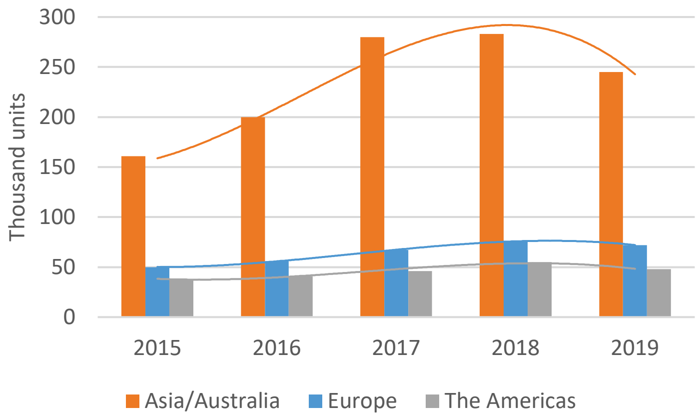


Figure 2. Annual installations of industrial robots (International Federation of Robotics, 2020).

The main reasons for investing in new robotics systems are a reduction in production costs, an increase in quality and productivity, and the increased technological capabilities of robotics units (Teulieres, Tilley, Bolz, Dehm, & Wägner, 2019). The main obstacles to the implementation of new robotics systems are the high total cost of ownership, the lack of a standardized programming environment, and the shortage of integrators with the necessary experience. These reasons apply to the industries mentioned above with high investment capacity. If we look at SMEs, where the turnover and resulting investment capacity are much lower than that for large companies, a robot production unit that requires a large capital outlay is still a doubtful investment. However, recent developments in the field of industrial robots, mainly the emergence of collaborative robots, have also generated interest among SME's. At present, the development of industrial robots has reached a stage where there is an available solution for almost every material handling or assembly operation. Also, the cost of computing power has decreased, making it possible to use AI solutions in industrial robot control systems.

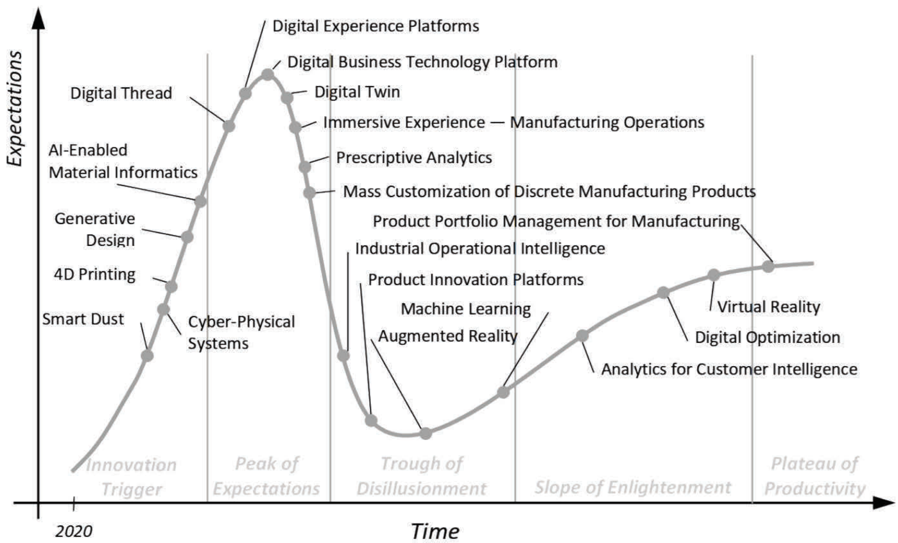


Figure 3. Manufacturing Technology Innovation Hype-Cycle (Simon, Michelle, & Marc, 2019).

New technologies shown in Figure 3. For the SME the following industrial developments have been introduced:

- Big Data Analysis at a different level of management,
- Adoption of the Industrial Internet of Things (IIoT) Technology,
- Industrial Cybersecurity,
- Open Automation Architectures Implementation,
- Virtual Solutions Assisted Physical Processes,
- Collaborative Robots.

The forecast refers to a type of production where the production system has a high throughput but still retains a high degree of flexibility. The manufactured products are exchanged on the production line without stopping the line, and the product variations are enormous. To enhance those changes, a new type of industrial robot, a co-working robot (Peshkin, Colgate, Moore, Gillespie, & Akella, 2001), has been integrated with open architecture and with the integration of different control systems. Such production units have come to be called Agile Production Systems (McKinsey & Company, 2017).

1.3 Objectives and Research Questions

The objective of this research is to develop a robotic workplace design methodology for a productive, highly automated, and intelligent robot integrated production cell, taking advantage of artificial intelligence capabilities and multi-criteria decision algorithms. The approach developed considers a company’s production needs and restrictions to ensure an efficient workflow in the planned production system.

The main goals of the thesis are as follows:

- To develop a methodology for the design and redesign process for a robot-based production cell. This includes an integrated data analysis based on selected indicators to assess the feasibility and suitability of robotization and a prediction of robot cell performance.
- To develop methods for the economic and technical performance evaluation of robot-based production cells based on decision algorithm and simulation techniques. To implement practical solutions for selecting components required by the robotic workplace. This includes the design of a robot-based workplace performance simulation in a 3D virtual environment and validation of results for final decisions.

This thesis aims to help SMEs gather necessary information about their production and to develop a specific production Performance Evaluation Model (PEM). Using the PEM in the context of the company’s strategy, it is possible to evaluate its Key Performance Indicators. In the future, using the Dual Approach Model, it will be possible to predict the output parameters of the robot integrated solution that has been implemented or is still under development. To find the optimal solution for the company, the Dual Approach Model uses knowledge openly available in the industry and incorporates different levels of analysis, including feasibility, technology selection, suitability, and efficiency analysis. The analysis is carried out recursively, making it possible to correct the input data at each stage and thereby achieve the desired results. The following research questions (RQ) are thus considered:

RQ1: What is the current state of development of the Estonian manufacturing industry regarding robotization?
RQ2: How will the robot integrated production cell output given the company's strategic plan be assessed and modelled?
RQ3: How will the knowledge-driven design process of a robot integrated production cell be optimized?
RQ4: How will the suitability and performance of a robot integrated production cell be analyzed?

The research questions are answered stepwise in the following articles.

Article I has answered RQ1, giving an overview of robotization in Estonian production companies.
Article II has explained the concept of performance evaluation modelling and the decision support system to use in the robot integrated production cell design phase, answering RQ2.
Article III has developed a knowledge-driven decision support model for optimal robot integrated production cell design, thereby answering RQ3.
Article IV has assisted in answering RQ4. In this article, a suitability analysis method was described.
Article V has assisted in answering RQ4. In this article, a performance analysis case study was conducted.
Article VI has assisted in answering RQ4. In this article, a performance analysis method was described.

1.4 Contribution of the Thesis and Dissemination

In this chapter, the novelty of the thesis from a scientific and practical point of view and the dissemination of results is discussed. The thesis involves a novel recursive and integrated decision-making process based on multi-criteria decision algorithms and artificial intelligence solutions for the effective planning and evaluation of robot integrated production cells for SMEs.

The scientific novelty of the thesis consists of the following:

- A knowledge-driven decision-making method for robot integrated production cell design and redesign.
- A method for the assessment of the feasibility of robotization for an IR integrated production cell.
- A suitability index calculation method for a robot welding production cell.
- A performance evaluation method for a robot integrated CNC manufacturing and welding cell.

The practical novelty of the thesis consists of the following:

- Determination of the level of automatization, intelligence, and competence of Estonian manufacturing industry robot integrated production cells. Analysis of the fulfilment of production cell design goals.
- Implementation of analyses of suitability and performance of robot integrated production cells.
- Implementation of the design methodology developed and analysis of a method for redesigning a company production cell into a robot integrated production cell.

Dissemination of the Results and Publications

The research study was carried out from 2016 to 2020 at TalTech University and the TTK University of Applied Sciences and over a three-month period in 2019 at the Faculty of Mechanical Engineering of the Brno University of Technology. The results of the PhD thesis have been presented at five international conferences. One article was published in the Journal of Machine Engineering and the rest in the proceedings of conferences: Proceedings of the ASME (American Society of Mechanical Engineers), Proceedings of Estonian Academy of Sciences, Proceedings of International DAAAM Symposium (Danube Adria Association for Automation & Manufacturing), and Procedia CIRP (The International Academy for Production Engineering).

1.5 Research Process and Structure of the Dissertation

Several methods and techniques have been used in different phases of the research. In the initial stages of the research, pilot data was collected from the management of the companies and researchers and was analyzed. Information was collected through literature review and interviews, and the research area, aim, and questions were formulated. A broader literature review was then performed to obtain additional information and to define a research gap. A multi-stage survey was also conducted of the Estonian manufacturing industry. Based on the data collected, an analysis was performed, and conclusions made. Using the case study methodology, possible solutions were proposed and then validated either by experiments in university laboratories and company production cells or simulations, using various commercial software. Final conclusions were reached based on the results, and research limitations and suggestions for future research were proposed.

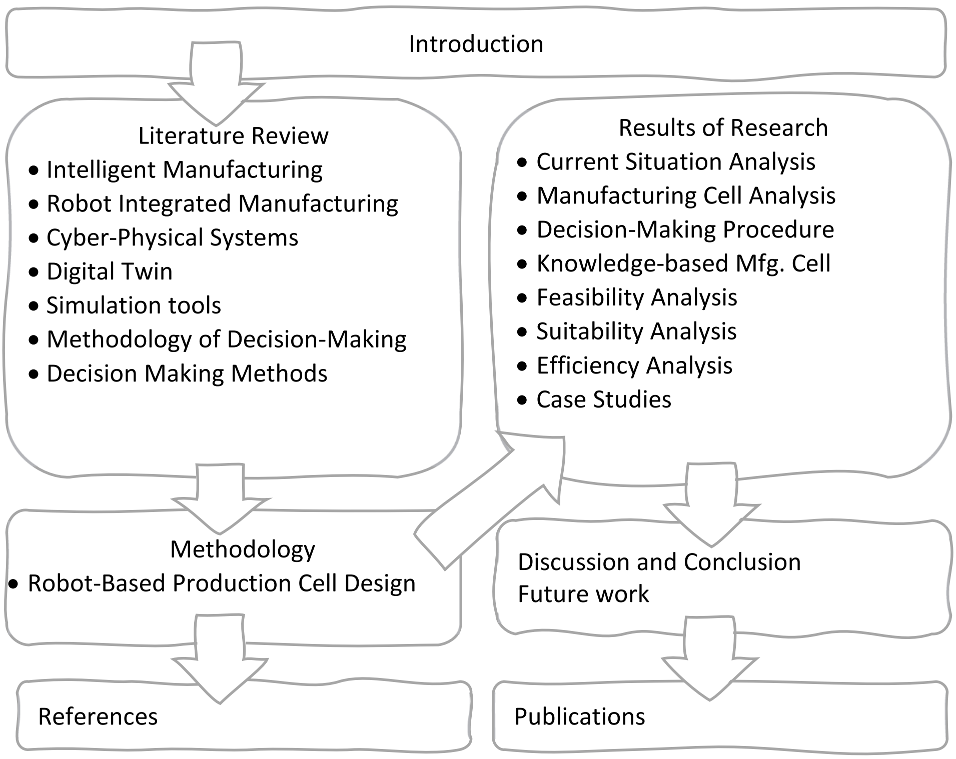


Figure 4. Structure of the Dissertation.

2 Literature review

The literature review consists of explanations of the concepts, methods, and definitions needed to compile the thesis. In addition, this chapter will provide the necessary technological framework into which the solution proposed in this thesis has to fit.

2.1 Intelligent Manufacturing

The term Intelligent Manufacturing System (IMS), sometimes referred to as Smart Manufacturing (SM), appeared in the literature in the early 90s (Kusiak A., 1990). In the United States, similarly, the term Next Generation Manufacturing Systems (NGMS) is used. However, so far, there is no standard approach and definition of this concept. According to the National Institute of Standards and Technology (NIST), smart manufacturing is a fully integrated, collaborative manufacturing system that responds in real-time to meet customer needs and changing demands and conditions in the factory and the supply network. To this date, quite extensive research has been done in this field, and standards and case studies have been created.

Intelligent Manufacturing involves manufacturing as a physical process that employs a high level of digital information technology, forming a flexible, rapidly responsive, effective, and environmentally friendly way to produce goods. IM consists of six base technologies or engineering domains: manufacturing technology and process, materials, data, predictive engineering, sustainability, resource sharing, and networking (Kusiak A., 2018). By implementing or combining the above-mentioned technologies or engineering domains, it is possible to ensure that production is cost-effective and environmentally friendly while maintaining the company’s competitive advantage.

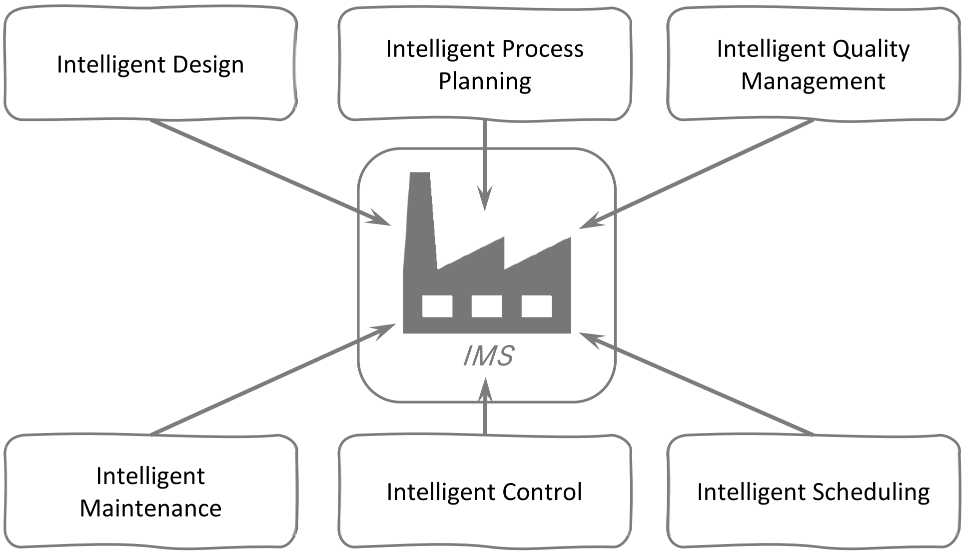


Figure 5. Intelligent Manufacturing Subsystems (Košťál & Holubek, 2013).

To understand an intelligent manufacturing system, we should compare it to classical automated manufacturing systems. The automated manufacturing system (AMS) today is understood as the manufacturing of a device or devices with various levels of automation of operating and nonoperational activities, with various levels of subsystems integration (technological, supervisory, transportation, manipulating, controlling). Automatic manufacturing systems designed for repetitive production, where a significant rate of flexibility is demanded, are called flexible manufacturing systems (Košťál & Holubek, 2013). The IMS differs from this in that its systems and subsystems (see Figure 5) are equipped with aids that enhance intelligence. Subsystems can make necessary decisions independently and on the spot, decisions involving self-awareness, self-configuration, self-optimization, etc. (Qina, Liua, & Grosvenora, 2016).

2.1.1 Cyber-Physical Systems

In the rapidly evolving field of industrial IT, more and more software-based solutions are being developed for workplace automation. These solutions are mainly designed to reduce workload and optimize useful working time related to planning, configuration, reporting, and operation. The development of such a relation where the physical process is enhanced using advanced digital technology may be defined as a Cyber-Physical System. The system, on its own, is one component of IMS. The National Institute of Standards and Technology describes Cyber-Physical Systems as "Smart Systems that include engineered interacting networks of physical and computational components (National Institute of Standards and Technology, 2020). These highly interconnected and integrated systems provide new functionalities to improve the quality of life and enable technological advances in critical areas, such as personalized health care, emergency response, traffic flow management, smart manufacturing, defence and homeland security, and energy supply and use" (National Institute of Standards and Technology, 2017).

Manufacturing CPS architecture usually consists of five levels or five components (5C):

- *Connection* – Acquiring raw data from machines, workstations, measuring points, and enterprise manufacturing information systems (ERP, MES) for transferring to a central server.
- *Conversion* – Analyzing the data collected and converting it to information using data conversion algorithms (data mining, data visualization, etc.).
- *Cyber* – Serving as an information cloud where all the information is collected for future analysis.
- *Cognition* – Transformation of information to knowledge to be used by decision making applications.
- *Configuration* – Based on decisions, feedback is provided to the physical process. It acts as the Resilience Control System (RCS), applying controls to machines in correspondence with the decisions made at the cognition level.

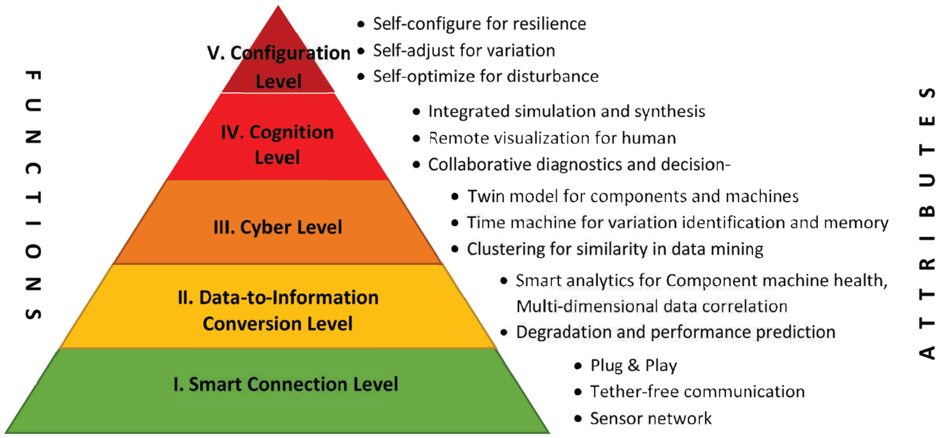


Figure 6. Cyber-Physical System 5C architecture (Bagheri, Yang, Kao, & Lee, 2015).

2.1.2 Digital Twin

The Digital Twin (DT) first proposed in 2003 by Grieves (Grieves & Vickers, 2017) and later developed by NASA (Glaessgen & Stargel, 2012) is a vital part of a CPS. It is a virtual representation of the physical process, including its machines, equipment, working conditions, and layout. The DT model is synchronized continuously and updated through IoT or M2M connectivity (Wu, Talwar, Johnsson, Himayat, & Johnson, 2011), assuring near-real-time information processing. This makes it possible to monitor, control, diagnose, and predict situations and perform what-if scenarios through simulation, optimization, and analysis. After the simulation and optimization of product design, manufacturing, and maintenance processes, it guides the physical process to perform an optimized solution (Tao, et al., 2017).

Digital Twin plays a pivotal role in the vision of smart manufacturing. It enables the shift from analyzing the past to predicting the future. Digital Twin development consists of three major components, as shown in Figure 7 (Lua, Liub, Wangc, Huanga, & Xua, 2020):

- A specific information model for a physical object. For a production unit, a 3D model in a simulation environment showing behaviors similar to those of the real-life unit.
- Two-way communication between DT and the manufacturing cell.
- A data processing module that can extract information from heterogeneous multi-source data to construct the live representation of a physical object.

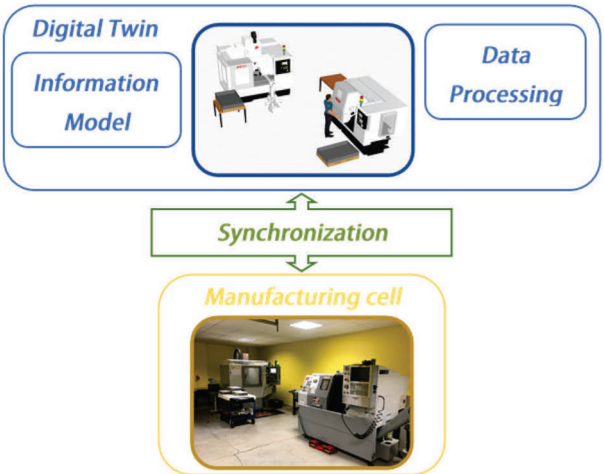


Figure 7. A Digital Twin reference model.

Information models for the manufacturing equipment (CNC machines, Industrial robots, etc.) are mainly managed by CAM software. CAM software is used to plan and simulate machining steps prior to manufacturing. Only verified and approved operations are sent to the machine for processing. As machines and cell capabilities and complexity increase, simulations become critical for verifications. The same rule also applies to cell monitoring, controlling, optimizing, diagnosing and predicting (Zhou, Chao, Li, Kai, & Chuang, 2020).

As Digital Twin development advances, it is possible to define key research areas:

- Architecture pattern – the developing, testing, and selecting of the best solutions for a particular application,
- Communication latency requirement – with increased data volumes the ensuring of a sufficient synchronization speed for real-time operations,
- Data capturing – the development of a network of sensors, devices and robots,
- Development of standards – for accelerating the development of new applications,
- Extension of functionality – the adding of functionality according to specific applications,
- DT model version management – for the mapping of development leaps,
- Human involvement.

All of the above-mentioned research areas are necessary for the development of a next-level Digital Twin application for the CPS. It is then essential to expand the functionality of the technologies in the coming years for a technological leap. Existing applications are mostly used to monitor the production process and make predictions for decision-making support applications. Most of the decisions are still made by experts or process operators. Hence the autonomy of decision making should be increased in the future.

2.1.3 Simulation tools

Simulation, in general terms, can be seen as the activity of experimenting with a model of a real or imaginary system. The main goal of simulation lies in the gain of insight into the behavior of the system. Simulation renders itself especially valuable and comfortable to use for the purpose of performing experiments and testing out solutions without the costs of physically changing the system. The use of simulation tools makes it easier and faster to achieve the goal of constructing an efficient robot integrated production cell. Simulation has become a powerful tool in most areas of technology. It is extensively used in manufacturing, transport and logistics, the military, construction operations, and more (Demirbaş & Üna, 2018). All kinds of processes and facilities can be modelled – restaurants, airports, theme parks, manufacturing plants, etc. (Bandyopadhyay & Bhattacharya, 2017). In a real production environment, activities performed can fail, resulting in scrap, be delayed, get cancelled, and so forth. Such random behaviors can be addressed during the simulation using a probabilistic distribution, as it can be set for every activity to obtain more realistic end values (Tolio, Sacco, Terkaj, & Urgo, 2013).

In manufacturing, it is possible to use different simulation solutions at different levels of the production system. Based on the manufacturing system architecture, there are three levels: Machine, Sub-system, and System level. It is possible to use a specific solution at each level to obtain new data and knowledge. At the lowest level, the Machine level, the goal is generally the effective operation of the machine. Therefore, the simulations at this level are intended to ensure the simultaneous movement of the CNC machine on all axes without collision. This kind of simulation is usually performed using the CAM software. At both the Sub-system and System level, the objective is the optimization of the usage of a resource (equipment, workforce, time) at the workplace, which consists of an industrial robot and CNC machine, or more broadly by the production unit. At those levels, Discrete Event Simulation, 3D factory, and other more specific simulation software are used (Mahmood, Otto, Kuts, & Kangru, 2020).

2.2 Decision-Making System Methodology Development

This chapter discusses the decision-making methodology and Decision Support Systems available for implementation in the industrial robot-based production cell design process.

Decision-making problems have been treated individually so that consistency is not maintained between the decision-making functions regarding assumptions and data structures (Kangru, Otto, Riives, Kuts, & Moor, 2020). These isolated decision-making stages do not help to achieve an optimum solution, as decision-making problems in manufacturing involve very complex data processing. Elementary estimations are very strongly dependent on each other, and real technological resources (capabilities) must be taken into consideration. Therefore, rational decisions cannot usually be made simply using sequential procedures. However, using modelling and simulation procedures, it is possible to analyze the alternatives and find the best solution. The other possibility is to apply complex systems theory (Ladyman, Lambert, & Wiesner, 2013) (Efthymiou, Pagoropoulos, Papakostas, Mourtzis, & Chryssolouris, 2012) and develop a solution system architecture, allowing the reduction of the complexity of the design process, minimizing risks in production system planning, and enabling the analysis of production variants. For a better understanding of the entire complexity of the problem setup, it is useful to consider the broader picture based on the ontology model in Figure 8. (Lõun, Riives, & Otto, 2011). The Robot Cell Utilization Ontology Model shows task positioning in the field of manufacturing in its entire complexity (Kangru, Otto, Riives, Kuts, & Moor, 2020).

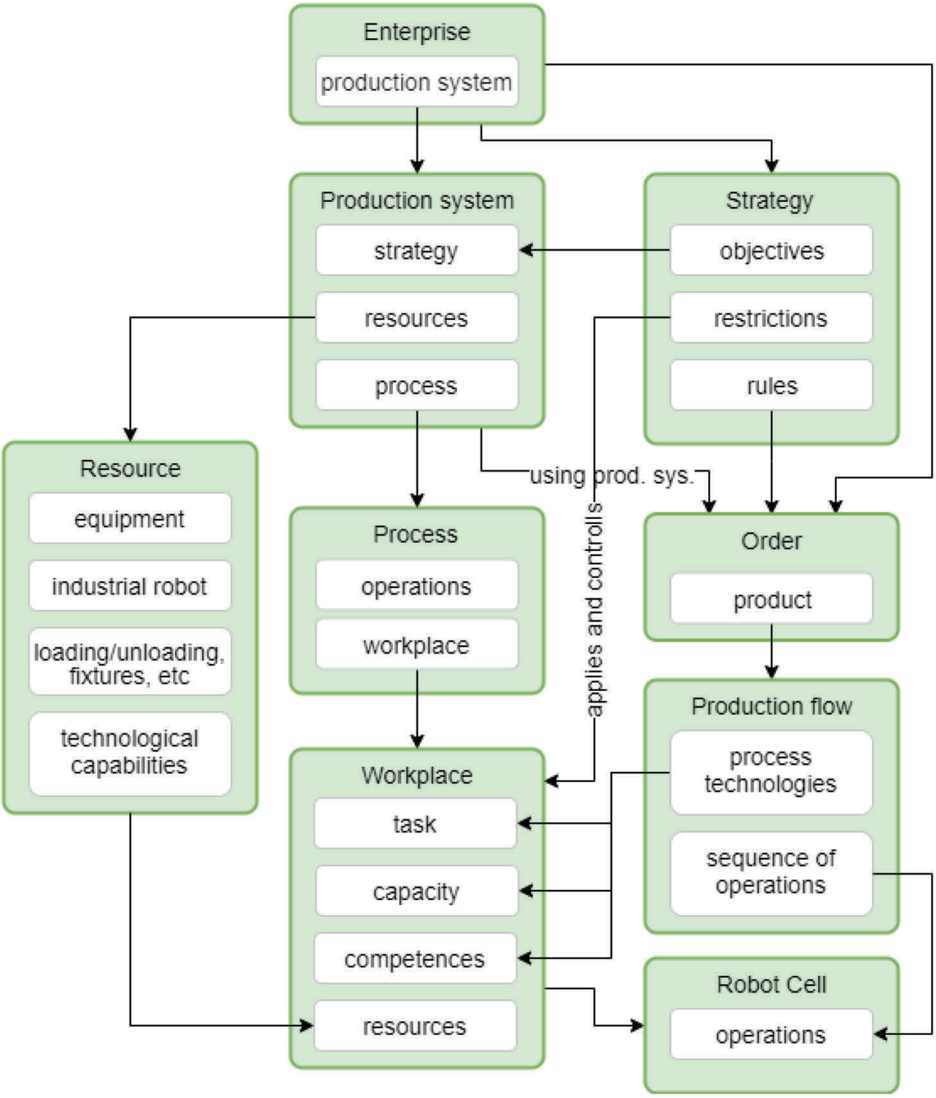


Figure 8. Robot Cell Utilization Ontology Model (Kangru, Otto, Riives, Kuts, & Moor, 2020).

Manufacturing efficiency depends on the suitability of the manufacturing system to the fulfilment of the company's strategy and the matching of the product portfolio with the technological capabilities of the manufacturing system, as well as the efficiency with which the company is using its resources to fulfill orders. Results depend directly on the quality of the decision-making process. Nowadays, in manufacturing, the DSS is used for complicated tasks like supply chain management (Cabral, Grilo, & Cruz-Machado, 2012) and the handling of used industrial equipment (Karaulova & Bashkite, 2016). A DSS (Burstein & Holsapple, 2008) is a computer-based information system that supports business or organizational decision-making activities, typically resulting in ranking, sorting, or selection from among alternatives.

A properly designed DSS is an interactive knowledge-based software system intended to help decision-makers compile useful information from a combination of raw data, documents, and personal knowledge, or business models to identify and solve problems (Sprague, 1980). DSS is generally a system built on mathematical algorithms and methods. The system can be entirely computer-based, operating in the background of the main processes, providing additional information to the decision-maker at the right time for decision-making, but it can also be a step-by-step methodology with the involvement of different tools. A combined system is most commonly used because of its ease of use, and at the same time, the user has complete control over the formation of the decision. Typical information that a decision support application may collect include the following:

- Historical data (inventory, sales, throughput, cycle times),
- Datafeed (current production flow data, OEE, OLE)
- Predefined parameters (production capacity, maintenance)
- Forecast (sales, inventory).

The whole planning system is based on a hierarchical decision-making scheme. Nodes represent decision centers. At those centers, elementary estimations are carried out. These elementary decision-making procedures are carried out on the basis of different mathematical methods and systems. These elementary decisions can not be in conflict with each other (Kangru, Otto, Riives, Kuts, & Moor, 2020).

Using the above, we can compile a decision support system. The system should have coordination levels which take care of elementary decisions, analyzes them, and provides the rules for further activities. That means modelling and optimization techniques are integrated with an expert system. The basic components of the system planning architecture are data storage, a decision-making mechanism, a knowledge base, and an interpreter. The last one is responsible for the following main activities: calling up the required solution module, analyzing the obtained results, generating rules and instructions in case of contradictions, issuing sorting and search commands to the database. The interpreter makes it possible to revise the problem-solving process. A modular architecture guarantees the flexibility of the planning system. The result would be obtained using different modules and models. The order of use of these modules must not be strictly determined. This kind of flexibility gives users a more extensive goal (Kangru, Otto, Riives, Kuts, & Moor, 2020).

2.2.1 Decision Making Methods

An expert decision-making system has been developed and used for human resources development, relying on required skills and knowledge. Such systems have been used in particular when the influence of human factors on productivity is large and the process is less automated (Riives, Otto, & Lõun, 2007). Possible methods for decision making in manufacturing applications are briefly discussed below.

Weighted Sum Decision Model

The Weighted Sum Model (WSM) is the simplest multi-criteria decision analysis method for evaluating alternatives using decision criteria. This method (Goh, Tung, & Cheng, A Revised weighted sum decision model for robot selection., 1996) assesses critical factors or performance values. In IR selection, those critical values are derived from three categories: the minimal environmental conditions, the minimal performance conditions, and the budget ceiling (Kangru, Otto, Riives, Kuts, & Moor, 2020). If the proposed solution meets all the requirements (critical values), this can be considered one alternative. The method relies on expert opinions to determine criteria weights, which can be summed in the decision matrices to rank alternatives.

Data Envelope Analysis

Data Envelope Analysis (DEA) is a performance evaluation or benchmarking method where performance is assessed against best practice. The DEA model consists of inputs, decision-making units (DMU), and outputs. Inputs and outputs are performance measures and may or may not be directly linked to the production process. DMUs are units under evaluation and are composed of performance metrics that characterize the units (Örkcü & Örkcü, 2011). DEA evaluates minimum inputs against maximum output (Kangru, Otto, Riives, Kuts, & Moor, 2020).

Analytic Hierarchy Process

Many decision support systems are based on the Analytic Hierarchy Process (AHP), which was developed for use in complex decision making in 1980 by Saaty. This method and its refined successors (Goh, 1997) (Reddy, Kumar, & Padmanabhan, 2015) are still in wide use due to their ability to deal with objective as well as subjective attributes efficiently. The method's first step is to build a problem hierarchy containing criteria whose importance is compared pairwise by different experts. The final step is obtaining and summarizing composite performance scores for alternatives and making a final decision. This method has been improved using Fuzzy numbers for linguistic expressions in the pairwise comparison of criteria (Ic, Yurdakul, & Dengiz, 2013) (Kangru, Otto, Riives, Kuts, & Moor, 2020).

A Technique for Order Preference by Similarity to Ideal Situation

The Technique for Order Preference by Similarity to Ideal Situation (TOPSIS) is a method that compares a set of alternatives by identifying weights for each criterion (Kangru, Otto, Riives, Kuts, & Moor, 2020). Scores are normalized for each criterion, and the geometric distance between the alternative ideal positive and ideal negative solution is calculated. The best solution is nearest to the ideal positive solution and farthest from the ideal negative solution. The method has been improved by using Fuzzy numbers for criteria analysis (Chu & Lin, 2003) .

Artificial Neural Network

The Artificial Neural Network (ANN) method has been used in many applications where real-world data variables are available (Yazgana, Borana, & Goztepe, 2009). ANN is a computing system that consists of nodes or artificial neurons connected like synapses to transmit signals from the input layer through one or more hidden layers to the output layer. The method's main advantages are the so-called learning effect from considering examples and the ability to work with a tremendous amount of data.

2.2.2 Advanced Analytics

Advanced Analytics (AA) is becoming vital to making so-called "best decisions" in modern manufacturing. AA enables companies to efficiently and effectively make both narrow and extensive data and modelling decisions and facilitate capitalization in short, medium and long-term activities. Support for the decision-maker involves an automated process with visualized output rather than manual spreadsheet calculations. AA can be divided into the following three computerized data processing analytic methods:

- *Descriptive analytics:* involves accounting and the analysis of historical data. This method is used in backcasting practices and forecasting of seasonal demands.
- *Predictive analytics:* considers near past data to predict future trends, biases, tendencies, behaviors, etc. using causation and correlation.

- *Prescriptive analytics:* finds or prescribes the best mode, route, manner, or moves to operate (outputs) based on given data and models (inputs). (Menezes, Kelly, Leal, & Le Roux, 2019)

The application of Advanced Analytics requires a sufficiently extensive database. By combining existing information gathered from MES and ERP databases with the effects of external factors, it is possible to use Advanced Analytics to extend a simulation model so that forecasts are as precise as possible. Potential application scenarios could involve the optimization of manufacturing parameters, predictive maintenance, available capacity or capacity needs prognosis, and process performance, among others (Groggerta, Elsera, HaoNgoa, & Schmitt, 2018). The analysis process itself is cyclical in nature and consists mainly of the following steps (Chapman, et al., 2020):

- Business understanding – objectives and requirements from a business perspective,
- Data understanding – data collection, data quality,
- Data preparation – construction of final dataset,
- Modelling – applying different modelling techniques. Some of the main methods used for modelling in this research are correlation, regression and prognosis,
- Evaluation – verifying the model and dataset,
- Deployment – presenting results in a form that can be used.

2.3 Manufacturing System Decision Support Systems

Different robot classifications, selection systems, and methods used for decision-making are defined in the following paragraphs. Designing a robotic cell and selecting the most suitable components, for example, an industrial robot (IR), end-effectors (EF), loading-unloading positions (LP), working tables (WT), transporting equipment (TR), etc. is a complex task entailing multi-criteria decision-making procedures. For the most part, decision-making means selecting the best type of industrial robot for performing a range of activities. These activities may include welding, painting, assembly, machine tending, inspection, grinding, polishing, or other manufacturing operations. Due to the dynamic nature of production processes and the ever-changing market conditions under which SMEs are operating, the adequacy of decisions taken may change over time. Therefore, decisions should not only be based on technological and economic parameters but also take into account real-life experience (successes and failures) in the industry.

2.3.1 Knowledge-Based Architecture

In the following chapter, Knowledge-based Engineering (KBE) is introduced. KBE is the application of knowledge-based systems technology in the domain of manufacturing design, production, and production planning (Halevi & Wang, 2007). Production systems (robot-cell) can be defined as a kind of cognitive architecture in which knowledge is represented in different forms. Thus, typically, a robot-cell as part of a production system is a complex system with a specific architecture. According to Scholz-Reiter, a physical hierarchical system should have three levels with various parameters (Benkamoun, ElMaraghy, Huyet, & Kouiss, 2014):

1. The system level – production can be defined as stations or cells which are usually linked with predicted storage and transport systems;
2. The sub-system level – a workplace is considered a pack of support resources for operations (e.g., robots and different devices);
3. The machine level – an environment to which different tools, grippers, data, and programs belong, as required by the equipment.

As previously stated, the physical hierarchical system is combined with components (e.g., a CNC machine or manipulator), each having the knowledge to configure and operate themselves. By storing these observations, skills, and expertise as knowledge and combining different levels and systems automatically, we can create a knowledge-based system.

2.3.2 Design Inputs

Manufacturing System Design (MSD) inputs are based on numerous parameters and variables from internal and external sources. The wide range of selectable variables makes it complicated to select the most vital ones (e.g., enterprise needs and objectives, controllable factors, constraints, and targets). A precisely described manufacturing vision and strategy and automated selection systems (Kaganski, Majak, Karjust, & Toompalu, 2017) can lead to a refined result in the design process. It is assumed that not all factors affect MSD directly.

The following factors are indicated as major parameters (Vaughn, Fernandes, & Shields, 2002):

- Market Uncertainty (MU),
- Product Volume (PV),
- Product Mix (PM),
- Frequency of Changes,
- Complexity,
- Process Capability,
- Worker Skill,
- Type of organization,
- Time to the first part,
- Investment,
- Available/Existing Resources.

MU can be defined as fluctuations in product demand. Demand affects manufacturing operations, creating an over or under capacity in the manufacturing system. Another important factor that is tightly connected with MU is Product Volume (PV). Maximizing PV has an impact on the physical design of the manufacturing cell, affecting factors like space required, machine selection, and layout. Furthermore, the MSD process certainly includes a level of flexibility that can be associated with Product Mix. If an extensive product mix is expected from the manufacturing system, production volume may be considerably reduced. On the other hand, not all the major parameters listed above facilitate the MSD process. For example, the size of investments is treated as a constraint and limits the choices available to designers. This can be connected with several variables, such as cost of implementation, payback period, or time needed for MSD. For investments, we can consider Available Resources to be a constraint on the design process. Available Resources, such as time, finances, existing technologies can limit the complexity which is expected of a designed manufacturing system. These crucial factors should be considered carefully when they become inputs for manufacturing system design and must be chosen according to the specific needs of the enterprise.

2.3.3 Performance Indicators

Key Performance Indicators (KPIs) should be considered a company vital sign, characterizing the actual situation and goal fulfilment. The use of these as a tool provides an opportunity to measure, analyze, make decisions, and keep production on track. They also help to identify bottlenecks in production and possibilities to increase the effectiveness of employees and machines and provide a way to monitor the progress of production orders. Today, KPI monitoring is a multi-level, real-time process that begins on the shop-floor and extends to company strategy, concentrating the information collected for higher-level KPIs. The selection of KPIs for different companies and different levels is generally a multi-criterion decision-making problem, and the choice must reflect the subject as accurately as possible. KPI selection problems have been addressed by earlier studies (Kibira, Brundage, Feng, & Morris, 2017), (Kaganski, Majak, Karjust, & Toompalu, 2017).

Solutions for SMEs have been developed to assess production unit performance (Mahmood, Lanz, Toivonen, & Otto, 2018), focusing mainly on the evaluation process: defining of the system, selection of KPIs, process modelling simulation, data collection, analysis, and real-time visualization. A hierarchical linking between KPIs through all levels has been mapped. The KPIs proposed for the SME production unit (see Table 1) are used in the upcoming simulation models. The hierarchy starts at the lowest level, where inputs are measured directly at the workplace or machine, and ends at the highest level, where outputs are usually calculated.

Table 1. KPI selection hierarchy (Kangru, Mahmood, Otto, Moor, & Riives, 2020).

Level	Performance Indicators
I Strategic	Utilization Overall Equipment Effectiveness Throughput Discounted Payback Period
II Tactical	Availability Performance Quality Planned Production Time Actual Production Rate Set-up Time vs Cycle Time Operating Time/Idle Time vs Cycle Time
III Shop-Floor	Total Products Produced Finished Products Rejected Products Activity Processing Time Operating Time Ideal Processing Time Total Run Time

2.3.4 Industrial Component Selection Systems

Factual selection of industrial components, e.g., industrial robots, CNC machines, and auxiliary equipment, can be defined as a multi-criteria decision problem. A general process flow can be seen in Figure 9. For the decision-making process, additional data, information, and knowledge are essential. The first step in solving the selection problem is always defining the objective function. In the case of the selection task, an objective function is almost always choosing the most optimal machine or equipment. Still, again it is always accompanied by restrictions due to the specifics of the company or production. Limitations are set by the company's strategy, development plan or production task. The second step consists of multiple sub-processes and decisions and is supported by the knowledge of an expert group. The contribution of the expert group can be gradually reduced over time, as decision-making activities are handed over to Artificial Intelligence with a Machine Learning capability. Such solutions have been proposed elsewhere (Castellano & Fanelli, 2000) (Chan, Jiang, & Tang, 2000).

In the second step, the process begins with the selection of criteria from among all possible criteria that best correlate with the initial task. Criteria can be divided into two main groups: objective and subjective. Possible criteria and the principles of selection have been explained elsewhere (Tahriri & Taha, 2011). For example, objective criteria for industrial robot selection can be IR velocity, load capacity, repeatability, and cost, while subjective criteria can be reliability, ease of programming, and the human-machine interface. The selection of criteria depends on the task that requires equipment. The accuracy of results mainly depends on successful criteria selection and their weight factors in general problem-solving. A hierarchy model is composed from the criteria selected; examples are discussed elsewhere (Goh, 1997), (Reddy, Kumar, & Padmanabhan, 2015). Again, this would be supported by an expert group or AI routines (Zhang, et al., 2010).

While the hierarchy is being established, each criterion is given a weighting to reflect its impact. This can be done by an expert group assessment using the Simple Additive Weighting method or by determining priorities from pair-wise comparisons (Goh, 1997), (Reddy, Kumar, & Padmanabhan, 2015); one solution is shown in the section Performance Analysis Case Study. Exemplary scales for a pair-wise comparison are shown in Table 2; an unbiased solution is more probable after adjustments are made for consistency.

Table 2. Pair-wise comparison scale assessment (Kangru, Riives, Mahmood, & Otto, 2019).

Importance	***Description***
1	Equal Importance
3	Moderate importance
5	Strong importance
7	Very strong importance
9	Extreme importance
2, 4, 6, 8	Values between two adjacent values should be in considerations
Inverse	If an activity (i) got the point compared with activity (j), then (j) has the opposite value compared to (i)

Almost all mathematical multi-criteria decision support systems can be adopted to support selection problem-solving. Some of the methods used have been discussed above. The ranking performance of different techniques has been presented elsewhere (Tahriri & Taha, 2011), (Athawale & Chakraborty, 2011) and (Saha, 2015).

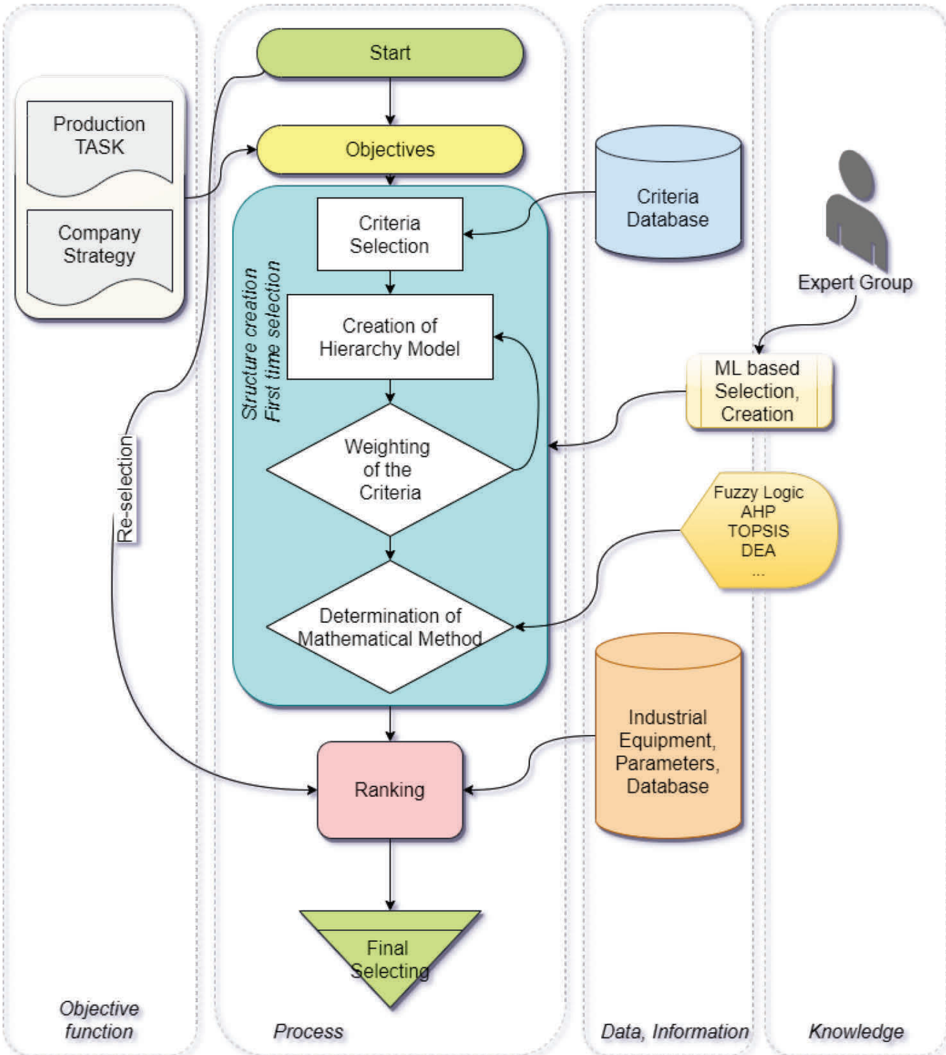


Figure 9. Industrial Component Selection System Architecture.

After the problem-solving structure is completed, parameters relevant to equipment selection are inserted in the ranking process, and the system ranks all the alternatives. Based on the ranking generated, according to the calculated score, the final decision can be made. After the first successful ranking, the system is easy to use in re-selection without the input of an expert group. This is only true as long as the objective function does not change.

3 Research on Intelligent Manufacturing Cell Structure Development

The following chapter provides an overview of robot manufacturing cells implemented in Estonia, analyzing their complexity, required competencies, and automation and intelligence levels. Decision-making procedures and Decision Support Systems for manufacturing cell design is further discussed. Finally, robot integrated cell design methodology and methods are proposed.

Modern manufacturing systems have evolved into complex ecosystems. Digital manufacturing and smart factories are becoming the norm in manufacturing. They depend on the leveraging of connected devices and technologies, numerically controlled machines and robots, advanced analysis with artificial intelligence, IoT, digital twins, advanced planning, and control capabilities, which operate through the entire value chain. In addition, these devices must be capable of sensing their environments and interacting with one another. Simulations using digital twins is a technology which makes it possible to decrease the time to design manufacturing systems and acquire information for decision-making in performance analysis. Development tools related to I4.0, such as advanced simulation, have proven to be of great importance in industrial applications. Hence, there is a need and demand for digital solutions for a production SME; these would aid the effective use of technologies implemented and resources involved. However, there is a lack of studies that offer and develop specialized digital solutions for production SMEs; this needs to be addressed comprehensively.

3.1 Current Situation Analysis

Currently, manufacturing is moving towards greater complexity, larger-scale integration, digitalization, and flexibility. All this began with the introduction of Cyber-Physical Systems (Gunes, Steffen, Givargis, & Vahid, 2014). Such a smart system is represented by industrial robots and robot-based manufacturing cells. Since 2010, the demand for industrial robots has accelerated considerably due to the ongoing trend towards increased automation and integration (International Federation of Robotics, 2017).

Industrial robots are now used in a wide range of manufacturing processes, such as welding, assembly, loading-unloading, palletizing, logistics, painting, etc. The problems encountered when implementing robot-cells in companies are the same: how to achieve the best results with limited resources – high productivity, low manufacturing cost, high product quality, and smooth integration into the production system. Typically, there are many different possibilities for improvement when implementing robot-cell applications. But the efficiency of a manufacturing cell can be measured by the expected results, such as cycle time, unit cost, cell productivity, and return on investments.

Therefore, a harmonized knowledge-oriented approach is needed to address the complexity and performance of production systems for decision-making enhancement. This led to the conclusion that a more in-depth study of the current situation in the manufacturing industry should be carried out.

3.1.1 Robot Integrated Manufacturing

Robot integrated manufacturing uses an industrial robot to perform machining, handling finalizing, inspecting or other work operations (Nof, 1999). A study was performed at the end of 2017 to determine the utilization of industrial robot-based manufacturing cells in Estonia. The goal of the study was to compare production cell design objectives to achieved KPIs. The study was carried out by interviewing executives from different company management levels (production managers, R&D engineers, and setup technicians). Where available, data were collected from the MES system implemented, and cell layout with technological capabilities was mapped.

Information was gathered in four main areas: company profile and strategy, cell layout and equipment, manufactured products, and process data. Documented shortcomings and improvements performed were recorded. Performance was assessed using the following parameters: setup-, cycle-, operational-, rework-, and maintenance times, personnel required, lot size, repeatability, and the total number of products. Throughput, cell utilization, and OEE were calculated and compared with cell design goals (Kangru, Otto, Riives, Kuts, & Moor, 2020).

8.5% of the companies participating in the survey belonged to the micro-enterprises group with a turnover of less than 2 million euros and a staff of around ten persons, 31.5% were small enterprises, and 59.6%, the majority, belonged to the medium-sized enterprises group. The companies were mainly located close to Estonian industrial centers (Tallinn, Tartu, Pärnu), and it can be assumed that this had a strong impact on the results. Some of them produced their own branded products, others were doing contractual work, but the majority did both. Products produced included different parts for agricultural and forestry machines (frames, grippers, and crane booms), small tractors, high-speed train and lift components, wind generator rotors, and sheet metal products.

In 58% of the cases, work was organized into two shifts, in 23%, there was a one shift workday, and in 19%, there were three shifts. 64% of the robot-based manufacturing cells, the majority, were welding cells, 22%, CNC machine tending cells, and 14%, material handling cells. The first cell was implemented in 2008, and the process of implementing last one was still ongoing. The total investment was between 50 thousand to 450 thousand euros (without taking inflation into account). Lot size and distribution are shown in Figure 10, and lot repeatability, in Figure 11.

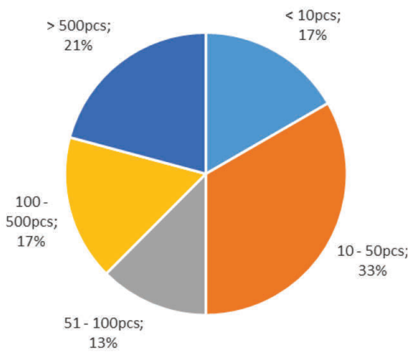


Figure 10. Lot sizes (Vaher, Kangru, Otto, & Riives, 2019).

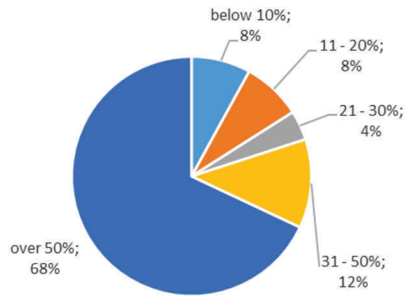
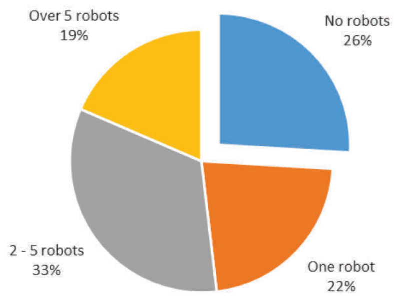


Figure 11. Repeated lot probability (Vaher, Kangru, Otto, & Riives, 2019).

55% of the companies stated that they had already implemented one to five industrial robots in their production process, as shown in Figure 12. Companies using only one IR robot in their production process provided feedback on the introduction of robotization in their company. The robotized processes and prognosis for planned processes in the coming three years is shown in Figure 13.

In total, 18% of manufacturing companies in Estonia were reported to be already using industrial robots, and 18% were planning to invest in industrial robots over the following two years (Swedbank Research, 2019).



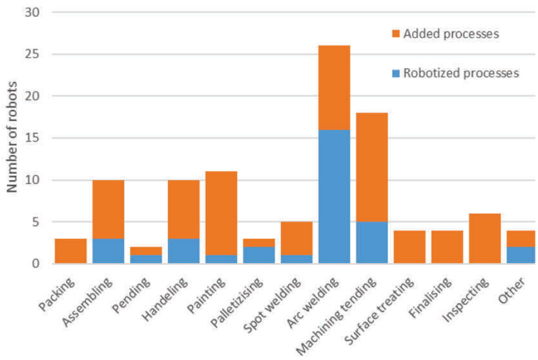
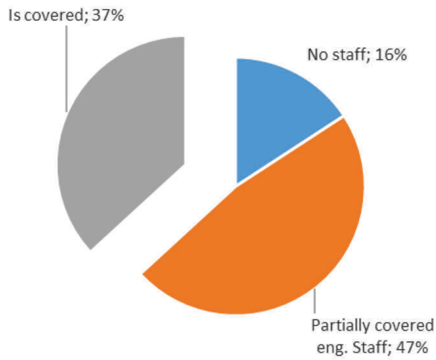


Figure 12. Industrial robots in use for manufacturing (Vaher, Kangru, Otto, & Riives, 2019).

Figure 13. Robotized processes and 3-year prognosis (Vaher, Kangru, Otto, & Riives, 2019).

The second part of the survey focused on workforce competencies, availability, and relocation within the company. When assessing the current situation in the workplace, 63% of the executives stated there was no staff or positions were only partially covered, as shown in Figure 14. This could become a determining factor in the development of new and highly complex production cells and their exploitation in the future. According to demographic trends, the workforce age 20-60 is expected to decrease by over 160 000 workers over the next 20 years (Priits, 2018). There will be a shortage of skilled workers: welders, operators, setup engineers, and assembly workers. The prognosis of the executives for skilled workforce demand can be seen in Figure 15.



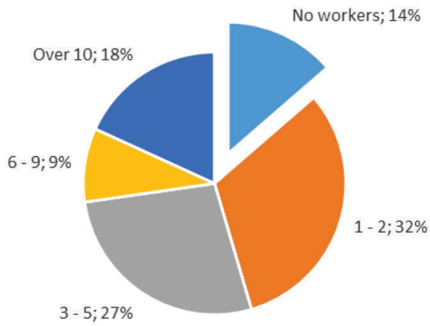


Figure 14. The presence of engineering staff.

Figure 15. Demand for workers, developed production cells.

3.1.2 Analysis

Although investments in machinery and R&D have increased by over 4% each year over the last five years (Statistikaamet, 2020) (Statistikaamet, 2020) and Estonia has held a high ranking in the Digital Economy and Society Index (DESI), with an index value of over 60 (European Commission, 2020), the number of IRs implemented in industry is still low. According to the International Federation of Robotics, Estonia has implemented 11 industrial robots per 10 000 employees. This is well below the European Union average of 115 units (International Federation of Robotics, 2018). In this light, the robot-based production units implemented in industry were then examined.

Economic input parameters were chosen that best described the goals set by the company or department managers. Among the parameters chosen were Net Income, Net Operating Profit, Cost per Hour, and Discounted Payback Period. A goal achievement analysis was then performed. Cell utilization, investment value, and overall goal fulfilment were mapped (see Figure 16) and compared, and production cell design objectives were once again assessed.

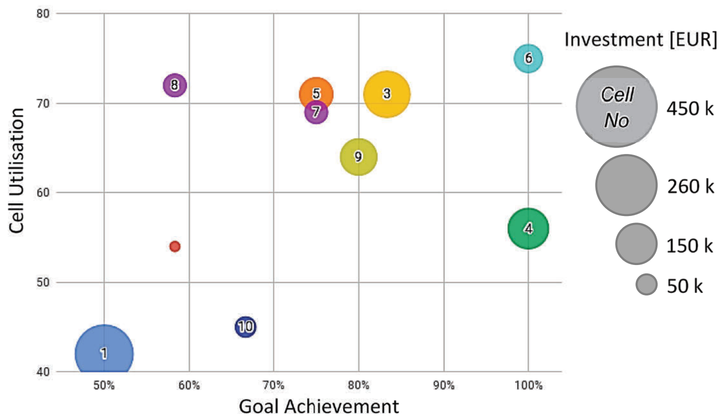


Figure 16. IR integrated production cell design goal fulfilment (Kangru, Otto, Riives, Kuts, & Moor, 2020).

As a second step, a wider analysis was performed to assess production cell intelligence, automation, and engineering competence levels using the categorical framework of manufacturing (Qina, Liua, & Grosvenora, 2016). This analysis shows the current state of production cells in comparison with global manufacturing trends (see Figure 17). This knowledge can also lead to the steps needed to improve manufacturing and make the leap to Industry 4.0 principles.

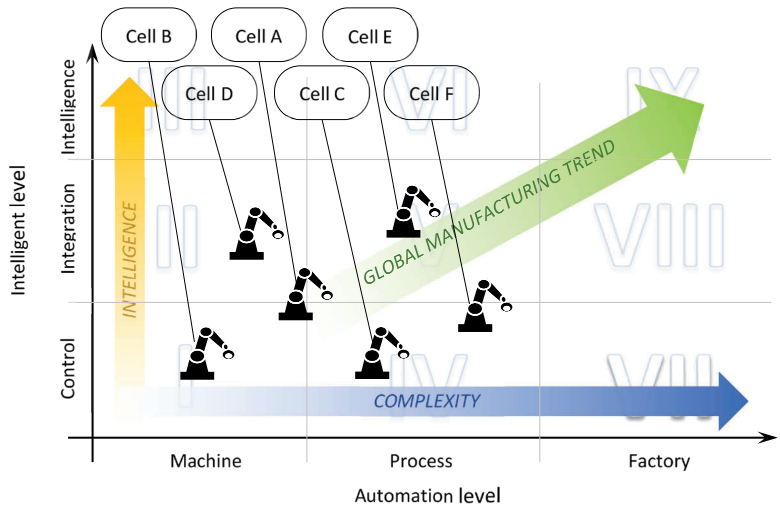


Figure 17. Production cell state in manufacturing categorical framework (Kangru, Otto, Riives, Kuts, & Moor, 2020).

3.1.3 Robot integrated production cell complexity and competence

Analyzing the data gathered from the survey, we get a picture of the current state of manufacturing industry robot integrated production cells, with regard to cell complexity and required competencies (see Figure 18). On the Genefke scale, which was developed by the Danish Technological Institute (Danish Technological Institute, 2020), robot integrated production cells are divided into five categories:

- Standard – Developed and thoroughly tested solutions with only one industrial robot performing a single task.
- Adapted standard – Developed and tested solutions with one or more robots performing a process.
- Special solution – The solution is specially developed to meet the company's needs. No exact solutions are present. Multiple robots with overlapping work zones, auxiliary equipment, and sensor inputs are used.
- Applied research – The robotization of complicated processes, where specific research is needed to complete the solution.
- Research – Long term technical development with a vision for the future.

58% of the production cells implemented were rated as level two – adapted standard. This was predictable due to the high number of modular welding cells in the industry. The prediction, according to Figure 13, shows growth at the special solution level, as the robotic processes planned to be implemented over the following three years would have to be integrated with the company's existing systems, such as machine tending and inspecting. Because no integrators, competence centers, or universities were included in the survey, level four and five were not identified.

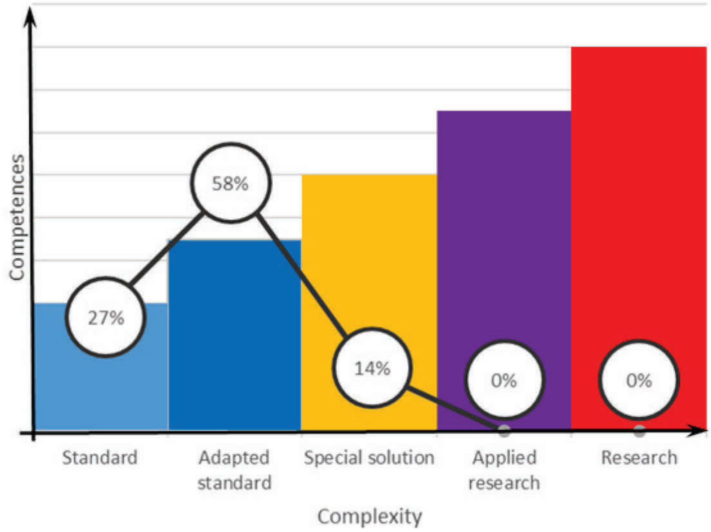


Figure 18. Production cell rating according to the Genefke scale (Vaher, Kangru, Otto, & Riives, 2019).

3.2 Decision-Making Procedure

In this section, a decision-making procedure and its substeps are explained, and this is followed by explanations of the knowledge-based robot-cell model structure.

An understanding of company strategy, management, and technology in manufacturing can lead to the main principles and decision-making rules (Kodua, Brown, Darlington, & Svetan, 2012) for the optimal selection and utilization of industrial robots and equipment. For decision-making, the following criteria are typically used (Kangru, Riives, Otto, Pohlak, & Mahmood, 2018):

- Increase in productivity
- Reduction of production costs
- Improvement of the working environment
- Increase in the security of supply
- Quality assurance
- Workforce insurance
- Increase in flexibility
- Stock depreciation

According to robot-cell development and behavior ontology, two decision-making circles or loops are proposed to achieve the desired goals and objectives. The design loop and implementation loop shown in Figure 19 are used to ensure the most optimal solution. The task of the design loop, as the primary task, is to check the robot's architecture and technical parameters, to be sure they are best suited for a selected job. The task of the implementation loop, as the secondary task, is to analyze the optimal utilization of the robot-cell implemented in a company. Based on the data analyzed in the secondary task, we can estimate the accuracy of the direct decision.

The best solution may not be immediately apparent because of contradictory criteria. To overcome this issue, the following tools are applied in the design and implementation loops (Kangru, Riives, Otto, Pohlak, & Mahmood, 2018):

- *Requirement analysis* is defining the technological capabilities of an industrial robot and the robot-based cell. For example, what kind of equipment could be used and what parameters are most suitable for the given industrial task?
- *Functional analysis* is based on simulation software like 3D simulation technology that would be able to describe the real production process: execution possibilities, possible bottlenecks, and alternatives with efficiency estimations.
- *Behavior analysis* is a reflection of real industrial applications. Using data obtained from different real cases, it is possible to compare the best solution description. The theoretically most suitable industrial robot is identified, and the behavior of the selected IR is observed under real industrial conditions.

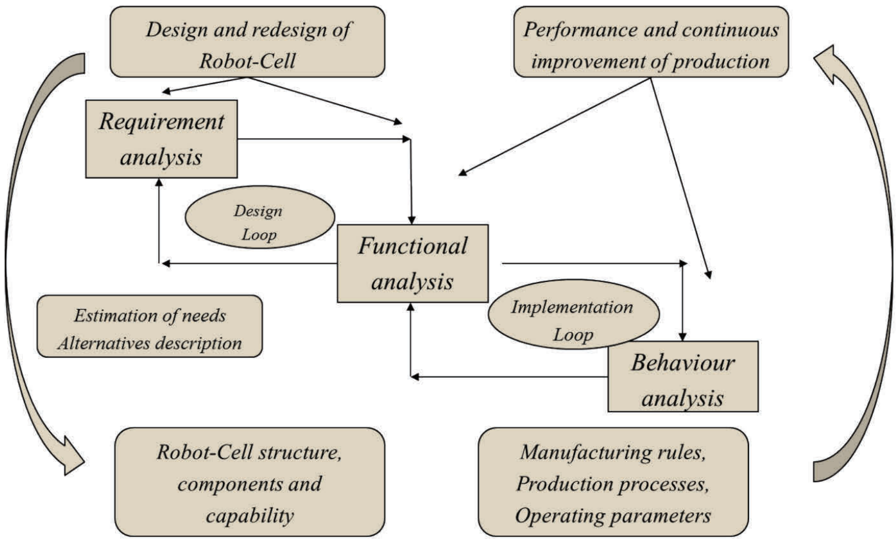


Figure 19. Recursive decision-making procedure (Kangru, Riives, Otto, Pohlak, & Mahmood, 2018).

3.2.1 Knowledge-based Manufacturing Cell

For the development of a conceptual model for the robot-cell, we considered a knowledge representation that would allow the decision support system to act intelligently. An intelligent decision support system must work as a professional consultant, giving explanations for decisions made, analyzing evidence, identifying and diagnosing problems, presenting possible cases for improvement, and evaluating the alternatives.

However, the implementation of a decision support system is not something new. DSSs have been used for different engineering tasks, like the design of flexible manufacturing systems. All the problems of decision-making lie in the information and how we use it. Here the novelty derives from the integrated multi-access model and decision-making logic. A wide range of IoT applications, cloud computing, big data, and data analytics instruments have recently led to possibilities for developing intelligent decision-making systems, where the expert system plays a significant role. Essential to the development of such tools is the primary decision-making model with data acquisition and knowledge representing principles, as shown in Figure 20. This event-driven conceptual model was generated by analyzing the robot-cells of real industrial companies and their manufacturing processes.

This model has four independent interacting entities (Kangru, Riives, Otto, Pohlak, & Mahmood, 2018):

- *Production task description entity* – The main components are product model (CAD), task model (ORDER), and process model (CAPP).
- *Robot-cell description entity* – This part formed a robot-cell design model. The DSS software helps to select the components and form the structure of a robot cell.
- *Task performance analysis* – Based on the parametrical model of performance description and model for the optimal selection of KPIs.
- *General output description* – Shows how the company has managed in general (turnover, profit, etc.) and reflects the implementation of a robot-cell in the manufacturing process through OEE, ROI, etc.

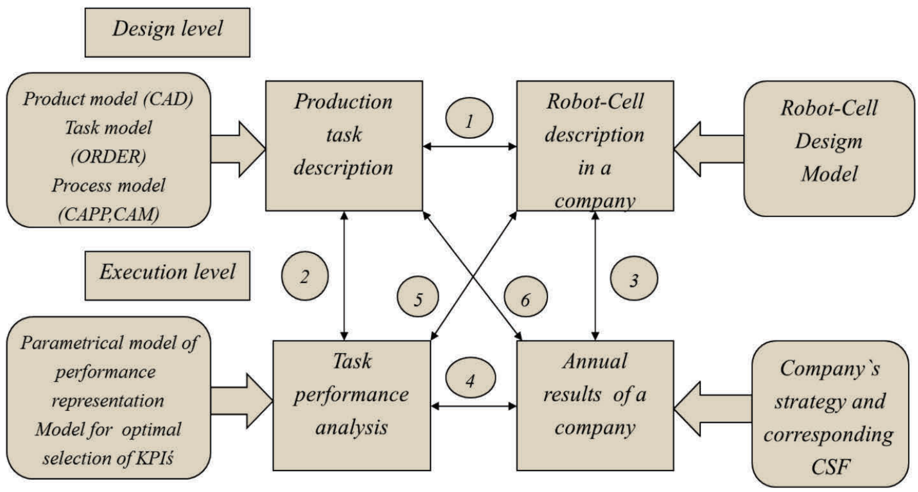


Figure 20. Knowledge-Based Robot-Cell Model (Kangru, Riives, Otto, Pohlak, & Mahmood, 2018).

The model has two levels:

1. The design level (primary task), which is planned for decision-making. Here the best correlation between products to be manufactured and robot cell parameters would be determined. The design parameters are shown in Table 3. This level gives the primary answer to the question of parameters for the robot-cell.
2. The execution level (contrary/reverse task) is based on the practical experience of using robot-based manufacturing systems. Here actual data from manufacturing are collected using MES or other possibilities. Based on this data, the elements for evaluation and analysis would be determined, as shown in Table 4. The data for performance analysis is essential and would also provide feedback on the quality of decisions to the first level.

Table 3. Design parameters general description (Kangru, Riives, Otto, Pohlak, & Mahmood, 2018).

Product features	Robot-cell features
Product portfolio	No of robots in a robot-cell
Product mix	Industrial robot technical parameters
Quantity per year	Type of end effector(s)
Order fulfilment time	Sensors needed
Product parametrical description (CAD model)	Turning table(s) parameters
The purpose of the product (Functional model)	Loading-unloading position parameters
Production process description (CAPP model)	Transport devises parametrical description
Operation description (CAM model)	

Table 4. General description of execution parameters (Kangru, Riives, Otto, Pohlak, & Mahmood, 2018).

Elements of evaluation	Elements of analysis
Order Fulfilment time	Use of working time
Manufacturing ratio of order Fulfilment	Main reasons for non-productive work
Cycle Time ratio of Throughput	Level of achieving the objectives
Machining Time ratio of Cycle Time	Index of employee competences
Loading and unloading Time ratio of Cycle Time	Contribution of an employee as a team member
Setup Time ratio of Cycle Time	Dynamics of effectiveness (changes and improvements in the production process)
Idle Time ratio of Throughput	Cost factors and their dynamics in production process
Idle Time ratio of Fulfilment Time	Quality assurance
	Robot-cell technological capabilities exploitation
	The robot-cell functionality correspondence to the industrial tasks

3.3 Decision Support System for Manufacturing Cell

In this section, a performance evaluation model and an evaluation method for the decision support system are proposed.

Over the years, many decision support systems (DDSs) have been developed (Athawale & Chakraborty, 2011) to help decision-makers select the most functional and cost-effective production cell equipment. The complexity of the selection problem is related to economic, technical, and social attributes, which are interconnected and may change in time. Economic attributes are likely to depend on the market situation and the enterprise's investment certainty. Both parameters are difficult to fix and predict. On the other hand, technical parameters are readily available from machine datasheets and are easily compared. A DDS should consider both qualitative and quantitative factors while selecting and evaluating the correct solution. Some of the methods used in DDSs are discussed below.

3.3.1 Performance Evaluation

For manufacturing processes, the Performance Evaluation Model (PEM) was developed, as shown in Figure 21. The PEM is in correspondence with the conceptual model described in Figure 20. The model facilitates a practical analysis of the suitability of robot-based manufacturing cells and the execution of the planned task (nomenclature of products, amounts of production, etc.).

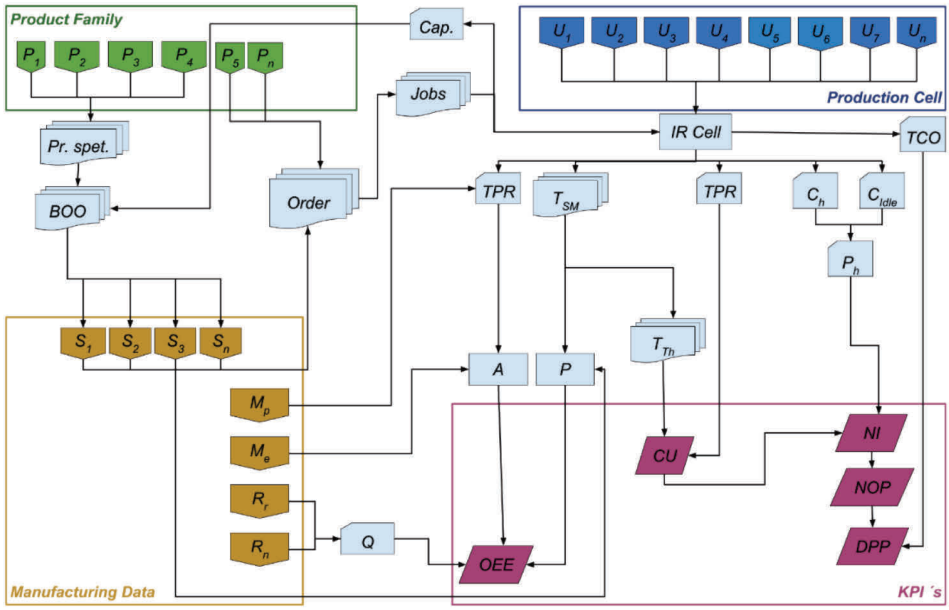


Figure 21. Performance Evaluation Model (Kangru, Riives, Otto, Pohlak, & Mahmood, 2018).

The model aims to understand the performance of a manufacturing cell when carrying out a particular task. There are two input modules, the product family module and the production cell description module, one manufacturing data module, and an output data module (a KPIs module). To evaluate cell technological capacity and economic profitability, a set of key performance indicators were selected based on literature reviews (Kaganski, Majak, Karjust, & Toompalu, 2017), as defined in the KPIs module of the PEM. OEE, CU, DPP, NI, and NOP are the outcomes used to determine the performance of production cells chosen for the case studies.

The modules make it possible to understand the correlation of input data with output data and determine dependencies between input data and output data. These are then used to develop knowledge-based decision-making rules to be used in manufacturing cell design and operating processes.

The model can be formulated mathematically as a multi-criteria optimization problem. The objective functions considered are as follows (Kangru, Riives, Otto, Pohlak, & Mahmood, 2018):

$$\max F_1(\bar{x}) \text{ - net income (EUR),} \tag{1}$$

$$maxF_2(\bar{x}) \text{ - net operational profit (EUR),} \tag{2}$$

$$maxF_3(\bar{x}) \text{ - overall equipment effectiveness (\%),} \tag{3}$$

$$maxF_4(\bar{x}) \text{ - usage factor (\%),} \tag{4}$$

$$minF_5(\bar{x}) \text{ - payback period (years).} \tag{5}$$

The functions have different units and range and should be normalized by applying the following equations:

$$f_i(\bar{x}) = \frac{max\,F_i(\bar{x}) - F_i(\bar{x})}{max\,F_i(\bar{x}) - min\,F_i(\bar{x})}, \tag{6}$$

$$f_i(\bar{x}) = \frac{F_i(\bar{x}) - min\,F_i(\bar{x})}{max\,F_i(\bar{x}) - min\,F_i(\bar{x})}. \tag{7}$$

In Eq. (6) and Eq. (7), $\bar{x}$ is the design variables vector, and the values $maxF_i(\bar{x})$ and $minF_i(\bar{x})$ are estimated values for the function maximum and minimum, respectively. Equations (6) and (7) are applied to objectives subjected to maximization ($F_1(\bar{x}), F_2(\bar{x}), F_3(\bar{x}), F_4(\bar{x})$) and minimization ($F_5(\bar{x})$), respectively. As a result, the normalized objective functions $f_i(\bar{x})$ are in the range [0;1] (though they may slightly exceed the limits of the interval [0;1] since $maxF_i(\bar{x})$ and $minF_i(\bar{x})$ are estimated values). Furthermore, all non-dimensional objectives are subjected to minimization, i.e.

$$f(\bar{x}) = (f_1(\bar{x}), f_2(\bar{x}), f_3(\bar{x}) \ldots, f_5(\bar{x})) \to min. \tag{8}$$

The objectives considered are not conflicting (this can be verified by performing a pairwise analysis of the objectives). Thus, the objectives can be combined into one by applying a weighted summation technique (in the case of conflicting objectives, it is justified to apply a Pareto analysis). Thus, the configuration/type of production cell f_c can be expressed as

$$f_c = \sum_{i=1}^{N} c_i f_i\,(\bar{x}) \to min. \tag{9}$$

In Eq. (9), $N=5$, the number of objectives, and c_i stands for the weight of the objectives, as determined by the particular company/problem being considered. However, the main impact factors for the objective functions are determined on the basis of the analysis performed in the companies. Those impact factors are divided into the following three groups:

- Product Family inputs,
- Manufacturing Data inputs,
- Production Cell inputs.

The effect of each subfactor on the objective functions f_i may be derived from the production data or estimated by experts based on the production data (system and process specifications) and experience (in the case of cell type selection before the production process). To take into account the three groups of impact factors, the objective function (9) can be completed as follows:

$$f_c = \sum_{i=1}^{N} c_i f_i \sum_{k=1}^{M} W_k \sum_{j=1}^{G_k} w_{ikj} \rightarrow min. \quad (10)$$

In Eq. (10), $M=3$, number of groups, $W_k (k=1,2,3)$ is the weight of a group (in different companies, the importance of a group may be different), G_k is the number of subfactors in group k, and the weight w_{ikj} describes the effect of subfactor j in group k on objective f_i.

The multi-criteria optimization problem considered is a constrained optimization problem with limits on different resources (time, technology, etc.) and design variables

$$r_l^{low} \leq r_l(\bar{x}) \leq r_l^{up}, (l = 1 \ldots L). \quad (11)$$

Where r_l, r_l^{low}, and r_l^{up} stand for the resource, its lower limit, and its upper limit, respectively.

3.4 Robot Integrated Manufacturing Cell Design

A multi-stage robot integrated manufacturing cell design evaluation process has been developed (Kangru, Otto, Riives, Kuts, & Moor, 2020), as shown in Figure 22. The process is a recursive decision-making procedure, as shown in Figure 19. The process structure is derived from the knowledge-based robot cell model shown in Figure 20. Three decision-making tasks are integrated in the process (shown in red in the figure). If the input data output does not fulfil the task objectives, the previous loop will be executed again. Two distinct loops are built into the process: a design loop and an implementation loop. The design loop is performed at the knowledge-based robot cell model design level, and the objective is to ensure that the robot's architecture and technical parameters are best suited for a selected job. The implementation loop is performed at the execution level, and the objective is to assess the optimal utilization of the implemented robot-cell in a company.

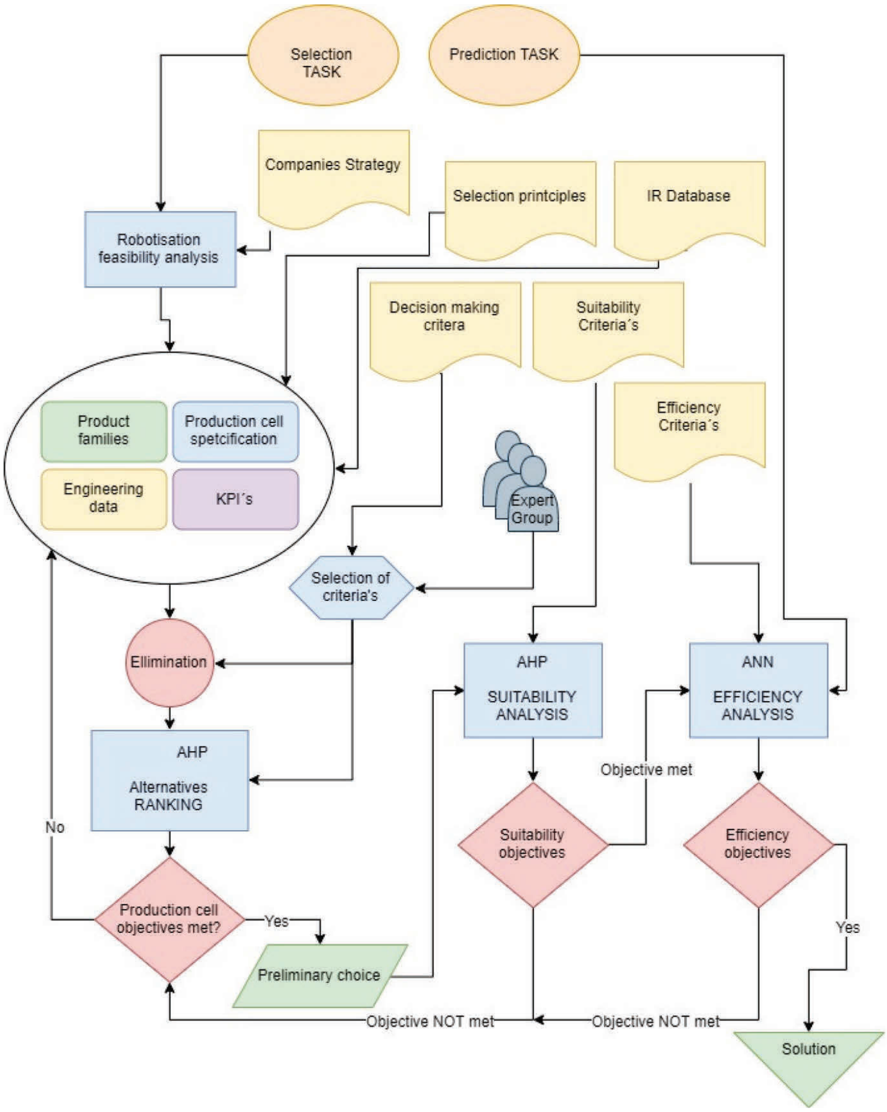


Figure 22. Proposed DSS General Model (Kangru, Otto, Riives, Kuts, & Moor, 2020).

As shown in Figure 19, the design loop consists of a requirements analysis and functional analysis. The aim of the requirements analysis is to define the kind of industrial robots, CNC machines, jigs, and fixtures that should be used for the selected production task. In the requirements analysis, all possible combinations are included. Prior to the functional analysis, an elimination cycle is performed. Only the most promising combination of equipment is selected and passed on to an alternative selective block (shown in blue in Figure 21). The task of the functional analysis is to add all the necessary setup conditions and cycle times to the solution selected. Part of the functional analysis is performed in the suitability index calculation block.

The last analysis module is a behavioral analysis, which includes an efficiency analysis. The behavioral analysis is performed according to the production cell performance evaluation model shown in Figure 21. The goal of the evaluation is to assess the performance of the robot integrated production cell according to the KPIs selected. The KPIs may vary, depending on the company or particular production cell.

3.4.1 Feasibility Analysis

The main task of the feasibility analysis is to ascertain whether robotization in a company is practical or not. To attain the feasibility estimation, an index calculation algorithm with the following criteria should be iterated:

- Increase in productivity,
- Reduction of production costs,
- Improvement of the working environment,
- Increase in the security of supply,
- Quality assurance,
- Workforce insurance,
- Increase in flexibility,
- Stock depreciation.

For each of the above-mentioned criteria, a specific questionnaire is composed and answered by relevant company staff. The relative priority of the attributes should differ in different companies. The superior solution is shown in equation (12), where the list of criteria attributes *Ki(i=1, 2, …,m)* and each criterion Ki has a list of factors *Fj(j=1, 2, …, n)* having a certain weight factor βi.

$$F(Ki)_{max} = \sum_{i}^{m} \beta i \left(\sum_{j}^{n} Fj \right) \tag{12}$$

One possible application is shown in Figure 23. The application uses a selection of fifteen questions divided into three groups to assess the feasibility of robotization in the company. The application was developed and tested together with IMECC (Kangru & Riives, Robotiseerimise otstarbekus, 2018).

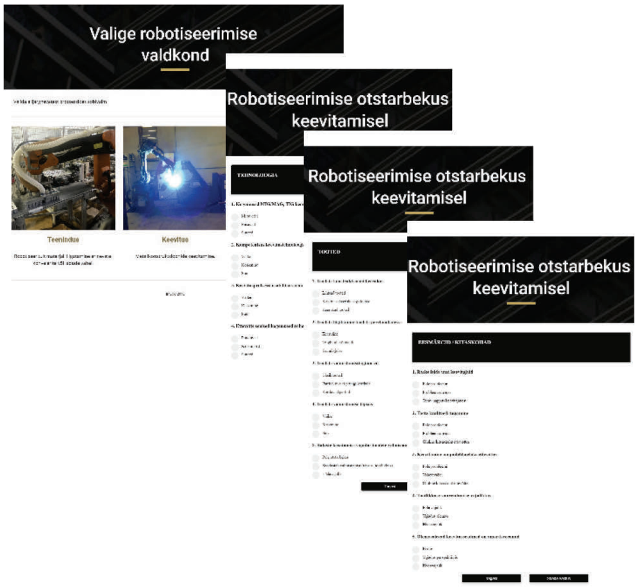


Figure 23. Feasibility analysis application (Kangru & Riives, Robotiseerimise otstarbekus, 2018).

The estimation is calculated using equation (12). One possible result is shown in Figure 24.

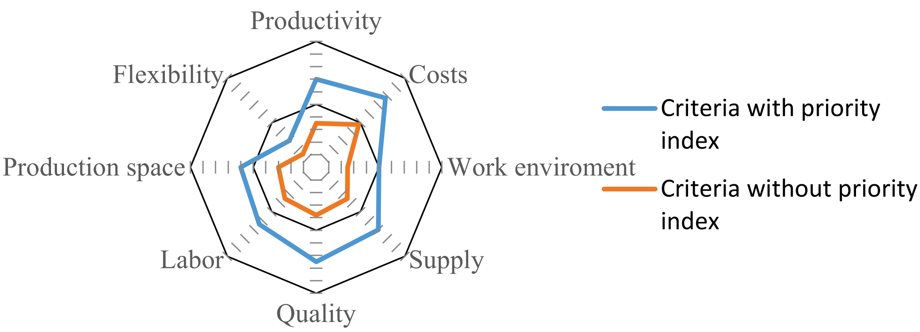


Figure 24. Feasibility analysis results (Kangru, Otto, Riives, Kuts, & Moor, 2020).

The higher the feasibility index, the sum of all criteria, the greater the real need to implement industrial robots in the production process of the given company and the more effective this implementation will be. As there is a limited number of questions for each criterion for index evaluation, this analysis can give only a general picture. For a more exact solution, further investigation is necessary.

3.4.2 Suitability Analysis

The suitability analysis is based on the task description (Kangru, Otto, Riives, Kuts, & Moor, 2020). Using the task description, a set of required parameters and requirements for an IR is determined. This set is formed based on the technological capabilities of an IR that are crucial for fulfilment of the industrial task. This new set would be compared with a set for an existing well-proven robot integrated production cell. The largest common part will give the best result.

An AHP based suitability analysis method uses product, technology and objective parameters to derive the cell suitability index. The knowledge of an expert group has been used to evaluate application-based criteria. In the future, an ANN-based prediction model together with fewer experts can be used to evaluate application-based criteria (Yazgana, Borana, & Goztepe, 2009). In this study, an IR welding application model was used. The indexes calculated were compared with the main suitability decision categories for final assessment.

The main concern of the suitability analysis process is to find the best solution according to the set of criteria, using a method which allows the most realistic input (weight) for each criterion. There are different ways to influence the role of criteria, i.e., using the equal weight (EQW) heuristic or the weighted additive (WADD) rule. However, the main risk is in overestimating the importance some criteria or not paying enough attention to others (Pfeiffer, 2011). Therefore, artificial intelligence (AI) methods may be used (Zhang, et al., 2010).

When analyzing robot welding applications, three general groups of criteria (shown in Table 5) were developed. The criteria listed have the greatest influence on the suitability of using welding robots in the company. Having knowledge of the welding process and its parameters makes the welding process more efficient.

Table 5. Suitability criteria for robot welding (Kangru, Riives, Mahmood, & Otto, 2019).

Product view	***Technology view***	***Objectives' view***
1. The products are complicated from the technology point of view.	1. Experiences in MIG/MAG and TIG welding.	1. To shorten the throughput time.
2. The products can be classified into product families.	2. Competences in welding technologies.	2. To increase productivity in the workplace.
3. The products are produced in repeatable batches.	3. Welding processes play a very important role in the company's production processes.	3. To improve product quality.
4. The products are of high quality.	4. Experience in robot welding already exists.	4. To increase the precision of delivery.
5. It is necessary to use welding fixtures.	5. It is necessary to increase the productivity of welding processes.	5. To reduce product cost.

Several criteria should be used to decide on the suitability of welding robots implementation in the company. Multiple criteria are listed in Table 5. Each decision corresponds to a variable, relation or predicate, whose possible values are listed among the condition alternatives.

3.4.3 Efficiency Analysis

The efficiency analysis evaluates the designed or installed solution on the basis of the best competences. For an adequate estimation of production unit manufacturing efficiency and assessment of production unit process failures, the whole system, its components, and their relations must be evaluated (Lõun, Laavin, Riives, & Otto, 2013), (Mahmood & Ševtšenko, 2015).

A computerized performance assessment of a production unit based on the (Mahmood, Otto, Kuts, & Kangru, 2020) methodology, the objectives set in the company's strategy and industry-based collected production data can be seen in Figure 25. The proposed system evaluates a company production process by comparing it with an ideal process set up in the proposed model. In addition, it is a useful tool in the design phase of a new production unit, as it allows us to assess productivity based on collected production data. The efficiency analysis is divided into three steps, as shown in Figure 25, where each step increases the accuracy of the selection. In the first step, production type, production volume, and production technology are determined for the designed or redesigned cell. Inputs for this step are design rules and constraints (Vaughn, Fernandes, & Shields, 2002). At the end of this step, general requirements for the production unit have been determined. In the second step, a simulation model is created according to the selected rules and constraints. Different scenarios are inserted into the developed model, and an optimal scenario or scenarios are selected. At the end of this stage, a parametric model of the cell has been developed. The model is then used to simulate technical-economic results. In the last step, a 3D simulation model is created based on the information provided earlier, and the most accurate results using different layouts and settings are acquired.

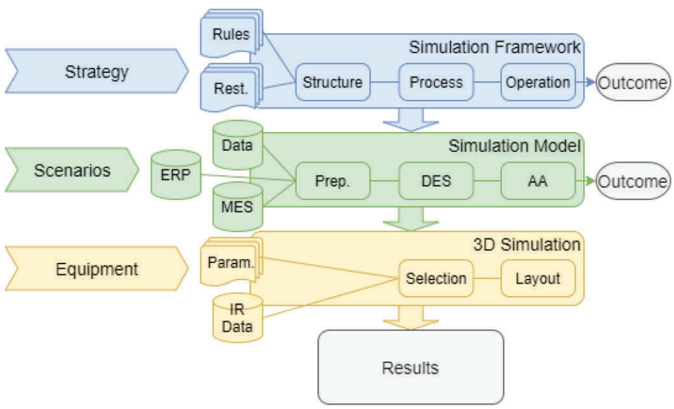


Figure 25. Efficiency Analysis (Kangru, Mahmood, Otto, Moor, & Riives, 2020).

After successful OEE prediction, tactical and strategic KPIs for the company can be calculated. Theoretical return on investment (ROI) and payback period (PP) or discounted payback period (DPP) relations to the actual Gain of Investment (GI) are calculated among other parameters.

4 Analysis

This chapter discusses the different DSS methods and tools to analyse, evaluate or predict integrated robot production cell suitability for performing a certain manufacturing task and its performance scores or KPIs. The tools discussed in this section have been developed with a view to their possible development for use in automated DSS.

4.1 Suitability Analysis Case Study

This chapter discusses the DSS method used to evaluate and analyse robot integrated production cell compliance with a given production task.

Twenty SME robot integrated production cells were investigated, with the number of employees ranging from 20–150. The companies produced different parts for agricultural and forestry machines, small tractors, and high-speed trains, lifts components, wind generator rotors, and other sheet metal products. The information was acquired by interviewing company management and engineering staff and extracting data from enterprise resource planning (ERP) software. Data gained from the interviews and ERP system contained both quantitative and qualitative data. Only data related to robot welding was used in the following suitability analysis (Kangru, Riives, Mahmood, & Otto, 2019).

The performances of three production units were used as a benchmark for the suitability analysis. The production cells, shown in Table 6, were chosen for their excellent KPI values. KPIs were selected according to the performance evaluation model, and they were as follows: discounted payback period (DPP), cell utilization (CU), and overall equipment effectiveness (OEE).

Table 6. Production unit description and performances (Kangru, Riives, Mahmood, & Otto, 2019).

Company	*Production cell*	*Products*	*Shifts*	*DPP, years*	*CU, %*	*OEE, %*
No. 1	Yaskawa IR, two-axis positioner	Heat exchangers	2	3	51	72
No. 2	ABB IR, single-axis positioner	Trailer frames	2	2	40	70
No. 3	Yaskawa IR, single-axis 2-station positioner	Forestry machine frames	1 (2)	3	45	70

Criteria for Decision Making

In this study, the main task of the multi-criteria decision analysis was to estimate the suitability index on the basis of the following criteria and sub-criteria, as shown in Figure 26 (Kangru, Riives, Mahmood, & Otto, 2019):

- Production unit (PU):
    - cost (C): total investment (C1), cost of utilities (C2), running costs (C3);
    - maintenance (M): maintenance cost (M1), emergency maintenance cost (M2);
    - level (L): use of CAD/CAM (L1), automated storage (L2), machine vision (L3);

- Product (P):
  - physical properties (PP): the complexity of parts (T1), parts manufacturing precision (T4), mass (T6);
  - productivity (PR): product families (T2), patch size (T3), patch repeatability (T9), overall welding ratio (TE3), average cycle time (TE9), average setup time (PR2), quality assurance (E2);
- Company environment (CE):
  - workforce (WF): workstation fulfilment (E1), workers salary (E6), production engineer's involvement (E8), shifts (W2), shifts durations (W3);
  - performance indicators (PI): increment of productivity (E4), an increment of on-time delivery OTD (E9), increment overall equipment effectiveness OEE (E10), payback period (K1).

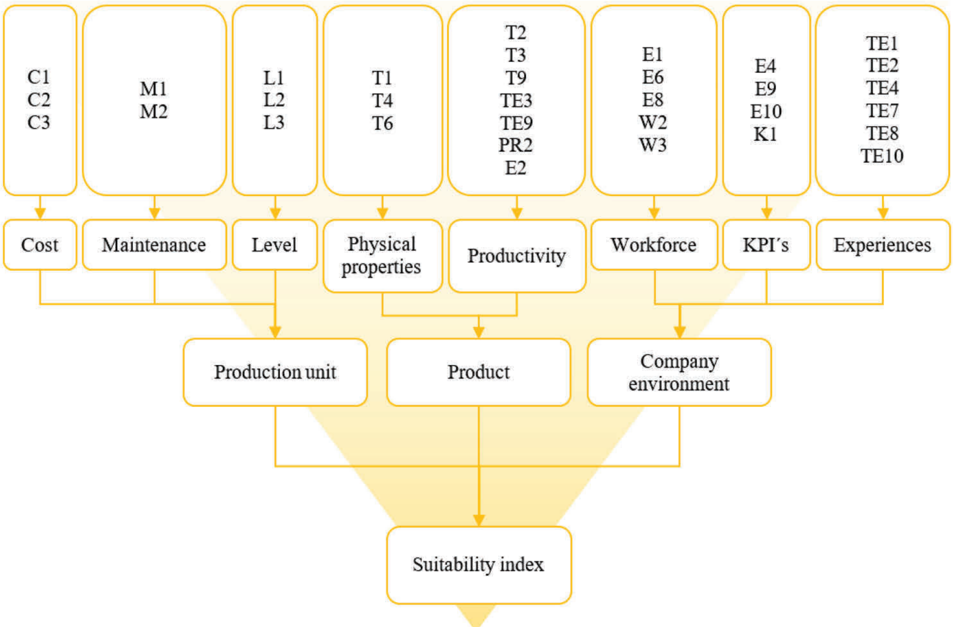


Figure 26. Production Cell Suitability Hierarchy (Kangru, Riives, Mahmood, & Otto, 2019).

Performance Scores

The assessments obtained from the decision-makers were pair-wise compared. Performance scores and consistency ratios were then calculated, as shown in Table 7.

Table 7. Performance scores of main criteria (Kangru, Riives, Mahmood, & Otto, 2019).

Criteria	CR	Priority	Criteria	CR	Priority
Production unit		21	Physical properties	0	66.7
Product	1.9	24	Productivity		33.3
Company environment		55	Workforce	9.8	19.5
Cost		51.3	Performance		8.8
Maintenance	5.6	8.1	Experiences		71.7
Level		40.6			

Decision Matrix

The normalized inputs were multiplied by their corresponding performance scores, and the local and global scores were summed up. The results are shown in Table 8.

Table 8. Suitability index results (Kangru, Riives, Mahmood, & Otto, 2019).

Production cell	Production unit	Product	Company environment	Suitability index
Cell No. 1	0.567	0.699	0.664	0.652
Cell No. 2	0.494	0.709	0.804	0.716
Cell No. 3	0.524	0.849	0.810	0.717

Results

The highest overall suitability score was obtained in the case of No 3. with an index of 0.717. The extremely high score was received in both product and company environment categories, 0.849 and 0.810, respectively. The suitability analyses confirmed an excellent choice of product to be produced in a well-organized cell and automated company environment. For the suitability decision, four categories were proposed, as shown in Table 9, based on suitability criteria for robot welding, as shown in Table 5.

Table 9. Suitability decision categories (Kangru, Riives, Mahmood, & Otto, 2019).

Suitability index	Decision	Description
≤ 0.25	No expediency	Product portfolio, analysis of the current process and general conditions indicate the lack of essential need for using robots in the company.
≤ 0.5	To a certain extent expedient	A strong point (products, process, general conditions) and problematic places are indicated. The final decision lies with the industrial expert.
≤ 0.75	Robotization is recommended	Some minor risks are indicated.
> 0.75	Robotizing is feasible	Each group (product, process, manufacturing conditions) has an index higher than 0.75, making it certain that robotization of the process will yield significant returns to the company.

For more precise results, it is possible to simulate the planned robot cell and to calculate the break-even point. This presumes sufficient competence in all the relevant areas. Therefore, a tool which makes it possible to estimate the suitability of using industrial robots to automate a certain manufacturing process is important in the early planning stages (Kangru, Riives, Mahmood, & Otto, 2019).

4.2 Performance Analysis Case Study

This chapter discusses the DSS method used to simulate production workflow by the bill of operation and available capacity. The method is used to evaluate or to predict production cell KPIs.

The company was manufacturing small and medium-sized mechanical components for industrial machines and medical devices. Work was organized mainly in one shift and sometimes in two shifts. This case study focused on the CNC machine-tending cell shown in Figure 27. The production cell consisted of a medium-sized turning center, a co-working robot connected to it, and work in progress (WIP) storage. The following KPIs were chosen: Throughput, Total Number of Orders, Total Products Produced, Overall Equipment Effectiveness, Utilization TPU, and Discounted Payback Period.

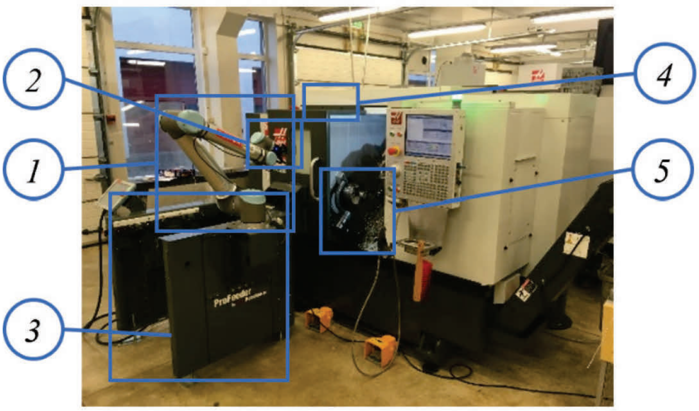


Figure 27. CNC Manufacturing Case Study Cell (Kangru, Mahmood, Otto, Moor, & Riives, 2020).

The cell was composed as follows: 1 – Co-working robot, 2 – universal prism gripper, 3 – work in progress storage, 4 – part overturn position, 5 – machining position. Operations for the cell's typical workflow are listed and explained in Table 10. Operation availability and performance indicators were acquired from the company MES database. Order volume distribution, parts distribution, and cycle times were obtained from the company ERP system database.

Manufacturing Cell Simulation Model

The manufacturing cell model was based on a robot-based manufacturing cell PEM and was programmed using Rockwell Automation Technologies Inc. Arena DES software. An overview of the model is given in Figure 28 and one of the sub-models in Figure 29.

The model was used to simulate different production orders simultaneously, as in "real life", according to their operation sequence and order-specific data. An order could exit the system only when all necessary operations and rework had been performed and the order had been successfully completed.

By using concurrent simulations, it was possible to assess the combined effects of orders, identify bottlenecks, and incorporate improvements, which are directly reflected in production unit performance records. Entities for the model were defined as an order where part production information (operations, cycle times, quality parameters, etc.) together with production volume had been assigned. Outputs were defined as both completed orders and rejected orders. Throughput and net value were calculated for each completed order. Similarly, the unearned cost was calculated for rejected orders. After simulating parts and volume by their distribution, KPIs could be calculated. For this model, a simple KPI selection of total production units, Utilization, Net Income, and Discounted Payback Period were included (Kangru, Mahmood, Otto, Moor, & Riives, 2020).

The model first assessed the existence of production capacity. In case of no capacity, the order was sent directly to Rejected orders.

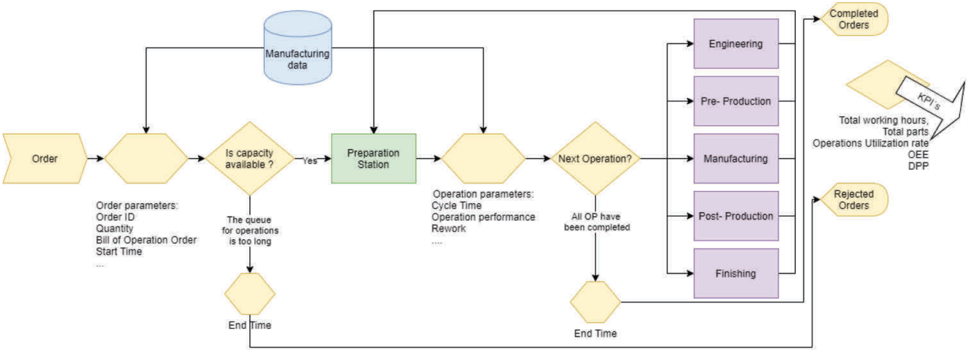


Figure 28. CNC Manufacturing Cell Model (Kangru, Mahmood, Otto, Moor, & Riives, 2020).

If the production unit had free capacity to utilize, the order started to execute according to the order Bill of Operation (BOO).

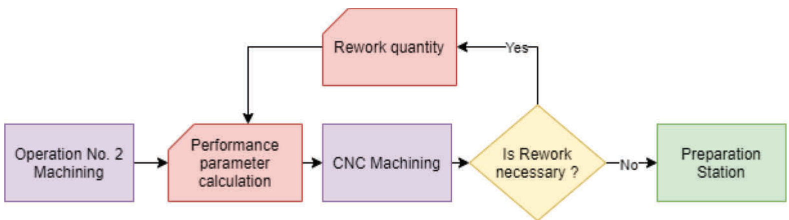


Figure 29. CNC Manufacturing Cell Sub Model (Kangru, Mahmood, Otto, Moor, & Riives, 2020).

In the model, the operations are described more broadly than normally in industry production planning. The model combines similar industrial operations such as turning, milling, and bending into one manufacturing operation with a cycle time and operation-specific productivity, availability, and quality. The operations used in the model are shown in Table 10.

Table 10. CNC Manufacturing Case Study Operations (Kangru, Mahmood, Otto, Moor, & Riives, 2020).

Op. ID	Operation	Explanation
1	Engineering	The order has been accepted and production planning starts.
2	Engineering	CAM programming the part.
3	Pre-Production	CNC machine and IR robot setup and test run.
4	Manufacturing	Blanks are inserted into the WIP, and manufacturing is started.
5	Post-production	Quality control is carried out.
6	Finishing	The batch is finished, and the setup is taken down.

Each operation in the model is associated with a database from which the required data for the operation is loaded according to the product. Operation cycle time is calculated according to equation (13).

$$O_{Th} = \frac{Q * CT * \sqrt{P_O * P_P}}{C * A} \tag{13}$$

O_{Th} represents operation throughput time, Q, production quantity, CT, planned cycle time, P_O, operation performance value, P_P, part performance value, C, capacity, and A, availability. Similarly, in the rework RO equation (14), a product-specific quality coefficient P_q directs Q_P products to reprocessing. Normative times for moving batches are set between operations. When all operations for the batch have been performed, the batch is sent to Completed Orders.

$$R_O = Q * P_q * Q_P \tag{14}$$

Results

The production unit model was simulated using ten preset products, each with a different configuration. The minimum parts quantity was ten and the maximum 500 parts per order. The simulation duration was 4.5 years, for a total of 9,000 working hours, with work performed in one shift. As a result, a total of 100 thousand parts were produced across 430 orders, making the average number of parts per order 230 pc. The overall utilization rate for the production unit was 40% during this period. The CNC machining operation had the highest rate, with a utilization of 83% in some cases. The lowest value for overall equipment effectiveness (OEE) for the CNC machining center was 52%, the highest, 90%, making the average value 87%. Based on these values, the calculated discounted payback period DPP was 3.2 years.

4.3 CNC Manufacturing Cell Redesign Case Study

This chapter provides a case study of a company's labour-intensive redesign of a production unit to make it a more efficient robot integrated production cell.

Production cell description and redesign objectives

The company provided CNC cutting outsourcing services. Parts were manufactured in small batches, 1–100pc., and medium-sized batches, 100–1000pc., half of which were repeat orders (see Figure 30). They also manufactured a small number of their own-brand products, which were marketed using a reseller network. The sizes of the parts ranged from 10g to 3kg. The technologies used were sawing, turning, and milling, and each machine was operated by a single operator. The work was organized in one shift, and production planning was carried out in the order of arrival of orders. There was no warehouse management for either the material or the finished products.

Figure 30. Production unit layout before redesign.

The main goal of the restructuring of production was to reduce costs due to waiting times and increase the efficient use of machining centers, thus increasing profitability for the department. The objectives of the restructuring were as follows:

- Robotic processing of repeated batches,
- Production planning according to batch size and automated production outside the working hours of the operators,
- Increase of the OEE of machining centers,
- Increase of the OLE of operators,
- Reduction in throughput for repetitive batches.

Feasibility study

The company's feasibility assessment had been prepared based on the methodology presented in section 3.4.1. The assessment was carried out by conducting an interview with the company's CTO and together setting the weights of the various criteria. The results are shown in Figure 31.

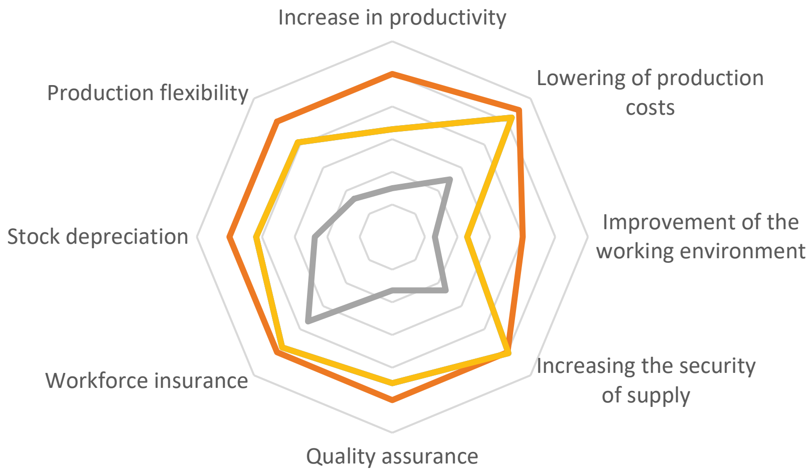


Figure 31. Company feasibility study.

The results of the assessment of the impact of robotization are shown in Figure 31 (grey indicating the current situation in the company). From that chart, we can conclude that integration of the industrial robot with the existing production cell would lead to relatively modest results when compared with the ideal solution shown in orange. Therefore, moving forward, a situation could arise where robotization in fact hindered production even more. The most significant negative factors were inadequate or incomplete planning, production of complex parts in very small batches, and the low qualification of operators. It was recommended to re-evaluate the situation and place a greater focus on medium-complexity products made in repeated batches. It was also proposed to evaluate the operator's skills and provide all necessary training. Introducing the proposed changes to the company's production would provide a stronger basis for the robotization of the company. The predicted result is shown in yellow.

Production Cell Components and Scenarios

Due to the company's desire to robotize CNC work centers and incur the lowest possible investment costs, it was not then possible to replace existing CNC machines with newer ones. Therefore, an increase in productivity through a change in the capabilities of the machines would not be possible.

The main parameters of the industrial robots included are shown in Table 11. As the work was partly planned to take place in parallel with human operators, all robots would be in the co-robot class.

Table 11. Selected industrial robots.

No	*Manufacturer*	*Type*	*Reach [mm]*	*No. of axes*	*Positioning accuracy [±mm]*	*Payload [N]*
1	Kukka	KR 3 Agilus	541	6	0,02	30
2	ABB	YuMi	559	14	0,02	5
3	Universal Robots	UR 5	850	6	0,1	50

Based on the suitability analysis, the two main scenarios for moving forward were decided. The main parameters for the scenarios are presented in Table 12, together with Scenario one, which characterizes the work arrangement now and is for later comparison.

In scenario one, the work was arranged and the initial setup and lot set up were carried out by the senior CNC operator, who set up tools, blanks, and programs and makes all the necessary small adjustments. When the setup was complete, the cell was handed over to the CNC operator, who ensured that the cell was working optimally. The main tasks of the operator were changing planks, on-site quality control, cleaning, and tool maintenance.

In Scenario two and three, the initial setup and setup were arranged similarly. The only difference was when the lot size was larger than the Switch lot size. In this case, the senior operator would program the machine tending robot to carry out some of the operator's tasks like changing planks, automated quality control, and cleaning.

Table 12. Main parameters of the scenarios.

	Description	*Switch lot size [pcs]*	*Init. setup time [min]*	*Setup time [min]*	*Change[1] [sek]*	*Change[2] [sek]*	*End time [min]*
1	Human operated - initial	None	60	10	30	20	10
2	Human and co-working robot	50	120	20	30	20	15
3	Human and co-working robot	250	120	20	30	20	15

[1]Human operated production cell. [2]Robot operated production cell.

The outcomes for the form performance analysis using the methods discussed in section 3.4.3 are shown in Figure 32.

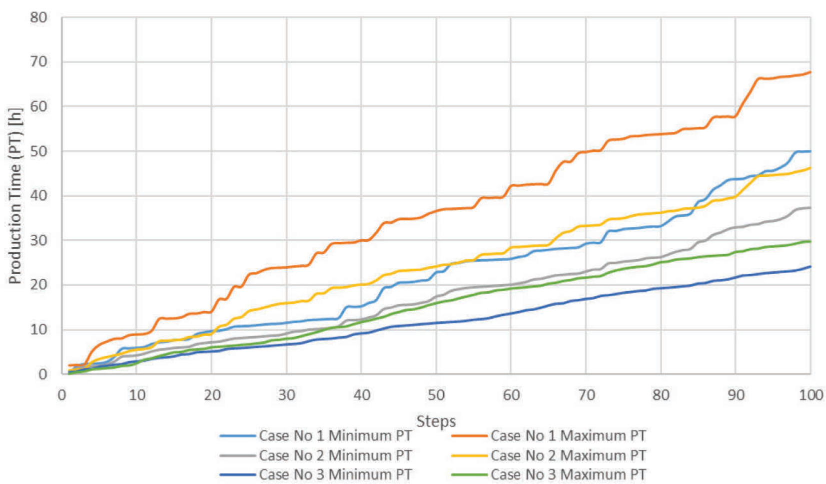


Figure 32. Cumulative production time.

The results show that by using a well-optimized CNC production unit with machine-tending and dividing the batch in two, it was possible to reduce the theoretical throughput by 11.7%. The results for the scenarios are presented in Table 13.

Table 13. Scenario results.

	Description	Throughput [sec]	Standard dev.	Difference [%]
1	Human operated production cell	37,6	0,39	0
2	Human and co-working robot cell	33,6	0,74	11,7
3	Human and co-working robot cell	35,6	0,92	5,4

In scenario two, the switch batch size was set at 50 parts. By increasing the batch size to 250 parts, throughput was reduced again by 5.4%. In both scenarios, the reduction in throughput was mainly due to the constant and predetermined robot cycle time. In those scenarios, it was assumed that the work would be done in one shift only. However, if the production planning strategy was to be changed so that initial batch setups and small-batch processing would be done on the day shift, when the presence of an operator was continuously required, and large batch processing would be done on the night shift, performance would be further enhanced.

Modelling and Visualizing in a 3D Environment

The information gathered on-site from the production unit and the data and behavior created in the previous analyses were a good indicator of how effectively the redesigned production unit could operate. However, there was still a desire for a more accurate 3D analysis to optimize the workflow. For the workflow analysis, a developed production cell performance methodology (Mahmood, Otto, Kuts, & Kangru, 2020) and methods (Kangru, Mahmood, Otto, Moor, & Riives, 2020) are used. In addition, it was necessary to analyze the optimal layout, the degree of accessibility, the safety of the workers, and possible collision causes. A 3D simulation model of the production unit was created and simulated using Visual Components Premium 4.2 software. The 3D simulation model is shown in Figure 33.

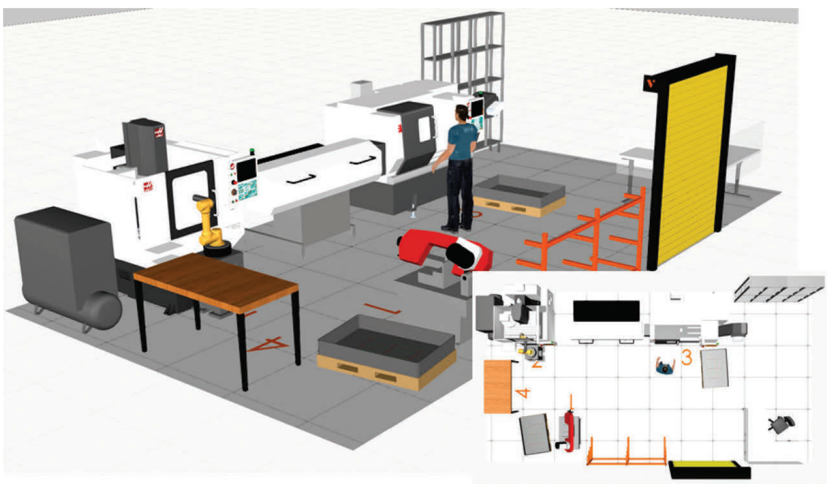


Figure 33. A 3D model of the case study environment.

Results

A robotization analysis was carried out for the manufacturing company's low-performing production unit. After the main goals were identified, a feasibility analysis was performed. The analysis revealed that successful robotization demanded a re-planning of the work of the production unit. Two shifts would have to be implemented, the skill and knowledge level of operators would have to be raised, and the nomenclature of manufactured products would have to be narrowed. The implemented changes would lay a solid foundation for robotization.

An analysis of existing production equipment was performed, and the most optimal industrial robots were selected for the production task. In the efficiency analysis, two scenarios were simulated, and on the basis of these, a 3D simulation of the redesigned production unit was created. The 3D simulation model was used to determine the most optimal equipment layout and workflow. In addition, the safety of workers in the production environment was examined. With these changes, the OEE of the production unit would increase by 25% and the throughput would decrease by more than 10%.

5 Conclusion and Future Work

This dissertation presented a digital evaluation system for SME robot integrated production cell design and redesign. The proposed work can improve the design process by requiring minimal human and financial input.

The proposed approach, set in the thesis objective, to the design and redesign of a productive, highly automated and intelligent, robot integrated production cell was composed by conducting a comprehensive study of relevant methodologies and methods. The time-consuming and complicated design problems are divided into stages. In each step, sub-goals are derived from overall goals, focus points are determined, and control criteria specified.

The developed methodology, discussed in paragraph 3.4, is derived from a knowledge-based model and a recursive decision-making procedure introduced in section 3.2. The knowledge-based model was composed and optimized using information acquired from the Estonian manufacturing industry robotization survey discussed in paragraph 3.1 and a more specific robot integrated production cell study discussed in section 3.1.3. According to the survey conducted among Estonian manufacturing companies, there is a desire to robotize labor-intensive processes, and good examples are presented. However, there is still a need to develop new solutions to overcome company skepticism.

Two decision loops are implemented in the recursive decision-making procedure. First, there is a design loop, whose objective is to check the robot's architecture and technical parameters for the manufacturing task ahead. Second, there is an implementation loop, whose objective is to assess or predict the utilization of the implemented robot-cell.

To fulfil the second thesis objective, a toolset of methods was developed to evaluate the economic and technical performance of a robot integrated production cell according to a company´s strategic plan. The developed method was validated using different case studies. A feasibility analysis was designed as an online program using a weighted sum decision model. For the analysis, eight criteria were finally selected among many others that best characterized the implementation process outputs of the robot cell. With the help of expert groups, a set of questions was compiled, and weights were determined for each criterion. Different weights were used in other manufacturing fields. The model was verified and tested by IMECC.

The robot integrated production cell equipment selection problem was studied and different methods were investigated and rated. An improved analytic hierarchy process was chosen for this problem. The selected method has been extensively studied and tested over several years, the created model is easily configurable, and the results were consistent.

A more precise suitability analysis tool was developed to assess the overall performance of previously selected components. To validate the method, the case study discussed in the section Suitability Analysis Case Study of robot welding was carried out. A multi-criteria multi-level hierarchical model was created with three product, technology, and objectives main criteria groups. An expert group was used to select and pair-wise assess the sub-criteria. Information gathered from the robot integrated production cell study was used to optimize and test the model.

Following this, a robot integrated production system efficiency analysis tool was developed to predict the impact of different production strategies and scenarios. The tool was validated by the case study discussed in section Performance Analysis Case Study.

A robot integrated production cell model with operations, routes, and specific parameters was programmed using Discrete Event Simulation software. Different scenarios were simulated, optimized, and the most promising selected.

Finally, a 3D factory simulation using the previously generated data was created. The most optimal solutions were selected from among different layouts and scenarios for the company's production floor.

5.1 Further Research

- The proposed approach can be further developed by creating a common digital environment for the developed methods. The easily followed environment would show more clearly the implemented decisions, their reasons, and possible further recommendations.
- The developed tools can be improved in future by widening their scope with different robot integrated processes and new technology.
- The performance model can be further developed by including a wider range of production processes, product-related parameters, and a more comprehensive selection of KPIs.

References

Athawale, V. M., & Chakraborty, S. (2011). A comparative study on the ranking performance of some multi-criteria decision-making methods for industrial robot selection. *International Journal of Industrial Engineering Computations., 2*(4), 831–850.

Bagheri, B., Yang, S., Kao, H.-A., & Lee, J. (2015). Cyber-physical Systems Architecture for Self-Aware Machines in Industry 4.0 Environment. *International Federation of Automatic Control, 48*(3), 1622–1627.

Bandyopadhyay, S., & Bhattacharya, R. (2017). *Discrete and Continuous Simulation: Theory and Practice. 1st Ed.* CRC Press.

Benkamoun, N., ElMaraghy, W., Huyet, A.-L., & Kouiss, K. (2014). Architecture Framework for Manufacturing System Design. *Procedia CIRP, 17*, 88–93.

Burstein, F., & Holsapple, C. (2008). *Handbook of Decision Support Systems.* Berlin: Springer Verlag.

Cabral, I., Grilo, A., & Cruz-Machado, V. (2012). A Decision-Making Model for Lean, Agile, Resilient and Green Supply Chain Management. *International Journal of Production Research, 50*(17), 4830–4845.

Castellano, G., & Fanelli, A. M. (2000). Variable selection using neural-network models. *Neurocomputing, 21*, 1–13.

Chan, F. T., Jiang, B., & Tang, N. K. (2000). The development of intelligent decision support tools to aid the design of #exible manufacturing systems. *International Journal of Production Economics, 65*, 73–84.

Chapman, P., Clinton, J., Kerber, R., Khabaza, T., Reinartz, T., Shearer, C., & Wirth, R. (2020). *C RISP-DM 1.0 Step-by-step data mining guide.* SPSS Inc.

Chu, T. C., & Lin, Y. C. (2003). A fuzzy TOPSIS method for robot selection. *The International Journal of Advanced Manufacturing Technology, 21*(4), 284–290.

Dalmarco, G., Ramalho, F. R., Barros, A. C., & Soaresa, A. L. (2019). Providing industry 4.0 technologies: The case of a production. *Journal of High Technology Management Research, 30*(2), 1–9.

Danish Technological Institute. (2020, 09 12). *Robot Technology Driven Innovation - Examples and Trends*. (Danish Technological Institute) Retrieved 10 04, 2017, from https://conference.vde.com/isr2016/papsub/download/Documents/Presentation_Risager.pdf

Dechezleprêtre, A., & Sato, M. (2018). *Green policies and firms' competitiveness.* Paris: OECD.

Demirbaş, Z. A., & Üna, C. (2018). Creating an Alternative Production Line by Using a Simulation Technique in Duvet Cover Production. *Fibres and Textiles in Eastern Europe, 130*, 8–12.

Efthymiou, K., Pagoropoulos, A., Papakostas, N., Mourtzis, D., & Chryssolouris, G. (2012). Manufacturing Systems Complexity Review: Challenges and Outlook. *Procedia CIRP, 3*, 644–649.

European Central Bank Eurosystem. (2020, 10 15). (European Central Bank) Retrieved 05 08, 2020, from Structure of the euro area economy: https://www.ecb.europa.eu/mopo/eaec/html/ index.en.html

European Commission. (2017). *User guide to the SME Definition.* Luxembourg: Publications Office of the European Union.

European Commission. (2020). *Digital Economy and Society Index (DESI) 2020 - Thematic chapters.* European Commission.

European Commission. (2020). *Report on the Generalised Scheme of Preferences covering the period 2018-2019.* Brussels.

Eurostat. (2020, 10 10). (Eurostat) Retrieved 04 15, 2020, from Population structure and ageing: https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Population_structure_and_ageing/et#Rahvastiku_vananemise_varasemad_ja_tulevased_suundumused_Elis.

Glaessgen, E. H., & Stargel, D. S. (2012). The Digital Twin Paradigm for Future NASA and U.S. Air Force Vehicles. *53rd AIAA/ASME/ASCE/AHS/ASC Structures, Structural Dynamics and materials Conference.* Honolulu.

Goh, C.-H. (1997). *Analytic Hierarchy Process for Robot Selection, Journal of Manufacturing Systems, 5*(16), 381–386.

Goh, C.-H., Tung, Y.-C. A., & Cheng, C.-H. (1996). A Revised weighted sum decision model for robot selection. *Computers & Ind. Engineering, 2*(30), 193–199.

Grieves, M., & Vickers, J. (2017). Digital Twin: Mitigating Unpredictable, Undesirable Emergent Behavior in Complex Systems. In *Transdisciplinary Perspectives on Complex Systems* (pp. 85–113). Springer.

Groggerta, S., Elsera, H., HaoNgoa, Q., & Schmitt, R. H. (2018). Scenario-based Manufacturing Data Analytics with the Example of Order Tracing through BLE-Beacons. *Procedia Manufacturing, 24*, 243–249.

Gunes, V., Steffen, P., Givargis, T., & Vahid, F. (2014). A Survey on Concepts, Applications, and Challenges in Cyber Physical Systems. *KSII transactions on internet and information systems, 8*(12), 4242–4268.

Halevi, G., & Wang, K. (2007). Knowledge based manufacturing system. *Journal of Intelligent Manufacturing, 18*(4), 467–474.

Hawksworth, J., Berriman, R., & Goel, S. (2018). *Will robots really steal our jobs? An international analysis of the potential long term impact of automation.* PricewaterhouseCoopers LLP.

Ic, Y. T., Yurdakul, M., & Dengiz, B. (2013). Development of a decision support system for robot selection. *Robotics and Computer-Integrated Manufacturing, 29*(4), 142–157.

International Federation of Robotics. (2017). *Executive Summary World Robotics 2017 Industrial Robots.* Frankfurt: International Federation of Robotics.

International Federation of Robotics. (2018). *World Robotics Report.*

International Federation of Robotics. (2020). *Executive Summary World Robotics 2020 Industrial Robots.* Frankfurt: International Federation of Robotics.

International Organization for Standardization. (2012). *ISO 8373:2012 Robots and robotic devices - Vocabulary.*

Kaganski, S., Majak, J., Karjust, K., & Toompalu, S. (2017). Implementation of key performance indicators selection model as part of the Enterprise Analysis Model. *Procedia CIRP, 63*(1), 283–288.

Kangru, T., & Riives, J. (2018). *Robotiseerimise otstarbekus*. (IMECC) Retrieved 05 12, 2019, from https://sites.google.com/tktk.ee/robotiseerimine/avaleht

Kangru, T., Mahmood, K., Otto, T., Moor, M., & Riives, J. (2020). Knowledge-Driven Based Performance Analysis of Robotic Manufacturing Cell for Design Improvement. *Proceedings of the ASME 2020: International Mechanical Engineering Congress and Exposition IMECE2020.* Portland.

Kangru, T., Otto, T., Riives, J., Kuts, V., & Moor, M. (2020). Optimisation of decision-making process in industrial robot selection. *Journal of Machine Engineering, 20*(1), 70–81.
Kangru, T., Riives, J., Mahmood, K., & Otto, T. (2019). Suitability analysis of using industrial robots in manufacturing. *Proceedings of the Estonian Academy of Sciences, 68*(4), 383–388.
Kangru, T., Riives, J., Otto, T., Pohlak, M., & Mahmood, K. (2018). Intelligent Decision Making Approach for Performance Evaluation of a robot-based Manufacturing Cell. *Proceedings of the ASME 2018 International Mechanical Engineering Congress and Exposition.* Pittsburgh.
Karaulova, T., & Bashkite, V. (2016). Decision-Making Framework for Used Industrial Equipment. *Inzinerine Ekonomika-Engineering Economics, 27*(1), 23–31.
Kibira, D., Brundage, M. P., Feng, S., & Morris, K. (2017). Procedure for selecting key performance indicators for sustainable manufacturing. *Journal of Manufacturing Science and Engineering, 140*(1).
Kodua, A., Brown, K., Darlington, R., & Svetan, R. a. (2012). An integrated product process design methodology for cost effective product realization. *International Journal of Computer Integrated Manufacturing, 25*(9), 814–828.
Košťál, P., & Holubek, R. (2013). The Intelligent Manufacturing Systems. *Journal of Computational and Theoretical Nanoscience, 19*(3), 972–975.
Kusiak, A. (1990). *Intelligent Manufacturing Systems.* Englewood Cliffs, NJ: Prentice Hall.
Kusiak, A. (2018). Smart manufacturing. *International Journal of Production Research, 56*(1), 508–517.
Ladyman, J., Lambert, J., & Wiesner, K. (2013). What is a Complex System? *European Journal for Philosophy of Science, 3*(1), 33–67.
Lua, Y., Liub, C., Wangc, K. I.-K., Huanga, H., & Xua, X. (2020). Digital Twin-driven smart manufacturing: Connotation, reference model, applications and research issues. *Robotics and Computer Integrated Manufacturing, 61*.
Lõun, K., Laavin, J., Riives, J., & Otto, T. (2013). High performance workplace design model. *Estonian Journal of Engineering, 15*(1), 47–61.
Lõun, K., Riives, J., & Otto, T. (2011). Evaluation of operation expedience of technological resources in a manufacturing network. *Estonian Journal of Engineering, 17*(1), 51–65.
Mahmood, K., & Ševtšenko, E. (2015). *Analysis of machine production processes by risk assessment approach, Journal of Machine Engineering, 15*(1), 112–124.
Mahmood, K., Lanz, M., Toivonen, V., & Otto, T. (2018). A Performance Evaluation Concept for Production Systems in an SME Network. *Procedia CIRP, 72*, 603–608.
Mahmood, K., Otto, T., Kuts, V., & Kangru, T. (2020). An Approach to Analyze the Performance of Advanced Manufacturing Environment. *Procedia CIRP.* Chicago.
McKinsey & Company. (2017). *The great re-make: Manufacturing for modern times.*
McKinsey Global Institute. (2017). *Making it in America: Revitalizing US manufacturing.*
Menezes, B. C., Kelly, J. D., Leal, A. G., & Le Roux, G. C. (2019). Predictive, Prescriptive and Detective Analytics for Smart Manufacturing in the Information Age. *IFAC PapersOnLine, 52*(1), 568–573.
National Institute of Standards and Technology. (2017). *Framework for Cyber-Physical Systems Volume 1, Overview.* Gaithersburg: NIST Special Publication.

National Institute of Standards and Technology. (2020, 10 12). *Cyber Physical Systems*. (National Institute of Standards and Technology) Retrieved 09 09, 2018, from https://www.nist.gov/el/cyber physical systems

Nof, S. Y. (1999). *Handbook of Industrial Robotics.* New York: John Wiley & Sons.

Peshkin, M. A., Colgate, E., Moore, C. A., Gillespie, B., & Akella, P. (2001). Cobot Architecture. *IEEE Transactions on Robotics and Automation, 17*(4), 377–390.

Pfeiffer, J. (2011). *Fundamentals on Decision-Making Behavior.* Berlin: Physica-Verlag.

Priits, M. (2018). *Estonian Labor Market: Current Situation and Future Prospects.* Tallinn: Poliitikauuringute Keskus Praxis.

Qina, J., Liua, Y., & Grosvenora, R. (2016). A Categorical Framework of Manufacturing for Industry 4.0 and Beyond. *Procedia CIRP, 52*, 173–178.

Reddy, E. S., Kumar, N. R., & Padmanabhan, G. (2015). Robot Selection Using Analytic Hierarchy Process and System of Equations of Matrices. *Elixir International Journal, Mechanical Engineering, 79*, 30511–30513.

Riives, J., Otto, T., & Lõun, K. (2007). Methods for Enhancing Productivity and Work Efficiency in the Workshop. *Journal of Machine Engineering, 7*(2), 86-95.

Saha, R. (2015). Selection of Industrial Robots for Packaging using Improved Analytic Hierarcy Process Method. *YMCAUST International Journal of Research, 3*(2), 19–23.

Simon, J., Michelle, D., & Marc, H. (2019). *Hype Cycle for Innovation in Manufacturing Industries*. (Gartner) Retrieved 09 15, 2020, from https://www.gartner.com/

Sprague, R. H. (1980). A Framework for the Development of Decision Support Systems. *MIS Quarterly, 4*(4), 1–25.

Statistikaamet. (2020, 12 11). *Statistikaamet*. Retrieved 12 11, 2020, from TD024: ETTEVÕTTESISESED JA -VÄLISED KULUTUSED TEADUS- JA ARENDUSTEGEVUSELE ETTEVÕTLUSSEKTORIS TEGEVUSALA (EMTAK 2008) JÄRGI: https://andmed.stat.ee/et/stat/majandus__teadus-tehnoloogia-innovatsioon__teadus-ja-arendustegevus__teadus-ettev-sektoris/TD024/table/tableViewLayout1

Statistikaamet. (2020, 12 11). *Statistikaamet*. Retrieved 12 11, 2020, from EM042: ETTEVÕTETE INVESTEERINGUD MATERIAALSESSE PÕHIVARASSE TEGEVUSALA (EMTAK 2008) JÄRGI JOOKSEVHINDADES (KVARTALID): https://andmed.stat.ee/et/stat/majandus__ettevetete-majandusnaitajad__ettevetete-investeeringud__luhiajastatistika/EM042/table/tableViewLayout2

Swedbank Research. (2019). *Estonian Economy. Business sector digitalisation and automation: opportunities and challenges.* Tallinn: Swedbank Macro Research.

Zhang, L., Li, J., Kong, C., Qu, L., Zhu, J., Chen, Z., & Luo, Y. (2010). Using Neural Network to Evaluate Construction Land Use Suitability. *IEEE Computer Society*, 331–334.

Zhou, G., Chao, Z., Li, Z., Kai, D., & Chuang, W. (2020). Knowledge-driven digital twin manufacturing cell towards intelligent manufacturing. *International Journal of Production Research, 58*(4), 1034–1051.

Tahriri, F., & Taha, Z. (2011). Critical success factors for technology selection specifically ROBOTS. *Journal of Business Management and Economics, 2*(3), 89–97.

Tao, F., Cheng, J., Qi, Q., Zhang, M., Zhang, H., & Sui, F. (2017). Digital twin-driven product design, manufacturing and service with big data. *The International Journal of Advanced Manufacturing Technology, 94*, 3563–3576.

Teulieres, M., Tilley, J., Bolz, L., Dehm, P. M., & Wägner, S. (2019). *Industrial robotics – insights into the sector's future growth dynamics.* Paris: McKinsey & Company.

Tolio, T., Sacco, M., Terkaj, W., & Urgo, M. (2013). Virtual Factory: an Integrated Framework for Manufacturing Systems Design and Analysis. *Procedia CIRP, 7*, 25–30.

Vaher, K., Kangru, T., Otto, T., & Riives, J. (2019). The mobility of robotised work cells in manufacturing. *30th Daaam International Symposium On Intelligent Manufacturing And Automation*, (pp. 1049–1055). Vienna.

Vaughn, A., Fernandes, P., & Shields, J. T. (2002). *Manufacturing System Design Framework Manual.* Cambridge: Massachusetts Institute of Technology.

Wu, G., Talwar, S., Johnsson, K., Himayat, N., & Johnson, K. D. (2011). M2M: From Mobile to Embedded Internet. *IEEE Communications Magazine, 49*(4), 36–43.

Örkcü, H. H., & Örkcü, M. (2011). Data Envelopment Analysis Cross Efficiency Evaluation Approach to the Technology Selection. *Gazi University Journal of Science Part A: Engineering and Innovation, 3*(1), 1–14.

Yazgana, H. R., Borana, S., & Goztepe, K. (2009). An ERP software selection process with using artificial neural network based on analytic network process approach. *Expert Systems with Applications, 36*(5), 9214–9222.

Acknowledgements

This PhD thesis was supported by the European Union program I4MS Project "Digital Manufacturing Innovation Hub" in terms of this program 2016-2020, by Project AR16077 Smart Industry Centre (SmartIC) No. 2014-2020.4.01.16-0183, and also by TalTech ASTRA program "TalTech development program 2016-2022" Doctoral School of Energy and Geotechnology (2014-2020.4.01.16-0032), funded by EU Regional Development Fund.

I would like to express my gratitude to all those who are not named below but whose words or deeds helped me throughout this journey. Thank you.

While carrying out this research, I was always supported and supervised by two of the top specialists in manufacturing research, my supervisors prof. Jüri Riives and prof. Tauno Otto. Thank you for your guidance and expertise that helped me to complete my doctoral studies successfully.

I would also like to thank the TTK Tallinn University of Applied Science for adjusting my workload and especially the director of the Institute of Technology, Vello Vainola, for persuading me to take on this quest.

I am thankful to my colleagues at the TTK Tallinn University of Applied Science and the Tallinn University of Technology, Madis Moor, Kristo Vaher, Kashif Mahmood, Vladimir Kuts, and others for their valuable guidance.

Finally, I would like to thank my friends and family. Without their support and patience I could not have completed this dissertation.

Tavo Kangru

Abstract

Development of Intelligent Manufacturing Cell Structure for SME Digital Manufacturing Hub

To maintain the competitiveness of a manufacturing company in today's changing world, a company must take into account the growing expectations of customers for product quality and functionality, shortening product life cycle and the need to reduce time to market. As a result, production must become increasingly efficient, as flexible as possible, with the necessary level of automation and the effective use of digital solutions.

Today, with Industry 4.0, new digital technologies and solutions help to increase production efficiency significantly: the Internet of Things (IoT), high-speed device compatibility (M2M), industrial robots and cyber-physical systems (IR and CPS), data analytics and cloud solutions, the use of artificial intelligence, digital twins, simulation techniques, modelling solutions, virtual and augmented reality, etc. The list is just a brief example of products and technologies that today's production can not any longer handle.

One of the essential components of modern production systems is industrial robots. Their number increases, and the field of application expands rapidly. The main operations industrial robots are nowadays performing are welding, painting, gluing and similar operations, as well as machine tending, handling products, performing quality control, logistics (mobile robots). An evolving field is process robots: polishing, grinding, and machining.

Using industrial robots in production, it is necessary to realize a robotization solution. Robotization solutions, or robot cells, are usually solutions where the robot forms a complete integration with the device or other solution. There are many variants and possibilities of realization. The extensive range of robot functions, the large number of manufacturers, and the wide price range significantly contribute to diversity. Also, there is an excellent variety of options for the accessories that come with the solution. The main problem is the layout of the robotic workplace, the nature of the components (robot, implements, accessories) and the required functionality, the performance and efficiency of the system as a whole. All this is extremely important and necessary for the company to make rational decisions. As a rule, the wrong decision is expensive and, in the worst case, it is not possible to implement it in the company production system.

The company will only benefit if the designed robotic cell is used rationally according to needs. Both the correct design and rational use of the solution are complex engineering tasks due to a large number of variants and the variety of target functions (product cost, labour productivity, system cost, solution complexity, functional capability, etc.). Hence the task setting and the purpose of the work.

This doctoral thesis aims to develop a robotic workplace design solution (methodology) using the possibilities of artificial intelligence and based on multi-criteria decision possibilities, which take into account the company's production needs and ensures successful output from the planned production system. The implementation of the methodology includes solving the following integrated tasks:

1. Implementation of integrated data analysis to assess the suitability of robotization, based on the SME strategy, workplace, product parameters and the constraints from the company structure.
2. Development of a solution for practical robotic workplace components selection.

3. Development of a methodology for the robotic workstation effectiveness analysis.
4. Development of a methodology based on selected performance indicators (KPIs) to analyze the performance of a planned (or existing) robotic workplace.
5. Development of a 3D virtual environment simulation solution for designed robotic workplace rationality and performance analysis. Validation of the results and making of the final decision.

The novelty of the thesis is the development of an integrated and recursive artificial intelligence-based decision-making process for robotic workplace design and performance evaluation.

The developed methodology is built on different decision algorithms and is recursive between steps. The decision-making methods mainly used are a weighted sum method, different analytical hierarchical decision-making methods, and decision models based on artificial neural networks. These listed methods have been integrated into a knowledge-based system, the raw data collected from implemented robot-based production cells, experimental tests or based on simulations.

As the environment in which the production unit is designed is dynamically changing due to the nature of business and technology, it would be reasonable to apply the proposed methodology repeatedly for continuous process improvement. In summary, a systematic and assured robot production unit design methodology will help to determine with optimal time and human resources whether the planned production unit is technically feasible and cost-effective for use by an SME. In addition, a solid structure limit human mistakes and omissions in the planning process.

Lühikokkuvõte

Intelligentse robot-tootmise struktuuri arendus väike- ja keskmise suurusega ettevõtete digitaalsete töökohtade tarbeks

Tootmisettevõtte konkurentsivõime hoidmiseks tänapäevases muutuvas maailmas peab ettevõtja arvestama klientide järjest kasvavate ootustega toodete kvaliteedile ja funktsionaalsusele, toodete elukaare pideva lühenemisega, vajadusega vähendada toote turule toomise aega, aga ka ühiskonna vananemisega ja rohetehnoloogiate ilmnemisega, jms. Mistõttu peab tootmine muutuma järjest efektiivsemaks, olema võimalikult paindlik, vajaliku automatiseerituse tasemega ja kasutama tulemuslikult digilahendusi.

Tootmise tulemuslikkust aitavad tänapäeval oluliselt tõsta Tööstus 4.0-ga kaasnevad uued digitehnoloogiad ja lahendused: asjade internet (IoT), seadmete kiire ühilduvus (M2M), tööstusrobotid ja küber-füüsilised süsteemid (IR ja CPS), andmeanalüütika ja pilvelahendused, tehisintellekti väljundite kasutamine, digitaalsete kaksikute, simulatsioonitehnikate, modelleerimise lahenduste kasutamine, virtuaalreaalsuse-liitreaalsuse lahendused, sensorid, jms. Loetelu on vaid põgus näide toodetest ja tehnoloogiatest, milledeta tänapäeva tootmises enam hakkama ei saa.

Kaasaegsete tootmissüsteemide juures on üheks väga oluliseks komponendiks tööstusrobotid. Nende arvukus pidevalt suureneb ja rakendusvaldkond laieneb. Tööstusroboteid kasutatakse koostamisel, keevituse-, värvimise-, liimimise- jt taoliste operatsioonide sooritamisel aga ka seadmete teenindamisel, toodete pakkimisel, pakendite teisaldamisel, mõõte- ja kontrolli operatsioonide läbiviimisel, tootmislogistikas (mobiilsed robotid). Arenevaks valdkonnaks on tööd sooritavad robotid: poleerimine, lihvimine, mehaaniline töötlemine. Rakendusvaldkondi on veelgi ja robotite kasutusvõimalused aina suurenevad.

Tööstusrobotite kasutamiseks tootmises on tarvilik realiseerida robotiseeritud kooslus. Robotiseeritud kooslused ehk robot-rakud on reeglina lahendused, kus robot moodustab seadmega vm lahendusega integreeritud terviku. Realisatsiooni variante ja võimalusi on palju. Paljususele aitab oluliselt kaasa robotite väga laialdased funktsionaalsed võimalused, suur tootjate arv ja lai hinnaskaala. Lisaks on suur varieeruvus ka lahendusega kaasnevate lisaseadmete võimalustes. Põhiprobleem seisneb robotiseeritud töökoha ülesehituses (layout), koostisosade (robot, tööorganid, lisaseadmed) olemuses ja vajalikus funktsionaalsuses, süsteemi kui terviku toimivuses ja tulemuslikkuses. See kõik on ettevõttele äärmiselt oluline ja vajalik ratsionaalsete otsuste tegemiseks. Vale otsus läheb reeglina kalliks maksma ja halvimal juhul ei olegi võimalik juurutada ettevõttes.

Kasu ettevõttele on vaid siis kui planeeritud robotiseeritud töökoht on vajadustele vastavalt kavandatud ning ratsionaalselt kasutatud. Nii lahenduse õige disain kui ka ratsionaalne kasutamine on keerulised inseneriülesanded variantide suure hulga ja sihifunktsioonide (toote omahind, töö tootlikkus, süsteemi maksumus, lahenduse keerukus, funktsionaalne võimekus, jt) mitmekesisuse tõttu. Siit tuleneb ülesande postitus ja töö eesmärk

Doktoritöö eesmärgiks on välja töötada tehisintellekti võimalusi kasutav ning mitme-kriteeriumilisele otsustusvõimalustele tuginev robotiseeritud töökoha kavandamise lahendus (metoodika), mis arvestab ettevõtte tootmise vajadusi ning tagab tulemusliku töö planeeritud tootmissüsteemis.

Metoodika rakendamine sisaldab alljärgnevate integreeritud ülesannete lahendamist:

1. Integreeritud andmeanalüüsi teostus robotiseerimise sobivuse hindamiseks tuginedes VKE tegevusstrateegiale, robotiseeritud töökoha olemusele, planeeritavate toodete parameetritele ning ettevõtte struktuurist tulenevatele piirangutele
2. Lahenduse leidmine robotiseeritud töökoha kavandamiseks vajalike komponentide otstarbeka valiku teostamiseks
3. Metoodika väljatöötamine valitud komponentide alusel kavandatud robotiseeritud töökoha kui süsteemiüksuse toimivuse analüüsiks.
4. Metoodika väljatöötamine kavandatud (või olemasoleva) robotiseeritud töökoha toimivuse analüüsiks valitud tulemusnäitajate (KPI) alusel
5. Simulatsioonilahenduse väljatöötamine kavandatud robotiseeritud töökoha olemuslikkuse ja toimivuse analüüsiks 3D virtuaalkeskkonnas ning leida lahend tulemuste valideerimiseks ja lõppotsuse langetamiseks

Töö uudsus seisneb integreeritud ja rekursiivses tehisintellektile tuginevad otsustusprotsessi väljatöötamises robotiseeritud töökohtade tulemuslikuks kavandamiseks ja saadud lahenduste hindamiseks ning töö soorituse tulemusnäitajate prognoosimiseks.

Välja töötatud metoodika on üles ehitatud erinevatele otsustus algoritmidele ning on rekurseeriv erinevate sammude vahel. Otsustumeetoditena on kasutatud peamiselt kaalutud keskmise meetodit, erinevates variatsioonides analüütilist hierarhilist otsustusprotsessi ning on kaasatud tehisnärvivõrkudel põhinevad otsustusmudeleid. Neid loetletud meetodeid on kasutatud teadmispõhise süsteemi loomiseks mille algandmed on kogutud tööstusettevõtete robottootmisüksustest, eksperimentaalkatsetuste käigus või simulatsioon-katsete baasil. Kuna keskkond kuhu tootmisüksus planeeritakse on dünaamiliselt muutuv ettevõtluse eripärade ja tehnoloogiate arenemise tõttu oleks mõistlik selgitatud metoodikat protsesside pideva täiustamise teostamiseks korduvalt rakendada.

Kokkuvõtvalt aitab süstematiseeritud ja korrastatud robottootmisüksuse planeerimise metoodika jõuda optimaalseima aja ja inimressursiga teadmiseni kas planeeritav tootmisüksus on tehniliselt teostatav ja rentaabel kasutamiseks VKE. Lisaks aitab kindel struktuur vältida inimlikke vigu ja tegematajätmisi planeerimise käigus.

Appendix 1

Publication I

Vaher, K.; **Kangru, T.**; Otto, T.; Riives, J. (2019). The Mobility of Robotised Work Cells in Manufacturing. Proceedings of the 30th DAAAM International Symposium pp. 1049–1055, B. Katalinic (Ed.), Published by DAAAM International, Vienna, Austria. DOI: 10.2507/30th.daaam.proceedings.146

DOI: 10.2507/30th.daaam.proceedings.146

THE MOBILITY OF ROBOTISED WORK CELLS IN MANUFACTURING

Kristo Vaher, Tavo Kangru, Tauno Otto, Jüri Riives

This Publication has to be referred as: Vaher, K[risto]; Kangru, T[avo]; Otto, T[auno] & Riives, J[yri] (2019). The Mobility of Robotised Work Cells in Manufacturing, Proceedings of the 30th DAAAM International Symposium, pp.1049-1055, B. Katalinic (Ed.), Published by DAAAM International, ISBN 978-3-902734-22-8, ISSN 1726-9679, Vienna, Austria
DOI: 10.2507/30th.daaam.proceedings.146

Abstract

Many companies are already using robots, but many have not found enough applications for the robot and therefor they have not purchased it jet. One robot can be used to perform several different tasks, but it also raises the question of whether the production needs to be reorganized so that these multiple tasks are directed to the robot, or it can be solved differently where the robot moves between different tasks. In this paper different concepts will be discussed and each of its disadvantages and advantages will be highlighted. Paper also includes survey among Estonian manufacturing companies to find out which tasks are robotized and which tasks are desired to give over to robots in future. Paper also include short description about recently opened Industry 4.0 test hub where mobile robot applications are being tested and paper results will be also tested in this test hub. In general, this paper focus on solution how to use robot arm most efficient way if there is not enough job for stationary robot solution.

Keywords: Mobile robot, robot arm, manufacturing, industry 4.0

1. Introduction

One of the biggest problems of industry today is the shortage of qualified workforce. The development of technologies in the last decades has been extremely fast, the technologies today change much faster than generations. People from older generations often lack the knowledge and the courage to use the newest technologies. At the same time, children (and youngsters) from the younger generations lack the patience and willingness to study complicated engineering specialties. It is difficult to pinpoint the causes of this behaviour, but it is becoming clear that the industry must learn to deal with the situation and find new ways to keep the production ongoing and making profit in the future.

In order to alleviate the problem of qualified workforce, it is possible to use industrial robots and increase the automation of production. Robotization is, of course, more affordable to larger companies than to small and middle-sized enterprises (SMEs). The main precondition for using industrial robots is the production in large batches, especially in cases when there are multiple robots working simultaneously in the same system. Production monitoring system helps to identify the needed predictive maintenance and tool exchange times [1]. This, however, does not mean SMEs should not use robots at all. Collaboration robots can be successfully integrated into the work process of smaller enterprises, using interaction technologies [2]. Predictive simulations are used for fastest route planning in an industrial environment [3].

The development of collaboration robots and the general compliance of Industry 4.0 principles have made the implementation of industrial robots fairly easy [4], [5], [6], [7], [14].

One of the preconditions of operating an industrial robot is that it has enough working hours per day. In case of smaller enterprises that produce small batches, it would mean the reorganization of production so that the tasks performed by the robot would be directed to a stationary robot. Another option is to move manually the robot between different units of production. This may result in long pauses in working time and degrees of efficiency. The robot could, instead of waiting, fulfil another task or serve other benches. To achieve this, the production must be planned so that the benches the robot needs to serve are placed around the robot. Another option is to move the robot arm from one bench to another in the production area. It can be done by lifting it manually or by mobile robot.

In addition to the shortage of skilled labour, industries also have to deal with issues such as optimizing production times, using resources more efficiently, producing faster and smaller quantities, while ensuring high quality [13]. Robotic solutions are one of the key factor in solving these issues as well. Lack of knowledge to guide potential users of robotic sell is an essential barrier to more extensive use of robotised solutions [9].

2. Survey among Estonian Enterprises

In 2017, a survey was conducted among Estonian enterprises in order to map the level of robotization in production companies. Among other questions, the companies were asked about the characteristics of production in terms of batch sizes, in order to evaluate which companies could benefit from stationary and which from mobile robot cell solutions. 30 enterprises took part in the survey. The average size of the enterprises was 140 people, and according to turnover data, most of the companies could be defined as SMEs (small and middle-sized enterprises).

In addition, the survey included questions about batch/lot sizes of products and parts, and about the repeatability factor of a batch – meaning whether one part is produced multiple times or is every operation different. The survey showed that the batch sizes in 1/3 of the enterprises correspond to 10 – 50 units. In most cases, the repeatability of a batch was more than 50%. In case of batch sizes of less than 10 units, we could see a low repeatability level (ca 10%). With batches of more than 50 units, the repeatability level was high, more than 50%. Over 60% of companies answer that more that 50% of batches are repeated constantly over the time.

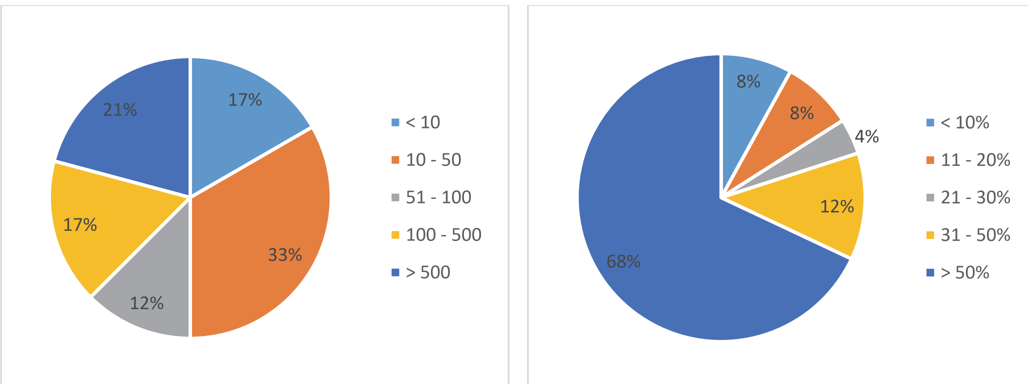


Fig. 1. Parts in lot size (left) and repeatability of the lots (right)

Based on the information from the survey, it can be concluded that most enterprises produce relatively small batches with high level of repeatability. This means that one bench is not only used for producing one product or part, and that products are being manufactured repeatedly. From the viewpoint of robotization, it means creating multiple programmes. When repeating the production cycle, a programme that has already been written can be used again.

The survey also indicates that the robots used in manufacturing are not fully occupied. Half on the enterprises use robots for up to 50-70% of their capacity. It shows that robots could be given additional tasks, but since the companies are using mainly welding robots, it is hard to assign other jobs for them. The data shows that only 25% of enterprises use more than 70% of their robots capacity.

According to the survey, up until now, industrial robots have mainly been used in welding operations. However, the data shows that enterprises would like to use robots for other operations as well, such as mechanical processing, painting, assembling and quality control (Fig. 2). In these areas, there are various tasks that can be assigned to one robot. If it is not possible to occupy a robot fully with a certain task, it is reasonable to use the robot for many different tasks.

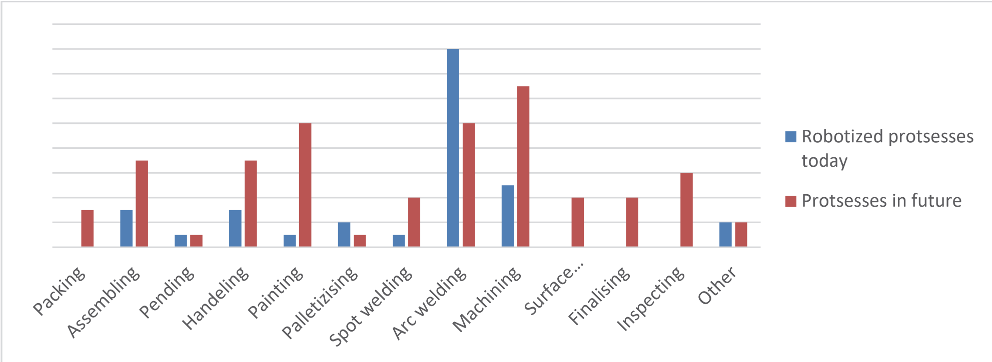


Fig. 2. Robotized protsesses today and desired processes for future

According to the Genefke scale, elaborated at Danish Technological Institute by Bo Genefke, the enterprises that took part in the survey mainly operate with tasks requiring standard and adaptable knowledge, which could be easily automated (Fig. 3). Genefke scale divides enterprises into five categories. The enterprises that belong to the first group can use standardized, easily applicable solutions. When moving to the right end of the scale, we see the complexity of tasks rising. The right end of the scale indicates enterprises who need completely new knowledge in their processes, such as enterprises and organisations dealing with research.

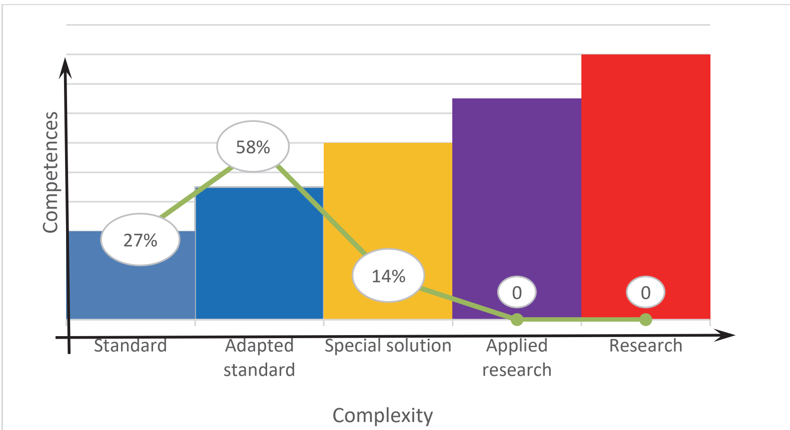


Fig. 3. Genefke scale

The survey conducted among Estonian enterprises shows that the robots used in production are mainly welding robots which are not used to their 100% capacity. At the same time, enterprises would like to use robots for other operations as well. The problem is that it is difficult to implement welding robots for other tasks, as their tool and installation is meant only for welding operations and it would be too costly to exchange those. Instead, it would be feasible to use a new robot for operations other than welding. In case the new robot cannot be fully occupied with one type of task, it would be beneficial to find a universal solution where the robot could perform different types of tasks, such as serving the CNC bench and packaging.

3. Manufacturing testbed for Industry 4.0

Most of the testbeds related research is related to cyber security and electrical grids, while robotics and manufacturing are in minority [10]. In current research the testbed for applying Industry 4.0 principles through robotics and manufacturing has been developed at TTK University of Applied Sciences [8]. The testbed laboratory features a functioning production system, starting from entering the order to Enterprise Resource Planning (ERP) until the pickup at the package station by an end consumer. In between, there is the whole manufacturing process together with several robots. The production system is modular and flexible. The system is easily reconfigurable when new products are added, and modules can be added or reconfigured when production volumes increase. Main purpose of this lab was to get test bed where different scenarios can be tested according to Industry 4.0 principles. Automatization components from Estonian manufacturers were also integrated to connect the concept regionally and also educate visitors and students.

One of the modules of this testbed manufacturing system is a mobile robot arm, the task of which is to serve all the other modules (Fig. 4). The main tasks of the robot arm include transporting the warehouse container between different modules and changing the plate in the 3D printer. In the testbed, similarly to state of the art international labs [11] robots from two different manufacturers have been used – the robot arm Universal Robots UR 10 and the mobile robot Mobile Industrial Robots MIR 100.

Fig. 4. Robot arm and mobile robot tandem.

Based on the mobile robotic arm module described above, practical tests will be conducted, and a prototype model developed for supporting the theoretical part of the current study. The aim is to build a base frame or a platform to the robot arm that would be separate from the mobile robot and that would be transportable by the mobile robot in the automated process together with the robot arm.

4. Alternative solutions for increasing the performance of a robot-cell

Today there are several different mobile robots available that are capable of moving the robot arm around in a room. For this, two different technologies must be combined. The result is a flexible solution that enables to use one robot arm in many working positions. There are solutions where a robot arm has been permanently installed into a mobile robot, such as KUKA KMR Quantec, KUKA KMR iiwa, Robotnik Kairos 3. In addition, there are many solutions of combining MIR 100 + UR10, and other robots from different manufacturers. In this case, the cost of the robot cell would be the sum of a robot arm and a mobile robot, therefore approx. doubling the cost.

However, the two work cells could be separated when, for example, more than one robot arm is used in manufacturing. In this case, one mobile robot can serve many robot arms. When combining a mobile robot and a robot arm, only one of them can work simultaneously with the other in most cases. During transport, the robotic arm is not working and when the robot arm is working, the mobile robot is standing idly. Separation of the tandem of a mobile robot and a robotic arm (fig. 5.) would considerably raise the efficiency of both units.

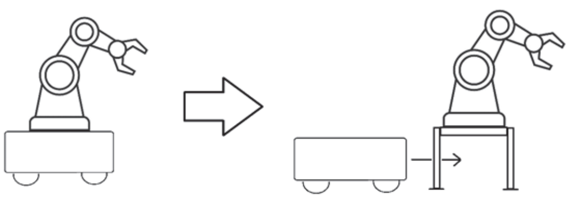


Fig. 5. Separating mobile robot from robot arm tandem

One industrial robot may easily be used for performing different working tasks. For this, a robot cell with different functionalities is needed. Many different tools can also be assembled to one robotic arm. For example, several work tools can be assembled to a robotic arm with a rotating multi-tool mount. Another option is to use a quick-change system (tool-change solution for immediate use). Using a rotatable multi-tool solution is a good and fast option, but its extra hardware and it add a lot of weight to the robot arm, which will therefore lower the maximum weight limit of the working task. The rotating multi-tool solution is being produced, for example, by New Scale Robotics. The advantage of a quick-change system compared to the rotatable multi-tool solution is its smaller weight. However, with this solution, less time will be left for the production process itself, as the change of the tool must be done in distance from the work object, therefore, it will take some time to detach a tool and replace it with a new one. Quick-change solutions are offered, for example, by the company Stäubli. Both solutions have their advantages and disadvantages and the choice depends largely on the implementation specialty and the characteristics of the working process.

Regardless of the type of a work tool of a robotic arm, the more important question is whether to bring the work tasks to the robot or to take the robot to the task(s). In case a robot will be brought into a working production facility, it is important to assess whether and how much will the system be reorganized and how much additional investments will be needed. The following pages focus on the three possible options of integrating robots with different working tasks.

4.1. Solution 1

In order to use one robot for many different operations, production should be planned so that the automated tasks are moved to the robot and the robot itself is stationary (Fig. 6.). In this case, the robot is the central object of production and everything else should be positioned accordingly. This would be a typical solution for a production facility using cage robots, where, in addition to the investment of buying a new robot, a security zone must be built around the robot. This is the option where the integration of a robot to an existing industrial environment will require a certain amount of reconfiguration. Production lines and other tasks should be moved towards the robot. In most cases, this means production would be stopped for a longer period of time.

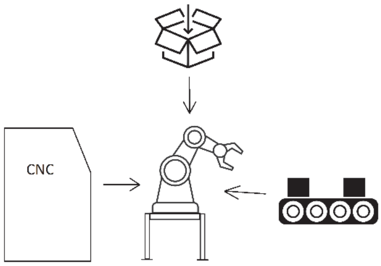


Fig. 6. Tasks directed to robot

4.2. Solution 2

The second option is to leave the existing production environment as it is and move the robot in between different working positions. In this case, the robot will be taken from one working position to another by a human (Fig. 7). The central object in the process is the human who has to be ready to move the robot at any time as soon as the production process requires. In this case, the manufacturing process will not change much. The moving of the robot requires the presence of a human, who will move the robot from one position to another in between working tasks. To employ an individual just for moving robots, however, may not be efficient. This solution may also cause time delays, at it may take time for a human to arrive to the robot after it has finished work. Similar solution was done by OpiFlex.

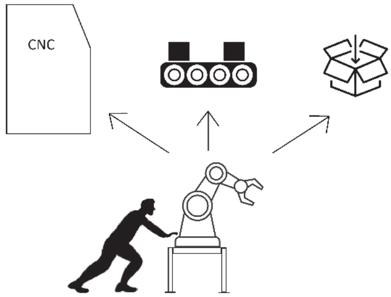


Fig. 7. Robot arm is moved between tasks by human

4.3. Solution 3

The third option is to automate the moving process of the robot arm by using a mobile robot (Fig. 8). With this solution, no part of the production takes the central role, as the whole process is fully automated and works as a compact whole. The manufacturing process can be planned with high accuracy level. For example, in case of a robot serving a CNC machine, it can be quite accurately calculated when the batch will be finished. By this time, a mobile robot can be sent to fetch the robotic arm, and it can be moved to the next task. In this option, there is no need for a human who would take the robot arm from one working station to another. Connecting the robot arm to the electricity network and other communications will take place automatically through the base frame of the robotic arm.
This solution presupposes that every working position need for the robot arm an automatic docking station, which has been linked with the centralized systems such as electricity, compressed air, data, etc.

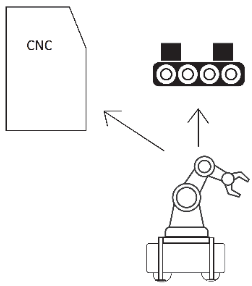


Fig. 8. Robot arm is moved between tasks by mobile robot

4.4. Comparison of solutions

The following charts (Table 1.) illustrate the levels of the changes that need to be done and the impact to the manufacturing process in case of different options of taking in use a robot arm solution. The chart does not bring out the factors that are similar for all the options, such as programming, implementation to the process, maintenance etc. Evaluation is done based on comparing those three solutions with each other and marks are given witch solution takes the highest credit and witch one the least.

	Need for reconfiguring the production	**Need for additional appliances**	**Need for additional software**	**Need for additional human work hours**
Solution 1	High	Low	Low	Low
Solution 2	Low	Low	Low	Medium
Solution 3	Low	High (mobile robot, dock's)	High (MES[1])	Low

Table 1. Integration needs for a robot solution implementation

The chart below (Table 2) compares the benefits of integrating a robot arm solution in factory. Case by case it can be different but in general it shows the different between those three solution results.

	Level of automation	**Rise of Efficiency level**	**24/7 (full time) working capacity**	**Flexibility**
Solution 1	High	High	High	Low
Solution 2	Medium	Medium	Medium	High
Solution 3	High	Rather high	High	High

Table 2. Benefits of integrating a robot arm to a production facility

[1] MES - Manufacturing execution systems

Different solutions require very different investments. Investing in automation is inevitable. New equipment and software must be introduced and money spent on programming. As a result, the goal is to achieve more efficient production. Efficiency gains are expressed differently by each company. It can be one of the factors in the table, or it can be all of the actions taken together. In solution three the score is high for all the factors. In future developments the testbed can be implemented for investigation of Industry 4.0 Digital maturity Model 4.0 [12].

5. Conclusion

Survey among Estonian companies brought out that implementation of industrial robots by SMEs has been slow. One reason for that is that, there is not enough work assignments for stationary robots without reorganize production in a big scale. At same time, the companies are interested to give more jobs to the robots. As a result of this work, a solution has been proposed in which the robot arm is moved between different working positions and the transport part is filled by another robot - a mobile robot. Such a solution can give high level of work hours to the robotic arm without the need to reorganize existing factory in big scale. When using a mobile robot, there is no need for a separate person who should take care to move the robot arm between different workstations. Carrying a robotic arm on a mobile robot gives you the opportunity to apply a robotic arm around the clock and it gives you flexibility to reconfigure your production more easily rather the solution where robot arm is stationary.

The aim of the thesis is to develop a technical solution for the mobile use of a robot arm, accompanied by a prototype and an assessment of its applicability. Further on, a design model will be developed for configuring a mobile robot to the robot arm. MIR 100 will be used as a mobile robot and UR 10 as a robot arm. A functional model and a cost-analysis will be developed. After this, a practical model will be built, and necessary tests completed for assessing the model's applicability.

6. References

[1] Eiskop, T.; Snatkin, A.; Karjust, K.; Tungel, E. (2018). Production monitoring system design and implementation. Proceedings of the Estonian Academy of Sciences, 67 (1), 10−16.10.3176/proc.2017.4.02/

[2] Berg, J.; (2019). Human-Robot-Interaction for mobile industrial robot teams. Procedia CIRP. 79. 10.1016/j.procir.2019.02.080.

[3] Grijalva, G.; Chavez D.; Camacho, O. (2018). Material Distribution with Mobile Robots in an Industrial Environment: System design and simulation. IFAC-PapersOnLine. 51. 650-655. 10.1016/j.ifacol.2018.07.354.

[4] Lu, Y. (2017). Industry 4.0: a Survey on Technologies, Applications and Open Research Issues, Journal of Industrial Information Integration. 6. 10.1016/j.jii.2017.04.005

[5] Robla-Gomez, S.; Becerra, V.M.; Llata, J.R, et al. (2017). Working Together: A Review on Safe Human-Robot Collaboration in Industrial Environments. IEEE Access. PP. 1-1. 10.1109/ACCESS.2017.2773127.

[6] Loun, K.; Riives, J. ; Otto, T. (2012). Workplace performance and capability optimization in the integrated manufacturing. Proceedings of 8th International Conference of DAAAM Baltic Industrial Engineering, 2: 8th International DAAAM Baltic Conference In Estonia. INDUSTRIAL ENGINEERING, 19 - 21st April 2012, Tallinn. Ed. Otto, T. Tallinn.

[7] Kuts, V.; Otto, T.; Tähemaa, T.; Bondarenko, Y. (2019). Digital twin based synchronised control and simulation of the industrial robotic cell using virtual reality. Journal of Machine Engineering, 19 (1), 128−145.2010.5604/01.3001.0013.0464.

[8] Vaher, K.; Vainola, V.; Otto, T. (2019). Industry 4.0 Laboratory. Industry 4.0, Technological Basis of "Industy 4.0", 1/5: IV International Scientific Conference, Industry 4.0. Summer session, 24-27.06.2019, Burgas, Bulgaria. Industry 4.0 Proceedings: 108 Rakovski str; 1000 Sofia.

[9] Iglesias, I.; Sebastián, M.A.; Ares. J.E. (2015). Overview of the State of Robotic Machining: Current Situation and Future Potential. Procedia Engineering. 132. 911-917. 10.1016/j.proeng.2015.12.577.

[10] Salunkhe, O.; Gopalakrishnan, M.; Skoogh, A. et al. (2018). Cyber-Physical Production Testbed: Literature Review and Concept Development, Procedia Manufacturing, 25: 2-9, http://dx.doi.org/10.1016/j.promfg.2018.06.050

[11] Papa, M.; Kaselautzke, D.; Stuja, K. & Wolfel, W. (2018). Different Safety Certifiable Concepts for Mobile Robots in Industrial Environments Proceedings of the 29th International DAAAM Symposium "Intelligent Manufacturing & Automation", 24-27th October 2018, Zadar, Croatia, Volume 29, No.1, ISSN 1726-9679, ISBN 978-3-902734-20-4. Ed. B. Katalinic / Published by DAAAM International, Vienna, Austria, EU, 2018

[12] Gajsek, B.; Marolt, J.; Rupnik, B.; Lerher, T. & Sternad, M. (2019). Using Maturity Model and Discrete-Event Simulation for Industry 4.0 Implementation International Journal of Simulation Modelling Volume 18: Number 3: September 2019.

[13] Reinhart G. (2017). Handbuch Industrie 4.0: Geschäftsmodelle, Prozesse, Technik. München: Hanser.

[14] Sell, R; Otto, T. (2008). Remotely controlled multi robot environment. Proceedings of 19th EAEEIE Annual Conference: 19th EAEEIE Annual Conference, Tallinn, Estonia, June 29 - July 2, 2008. Tallinn, 20−25.10.1109/EAEEIE.2008.4610152.

Publication II

Kangru, T.; Riives, J.; Otto, T.; Pohlak, M.; Mahmood, K. (2018). Intelligent Decision-Making Approach for Performance Evaluation of a Robot-Based Manufacturing Cell. Proceedings of the ASME 2018 International Mechanical Engineering Congress and Exposition. Volume 2: Advanced Manufacturing Pittsburgh, Pennsylvania, USA. November 9–15, 2018. V002T02A092. ASME https://doi.org/10.1115/IMECE2018-86666

Proceedings of the ASME 2018 International Mechanical Engineering Congress and Exposition
IMECE2018
November 9-15, 2018, Pittsburgh, PA, USA

IMECE2018-86666

INTELLIGENT DECISION MAKING APPROACH FOR PERFORMANCE EVALUATION OF A ROBOT-BASED MANUFACTURING CELL

Tavo Kangru
Tallinn University of Technology
Tallinn, Harju, Estonia

Jüri Riives
Innovative Manufacturing Engineering Systems
Competence Centre
Tallinn, Harju, Estonia

Tauno Otto
Tallinn University of Technology
Tallinn, Harju, Estonia

Meelis Pohlak
Tallinn University of Technology
Tallinn, Harju, Estonia

Kashif Mahmood
Tallinn University of Technology
Tallinn, Harju, Estonia

ABSTRACT

Manufacturing is moving towards complexity, large integration, digitalization and high flexibility. A combination of these characteristics is a basic for forming a new kind of production system, known as Cyber Physical System (CPS). CPS is a board range of complex, multidisciplinary, physically-aware next generation engineered systems that integrates embedded computing technologies. Those integrated manufacturing systems usually consist of four levels: network, enterprise, production system and workplace. In this article we are concentrated to the workplace level, examining the implementation of the most suitable robot-cell and integration it into the production system and enterprise structure. The problem is actual for the big companies such as automobile industry, but very important is also for small and medium sized enterprises (SMEs) that tend to produce for example; small tractors, air conditioners for high speed trains or even different type of doors for houses. In all cases the best solution to response the situation is the implementation of robot-based manufacturing cell into a production system, which is not only a challenge but also need a lot of specific knowledge. Designing and selecting optimal solutions for robot-based manufacturing systems is suitable to carry out by a computer-based decision support systems (DSS). DSS typically works by ranking, sorting or choosing among the alternatives. This article emphasis to the problem of integration the DSS with the artificial intelligence (AI) tools. For this objective, the study has been focused to development of a conceptual model for assessing robot-based system by means of technical and functional capabilities, which is combined with cell efficiency based on process Key Performance Indicators (KPIs) and enterprise Critical Success Factors (CSFs). The elaborated model takes into consideration system design parameters, product specific indicators, process execution data, production performance parameters and estimates how the production cell objective can be achieved. Ten different types of companies were selected and their robot-based manufacturing systems were mapped by qualitative and quantitative factors based on the model, whereas executives were interviewed to determine companies` strategic objectives. The study results comprise of an approach that helps SMEs to gain additional economic-technical information for decision making at different levels of a company.

INTRODUCTION

Currently, manufacturing is moving towards complexity, bigger integration, digitalization and flexibility. This all appeared with introducing Cyber Physical Systems (CPS) [1]. The National Institute of Standard and Technology describes "Cyber Physical System" as an Internet of Things (IoT) which involves connecting of smart devices and systems in diverse sectors like transportation, energy, manufacturing and healthcare in a fundamental new way [2]. One of these smart systems and devices are industrial robots and robot-based manufacturing cells. Since 2010, the demand for industrial robots has accelerated considerably due to the ongoing trend towards automation and integration [3]. The industrial robots are used in a wide range of different manufacturing processes such as welding, assembly, loading-unloading, palletizing, logistics, painting, etc. The problems with the implementation of robot-cells for the companies are more or less same i.e., how with the limited resources to achieve the best results: high productivity, low manufacturing cost, high quality and smooth integration of a robot-cell into a production system. Typically, there are a lot of different improvement possibilities under the robot-cells applications, but the problem is to find the best solution for a manufacturing with certain workpieces, product families and process parameters. Since there are existing some technical restrictions and the efficiency of a manufacturing/production cell can be characterized by the expected results such as cycle time, unit cost, cell productivity, return on investments (ROI), etc. Therefore, a harmonized knowledge oriented approach is needed to address the complexity and performance of a production systems and/or cells for the decision making enhancement. A knowledge-based conceptual model for robot-based manufacturing is proposed in the article and the data, information and knowledge processing for decision support systems are mainly focused. The model can be used for different applications like welding, loading-unloading, palletizing. Moreover, it helps to design a suitable robot-cell structure and estimate the relationships between the parameters inside the cell and through this the possible problematic situations or cases can be evaluated. Based on workgroup longtime experience with development/adaption of global optimization methods and techniques for various engineering design problems [4-6], the robot-cell performance evaluation model (PEM) has been formulated as multi-criteria optimization problem and solved by applying global optimization methods [7, 8].

BACKGROUND

This section expresses the evolution and objectives of an integrated manufacturing system as a complex system, and the rising involvement of Industrial Robots (IR) into a manufacturing environment. Followed by the brief description of an overview of decision making principles for the designing and operation of a robot-based manufacturing cell.

Nevertheless, an increasing trend of the adoption of IR by SMEs to enhance the efficiency and effectiveness of their production systems as a robot-based production cell leads to develop an approach to evaluate the performance of a production cell. The approach helps the stakeholders to make a decision based on certain knowledge and Key Performance Indicators (KPIs), which has been developed in this paper. A conceptual model, which facilitates to establish a case-based model is included in the approach.

Integrated manufacturing based on complex systems

A company is an entire system that has to find the most effective and efficient ways to use its resources for realizing its strategic plans and producing the determined nomenclature of goods. A complex system is a system composed of many components which may interact with each other. The system is defined as a set of attributes that is through their interactions, relationships, or dependencies form a unified organization model [9, 10].

The schematic model of integrated manufacturing can be seen in the Fig. 1, it has four basic levels: network, enterprise, production system and workplace. Each level could be represented by the value composing frame V, having several indicators:

$$V = \{N, A, S, F, P\} \quad (1)$$

Where:

N – Components of the system (depending on the objective of the system);

A – Parameters describing the components of the system (for example technological parameters in the case of production system);

S – Structure of the system (in the case of production system the locations of existing equipment and connections between them);

F – Amount of functional connections between the elements of the system (depends on the ontology of the system and defines essence of single events). In the case of production system, the number and essence of events depends on used technology, rate of automatization and organization of production;

P – Set of transactions. In manufacturing system, it is the amount of manufacturing operations taking place, p_1 to p_k, (e.g. p_1 – milling, p_2 – turning; p_3 – boring etc), depends on technological possibilities of the system.

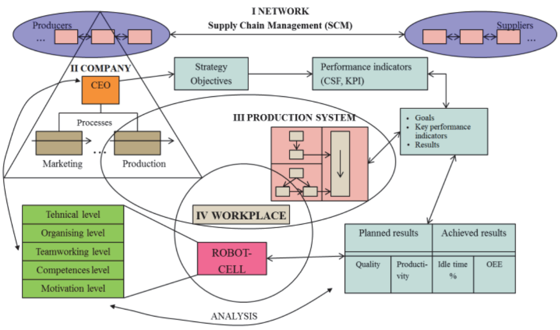


Fig. 1. SCHEMATIC MODEL OF INTEGRATED MANUFACTURING.

On each level of the integrated manufacturing, there are different objectives that would be fulfilled by various tasks which are considered in the strategy and production plan of a company. Practically direct manufacturing lies on the workplace, which is a basic for achieving the productivity, flexibility or needed quality through its integration with different processes and systems of a company [11]. The important question for every company is the expediency, suitability and functionality of each subsystem of the company and the enterprise as the whole to manage with the planned technological and organisational tasks. The level of executing these tasks would be expressed in results of the workplace, production process or whole company. The validation and estimation of such results can be possible through the analysis of obtained data and accumulated information. Here we can consider the technical, organizational, and other aspects [12].

Emergence of Industrial Robots in Manufacturing

The most active industry, implementing the industrial robots is automobile industry. In recent times, SME-s have a great interest of implementing industrial robots in different fields such as welding, assembly operations, material handling, palletizing and etc. [13-15]. The expectations are to achieve better results and to be more competitive due to the new investments. On the basis of analysis of different SMEs we can draw out different objectives in the different integration levels of manufacturing, which are described in the table 1.

Table 1. VARIETY OF OBJECTIVES IN THE INTEGRATION LEVELS

Goals	Objectives
System goal	Using the production system most suitable way for having maximum profit with proper utilization of resources.
Process goal	The evaluation of alternative routes for the determined set of products or product families based on the cost and total throughput time of these products (optimal fulfilling of the manufacturing task).
Workplace goal	Reducing all non-productive times by analyzing and eliminating the reasons of occurrence like by following the principles of Lean manufacturing.
Industrial robot goal	Using the most suitable industrial robot with the needed technological capabilities, considering also economical side like Return on Investment (ROI).

In order to choose the industrial robot, designing of the robot-cell and implementing it, it is essential to proceed from the goals that are given in table 1. Performance of such manufacturing systems are realized through the right decisions. First level decisions can be made by designing or redesigning the workplaces of the manufacturing system and the second level of decisions are connected with the operations in the workplace. Moreover, the technological capabilities of a production system depend mainly on the technological capabilities of workplaces a production system consists of. Therefore, workplaces are the main important parts of a production system. Presently, more significant are becoming robot-based workplaces. They have a large variety and different applications in the industry.

Technological capabilities of a robot-based workplace (robotic cell) depends on the characteristics of type of robots, end-effectors, turning tables, storage equipment, etc. As a result, the efficiency of manufacturing cell not only be influenced by the right decisions of designing a robot-cell, but also rely on the operating rules and procedures used in the workshop.

Intelligent Decision Principles for Robot-Cell Operations

Designing of a robotic cell and selecting the most suitable components for this system like industrial robot (IR), end-effectors (EF), loading-unloading positions (LP), working tables (WT), transporting equipment (TR), etc. is a complex task with multi-criteria decision-making procedures. There are different robot classifications and/or robot selection systems, some of them are described in [16-18] and methods for decision making are defined in [19, 20]. Mostly decision making includes the primary task i.e., selecting the best type of industrial robot for performing the several activities that may contain welding, painting, assembly, machine tool servicing, and inspection, grinding and polishing or doing other manufacturing operations. This task is solved by using the hierarchical decision-making approach and multi-criteria optimization [21]. The contrary task is the performance analysis of the implemented robot-cell in manufacturing conditions. Study of the results for practical use of robot-workplaces in an industry shows that the optimal solution in the upper level (robot selection) could not give the best result in lower level i.e., the integration of robot-cell into a manufacturing process. This integration and different aspects of manufacturing were described and previously reflected in the Fig. 1.

Due to the dynamic nature of production process and it takes place under fast-changing conditions. Especially, SMEs are working in the conditions of uncertainty where the production plans and production conditions could be changed. Therefore, in manufacturing planning and selection of necessary equipment, it is not only useful to move according to the straight path, but also to take into consideration the real examples (successes and failures) from the industry. In this paper a conceptual model is developed that consist of intelligent event-driven process engineering decision making procedure as shown in the Fig. 2. Where the primary task (robot-cell parametrical selection) and contrary task (robot-cell parametrical utilization) are in interaction. It means we have a basic issue in goal settings which are connected to each other through the design loop and implementation loop. Therefore, in the real company, the practical goals in different levels are normally different and the primary objectives are also different.

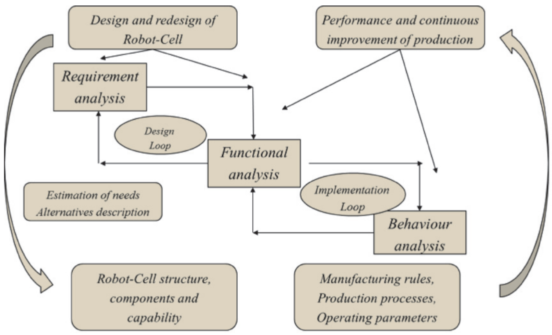


Fig. 2. RECURSIVE DECISION MAKING PROCEDURE.

According to the robot-cell development and behavior ontology, we can distinguish two decision making circles with three activities:

- Requirement analysis is defining the technological capabilities of an industrial robot and the robot-based cell. For example, what types of equipment could be used and what technological parameters are most suitable for the given industrial task.
- Functional analysis on the basis of simulation software like 3D manufacturing simulation technology that would be able to describe the real production process execution possibilities, the possible bottlenecks and alternatives with efficiency estimations.
- Behavior analysis is the reflection of real industrial applications. On the basis of obtained data from different real cases, it is possible to compare the best solution description. By getting the theoretical most suitable industrial robot and observe the behavior of the selected IR in real industrial conditions.

While the purpose of a primary task is to check the robot's architecture and technical parameters best suited for a selected job, the contrary task consists of the analysis of optimal utilization of the implemented robot-cell in a company. On the basis of this data, we can estimate the accuracy of the direct decision. The understanding of the utilization of industrial robots in manufacturing leads to the main principles and decision making rules [22] for the optimal selection of industrial robots in companies.

For decision making following criterions are normally used:

- Increase in productivity
- Lowering of production costs
- Improvement of the working environment
- Increasing the security of supply
- Quality assurance
- Workforce insurance
- An increase of flexibility
- Stock depreciation

METHODOLOGY

In this study a conceptual model for performance evaluation of a manufacturing cell is developed that based on recursive decision making procedure. A comprehensive literature review was carried out, expert opinions from the manufacturing industry related to the design and execution of robotic cell were gathered that helps to build the conceptual model. In order to verify and to see the relevance of the proposed conceptual model, a case study approach is used to as a research method [23]. Moreover, a case-based performance evaluation model for a robotic manufacturing cell, its implementation and results are described in the following sections.

Knowledge-based Conceptual Model

For the development of a conceptual model for the manufacturing robot-cell we considered the knowledge representation so that the decision support system can act in an intelligent manner. An intelligent decision support system must work as a professional consultant, giving explanations for made decisions, analysing evidence, identifying and diagnosing problems, presenting possible cases for improvement or evaluating the alternatives.

However, decision support systems implementation is not a new one. This has been used for different engineering tasks, like design of flexible manufacturing systems. All the problems of decision making lies on the used information and how we use this. Here the novelty is based on the integrated multi-access model and decision-making logic. Recently, wide range of IoT applications, cloud computing, big data and data analytics instruments, leads to the possibilities for developing intelligent decision-making systems where expert system have a great role. Very important for developing such type of tools is the basic decision-making model with data acquisition and knowledge representing principles as shown in the Fig. 3. The system is more capable for SME`s and could be used over the Internet. Proceeding from the real industrial companies and analysing their manufacturing processes, based on robot-cells, the developed event-driven conceptual model is described in the Fig. 3.

This model has four independent interacting entities:

- Production task description entity, where main components are: product model (CAD); task model (ORDER) and the process model (CAPP).
- Robot-cell description entity {IR, EF, LP, WT, TR}. This part formed a robot-cell design model and the simulation software helps to the robot selection and forming the structure of a robot cell.
- Task performance analysis, based on parametrical model of performance description and model for optimal selection of KPIs.
- General output description, which shows how the company has managed in general (turn-over, profit, etc.) and reflected the implementation of a robot-cell in manufacturing process through OEE, ROI, etc.

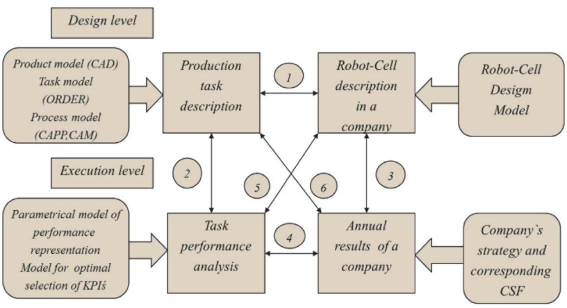


Fig. 3. KNOWLEDGE-BASED CONCEPTUAL MODEL FOR MANUFACTURING ROBOT-CELL.

The model has two levels:

1. Design level (primary task) which is planned for decision making. Here would be determined the best correlation between products to be manufactured and the parameters of a robot cell, can be seen in the table 2. This level gives the primary answer to the parameters of the robot-cell.

2. Execution level (contrary/reverse task) is based on practical experiences of using robot-based systems in manufacturing. Here the real data from manufacturing are gathered using MES (manufacturing execution system) or other possibilities. Based on these data there would be formed elements of evaluation and elements of analysis as defined in the table 3. These data for performance analysis are extremely important and they would also give a feedback of the quality of decisions to the first level.

Table 2. DESIGN PARAMETERS GENERAL DESCRIPTION

Product features	Robot-cell features
• Product portfolio • Product mix • Quantity per year • Order fulfilling time • Product parametrical description (CAD model) • The purpose of the product (Functional model) • Production process description (CAPP model) • Operation description (CAM model)	• No of robots in a robot-cell • Industrial robot technical parameters - no of axes - reach - payload - speed - acceleration - accuracy - repeatability • Type of end effector(s) • Sensors needed • Turning table(s) parameters • Loading-unloading position parameters • Transport devices parametrical description

Table 3. EXECUTION PARAMETERS GENERAL DESCRIPTION

Elements of evaluations	Elements of analysis
• Order fulfilment time • Ratio of manufacturing in order fulfilment process • Ratio of cycle time in throughput time • Ratio of machining time in cycle time • Ratio of loading and unloading time in cycle time • Ratio of setup time in cycle time • Ratio of machining time in cycle time • Ratio of idle time in throughput time and in order fulfilment time	• Use of working time (importance of value creating time in production process) • Main reasons of non-productive work • Level of achieving the objectives • Index of employee competences • Contribution of an employee as a team member • Dynamics of effectiveness (changes and improvements in production process) • Cost factors and their dynamics in production process • Quality assurance • Robot-cell technological capabilities exploitation • The robot-cell functionality correspondence to the industrial tasks

In the manufacturing process, one of the important indicator is the order fulfilment time, which depends on the cycle time. Cycle time is the operation fulfilling time at a workplace. Generally, cycle time consists of machining time, set-up time, loading-unloading time, inspection time and in principle, there is an idle time. For the efficient manufacturing, proportions of these time components are extremely important to know. Because at one hand it depends on the organisation of the manufacturing process and from the other hand, it depends on the decisions that were made in the designing phase.

The proposed knowledge-based model enables to respond the following conditions:

- Robot cell (workplace) suitability for the planned industrial task(s).
- Product portfolio, product mix, routing flexibility, compliance to the manufacturing system.
- Automation and digitizing level compliance to the production volume, production flow and company`s general strategy
- Selected KPI`s information reflection to the needed operational data for describing current situation in a company for example, efficiency and competitiveness.
- Product mix, product flexibility, routing flexibility influence to the expected results.
- Structure of a robot cell and operating rules impact to the expected rules and vice versa.

Furthermore, the model is capable to support decision making in terms of: to find the most suitable robot-cell for the given industrial task(s) and to determine the operating rules. However, the most important is to find out the relationships between the interacting entities as described in the Fig. 4 and formed these on the basis of knowledge engineering. The model is particularly important for SMEs, where the manufacturing situations are rapidly changed.

Performance Evaluation Model

In order to analyze the manufacturing processes, a Performance Evaluation Model (PEM) is developed as shown in Fig. 4. The PEM is in correspondence to the conceptual model described in the Fig. 3. The model is for practical analysis of the suitability of robot-based manufacturing cell and for carrying out the planned task (nomenclature of products, amounts of production, etc.).

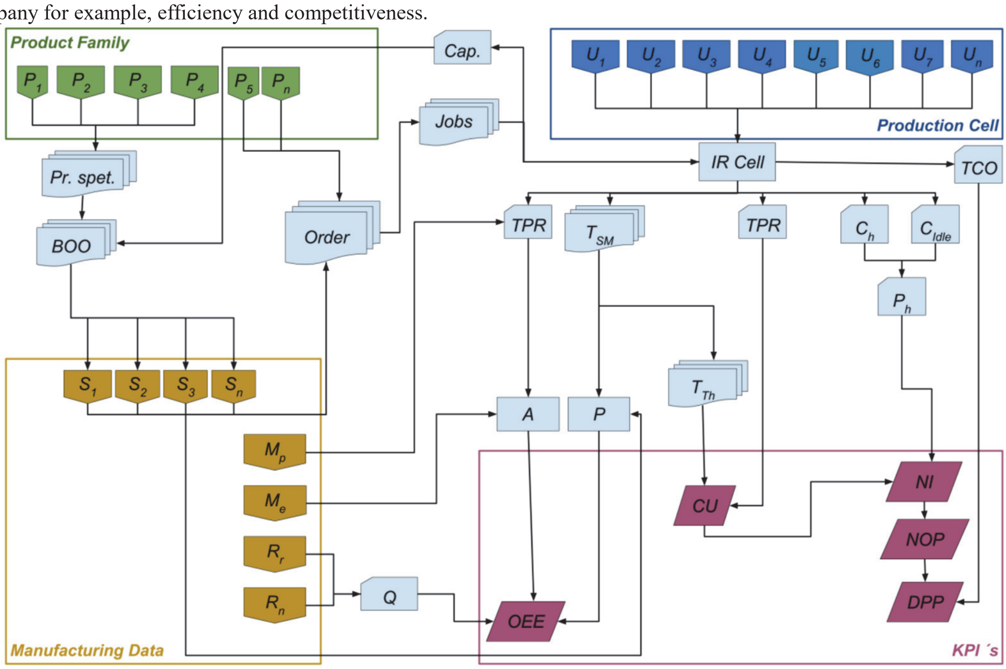


Fig. 4. PERFORMANCE EVALUATION MODEL.

Table 4. PEM INPUT, OUTPUT PARAMETERS AND FUNCTIONAL BLOCKS

	Symbol	Explanation
Product	P_1	Product mass
	P_2	Dimensions
	P_3	Manufacturing technology
	P_4	Lot size
	P_5	Lot repeatability
	P_n	Additional product parameters
Manufacturing data	S_1	Engineering time
	S_2	Setup time
	S_3	Machining time
	S_n	Inspection time etc.
	M_p	Planned maintenance
	M_e	Emergency maintenance
	R_r	Product reject ratio
	R_n	Number of reclamations
Production cell	U_1	IR parameters
	U_2	End effector parameters
	U_3	Auxiliary equipment parameters
	U_4	Workforce parameters
	U_5	Market environment parameters
	U_6	Indirect costs
	U_7	Payback period prognosis
	U_n	Other production cell parameters
KPIs	*NI*	Net income
	NOP	Net operating profit
	DPP	Discounted payback period
	CU	Cell utilization
	OEE	Overall equipment effectiveness
Functional blocks	*Pr. spet.*	Product specification list
	BOO	Bill of operations
	Cap.	Cell Technological Capabilities
	Order	Production order
	Jobs	Jobs to produce at the cell
	TPR	Total production time resource
	TCO	Total cost of ownership
	T_{SM}	Measured cycle times
	A	Availability
	P	Performances
	Q	Quality
	T_{Th}	Throughput time
	C_h	Production cell cost per hour
	C_{idel}	Production cell idling cost
	P_h	Value added per hour

The aim of the model is to understand the performance of a manufacturing cell for a certain task. There are two input modules: product family module and production cell description module; one manufacturing data module and an output data module (KPIs module). For evaluating a cell technological capacity and economic profitability a set of key performance indicators were selected based on literature reviews [24] as defined in the KPIs module of PEM. OEE, CU, DPP, NI and NOP are the outcomes used to determine the performance of a production cells chosen for case studies.

The PEM inputs, outputs parameters and functional blocks explanations are provided in the table 4. The modules give the possibility to understand the correlation of input data to the output data and find out dependences between input data and output data. These are used for developing the knowledge-based decision-making rules in manufacturing cell designing and operating process. The PEM model can be formulated mathematically as multi-criteria optimization problem. The objective functions considered are as follows (see table 4):

$$F_1(\bar{x}) \text{ - net income (EUR),} \tag{2}$$

$$F_2(\bar{x}) \text{ - net operational profit (EUR),} \tag{3}$$

$$F_3(\bar{x}) \text{ - overall equipment effectiveness (\%),} \tag{4}$$

$$F_4(\bar{x}) \text{ - usage factor (\%),} \tag{5}$$

$$F_5(\bar{x}) \text{ - payback period (years).} \tag{6}$$

Functions have different units, range and should be normalized by applying the following equations:

$$f_i(\bar{x}) = \frac{\max F_i(\bar{x}) - F_i(\bar{x})}{\max F_i(\bar{x}) - \min F_i(\bar{x})}, \tag{7}$$

$$f_i(\bar{x}) = \frac{F_i(\bar{x}) - \min F_i(\bar{x})}{\max F_i(\bar{x}) - \min F_i(\bar{x})}. \tag{8}$$

In Eq. (7) and Eq. (8) $\bar{x}$ stand for the vector of design variables and the values $maxF_i(\bar{x})$ and $minF_i(\bar{x})$ are estimated values for function maximum and minimum, respectively. Equations (7) and (8) are applied to objectives subjected to maximization ($F_1(\bar{x})$, $F_2(\bar{x})$, $F_3(\bar{x})$, $F_4(\bar{x})$) and minimization ($F_5(\bar{x})$), respectively. As result, the normalized objective functions $f_i(\bar{x})$ are in range [0;1] (may slightly exceed limits of the interval [0;1] since $maxF_i(\bar{x})$ and $minF_i(\bar{x})$ are estimated values). Furthermore, all non-dimensional objectives are subjected to minimization i.e.

$$f(\bar{x}) = (f_1(\bar{x}), f_2(\bar{x}), f_3(\bar{x})..., f_5(\bar{x})) \to \min. \tag{9}$$

The objectives considered are not conflicting (can be verified by performing pairwise analysis of the objectives). Thus, the objectives can be combined into one by applying weighted summation technique (for conflicting objectives it is justified to apply Pareto concept).

Thus, the configuration/type of production cells f_c can be expressed as

$$f_c = \sum_{i=1}^{N} c_i f_i(\bar{x}) \to \min . \quad (10)$$

In Eq. (10) $N=5$ (number of objectives) and c_i stand for weights of the objectives, determined for particular company/problem considered. However, based on analysis performed in companies, main impact factors for objective functions are determined. Based on table 4, these impact factors (model inputs) are divided into following three groups:

- Product Family inputs,
- Manufacturing Data inputs,
- Production Cell inputs.

The effect of each subfactor on objective functions f_i may be obtained by evaluated based data, gathered from production or estimated values from experts based on production data (system and process specifications) and experience (in the case of selection cell type before production process). In order to consider the effect of impact factors given in three groups the objective function (10) can be completed as

$$f_c = \sum_{i=1}^{N} c_i f_i \sum_{k=1}^{M} W_k \sum_{j=1}^{G_k} w_{ikj} \to \min . \quad (11)$$

In Eq.(11) $M=3$ (number of groups), $W_k(k=1,2,3)$ are the weights of the groups (in different companies the importance of the groups may be different), G_k is number of subfactors in group number k, the weight w_{ikj} describes the effect of the subfactor j in group k on objective f_i.
The considered multi-criteria optimization problem is constrained optimization problem with limits on different resources (time, technological, etc.) and design variables

$$r_l^{low} \le r_l(\bar{x}) \le r_l^{up}, (l = 1 \ldots L). \quad (12)$$

Where r_l, r_l^{low} and r_l^{up} stand for the resource, its lower and upper limit values, respectively.

CASE STUDY

Information for the case study was acquired by interviewing the management and engineering staff of ten chosen companies. All of the assessed companies belongs to the SME class, with the total number of employees 20-150. With some exception all of the companies have integrated only one robot cell in their production at the moment. The investment for the cells have been 30,000 to 450,000 euros. The produced products included different parts for agricultural, forestry machines (frames, grippers and crane boom), small tractors, high speed trains and lifts components, wind generator rotor and sheet metal products. Largest products being produced weights 300kg and the smallest 150g, similarly cycle times varies from 1 minute to 4 hours.

Data gain from the interviews contains both quantitative and qualitative data. Quantitative data such as product dimension, mass etc. are shown on table 4. Qualitative data such as complexity of operations, manufactured parts precision, experience and competencies of engineering stuff and workers, etc. are considered as the relations to production time gained or lost from total production resource. By implementing PEM for the ten companies' case studies, cell utilization and discounted payback period are presented in table 5.

Table 5. ROBOT CELLS PEM CALCULATED OUTCOMES

Company	Technology	Cell description	Investment [€]	*CU [%]	*DPP [y]
1	MT	Robotic Press Brake Amada Astro 100NT HDS1030	450k	42	8
2	MT	Mitsubishi RV-4FRM	30k	54	6
3	W	ABB IRB2400, IRBP750A with automated storage	270k	71	3
4	W	ABB IRB2600	200k	56	4
5	W	Yaskawa HP-20 mounted on TSK, RM2-4000	130k	71	4
6	W	Yaskawa HP-20, turntable MT1-500	90k	75	3
7	W	Yaskawa MH12 with turntable MT1 / 2016	60k	69	4
8	W	ABB IRB2400 mounted on track, two positioners	60k	72	6
9	W	Yaskawa MH50-2011 mounted on track, positioner HSB-1000	159k	64	5
10	P	ABB IRB2600	50k	45	6

MT - Machine Tending, W – Welding, P – Palletizing.
* - PEM Model calculated values.

For illustrating the PEM in practice one company was chosen for the detailed analysis. There are about 135 employees and the main products are trailers, forklifts, etc. for forestry and agricultural industry. Welding is one of the mostly used manufacturing process in the company, for that reason the robot-based welding cells were implemented in the manufacturing process. The 3D layout and specifics of the welding cell is given in the Fig. 5. The maximum capacity of the studied production cell is to produce the products having weight about 1000 kg and with 1500x1500x6000 mm dimension. Average cycle time for welding the parts is about 90 – 150 min, set-up time in between 10-15 min.

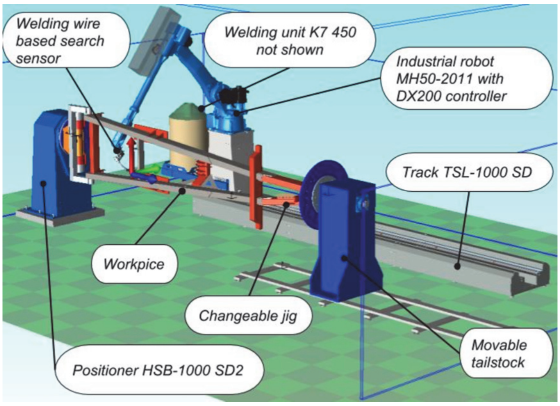


Fig. 5. PRODUCTION CELL COMPONENTS AND LAYOUT.

Analysing the obtained data from the model and comparing it to the company's assessment gathered through management interviews. It was found out that the management has estimated the operation of the production unit to be considerably optimistic. Company prognosis for payback or return of investment was set to three years but model calculation clearly shows that by continuing given production volume the payback period appeared to be five years. The particular production cell was designed to reduce the manual welding and to consider different product specifications. However, the product length is one the driving factor of the total cost of ownership. The corresponding weight for impact factor groups was calculated as following: Product Family W_1=0,578, Manufacturing W_2=0,199 and Production Cell W_3=0,223. The information gained from the model shows that to meet the objective of three years DPP, the total production time has to be increased by 21%. In addition, it was noted that the production cell utilization factor appeared to be 64%, which may be a sign of unorganized production flow. Furthermore, transportation and queue times together with product initial setup time are critical to be looked over.

CONCLUSION AND FUTURE WORK

This study described how knowledge-based conceptual model can be created and implemented as a performance evaluation model. The knowledge-based conceptual model consists of intelligent event-driven decision making procedures. The multi-criteria mathematical model was developed based on manufacturing industry experts' experience related to the design and execution of robotic cells. Case study research approach was used to verify the PEM model.

For the case study ten companies were chosen, their production cells qualitative and quantitative data together with company's strategic and production plan objectives were used to execute performance evaluation model. For evaluating of production cell's capacity and profitability, a set of key performance indicators were chosen based on literature reviews. The presented case study economically assessed by using following key performance indicators: OEE, CU, NI, NOP and DPP. The obtained data was compared and analyzed with companies strategic and production plan and a new sets of knowledge-based rules were created. One rule was found out that to fulfill the objectives, the effective production time should be increased by 21%.

However, the most important is to find out the relationships between the interacting entities as described and formed these on the basis of knowledge engineering. So the process in transforming the data and information into knowledge for decision making. Other benefit of the developed model is to use it as a tool at the production cell design phase. Where it is possible to simulate different combination of production cell components that creates simple and combined capabilities. Those sets of capabilities are inputs for the best-fit product analysis, at the same time user or cell-based selection of KPIs can be calculated. For the future development of the model, a wider range of production processes and product related parameters can be included into the model input module and wider selection of KPIs for the model output module. Moreover, different rule based sets of KPI can be put together and inserted to describe an AI model. Likewise, it is vital to increase the model capacity to operate a large amount of data collected from different industries.

ACKNOWLEDGMENTS

The research was supported by EU Regional Development Fund supported project AR16077 Smart Industry Centre (SmartIC) No 2014-2020.4.01.16-0183; Estonian Research Council grant PUT1300; Estonian Centre of Excellence in Zero Energy and Resource Efficient Smart Buildings and Districts, ZEBE, TK146 funded by the European Regional Development Fund (grant 2014-2020.4.01.15-0016).

REFERENCES

[1] Gunes, Volkan, Peter, Steffen, Givargis, Tony and Vahid. Frank. “A Survey on Concepts, Applications, and Challenges in Cyber-Physical Systems.” *KSII transactions on internet and information systems* Vol. 8, No. 12, (2014).

[2] National Institute of Standards and Technology (NIST), 2014, https://www.nist.gov/el/cyber-physical-systems.

[3] Executive Summary World Robotics 2017 Industrial Robots [https://ifr.org/downloads/press/Executive-summary_WR_2017_Industrial.Robots.pdf]

[4] Majak, Jüri and Hannus, Sander. “Orientational design of anisotropic materials using the Hill and Tsai-Wu strength criteria”. *Mechanics of Composite Materials*, Vol. 39, No. 6, 509−520 (2003).

[5] Majak, Jüri, Pohlak, Meelis, Eerme, Martin and Velsker, Tarmo. “Design of car frontal protection system using neural networks and genetic algorithm”. *Mechanika*, Vol.18, No. 4, 453−460 (2012).

[6] Lellep, Jaan and Majak, Jüri. “On optimal orientation of nonlinear elastic orthotropic materials”. *Structural Optimization*, Vol. 14, 116−120 (1997).

[7] Aruniit, Aare, Kers, Jaan, Goljandin, Dmitri, Saarna, Mart, Tall, Kaspar, Majak, Jüri and Herranen, Henrik. “Particulate Filled Composite Plastic Materials from Recycled Glass Fibre Reinforced Plastics”. *Materials Science (Medžiagotyra)*, Vol. 17, No. 3, 276−281 (2011).

[8] Aruniit, Aere, Kers, Jaan, Majak, Jüri, Krumme, Andres and Tall, Kaspar. “Influence of hollow glass microspheres on the mechanical and physical properties and cost of particle reinforced polymer composites”. *Proceedings of the Estonian Academy of Sciences*, Vol. 61, No. 3, 160−165 (2012).

[9] MacCormach, Alan, Baldwin, Carliss and Rusnak, John. “The Architecture of Complex Systems: do Core-periphery Structures Dominate.” MIT Sloan School of Management - Working Paper N0. 4770-10, (2010).

[10] Efthymiou, Konstantinos, Pagoropoulos, Aris, Papakastos, Nikolaos, Mourtzis, Dimitris and Chryssolouris, Giannoulis. “Manufacturing Systems Complexity Review: Challenges and Outlook.” *CIRP-CMS Procedia CIRP* Vol. 3, 644-649 (2012).

[11] Lõun, Kaia Lavin, Jaak Riives, Jüri and Otto, Tauno. “High Performance Workplace Design Model.” *Estonian Journal of Engineering*, Vol. 19, No. 1, 47-61 (2013).

[12] Bergweiler, Sergweiler. “Intelligent Manufacturing based on Self-Monitoring Cyber-Physical Systems.” *The 2015 ACM International Joint Conference on Pervasive and Ubiquitous Computing (UbiComp)*: pp. 108-113, 2015.

[13] Pires, J. Norberto Laureiro, Altino and Bölsjo, Gunnar. “Robotic Welding: System Issues.” *Welding robots: technology, systems issues and application*, Springer-Verlag, London (2006): pp. 105-145.

[14] Brumson, Bennett. “Robotics for Assembly Automation Tutorial.” Robotics Industrial Association, Michigan, USA, 2011.

[15] Dowsland, A., Kathryn and Dowsland, B., William. "Packing problems." *European Journal of Operational Research*, Vol. 56, No. 1, (1992): pp. 2-14.

[16] KUKA Solution database, KUKA, [access 2017]. (https://www.kuka.com/en-us/industries/solutions-database)

[17] Robot Finder, Fanuc, [access 2017]. (http://www.fanuc.eu/es/en/robots/robot-filter-page)

[18] Robot Selector, ABB, [access 2017]. (http://new.abb.com/products/robotics/industrial-robots/robot-selector)

[19] Hitomi, Katsundo. *Manufacturing Systems Engineering: A Unified Approach to Manufacturing Technology, Production Management and Industrial Economics*. Taylor & Francis, London (1996).

[20] Burstein, Frada and Holsapple, Clyde. *Handbook on Decision Support Systems*. Spriner Verlag, Berlin (2008).

[21] Dimopoulos, Christos. “A review of evolutionary multiobjective optimization applications in the area of production research.” *Proceedings of the 2004 Congress on Evolutionary Computation*, IEEE Cat. No.04TH8753, 1487-1494, 2004.

[22] Agyapong-Kodua, Kwabena, Brown, Rosemary, Darlington, Rob, and Ratchev, Svetan. “An integrated product–process design methodology for cost-effective product realization.” *International Journal of Computer Integrated Manufacturing* Vol. 25, No. 9, 814-828 (2012).

[23] Yin, K., Robert. *Case Study Research: Design and Methods*, Sage Publications, Inc., California, USA (2003).

[24] Kaganski, Sergei, Majak, Jüri, Karjust, Kristo, and Toompalu, Silver. “Implementation of key performance indicators selection model as part of the Enterprise Analysis Model.” *Procedia CIRP*, Vol. 63, No. 1 283-288 (2017).

Publication III

Kangru, T.; Riives, J.; Otto, T.; Kuts, V. (2020). Optimisation of decision-making process in industrial robot selection. Journal of Machine Engineering 2020;20(1):70–81. DOI: https://doi.org/10.36897/jme/117788

Journal of Machine Engineering, 2020, Vol. 20, No. 1, 70–81
ISSN 1895-7595 (Print) ISSN 2391-8071 (Online)

Received: *16 December 2019* / Accepted: *28 January 2020* / Published online: *05 March 2020*

Industry 4.0, industrial robot,
performance evaluation,
dual optimisation principles

Tavo KANGRU[1,2*]
Jüri RIIVES[1]
Tauno OTTO[1]
Vladimir KUTS[1]
Madis MOOR[2]

OPTIMISATION OF DECISION-MAKING PROCESS IN INDUSTRIAL ROBOT SELECTION

The successful selection process of industrial robots (IRs) for today's Cyber-Physical Systems is an important topic and there are different possibilities to solve the task. The primary task is to estimate the existing IR selection systems according to the suitability analysis and to highlight the main positive features and problematic areas. The objective of the reverse task is to carry out the sensitivity analysis of the existing robot-based manufacturing systems. The matching of these two approaches helps decision makers to develop the main principles of IR selection in today`s multidimensional and fast-changing economic world.

1. INTRODUCTION

The importance of industrial robots (IRs) in manufacturing is increasing continuously. This is caused by their flexibility, productivity, relatively low cost and large technological capabilities. The nomenclature and functionality of modern IRs are remarkable. IRs are also basic components of Cyber-Physical Systems (CPS), which, at the same time, form an important part of Industry 4.0 [1]. Due to their large variety and application possibilities, the selection of a most suitable IR is a complicated task. Several selection criteria need to be taken into consideration. The challenge of choosing a suitable robot for a certain manufacturing application lays often not only in knowing whether a robot is needed but in predicting what tasks are the most suitable for the current application. It is also necessary to consider that today's IRs are becoming smarter, faster, and more and more adaptable and collaborative.

[1] Tallinn University of Technology, School of Engineering, Department of Mechanical and Industrial Engineering, Tallinn, Estonia
[2] TTK University of Applied Sciences, Institute of Technology, Mechanical Engineering. Tallinn, Estonia
[*] E-mail: tavo@tktk.ee
https://doi.org/10.36897/jme/117788

2. ROBOT-BASED MANUFACTURING CELL

A robot-based manufacturing cell (system) can be considered as a closed system within a larger unit (workshop). The system can be described with the help of dimensioning its main parts, giving the relations between the parts, and forming the structure of the system. These relations are workpiece loading-unloading equipment, gripper (end effector), IR working area, range, loading capacity, controlled coordinates of IR and MT, etc.

A study was performed at the end of 2017 to determine the utilization of robot-based manufacturing cell´s in Estonian industry. The goal of the study was to compare production cell design objectives to achieved KPI´s. The study was carried out by interviewing executives from different company management levels (production managers, R&D engineers and setup technicians), gathering data from implemented MES system, where it was available and mapping the cells layout with technological capabilities. Altogether 14 robot based manufacturing cell´s where investigated of which a majority 64% where welding, 22% CNC machine tending and 14% material handling cell´s. The first cell was implemented at 2008 and the last one implementation process where ongoing. The total investment between 50k to 450k EUR, inflation not taken in to account.

Information was gathered in four main fields: company profile and strategy, cell layout and equipment, manufactured products and process data and shortcomings or improvement necessary to perform. From that data, a preliminary report was made which evaluated the production cells performance values and economical aspects.

Performance was assessed through following parameters setup, cycle, operational, rework and maintenance times, operators needed, lots size and repeatability, total number of setup products at the cell. Throughput, cell utilization and OEE was calculated and compared with cell design goals.

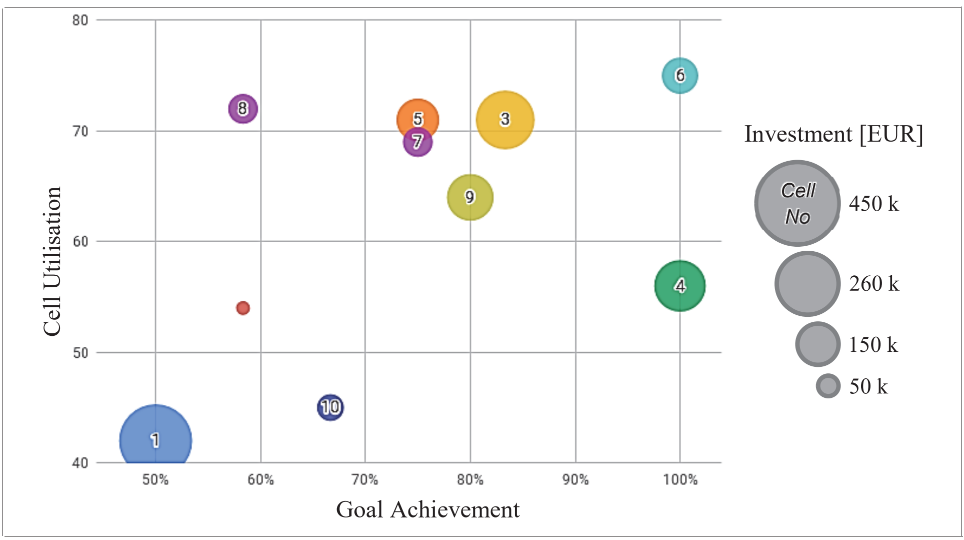


Fig. 1. Production cell design goal fulfilment

Economical input parameters where chosen that best described the goals set by the company or department management. Parameters included among others where net income, net operating profit, cost per hour, discounted payback period. As a result goal achievement analysis [2] where performed, where cell utilization, investment value and overall goal fulfilment where mapped (see Fig. 1) and compared. Production cell design objectives where once again assessed.

As a second step, a wider analysis where performed to assess production cell intelligent level and automation or engineering level by the categorical framework of manufacturing [3]. This analysis shows the production cells current state, compared to global manufacturing trends (see Fig. 2) and can lead to steps needed to perform for improve manufacturing and leap to Industry 4.0 principals.

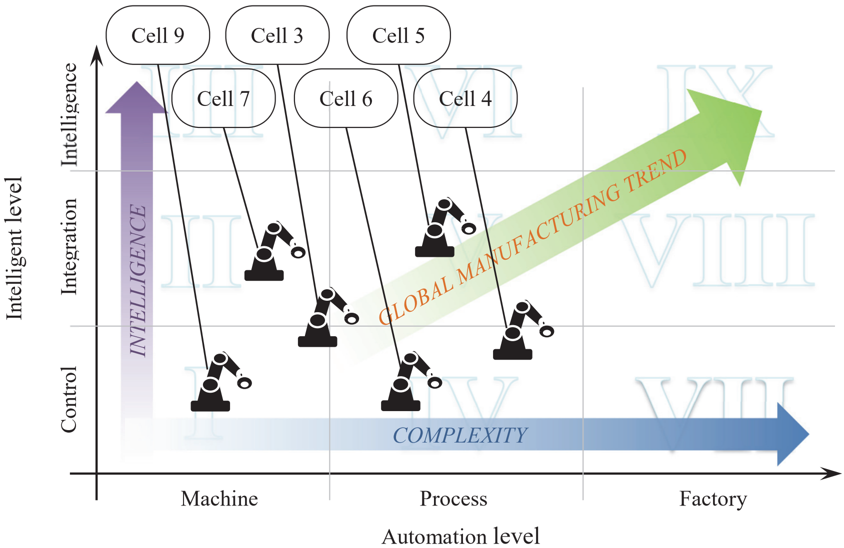


Fig. 2. Production cells state on manufacturing categorical framework

Based on this generalization, it is possible to develop a set of industrial robot selection principals and rules which best suits regional industry level. Furthermore, gathering different production cell development approaches from industry and judging their accuracy is a vital input for developing robot selection workflow. This can be used as an expert advice in the decision-making process.

3. DECISION-MAKING TASK FOR ROBOT-CELL COMPONENT SELECTION

The decision-making problems have been treated individually, consistency is not kept between the decision-making functions regarding the assumptions and data structures. These isolated decision-making stages do not help to achieve the global optimum solution because the decision-making problems in manufacturing involve very complex data processing. The elementary estimations are very strongly dependent on each other and the real technological resources (capabilities) must be taken into consideration. Therefore, rational decisions usually cannot be made simply with sequential procedures. However, with modelling and simulation procedures, it is possible to analyse the alternatives and find the best solution. The other possibility is to start from the complex systems theory [4, 5] and to develop a solution system architecture, allowing the reduction of complexity of a design process, minimizing risks in production system planning and enabling analysis of various production variants. For a better understanding of the whole complexity of the problem setup, it is useful to see the wider picture based on the ontology model (see Fig. 3) [6]. This shows the task positioning in the field of manufacturing in its whole complexity.

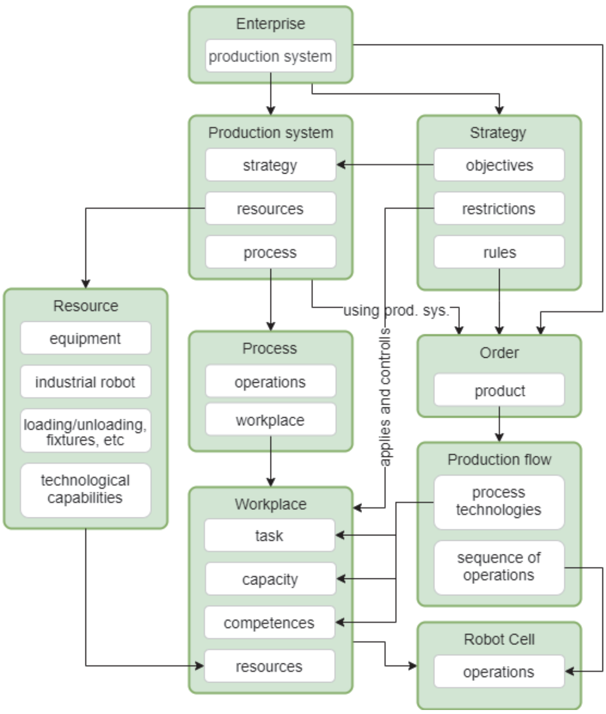


Fig. 3. Robot Cell Utilisation Ontology Model

The efficiency of manufacturing depends on how suitable the manufacturing system is for fulfilling of the company's strategy and how completely the product portfolio fits the technological capabilities of the manufacturing system, but also of course on how efficiently the company is using their resources and how productive they are in fulfilling orders. The results depend directly on the quality of decision-making process. Nowadays in manufacturing, decision support system (DSS) are used for complicated tasks. DSS [7] is a computer-based information system that supports business or organizational decision-making activities, typically resulting in ranking, sorting or choosing from among alternatives.

DSS's serve the management, operations, and planning levels of an organization (usually mid- and higher management) and help people make decisions about problems that may be rapidly changing and not easily specified in advance – i.e. unstructured and semi-structured decision problems. Decision support systems can be either fully computerized, human-powered or a combination of both. While academics have perceived DSS as a tool to support the decision-making process, DSS users see DSS as a tool to facilitate organizational processes that might support decision making. DSS is defined as follows:

1. DSS tends to be aimed at the less well structured, underspecified problem that upper-level managers typically face;
2. DSS attempts to combine the use of models or analytic techniques with traditional data access and retrieval functions;
3. DSS specifically focuses on features which make them easy to use by non-computer-proficient people in an interactive mode; and
4. DSS emphasizes flexibility and adaptability to accommodate changes in the environment and the decision making approach of the user.

Properly designed DSS is an interactive knowledge-based software system intended to help decision makers compile useful information from a combination of raw data, documents, and personal knowledge, or business models to identify and solve problems [8].

Typical information that a decision support application might gather and present includes:

– inventories of information assets (including legacy and relational data sources, data cubes, data warehouses, and data marts),
– comparative sales figures between one period and the next,
– projected revenue figures based on product sales assumptions.

The whole planning system is based on a hierarchical decision-making scheme. Nodes on it represent the decision centres. On those centres, the elementary estimations are carried out. These elementary decision-making procedures are carried out on the basis of different mathematical methods and systems. These elementary decisions could not be in conflict with each other. For this reason, there are coordination levels, which take care of the elementary decisions, analysing these and giving the rules for further activities. That means that modelling and optimization techniques are integrated with the expert system. The basic components of the system planning architecture are data storage, decision-making mechanism, knowledge base and interpreter. The last one has the following main activities: to call out the needed solution module, to analyse the obtained results, to generate the rules and instructions on the existence of contradictions, to issue the sorting and searching commands to the database. Through the interpreter, the revision of problem-solving is possible. A modular architecture guarantees the flexibility of the planning system. The result would be obtained on the basis of different modules and models. The order of using these modules must not be strictly determined. That kind of flexibility gives users more extensive goal.

A modular architecture guarantees the flexibility of the planning system. The result would be obtained on the basis of different modules and models. The order of using these modules must not be strictly determined. That kind of flexibility gives users more extensive goal.

4. DECISION MAKING METHODS FOR INDUSTRIAL ROBOT-CELL COMPONENT SELECTION

Over the year many decision support systems (DDS) has been developed [9] to help decision makers to select most functional and cost-effective equipment for production cell. The complexity of the selection problem are related to economical, technical and social attributes, which are interconnected and may change in time. Economical attributes are likely to dependent on the market situation and entrepreneur's investment certainty. Both parameters are hard to enquire and predict. Other hand technical parameters are readily available from machines data sheets and are easily compared. DDS should consider both qualitative and quantitative factors while selecting and evaluating correct solution. Some of the methods used in DDS are discussed below.

4.1. WEIGHTED SUM DECISION MODEL (WSM)

Weighted sum model is the simplest multi-criteria decision analysis method for evaluating alternatives by decision criteria. In this method [10], critical factors or performance values are assessed. In IR selection those critical values are derived from three categories: the minimal environmental conditions; the minimal performance conditions; and the budget ceiling. If proposed solution meets all the requirements (critical values) this can be considered as one alternative. The methods relays on expert's opinions to value criteria weights, which can be summed at the decision matrices to rank alternatives.

4.2. DATA ENVELOPE ANALYSIS (DEA)

Data envelope analysis is a performance evaluation or benchmarking method where appreciable is assessed against the best practice. DEA model consist of inputs, decision-making units (DMU) and outputs. Inputs and outputs are performance measures and may or may not be directly linked to production process. DMU´s are units under evaluation which are composed performance metrics that characterize the units [11]. DEA evaluates minimum inputs against maximum output.

4.3. ANALYTIC HIERARCHY PROCESS (AHP)

Many of the decision support system are based on analytic hierarchy process (AHP), developed for use in complex decision making in 1980 by Saaty. The method and its refined successors [12, 13] are still widely used due to its ability to efficiently deal with objectives as well as subjective attributes. Methods first step is to build a problem hierarchy, containing criteria which importance are pairwise compared by different experts. Final step is obtaining and summarising composite performance scores for alternatives and making a final decision. The method has been improved by using Fuzzy numbers for linguistic expressions to pair-wise comparison of criteria [14].

4.4. TECHNIQUE FOR ORDER PREFERENCE BY SIMILARITY TO IDEAL SITUATION (TOPSIS)

TOPSIS is a method that compares a set of alternatives by expert group evaluated weights for criterion. Scores are normalised for each criterion and geometric distance between alternative ideal positive and ideal negative solution is calculated. The best solution is nearest to ideal positive solution and farthest from ideal negative solution. The method has been improved by using Fuzzy numbers for criteria analysis [15].

4.5. ARTIFICIAL NEURAL NETWORK (ANN)

Artificial Neural Network method has been used in many applications where real world data variables are available [16]. ANN is a computing system that consist of nodes or artificial neurons, which are connected like synapses to transmit signal from input layer through one or many hidden layers to output layer. The main advantages of the method are so called learning effect from considering examples and ability to work whit great amount of data.

5. PROPOSED DUAL APPROACH MODEL

Most IR selection and decision making application includes only primary tasks – selecting the best type of industrial robot for a determined industrial task (welding, painting, assembly, machine tool servicing, and inspection, grinding and polishing or doing other manufacturing operations). Such a decision-making expert system has been developed and used for human resources development depending on needed skills and knowledge, whereas influence of human factor to productivity is larger when process is less automated [17]. Mapping of capabilities in managements systems described in [18] needs also input from process level.

However, at the same time, the robot cells are integrated into the manufacturing systems. This integration and different aspects of manufacturing were described in the ontology model (see Fig. 3). Proceeding from the manufacturing strategy and production principles of a company, new aspects will arise which are needed to take into consideration in the robot selection process (break-even point, increasing of productivity, OEE, etc.). All these are also directly connected to the products (product families) to be manufactured and to the task description (annual quantities, delivery times, batch sizes, quality and/or cost restrictions, etc.).

While the purpose of a primary or selection task is to check the robot's architecture and technical parameters best suited for a selected job, the reverse or prediction task consists of the analysis of optimal utilization of the implemented robot-cell in a company (see Fig. 4). Understanding the utilization of industrial robots in manufacturing will give us the main principles and decision-making rules for the optimal selection of industrial robots. Based on iterations of those tasks, we can derive optimal solution and estimate the accuracy of the decision.

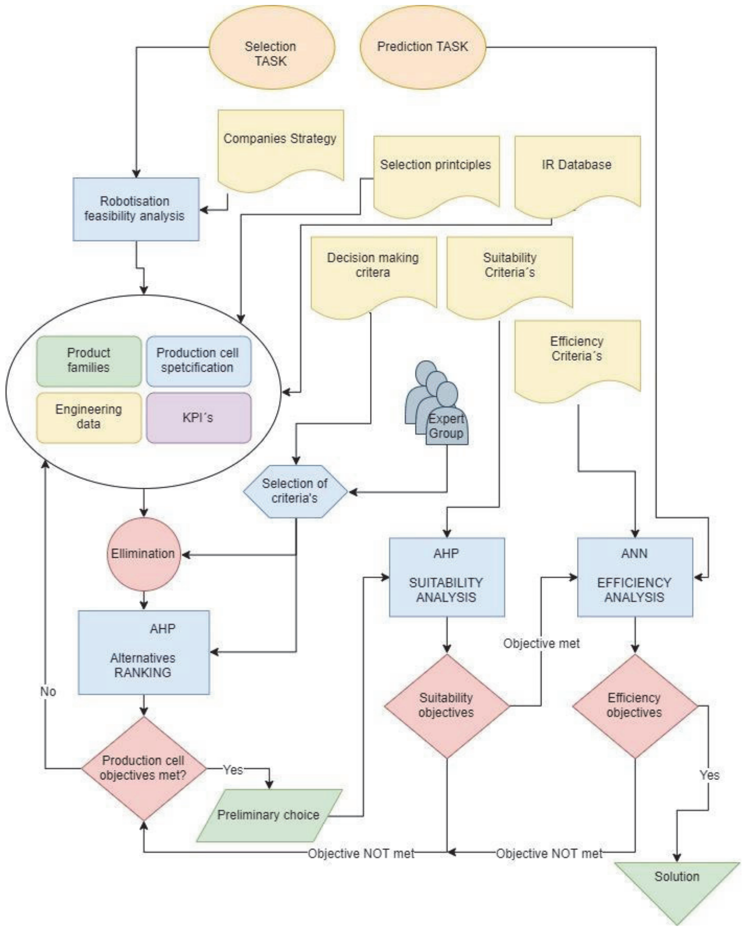


Fig. 4. Proposed DSS General Model

5.1. FEASIBILITY ANALYSIS AND ESTIMATION

Principle estimation on the bases of following criteria {Increase in productivity, lowering of production costs, improvement of the working environment, increasing the security of supply, quality assurance, workforce insurance, an increase of flexibility, stock depreciation}. The estimation could be calculated using different decision-making algorithms. We have used a self-adjustment algorithm (see one possible result on the Fig. 5).

5.2. THE SUITABILITY ANALYSIS

The suitability analysis is based on the task description. From the task description, the set of needed parameters {SNP} of an industrial robot (IR) would be determined. This set is formed based on the technological capabilities of an IR, which are crucial for fulfilling the industrial task. This set would be compared with the set of existing parameters of IR {SEP}. The largest common part will give the best result.

$$\text{Max} \quad \{SNP\} \cap \{SEP\}$$

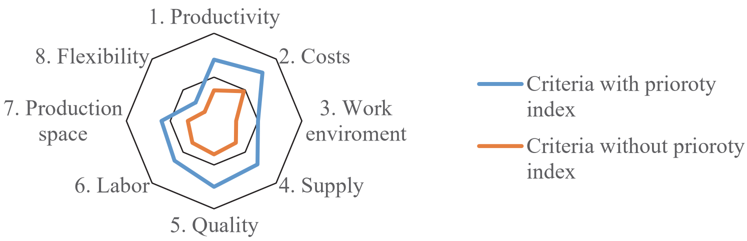


Fig. 5. Company feasibility analysis

We have used AHP based suitability analysis method [19], which uses product, technology and objective based parameters to evaluate suitability index. Expert group knowledge has been used for application-based criteria's evaluation. Future an ANN based prediction model together with fewer experts can be used for evaluating application-based criteria's [16]. For this study, IR welding application model has been used. Calculated indexes are compared to main suitability decision categories [19] for final assessment.

5.3. THE EFFICIENCY ANALYSIS

The efficiency analysis evaluates the designed or installed solution, based on best competences. For adequate estimation of production unit manufacturing efficiency and assessment of production unit process failures, the whole system, components and their relations must be evaluated [20, 21].

The output of a production unit are determined by the manufacturing task, which explains what is produced, which technologies are needed and which production type is used. The production type is one of the most important factors affecting productivity. According to production type (single, series or mass production), necessary technologies and equipment are selected. Those parameters and factors are summarised in Task Description. Selected technological capabilities and production program will form the production cell layout. In this case, selected system degree of flexibility is dependent on production equipment and their parameters for a chosen production program and layout. Depending on the flexibility of a production unit, it is possible to combine production structures to achieve minimum production time.

An outside factor affecting the efficiency of a production unit is the control over waiting times. The lack of balance in processing times and waiting times may result in production unit stalling or workplace congestion, which clogs the production flow and negatively affects Total Effective Equipment Performance (TEEP). Thus, one of the most important factors in assessing the efficiency of a production system is the degree of integration at a production unit. In the integrated system, it is possible to plan ahead and optimize the production flow to maximize Overall Equipment Effectiveness (OEE).

Prediction of manufacturing cell efficiency are performed by using Deep Learning (DL) ANN. An OEE prediction study comparing different machine learning algorithms have shown better reliability and performance dealing with given data [22].

DL is a neural network with a multilayer architecture capable of processing large amounts of data. While the architecture is significantly complex, DL algorithms are one of the best performing. Their performance will improve future by increasing the number of data. After every data iteration through ANN, back-propagation process is called and synapsis weights are adjusted using Gradient Descent, maximizing the correlation between the output and the residual error of the model [19]. The DL networks are built using Artificial Intelligence Techniques Inc., Neural Designer software. Technical parameters and operational data from similarly structured real production cell Manufacturing Execution Systems (MES) are used to train and test prediction model.

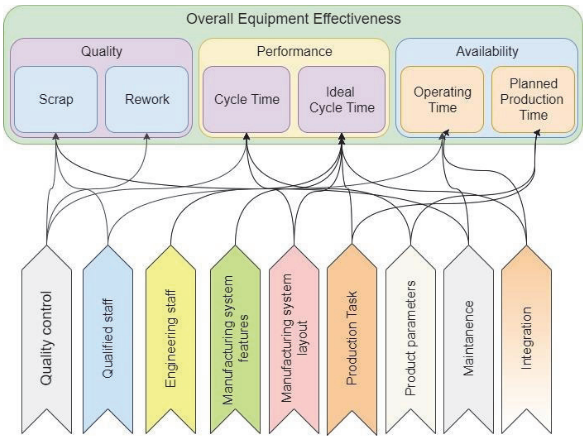


Fig. 6. OEE Prediction Model

The developed neural network are used to predicting production unite OEE [23] from input data shown on Fig. 6. After successful OEE prediction, company tactical and strategic KPI´s can be calculated. Theoretical break-even point (BEP), return on investment (ROI), payback period (PP) or discounted payback period (DPP) relations to the actual Gain of Investment (GI) were calculated among the other parameters.

6. CONCLUSION

Robotized production cells are complex systems and they consist of several specialty components. The selection of robots and all necessary components for robotized system design is not only a decisive task. Even less can be achieved by using available industrial robot classification systems. For a successful robot cell components selection, there are two prerequisites: firstly, we have to have a good overview of industrial robots and their technological capabilities; and, secondly, we have to assess the company's ability to integrate new systems to production and execution processes. To address those problem a concept model is proposed in which firstly a combined robot classification system together with robotisation feasibility analysis are performed. Subsequently, for achieving best possible results, a suitability and efficiency analysis loop are designed into the selection process. Suitability analysis is used to evaluate the selected solution correspondence to design requirements. As a last step an efficiency analysis is used to predict production cell parametrical model key performance indicators values. Both analysis steps are designed as a loop sub processes, in case of non-correspondence a previous step is again executed. Performing step iterations a optimal parametrical solution can be formed. Obtained results can be use to build and simulate virtual production cell model. Although each system component on its own has demonstrated good performance, the whole system still needs testing, and verifications. A proposed dual concept is an expedient approach because, on one hand, it is based on the analytic hierarchical task solving process of decomposition method; and on the other hand, systematically collected data allows us continuously to evaluate the system's operational efficiency in a company. On the basis of accumulated data, new knowledge is generated constantly, which can be used for robot selection, feasibility analysis and for the evaluation of results.

REFERENCES

[1] GEISERT C., HOHWIELER E., UHLMANN E., 2017, *Intelligent production systems in the era of Industrie 4.0 – changing mind sets and business models*, Journal of Machine Engineering, 17/2, 5–24.

[2] KANGRU T., RIIVES J., OTTO T., POHLAK M., MAHMOOD K., 2018, *Intelligent Decision Making Approach for Performance Evaluation of a Robot Based Manufacturing Cell*. Proceedings of ASME Mechanical Engineering Congress and Exposition, 2, ASME, USA, 1–10.

[3] QIN J., LUI Y., GROSVENOR R., 2016, *A Categorical Framework of Manufacturing for Industry 4.0 and Beyond*, Procedia CIRP, 52, 173–178.

[4] LADYMAN J., LAMBERT J., WIESNER K., 2013, *What is a Complex System?*, European Journal for Philosophy of Science, 3/1, 33–67.

[5] EFTHYMIOU K., PAGOROPOULOS A., PAPAKOSTAS N., MOURTZIS D., CHRYSSOLOURIS G., 2012, *Manufacturing Systems Complexity Review: Challenges and Outlook*, Procedia CIRP, 3, 644–649.

[6] LÕUN K., RIIVES J., OTTO T., 2011, *Evaluation of operation expedience of technological resources in a manufacturing network*. Estonian Journal of Engineering, 17/1, 51–65.

[7] BURSTEIN F., HOLSAPPLE C. (Eds), 2008, *Handbook of Decision Support Systems*, Berlin, Springer Verlag.

[8] SPRAGUE R., 1980, *A Framework for the Development of Decision Support Systems*, MIS Quarterly, 4/4, 1–25.

[9] ATHAWALE V.M., CHAKRABORTY S., 2011, *A comparative study on the ranking performance of some multi-criteria decision-making methods for industrial robot selection,* International Journal of Industrial Engineering Computations, 2, 831–850.

[10] GOH C., et al. 1996, *A Revised weighted sum decision model for robot selection*, Computers & Ind. Engineering, 30/2, 193–199.

[11] ÖRKCÜ H.H., ÖRKCÜ M., 2015, *Data Envelopment Analysis Cross Efficiency Evaluation Approach to the Technology Selection*, Gazi University Journal of Science Part A: Engineering and Innovation, 3/1, 1–14.

[12] GOH C.,H., 1997, *Analytic Hierarchy Process for Robot Selection*, Journal of Manufacturing Systems, 16, 5, 381–386.

[13] KUMAR N.R., 2015, *Robot Selection Using Analytic Hierarchy Process and System of Equations of Matrices*, Elixir International Journal, Mechanical Engineering, 79, 30511–30513.

[14] IC Y.T., YURDAKUL M.,. DENGIZ B., 2012, *Development of a decision support system for robot selection*, Robotics and Computer-Integrated Manufacturing, 29, 142–157.

[15] CHU T.-C., LIN Y.–C., 2003, *A fuzzy TOPSIS method for robot selection*, The International Journal of Advanced Manufacturing Technology, 21/4, 284–290.
[16] YAZGAN H.R., et al., 2009, *An ERP software selection process with using artificial neural network based on analytic network process approach*, Expert Systems with Applications, 36, 9214–9222.
[17] RIIVES J., OTTO T., LÕUN K., 2007, *Methods for Enhancing Productivity and Work Efficiency in the Workshop*, Journal of Machine Engineering, 7/2, 86−95.
[18] KANGILASKI T.; ŠEVTŠENKO E., 2017, *Do we need capabilities in our management system?* Journal of Machine Engineering, 17/1, 88−100.
[19] KANGRU T., RIIVES J., MAHMOOD K., OTTO T., 2019, *Suitability Analysis of Using Industrial Robots in Manufacturing*, Proceedings of the Estonian Academy of Sciences, 68/4, 383–388.
[20] LÕUN K., LAAVIN J., RIIVES J., OTTO T., 2013, *High performance workplace design model*, Estonian Journal of Engineering, 19/1, 47–61.
[21] MAHMOOD K., ŠEVTŠENKO E., 2015, *Analysis of machine production processes by risk assessment approach,* Journal of Machine Engineering, 15/1, 112−124.
[22] EL HASSANI I. et al., 2019, *Artificial Intelligence and Machine Learning to Predict and Improve Efficiency in Manufacturing Industry*, Mathematics, Computer Science Published in ArXiv 2019, Retrieved from https://www.researchgate.net/publication/330241437.
[23] MAHMOOD K. et al., 2018, *A Performance Evaluation Concept for Production Systems in an SME Network*, Procedia CIRP, 72, 603–608.

Publication IV

Kangru, T.; Riives, J.; Mahmood, K.; Otto, T. (2019). Suitability Analysis of Using Industrial Robots in Manufacturing. Proceedings of Estonian Academy of Sciences, 2019, 68, 4, 383–388. https://doi.org/10.3176/proc.2019.4.06

Proceedings of the Estonian Academy of Sciences,
2019, **68**, 4, 383–388
https://doi.org/10.3176/proc.2019.4.06
Available online at www.eap.ee/proceedings

MANUFACTURING ENGINEERING

Suitability analysis of using industrial robots in manufacturing

Tavo Kangru[a*], Jüri Riives[b], Kashif Mahmood[c], and Tauno Otto[c]

[a] Institute of Technology, TTK University of Applied Sciences, Pärnu mnt 62, 10135 Tallinn, Estonia
[b] Innovative Manufacturing Engineering Systems Competence Centre, Teaduspargi 8, 12618 Tallinn, Estonia
[c] Department of Mechanical and Industrial Engineering, Tallinn University of Technology, Ehitajate tee 5, 19086 Tallinn, Estonia

Received 12 April 2019, accepted 9 May 2019, available online 28 October 2019

Abstract. Manufacturing industry robotization is spreading into wider range of processes. Determination if robotization is suitable for the company is one of the most critical issues before selecting industrial robot and designing the robot cell. A survey was carried out among Estonian small and medium sized manufacturing enterprises (SMEs) for this study to determine the utilization of industrial robot (IR) in the industry. More specific study of production unit was conducted, using gathered information, to estimate how the objectives of the production cell design were achieved. The aim of the present scientific work is to map the knowledge whether robotization is suitable or not for the company or working processes and to appoint parameters obtained after using the robot cell for practical manufacturing processes. The study results comprise the suitability assessment method with the set of criteria and key performance indicators (KPIs), that best describe implemented production unit profitability and help SMEs to gain additional economic-technical information for future robot-based unit development.

Key words: industrial robots, feasibility analysis, suitability analysis.

1. INTRODUCTION

Suitability analysis is the process and procedure used to establish a system that meets the needs of users. Suitability of robotization is a basic question for managers who are planning changes in the company. For producing goods, companies have to perform different processes and industrial tasks. There are certain aspects why industrial robots are used for those processes. Theoretically, the basic aspects concern humans, productivity and quality [1–3].

The widest areas using industrial robots are: welding, machine tool servicing, assembling, painting, loading-unloading, packaging, palletizing, and medical applications. Welding ranks among the most important joining processes and has special features for the industrial robots, such as programming task sequences, free definition and parameterization of robot positions/orientations, high repeatability and positioning accuracy of moving paths, high speed of end effector, minimum six degrees of freedom (6DOF), variable payloads depending on the welded products (2–150 kg), advanced programmable logic controllers (PLCs). The vision, strategy and action plans for implementation of robots are described in [4] and statistics about using robots in industry can be found in [5].

Literature review and efficiency analysis of IR cells are important basis for gathering information. To estimate the suitability of using industrial robots in different application areas, it is necessary to analyse the applications of the robot in the industry and to solve a decision-making task.

* Corresponding author, tavo.kangru@tktk.ee

2. BACKGROUND

Suitability analysis belongs to the tasks of dual approach. From one hand, it is an application area for the efficient use of industrial robots and on the other hand it supports decision making methods. The decision maker (expert) must have an excellent understanding about the application area and should be familiar with the factors influencing the effective use of industrial robots. For this purpose, a robot-based manufacturing cell performance evaluation conceptual model was developed, which is based on a recursive decision-making procedure [6]. In the model shown in Fig. 1, there are four groups of parameters: product features, robot cell features, elements of evaluation and general output description. The first two groups are the parameters of the design level (parameters of the product portfolio and their manufacturing processes) and the last two groups are the execution outcomes (different KPIs, that measure, and critical success factors – cost factors, level of achieving the general objectives, dynamics of effectiveness, employee competencies, etc.). These interactions reflect the suitability of using the real IR cell in the company.

The main concern in the suitability analysis process is to find the best solution, according to the set of criteria using the method, which allows the most realistic input (importance) of each criterion. There are different possibilities to influence the roles of criteria: the equal weight (EQW) heuristic [7], the weighted additive (WADD) rule [7]. However, the main risk is over-estimating some of the criteria or not paying enough attention to others. Therefore, artificial intelligence (AI) methods may be used [8].

Analysing industrial robot's applications for welding, there were developed three general groups of parameters, shown in Table 1. Those listed parameters have the greatest influence to the suitability of using welding robots in the company.

Having knowledge about the welding process and parameters make the welding process more efficient. It is possible to find the tools for suitability analysis. To solve the engineering task, such as making a decision about the suitability of welding robots in the company, multiple criteria should be used (see Table 1). Each decision corresponds to a variable, relation or predicate, whose possible values are listed among the condition alternatives. Each action is a procedure or operation

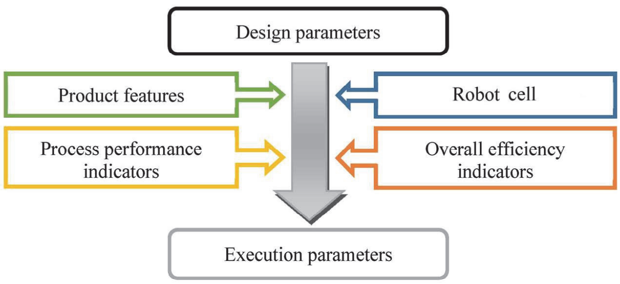


Fig. 1. Efficiency analysis of implementing robot cells in the companies.

Table 1. Suitability criteria for robot welding

Product view	Technology view	Objectives' view
1. The products are complicated from the technological point of view 2. The products can be classified into product families 3. The products are produced in repeatable batches 4. The products are of high quality 5. It is necessary to use welding fixtures	1. Experiences in MIG/MAG and TIG welding 2. Competences in welding technologies 3. Welding processes have great importance in the company's production processes 4. There are already experiences with robot welding 5. It is necessary to increase the productivity of welding processes	1. To shorten the throughput time 2. To increase the productivity in the workplace 3. To increase the product quality 4. To increase the precision of delivery 5. To reduce the product cost

to perform, and the entries specify whether or in what order the actions should be performed for the set of condition alternatives the entry corresponds to.

3. ANALYTIC HIERARCHY PROCESS

Solving the engineering decision making problem of IR cell suitability, which has multiple criteria and alternatives, is a difficult task. One of the techniques for solving multi-criteria decision making (MCDM) problems is analytic hierarchy process (AHP). AHP was proposed by Saaty [9] and developed further by [10,11]. Those methods use fundamental scale of relative importance to construct a pairwise comparison matrix of attributes. Likewise, consistent weight of attributes is determined, which help evaluating composite performance score of alternatives. The alternatives are then ranked according to their composite performance score. Several steps and principles should be considered and understood for constructing a MCDM problem solving tool. The steps are the following:

(1) Developing the hierarchy criteria model for decision;
(2) Deriving priorities by pair-wise comparison for the criteria. Pair-wise comparison scales are shown in Table 2;
(3) Determining local priorities for alternatives;
(4) Calculating and adjusting the consistency:
   (a) Multiplying the matrix of judgements by the eigenvector, obtaining a new vector ($A\omega$);
   (b) Dividing each component of a new vector of $A\omega$ by the corresponding eigenvector element;
   (c) The mean value from the point b is the estimated for λ_{max};
   (d) Calculating the consistency index (CI) by:

$$CI = \left(\lambda_{\max} - n\right)/n; \quad (1)$$

   (e) Calculating the consistency ratio (CR) by:

$$CR = CI/RI; \quad (2)$$

   (f) Checking the consistency of the hierarchy. CR should be below or equal to 10 %;
(5) Populating the judgement matrix with input data: quantitative data, such as product payback period total investment etc. are normalized by using Eq. (3). Dimensions, mass etc., are normalized by using Eq. (4). Qualitative data, such as complexity of operations, manufactured parts precision, experience and competencies of engineering stuff and workers, etc., are graded by the scale of 1–5 and normalized.

$$Z = 1 - \frac{x - x_{\min}}{x_{\max} - x_{\min}}, \quad (3)$$

$$Z = \frac{x - x_{\min}}{x_{\max} - x_{\min}}; \quad (4)$$

(6) Making the final decision.

4. CASE STUDY

Production cells were investigated in twenty SMEs with the number of employees ranging from 20 to 150. They produced different parts for agricultural and forestry machines, small tractors, high speed trains, lifts' components, wind generator rotors and other sheet metal products. The information was acquired by interviewing companies' management, engineering staff and data extracted from the enterprise resource planning (ERP) software. Data gained from the interviews and ERP system contained both, quantitative and qualitative data. From the collected data, the information about the robot welding production units was the only one used for the following suitability analysis.

Three performances of production units were stated as a benchmark for the suitability analysis. Production cells, shown in Table 3, were chosen by their excellent KPIs' outcomes. KPIs were selected according to the performance evaluation model [6] and they are as follows: discounted payback period (DPP), cell utilization (CU) and overall equipment effectiveness (OEE).

Table 2. Pair-wise comparison scale assessment

Importance	Description
1	Equal Importance
3	Moderate importance
5	Strong importance
7	Very strong importance
9	Extreme importance
2, 4, 6, 8	Values between two adjacent values should be in considerations
Inverse	If activity (i) got a point compared with activity (j), then (j) has the opposite value compared to (i)

Table 3. Production unit's description and performances

Company	Production cell	Products	Shifts	DPP, years	CU, %	OEE, %
No. 1	Yaskawa IR, two axes positioner	Heat exchangers	2	3	51	72
No. 2	ABB IR, single axes positioner	Trailer frames	2	2	40	70
No. 3	Yaskawa IR, single axes 2-station positioner	Forestry machine frames	1 (2)	3	45	70

5. CRITERIA AND SUB-CRITERIA

Regarding this study, the main task of multi criteria decision analysis (MADM) is to estimate the suitability index and it is based on the following criteria and sub-criteria (see Fig. 2):

- Production unit (PU):
  - cost (C): total investment (C1), cost of utilities (C2), running costs (C3);
  - maintenance (M): maintenance cost (M1), emergency maintenance cost (M2);
  - level (L): use of CAD/CAM (L1), automated storage (L2), machine vision (L3).
- Product (P):
  - physical properties (PP): complexity of parts (T1), parts manufacturing precision (T4), mass (T6);
  - productivity (PR): product families (T2), patch size (T3), patch repeatability (T9), overall welding ratio (TE3), average cycle time (TE9), average setup time (PR2), quality assurance (E2).
- Company environment (CE):
  - workforce (WF): workstation fulfillment (E1), workers salary (E6), production engineer's involvement (E8), shifts (W2), durations of shifts (W3);
  - performance indicators (PI): increment of productivity (E4), increment of on time delivery OTD (E9), increment overall equipment effectiveness OEE (E10), payback period (K1);
  - experiences (E): experiences with MIG/MAG, TIG (TE1), competencies in welding technology (TE2), experiences with robotization (TE4), experiences with jigs and fixtures (TE7), workstation organization level (TE8), overall automatization level (TE10).

6. PERFORMANCE SCORES

The assessments obtained from the decision makers are made by pairwise comparisons. Performance scores and consistency ratio are calculated and given in Tables 4 and 5.

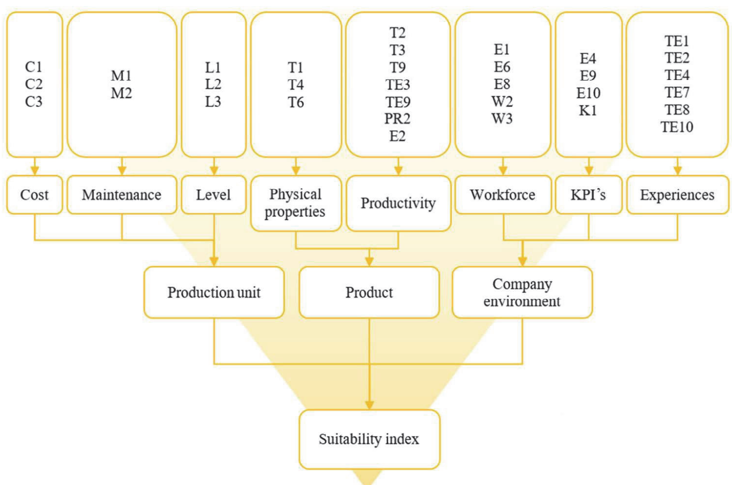


Fig. 2. Production cell suitability hierarchy.

Table 4. Performance scores of main criteria

Criteria	CR	Priority	Criteria	CR	Priority
Production unit	1.9	21	Physical properties	0	66.7
Product		24	Productivity		33.3
Company environment		55	Workforce	9.8	19.5
Cost	5.6	51.3	Performance		8.8
Maintenance		8.1	Experiences		71.7
Level		40.6			

Table 5. Sub-criteria, local performance scores

Criteria	CR	Priority	Criteria	CR	Priority	Criteria	CR	Priority
C1	7.4	74.3	T2	8.9	4.4	W3	2.6	18
C2		6.3	T3		18.1	E4	7.6	23.8
C3		19.4	T9		35.5	E9		28
M1	0	66.7	TE3		9.6	E10		8.9
M2		33.3	TE9		16.6	K1		39.3
L1	5.6	26	PR2		7.5	TE1	7.7	20.2
L2		41.3	E2		8.3	TE2		24.5
L3		32.7	E1	2.6	25.4	TE4		20.6
T1	5.6	41.3	E6		33.9	TE7		8.8
T4		32.7	E8		7.5	TE8		10.1
T6		26	W2		15.2	TE10		15.8

Explanations for the abbreviations are given in paragraph 5. Criteria and sub-criteria.

7. DECISION MATRIX

The normalized inputs are multiplied by their corresponding performance scores and the local and global scores are summed up. Results are shown in Table 6.

8. DISCUSSION AND CONCLUSIONS

In this study an AHP based suitability analysis for robot integrated production cells was developed. Twenty production cells in different industries and at different levels were investigated. Based on the literature, review input parameters were selected, criteria set up and hierarchy of the problem were developed. To ensure the objectivity of experts' pairwise comparisons of the responses of criteria, consistency ratio was calculated and controlled. For testing the developed tool, a case study approach was used. Three welding cells were selected based on their excellent KPIs' outcomes and set as a benchmark for suitability analysis. The highest overall suitability score was obtained in case of No. 3 with index of 0.17. The extremely high score was received in both, product and company environment categories, i.e. 0.849 and 0.810, respectively. The suitability analyses confirmed an excellent choice of product to be produced in a well-organized cell and automated company environment. For decision of suitability, four categories were proposed in Table 7, based on suitability criteria for robot welding, shown in Table 1.

For more precise results, it is possible to simulate the planned robot cell and to calculate the break-even point. Having enough competence in all these areas is quite sophisticated. Therefore, the tool which gives the possibilities to estimate the suitability of using industrial robots for the automation of a certain manufacturing

Table 6. Suitability index results

Production cell	Production unit	Product	Company environment	Suitability index
Company cell No. 1	0.567	0.699	0.664	0.652
Company cell No. 2	0.494	0.709	0.804	0.716
Company cell No. 3	0.524	0.849	0.810	0.717

Table 7. Suitability decision categories

Suitability index	Decision	Description
Smaller than 0.25	No expediency	Products portfolio, analysis of the current process and general conditions are indicating the lack of essential need for using robots in the company.
Smaller than 0.5	To a certain extent expedient	There is indicated the strong point (products, process, general conditions) and also the problematic places. The final decision lays on the industrial expert.
Smaller than 0.75	Robotization is recommended	There are indicated some risks which are not so much important.
Higher than 0.75	Robotizing is feasible	Each group (product, process, manufacturing conditions) has an index higher than 0.75, which gives a solid knowledge that robotization of the process would give significant benefits to the company.

process, is important in the early stage of planning. For future work, more robot integrated processes like machine tending, palletizing, etc. can be added to the tool.

ACKNOWLEDGEMENTS

We thank our colleagues from Taltech, IMECC and TTK UAS who provided insight and expertise that greatly assisted the research. The publication costs of this article were covered by the Estonian Academy of Sciences.

REFERENCES

1. Miller, R. K. *Industrial Robot Handbook*. Springer, New York, 1989.
2. Nof, S. Y. *Handbook of Industrial Robotics, Second Edition*. John Wiley & Sons, New York, 1999.
3. Koren, Y. *Robotics for Engineers*. McGraw-Hill Book Company, New York, 1985.
4. New Robot Strategy. Japan's Robot Strategy. Vision, Strategy, Action Plan. https://www.meti.go.jp/english/press/2015/pdf/0123_01b.pdf
5. World Robotics Report 2016. International Federation of Robotics. https://ifr.org/ifr-press-releases/news/world-robotics-report-2016
6. Kangru, T., Riives, J., Otto, T., Pohlak, M., and Mahmood, K. Intelligent Decision Making Approach for Performance Evaluation of a Robot-Based Manufacturing Cell. In *Proceedings of the International Mechanical Engineering Congress and Exposition, November 9–15, 2018, Pittsburgh, Pennsylvania, USA*. https://asmedigitalcollection.asme.org/IMECE/proceedings-abstract/IMECE2018/52019/V002T02A092/276341
7. Pfeiffer, J. Fundamentals on Decision-Making Behavior. In *Interactive Decision Aids in E-Commerce*. Physica-Verlag HD, Berlin, Heidelberg, 2011, 15–45. https://link.springer.com/chapter/10.1007%2F978-3-7908-2769-9_2
8. Zhang, L., et al. Using Neural Network to Evaluate Construction Land Use Suitability. In *Proceedings of the 2010 Second International Workshop on Education Technology and Computer Science, March 6–7, 2010, Wuhan, China*. https://ieeexplore.ieee.org/document/5459823
9. Saaty, T. L. *The Analytic Hierarchy Process*. McGraw-Hill, New York, 1980.
10. Kaganski, S., Majak, J., and Karjust, K. Fuzzy AHP as a tool for prioritization of key performance indicators. *Procedia CIRP*, 2018, **72**, 1227–1232.
11. Paavel, M., Karjust, K., and Majak, J. Development of a product lifecycle management model based on the fuzzy analytic hierarchy process. *Proc. Est. Acad. Sci*., 2017, **66** (3), 279–286.

Tööstusrobotite kasutatavuse sobivusanalüüs

Tavo Kangru, Jüri Riives, Kashif Mahmood ja Tauno Otto

Tootmisettevõttes on määrava tähtsusega enne robottootmisüksuse loomist läbi viia tööstusrobotite sobivusanalüüs. Selle väljatöötamiseks tehti Eesti väikese ja keskmise suurusega ettevõtete hulgas uuring, määramaks tööstusrobotite kasutust. Kogutud andmete põhjal viidi läbi spetsiifilisem tootmisüksuste uuring, millega hinnati tootmisrakkude projekteerimisel püstitatud eesmärkide saavutamist. Tulemusena loodi tööstusrobotite sobivuse hindamise meetod koos kriteeriumide ja tulemuslikkuse võtmenäitajate kogumiga. Hindamismeetod võimaldab hinnata rakendatud tootmisüksuse kasumlikkust ja saada täiendavat majanduslik-tehnilist teavet tulevaste robottootmisüksuste arendamiseks.

Publication V

Mahmood, K.; Otto, T.; Golova, J.; **Kangru, T.**; Kuts, V. (2020). An Approach to Analyze the Performance of Advanced Manufacturing Environment. Procedia CIRP, 93, 2020, 628–633. doi.org/10.1016/j.procir.2020.04.042

Available online at www.sciencedirect.com

ScienceDirect

Procedia CIRP 93 (2020) 628–633

www.elsevier.com/locate/procedia

53rd CIRP Conference on Manufacturing Systems

An Approach to Analyze the Performance of Advanced Manufacturing Environment

Kashif Mahmood[a]*, Tauno Otto[a], Jelena Golova[a], Tavo Kangru[a], Vladimir Kuts[a]

[a]Tallinn University of Technology, Department of Mechanical and Industrial Engineering, Ehitajate tee 5, Tallinn, 19086, Estonia

* Corresponding author. Tel.: +372 58254893; *E-mail address:* kashif.mahmood@taltech.ee

Abstract

The recent shift in manufacturing paradigm in terms of reconfigurable automation technologies invites the involvement of industrial mobile robots, highly automated production systems and digital information models to support manufacturing. Therefore, in the future, manufacturers need to complete automated production lines to compete in the global market. However, a current lack of performance assessment methods for the successful functioning of an advanced manufacturing line demands to describe a concept for the evaluation of such a manufacturing environment. This paper presents a concept to analyze the performance of advanced technologies integrated manufacturing line. Modeling and simulation of a case study are performed to validate and to attain the results of the proposed concept.

Keywords: Performance analysis; Advanced manufacturing environment; Performance indicators; 3D modeling and simulation

1. Introduction

In recent years, technologies evolved rapidly, manufacturing became more complex, and companies are getting specialized in their respective fields [1]. Manufacturing has been an essential economic driver in developed nations since the Industrial Revolution, and it continues to play a significant role in the process of wealth creation in today's world. To attain higher profit margins, continuous evaluation and improvement of business processes and production flows are required. A factory can be analyzed at different control levels, spanning from the more general enterprise-level until the more refined process level [2, 3]. Global organizational changes can influence the performance of a production facility, but new business models commonly affect only a type of product being manufactured, not the efficiency of the production itself.

Modern manufacturing involves the use of technology-supported decision-making on the managerial side, the implementation of Internet of Things (IoT) in factories, the integration of novel technologies like Augmented Reality (AR) and Virtual Reality (VR) within existing production environments, as well as the further development towards an autonomous and seamlessly working smart factory. The term that encompasses all aforementioned components is known as "Industry 4.0", a neologism coined at the "Hannover Messe" held in 2011 [4]. The nine pillars of Industry 4.0 are as follows: Big Data and Analytics, *Autonomous Robots*, *Simulation*, Horizontal and Vertical System Integration, IoT, Cloud Computing, Additive Manufacturing, Augmented Reality and Cyber Security [5].

This paper proposes a concept of performance evaluation of a manufacturing line integrated with modern manufacturing technologies such as industrial mobile robots and IoT sensors. The manufacturing line to be analyzed as a case study uses Automated Ground Vehicles (AGVs) or mobile robots that collect and send data via Infra-red (IR) sensors. As such, it includes some elements of the 4th Industrial Revolution Concept.

2212-8271 © 2020 The Authors. Published by Elsevier B.V.

10.1016/j.procir.2020.04.042

2. Literature Review

The increased degree of complexity in modern manufacturing facilities, stemming from a larger number of Internet-connected devices used on the shop-floor, calls for advanced performance evaluation techniques to be implemented. There are methodologies covered the topic of performance evaluation of production lines, but they mainly based on complex mathematical models, aside from the physical enactment of the model in a factory environment [6, 7 & 8]. For manufacturers, such methods and approaches are difficult to construct and adopt.

Moreover, there are studies of lean and throughput assessment of production systems [9, 10], some researches are based on complex distribution and statistical process control analysis of manufacturing systems [11, 12]. Those studies lacking in the exploration of digital tools that can be used in the evaluation of manufacturing lines and they are falling behind to describe the evaluation process in a harmonized way. This research defines an approach to evaluate a manufacturing environment that reflects the harmonization of activities and supported by digital tools. Those digital tools can be integrated like process modeling tool connects to discrete event simulation tool and to 3D geometric simulation tool, which helps to evaluate manufacturing systems from definition to realization in a virtual environment.

Modeling and simulation technique allows constructing both 2D and 3D representations of the production line. They offer the possibility to make changes to the model quickly and easily, while also providing a substantially better depiction of the to-be-built or to-be transformed factory. The current study comprises of the Integrated Definition (IDEF3) process modeling method for the static representation of the production line, alongside the animated 2D and 3D models for analysis built in a Discrete Event Simulation (DES) software i.e., ARENA and 3D simulation were performed on Visual Components 4.1 respectively.

2.1. New Technological Impact on Manufacturing

From a technological standpoint, change towards more integration is observable. This is manifested through the idea of a “smart factory” where all machines are in the process of constant exchange of information with each other, thus working together and working autonomously. *Vanderspek* named three factors that would influence the rate at which a fully automated factory would be adopted:

1. Low-cost, yet highly modern automated equipment;
2. Successful implementation of that equipment into a “comprehensive production system”;
3. Absence of nontechnical issues and influences that would prevent the integration of automation in a factory [13].

These three requirements have been on the path of being fulfilled in the past decade, as we see the creation of fully automated, flexible manufacturing systems and their performance analysis were conducted [13, 14]. Now the concurrent goal is moving to digital manufacturing. The impact can be observed as the recent manufacturing system incorporates a variety of automation tools, including AGVs, sensors, RFIDs, etc.

2.2. Selection of Key Performance Indicators

The use of a certain set of metrics to evaluate the current performance of a company is an essential part of business management. Nowadays, product managers receive an enormous dataset with statistics which can be difficult to follow through, so it is only appropriate for a company to select only the most relevant ones that would align with their values and business goals. In this study, only KPIs at the shop-floor level were considered and evaluated; metrics that involve external factors, such as supply chain partners and the end-users, are not included.

Hopp and Spearman [15] defined “The 7 Efficiencies” that best showcase the performance of a manufacturing company. They are throughput, utilization, cycle time, inventory, quality, customer service, and lead time. There are other KPIs metrics, optimized with the help of mathematical models and recommended for the shop-floor level [16].

2.3. Simulation as an analysis tool

Simulation has become a powerful tool in most areas of technology. It is extensively used in manufacturing, transport and logistics, military, construction operations, and more [17]. All kinds of processes and facilities can be modeled – restaurants, airports, theme parks, manufacturing plants, etc. [18]. In a real production environment, activities performed can fail, resulting in scrap, be delayed, get canceled, and so forth. Such kind of random behaviors can be addressed during the simulation through probabilistic distribution as it can be set to every activity to obtain more realistic end values [19, 20]. Moreover, simulation especially discrete-event simulation (DES) models can be connected to the different process modeling technique such as Integrated DEFinition (IDEF3) for a comprehensive description and analysis of manufacturing systems. DES model on ARENA can be generated based on IDEF3 process modeling [21, 22 & 23].

2.4. 3D Configuration and Visualization

In addition to simulating the overall process flow using DES, a virtual prototype of the production line in a three-dimensional environment can be constructed and simulated. It enables to enhance the visualization, which also encompasses a more specific emulation of a manufacturing unit. For the performance evaluation, the 3D configuration of work stations, AGVs, workers, and the products can be taken into consideration, resulting in the creation of a replica of the production line that is closer to real life. Moreover, 3D configuration in the virtual environment helps to check the feasibility of a production line before the actual physical implementation. Authors used 3D manufacturing simulation software, Visual Components Premium 4.1 [24] for the case study.

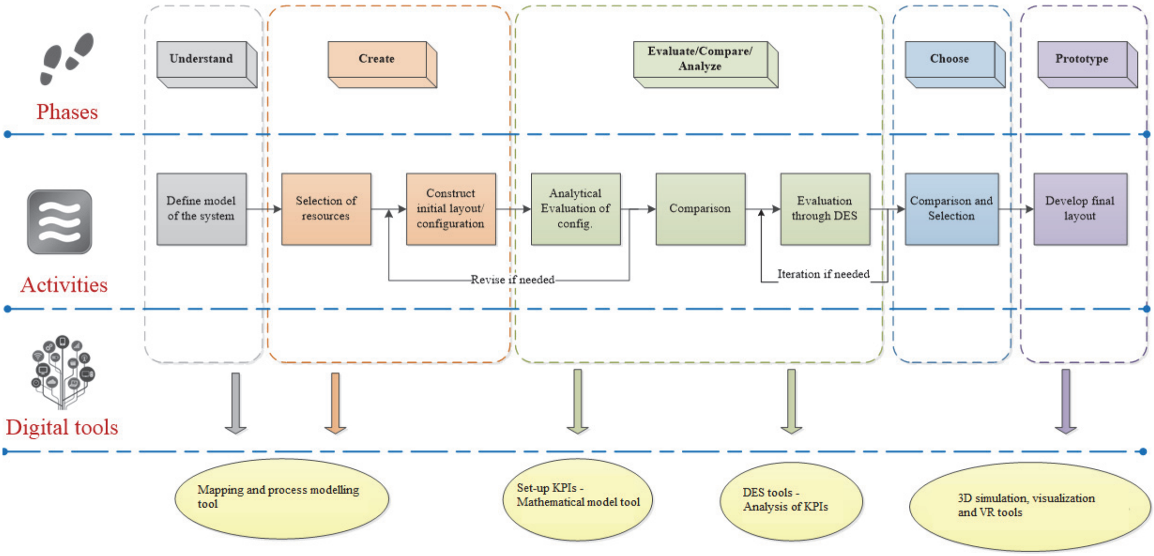


Fig. 1. An approach to analyse the performance of a manufacturing environment

3. Methodology

To realize and signify the proposed approach for performance analysis of an advanced manufacturing environment, a case study practice was used as a research method. Moreover, a literature review of the related context was carried out to describe and understand the key techniques that help to build a concept of performance analysis. The concept can be depicted in Fig. 1 and it is a continuous improvement approach. It describes a workflow for the analysis of a manufacturing system/line and structured as a sequence of activities. There are three layers in the approach: phase layer, activities layer, and digital tools layer. The description of each layer and how layers are corresponding to each other explained in this section.

3.1. Understand Phase

Activities: It delivers the modeling of the system and steps of the working of a system. In the case of configuration, it can be a new one or in case of reconfiguration, it can be the selected one.

Digital Tools: Mapping and modeling digital tool can be used to portray the idea for understanding. A software tool for basic system modeling helps to execute this phase.

3.2. Create Phase

Activities: Resources should be selected based on the system model and the tasks – a system performs. A logical initial layout should be developed that executes the desire steps or define the process flow.

Digital Tools: Similar mapping and modelling digital tools can be used as in the 1st phase. However, DES software such as *ARENA* can also be used to develop a logical model.

3.3. Evaluate/Compare/Analyze Phase

Activities: It provides the KPIs or parameters which are needed for the system evaluation. An analytical model of KPIs can be called here. Analysis can be done by DES, based on the selected KPIs and their relationship. Sensitivity analysis can be considered as well. Digital discrete-event simulation tools could be utilized here. ARENA results were used for the selected use-case.

3.4. Choose and Prototype Phase

Activities: Based on the analysis the final configuration/layout of a manufacturing system can be selected. The selected final layout can be modelled/configured in a 3D environment for 3D simulation and serve as a virtual model of a physical system. 3D manufacturing simulation, VR/AR and digital dashboard tools can be applied here. Visual Components Premium 4.1 used for the case study.

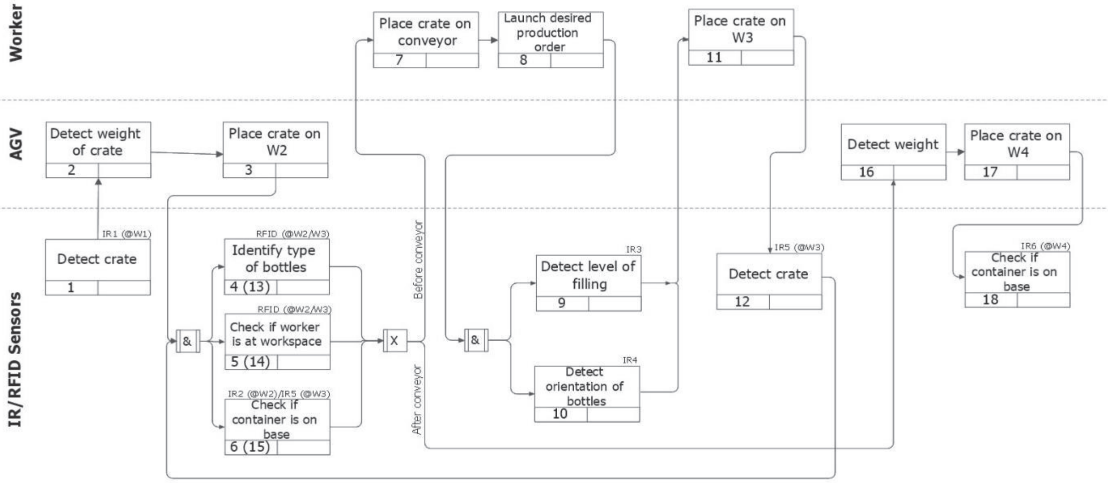


Fig. 2. IDEF3 Process Flow Description of the production line

4. Case Study

The developed approach for performance analysis was applied to a production process carried out in a chemical manufacturing company. The studied production line fills empty bottles with liquid, labels and caps the bottles, at the same time transferring them throughout the production line, from one workstation to another, accordingly. The bottles enter the system in crates, each crate containing 12 of them. The crate travels through the production line by the means of an AGV. At certain points, it is handled by a human worker (for example, the worker lifts the crate or scans the RFIDs on the crate). The three main operations – labeling, filling and capping – are performed by three separate machines respectively, all connected by a conveyor.

4.1. Process Model

IDEF3 model of the selected production line that described its process flow can be seen in Fig. 2. Processing time in seconds of each activity is also mentioned in the corresponding rectangular activity box.

The production line consists of four workstations and one waiting area for the AGV. The processes related to every workstation, as well as the transfers and the data acquisition by the sensors, are described in the steps below:

- A crate enters the facility via store outlet which is signified as Workstation 1 (W1). IR sensor #1 at this point detects whether there is a container on the loading area or not.
- AGV, before residing at its waiting area (W), moves to W1, picks up the crate and measures its weight.
- AGV takes the crate from W1 to Workstation 2 (W2) which is the start of the conveyor.
- As the AGV puts the crate onto the loading area of W2, a human worker scans the crate using an RFID sensor. The sensor records data on which bottles are in the crate currently. IR sensor #2, installed on the loading area, checks whether the crate is placed on the base correctly.
- The human worker opens the crate, places the bottles onto the conveyor and launches the desired production order.
- Bottles are labeled, filled and capped at the respective machines, with IR sensors #3 and #4 checking the levels of filling and the orientation of the bottles at area M.
- At the end of the conveyor, a human worker puts the filled bottles back into the crate, sticks a label onto the box, scans the crate with an RFID sensor, and loads it onto Workstation 3 (W3).
- At W3, IR sensor #5 detects the crate and checks its positioning on the base. If all conditions are met, the AGV is called to pick up the crate.
- AGV moves from W to W3. As it takes the crate and re-checks the weight, and then transfers it to the final workplace - Workstation 4 (W4). At W4, the production line ends, and the warehousing activities begin.
- AGV moves from W4 to W, after releasing the crate. IR sensor #6, installed on W4, checks the presence of the crate in this area.

4.2. DES Model

The DES model of the production line was created on ARENA software. Entities were defined as bottles and crate, resources were assigned as AGV, worker, labelling machine, filling, machine and capping machine. KPIs such as parts produced, throughput, cycle time and utilization were chosen for the analysis. The simulation run for eight hours and results are portrayed in Fig. 3.

The goals were to improve throughput, cut-down waiting time and balancing of resource utilization. Several iterations were executed, the different combinations of resources and changes in the layout were made to get the optimized results. A couple of steps were taken in the virtual environment for the improvement of the KPIs, these changes are:

- Change 1 – Increase the speed of the filling unit by installing new motors
- Change 2 – Installed an additional filling unit parallel to the existing one also serves as increased capacity.

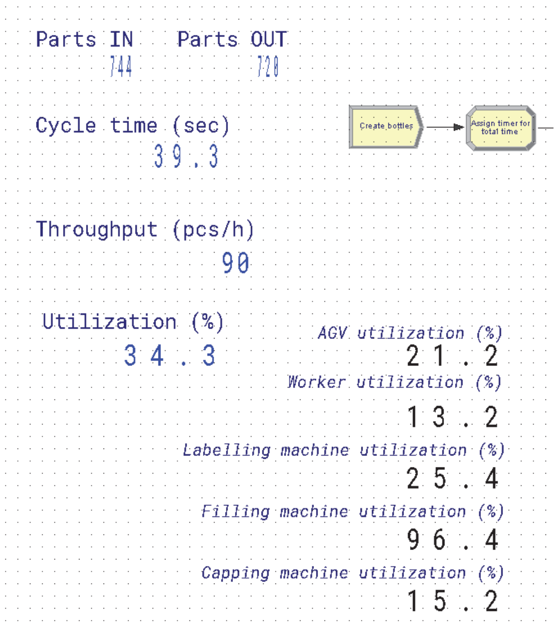


Fig. 3. KPI dashboard in the Arena model at the end of a simulation run

As a result of the steps taken, the production line was successfully analyzed. The large queue and the high waiting time of the bottle filling machine recognized as the bottleneck of the system, as it showed a waiting time of 153 seconds per bottle. To mitigate the issue both changes were practiced and variations in the waiting time are shown in Fig. 4.

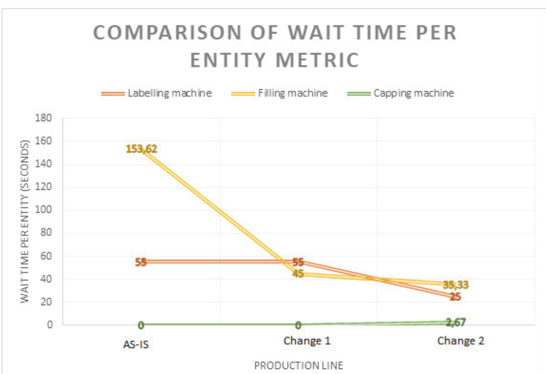


Fig. 4. Comparison of Wait Time per Entity metric for all machines in all three scenarios AS-IS, Change 1 and Change 2.

By increasing the capacity of the filling resource, resulting in the reduction of the Wait Time per Entity by one third (67%).

4.3. Modeling and Visualization in 3D Environment

DES provides the relevant information, the behaviour of the production line in regards to how efficiently it handles the entities and resources. Nonetheless, a higher level of visualization was desired to observe the viability of changes. For that purpose, physical elements of the production line placed in a 3D simulated space, this step can create a perception towards the planning of layout in the production facility. Collisions can be prevented, the safety of the workers and the degree of accessibility to a machine or workstation can be visualized, and that all can be done before the actual construction or reconstruction of the manufacturing unit in the real environment. Visual Components Premium 4.1 was used to build a 3D simulation model of the selected manufacturing environment and exported to the Virtual Reality (VR) setting for comprehensive visualization and can be used for training purposes.

The manufacturing environment was shaped in the form of an elongated rectangle, thus creating a loop. The AGV travels along from one workstation to another and following the pathways designated specifically for it. The workstations were not labeled in the model, aside from the waiting area W of the AGV. The separating and batching processes were presented through two funneling conveyor elements at the beginning and ending points of the conveyor. A human worker is shown at Workstation 2, and depending on the arrival time of the bottles, he or she may move to the position Workstation 3 to perform further tasks there. The 3D setup design was safe for the worker and facilitates a collision-free workflow. The 3D environment can be seen in Fig. 5.

5. Conclusion

The proposed approach is a contribution to the performance evaluation of the manufacturing environment integrated with mobile robots or AGVs. This work presents how the performance evaluation of manufacturing lines should be conducted in a unified way and how it may visualize in a 3D simulated world through VR application. Firstly, the production processes were described using IDEF3 diagrams. Secondly, a simulation of the production line was constructed using DES. As the third step, the factory system was configured and simulated for comprehensive visualization and to endorse the changes. The test case enabled the validation of the proposed approach and showed positive results. The analysis of the production line yielded good results, as both the issues and the solutions were successfully found. This research may be deemed as yet another proof of concept that the performance evaluation of production lines by the deployment of modern software solutions is feasible and fruitful. The limitation in this approach is that while the other technical challenges were solved, the interoperability aspect such as the integration of the used 3D software tool was not considered. The approach will be enhanced in the future with more real test cases with digital tools integration. Another future step would be the collected data from the real system and its integration to the simulation mode.

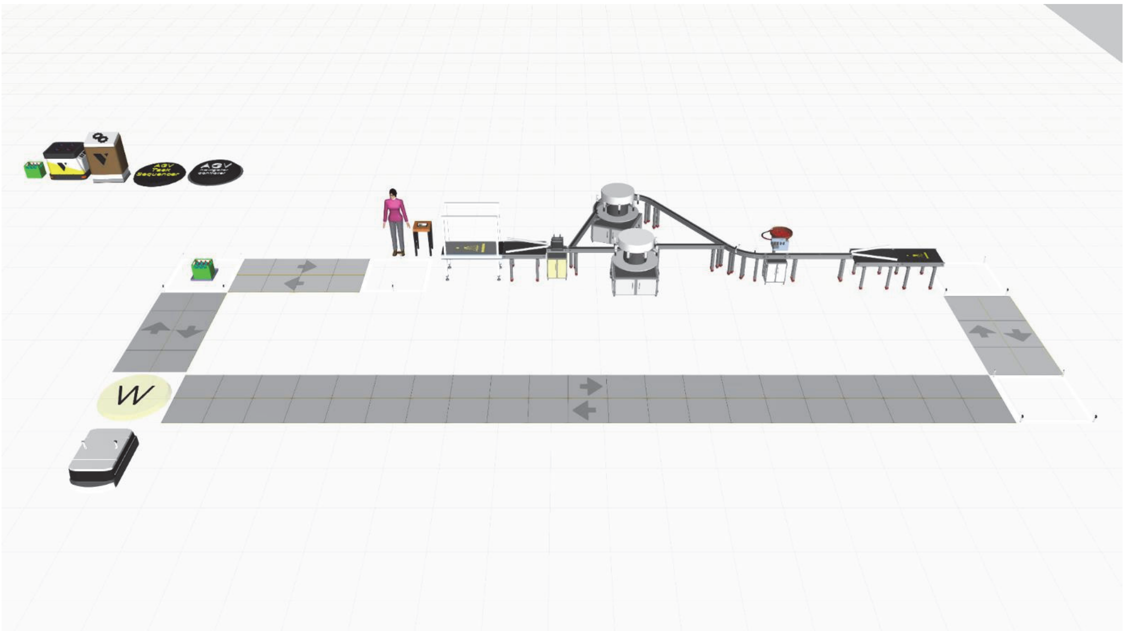


Fig. 5. 3D manufacturing environment of the selected case study

References

[1] Mahmood K, Lanz M, Toivonen V, Otto T. A Performance Evaluation Concept for Production Systems in an SME Network. Procedia CIRP 72 (2018) 603 – 608.

[2] Kangru T, Riives J, Otto T, Pohlak M, Mahmood K. Intelligent Decision Making Approach for Performance Evaluation of a Robot-Based Manufacturing Cell. ASME 2018 International Mechanical Engineering Congress and Exposition, November 9–15, (2018), Pittsburgh, Pennsylvania, USA.

[3] Groover MP. Automation, Production Systems, and CIM., 3rd Ed. (2014), Pearson, USA.

[4] Gunal MM. Simulation for Industry 4. 0: Past, Present, and Future., (2019), Springer.

[5] Erboz G. How To Define Industry 4.0: Main Pillars Of Industry 4.0., 7th International Conference on Management (ICoM 2017), Nitra, Slovakia, 2017.

[6] Paavel M, Karjust K, Majak M. PLM Maturity Model Development and Implementation in SME. Procedia CIRP 63 (2017) 651 – 657.

[7] Fitouhi MC, Nourelfath M, Gershwin SB. Performance evaluation of a two-machine line with a finite buffer and condition-based maintenance. Reliability Engineering and System Safety, 2017, vol. 166, 61-72.

[8] Lee H, Seo DW. Performance evaluation of WIP-controlled line production systems with constant processing times. Computer & Industrial Engineering, 2016, vol. 94, 138-146.

[9] Diaz-Elsayed N, Jondral A, Greinacher, S, Dornfeld D, Lanza G. Assessment of lean and green strategies by simulation of manufacturing systems in discrete production environments. CIRP Annals - Manufacturing Technology, 2013, vol. 62, 475–478.

[10] Jingshan Li, Blumenfeld DE, Huang N, Alden JM. Throughput analysis of production systems: recent advances and future topics. International Journal of Production Research, 2009; 47 (14), 3823-3851.

[11] Colledani M, Tolio T. Performance evaluation of production systems monitored by statistical process control and off-line inspections. Int. Journal of Production Economics, 2009, 120, 348–367.

[12] Becker T, Meyer M, Windt K. A manufacturing systems network model for the evaluation of complex manufacturing systems, International Journal of Productivity and Performance Management, 2014, 63 (3), 324-340.

[13] Vanderspek P., Planning for Factory Automation: A Management Guide to World-class Manufacturing, (1993), McGraw-Hill.

[14] Mahmood K, Karaulova T, Otto T, Shevtshenko E. Performance Analysis of a Flexible Manufacturing System (FMS). Procedia CIRP 63 (2017) 424 – 429.

[15] Hopp WJ, Spearman ML. Factory Physics. 3rd Ed. (2011), McGraw-Hill.

[16] Durkacova M, Lavin J, Karjust K. KPI optimization for product development process. 23rd DAAAM International Symposium on Intelligent Manufacturing and Automation, Vol 2, (2012), 1079-1084.

[17] Can U, Demirbaş Z. Creating an Alternative Production Line by Using a Simulation Technique in Duvet Cover Production. FIBRES & TEXTILES in Eastern Europe. Vol. 130 (2018), 8-12.

[18] Bandyopadhyay S, Bhattacharya R. Discrete and Continuous Simulation: Theory and Practice. 1st Ed. (2017). CRC Press.

[19] Tolio T, Sacco M, Terkaj W, Urgo M. Virtual Factory: an Integrated Framework for Manufacturing Systems Design and Analysis. Procedia CIRP, 2013; 7: 25 – 30.

[20] Kuts V, Modoni G. E, Terkaj W, Tähemaa T, Sacco M, Otto T. Exploiting factory telemetry to support Virtual Reality simulation in robotics cell. Augmented Reality, Virtual Reality, and Computer Graphics, 1: 4th International Conference, AVR 2017, Ugento, Italy, June 12-15, 2017. Ed. L. Tommaso De Paolis, P. Bourdot , A. Mongelli. Springer, 212−221.

[21] Cellier FE, Greifender J. Continuous System Modeling, Int. Edition, (2013), Springer Science & Business Media.

[22] Ki-Young J, Lei W, Jae-Dong H. IDEF method-based simulation model design and development. Journal of Industrial Engineering and Management, 2009, vol. 2, 337-359.

[23] Rockwell Automation, "Arena Simulation Software," Rockwell Automation, [Online]. Available: https://www.arenasimulation.com/. [Accessed 14 October 2019].

[24] Visual Components Premium 4.1. https://www.visualcomponents.com/ [Accessed 22 October 2019].

Publication VI

Kangru, T.; Riives, J.; Otto, T.; Mahmood, K.; Moor, M. Knowledge-driven robotic manufacturing performance simulation for cell design improvement. Proceedings of the ASME 2020 International Mechanical Engineering Congress and Exposition: IMECE2020, November 9–15, 2020. Portland, PA, USA: ASME, Paper No. IMECE2020-23541. (accepted to publish 18.08.2020)

Proceedings of the ASME 2020
International Mechanical Engineering Congress and Exposition
IMECE2020
November 16-19, 2020, Portland, OR, USA

IMECE2020-23541

KNOWLEDGE-DRIVEN BASED PERFORMANCE ANALYSIS OF ROBOTIC MANUFACTURING CELL FOR DESIGN IMPROVEMENT

Tavo Kangru[1], Kashif Mahmood, Tauno Otto
Tallinn University of Technology
Tallinn, Estonia

Madis Moor
TTK University of Applied Sciences
Tallinn, Estonia

Jüri Riives
Innovative Manufacturing Engineering Systems Competence Centre
Tallinn, Estonia

ABSTRACT

Manufacturing companies must ensure high productivity and low production cost in rapidly changing market conditions. At the same time products and services are evolving permanently. In order to cope with those circumstances, manufacturers should apply the principles of smart manufacturing together with continuous processes improvement. Smart manufacturing is a concept where production is no longer highly labor-intensive and based only on flexible manufacturing systems, but production as a whole process should be monitored and controlled with sophisticated information technology, integrated on all stages of the product life cycle. Process improvements in Smart Manufacturing are heavily reliance on decisions, which can be achieved by using modeling and simulation of systems with different analyzing tools based on Big Data processing and Artificial Intelligence (AI) technologies.

This study was performed to automate an estimation process and improve the accuracy for production cell´s performance evaluation. Although there have been researches performed in the same field, the substantial estimation process outcome and accuracy still need to be elaborated further.

In this article a robot integrated production cell simulation framework is developed. A developed system is used to simulate production cell parametric models in the real-life situations. A set of rules and constraints are created and inserted into the simulation model. Data for the constraints were acquired by investigating industries' best production cells performance parameters. Information was gathered in four main fields: company profile and strategy, cell layout and equipment, manufactured products process data and shortcomings of goal achievements or improvement necessary to perform. From those parametric case model, a 3D virtual manufacturing simulation model is built and simulated for achieving accurate results.

The integration of manufacturing data into decision making process through advanced prescriptive analytics models is a one of the future tasks of this study. The integration makes it possible to use "best practice" data and obtained Key Performance Indicators (KPIs) results to find the optimal solutions in real manufacturing conditions. The objective is to find the best solution of robot integrated cell for a certain industry using AI enabled simulation model. It also helps to improve situation assessment and deliberated decision-making mechanism.

Keywords: Knowledge driven manufacturing, robot-cell performance analysis, data analytics, simulation applications, digital twins.

1. INTRODUCTION

In 2011 the Industry 4.0 philosophy was widely introduced, followed by a systematic and determined development in this field. An architecture based on seven pillars has developed related to Industry 4.0 (I4.0), which describes the modern production system more narrowly and the main development trends of all production more broadly. As production in European countries accounts for a large share of GDP at 24.9% [1], development of this sector has a major impact on all other sectors. Nevertheless, major changes are taking place in the population structure due to low birth rates and high life expectancy. The last decade has seen an increase in the proportion of people aged 65 and over in the European Union of more than 2.6%, leading to an increase in the dependency ratio to over 21% [2] of the total population. There are currently just over three people of working age for every person aged 65 or

[1] Contact author: tavo.kangru@tktk.ee

over [2]. This indirectly affects the number of employees in the industrial sector and there is rather pressure to increase the growth of value added in production, then in future the low birth rate directly affects the share of people of working age in the industrial sector.

In addition to labor market problems, European industry is under constant pressure from cheaper production in developing countries. Over the years, exports to the European Union have been in constant profit, growing by 16.2% in 2016-2018 [3].

The EU is one of the world's leading environmental regulations. Environmental regulations generally require polluting facilities to undertake abatement activities and may impose costs on businesses. Thus, regulatory differences across firms, sectors or jurisdictions can cause changes in relative production costs. Differences in environmental regulations can thus alter the competition between firms by changing their relative production costs. [4]. These difficulties drive the development of industrial technologies for reducing the labor force, using resources efficiently, and shorting the developing time of the product.

The trends of digitalization have a great importance in US manufacturing [5]. More firms are making footprint decisions using a “total factor performance” approach that considers logistics, lead time, productivity, and risk as well as proximity to suppliers, other company operations, and final demand. Fundamentally, manufacturers need to identify strategic use cases that are linked to their digital initiatives and business strategy. Furthermore, they need to consider how to begin working alongside machines in a more automated and data driven way.

Large companies with more resources are more likely to be able to invest in and develop new I4.0 technologies to stay competitive and tackle these challenges. However, small and medium-sized enterprises (SMEs) are certainly not able to adapt similar solutions. This is also one of the reasons why technical solutions for companies of different sizes in the industrial sector should be considered according to the company's investment potential. It is important to ensure the competitiveness of small and medium-sized enterprises by finding solutions to labor problems, trying to increase productivity with equivalent resources, shorten the time to market, and produce products in compliance with current environmental standards. The biggest challenge for SMEs is to fulfill these conditions simultaneously. It certainly cannot be a single solution, but rather a continuous process improvement that could be based on the well-known Deming's Plan (P) - Do (D) - Check (C) - Act (A) cycle, one possible implementation of such kind of work has been discussed in high performance workplace design model [6].

Currently, SMEs use different types of production units such as single station automated cell, automated assembly system, flexible manufacturing system, computer integrated manufacturing systems, reconfigurable manufacturing systems and in these units the level of automation and intelligence vary greatly. Analyzing the current situation in the industry like digitalization via digital twin, communication, standardization, flexibility, customization, real-time monitoring, predictive maintenance, and industry lower level evaluations, upper level self-optimization and self-configuration [7, 8] and comparing it I4.0 principles lead to separate development areas for each company that should be addressed. This paper described a digital analyzing tool based on continuous process improvement philosophy to optimize production cell workflow for the SME´s. Some of the key aspects for optimization are workforce shortage and age peculiarity, assessment of investment compared to production output and maintaining a competitive advantage in high environmental regulations region.

2. MODERN MANUFACTURING

Modern manufacturing systems have evolved into complex ecosystems. Digital manufacturing and smart factories are becoming the norm in manufacturing, they depend on leverage of connected devices and technologies, numerically controlled machines and robots, advanced analysis with artificial intelligence, IoT, digital twins, advanced planning and control capabilities, which operates through the entire value chain. In addition, these devices must be capable of sensing their environments and interacting with one another. Simulation through digital twin is the technology for decreasing the time to design manufacturing systems and having information for decision making in performance analysis. Development tools related to I4.0 such as advanced simulation have great importance in industrial applications. Hence, there is a need and demand of digital solutions from production SME, which would help effectively use implemented technology and involved recourses. However, the studies offered and developed specialized digital solutions for production SMEs are lacking and need to be addressed comprehensively.

2.1 Manufacturing System Knowledge Based Architecture

Knowledge-based engineering (KBE) is the application of knowledge-based systems technology into the domain of manufacturing design and production. Production systems (robot-cell) can be defined as a kind of cognitive architecture, in which knowledge is represented in different forms. So, typically robot-cell based workplace as a part of a production system is a complex system with a specific architectural structure. To have a better understanding, according to Scholz-Reiter, a physical hierarchical levelling system should have three levels with various parameters: [9]

1. The system level, a production can be defined as stations or cells which are usually linked with predicted storage and transport systems;
2. The sub-system level, a workplace is considered as a pack of support resources for operations (e.g. robots and different devices);
3. The machine level, an environment with different tools, grippers, data, programs according to the necessity of the required equipment.

Previously stated physical hierarchical levelling system is combined with components (e.g. CNC machine or a manipulator). According to the complexity of different level systems, these resources can be described in several levels. In this study, we have been using two different robot cells which range between Sub-system to System level in principle. It allows to define certain constraints and input for work cells used for case studies.

2.2 Manufacturing System Design Inputs

Manufacturing System Design (MSD) inputs are based on numerous different parameters or keywords for "how to design". The wide range of variables makes it complicated to select important design input parameters (e.g. enterprise needs and objectives, external factors, controllable factors, constraints and targets), but precisely described manufacturing vision that leads to refined result in design process. Moreover, not all these factors affect the MSD directly, factors such as Market Uncertainty (MU), Product Volume (PV), Product Mix (PM), Frequency of Changes, Complexity, Process Capability, Worker Skill, Type of organization, Time to first part, Investment, Available/Existing Resources pointed out major parameters [10]. Starting with MU, it can be defined with fluctuations of a product demand. The demand affects manufacturing operation, creating an over or under capacity in the manufacturing system. Another important factor which is tightly connected with MU is the Product volume. Maximizing the PV determines manufacturing physical design by affecting factors like needed space, machine selection and layout. Furthermore, MSD process certainly includes the level of flexibility which can be associated with Product Mix. If the manufacturing system is expected a large product mix, it would lower the product volume produced per part. On the other hand, not all these factors stated above favor the MSD process. For example, the amount of investments is treated as a constraint and limits available choices to the designers. This can be based on several variables such as cost of implementation, payback period or time needed for MSD. For investments, we can consider Existing Resources to be a constraint in the design process. These availabilities such as time, finances, existing technologies can set limitation to the complexity which are expected from designed manufacturing system. All in all, these crucial factors should be considered carefully to use as inputs for fundamentals of manufacturing system design which should be chosen according to specific needs of enterprise.

2.3 Advanced Analytics

Advanced Analytics (AA) are becoming more and more vital for making so called "best decisions" on today's field of manufacturing. AA enables companies to efficiently and effectively make both narrow and extensive data-and modelling decision and facilitates on how to capitalize within the short-, medium- and long-term activities. Support for the decision maker comes to an automated process with visualized output rather than manual calculations on spreadsheet. AA can be divided into three computerized data processing analytic methods which are listed below:

- *Descriptive analytics:* accounting and analysis of historical data. Used in back casting practices and forecasting of seasonal demands.
- *Predictive analytics:* considers near past data to predict coming future trends, biases, tendencies, behaviors, etc., through causation and correlation.
- *Prescriptive analytics:* finds or prescribes the best mode, route, manner or moves to operate (outputs) based on given data and models (inputs). [11]

Data Analytics application requires a sufficient available database. By combining existing information gathered from MES and ERP databases with the effects of external factors, it is possible to use advanced analytics to extend the simulation model so that the forecast for the future is as real as possible. Possible application scenarios could be from manufacturing parameters optimization, predictive maintenance, available capacity or capacity needs prognosis and process performance among others [12]. The analysis process itself is designed cyclical nature and consists mainly of following steps [13]:

- Business understanding - objectives and requirements from a business perspective,
- Data understanding - data collection, data quality,
- Data preparation – construction of final dataset,
- Modeling – applying different modeling techniques. Some of the main methods used for modeling is this research are correlation, regression and prognosis,
- Evaluation – verifying model and dataset,
- Deployment – presenting results in a form that can be used.

2.4 Performance Monitoring

Key Performance Indicators (KPI) should be consider as a company vital sign, describing the actual situation and goal fulfillment. Using those as a tool, provides an opportunity to measure, analyze and make decisions for keeping production on track. At the same time, it is possible to identify bottlenecks in production, possibility to increase the effectiveness of employees and machine or to monitor the progress of production orders. Today, KPI monitoring is a multi-level, real-time process which begins at the shop-floor and reaches to the company strategic level, concentrating collected information for higher level KPIs. Selection of KPI for different companies and for different levels is generally a multi-criterion decision-making problem (MCDM) and it is important that the choice reflects the subject as accurately as possible. KPI selection problem have been addressed in those following researches [14, 15].

Solution for SME have been developed to assess the production unit performance [16], focused particularly on the evaluation process: Define System, Selection of KPIs, Process Modeling Simulation, Data Collection and Analysis and finally, Real Time Visualization. Hierarchical linking between KPIs through all levels have been mapped. The proposed KPIs are shown in Table 1. for SME production unit and are used in simulation model. Starting from the third and lowest level where inputs are measured directly from workplace or machine and ending at the highest where outputs are calculated.

TABLE 1. SELECTED KPI HIERARCHY

Level	Performance Indicators
I Strategic	Utilization Overall Equipment Effectiveness Throughput Discounted Payback Period
II Tactical	Availability Performance Quality Planned Production Time Actual Production Rate Set-up Time vs. Cycle Time Operating Time/Idle Time vs. Cycle Time
III Shop-Floor	Total Products Produced Finished Products Rejected Products Activity Processing Time Operating Time Ideal Processing Time Total Run Time

2.5 Production Cell Efficiency Analysis

Over the years many decision support systems (DSS) has been developed to help decision makers to select most functional and cost-effective equipment for production cell. One of the IR manufacturing cell design and redesign DSS system are shown in Fig 1.

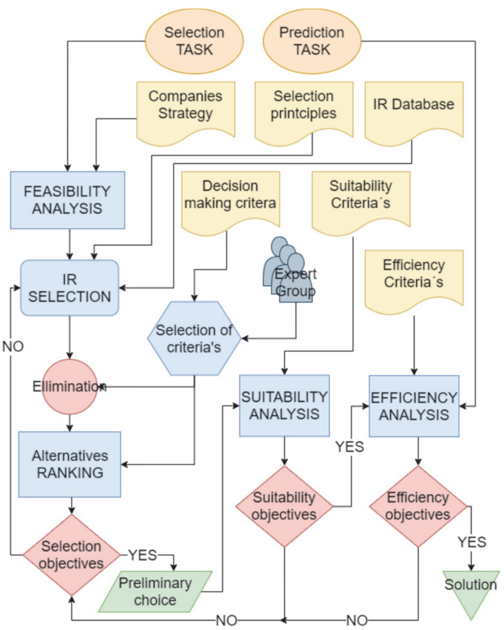


FIGURE 1: IR SELECTION DSS GENERAL MODEL [19]

Primary task is to check the cell architecture and technical parameters best suited for a selected job, and the reverse or prediction task consists of the analysis of optimal utilization of the implemented robot-cell in a company. One of the key components of reverse task is production cell efficiency analysis. The efficiency analysis evaluates the designed or installed solution, based on best competences. For adequate estimation of production unit manufacturing efficiency and assessment of production unit process failures, the whole system, components and their relations must be evaluated [17, 18]. Next section focuses on the development of the efficiency analysis module.

3. METHODOLOGY

To develop the efficiency analysis module of the production unit, a case study methodology was applied, for which the necessary theoretical material was investigated in the literature review. The proposed model (Fig. 2) is intended for computerized performance assessment of a production unit based on the objectives set in the company's strategy and industry-based collected production data. The model can be used to evaluate a company production process (CNC production cell) for a comparison with an ideal process set up in the proposed model. In addition, the proposed model is a useful tool in the design phase of a new production unit, as it allows to assess productivity based on the collected production information. The advanced data analysis of the model provides information for further improvements.

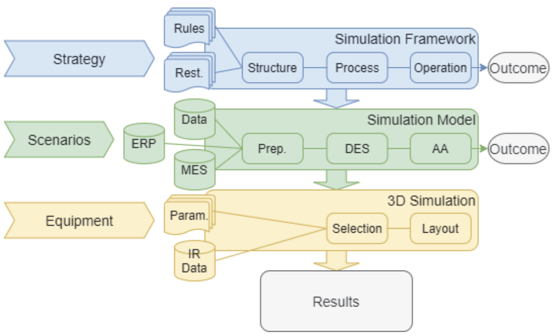


FIGURE 2: PRODUCTION SYSTEM EFFICIENCY ANALYSIS

The efficiency analysis is divided into three steps as shown in Fig. 2., where each step increases the accuracy of the selection. In the first step, production type, production volume and production technology are determined for the designed or redesigned cell. Inputs for this step are the design rules and constraints [10]. At the end of this step, the general requirements of the production unit have been determined. In second step, a simulation model is created according to the selected rules and constraints. Different scenarios are inserted into the developed model and the optimal scenario or scenarios are selected. At the end of this stage, a parametric model of the cell has been developed with a simulated technical economic result. At last step 3D simulation model is create based on the information provided earlier and most accurate results in different layouts and settings are acquired.

Information and data for the simulation model have been collected through various studies and databases. Studies on companies' products, production capacity and production units have been included [20, 21]. Production-specific data have been collected from companies' Manufacturing Execution Systems (MES) databases. The parameters and sub-parameters are selected according to the literature [10] and vary depending on the production capacity and type of the company. A list of the parameters used are given in table 2. From companies MES databases, the list and order of operations, their planned and actual cycle times, amount of scrap and rework needed to manufacture the products are used. The number of operations, cycle times and the number of reworks give an estimation of the product complexity.

TABLE 2: PARAMETER AND SUB-PARAMETER LIST

Parameter	Sub-parameter
Company	No of production machines Shifts Investment
Manufacturing	Operation orders Volume Performance
Operation	Start Time End Time Availability Performance Quality Process Capability
Product	Complexity Variety Quantity “New Products”

Part of the collected data (No of production machines, Shifts, Investment), the smallest in volume, can be used in the raw form. The second part of the data (product variability, quantities, new products) was processed statistically and their distribution was calculated. The third part and largest of the data were processed using artificial neural network classification [22, 23]. Neural Designer software was used for this purpose.

3.1 Manufacturing Cell Model

The manufacturing cell model is based on robot-based manufacturing cell Performance Evaluation Model (PEM) [19] and is programmed using Discrete Event Simulation (DES) software, Rockwell Automation Technologies Inc. Arena. An overview of the model is given in Fig. 3 and one of the sub-models in Fig 4.

The model is used to simulate different production orders simultaneously, like in “real life”, according to their operation sequence and order specific data. Order can exit the system only when all the necessary operation and occasional rework have been performed, and order has been successfully completed. Simulating concurrently, it is possible to assess the combined effects of orders, identify bottlenecks and incorporate improvements, which are directly reflected on production unit performance records.

Entities for the model were defined as an order where part production information (operations, cycle times, quality parameters, etc.) together with production volume are assigned. Outputs were defined as completed orders and rejected orders. Throughput and net value are calculated for each completed order. Similarly, unearned value is calculated for rejected orders. After simulating parts and volume by their distribution a KPI can be calculated. For this model a simple KPI selection of total production unite Utilization, Net Income and Discounted Payback Period were included. At first the model asses the existence of production capacity, in case the operations are busy and there is no free capacity, the order is sent to Rejected orders.

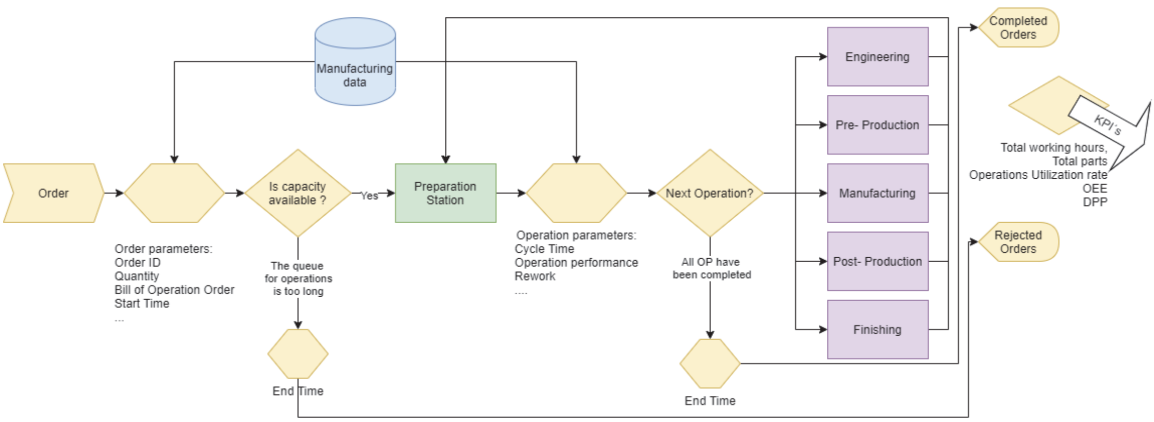


FIGURE 3: MANUFACTURING CELL MODEL

If the production unit has free capacity to utilize, the order will start to execute according to the order bill of operation BOO list.

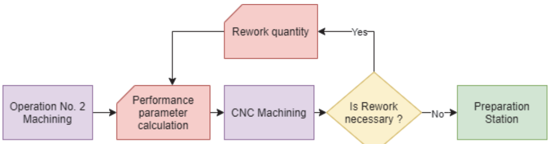


FIGURE 4: MANUFACTURING CELL SUB MODEL

In the model, the operations are described more broadly than normally in industry production planning. The model combines similar industrial operations such as turning, milling, bending into one manufacturing operation with a cycle time and operation specific productivity, availability and quality. Fig. 2. The following operations are used in the model: Engineering, Pre-processing, Manufacturing, Post-processing and Finishing. Each operation in the model is associated with a database, from which the required data for the operation is loaded according to the product and the operation cycle time and calculated according to equation (1).

$$O_{Th} = \frac{Q * CT * \sqrt{P_O * P_P}}{C * A} \tag{1}$$

Where O_{Th} - represents operation throughput time, Q - production quantity, CT - planned cycle time, P_O - operation performance value, P_P - part performance value, C - capacity and A - availability. Similarly, rework RO equation (2). is calculated where a product-specific quality coefficient P_q directs Q_P products to reprocessing. Normative times to move batches are set between operations. When all operations for the batch have been performed, the batch is sent to Completed Orders.

$$R_O = Q * P_q * Q_P \tag{2}$$

4. CASE STUDY

The validation of the model was accomplished by using cases studies. Two cases were chosen, a CNC manufacturing cell and a robot welding cell. The reason to select those cases was that there are large number of such production cells available in the regional industry. Another consideration was the availability of necessary production data and the structure of collected data. During the validation process, the correlation of production unit performance values and KPI´s, was observed at the same production program.

4.1 CNC Manufacturing Case Study

For the CNC Manufacturing case a small company was chosen. The company is manufacturing small and medium sized mechanical components for industrial machines and medical devices. Work is organized mainly in one shift and sometimes in two shifts. This study focused on the CNC machine-tending cell shown in Fig. 5. The production cell consists of medium sized turning center, co-working robot connected to it and WIP (work in progress) storage. The KPI where chosen as following: Throughput, Total Number of Orders, Total Products Produced, Overall Equipment Effectiveness, Utilization TPU and Discounted Payback Period.

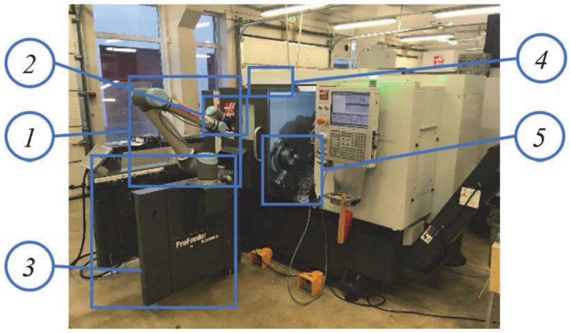


FIGURE 5: CNC MACHINE-TENDING CELL

Where: 1 - Co-working robot, 2 - universal prism gripper, 3 - work in progress storage, 4 - part overturn position, 5- machining position. Operations for the cells normal workflow are listed and explained in table 3. Average operations availability and performance was acquired from the company MES database. Order volume distribution, parts distribution and part cycle times for the operation where acquired from the company ERP system and MES database.

TABLE 3: CNC MANUFACTURING CASE STUDY OPERATIONS

Op.	Operation	Explanation
1	Engineering	The order has been accepted and planned for production starts.
2	Engineering	CAM programming the part
3	Pre- Production	CNC machine and IR robot setup and test run.
4	Manufacturing	Blanks are inserted to the WIP and manufacturing is started.
5	Post- production	Quality control are carried out
6	Finishing	The batch is finished, and the setup is taken down

For further configuration a 3D simulation is used, see Fig. 6. Visual Components 4.2 software was used to perform the analysis. By experimenting with different layout variations, it is possible to find the most optimal solution for the company production floor. As in this case the real environment already exists, the simulation was used only to optimize the IR robot position according to robot reach. For the new layout design, different configuration robot can be used at different mount locations and these changes can be tested in the 3D simulation environment.

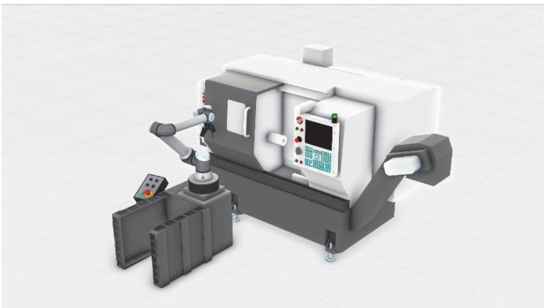


FIGURE 6: CNC MANUFACTURING CASE STUDY SIMULATION MODEL

4.2 Robot Welding Case Study

For the second case study a robotic welding unit of a small manufacturing company has been selected similarly as before. The company manufactures boiler housings and small assemblies for forest machines in small-scale serial production conditions. Six different products have been setup in this production unit. The work is organized in one shift. The production unit operator assembles parts from a pre-welded assembly in the jig, which is placed into the production unit for final welding. The KPI where chosen similarly as previous case.

FIGURE 7: ROBOTIC WELDING PRODUCTION UNIT

The production unit is shown in Fig. 7. where: 1 - robot manipulator, 2 - controller 3 - welding unit, 4 - programmable L-type positioners.

Operations for the regular workflow are listed and explained in table 4. For the welding cell case study 3D simulation, shown in Fig. 8, MotoSim EG-VRC software was used. As with the previous case 3D analysis, the optimal robot position was determined, same here but the main concern was whether the robot can reach all the assembly welding seams on the L positioner. Since the welding parameters had already been validated, it was possible to obtain accurate welding cycle times from the simulation.

TABLE 4: ROBOTIC WELDING CASE STUDY OPERATIONS

Op.	Operation	Explanation
1	Engineering	The order has been accepted and planned for production starts.
2	Engineering	CAM programming or teach in the assembly
3	Pre- Production	IR robot setup and test run.
4	Pre- Production	Spot welding parts in assembly jig
5	Manufacturing	Assembly are inserted to welding table and manufacturing are started.
6	Post- production	Quality control are carried out
7	Finishing	The batch is finished, and the setup is taken down

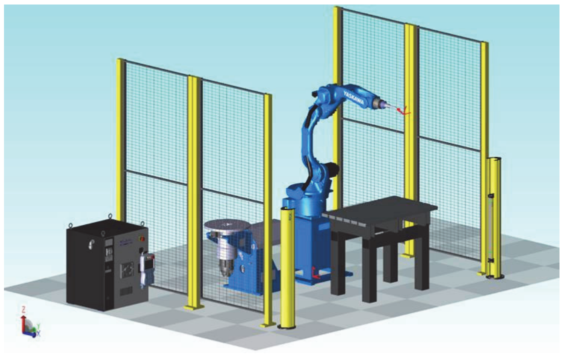


FIGURE 8: ROBOTIC WELDING CASE STUDY SIMULATION MODEL

4.3 Results and discussion

The production unit model was simulated using 10 preset products with different configuration, the minimum parts quantity was 10 and the maximum 500 parts per order. The simulation duration was 4.5 years, which in total was 9,000 working hours, working in one shift. As a result, a total of 100 thous. parts were produced during 430 orders, making the average number of parts per order 230 pc. The overall utilization rate for the production unit was 40% during this period, with CNC machining being the highest, with a utilization of 83% in some cases. CNC machining center overall equipment effectiveness OEE lowest 52%, highest 90% and average value 87%. Based on these data, the calculated discounted payback period DPP was 3.2 years.

The second case study production model was simulated for continuous work of 4000 hours, 2 years. As a result, 1400 assemblies where welded during 120 orders. The overall utilization rate for the production unit was 53% during this period, with robot welding operation being the highest, utilization of 80% in some cases. Overall equipment effectiveness OEE average value was calculated 72%. Based on these data, the calculated discounted payback period DPP was

4.8 years. Comparing the KPI numerical values obtained in both simulations with the actual KPI values of the company's production unit, the variation remains within 25% of the boundaries.

5. CONCLUSION

In this research, various possibilities were explored how to model semi robotized production unit workflow, using existing production information as input data. As a result, a methodology was developed to assess the performance of a production unit interactively by comparing it in digital twin modeled ideal process, where one of the main elements was a production unit knowledge-driven based discrete simulation operation model. The developed model was validated by using two case studies and modeled results compared and verified to the companies actual KPI´s. As a last step, a 3D simulation was created, based on the previous results, which was used to refine or reconfigure the production unit. Based on the developed methodology, it is possible to analyze the performance of an existing production units. It also helps to validate a new design of a production cell/unit and optimize their outputs through prescriptive analysis.

ACKNOWLEDGEMENTS

We thank our colleagues from Tallinn University of Technology, Innovative Manufacturing Engineering Systems Competence Centre and TTK University of Applied Sciences who provided insight and expertise that greatly assisted the research.

REFERENCES

[1] "Structure of the euro area economy", accessed May 08, 2020, https://www.ecb.europa.eu/mopo/eaec/html/index.en.html.

[2] "Population structure and ageing", accessed April 15, 2020, https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Population_structure_and_ageing/et#Rahvastiku_vananemise_varasemad_ja_tulevased_suundumused_Elis.

[3] European Commission, 2020, "Report on the Generalised Scheme of Preferences covering the period 2018-2019", JOIN (2020) 3 final.

[4] Dechezleprêtre, A., Sato, M., 2018, Green policies and firms' competitiveness, OECD, Paris.

[5] McKinsey Global Institute, 2017 "Making it in America: Revitalizing US manufacturing".

[6] Lõun, K., et al. 2013, "High-performance workplace design model", Estonian Journal of Engineering, Vol.19, No. 1, pp. 47 – 61.

[7] Qin, J., Liu, Y., Grosvenor, R. 2016 "A Categorical Framework of Manufacturing for Industry 4.0 and Beyond", Procedia CIRP 52, pp.173 – 178.

[8] Kuts, V., Modoni, G. E., Otto, T., Sacco, M., Tähamaa, T., Bondarenko, Y., Wang, R. 2019. "Synchronizing physical factory and its Digital Twin through an IIoT middleware: a case study." Proceedings of the Estonian Academy of Sciences, Vol. 68 (4), 364−370.

[9] Benkamouna, N., ElMaraghyb, W., Huyeta, A., L., Kouissa, K., 2014 "Architecture Framework for Manufacturing System Design", Procedia CIRP 17, pp. 88 – 93.

[10] Vaughn, A., Fernandes, P., Shields, J., T., 2002, "Manufacturing System Design Framework Manual", Massachusetts Institute of Technology, Cambridge.

[11] Menezes, C., B., Kelly, J., D., Adriano, G., L., Le Roux, C., G. 2019, "Predictive, Prescriptive and Detective Analytics for Smart Manufacturing in the Information Age". IFAC PapersOnLine 52-1, pp. 568–573.

[12] Groggert, S., Elser, H., Ngo, H., Q., Schmitt, R., H., 2017, "Scenario-based Manufacturing Data Analytics with the Example of Order Tracing through BLE-Beacons" Procedia Manufacturing 24, pp. 243–249.

[13] Chapman. P., Clinton, J., Kerber, R., Khabaza, T., Reinartz, T., Shearer, C., Wirth, R., 2020, "C RISP-DM 1.0 Step-by-step data mining guide", SPSS Inc.

[14] Kibira, D., Feng, S., Brundage, M., Morric, KC., Leong, S. 2017, "Procedure for selecting key performance indicators for sustainable manufacturing". Proceedings of the ASME 2017 International Manufacturing Science and Engineering Conference. MSEC2017.

[15] Kaganski, S., Majak, J., Karjust, K., and Toompalu, S. 2017, "Implementation of key performance indicators selection model as part of the Enterprise Analysis Model."Procedia CIRP, Vol.63, No. 1 pp. 283-288.

[16] Mahmood, K., Lanz, M., Toivonen, V., Otto, T. 2018, "A Performance Evaluation Concept for Production Systems in an SME Network", Procedia CIRP 72, pp. 603 – 608.

[17] Kangru, T., Riives, J., Otto, T., Kuts, V., Moor, M., 2020, "Optimization of decision-making process in industrial robot selection" Journal of Machine Engineering, Vol. 20, No. 1, pp.70 – 81.

[18] Mahmood, K., Shevtshenko, E. 2015, "Analysis of machine production processes by risk assessment approach." Journal of Machine Engineering, Vol. 15 (1), 112−124

[19] Kangru T., Riives J., Otto T., Pohlak M., Mahmood K., 2018, "Intelligent Decision-Making Approach for Performance Evaluation of a Robot Based Manufacturing Cell." Proceedings of ASME Mechanical Engineering Congress and Exposition, 2, ASME, USA, 1–10.

[20] Kangru, T., Riives, J., Mahmood, K., Otto, T., 2019, "Suitability analysis of using industrial robots in manufacturing", Proceedings of the Estonian Academy of Sciences, Vol. 68, No. 4, pp. 383 – 388.

[21] Vaher, K., Kangru, T., Otto, T., Riives, J., 2019, "The Mobility of Robotised Work Cells in Manufacturing", Proceedings of the 30th DAAAM International Symposium, pp. 1049-1055.

[22] Hassani, E., Mazgualdi, E., Masrour, T., 2019, "Artificial Intelligence and Machine Learning to Predict and Improve Efficiency in Manufacturing Industry".

[23] Saric, T., Simunovic, G., Svalina, K., 2016, "Estimation of machine time for cnc manufacturing using neural computing", Int j simul model Vol. 15, No. 4, pp. 663 – 675.

Appendix 2

Kangru, T.; Riives, J.; Otto, T. Survey questionnaire. Utilization of robot-based manufacturing cells in the Estonian industry.

Robotiseerimis tase SME´des

Uuringu eesmärgiks on välja selgitada Eestis keskmiste ja väikeste ettevõtetes robotiseerimise ulatus ja tase. Uuringu käigus kogutud andmeid töödeldakse ja avalikustatakse üldistades.

1. Ettevõte nimi

   ____

2. Mis on teie ettevõtte põhitegevusala?

   ____

3. Mitu töötajat on teie ettevõttes?

   ____

4. Mitu töötajat on teie ettevõttes tootval töökohal ?

   ____

5. Kui suur on teie ettevõtte käive ?

   ____

6. Millises vahemikus on teie toodete partiide levinuimad suurused?

Märkige ainult üks ovaal.

- < 10
- 10 - 50
- 51 - 100
- 100 - 500
- > 500

7. Kui suur on korduvate toodete osakaal?

Märkige ainult üks ovaal.

- < 10%
- 11 - 20%
- 21 - 30%
- 31 - 50%
- > 50%

8. Mitmes vahetuses on töö organiseeritud teie ettevõttes?

Märkige ainult üks ovaal.

- Ühes vahetuses
- Kahes vahetuses
- Kolmes vahetuses

Ettevõttes on kasutusel tööstusrobotid.

Vastake juhul kui ettevõttes on juba juurutatud tööstusrobotid.

9. Mitu robotit on teie ettevõttes kasutusel?

____

10. Kas te kasutate robotiseeritud töökohtadel traditsioonilist või koostöörobotit (robot töötab ilma eriliigiliste turanõueteta)?

Märkige kõik sobivad.

- [ ] Traditsioonilist robotit
- [ ] Koostöö robotit

Muu: [ ] ______________________________

11. Millistes protsessides/operatsioonides on teie ettevõttes robotiseeritud?

Märkige kõik sobivad.

- [ ] Pakkimine
- [ ] Koostamine
- [ ] Materjali liigutamine
- [ ] Värvimine
- [ ] Palletiseerimine
- [ ] Punktkeevitus
- [ ] Kaarkeevitus
- [ ] Mehaaniline töötlus
- [ ] Lõpptöötlus
- [ ] Pinnakatmine
- [ ] Inspekteerimine

Muu: [ ] ______________________________

12. Kui suureks te hindate oma ettevõttes kasutatavate robotite koormatust?

Märkige ainult üks ovaal.

- < 30%
- 31 - 50%
- 51 - 70%
- > 70%

13. Kas robotiseeritud töökohal teostatakse põhi või abioperatsioone?

Märkige kõik sobivad.

- Põhioperatsiooni
- Abioperatsiooni

Muu: ______________________

14. Kas robotiseeritud töökohal on kasutusel lisaseadmed?

Märkige kõik sobivad.

- Ei kasuta
- Lisateljed, pöördlauad
- Liikumisrajad

Muu: ______________________

15. Kas roboti tööriist või haarats vajas eraldi projekteerimist, valmistamist?

Märkige ainult üks ovaal.

- Jah
- Ei

16. Kuidas on tagatud töölise ohutus robotiseeritud töökohal?

Märkige ainult üks ovaal.

- ( ) Ei ole tagatud
- ( ) Kaitseekraan
- ( ) Eraldatud tsoon
- ( ) Inimese tuvastamise süsteem
- ( ) Muu: ____________________

17. Kas robotiseeritud töökohad on piisavalt kaetud insener-tehnilise personaaliga?

Märkige ainult üks ovaal.

- ( ) Ei ole kaetud, ostetakse teenusena sisse
- ( ) On osaliselt kaetud, osaliselt ostetakse sisse
- ( ) On kaetud

Ettevõtte tulevikuprognoos tööstusrobotite kasutuselevõtuga.

Küsimustele vastates tugineda ettevõtte järgmise 3 aasta arengustrateegiale.

18. Kas loodaval robotiseeritud töökohal võiks kasutada traditsioonilist või koostöörobotit (robot töötab ilma eriliigiliste turanõueteta)?

Märkige kõik sobivad.

- [ ] Traditsiooniline robot
- [ ] Koostöö robot

Muu: [ ] ____________________

19. Milliseid protsessides/operatsioonides teie ettevõttes võiks robotiseerida?

Märkige kõik sobivad.

- [ ] Pakkimine
- [ ] Koostamine
- [ ] Materjali liigutamine
- [ ] Värvimine
- [ ] Palletiseerimine
- [ ] Punktkeevitus
- [ ] Kaarkeevitus
- [ ] Mehaaniline töötlus
- [ ] Lõpptöötlus
- [ ] Pinnakatmine
- [ ] Inspekteerimine

Muu: [ ] ____________________

20. Kas loodaval robotiseeritud töökohal oleks vaja lisaseadmeid?

Märkige ainult üks ovaal.

- ( ) Ei ole vaja
- ( ) Lisateljed, pöördlauad
- ( ) Liikumisrajad

21. Kas robotile oleks vaja projekteerida eraldi tööriist/haarats?

Märkige ainult üks ovaal.

- ( ) Jah
- ( ) Ei

22. Mitu inimest hetkel töötab robotiseeritaval töökohal?

____

23. Kas ettevõttes on olemas inimene kes tegeleb töökoha robotiseerimisega?

Märkige ainult üks ovaal.

- Jah
- Ei

24. Kas teie ettevõttes on võimalik tööjõudu ümber paigutada?

Märkige ainult üks ovaal.

- Jah, ettevõte ise tegeleb ümberkoolitusega
- Jah, kuid on vajalik tööjõu ümberkoolitus
- Ei

25. Kommentaarid

Appendix 3

Kangru, T.; Riives, J.; Otto, T. Survey interview questions. Robot-based production cell study.

ROBOTISEERITUD TOOTMISÜKSUSE UURING

Kuupäev:			20

I Üldandmed

Ettevõtte nimi:
Intervjueeritava nimi ja amet:
Töötajate arv:
Vahetuste arv:
Ettevõtte käive:
Ettevõtte bilansimaht:

II Tootmisüksus

Valdkond:
Tehnoloogia:
Tootmisüksuse plaan:
Robotite arv ja ülesanne:
Lahendus: (standardlahendus, stand. adapt, erilahendus, sisseostetud erilahendus, uus lahendus)

ROBOTISEERITUD TOOTMISÜKSUSE UURING

Protsess: (materjali paigutus, protsessi robot, üks protsessi osa, keeruline protsess, erilahendus)
Lisaseadmed: (ei, lisateljed, lisateljed ja juhtrööpad, koostöö robotid, mobiilsed avatud kk.)
Robotite põhiparameetrid:
Tootmisüksuse maksumus:
Tootmisüksuse planeeritav tasuvusaeg:
Tootmisüksuse koormatus (h):
Tootmisüksuse seisakud (h):
Toodete praagiprotsent / reklamatsioonid (Quality):
Tootmisüksuse hooldus:
Tootmisvõimekuse muutus (%):
Tööliste arve enne ja pärast robotiseerimist:
Insener-tehnilise personali arv (vajadus):
Esinenud probleemid:

ROBOTISEERITUD TOOTMISÜKSUSE UURING

III Tooted

Tootepere nimetus:
Erinevate toodete arv tooteperes:
Partii suurused ja korratavus:
Keskmine seadistusaeg:
Keskmine tsükliaeg:
Hinnanguline tsükliaja võit protsesside optimeerimisega (Availability) :
Töölise abi toimetamine, tegevus ja keskmine aeg:

IV Märkused

Curriculum vitae

Personal data

Name:	Tavo Kangru
Date of birth:	20.12.1982
Place of birth:	Türi
Citizenship:	Estonia

Contact

E-mail:	tavo.kangru@tktk.ee

Education

2017 –	Tallinn University of Technology, PhD studies in Department of Mechanical and Industrial Engineering
2006 – 2012	Tallinn University of Technology, MSc studies in Product Development
2001 – 2005	TTK University of Applied Sciences, Mechanical Engineering
1989 – 2001	Türi Gymnasium of Economics

Language competence

Estonian:	Native speaker
English:	High Level

Professional employment

2017 –	TTK University of Applied Sciences, Institute of Technology, curriculum coordinator of Mechanical Engineering
2016 –	Vahva Solution OÜ, product development
2015 –	OÜ Toucan Engineering, CTO
2012 –	TTK University of Applied Sciences, Institute of Technology, lecturer
2014 – 2017	TTK University of Applied Sciences, Chair of Mechanical Engineering
2008 – 2012	TTK University of Applied Sciences, assistant
2003 – 2005	OÜ Kavor Motorsport, production engineer

Honours & awards

2020	Product design contest “Bruno” Special Award Edasi 2020
2019	Professional certificate 151504 Chartered Mechanical Engineer, EstQF level 8
2012	Professional certificate 075896 Diploma Mechanical Engineer, EstQF level 7

Patents

A pair of wind rotors; Owners: TTK University of Applied Sciences; Authors: Erich Rannat, Tavo Kangru, Rein Mägi, Tiit Tiidemann; Priority date: 27.12.2007.

Elulookirjeldus

Isikuandmed

Nimi:	Tavo Kangru
Sünniaeg:	20.12.1982
Sünnikoht:	Türi
Kodakontsus:	Eesti

Kontaktandmed

E-post:	tavo.kangru@tktk.ee

Hariduskäik

2017 –	Tallinna Tehnikaülikool, doktoriõpingud Mehaanika ja Tööstustehnika instituudis
2006 – 2012	Tallinna Tehnikaülikool, magistriõpingud, Tootearendus
2001 – 2005	Tallinna Tehnikakõrgkool, rakenduskõrgharidusõpe, Masinaehitus
1989 – 2001	Türi Majandusgümnaasium

Keelteoskus

Eesti keel:	Emakeel
Inglise keel:	Kõrgtase

Töökogemus

2017 –	Tallinna Tehnikakõrgkool, Tehnikainstituut, Masinaehituse õppekava juht
2016 –	Vahva Solution OÜ, tootearenduse insener
2015 –	OÜ Toucan Engineering, tootmisjuht
2012 –	Tallinna Tehnikakõrgkool, Tehnikainstituut, lektor
2014 – 2017	Tallinna Tehnikakõrgkool, Masinaehituse õppetooli hoidja
2008 – 2012	Tallinna Tehnikakõrgkool, assistent
2003 – 2005	OÜ Kavor Motorsport, tootmisinsener

Tunnustused ja preemiad

2020	Disaini konkursi “Bruno” eriauhind Edasi
2019	Kutsetunnistus 151504 Volitatud mehaanikainsener, tase 8
2012	Kutsetunnistus 075896 Diplomeeritud mehaanikainsener V, tase 7

Patendid

Tuulerootoripaar; Omanikud: Tallinna Tehnikakõrgkool; Autorid: Erich Rannat, Tavo Kangru, Rein Mägi, Tiit Tiidemann; Prioriteedi kuupäev: 27.12.2007.

ISSN 2585-6901 (PDF)
ISBN 978-9949-83-657-4 (PDF)