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A data-driven approach for Decision-Making support of factory simulation solutions

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Abstract

Factory simulation, one of the Industry 4.0 technologies, has increased in popularity. However, there is a limited number of strategies on how to implement this technology. This paper describes a data-driven approach that supports the Decision-Making process of factory simulation solutions. A performed literature review focused on manufacturing simulation frameworks, criteria for simulation solution selection, software evaluation methodologies, and simulation solutions, creates the foundation for the key contribution. An industrial case is used to test the initial findings. In addition, to suggest solutions as the output, the approach triggers the process of learning and thinking, which shows more value to practitioners.

Keywords: Decision-making; factory simulation; Data-driven approach

1. Introduction

Industry 4.0 practices have increased in popularity over recent years. Simulation for factories, as one of the core Industry 4.0 technologies, creates a disruptive impact on manufacturing companies [1]. The benefits of implementing simulation practice have been addressed in several studies, such as optimizing production layout [2], minimizing investments [2], performing what-if scenario analyses [3], the foundation for digital twins [4] to exemplify a few benefits. Many multinational companies have established implementation strategies, and, to a certain degree, they have adapted these principles. For the small and medium-sized enterprises (SMEs), this tends to be different. They are hesitating to invest in these technologies. Schröder [5] addresses several challenges that hinder the implementation of Industry 4.0 technologies in SMEs, including a lack of a comprehensive strategy, a lack of resources (or a low priority on technology implementation), a lack of competences at both technology level and management level, as well as a lack of standards and norms regarding the integration of various IT systems. Even though sometimes there is no direct value added to SMEs in short terms, the pressure from the big players in the value chain, e.g. the original equipment manufacturers (OEMs), and the pressure from the competitors force them to follow the trend. For instance, they need to develop a digital twin of their factory to continue the contract with the OEM. Great efforts from both academia and industry provide a big number of simulation tools, which, however, creates another challenge for the SME: The overwhelming challenge for selecting the right solution. Therefore, the objective of this study is to provide a tool based on a Decision-Making framework to help the SMEs make the right choice of simulation solutions. By adopting the tool, it should simplify the Decision-Making process and further increase the likelihood for SMEs to test and implement the new technologies.

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2. Related Work

Several methodologies to select the appropriate simulation solution have been identified in the literature. In addition, several simulation solutions are available for the practitioner, where some are depending on specific fields, while others are more generally applicable. This section describes the related work on frameworks for simulation studies, software selection criteria, evaluation approaches, and the currently available software solutions.

2.1. Frameworks for manufacturing simulation

Several frameworks to support the selection of software have been presented in early studies. Some of them can be adopted generically for software evaluation and selection [6,7], while others focus on simulation, such as software evaluation [8], software selection [9–11], and building simulation models [12,13]. Among these efforts, Bank [10] presents a framework that shows the overall process from defining a problem formulation to the final implementation in production. Comparably, Law and Kelton [13] proposed another framework, which contains similar steps as the first one, but in a different structure. Bank [10] suggests building the simulation model after data collection and conceptualization, while Law and Kelton [13] recommend a step in between to validate the conceptual model. The latter framework also elaborates on the process in the implementation stage. Both frameworks show an overview of the process of implementing simulation solutions. However, these frameworks do not include a step of software selection in the process, which is rather important and can be time-consuming. Knowing when should make this decision and how to choose the most suitable software solution are highly important.

2.2. Selection criteria of simulation software

Andreou and Tziakouris [6] adopt the ISO9126 quality model in their framework to evaluate software quality. According to the ISO9126 standard, software quality can be classified as a set of characteristics and sub-characteristics. The main characteristics include functionality, reliability, usability, efficiency, maintainability, and portability. Jadhav and Sonar [14] present a systematic approach to evaluate software packages, including three levels of criteria. In the top level, in addition to quality, there are additionally six criteria, including functionality, technicality, vendor, output, cost and benefit, and opinion. Each of them is elaborated to sub-criteria and further interpreted in the basic criteria level. Comparing to the ISO9126 standard, the sub-criteria of quality includes all the characteristics in the standard except functionality. In addition to this, the authors include customizability and security. These efforts create a generic foundation for software selection.

A few studies focus on the selection of simulation software. Banks [9] provides a list of features to support the selection criteria, including Input Features, Processing Features, Output Features, Environment Features, and Cost Features. Each section furthermore contains a number of parameters that influence the decision.

Table 1 Methodologies for software selection

Method	Explanation	Complexity
Analytic Hierarchy Process (AHP) [15]	The analytic hierarchy process is a methodology applied in a variety of different fields. It is divided into several steps, where the first stage is to define a decision hierarchy. In this hierarchy, the goal, criteria, sub-criteria, and alternatives are defined. Afterward, the pair-wise comparison matrix is created and then normalized. This is done for each sub-criteria. The next step is calculating the aggregate score of each alternative, where the highest score indicates the preferred solution.	Medium
Weighted Scoring Method (WSM) [16]	The weighted scoring model is based on a given score multiplied with the weight for each criterion. The results are then summed in order to give a final score. The highest score does, in this way, specify the optimal solution.	Low
Hybrid Knowledge Based System (HKBS) [7]	The Hybrid Knowledge Based System is divided into two components. First, the Rule Based Reasoning (RBR) and then the Case Based Reasoning (CBR). The RBR allows the practitioner to select the criteria that are characterized as important, and based on these, develop a problem case. This information is then transferred to the CBR, where the comparison and ranking are happening based on a similarity score equation.	High

The author suggests using a scoring model to rank and screen the simulation software. Cochran and Chen [17] develop a fuzzy set approach to select object-oriented simulation software. They identify desired features for simulation software and classify them into four categories, Object-Oriented Features, Programming Features, Simulation Features, and Environment Features. Hlupic and Paul [18] also identify several characteristics that are important for the selection of manufacturing simulation software. Different from other studies, they introduce the level of importance (LoI) into the selection mechanism and distinguish them according to the application domain, i.e., for education or the industry. They further distinguish the selection of software for the industry according to the speed of modeling and the fidelity of a model, i.e., for rapid modeling or detailed/complex modeling. As certain characteristics are more important than others according to the given application area or even the individual firm, it is therefore important to define them for the individual needs to obtain the most successful result. Interestingly, the authors also provide the score of LoI to each characteristic. They do though also claim that these scores were derived based on their extensive experience in "selecting and using simulation packages for teaching, research, and consulting assignments [18]." Constantinescu et al. [19] collect different criteria for the selection and evaluation of Efficient Agile Manufacturing tools. They target the scenario in SMEs, i.e., the best practice of the technology has to fit the needs of the SMEs. The criteria they suggest, tend to have the focus from the managerial perspective including Pragmatic usability, Applicability in daily business with low overheads, Zoom capability, SME

Customization, Specificity, Comparability, Degree of Independence, Coupling, Sustainability, Scalability, Agility, Legal aspects, Consensus, Cost, and Elasticity. The authors further weight each criterion.

2.3. Simulation selection methodologies

To evaluate and select software, different methodologies exist to assist this Decision-Making process. Jadhav and Sonar [16] identify and compare three commonly applied methodologies, as summarized in Table 1.

2.4. Simulation software

Several simulation solutions are commercially available. Some are targeted specific fields, while others are more generally applicable. To limit the selection of software solutions, only software containing a graphical user interface has been considered, thus eliminating dedicated programming languages due to the complexity hereof. Furthermore, all solutions should focus on manufacturing simulation. A preliminary list of manufacturing simulation software is provided below. Here, we need to highlight that it is not a complete list of available tools. New simulation solutions should be added in future work.

- Visual Components (Visual Components, Espoo, Finland)
- Tecnomatix Plant Simulation (Siemens, Stuttgart, Germany)
- Experior (Xcelgo, Ry, Denmark)
- Delmia (Dassault Systemes, Vélizy-Villacoublay Cedex, France)
- Flexsim (FlexSim Software Products, Inc., Orem, United States of America)
- Simul8 (Simul8, Boston, United States of America)
- Simio (Simio LLC, Sewickley, United States of America)
- Anylogic (The AnyLogic Company, Oakbrook Terrace, United States of America)
- MatLAB (MathWorks Inc., Natick, United States of America)
- Enterprise Dynamics (INCONTROL, Utrecht, Netherlands)

3. Research design

This study follows an exploratory research approach, describing a development process of a conceptual structure to support the Decision-Making for SMEs on the selection and implementation of factory simulation solutions. Fig. 1 shows the research design and its connection to the research output. The research design contains three steps. Initially, we did a literature review to create an overview of studies on simulation software selection and evaluation, including Decision-Making frameworks, software selection criteria, selection methodologies, and commercially available software. Based on the findings from the literature review, we formulate a conceptual Decision-Making structure and further develop a Decision-Making tool for best practice. In the last step, we tested the tool in a case study for validation and improvement.

4. Development of conceptual structure for software selection

4.1. Conceptual Decision-Making structure

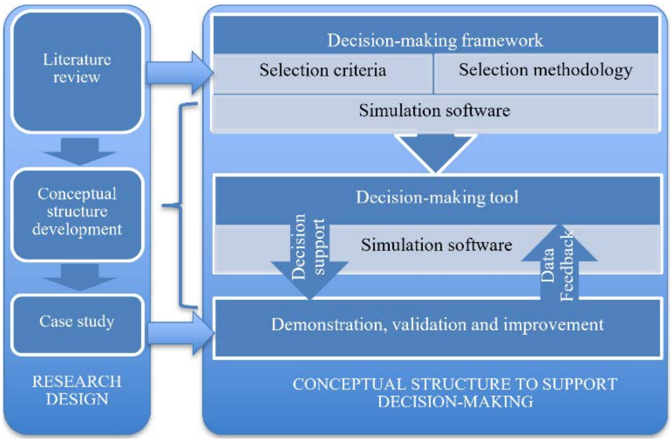

Fig. 1. Research design and the conceptual Decision-Making structure

Table 2 Selection criteria

Criteria	Sub-criteria	Weight*	Score
Functional[1] & Technical[1]	Visual aspects[3]	1	
	General features[3]	1	
	Physical elements[3]	1	
	Scheduling features[3]	2	
	Coding aspects[3]	2	
	General modelling features[3]	2	
	Statistical features[3]	2	
	Experimentation features[3]	2	
	Software compatibility[3]	3	
Quality[1]	Pragmatic usability[2]	3	
	Efficiency[3]	1	
	Testability[3]	1	
	Specificity[2]	2	
	Manufacturing performance[3]	1	
Vendor[1]	Modeling assistance[3]	1	
	User support[3]	1	
Output[1]	Input/Output[3]	1	
Cost and benefit[1]	Cost elasticity[2]	2	
	Financial and technical features[3]	1	
Opinion[1]	Consensus[2]	1	
	Pedigree[3]	3	
Managerial	Applicability in daily business[2]	3	
	Zoom capability[2]	3	
	SME customization[2]	3	
	Comparibility[2]	3	
	Degree of independence[2]	3	
	Coupling[2]	2	
	Sustainability[2]	2	
	Scalability[2]	2	
	Agility[2]	3	
	Legal aspects[1]	1	

[1] Software selection criteria defined by [14]
[2] Selection criteria defined by [19]
[3] Selection criteria defined by [18]
* Weight for each criterion refer to [20,21]

Fig. 1 indicates a basic conceptual Decision-Making structure on how to support the process of selecting and implementing simulation solutions. It requires a Decision-Making framework in the first layer to provide a generic procedure for technology implementation.

Under the framework layer, selection criteria and methodology form the second layer. The selection criteria identify what should be considered and the priority of each criterion, while the selection methodology reveals how to proceed with the actual selection. In combination of the two, a Decision-Making tool is developed to provide support for choosing the most suitable software solution. The validity of the tool depends on the evaluation quality of each simulation software. On one hand, the tool provides decision support to firms. On the other hand, actual decisions in firms and the score of criteria from the experts improve the suggested decisions by the tool. Therefore, it is crucial that the conceptual structure highlights the data feedback to the Decision-Making tool.

4.2. Decision-Making tool

Our selection criteria are based on earlier studies by [14,18,19]. According to [14], we have the first class of criteria, since they are defined for general software selection. We chose the criteria from [18,19], because they are defined for the selection of manufacturing simulation software, and the authors provide their estimation of the weight for each criterion. They are classified into the criteria categories and served as sub-criteria. Furthermore, Constantinescu et al. [19] take the consideration of the implementation scenario in SMEs. A number of sub-criteria cannot be classified into any of the criteria categories. Since they tend to be aimed at a managerial perspective, we define them as managerial criteria. Table 2 lists the selection criteria and the weight for each criterion.

The described tool is developed in Microsoft Excel, primarily due to the simplicity of the program, but also the wide availability that allows SMEs to easily open and apply the program without any prior knowledge. As Microsoft Excel allows saving different files, it would be possible for the SME to save the selection and reapply the tool for a new project, thus enabling a continuous innovation process in the company. To decrease complexity, the tool consists of one Microsoft Excel sheet where the practitioner evaluates the criteria listed in Table 2, and the suggested simulation software is shown as the output. We applied the WSM for determining the optimal simulation solution. The WSM has been selected due to the low complexity of implementation, allowing customization, expandability, and flexibility [17]. It is in this way also possible for the SMEs to easily implement custom parameters relevant to either a specific industry, customer, use case, or similar. The low complexity of the WSM furthermore enables continuous improvements, evaluation, and updates of the criteria as well as the weights. The equation below illustrates the WSM.

$$R_i = \sum_{j=1}^{n} w_j r_{ij} \ , \quad i = 1,2,\dots,m \qquad (1)$$

Where R_i determines the overall score for instance i, w_j indicates the weight for the selected criterion, and r_{ij} represents the score of criterion j for instance i. Furthermore, m indicates the alternatives, where n represents criteria. An estimated score for each criterion has been pre-set for all the included simulation software. When practitioners use the tool for Decision-Making support, they need to score the criteria according to their demand, then the overall score R_i is calculated. The software that has the closest pre-setting score to R_i is selected and displayed as the suggested solution.

Currently, the pre-setting score is based on rough estimation by the authors. A quantitative study with experts within the different simulation solutions needs to be done in order to determine these scores more precisely prior to industrial implementation.

4.3. Case Study

To verify the performance of the decision-supporting tool, a case study has been performed. A German high-tech SME, specialized in control and automation, participated in the case study. They develop automation solutions to their customers who are suppliers to the automotive industry. The SME has just received a request from a customer to upgrade a production line. The sales manager is in charge of the project. He wants to investigate the efficiency and safety of different production setups. It has been determined that simulation is needed prior to investing in upgrading the production line. They have researched numerous solutions, although uncertainty exists in selecting the right simulation solution. The use of the developed tool is to support in the Decision-Making process of selecting the appropriate simulation solution.

The sales manager scored each criterion on a scale from the lowest priority 1 to the highest priority 7. Furthermore, he determined the application area for the simulation solution to be used for rapid modeling. We observed the whole process while the manager was filling the scores. Afterward, we had an interview with the manager to get his feedback.

Following the weight of each parameter, a summed score results in a numerical value of 304. Three simulation software is presented, in which, Anylogic with a match of 97.44%, is suggested as the first option. Since the pre-setting scores for each software are based on rough estimation, the purpose of this case study is purely for demonstrating the Decision-Making tool and getting feedback for improvement.

It is with this information now possible for the decision-maker to quantify certain input criteria and get a suggested simulation solution. It is though important to highlight that the suggested simulation solution might not be the ideal case. This is partially documented by the “Match” value, but also other non-identified parameters might influence the Decision-Making process. The manager expressed that they would most likely choose Siemens software because they are a Siemens solution partner, and they get supports from Siemens. Even though he still confirmed that the tool is very helpful. It clears his mind on what are the most important features to them. Furthermore, he addressed that only a suggestion as the output of the tool would not be enough. The pros and cons of different software and a comparison of the features would be interesting as well.

5. Discussion

5.1. Improvements

From the case study, it has been identified that the criteria often require further explanation for the practitioner to understand and score it accordingly. Efforts are, therefore, put into developing a more user-friendly way to evaluate the criteria. Additionally, an improvement adds a criterion on a preferred simulation solution. This addresses the suggestion from the German high-tech SME that they would be using the tool due to strategic collaborations. In the results, a simulation solution, according to their preference, will be listed in addition to three recommended solutions that match the practitioner's inputs. The differences in each criterion are highlighted to support the Decision-Making process.

We used WSM as the selection methodology, which is based on the average of the scores but not the individual criterion. This may give unprecise suggestions. Different machine learning algorithms, such as decision tree, K-nearest neighbors, logic regression, and artificial neural network [22], will be tested and compared. A better selection methodology will be used in the development of the final version of the tool. It is though important to highlight that the quality of the data plays an important role in order for the different selection methodologies to yield the optimal results. The final tool will adopt best practices to ensure the high quality of the input data.

The final improvement will include further development of the database to allow web crawlers to extract the data from current literature for further selection criteria, which is afterward analyzed. Experts will then verify and validate these criteria as well as provide a score. This enables continuous improvement of the database, ensuring the results are always based on the latest research.

5.2. Scholarly Implementations

One of the main findings of the study is the conceptual structure. Based on a collection of research outputs from different perspectives, i.e., decision-support framework, criteria, and models, we unify the conceptual structure of the whole Decision-Making support process. It shows the hierarchy and the links of the elements, as well as indicates the connection from theory to best practice. The structure provides the foundation for us to build the Decision-Making tool, which is the main objective of this study. The tool development is still in the pilot phase, but the test results have shown the potential value of the work.

We suggest adding an extra step to the presented frameworks [10,13], i.e., a step of Decision-Making of Software Selection after the initial step – Problem Formulation. We think it is necessary for decision-makers, especially those from SMEs who do not have rich experience in simulation software, to choose the appropriate simulation solution at the early stage. While going through the selection process, it will increase their awareness of the technology. The better they understand the technology, the clearer they can identify the added value to the firm, resulting in a higher likelihood of final implementation. This has been observed from the case study that the manager became convinced to acquire the technology after trying the selection process. The selection process increases the absorptive capacity [23]. When further implementing the simulation solution, they will gain new knowledge about other technologies, e.g., robotics. Adoption of these technologies will emerge.

The findings from the case study show that only getting a suggestion is not enough for decision-makers. They also benefit from this learning process to gain new knowledge about simulation solutions. While scoring the criteria, it forces them to think systematically about their needs and the options, which already supports them for Decision-Making.

The case study also identifies a weakness of the existing Decision-Making models that case-sensitive factors, such as human factors, are not considered in the models. None of the reviewed literature has addressed it. Individuals' knowledge and experience and other subjective factors influence the decision significantly. According to the path dependency theory [24], the historical experience matters.

5.3. Managerial implementations

This study provides a best practice tool that supports decision-makers in selecting the most appropriate simulation solution in a more efficient and systematic way. This is highly important for SMEs. As Chau [25] pointed out, the timing of selecting and implementing the simulation solution is additionally critical for successful adoption in SMEs. It is commonly known for SMEs that in the period with a high number of customer orders, the financial prerequisites are present, but result in a short of time. Contrary, in the period with low customer orders, the time available for adoption is present, but the financial aspects might not be. It is, therefore, important to have an efficient way for Decision-Making.

It is also necessary to select the appropriate timing of the adoption of the simulation solution as the score of certain criteria might be influenced by the financial status of the company in the given moment. Our suggestion to the company owners or managers is to get experience in this Decision-Making process at the early stage, even though it may not be the right time for technology acquirement and implementation. The learning process is more valuable than a decision.

5.4. Limitations and Future work

As the presented case study shows, it is possible to obtain a suggested simulation solution by quantifying certain criteria. The developed tool is still in the very early phase and does, though, have certain limitations. First of all, the parameters identified in literature might not be the complete foundation for the Decision-Making process, due to the high complexity of this process by nature. In addition to this, the developed tool only consists of the parameters identified in literature containing a weight. The other parameters that also influence the decision are not implemented in this iteration of the tool, due to the lack of data. Case-sensitive factors should also be considered in Decision-Making models.

Another limitation of the developed tool is the methodology applied to calculate the score. The WSM applied to both the input criteria as well as on the simulation solutions does not differentiate between each criterion. The same overall score may have a totally different score pattern. As this value is compared to a combined score of the simulation solutions, a risk of a misleading result exists. Different methodologies, such as conventional neural networks or other machine learning algorithms, should be applied in order to better estimate the optimal output, even though scoring models are suggested in other studies [26].

One of the key points to improve in the Decision-Making tool is the scores of the simulation solutions since the current state is based on rough estimation. These values will be performed by following a quantitative study between experts in the specific simulation solution. An expert could, for example, be a researcher in factory simulation or an experienced practitioner, including both users and technology providers.

Secondly, the parameters will need verification through a quantitative study of potential decision-makers in small and medium-sized enterprises. In this way, it will furthermore be possible to decrease the number of parameters to only the most important and in this way decrease the complexity of the tool while remaining valid. Another option could be to implement artificial intelligence principles, such as unsupervised learning to implement a pattern recognition algorithm, for example k-means clustering. Alternatively, supervised learning could be implemented by designing a quantitative study to acquire data from experts on selecting the appropriate software for specific tasks. In this case, a random forest approach could be applied.

Finally, as the tool is a part of a bigger Decision-Making framework for implementing factory simulation solutions in small and medium-sized enterprises, more extensive research will be performed to implement this tool into the framework. This framework will support the SME from the very early stage of the process to the continuous improvement and innovation stage. The details of the framework will be described in a following study.

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