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KNOWLEDGE BASE DEVELOPMENT FOR ASSEMBLY PLANNING USING EVIDENCE THEORY

This paper presents an approach to assembly planning in the early phase of product development. The product specification, workstation, environment, equipment and tools are not fully known in the early stage of product development. When comparing product variants at this stage there is a lack of data that affects the efficiency of the manufacturing process. It is therefore necessary to apply methods useful in processing incomplete and uncertain data. The main indicator which helps in comparing different product variants is manufacturing time standard. This papier is focused on assembly tool selection which is one of important data influenced assembly time. Based on the proposed algorithm and case study, a tool selection method using a decision tree induced from a training set with reduced uncertainty is presented.

1. INTRODUCTION

The efficiency of the manufacturing process depends on the solutions established during the product design phase. It is therefore necessary to develop a method useful for comparing different product variants at the product design stage. In the design and manufacturing process, the importance of product assembly increases when customized products are offered. The assembly process is complex, so managing it during the manufacturing and product design phases is a challenge [1]. Researchers have focused on different aspects of the assembly process in their analysis. Modrak et al [2] discuss the assembly of custom product configurations and its complexity. Kern et al [3] discuss methods for planning modular assembly systems.

The importance of machine learning and uncertainty processing is growing, and the authors discuss the application of artificial intelligence methods in various areas of manufacturing. Baas and Kwakernaak [4] proposed a method involved fuzzy sets to deal with multiple alternative decision problems under uncertainty. Möhring et al [5] present future opportunities related to new approaches to intelligent process control in woodworking. Tools

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development of in intelligent mechatronic systems is discussed by Guergov [6]. Dalvi [7] uses artificial neural network (ANN) and motion study as tools for assembly sequence optimization.

At the product design stage, some of the data involved in the assembly process is uncertain, so it is necessary to use methods such as evidence theory, which are useful in processing such data.

The aim of the research is to develop a method for the selection of assembly tools taking into account the incomplete characteristics of the production process. The scope of the research concerns the example of assembly a bearing on a shaft.

2. STATE OF ART

2.1. EVIDENCE THEORY

Evidence theory known as Dempster-Shafer theory (DST) is one of the effective methods of uncertain information processing [8, 9].

An analysis of the literature on DST applications presents different concepts of data analysis, which come from different sources. DST can be combined with other methods such as fuzzy sets, rough sets and neural networks, for example.

DST has been applied, for example, by Yu et. al. [8] to clustering error reduction, where evidence theory was used to construct and collect K-nearest neighbour information to assign uncluttered objects to the most appropriate cluster, effectively solving the cluster label error propagation problem.

Liu et al. use DST for glass defect identification [9]. In this approach, DST was combined with image classification methods using artificial neural networks and fuzzy k-nearest neighbour classifier.

Qing et al. [10] apply DST and rough sets for internet intrusion detection system. This approach combines rough sets theory and the evidence theory, which can solve the difficulty of acquiring the Basic Belief Assignment's, reducing the correlativity among the evidences and weakening the subjectivity of evidences. The illustrative example shows that it is feasible and effective.

Dymova et al. [11] applied DST and fuzzy sets to rule-based evidential inference in expert systems. DST is used to consider different data sources and fuzzy sets are used to apply linguistic terms in decision rules.

Chen et al [12] use DST as a tool for multisensory data analysis in welding process. This method first uses the distance between the evidence to obtain the weights of the different evidences, and then fuzzy inference theory was applied to adjust the basic probability assignment (BPA) for each piece of evidence according to the resulting weights, and then the adjusted BPAs were combined using DST fusion rules to obtain finally the fusion results.

Wu et al [13] propose to analyse big data from assembly process and make decisions with uncertain information through locally linear embedding, evidence theory, support vector machine and adaptive boosting. Lv et al [14] uses Dempster-Shafer theory to combine the aposteriori classification capabilities generated from different support vector data description for assembly lines to improve their production plans according to constantly changing customer requirements. The topics discussed above illustrate the complexity of the problem.

Antonsson and Otto [15] discuss methods for incorporating inaccuracy into engineering design decision making based on fuzzy set for representing and manipulating inaccuracy in engineering design.

The literature analysis shows that DST is an effective method for processing uncertain data. It gives good results when combined with other data analysis methods.

2.2. ASSEMBLY PLANNING

Integrating manufacturing and assembly techniques into the design process at an early stage will have a significant impact on productivity and customer satisfaction. The literature analysis presents different approaches to assembly planning.

Michniewicz et al [16] developed approach in witch assembly process is automatically extracted from the CAD-file of the individual product.

Sinha et al [17] proposes a novel object shape error response approach to estimate the dimensional and geometric variation of assembled products and then, relate these to process parameters, which can be interpreted as root causes of the object shape defects. Their approach leverages Bayesian 3-D convolutional neural networks integrated with CAD engineering simulations for root causes isolation.

Ong et al. [18] presents a methodology that integrates the assembly Product Design and Planning (PDP) activities with the Workplace Design and Planning (WDP) activities to improve the efficiency and quality of assembly design and planning at the early design stage.

Franciosa et al. proposes a novel methodology to optimize heterogeneous design tasks with competing parameters [19].

Design verification in the digital domain, was discuss by Maropoulos et al. [20] who describes a novel, hybrid design verification methodology that integrates model-based variability analysis with measurement data of assemblies, in order to reduce simulation uncertainty and allow early design verification from the perspective of satisfying key assembly criteria.

Assembly systems configurations was discuss by Paralikas et al. [21]. Krüger et al [22] propose hybrid approaches integrated assembly automated processes with humans. Boerl et al. [23] aim their research on methodologies and tools to design and manage a complete flexible assembly system. Lange et al. [24] analysed several design and assembly alternatives and selected an optimized solution based on numerical simulation. Bley et al. [25] proposed an approach that helps to reduce redundant tasks and supports continuous data exchange in the assembly process.

Comparing product variants in the early stages of product development requires data that are missing, which have an impact on the efficiency of the manufacturing process. This is a limitation that is also discussed in the literature. Paying attention to the assembly planning approach in the early phases of product development is important to achieve the target standards of Industry 4.0, which includes material use, manufacturing operations, machine use, tool selection and product features, as well as the development of knowledge bases and other emerging technologies. Design for Manufacturing (DFM) and Design for Assembly (DFA) aim to correct and overcome the difficulties and waste associated with manufacturing and assembly at the design stage [26]. In addition, this field includes a decision support system and a knowledge base with guidelines for manufacturing and design that have emerged from the adoption of information and communication technologies. The development of a knowledge base for assembly planning using evidence theory is important in modern manufacturing systems because failure to consider this aspect can lead to excessive material consumption, which has a significant impact on production cost and time.

Putz et al. [27] presents a new approach for permanent productivity determination of assembly systems based on the usage of in-process acquired product data.

The literature analysis shows that the assembly process is analysed by authors from different points of view. There is a lack of methods that are helpful in predicting the data needed to set time standards in the early stages of product development. The basic data needed for planning are time standards. The standard of time, which is a measure of the efficiency of the manufacturing process, depends, among other, on the tools used in the assembly process. In the product development process, all the detailed information related to the manufacturing process is not known, so it is necessary to use machine learning methods such as decision tree and DST to process uncertain data.

2.3. KNOWLEDGE BASE

One of the well-known method of knowledge representation is rule-based approach [28]. The knowledge base consists of IF-THEN rules and is commonly used to represent knowledge about manufacturing processes. Advantages and disadvantages of different methods of knowledge representation was discussed by Li et al. [28]

Kusiak et al. [29] proposed a knowledge-based system KBSES for the selection of production equipment, i.e. machine tools and material handling carriers in an automated manufacturing system. Another approach proposed Geiskopf et al. [30] who presented detailed design of the tool assembly.

The KBS for sustainable material selection proposed by Zarandi et al. [31] was developed based on heuristic rules and the experience of design experts.

A knowledge prototype system for unit processes was developed by Zhang et al. [32].

The literature analysis shows that the rule-based approach is an effective approach in solving decision-making problems concerning manufacturing processes.

3. PROBLEM DEFINITION

There is a gap in assembly planning at an early stage of product development. The efficiency of the assembly process depends on factors such as the assembly method, connection type, tools used, etc. The connection type is determined during the design phase, but the assembly method and tools are determined during production planning. The question is how to determine the likely assembly method and tools in the early stages of product development to compare different product variants.

The aim of this article is finding the proper assembly tools with the use of machine learning method such as decision tree induced based on training set.

In cases where the classification of the appropriate assembly tools in training set is uncertain, the method based on the evidence theory is used, which helps to classify a given case into the appropriate category and assign the right assembly tool to the given assembly task.

4. PROPOSED APPROACH

Proposed approach is focused on finding the right assembly tool for given assembly task. Assembly process can be divided into tasks according to liaison graph [33]. The assembly task can be analysed with the following movements [34]:

- picking up a component,
- assembly - connection of two components, or disassembly - disconnection of the components,
- putting down a component.

The separated assembly task can be characterised by an object-attribute-value (OAV) framework [34], from which a training set for tool selection can be created.

Assembly tools selection algorithm was presented in the Fig. 1.

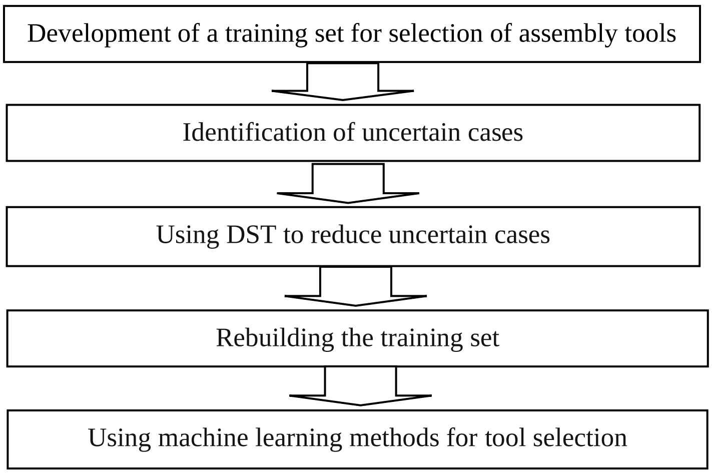

Fig. 1. The proposed approach

The first step in proposed approach is focused on development of a training set for selection of assembly tools. The training set in the proposed approach contained a selected assembly task characterized by attributes derived from the product design characteristics. The second step in proposed approach is focused on identification of uncertain cases. It may happen that there are uncertain cases in the training set, where there are different outputs for the same input characteristics.

The uncertain cases in the training set according to the third step of proposed approach, can be analyzed using DST.

DST assumes that $\Theta=\{H_1,H_2,\ldots,H_X\}$ be a finite non-empty set of mutually X exhaustive and exclusive states of system under consideration (hypothesis) known as frame of discernment. The power set denote 2^{Θ}, composed with the 2^X propositions of Θ, then $2^X=\{\emptyset, \{H_1\}, \{H_2\},\ldots, \{H_X\}, \{H_1,H_2\},\ldots, X\}$. DST assigns a belief mass to each element of the power set. Function $m: 2^X \rightarrow [0,1]$ is called basic belief assignment (BBA), where mass of empty set is zero $m(\emptyset)=0$ and mass of all the members of the power set add up to a total of 1, $\sum_{A\in 2^X} m(A) = 1$.

The mass $m(A)$ represents how strongly the evidence supports A which, in a case of disjunction of states (hypothesis), has not been assigned to a subset of A because of insufficient information. Each subset $A\subseteq\Theta$ such as $m(A)>0$ is called the focal element.

DST introduce belief function and plausibility function as the upper and lower bounds of a probability interval.

The belief function $Bel(A)$ for a set A is defined as the sum of all the masses of subsets of the set of interest according to formula (1).

$$Bel(A) = \sum_{B\subseteq A} m(B) \tag{1}$$

The Plausibility function $Pl(A)$ is the sum of all the masses of the sets B that intersect the set of interest A according to formula (2).

$$Pl(A) = 1 - Bel(\bar{A}) = \sum_{B\cap A\neq\emptyset} m(B) \tag{2}$$

where $\bar{A}$ is negation of A.

The value of $m(A)$ relates only to the set A and gives no additional information about any subsets of A.

From the mass assignment the probability interval is bounded according to formula (3).

$$Bel(A) \leq P(A) \leq Pl(A) \tag{3}$$

For multiple evidences, Dempster's rule of combination provides an approach to impacting several belief functions on the same frame of discernment. Let A and B be used for computing two belief functions $Bel1$ and $Bel2$, Dempster's rule of combination can be defined in terms of two corresponding mass functions m_1 and m_2 according to formula (4).

$$m1{,}2(C) = m1 \oplus m2(C) = \frac{1}{1-R} \sum_{A\cap B=C\neq\emptyset} m1(A)m2(B) \tag{4}$$

where R is calculated according to formula (5) and denotes the conflict degree between two pieces of evidence $Bel1$ and $Bel2$, where 0 means no conflict and 1 means total conflict.

$$R = \sum_{A\cap B\neq\emptyset} m1(A)m2(B) \tag{5}$$

It is obviously that if R is too large, the Dempster's rule of combination will fail [9, 10].

In the decision-making process related to the choice of assembly tools, the opinions of different experts can be used. Each expert can give his/her opinion on a particular option, e.g. yes, no, don't know. In this way, the evaluation results are presented as probabilities.

Based on the experts evaluation, the training set output probability can be calculated and the uncertain cases will be reduced. The criteria used by experts in assembly tools selection in uncertain cases are: quality, productivity and costs. The evaluation options given use criteria that can be assessed as probabilities based on the number of expert answers.

In the next step of the proposed approach, the training set should be rebuilt and the lower probability cases should be removed from it. Finally, the machine learning method include e.g.: data-driven decision tree (DT) induction or artificial neural network (ANN) can be used for tool selection. Both methods can use the training set developed by the proposed algorithm.

5. EXPERIMENTAL STUDY

Experimental study concern shaft-bearing assembly tools selection for a given bearing type. The bearings can be cold pressed onto the shaft using a hydraulic tool using the appropriate mounting bushings. It is also possible to put the bearings on the shaft with a mechanical tool, striking lightly and evenly so that the force is distributed over the entire circumference of the ring and the bearing is not damaged. To facilitate understanding of the described process, a figure of the shaft-bearing assembly process is provided below (Fig. 2) [35].

Training set (Table 1) contain bearing assembly characteristic which included:

- bearing seat type marked with *ro,* which may have the following values: cylindrical marked with the number 1, tapered marked with the number 2,
- diameter marked with *sr*, which may have the following values: up to 80 mm marked with the number 1, from 80–220 mm marked with the number 2, above 220 mm marked with the number 3,
- tools type, which is the output in the classification process and may have the following values: mechanical marked with the number 1, hydraulic marked with the number 2, none marked with the number 0.

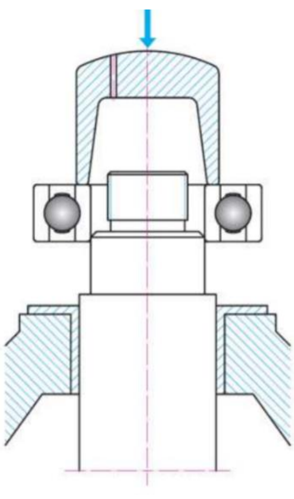

Fig. 2. An example of small bearing assembly [35]

The training set included uncertain cases 4 and 5 as well as 6 and 7 in which different outputs are obtained for a common input characteristic, highlighted in grey in Table 1. Based on the Table 1, a decision tree was generated (Fig. 3). The number of incorrect classified cases in training set equal 2.

Table 1. Training set

No	Input		Output
	Bearing seat type (cylindrical *1*, tapered *2*) - *ro*	Diameter (up to 80 mm *1*, from 80–220 mm *2*, above 220 mm *3*) - *sr*	Tools (mechanical *1*, hydraulic *2*, none *0*)
1	1	1	1
2	1	2	0
3	1	3	0
4	2	1	1
5	2	1	2
6	2	2	1
7	2	2	2
8	2	3	2

Cases 4 and 5 from training set (Table 1) were analysed using DST. Simulated experts opinions were used and the probability of using the right tool was calculated. In the example shown, the first group of experts assesses quality (m1), the second assesses productivity (m2) and the third assesses costs (m3). Experts evaluated two options, the first (a) is about choosing a mechanical tool, the second (b) is about choosing a hydraulic tool for bearing assembly with diameter less than 80 mm. An example of the probability distribution is shown in Table 2. Fused belief degree of two pieces of evidence (join assessment of quality and productivity) is presented in Table 3, confidence intervals are presented in Table 4.

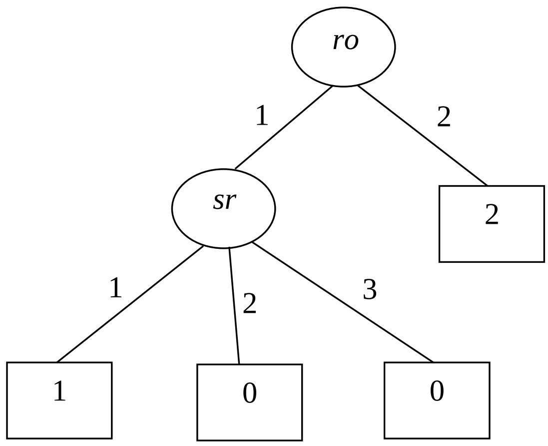

Fig. 3. Decision tree induced from the training set with uncertain data

Table 2. Probability assessment

Variants	m1	m2	m3
a (1)	0.5	0.3	0.3
b (2)	0.4	0.4	

Table 3. Fused belief degree of two pieces of evidence m1+m2

Experts 2 / Experts 1		m2(a)	m2(b)	m2(S)
		0.3	0.4	0.3
m1 (a)	0.5	0.15	0.20	0.15
m1 (b)	0.4	0.12	0.16	0.12
m1(Θ)	0.1	0.03	0.04	0.03

Table 4. Confidence intervals

Experts 12	*Bel*	*Pl*
m12(a)	0,49	0,53
m12(b)	0,47	0,51

Fused belief degree of two pieces of evidence (join assessment of quality and productivity calculated in Table 3 and costs) is presented in Table 5, confidence intervals are presented in Table 6, where Bel is the probability of the variant occurring if all known data support it, and Pl is the probability of the variant occurring if known and unknown data support it.

Table 5. Fused belief degree of two pieces of evidence m12+m3

Experts 3 / Experts 12		m3(a)	m3(b)	m3(S)
		0.3	0	0.7
m12 (a)	0.49	0.15	0.00	0.34
m12 (b)	0.47	0.14	0.00	0.33
m12(Θ)	0.04	0.01	0.00	0.03

Table 6. Confidence intervals

Experts 123	*Bel*	*Pl*
m123(a)	0.58	0.62
m123(b)	0.38	0.42

The same procedure was repeated for the next uncertain cases in the training set, namely cases 6 and 7.

Finally, the training set with reduced uncertainty is shown in Table 7 and the DT built from it is shown in Fig. 4.

Table 7. Training set with reduced uncertainty

Bearing seat type (cylindrical *1*, tapered *2*) - *ro*	Diameter (up to 80 mm *1*, from 80–220 mm *2*, above 220 mm *3*) - *sr*	Tools (mechanical *1*, hydraulic *2*, none *0*)
1	1	1
1	2	0
1	3	0
2	1	1
2	1	1
2	2	2
2	2	2
2	3	2

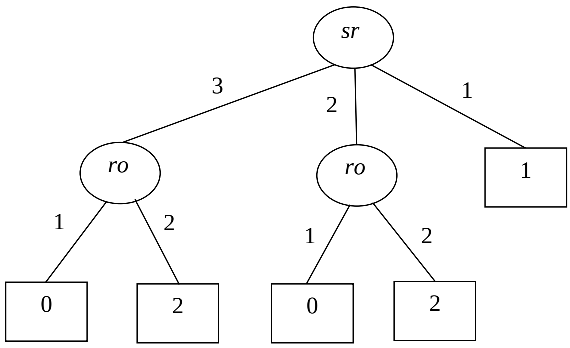

Fig. 4. Decision tree induced from the training set without uncertain data

Table 8. Results comparison

No	Input training set		Output training set before DST	Output DT (Figure 2)	Output training set after DST	Output DT (Figure 3)
	Bearing seat type (cylindrical 1, tapered 2) - *ro*	Diameter (up to 80 mm *1*, from 80–220 mm *2*, above 220 mm *3*) - *sr*	Tools (mechanical 1, hydraulic 2, none 0)	Classification according to DT from Figure 2	Tools (mechanical 1, hydraulic 2, none 0)	Classification according to DT from Figure 3
1	1	1	1	1	1	1
2	1	2	0	0	0	0
3	1	3	0	0	0	0
4	2	1	1	2	1	1
5	2	1	2	2	1	1
6	2	2	1	2	2	2
7	2	2	2	2	2	2
8	2	3	2	2	2	2
Incorrect classification				2		0

A comparison of the results is shown in Table 8, where the classification of tools from the DT shown in Fig. 2 and Fig. 3 is analysed. The number of misclassifications in the DT shown in Fig. 2 is 2, the DT shown in Fig. 3 has no errors in the training set.

The approach presented above allows to generate rules that can be added to the knowledge base for its development. The decision rules generated by DT (Fig. 4) are shown below:

R1. If sr=3 and ro=1 then tool =0
R2. If sr=3 and ro=2 then tool =2
R3. If sr=2 and ro=1 then tool =0
R4. If sr=2 and ro=2 then tool =2
R5. If sr=1 then tool =1.

6. CONCLUSIONS

The assembly process is complex, and planning it early in product development is challenging. In order to compare different product variants, it is necessary to take into account attributes that depend on the structure of the product and those that depend on the planning of the production process, such as tools, equipment, workstation layout.

Literature analysis presents different approaches to deal with uncertainty in design and manufacturing. DST applied in the article was combined with graph theory and rule-based approach and give good results.

At the product design stage, some data from the manufacturing process is uncertain. DST is an effective method for uncertain data processing. The proposed approach focused on tool selection in assembly process using DST and machine learning method.

Proposed approach based on the following stages: development of a training set for selection of assembly tools, identification of uncertain cases, using DST to reduce uncertain cases, rebuilding the training set, using machine learning methods for tool selection.

A bearing assembly process was used as an example of the application of the proposed method. The uncertainty reduction of the training set using DST was analysed for two variants of bearing assembly using a hydraulic or a mechanical tool. Taking into account criteria such as quality, productivity and cost, the training set was reduced and a decision tree was constructed.

The analysis of the results shows the number of errors in the training set extracted from the DT induced by the original training set and that from the reduction using DST. The DT induced from the reduced training set gives better results, there are no misclassified cases in the training set.

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