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Expert systems in special machinery: Increasing the productivity of processes in commissioning

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Abstract

Due to the megatrend globalization, special machinery is gaining significance for the capital goods sector. Characterized by the fulfillment of individual customer requirements, companies in special machinery have to deal with very specific and technologically complex tasks. Hence, managing information and knowledge becomes vital for a company's competitive ability, notably when it comes to expert knowledge. The characteristics of special machines leads to iterative processes for problem solving and thereby, increase lead times significantly. The more technologically complex a machine is, the more scattered the expert knowledge, meaning that many different experts need to be consulted before solving a problem. Up to now, in scientific literature, there has been little discussion about the challenges of special machinery and practical solutions regarding an implementation of technical intelligence in a special machinery environment. Therefore, the goal of this paper is to give an example of how an expert system can be applied to special machinery surroundings and thus, increases productivity. A Bayesian network forms the basis of the system as it allows efficient inference algorithms and reasoning under uncertainty, despite its ability to describe complex dependencies. The expert systems capability has been proven in industrial laser manufacturing.

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Keywords: Expert systems, special machinery, knowledge management

1. Introduction

Due to the megatrend globalization, special machinery is gaining significance for the capital goods sector [1]. Characterized by the fulfillment of individual customer requirements, companies in special machinery have to deal with very specific and technologically complex tasks [2]. An examination of a special machinery manufacturer displayed how the complexity of special machines leads to iterative processes for diagnosing and problem solving and thereby, increases lead times significantly. Hence, an intelligent management of information and knowledge becomes vital for a company's competitive ability, notably when it comes to expert knowledge.
"Intelligence is the capacity to learn, the capacity to acquire, adapt, modify and extend knowledge in order to solve problems." [3] Thus, when building intelligent entities, problems cannot only be solved by human experts but also by artificial intelligence. One very successful application of artificial intelligence technology are expert systems [4]. According to Maus and Keyes, "expert systems use artificial intelligence concepts to enable computers to function in decision-support roles as advisors, personifying human expert decision-making capabilities." [5] Hence, expert systems cannot replace human specialists, but they can serve as highly efficient support-tools in the decision-making process. In general, expert systems can be used for analyzing, diagnosing, monitoring, forecasting, planning, and designing [6] and have been successfully implemented in various fields; predominantly in medical, manufacturing and business fields

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as shown by Durkin [7]. Nonetheless, there has been little discussion in scientific literature about the challenges of special machinery and practical solutions regarding an implementation of an expert system dealing with uncertainty in a special machinery environment, even though there is a broad consensus on the potential benefits of expert systems [4,5,8,9]

When it comes to the design of knowledge-based methods for reasoning and decision-making, uncertainty plays a significant role [8]. With regard to technical intelligence in manufacturing, Kobbacy and McNaught et al. accentuate that Bayesian Networks are most beneficial when dealing with uncertainty [9].

Therefore, the aim of this paper is to give an example of an interactive probabilistic expert system design using Bayesian Networks and its implementation in a special machinery environment, more precisely in commissioning.

2. Commissioning in special machinery

Special machinery can be described as a function of mechanical engineering with the purpose of producing specialized machines according to customer specifications [10]. The main criteria for a differentiation between mechanical engineering and special machinery is the degree of individuality and the batch sizes of the products [2,11]. A typical batch size of one machine and the high degree of individuality in special machinery leads to an Engineer-to-Order manufacturing concept and mostly to a manual and individually modified production process [2,10]. Special machines are designed to fulfill very specific and technologically challenging tasks. Hence, manufacturers in special machinery need to act globally in order to be able to generate sufficient demand to be profitable. But by virtue of a global presence, these companies also face great challenges due to a higher cost pressure. Therefore, international companies need to generate competitive advantages through short time-to-market cycles. [2] In this respect, a high potential for rationalization can be exploited in the commissioning phase, since problems that have not been detected in earlier production stages concur during commissioning [12]. According to Weber, commissioning describes the transfer of a machine from idle state to a continuous operating state. Ideally, commissioning in special machinery results in a fast transfer into a stable continuous operating state, as special machines are usually linked to high investment costs [13]. Therefore, problems need to be detected and eliminated quickly [12]. Systematic knowledge acquisition and management in commissioning can increase efficiency and, thus, the competitiveness of future projects significantly [13,14]. In the form of so-called expert systems, knowledge management provides a powerful tool for diagnosing and decision making and, thus, can shorten commissioning and time-to-market cycles substantially.

3. Expert systems

3.1 Characteristics

Puppe separates the architecture of expert systems (XPS) into two main modules: the knowledge base and the control system. The knowledge base consists of domain-specific, case-specific knowledge and (intermediate and final) results, whereas, the control system, also known as shell, contains an inference component that provides problem solving strategies as well as the user interface. [15] The main purpose of the user interface is to gather factual data. It can either interact with the user in a dialogue and, thereby, acquire knowledge or read in measured data. In addition the user interface should provide an explanation component since a transparent presentation of results and the underlying reasoning correlates strongly with the acceptance of an expert system [16]. A key factor for the effectiveness of an expert system is the quality of the knowledge base [17]. Expert systems can provide fast and reliable answers and based on the studies of Tversky, Kjræulff and Madsen conclude that the quality of decisions improves when human decisions are being supported by recommendations from an expert system [19,20,18].

3.2 Knowledge acquisition as bottleneck

The acquisition of knowledge is often the bottleneck in the construction of expert systems [17,21–23]. The reasons for this are diverse but one of the main difficulties is to make the knowledge of a human expert explicit. For one, human experts use tacit or implicit knowledge and common sense as well as everyday knowledge to solve problems. Furthermore, expert knowledge is characterized by complex and large amounts of information and human experts occasionally give inaccurate or incomplete descriptions of problems and solutions. [8,17,24]

3.3 Uncertainty in knowledge

Decision environments and data sources are often afflicted with uncertainty and, therefore, most cause effects are uncertain [18,26,25]. Consequently the management of uncertainty is central for decision support systems. While rule-based systems have serious limitations when it comes to reasoning under uncertainty, inference nets and namely Bayesian networks "(…) enable to perform probabilistic calculus and statistical analyses in an efficient manner [18,27]."

4. Bayesian networks for diagnosis

A Bayesian network (BN) is a directed acyclic graph (DAG) in which nodes represent events and directed links causal dependencies. When observing new evidences, the updated probability distribution can be calculated for the remaining variables. [28] Moreover, it is possible to combine hard statistical data with softer expert knowledge as well as handling incomplete data sets and, thus, provide a powerful tool for diagnostic expert systems [29,31,30].

5. Literature review on BN and expert system applications in manufacturing

An extensive literature review on Bayesian networks and expert systems that have been applied in manufacturing from 2000 to 2016 has been conducted. Therefore, categories have been defined according to Stefik and Mertens characterization of expert tasks [32,6].

This categorization includes:

- Analysis
- Diagnosis
- Monitoring
- Prognosis
- Planning
- Design
- Consulting

Table 1 - Review on Bayesian Networks in Production from 2000 to 2016

	Expert Task							
Author	Interpretation	Diagnosis	Monitoring	Prognosis	Planning	Design	Consulting	Journal H Index[a]
Ben Said et al. (2016)[b]	x			x	x			21
Bouissou & Pourret (2003)[b]		x						22
Correa et al. (2009)			x					112
Dey & Stori (2005)		x	x					100
Garcia et al. (2008)		x	x					22
Hamamoto et al. (2016)		x						21
Huang et al. (2008)		x						54
Jones et al. (2010)	x				x			93
Kobbacy et al. (2011)		x					x	45
Li & Shi (2007)[b]			x					70
Liu & Jin (2009)		x	x					2
Liu & Jin (2013)		x						71
Mansour et al. (2012)		x						32
Masruroh & Poh (2007)[b]					x			9
McNaught & Zagorecki (2009)[b]				x				8
Mechraoui et al. (2008)[b]		x						19
Mengshoel et al. (2008)		x						-
Penya et al. (2008)				x				19
Pradhan et al. (2007)[b]		x						8
Ramesh et al. (2003)				x				100
Rodrigues et al. (2000)	x	x						177
Romessis & Mathioudakis (2006)		x						61
Tobon-Meija et al. (2012)		x		x				100
Yang & Lee (2012)		x		x				61
	3	16	5	6	3	0	1	

[a]SCImago. (2007). SJR — SCImago Journal & Country Rank. Retrieved October 14, 2016, from http://www.scimagojr.com

[b]Study

The review shows that, to date, few practical examples are being documented and published. The vast majority of published Bayesian network applications are being used for diagnosing, some for monitoring and prognosis but only a few for analysis and planning purposes, as Table 1 shows. None of the reviewed practical applications is being used for designing or consulting. Only Kobaccy et al. combine a BN with a user interface. Thereby, they create an expert system and use the BN for diagnosis and consulting. Table 2 gives an overview of XPS applications. Besides the categorization into expert tasks, a distinction between probabilistic and non-probabilistic inference methods was drawn. Unlike BN applications, most of the XPS applications concern analysis and consulting. However, a greater diversity amongst XPS in fulfilling expert tasks was found, but none concerning design. Regarding inference methods, 15 out of 17 of the examined XPS are non-probabilistic and only 2 of 17 probabilistic. Nevertheless, there is a great potential for probabilistic XPS, when combining inference nets with user interfaces. With this paper the authors narrow the research gap by describing the design of an interactive probabilistic expert system using Bayesian networks.

6. Design of an interactive probabilistic expert system

6.1 Knowledge acquisition

The aim of the knowledge acquisition process is to gather all relevant information about a specific domain or topic where the XPS is intended to be applied. Considering the difficulties in converting expert knowledge into explicit, formalized and operational knowledge an eclectic approach is essential. Therefore, interviews or workshops with experts are good instruments to get an overview and find a common understanding of the subject and to structure the knowledge according to a taxonomic scheme. This structure can be further refined through iteration loops and observation, for example when the expert solves a representative problem. Additionally, a learning component can attenuate incomplete or inaccurate information and provide access to structural changes for the user.

Table 2 - Review on Expert Systems in Manufacturing from 2000 to 2016

	Expert Task							Inference method		
Author	Interpretation	Diagnosis	Monitoring	Prognosis	Planning	Design	Consulting	Non-Probabilistic	Probabilistic	Journal H Index[a]
Ahmed Ali et al. (2015)	x						x	x		96
Balachandra (2000)	x						x	x		69
Batista et al. (2013)			x				x	x		112
Chan (2005)			x				x	x		112
do Rosário et al. (2015)[b]				x	x				x	112
Ebersbach & Peng (2008)			x					x		112
Hussain et al. (2015)	x	x						x		112
Li et al. (2000)	x				x			x		181
Li et al. (2013)		x					x		x	38
Liao et al. (2004)	x						x	x		112
Liukkonen et al. (2011)	x							x		112
Mazurkiewicz (2015)			x				x	x		19
Metaxiotis et al. (2002)					x			x		69
Möller (2005)		x					x	x		-
Nikolopoulos & Assimakopoulos (2003)				x				x		69
Rao et al. (2005)	x	x						x		112
Urrea et al. (2015)	x	x						x		112
	8	5	4	2	3	0	8	15	2	

[a]SCImago. (2007). SJR — SCImago Journal & Country Rank. Retrieved October 18, 2016, from http://www.scimagojr.com

[b]Study

6.2 Architecture

In order to make the collected and structured knowledge accessible and operational it will be modeled in the form of a Bayesian network. As a example a simple structure of this network is shown in Fig.1. The knowledge in general can be categorized as symptoms, causes and solutions which are modeled as individual nodes. The relationships between the variables can be defined through a probability distribution.

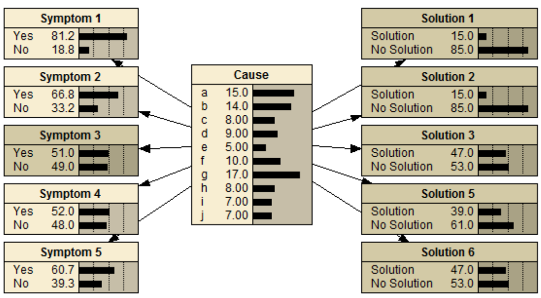

Fig. 1 - Taxonomic scheme for BN modeling

As shown in Fig. 1 and according to the categorization of the knowledge the net consists of three different types of nodes: the symptom nodes, the cause node and the solution nodes. The cause node is connected with all of the other nodes. This allows to define a prior probability. The relation between the cause node and either the symptom nodes or the solution nodes can be defined by expert consultations. Following, a case can be entered into the symptom nodes. Thus, the symptoms influence the distribution of the failure causes. Furthermore, the distribution of all failures influence the probability that a certain solution node contains the proper solution. To define the causual dependencies, prior probabilities need to be determined. According to Pearl, it is possible to obtain the relational probability distribution from the expert knowledge [33]. In order to derivate prior-probabilities, past information can be used. This kind of information usually exists in every company for example as quality reports. The BN, thus, functions as a knowledge base, whereas, Bayesian inference rules become part of the control system. To achieve a user-friendly tool, certain steps in the programmed interface have to be complied with. For example a dynamically programmed user interface (GUI) permits an independent knowledge base, therefore, changes in the knowledge base of the Bayesian network do not require a change in the program code of the GUI. Via dynamic computer-initiated dialogues, new evidences can be entered into the BN. The dynamic dialogue states the most expedient questions first and skips redundant ones. Furthermore, the learning component trains the network by saving cases each time the XPS has been used. Therewith, prior probabilities are being updated.

Additionally, a user feedback about the suggested solution will be demanded in order to increase the overall effectiveness. Concerning transparency, displaying a real-time probability distribution of the causes and a questionnaire log to ensure traceability are proposed.

6.3 Validation

The presented design of an interactive probabilistic expert system in this paper has been applied at a company that produces special machinery in the field of industrial high power lasers and shows promising first results.

The application of the developed method has been conducted at a process for the testing of a vacuum chamber and the detection of leaks. Therefore, all possible symptoms of a leak are entered as single nodes. Furthermore, all known causes for leaks are entered into the cause node and combined with the known failure distribution. In a workshop with process experts all known types of solutions are found and entered into the net. Finally, all causual dependencies are defined with process experts.

The result of the validation is a Bayesian network which is capable of modeling failures in special machinery processes. Furthermore, a symptom can be related to a possible solution of a failure.

7. Summary and outlook

Manufacturers in special machinery are facing great challenges since globalization expedites stronger competition and, along with that, higher cost and time pressure. Therefore, special machinery manufacturers need to create competitive advantages through shorter time-to-market cycles by increasing efficiency. In this respect, commissioning provides a great lever since problems that have not been detected in earlier production stages concur during commissioning. By means of an expert system, productivity can be increased substantially. Therefore, this paper presents a concept of a probabilistic expert system using Bayesian networks in order to effectively support human decision making and to accelerate problem solving processes. Bayesian networks form the knowledge base so that reasoning under uncertainty is possible and effective. The concept has been validated at a high power industrial laser manufacturer and shows very promising first results. A long term validation will verify the expert systems effectiveness.

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