9th International Conference on Mass Customization and Personalization – Community of Europe (MCP - CE 2020)
Re-innovating Business in the Digital Era
September 23-25, 2020, Novi Sad, Serbia

PRODUCT CONFIGURATION WITH BAYESIAN NETWORK

Stefan Plappert, Paul Christoph Gembarski and Roland Lachmayer
Leibniz University of Hannover, Institute of Product Development, Hannover, Germany

Abstract: *For the satisfaction of individual customer requirements, products with many options are offered in mass customization. However, in the area of e-commerce, the large number of possible product configurations can overwhelm the customer, as he or she is not supported by a human sales expert. To minimize the customer's overload, this paper examines the combination of a knowledge-based product configurator with an upstream probabilistic recommender system to provide a quick, individual and dynamic initial orientation for the customer. The application of the approach is demonstrated using an example from engineering design.*

Key Words: ***Product Configuration, Recommender System, Bayesian Network, Knowledge-based System, Engineering Design***

1. INTRODUCTION

Customization enables customers to realize their own ideas when choosing or co-designing a product according to their individual needs [1]. However, the variety of options for customization can also overwhelm the customer which is discussed as *mass confusion* or the *burden of choice* [2]. Especially when configuring high-involvement products, such as cars or kitchen machines, domain knowledge is required to compare the product properties and their effects on usage with the individual requirements of the customer [3]. This domain knowledge is particularly absent for new or unexperienced customers, so that he or she cannot make a purchase decision due to the uncertainty associated with the product selection [4].

Another problem is the phenomenon that customers do not know exactly which product they want, when they are confronted with a selection of product alternatives [5]. The theory of preference construction e.g. describes that customers do not know their preferences in advance, instead they develop them during the selection process and adapt them to the selection situation [6]. The same can be observed from the supplier side where a wide spectre of product variants leads to a loss of prediction precision and a high degree of uncertainty regarding ordering quantities [7, 8, 9].

From this point of view, a system that can handle uncertain input parameters, incomplete data and changing customer preferences is a valuable support, so that the customer is provided with a personalized recommendation for a product and the manufacturer can reduce uncertainties.

In order to support the customer in transferring his needs to a customized product and to reduce the information overload, this paper proposes an extension of a knowledge-based product configurator by a probabilistic recommendation system.

In the following section 2, related work is presented to put the approach of a combination of a probabilistic recommendation system and a knowledge-based product configurator mainly in the context of configuration systems and recommendation systems. Furthermore, the method of Bayesian networks is introduced. Section 3 describes the architecture and modeling of the probabilistic recommendation system. Afterwards in section 4 the presented approach is demonstrated with an application example and discussed in more detail in section 5. The last section 6 summarizes the article and presents a further research agenda.

2. RELATED WORK

2.1. Configuration Systems

Configuration systems have proven to be a leading technology in supporting mass customization, which as a production paradigm supports the manufacture of highly-variant products under pricing conditions similar to mass productions [10, 11]. According to Sabin [12], configuration systems in the area of mass customization can be divided into two levels: order-realization and design-realization.

- At the order-realization level, the requirements are to understand the customer's needs and to describe a product variant that can meet these needs [4].
- At the product-realization level, the goal is to design product families rather than individual, independent products [13].

Sales support systems can also be assigned to the order-realization level. These help sales staff to define products by identifying customer requirements or they guide customers as stand-alone systems through the choice and configuration process [14]. Sales support systems are characterized mainly by product illustration and decision support [15]. Since configuration systems go beyond the use of filters, the implementation of a knowledge base is necessary to define the possible combinations of components or restrictions [14].

In general, configuration systems can be assigned to knowledge-based systems (KBS), which are based on the product domain and problem-solving knowledge [11, 12]. In turn, the knowledge-based engineering systems (KEBS) are a specialization of these that extend the capabilities of the KBS by computer aided analysis (CAE) and computer aided design (CAD) and serve decision support or design automation tools [16].

2.2. Recommender Systems

Recommendation systems (RS) guide customers in a personalized way to interesting and useful objects in a wide range of possible options or generate these objects as a result [5]. By guiding the customer through the selection process to their product, sales can be increased [17]. For this reason they have become an essential part of the e-commerce business. According to Thakur et al. [18] the following properties of a RS can be defined:

- RS use databases that contain the interactions between customers and products.
- RS produce recommendations for products that the customer might prefer.
- RS learn to provide better recommendations over time through continuous interaction with the customer.
- RS are interactive as they adjust recommendations in real time based on interactions with the customer.

These described characteristics for an RS can be implemented by different techniques, since a recommendation depends on the products, the available data and the required knowledge. Burke [19] distinguishes four classes of RS based on their source of knowledge:

- Collaborative: RS generates recommendations based on rating information about products from different users.
- Content-based: The RS generates recommendations based on the assignment of features to products and the rating that the user has given the product.
- Demographic: A demographic RS uses a demographic profile of the user to generate recommendations.
- Knowledge-based: A knowledge-based RS makes inferences based on the user's needs and preferences to propose a product.

In the case of a product recommendation of high-involvement products, the weaknesses of the recommendation techniques collaborative, content-based and demographic, such as sparsity and cold-start, lead to a poor quality of the product recommendation [17]. The problem of sparsity describes the need for sufficient users and rated items to make a recommendation based on user similarities [20]. The cold-start problem occurs when new users or new items are added to the system where little information is available or few ratings are available to generate a recommendation [21]. A KBS avoids these disadvantages because a recommendation is based on stored knowledge and not on user ratings. This is because a KBS focuses on the situation of the user and how the recommended products can meet the specific needs [5].

RS based on probabilistic methods such as Bayesian networks (BN) are used to represent uncertain dependencies between users and products or in case of an incomplete database. Thus, de Campos et al. [22] use a BN to link content-based and collaborative recommendations. They combined a qualitative representation of the relationship between users and items, and a quantitative representation to express the weight of the relationship. Weng et al. [23] use a BN to suggest related products to customers when they purchase certain products. These approaches are based on a large database and on products that are regularly rated or purchased. The possibility of using a BN as a knowledge-based RS is not considered in this context.

2.3. Bayesian Network

Bayesian networks (BN) are today one of the most important approaches for processing uncertain knowledge with the help of probabilities in the field of artificial intelligence (AI) [22, 24]. Furthermore, BN seem to mimic humans in reasoning complex tasks by linking known factors with others [25] and they allow a complex system to be built by combining simpler parts [26].

According to Russel and Norvig [27] the structure of a BN describes a directed acyclic graph (DAG) in which each node is provided with quantitative probability information:

1. Each node in the BN corresponds to a random variable, which can be discrete or continuous.
2. A set of directed arcs connects pairs of nodes. The arcs specify the causal relations between the nodes [28].
3. each node has a conditional probability distribution that quantifies the effects of the previous or parent nodes on the observed node.

The main application for BN is inference, where the probability distribution of unobserved nodes is calculated or updated as new knowledge or observed variables become available [29]. The possibility of representing BN knowledge is discussed in more detail in chapter 3.2, as this is an important prerequisite for using BN as a recommender system. In chapter 4, a BN is presented as a graph in the context of a application example (Fig. 4).

3. MODELLING OF A PRODUCT CONFIGURATOR WITH A PROBABILISTIC RECOMMENDER SYSTEM

The integration of RS into existing configuration technologies is crucial for effective support of customers in selecting products with many variants [5]. Even if the product configuration systems and RS can be counted among the KBS, Falkner et al. [30] sees a difference in the representation of knowledge. For him, product configurators often use a knowledge base, whereas RS use a table of explicit solution alternatives [11]. This assumption applies to case-based and constraint-based RS, which find a suitable solution based on similarities or by an elimination procedure. For probabilistic RS, which are also based on domain-specific knowledge, this assumption is not completely true. A detailed description of the modelling and knowledge representation of a probabilistic RS is given in section 3.2.

Our approach describes an extension of a product configuration system by a probabilistic RS to facilitate the customer's entry into the product configuration process by a probably suitable initial configuration. Based on this initial configuration, the customer can use the product configurator without any restrictions. This support of the customer by means of a initial configuration is primarily intended for those who do not have broad domain knowledge or have uncertain preferences. Advanced customers can use the product configurator user interface as usual and configure their product using the product options. The goal of combining a product configurator and RS is to merge the respective advantages of the systems in finding solutions, in order to provide proactive support to customers.

3.1. Product Configurator System in Engineering Design

For product configuration at the product-realization level, KBS are often used because they are particularly suitable for representing a solution space [16]. Since detailed domain knowledge is required for the development of KBS and in order to keep iteration loops to a minimum, KBS are often used in the embodiment and detail design phase of the product development process [31]. Hopgood [32] divides a KBS into three essential components: knowledge base, inference engine and interface to the environment (Fig. 1). By this structure, the explicit knowledge is stored separately from the inference engine. The knowledge is programmed either in the form of rules or in tabular form, so that standard part catalogues or design rules can easily be implemented, so that even complex tasks can be represented systematically [33].

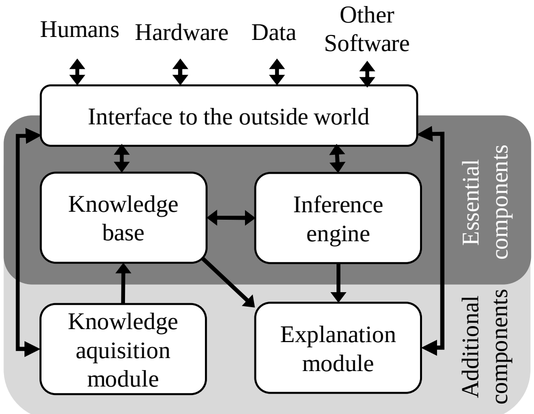

Fig. 1. *Components of a knowledge-based system [30]*

Through the interface to the environment, information can be exchanged, as in our case the product options from the RS to the product configurator. In addition, the customized product variant can be transferred to a CAD program or visualized on a website.

3.2. Modelling of a Bayesian Network as a Recommender System

Due to the use of BN in the field of AI with a broad and successful application for problems with high uncertainty, the field of RS seems to be an interesting area of use [22]. In order to be able to use them also for high-involvement products, the so-called "knowledge bottleneck" has to be overcome. In KBS this represents the acquisition and organization of a large amount of domain-specific knowledge [25]. A decisive advantage of BN is that it allows the combination of several sources of knowledge, such as different experts or data together with incomplete knowledge, that is recognized to a certain extent [34]. The structure as a DAG makes BN a globally consistent knowledge base [35].

Korb and Nicholson [36] propose a two-step approach for modeling a BN: (1) building the structure (nodes with values and arcs) and (2) assigning the parameters (probabilities). This approach can also be applied to the modelling of a BN as a RS, as it is possible to avoid iterations, if the conditional probabilities have to be adjusted due to a structural change.

The first step is to define the variables or nodes. Due to the combination with a product configurator, the leaf or output nodes (nodes without children) of the BN represent the product options, so that a direct transfer of the product options to the product configurator is possible. The root or input nodes (nodes without parents) of the RS represent the customer needs or usage specifications. Further nodes can be defined between the root and leaf nodes to increase the accuracy of the BN and to reduce the computing effort, if many parent nodes are linked to a child node. Furthermore, these nodes can also combine requirements from different needs or usage specifications and pass them bundled to a leaf node.

As the nodes can take on different values, these have to be defined as well. The values can be divided into different types: discrete values (Boolean nodes, integer valued or multinominal categories) and continuous values [36]. In general, the use of discrete values is useful for the RS in order to reduce the computational effort and to enable easier traceability.

The second step is to connect the nodes with arcs. The focus should be on the relationships between the nodes or variables, such as a causal relationship [36]. For the BN as RS, attention should be paid to which customer needs or usage specifications have an influence on the selection of product options and thus a dependency exists between these nodes. This can be done by experts or by analyzing products already sold together with their options and the specified customer needs.

The third step is to determine the parameters that represent a set of conditional probability distributions of children's values at given parental values [36]. These parameters can be determined from data using data mining methods or expert interviews. Despite the fact that this information is usually subject to uncertainty, a BN allows the direct expression of fundamental and qualitative relationships of direct influences, which are expanded and preserved by a BN with relationships of indirect influence [35]. By storing the customer needs and the finally selected product variant, the parameters can be continuously improved by inference or learning, so that the precision of the BN for the recommendation can be optimized over time.

After the BN has been modelled, an appropriate inference strategy must be defined. Various inference algorithms can be used for this. For small networks an exact inference can be performed e. g. by inference by enumeration, variable elimination or a join tree algorithm. For larger networks this is only possible appoximatively by different sampling methods, such as direct sampling, rejection sampling, likelihood weighting or Markov Chain Monte Carlo (MCMC) algorithms [27].

3.3 Application of a Bayesian Network as a Recommender System

In order to provide the customer with a probably suitable initial configuration, the product configurator has to be extended by a proabilistic RS. Fig. 2 describes the flowchart for a product recommendation with subsequent product configuration.

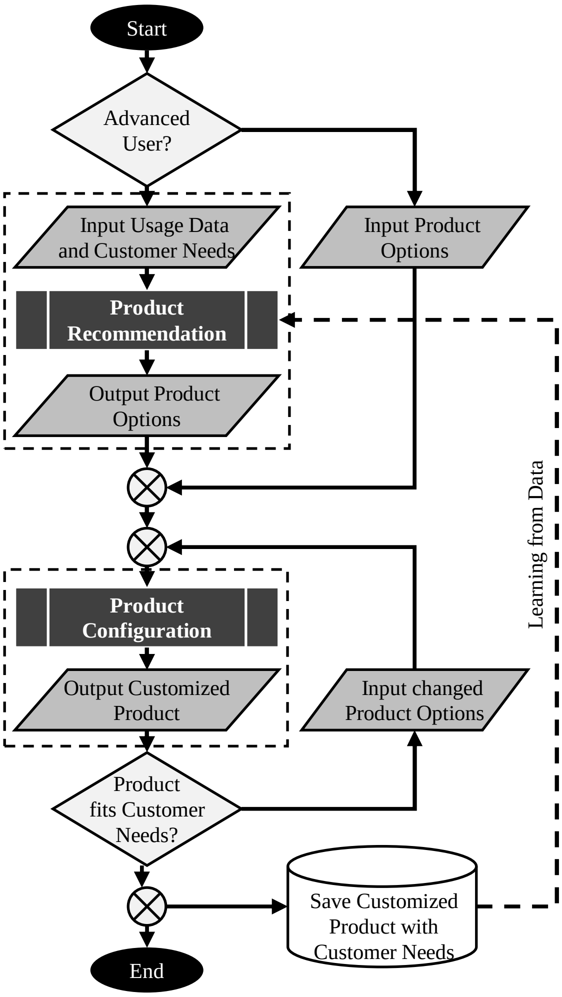

Fig. 2. *Flowchart of a Product Configurator with a Probabilistic Recommender System*

Due to the separation of the recommendation system and the product configurator, experienced customers can directly enter their desired product options and the updating of the systems is facilitated in case of changed usage data or product variants. As already described in chapter 3.2, the usage data and customer needs are queried as input for the RS. This can be done by means of a drop-down selection or sliders. The inputs are then processed in the RS and the recommended product options are returned. The recommended product options serve as initial input for the product configurator, which then generates a product variant. During the configuration process, the customer has the possibility to change his entries to adapt the product to his needs. As soon as the customer has configured his customized product, it is saved together with the usage data and customer requirements. This data can then be reused for training the RS and the system can suggest better recommendations over time.

4. APPLICATION EXAMPLE

This section describes the application of the approach for the combination of a product configuration system and a probabilistic RS using an application example from engineering design. For this purpose, an existing product configurator of a tea brewing machine (Fig. 3.) was used, which enables a configuration within the CAD system Autodesk Inventor [37]. The knowledge base and the user interface were set up in Excel, so that a transfer of product options through the RS is possible using standardized formats, such as XML or CSV.

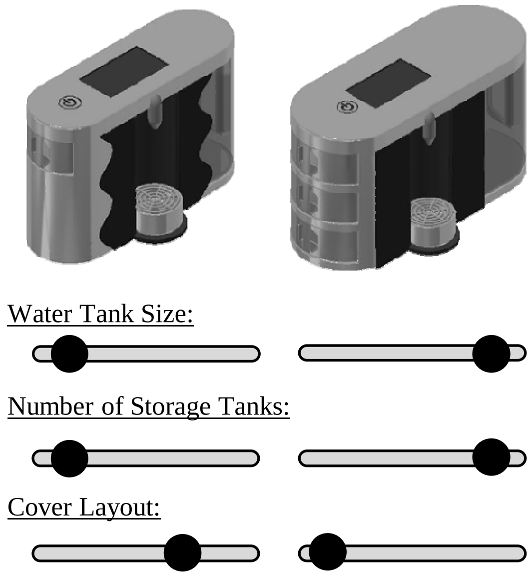

Fig. 3. *Tea Brewing Machine with customizable Covers and Tanks*

The probabilistic RS in the form of a Bayesian network (Fig. 4.) was built within MATLAB® using an open source package for directed graphical models called Bayes Net Toolbox (BNT). One of the strengths of BNT is the variety of implemented inference algorithms [38], so that a decision for an inference algorithm can be made at a late stage, when the modeling of the BN is already in progress.

The procedure described in Section 3.2 was applied in modelling the BN. The nodes were selected from the given product options of the product configurator and from an analysis of the usage scenarios for a tea brewing machine, which also led to the selection of the values for the nodes. The assignment of the dependencies or arcs was based on a causal approach of the nodes, as well as the estimation of experts. The structure of the BN for the tea brewing machine is shown in Fig. 4. Here, the black nodes represent the usage data and customer needs on a subjective level in order to be able to better inquire the preferences of the customers when selecting products. The dark grey nodes represent the product options of the existing product configurator. The light gray nodes have been added for a better overview and to reduce the computing effort. They also express conditional dependencies between the nodes of the same layer.

Expert knowledge was used for an initial selection of parameters or probabilities. During a verification of the prototype a product recommendation could already be transferred to the product configurator. A planned validation of the presented system will be executed as a field study, on the one hand to evaluate the quality of the recommendations and on the other hand to collect data for a training of the BN.

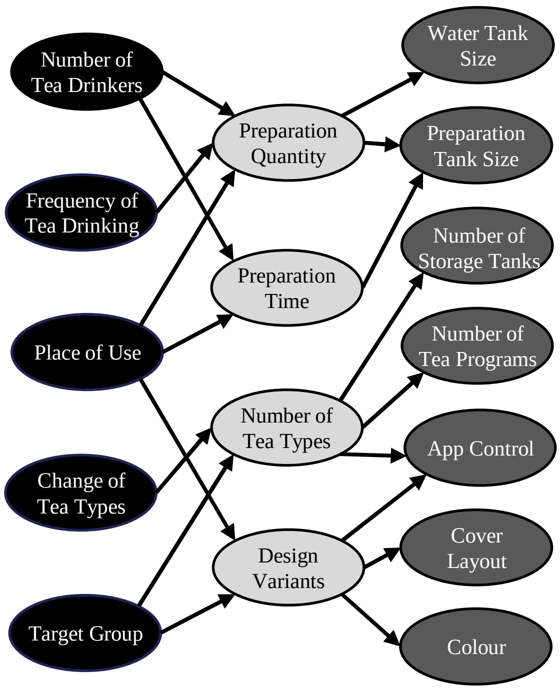

Fig. 4. *Bayesian Network for a Tea Brewing Machine*

5. DISCUSSION

The representation of uncertainties enables a qualitative inference or recommendation, which in many cases can already be sufficient for a decision between several options. The modelling of a BN as RS is based on the assumption that for a suitable start into a product configuration a first probable and useful product variant according to the »best guess« method is already adequate to allow customers an easy entry into the product configuration without overwhelming them. Under this background, the disadvantages of a BN as RS for high-involement products, such as the need for known or estimated probabilities and the dependence on subjective expert knowledge, can also be put into perspective. Nevertheless, further studies are needed to confirm this assumption.

6. CONCLUSION AND FURTHER RESEARCH

In order to avoid overwhelming customers in their choice of highly-variant products and to actively support them in their preference design process, this paper follows the approach of extending a knowledge-based product configurator by a probabilistic recommendation system. A method of artificial intelligence, Bayesian networks, is used as a knowledge-based recommendation system. They enable a combination of several sources of knowledge, such as expert knowledge and data, together with the processing of incomplete or uncertain knowledge. Due to its structure as a directed acyclic graph, the Bayesian network remains consistent throughout, so that no conflicts occur or need to be resolved. By updating the Bayesian network through inference, a learning process can also be initiated so that the accuracy of the recommendations improves over time. The presented approach was also applied and tested as an example on a tea brewing machine.

For further research, a validation in the form of a field study is planned in order to be able to evaluate the quality of the recommendations and to determine a reduction in the overwhelming of customers. By analyzing the recommendation data, the learning progress of the recommendation system can also be documented over time, which in turn can have an influence on product configuration, as rarely used options or variants can be adjusted. Furthermore, a benchmark for the widespread knowledge-based recommendation systems, such as constraint-based or case-based, could be interesting.

REFERENCES

[1] N. Franke, M. Schreier and U. Kaiser, “The “I designed it myself” effect in mass customization,“ *Management science*, vol. 56, no. 1, pp. 125-140, 2010. doi:10.1287/mnsc.1090.1077

[2] C. Huffman and B. E. Kahn, “Variety for sale: Mass customization or mass confusion?,“ *Journal of retailing*, vol. 74, no. 4, pp. 491-513, 1998. doi:10.1016/s0022-4359(99)80105-5

[3] M. Mandl, A. Felfernig, E. Teppan and M. Schubert, “Consumer decision making in knowledge-based recommendation,“ *Journal of Intelligent Information Systems*, vol. 37, no. 1, pp. 1-22, 2011. doi:10.1007/s10844-010-0134-3

[4] A. Felfernig, M. Mandl, J. Tiihonen, M. Schubert and G. Leitner, “Personalized user interfaces for product configuration,“ in *Proceedings of the 15th international conference on Intelligent user interfaces*, 2010, pp. 317-320. doi:10.1145/1719970.1720020

[5] A. Felfernig and R. Burke, “Constraint-based recommender systems: technologies and research issues,“ in *Proceedings of the 10th international conference on Electronic commerce*, 2008, pp. 1-10. doi:10.1145/1409540.1409544

[6] J. R. Bettman, M. F. Luce and J. W. Payne, “Constructive consumer choice processes,“ *Journal of consumer research*, vol. 25, no. 3, pp. 187-217, 1998. doi:10.1086/209535

[7] G. Frizelle, *The management of complexity in manufacturing: a strategic route map to competitive advantage through the control and measurement of complexity*, London, United Kingdom: Business Intelligence, 1998.

[8] J. Schaffer and H. Schleich, “Complexity cost management” in *G. Parry, A.P. Graves, Build to Order*, Berlin, Heidelberg, Germany: Springer, pp. 155-174, 2008. doi:10.1007/978-1-84800-225-8_9

[9] P. C. Gembarski and R. Lachmayer, “A business typological framework for the management of product complexity,“ In *Managing Complexity*, pp. 235-247, Springer, Cham, 2017. doi:10.1007/978-3-319-29058-4_18

[10] C. Forza and F. Salvador, *Product information management for mass customization: connecting customer, front-office and back-office for fast and efficient customization*, Basingstoke, United Kingdom: Palgrave Macmillan, 2007.

[11] A. Felfernig, L. Hotz, C. Bagley and J. Tiihonen, *Knowledge-based configuration: From research to business cases.* Newnes, 2014. doi:10.1016/b978-0-12-415817-7.00029-3

[12] D. Sabin and R. Weigel, “Product configuration frameworks - a survey,“ *IEEE Intelligent Systems and their applications*, vol. 13, no. 4, pp. 42-49, 1998. doi:10.1109/5254.708432

[13] P. C. Gembarski and R. Lachmayer, “Solution Space Development: Conceptual Reflections and Development of the Parameter Space Matrix as Planning Tool for Geometry-based Solution Spaces,“ *International Journal of Industrial Engineering and Management (IJIEM)*, vol. 9, no. 4, pp. 177-186, 2018. doi:10.24867/IJIEM-2018-4-177

[14] P. C. Gembarski and R. Lachmayer, “Degrees of Customization and Sales Support Systems – Enablers to Sustainibility in Mass Customization,” in *Proceedings of the 20th International Conference on Engineering Design (ICED15)*, pp. 191-198, Milan, Italy, 2015.

[15] G. Haubl and V. Trifts, “Consumer decision making in online shopping environments: The effects of interactive decision aids,” *Marketing Science*, vol. 19, no. 1, pp. 4-21, 2000. doi: 10.1287/mksc.19.1.4.15178

[16] N. R. Milton, *Knowledge technologies*, Polimetrica sas, 2008.

[17] M. Godse, R. Sonar and A. Jadhav, “A Hybrid Approach for Knowledge-Based Product Recommendation, “ in *Prasad S.K., Routray S., Khurana R., Sahni S. (eds) Information Systems, Technology and Management, ICISTM 2009, Communications in Computer and Information Science*, vol 31, Springer, Berlin, Heidelberg, 2009. doi:10.1007/978-3-642-00405-6_29

[18] S. S. Thakur, A. Kundu and J. K. Sing, “A Novel Approach: Using Bayesian Belief Networks in Product Recommendation,“ in *2011 Second International Conference on Emerging Applications of Information Technology*, pp. 37-40, 2011. doi:10.1109/eait.2011.21

[19] R. Burke, “Hybrid recommender systems: Survey and experiments,“ *User modeling and user-adapted interaction*, vol. 12, no. 4, pp. 331-370, 2002.

[20] J. A. Konstan, B. N. Miller, D. Maltz, J. L. Herlocker, L. R. Gordon and J. Riedl, “GroupLens: applying collaborative filtering to Usenet news,“ *Communications of the ACM*, vol. 40, no. 3, pp. 77-87, 1997.

[21] R. Burke, “Hybrid Web Recommender Systems,“ in *Brusilovsky P., Kobsa A., Nejdl W. (eds) The Adaptive Web. Lecture Notes in Computer Science*, vol. 4321, Springer, Berlin, Heidelberg, 2007. doi:10.1007/978-3-540-72079-9_12

[22] L. M. de Campos, J. M. Fernández-Luna, J. F. Huete and M. A. Rueda-Morales, “Combining content-based and collaborative recommendations: A hybrid approach based on Bayesian networks,“ *International journal of approximate reasoning*, vol. 51, no. 7, pp. 785-799, 2010. doi:10.1016/j.ijar.2010.04.001

[23] S. S. Weng, S. C. Liu and T. H. Wu, “Applying Bayesian Network and Association Rule Analysis for Product Recommendation,“ *International Journal of Electronic Business Management*, vol. 9, no. 2, pp. 149-159, 2011.

[24] W. Ertel and N. T. Black, *Grundkurs Künstliche Intelligenz*, Wiesbaden: Springer Fachmedien Wiesbaden, 2016. doi:10.1007/978-3-658-13549-2

[25] G. F. Luger, *Artificial intelligence: structures and strategies for complex problem solving*, 6th edn, Pearson education, 2005.

[26] M. I. Jordan (eds), *Learning in Graphical Models*, pp. 1-5, Springer, 1999. doi:10.1007/978-94-011-5014-9

[27] S. J. Russel and P. Norvig, *Artificial Intelligence – A Modern Approach*, 3rd edn., Pearson, 2016.

[28] J. Y. Zhu and A. Deshmukh, “Application of Bayesian decision networks to life cycle engineering in Green design and manufacturing,“ *Engineering Applications of Artificial Intelligence*, vol. 16, no. 2, pp. 91-103, 2003. doi:10.1016/s0952-1976(03)00057-5

[29] M. L. Moullec, M. Bouissou, M. Jankovic and J. C. Bocquet, “Product architecture generation and exploration using Bayesian networks, “ in *DS 70 - Proceedings of DESIGN 2012, the 12th International Design Conference*, pp. 1761-1770, Dubrovnik, Croatia, 2012.

[30] A. Falkner, A. Felfernig and A. Haag, “Recommendation technologies for configurable products,“ *Ai Magazine*, vol. 32, no. 3, pp. 99-108, 2011. doi:10.1609/aimag.v32i3.2369

[31] S. Plappert, P. C. Gembarski and R. Lachmayer, “The Use of Knowledge-Based Engineering Systems and Artificial Intelligence in Product Development: A Snapshot,“ in *International Conference on Information Systems Architecture and Technology*, pp. 62-73, Springer, Cham, 2019. doi:10.1007/978-3-030-30604-5_6

[32] A. A. Hopgood, *Intelligent systems for engineers and scientists*, CRC press, 2016. doi:10.1201/b11287

[33] S. Plappert, L. V. Hoppe, P. C. Gembarski, and R. Lachmayer, “Application of Knowledge-based Engineering for Teaching Design Knowledge to Design Students,” in *Proceedings of the Design Society: DESIGN Conference*, vol. 1, pp. 1795–1804, 2020. doi:10.1017/dsd.2020.300

[34] O. Pourret, P. Naïm, and B. Marcot (Eds.), *Bayesian networks: a practical guide to applications*. John Wiley & Sons, 2008. doi:10.1002/9780470994559

[35] J. Pearl, J., *Probabilistic Reasoning in Intelligent Systems: Networks of Plausible Inference*, Morgan Kauffman, 1997.

[36] K. B. Korb and A. E. Nicholson, *Bayesian artificial intelligence*, CRC press, 2010. doi:10.1201/b10391

[37] P.C. Gembarski and R. Lachmayer, “Business Models for Customer Co-Design,” in *Proceedings of the 7th International Conference on Mass Customization and Personalization in Central Europe (MCP-CE 2016)*, pp. 76-83, 2016.

[38] K. P. Murphy, “The Bayes Net Toolbox for Matlab,“ *Computing science and statistics*, vol. 33, no. 2, pp. 1024-1034, 2001.

CORRESPONDENCE

Stefan Plappert, M.Eng.
Institute of Product Development
Leibniz University of Hannover,
An der Universität 1,
30823 Garbsen, Germany
plappert@ipeg.uni-hannover.de

Dr.-Ing. Paul Christoph Gembarski
Institute of Product Development,
Leibniz University of Hannover,
An der Universität 1,
30823 Garbsen, Germany
gembarski@ipeg.uni-hannover.de

Prof. Dr.-Ing. Roland Lachmayer
Institute of Product Development,
Leibniz University of Hannover,
An der Universität 1,
30823 Garbsen, Germany
lachmayer@ipeg.uni-hannover.de