A SURVEY ON THE APPLICATIONS OF MACHINE LEARNING IN THE EARLY PHASES OF PRODUCT DEVELOPMENT

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ABSTRACT

Machine learning has shown its potential to support the knowledge extraction within the development processes and particularly in the early phases where critical decisions have to be made. However, the current state of the research in the applications of the machine learning in the product development are fragmented. A holistic overall view provides the opportunity to analyze the current state of research and is the basis for the strategic planning of future research and the actions needed. Hence, implementing the systematic literature survey techniques, the state of the applications of machine learning in the early phases of the product development process namely the Requirements, functional modelling and principal concept design is reviewed and discussed.

Keywords: Early design phases, Machine learning, System design, Requirements, Design knowledge

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1 INTRODUCTION

Artificial intelligence in general and machine-learning (ML) in particular are among the pioneering drivers of digitization and Industry 4.0. This is particularly evident in the sheer number of application areas in which the artificial generation of knowledge from experience is already being used by means of supervised and unsupervised learning methods. The methods of machine learning are used either to assign data to certain discrete values namely classes or to make predictions based on the data with continuous value. Among the best-known applications include the face recognition (Sun *et al.*, 2014), the recognition of critical machine conditions (Cubillo *et al.*, 2016), anomaly detection in the manufacturing processes (Ogbechie *et al.*, 2017) or the detection of the preceding vehicle in the context of driver assistance systems (Sivaraman and Trivedi, 2010).

As current research with focus on Affective design (Chan *et al.*, 2018), design feature recognition (Babic *et al.*, 2011) or Design Optimization (Chatterjee *et al.*, 2017) reveals, the use of machine learning seems promising in the context of the product development process with the main purpose of knowledge discovery. However, the contributions so far are rather isolated and a consolidated overall view of the state of research and its incorporation into a product development framework remains a desideratum to date. The early phases of the development are in particularly important, as knowledge extraction would have a large impact on the results in the presence of uncertainties (Kattwinkel et al., 2016) which are the consequence of insufficient experience and missing knowledge (Ehrlenspiel, 2007). Against this background, the aim of this work is to integrate the current research state in an analysis map summarizing machine-learning applications in the product development especially in the early phases of development. This will provide the opportunity to derive the current state and discuss an overview of future research and actions needed in a systematic way. The structures of the article is thus divided into the following sections.

In order to reflect the actual potentials of the use of machine learning in product development, it is necessary to build a foundation knowledge about each of these fields. At first, the early phases of development framework are explained. At the next section, the main methodologies of machine learning procedure are investigated and classified. The literature search and analysis initially serves to identify the respective machine-learning contributions or approaches and to classify them along the development process. The evaluation of this initial analysis thus provides information on current research priorities or possible thematic “white fields”. In addition, it is conceivable that initial findings for “best practices” are crystallized.

The concluding discussion brings together the two preceding work steps. It is discussed whether the current research approaches are located in those stages and situations of development, where their contribution is theoretically high. Thus, it is finally possible to disclose potential action and research needs and to discuss them in the research community.

The results of this contribution thus provide on the one hand assistance to both researchers and users in a relatively new subject area. On the other hand, the contribution should stimulate the debates made since early days of product development research on the possibility of algorithmic product development processes. The consideration of algorithmic product development requires thus new strategic planning in the context of product development.

2 EARLY PHASES OF THE PRODUCT DEVELOPMENT PROCESS

As it can be depicted from the design process paradox (Ullman, 2010), although the critical decisions have to be made early in the development process in order to bound the design space, the required information and necessary knowledge is fragmented and immature. In addition based on the studies on accruing design costs (Mavris and DeLaurentis, 2000), the costs taken place due to the decisions made or efforts to make changes in the early development phases is drastically less compared to the subsequent phases. In regard, the early phases of the development process can be seen as an opportunity to enhance the results with little efforts. Although the boundary separating the early phases of development from the rest of development tasks is fuzzy, in this case the first three sub-steps of product development process according to VDI 2221 (Verein Deutscher Ingenieure, 2018)) are considered as the early development phases.

Requirements elicitation: This is the starting point of an actual development process. Here the objectives are specified more precisely and described in the form of requirements. These very requirements at the same time are the basis criteria against which the final product is to be verified.

The main activities within this phase are requirements identification, organisation, analysis, specification and documentation (Lindemann, 2016).
Function modelling: According to VDI 2221, functional modelling is the link between the requirements and the generated concept. Here the main functionalities of the desired product are derived and relations between them studied.
Concept design: The goal is to build a cross-domain solution concept, which describes the main physical and logical operating characteristics of the product to be developed. This development stage is particularly based on synthesis/ analysis iterations and the subsequent assessment step. As the concept design can be executed in different levels of detail, here the phases which are part of the principal concept generation are considered. It is important to note that here the works belonging to the context of product development are considered. The generic problem solving techniques and the application of machine learning in them is out of the scope of this work.

3 MACHINE LEARNING

Machine-learning generally refers to the artificial extraction of knowledge from experience - the artificial system "learns" from examples (experience) and can generalize it at the end of the learning phase (knowledge). If a dedicated output value (label) is presented in the sample data, supervised learning methods are used. Otherwise, if no dedicated label was defined unsupervised methods would be implemented. If the learning phase is done based on a set of trials with respect to a predefined evaluation criteria (reward) the method is called reinforced learning.
In general, no all-purpose Machine learning method is available. The decision on which method to use depends on the field of application, the characteristics of the available data and the boundary conditions of the data analysis (e.g. accuracy, number of features, training time etc.).

3.1 Supervised learning

In these learning techniques, a forecasting model (hypothesis) is trained so that the output value for an unknown data record can be predicted. It must be distinguished whether the data should be assigned to certain discrete values or classes (classification problem) or a continuous value should be predicted (regression problem). The main supervised learning techniques in research and industry (Shalev-Shwartz and Ben-David, 2014) are introduced briefly in the Table 1.

Table 1. General review of supervised learning methods

Classification				
Algorithm	**Accuracy**	**Training time**	**Modelling**	**Notes**
Logistic regression	low	fast	Black-box	Simple to implement
Decision tree	low	fast	White-box	Simple to implement
Decision forest	high	moderate	White-box	High memory usage
Neural Networks	high	slow	Black-box	Customization possible
Support vector machines	moderate	moderate	Black-box	Large feature sets
Naïve Bayes	low	moderate	White-box	Simple to implement
Regression				
Linear	low	fast	Black-box	Simple to implement
Support vector Regression	moderate	moderate	Black-box	Large feature sets
Neural Network	high	slow	Black-box	Customization possible

3.2 Unsupervised learning

Since the labelling of the output values must be carried out by experts and this entails a corresponding expenditure of time and costs, data records are often initially in an unlabelled form and must be analysed and represented in a first step. For this purpose, unsupervised learning algorithms can be used to make inherent features or structures of the data transparent and to identify previously unknown patterns and relationships. Commonly used methods in the context of unsupervised learning are clustering and association analysis. **Clustering** is based on segmenting instances into groups with similar properties. In most applications, the **k-means** algorithm is used for the clustering. Here the number of segments should be defined prior to training. The segments are presented based on the average value (mean) of the data in that segment. **Association** methods look for correlations (the way they connect) between different features of a dataset. The **Bayesian Network** is a typical method used for association analysis. Here the nodes in the network represent the variables. Each nodes contains a probability function, which represent the probability value of the node variable based on the probability values of parent variables.

3.3 Reinforced learning

Reinforced learning uses the classical learning by doing technique to learn from several conducted trials. After each trial, based on an evaluation criterion (reward) a new strategy for the next trial is made and the state of the system is observed. The applications of this method are rather limited due to the need for performing trials.

4 LITERATURE SURVEY

The main objective of this manuscript is to have a general and complete view of the state of the machine learning applications on the early phases of the product development process. As a result, a systematic literature review is required in order to cover the different areas of research. As part of the systematic literature review, a survey strategy is defined. This survey strategy clarifies which search engines or publication sources to consider, what publication types to survey, what keywords to search with and where in the papers to look for the selected keywords.

The selected search engines include Scopus, Springer Link, IEEE Explore, Science Direct and Cambridge Core as they include a large number of scientific publications. In addition, all of these search engines have the option to an advance search. Here one major selection criteria for the publications is the quality of the papers, which was assured by reducing the publication type to reviewed Journal and proceedings papers.

The decision on the search keywords was based on an iterative process in order to select and optimize the keywords which are not too specific to narrow down the search to just few papers and not too general so that the number of found publications would be out of hand for further analysis.

With respect to machine learning these keywords were used: neur*, artificial, intelligen*, supervised, cluster*, bayes*, regression, kriging, “machine learning” and for the product development: “engineering Design”, “product development”, “systems engineering, “product requirements”.

Based on the defined keywords different search strings were constructed using Boolean operators, wildcards and loose phrases. Using the resulting search strings, the main search activity was conducted on the Article title and keywords. This restriction on the search field within each article leads to the detection of the papers whose main objective is related to this review manuscript. The initial results of the previous steps were further refined by the publication year (1990-2019) and publication language (English).

In total 143 articles with the focus on the integration of machine learning, methods within the whole product development process were identified. From these articles, 40 belong to the early phases of the product development as defined in the chapter 2.

5 MACHINE-LEARNING APPLICATIONS IN THE EARLY PHASES OF THE PRODUCT DEVELOPMENT

The results of the literature survey are shown in the Table 1. Here the number of case studies of each machine learning method for each development category is given. It is important to note that this number is not necessarily the same as the number of articles in the literature survey as some articles compare different machine learning methods for the same objective or by considering several phases of development, they use different machine learning methods for each phase. In the following, the contributions of the surveyed articles in each objective group is given.

5.1 Requirements

Requirements identification: In this category, the main objective is to mine end-user requirements from the textual content, which are mostly in the form of customer reviews and comments available in the internet. Christensen *et al*. (2017) used SVM to classify online community data (customer messages) into classes of containing suggestions either about products, improvements and business opportunities (ideas) or no suggestions (no ideas) based on the labels given by two raters (experts). It is shown that by applying the proposed methods the results are reliable. In order to extract product features from product reviews Xu *et al*. (2010) used conditional random fields to identify if a customer review contain product features or not and what are these features. Here it was discussed that the results quality depends on the predefined product features. Hence the more features integrated in the training the more accurate the results can be.

The methods proposed in this section are the first steps into the automatic requirements/opinions mining from the customer reviews. These text based approaches can be even later applied to audio or video sources. The main limiting point is that the accuracy of the classification methods used is based on the definition of the features, upon which the customer messages are classified. These features are usually defined with the help of the local experts and no predefined list of features characterising the customer suggestions or opinions exist.

Requirements categorization: This group of authors brought their focus into not just to extract requirements but also to categorize them as well. Aguwa *et al*. (2017) used text mining to extract critical to quality (CTQ) keywords from the costumer reviews. The relations between these CTQ keywords were modelled using apriori algorithm and the generated relations (rules) were clustered based on the respective CTQ. By implementing these rules to a fuzzy logic algorithm a framework to measure customer satisfaction namely, integrated customer satisfaction index was generated. Shakeri Hossein Abad *et al*. (2017) pre-processed (text mined) and classified requirements into functional requirements (FR) and non-functional ones (NFR) using Bayesian Networks. The functional requirements were later clustered into groups based on functional similarity. Here several clustering methods were compared and it is concluded that naïve Bayes method surpasses the other clustering methods in terms of accuracy. Laurent *et al*. (2017) implemented clustering algorithms to cluster incoming stakeholder requests into hierarchical feature sets. Barbosa *et al*. (2016) proposed an approach based on the clustering of textual requirements and on a data dictionary to organize the requirements. Lee and Bradlow (2011) applied text mining to extract pro and con information of the product attributes from customer reviews and clustered them into groups which were consequently labelled by the experts.

In this category, either classification methods or clustering is used to categorise the identified requirements. In case of classification, the definition of the classes depends on the experts opinions and hence difficult to generalise. In addition, the performance comparison of different classification or clustering methods is not studied.

Requirements analysis: in this group, the characteristics of the identified requirements are analysed. Pinquie *et al*. (2018) used text-mining techniques to identify requirements from documents. Further, they implemented support vector machine to segment them into communities related to the quality of the requirements. Hoornaert *et al*. (2017) used four different classification methods such as regularized logistic regression and random forests to estimate if a customer idea (requirement) will be implemented or declined in the final product. It is shown that the non-linear classification methods outperform the linear ones. The classifications were based on the idea attributes defined as criteria defining customer's experience, the feedback given by other customers on the idea and the degree of distinctiveness defined by the authors.

In these works, the authors have defined the end-user requirements characteristics / attributes themselves, which may not be applicable to other fields or product types. A further study on general end-user requirement attributes might be beneficial.

Requirements specification: the aim of this research group, which mostly belong to the context of quality function deployment (QFD), is to map the requirements to product specifications. This category also contains works on further substantiation of the requirements to the product attributes or development processes. Shabestari and Bender (2017) used regression methods to model the relation between product specifications and product attributes based on data made available via simulations. Yan *et al*. (2005), Zhao *et al*. (2004) and Zhang *et al*. (1996) modelled the relationship between requirements and specifications in the House of Quality (HoQ) of the QFD method based on the surveyed data from customers and designers with the use of neural networks.

Wang and Zhang (2017) extracted customer needs from product reviews and classified them to the predefined product specifications by applying the support vector machine and decision tree techniques. Here it is shown that the SVM performs more accurately than the decision tree.
There are two main types of research on the requirements specification in this group. One models the relations between requirements and the product specifications explicitly. The other type considers the relations of these domains as a black box and tries to map them together without investigating each relationship.
Attributes specification from variants: the main objective of this group of articles is mostly the same as conjoint analyses. Here the customer rating and scores on different product variants are collected and the relations between variation of product features and customers satisfaction are studied. In this context, a large number of publications focus on the relationship between customer perception and the form design features such as geometry attributes. Chen and Chang, (2009) initially used regression to model the correlation between the product form features (knife form design) and the consumers' perceptions of the product image (scoring of the knife images). Later they (Chen and Chang, 2016) implemented linear regression, neural networks and a combination of two and the results were compared. The neural network regression model provided better results than other two methods. In addition to the knife design case study, the application of the neural networks on modelling the customer satisfaction based on form features of the product has also been applied to mobile phone (Tang *et al*., 2013), vehicle (Tseng *et al*., 2012), high-price machine tools (Wang 2011) and chair (Hsiao and Huang, 2002) appearance design. Instead of neural networks, Yang (2011) developed a model of the affective response of customers to the mobile phone appearance using support vector regression method.
In addition to form design, machine learning methods have been used to model the customer preferences on the product features from different domains. In order to estimate the customer preferences on the technical features of digital products such as digital camera, mobile phone and computer tablets (features such as screen size) Huang and Luo (2016) used support vector machines, Kwong *et al*. (2009) implemented Neuro-fuzzy algorithms and Chen and Yang (2011) applied neural networks. Hoyle *et al*. (2009) used decision trees to model the relation between vehicle interior ergonomic factors to the customer ratings. In addition, the relations between customer characteristics such as age, height, etc. was studied using Bayesian networks.
Besides modelling the customer satisfaction, Afrin *et al*. (2018) used regression to model the relationship between market demand (number of products sold annually) and product differentiation (design specifications).
The difference between this category and the previous one is mainly based on the fact that in these works the customers satisfaction is directly mapped to the product specifications without expressing the requirement.

5.2 Function modelling

Function model characteristics modelling: In order to investigate the effect of the ability of different functional structure models to support decision-making Gill *et al*. (2017) modelled the relation between the complexity metrics of a functional models (e.g. number of elements or shortest paths between the inputs and outputs of the model) with respect to the market value using neural networks.

5.3 Concept design

Concept generation: the generation of creative solutions and concepts is still based entirely on human creativity. As a result, research on automatic generation of concept using machine learning is still immature, expressing ideas and wishes. In regard Hein and Condat (2018) proposed a framework towards machines with the general ability to design. This is based on the integration of a formal computational creativity framework into a reinforced machine-learning framework namely the Gödel machine. It is discussed that the proposed method have the potential to generate concept attributes based on the defined objectives of design (reward).
Categorizing and analysing the concepts: Here Zhang *et al*. (2017) used text mining to extract design concepts (in the format of natural language paragraphs) from design documentations and clustered them in groups of similar designs. The automatic clustering of the concepts were compared with human clustering of concepts (university students). It is shown that with respect to selecting the right number of clusters, human clustering surpasses the machine clustering. Hence, future work is required on the

selection criteria for the number of clusters. Reed and Duncan (2016) trained multiple decision trees to determine good or bad chair designs (two classes) with respect to each of the predefined design properties (ergonomic evaluation criteria). Dabbeeru and Mukerjee (2011) classified the design instances (design attributes) into feasible and infeasible classes based on a set of acceptability criterion which is itself a function of a set of predefined performance metrics of the system under study. Chen and Pao (1993) defined assembly pattern formats representing the geometry and topology attributes. The similar attributes were clustered together and each cluster was labelled. Later a neural network was trained to classify the assembly patterns to the labelled clusters defined previously.

Modelling the concepts: the analysis of the system concepts is often very difficult as the system itself in concept phase is complex and consists of different subsystems and domains. In order to support decision-making in this phase, one way is to build simple models (Meta or surrogate model) of the

Table 2. Machine-learning applications in the early phases of the product development

			Unsupervised Learning		Supervised Learning							Reinforced learning
	Objective of ML Application	Number of case studies in the Literature	Clustering	Bayesian Network	Linear regression	Logistic regression	Naïve Bayes classifier	Decision tree	Neural Networks	Support vector machine	Other	
Requirements	Requirements Identification	**3**	**1**							**1**	**1**	
	Requirements categorization	**12**	**9**	**2**			**1**					
	Requirements Analysis	**5**				**1**				**1**	**3**	
	Requirements specification	**8**			**1**			**1**	**5**	**1**		
	Attributes specification from variants	**15**		**1**	**3**			**1**	**7**	**3**		
Functional modelling	Function model characteristics modelling	**1**							**1**			
Concept Design	Concept Generation	**1**										**1**
	Categorizing and analysing the concepts	**5**	**2**					**1**	**2**			
	Modelling the concepts	**1**			**1**				**1**			
Sum		**51**	**12**	**3**	**4**	**1**	**1**	**3**	**16**	**6**	**4**	**1**

system. With this regard, Bertoni *et al*. (2017) modelled the performance (fuel consumption) of a wheel loader based on its specifications (e.g. weight) via regression method. Huang *et al*. (2006) used fuzzy neural network to model the design concept indicator (evaluation criteria based on the technical, economic, and social factors) based on the concept specifications.

6 CONCLUSION AND DISCUSSION

In this article, the results of a literature review on the applications of machine learning in early phases of product development are presented.

One major observation is that most of the current research is focusing on the knowledge extraction. This is because in early phases of product development the main sources of information on the desired product are in the form of requirements. These requirements in most cases however, are not readily available and have to be extracted from different sources such as text documents, audio or video recordings etc. In addition to identifying the requirements, it makes sense to put them in categories for the upcoming analysis steps. The main challenge however is the definition of these categories. For example, in case of "functional requirements" the main attributes of an extracted requirement, which indicate it belongs to this category, are not clear. As a result, different researches use varying perceptions of these attributes as it can be seen by requirements analysis. With respect to the requirements specification defining the relation between requirements and product attributes is a challenging task. The main drawback in mapping these two domains in the black-box manner, using designers and customers surveys is that, the results depend highly on the opinions of the surveyed group as well as the product itself and usually it is hard to extend the knowledge gained to other products or even new generations. At the other hand, analysing the relationships in white-box manner requires different physical or simulation based experiments, which is time consuming. Because of this, many researchers have brought their focus on mapping the quantified customer satisfaction to the product attributes using different variants of the product without further extracting and analysing the requirements.

Considering the principal conceptualisation phase, few works have been found with this regard. This might be due to the fact that as stated before the generic problem solving methods such as idea generation were not considered in this manuscript and only the ones using product developments terms and references were considered. As a result, we conclude that, there is a need to study the effect of machine learning in such generic methods as well and to investigate to which extent they are applied in the development processes.

Between the machine learning applications in the early phases, clustering methods are the main methods to be used. It is important to note that here the text mining methods used for the identification of the requirements are themselves machine learning classification methods, but they are not considered in this survey as text mining itself is a large research area. With beginning of the analysis phases, more supervised learning methods are used. Here neural network based methods have the highest ranking in the usage, as this is a well-studied method with various variants suitable for different application. Additionally neural networks, given enough training samples, usually provide accurate results even in non-linear data sets. In case of large number of features support vector machines have shown to provide accurate results with less efforts than the neural networks.

Based on the survey results it can be deduced that most of the case studies consider single domains of the systems under study. This might be due to the effort necessary to explain the complex research concepts containing machine-learning applications. Thus, simple examples were illustrated in the surveyed articles. Regardless, more detailed analysis is needed to clarify the applicability limits of the machine learning methods in the development phases with respect to the system complexity.

As stressed out previously at the beginning of this article, the research in this field still lacks a comprehensive overall view of the state of research into the product development framework. Naturally, the strategies used in this manuscript could be used to study the applications of machine learning on the rest of the product development phases as well. In addition to development phases, the focus of the future studies could be brought on the development process planning and to investigate the benefits of applying machine learning to it. Another interesting investigation area might be to study the degree of maturity of applied of machine learning techniques in the product development framework.

REFERENCES

Afrin, K., Nepal, B. and Monplaisir, L. (2018), "A data-driven framework to new product demand prediction. Integrating product differentiation and transfer learning approach", *Expert Systems with Applications*, Vol. 108, pp. 246–257. http://dx.doi.org/10.1016/j.eswa.2018.04.032.

Aguwa, C., Olya, M.H., and Monplaisir, L. (2017), "Modeling of fuzzy-based voice of customer for business decision analytics". *Knowledge-Based Systems*, Vol. 125, pp. 136–145.

Babić, B., Nešić, N., and Miljković, Z. (2011), "Automatic feature recognition using artificial neural networks to integrate design and manufacturing: Review of automatic feature recognition systems", *Artificial intelligence for Engineering Design, Analysis and Manufacturing*, Vol. 25 No. 3, pp. 289–304.

Barbosa, R., Januario, D., Silva, A.E., Moraes, R. and Martins, P. (2015), "An Approach to Clustering and Sequencing of Textual Requirements". *IEEE International Conference on Dependable Systems and Networks Workshops*, Rio de Janeiro, Brazil, 21 September, IEEE, pp. 39–44.

Bertoni, A., Larsson, T., Larsson, J. and Elfsberg, J. (2017), "Mining data to design value: A demonstrator in early design". *ICED 17 21st International Conference on Engineering Design*. Vancouver; Canada, Vol. 21 August, Design Society.

Chan, K. Y., Kwong, C.K., Wongthongtham, P., Jiang, H., Fung, C.K.Y., Abu-Salih, B., Liu, Z., Wong, T. C. and Jain, P. (2018), "Affective design using machine learning: a survey and its prospect of conjoining big data", *International Journal of Computer Integrated Manufacturing*. http://dx.doi.org/10.1080/0951192X.2018.1526412.

Chatterjee, T., Chakraborty, S. and Chowdhury, R. (2017), "A Critical Review of Surrogate Assisted Robust Design Optimization", *Archives of Computational Methods in Engineering*. https://doi.org/10.1007/s11831-017-9240-5

Chen, H. Y. and Chang and H.C. (2016), "Consumer's perception-oriented product form design using multiple regression analysis and backpropagation neural network", *Artificial intelligence for Engineering Design, Analysis and Manufacturing,* Vol. 30 No. 1, pp. 64–77. http://dx.doi.org/10.1017/S0890060415000165.

Chen, H.-Y. and Chang, Y.-M. (2009), "Extraction of product form features critical to determining consumers' perceptions of product image using a numerical definition-based systematic approach", *International Journal of Industrial Ergonomics*, Vol. 39 No. 1, pp. 133–145. http://dx.doi.org/10.1016/j.ergon.2008.04.007.

Chen, C. and Yan, W. (2008), "An in-process customer utility prediction system for product conceptualisation", *Expert Systems with Applications*, Vol. 34 No. 4, pp. 2555–2567. http://dx.doi.org/10.1016/j.eswa.2007.04.019.

Chen, M.-Y. and Chen, D.-F. (2002), "Early cost estimation of strip-steel coiler using BP neural network", *International Conference on Machine Learning and Cybernetics*, Beijing, China, 4–5 Nov, IEEE, pp.1326–1331.

Chen, C.L.P. and Pao, Y.-H. (1993), "An integration of neural network and rule-based systems for design and planning of mechanical assemblies", *IEEE Transactions on Systems, Man, and Cybernetics,* Vol. 23 No. 5, pp. 1359–1371. http://dx.doi.org/10.1109/21.260667.

Chowdhery, S. A. and Bertoni, M. (2018), "Modeling resale value of road compaction equipment. A data mining approach", *IFAC-PapersOnLine*. Vol. 51 No. 11, pp. 1101–1106.

Christensen, K., Nørskov, S., Frederiksen, L., and Scholderer, J. (2017), "In search of new product ideas: Identifying ideas in online communities by machine learning and text mining", *Creativity and Innovation Management*, Vol. 26 No. 1, pp. 17–30.

Cubillo, A., Perinpanayagam, S., Rodriguez, M., Collantes, I., and Vermeulen, J. (2016). "Prognostics Health Management System based on Hybrid Model to Predict Failures of a Planetary Gear Transmission", *Machine Learning for Cyber Physical Systems,* Springer, Berlin Heidelberg, Lemgo, Germany, October 1.

Dabbeeru, M.M. and Mukerjee, A. (2011), "Discovering implicit constraints in design", *Artificial intelligence for Engineering Design, Analysis and Manufacturing,* Vol. 25 No. 01, pp. 57–75.

Ehrlenspiel, K. (2007), *Integrierte Produktentwicklung – Denkabläufe, Methodeneinsatz, Zusammenarbeit*. Vol. 3. Carl Hanser Verlag München Wien, München, Auflage.

Gill, A.S., Summers, J.D. and Turner, C.J. (2017), "Comparing function structures and pruned function structures for market price prediction. An approach to benchmarking representation inferencing value", *Artificial intelligence for Engineering Design, Analysis and Manufacturing*, Vol. 31 No. 4, pp. 550–566.

Hein, A. M. and Condat H. (2018), "Can Machines Design? An Artificial General Intelligence Approach", *International Conference on Artificial General Intelligence.* Prague, Czech Republic, pp. 22–25 August.

Hoornaert, S., Ballings, M., Malthouse, E.C. and van den Poel, D. (2017), "Identifying new product Ideas. waiting for the wisdom of the crowd or screening ideas in real time", *Journal of Product Innovation Management*. Vol. 34 No. 5, pp. 580–597. http://dx.doi.org/10.1111/jpim.12396.

Hoyle, C., Chen, W., Wang, N. and Gomez-Levi, G.B., (2009), "Understanding heterogeneity of human preferences for engineering design", *ICED 09 17th International Conference on Engineering Design*. Design Society, Palo Alto, CA; United States, 24 August.

Hsiao S.-W. and Huang, H.C. (2002), "A neural network based approach for product form design", *Design Studies*, Vol. 23 No. 1, pp. 67–84.

Huang, D. and Luo, L. (2016), "Consumer preference elicitation of complex products using fuzzy support vector machine active learning", *Marketing Science*, Vol. 35 No. 3, pp. 445–464.

Huang, H.-Z., Bo, R. and Chen, W. (2006), "An integrated computational intelligence approach to product concept generation and evaluation", *Mechanism and Machine Theory*, Vol. 41 No. 5, pp. 567–583.

Kattwinkel, D., Song, Y.-W., Herzog, M., Neumann, M. and Bender, B. (2016). "Analysis of existing approaches for the support of planning processes within new product development projects", *Proceedings of NordDesign 2016,* pp. 380–389.

Kwong, C.K., Wong, T.C. and Chan, K.Y. (2009), "A methodology of generating customer satisfaction models for new product development using a neuro-fuzzy approach", *Expert Systems with Applications,* Vol. 36 No. 8, pp. 11262–11270. http://dx.doi.org/10.1016/j.eswa.2009.02.094.

İç, Y.T. (2016), "Development of a new multi-criteria optimization method for engineering design problems", *Research in Engineering Design*, Vol. 27 No. 4, pp. 413–436. http://dx.doi.org/10.1007/s00163-016-0225-4.

Laurent, P., Cleland-Huang, J. and Duan, C. (2017), "Towards automated requirements triage", *15th IEEE International Requirements Engineering Conference*, IEEE, Delhi, India, 19 November.

Lindemann, U. (2016), *Handbuch Produktentwicklung*, Carl Hanser Verlag GmbH & Co. KG. ISBN: 978-3-446-44518-5
Liu, H., Huang, Y., Ng, W.-K., Bin, S. Li., X. and Lu, W.-F. (2007), “Deriving configuration knowledge and evaluating product variants through intelligent techniques”, *6th International Conference on Information, Communications & Signal Processing*, IEEE, Singapore, Singapore, 12 February.
Lee, T.Y. and Bradlow, E.T. (2011), “Automated marketing research using online customer reviews”, *Journal of Marketing Research*, Vol. 48 No. 5, pp. 881–894.
Mavris, D.N. and DeLaurentis, D. (2000), “Methodology for examining the simultaneous impact of requirements, vehicle characteristics, and technologies on military aircraft design”, *22nd Congress of the International Council on the Aeronautical Sciences (ICAS)*, Harrogate, England, 27 Aug.-1 Sep.
Ogbechie, A., Díaz-Rozo, J., Larrañaga, P., and Bielza, C. (2017), “Dynamic Bayesian Network- Based Anomaly Detection for In-Process Visual Inspection of Laser Surface Heat Treatment”, *Machine Learning for Cyber Physical Systems*. Springer Berlin Heidelberg, Karlsruhe, Germany, 29 Sep., pp. 17–24.
Pinquié, R., Véron, P., Segonds, F., and Croué, N. (2018), “A requirement mining framework to support complex sub-systems suppliers”, *Procedia CIRP*, Vol. 70, pp. 410–415. http://dx.doi.org/10.1016/j.procir.2018.03.228.
Reed, K., and Gillies, D. (2016), “Automatic derivation of design schemata and subsequent generation of designs”, *Artificial intelligence for Engineering Design, Analysis and Manufacturing*, Vol. 30 No. 4, pp. 367–378. http://dx.doi.org/10.1017/S0890060416000354.
Ren, Z.-H., Wang, B.-C. and Wen, B.-C. (2004), “A model of HoQ templet automatic generation based on RBF-ANN”, *International Conference on Machine Learning and Cybernetics*, Shanghai, China, August, pp. 6–29. IEEE.
Seo, K.-K., Park, J.-H., Jang, D.-S. and Wallace, D. (2002), “Approximate estimation of the product life cycle cost using artificial neural networks in conceptual design”. *The International Journal of Advanced Manufacturing Technology*, Vol. 19 No. 6, pp. 461–471.
Shabestari, S. S., and Bender, B. (2017), “Enhanced integrated sensitivity analysis in model based QFD method”, *ICED17 21st International Conference on Engineering Design*, Design Society, Vancouver, Canada, 21-25 Aug.
Shakeri Hossein Abad, Z., Karras, O., Ghazi, P., Glinz, M., Ruhe, G. and Schneider, K. (2017), “What Works Better? A Study of Classifying Requirements”, *25th IEEE International Conference on Requirements Engineering*, IEEE, Lisbon, Portugal, 4-8 Sep.
Shalev-Shwartz, S., and Ben-David, S. (2014), *Understanding Machine Learning: From Theory to Algorithms*, Cambridge University Press, Cambridge. http://dx.doi.org/10.1017/CBO9781107298019
Sivaraman, S. and Trivedi, M.M. (2010), “A general active-learning framework for on-road vehicle recognition and tracking”, *IEEE Transactions on Intelligent Transportation Systems*, Vol. 11 No. 2, pp. 267–276.
Sun, Y., Chen, Y., Wang, X., and Tang, X. (2014), “Deep Learning face representation by joint identification-verification”, *Advances in Neural Information Processing Systems*, Montreal, Canada, 08-13 Dec., pp. 1988–1996.
Tang, C. Y., Fung, K.Y., Lee, Eric W.M., Ho, G.T.S., Siu, Kin W.M. and Mou, W.L. (2013), “Product form design using customer perception evaluation by a combined superellipse fitting and ANN approach”, *Advanced Engineering Informatics*, Vol. 27 No. 3, pp. 386–394. http://dx.doi.org/10.1016/j.aei.2013.03.006.
Tseng, I., Cagan, J. and Kotovsky, K., (2012), “Concurrent Optimization of Computationally Learned Stylistic Form and Functional Goals”, *Journal of Mechanical Design*, Vol. 134 No. 11, pp. 111006.
Ullman, D.G. (2010), *The mechanical design process*. McGraw-Hill Higher Education, Boston.
Verein Deutscher, I. (2018), *VDI Richtlinie 2221 Design of technical products and systems*, Beuth, Berlin.
Wang, Y. and Zhang, J. (2017), “Bridging the semantic gap in customer needs elicitation: A machine learning perspective”, *ICED17 21st International Conference on Engineering Design*, Design Society, Vancouver; Canada, 21-25 August.
Wang, K.-C. (2011), “A hybrid Kansei engineering design expert system based on grey system theory and support vector regression”, *Expert Systems with Applications*, Vol. 38 No. 7, pp. 8738–8750.
Xu, B., Zhao, T., Zheng D. and Wang, S. (2010), “Product features mining based on Conditional Random Fields model”, *International Conference on Machine Learning and Cybernetics*, Qingdao, China, 20 Sept., pp. 3353–3357.
Yan, W., Khoo, L.P. and Chen, C.-H. (2005), “A QFD-enabled product conceptualisation approach via design knowledge hierarchy and RCE neural network”, *Knowledge-Based Systems*, Vol. 18 No. 6, pp. 279–293.
Yang, C.-C. (2011), “Constructing a hybrid Kansei engineering system based on multiple affective responses. Application to product form design”, *Computers & Industrial Engineering*, Vol. 60 No. 4, pp. 760–768.
Zhang, C., Kwon, Y.P., Kramer, J., Kim, E. and Agogino, A.M. (2017), “Concept Clustering in Design Teams. A Comparison of Human and Machine Clustering”, *Journal of Mechanical Design*, Vol. 139 No. 11, pp. 111414. http://dx.doi.org/10.1115/1.4037478.
Zhang, X., Bode, J. and Ren, S. (1996), “Neural networks in quality function deployment”, *Computers & Industrial Engineering*, Vol. 31 No. 3-4, pp. 669–673.