DECISION SUPPORT WITHIN KNOWLEDGE-BASED ENGINEERING – A BUSINESS INTELLIGENCE-BASED CONCEPT

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ABSTRACT

Essential characteristics of products are set during early phases of product development as well as manufacturing. During these processes, decisions are made without awareness of their final impacts on long term key success factors. Industrial businesses lack concepts that enable decision-makers within knowledge based engineering processes, to anticipate possible impacts of their decisions. Due to this, many industrial companies employ so called knowledge engineers to manually gather and analyze information of product lifecycles. In order to improve the decision support within knowledge based engineering, a concept was developed, which contains the extension of business intelligence environments with product-orientated data warehouses. It is thus possible to combine technical information of product features with the traditional dimensions of managerial analysis in order to identify impacts of decisions on the product lifecycle and hence support knowledge engineers in their daily work.

Keywords

Knowledge engineer; Business Intelligence; Lifecycle management; Decision support; Knowledge management; Feature technology.

INTRODUCTION

Manufacturing enterprises are doubtlessly one of the mainstays of economic power in many countries. Especially excellent products and manufacturing processes determine the global success of this industry (Lindemann, 2006). Flexibility, resource efficiency, and time-to-market are key success factors to thrive in a market. Through developing a digital product model (Digital Mock Up (DMU)), which implements the product requirements adequately, essential decisions are made to ensure these qualities.

The development of DMUs is usually a complex process with many different people involved. The people in charge, e.g. designers and product managers, have to make various decisions in order to determine geometries, the choice of materials, aspects of quality etc. In this context, many decision-makers are supported by operational systems from fields close to product development / design (e.g. Computer Aided Design (CAD), Computer Aided Engineering (CAE)). Designers gather information about the impacts of geometric changes (e.g. the insertion of a hole) on strength, material usage and mass of the part, from established CAx systems. However, the person in charge is not provided with additional information. This is a significant deficit. For instance, no operational design system is able to analyze consequences of design changes on the whole product lifecycle (e.g. manufacturing and recycling) or to anticipate these simply based on comparable historic data.

Important questions concerning product lifecycle management (PLM) remain unanswered, e.g. how – and if – already existing parts could be re-used and which impact design changes may have on existing parts. Affected are therefore questions that are related to:

- Manufacturing processes (production costs)
- Usability in variants and the resulting diversity of variants including the consequences for stocking (warehousing) and the implications for after-sales-services
- Customer utility and therefore the market attractiveness of the product
- Resource efficiency (as a component of the company-specific sustainability management, e.g. changes of energy usage during manufacturing and utilization; ability to be recycled).

In the current lifecycle management processes, managerial analyses are primarily based on economic key figures in order to monitor process performance and to intervene ex-post in case of deviations. However, a marginal modification of a part could have significant consequences for subsequent stages of production, warehousing and services. The resulting increase in costs will not become apparent until the next quarter, if it is only possible to monitor them ex post.

The research question therefore is how the information supply of lifecycle-orientated decision-makers (knowledge engineers) can be improved by new IT-based concepts. The goal of the research is to develop and validate a framework, which enables a sufficient information supply and advanced decision support for knowledge engineers.

Therefore, this paper is structured as follows: After an introduction of the research design, the paper addresses the role of the knowledge engineer (KE) in literature as well as the product lifecycle-orientated *information supply*. Secondly, the *information demand* of KEs is explained. Thirdly, a business intelligence based framework is introduced, which is supposed to close the gap between information supply and information demand.

RESEARCH DESIGN AND RESEARCH FRAMEWORK

The object of the present research is information systems (IS) in industrial companies. The goal is to derive a 'to-be' conception of an enhanced Business Intelligence (BI) concept that can be applied in industrial companies. Thus, the action design research methodology was chosen (Österle et al., 2011). The research question is contained in an interdisciplinary field of engineering, information systems as well as business administration. Therefore, the research process has to include empirical activities on all of those disciplines. Also, the research topic is so far an unexplored field. For these reasons the study is designed as a multi-level exploration (Mayring, 2001), following the research process of design-orientated IS research with the phases of analysis, design and evaluation (cf. Figure 1) (Sein et al., 2011; Österle et al., 2011).

Like Figure 1 depicts, the preliminary empirical analysis started with an exploratory qualitative study in form of nine expert interviews to capture the product lifecycle in industrial companies. These interviews took place in German medium-sized engineering and construction companies in 2006 and 2007. The interview partners had an IT and engineering background. All these interviews took between 90 and 120 minutes. Another four interviews with experts of other companies (medium sized companies in the machinery and tools industry) were conducted to evaluate existing integration concepts like PLM. These interviews were conducted in the 2nd half of 2009 (also 90 to 120 minutes). Based on the insights, the general research gap of missing lifecycle-orientated information supply with integrated technical and financial information was identified. It was also deducted that a satisfying concepts was inexistent.

Another insight from the preliminary analysis is that the identified gap concerns many industrial processes and several decision-makers. The main analysis started with the identification of relevant use cases with 15 expert interviews in 10 companies within the 2nd half of 2010 and in 2011. Each interview took between 60 and 180 minutes. Goal of the interviews was to examine use cases as well as the *information demand* of important lifecycle decisions. Thereby one of the identified use cases, playing a very important role in lifecycle-orientated decision making, is the so called KE. At the same time eight interviews in eight industrial companies were conducted (duration of about 60 minutes each) to explore enterprise IT architectures, which is important in order to identify data sources (*information supply*).

In a next step (design phase), a concept of an enhanced BI-based framework (named Industrial Intelligence framework) was developed. Actually, the BI-based concept is in the stage of evaluation. The overall research design is depicted in Figure 1. The dashed line identifies the content of this paper.

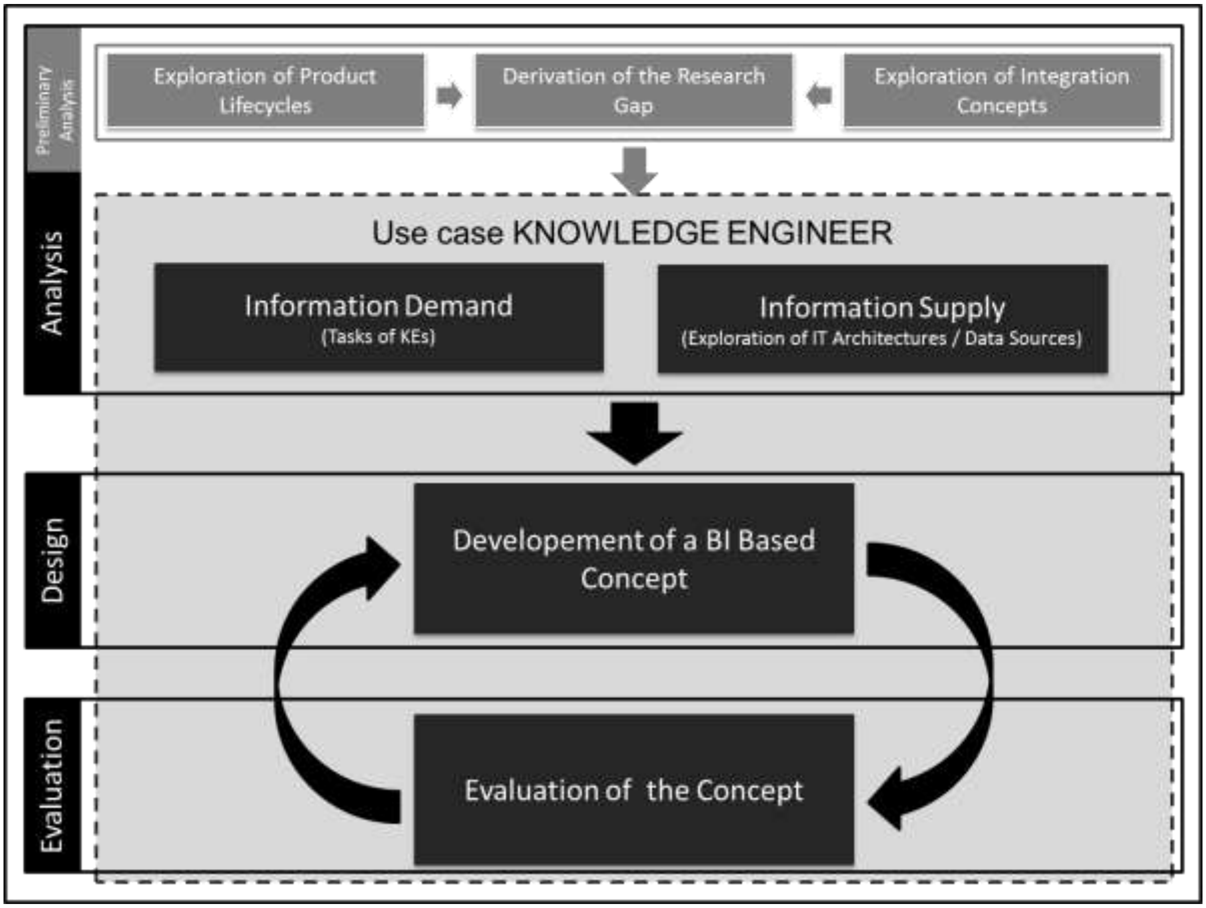

Figure 1: Research design

KNOWLEDGE ENGINEER AND PRODUCT LIFECYCLE-ORIENTATED INFORMATION SUPPLY

The role of KEs is described primarily in engineering literature. The definitions comprise a set of tasks that the KE has to deal with, e.g. identifying relevant engineering knowledge, acquiring knowledge, and encoding knowledge. By trying to point out a general description, the KE has to determine relevant knowledge and codify this into knowledge systems or expert systems, construction rules, (construction-) scripts or templates. Therefore, the primary task of these engineers is the acquisition and association of (fragmented) information to regulate construction, based on a holistic view of information (Giannakakis and Vosniakos, 2008; Chatterjea, 2000; Röhner et al., 2011). The goal of KEs is described as implementing a permanent active learning organization (Kendal, 2007; Shaw and Gaines, 1983). The KE is usually part of knowledge based engineering activities of a company (Schreiber, 2008). Therefore, the term "knowledge" is used in the context of the engineering domain and could be misleading in the context of the domain of information systems. For example, the "knowledge", which is determined by the KE, can be codified into scripts or templates: e.g. "if a hole has a diameter of 7mm, replace it with a hole of 8mm". Comparing the definitions of knowledge and information given in Kebede (Kebede, 2010), the engineering term "knowledge" is understood similarly to the term "information", as "data given context and endowed with meaning and significance" (Dodig-Crnkovi cited in Zins, 2007, p. 482). Due to this ambivalence, this paper will use the terms "knowledge" and "information" synonymously. Following the literature, the relevant sources of knowledge are on the one hand experts, whose knowledge has to be captured through methods like interviews. On the other hand all IT systems are potential information sources. Therefore, IT-based information supply is relevant for KEs. Focusing IT-based information supply in industrial processes, three layers have to be considered (McClellan, 1997; VDI, 2007): planning, execution, and control layer.

IT support in reseach and development (R&D) and manufacturing focuses primarily on the planning layer. On the one hand, in business units like R&D and manufacturing, there are product-orientated applications in use that support several early phases of the innovation process. Those systems are commonly called "computer aided …" (CAx), e.g. CAD, CAE or Computer Aided Quality (CAQ) (Ehrlenspiel, 2007; Rudolph and Dietrich, 2006; Weber, 2003). With the aid of these systems the DMUs are generated. Thereby the so-called feature technology plays an important role (VDI, 2003; Ophey, 2008). The feature technology is a common approach within engineering IT-systems and is applied in state-of-the-art CAx systems. With the feature technology it is possible to enrich geometrically orientated CAx data with data objects describing the semantics of the depicted parts. Examples for semantic objects include the purpose of the feature, material specifications, quality attributes or information on manufacturing processes. Semantic features can be either related to geometric features or to other semantic features. Condensed, using the feature technology, the DMU of physical parts can be described as the sum of feature elements. This means that the geometry of a part is the sum of geometric feature elements. Equally, all descriptions and specifications of a part consist of the sum of semantic feature elements. Further, feature elements can be classified in different "views". For example, all semantic feature elements, describing quality attributes, can be understood as the "quality view" of a part (VDI, 2003; Shah and Mäntylä, 1995; Molloy et al., 1998; Ovtcharova, 1997). This, in turn, means that a physical part can be analyzed in separate views (dimensions). Following the example, it is therefore possible to extract the "quality view" of several DMUs (all semantic feature elements with regard to quality aspects). So there is a possibility to compare quality aspects of e.g. product variants. To give insights in quantity aspects of DMUs, simple parts consist of up to 5.000 feature elements.

On the other hand, transaction-orientated systems, like Enterprise Resource Planning (ERP) systems, promise an integrated support for all kinds of operational processes within an enterprise. Usually, MRP (Manufacturing-Ressource-Planning)-II-and ERP-based scheduling and capacity planning is conducted on a macroscopic level that is both long term and product-orientated (McClellan, 1997; Monk and Wagner, 2007; Hossain et al., 2002).

However, these systems neglect the execution and control layers. Relevant tasks in those two layers include scheduling and planning on an atomic level, real-time process control, and active process control. Manufacturing Execution Systems (MES) attempt to address these layers in an integrated approach (Kletti, 2007). MES originates from the data collection technologies of the early 1980s. Initially, production environments were characterized by unrelated data gathering components. With the rise of integrated concepts like Computer Integrated Manufacturing (CIM), individual tasks were not seen any longer as independent, but rather related to a process. This led to benefits resulting from data integration. Unfortunately, the CIM concept was unable to achieve acceptance. A variety of reasons for the failure of CIM have been identified, e.g. unsatisfactory standardization, disappointing applications, and a tendency to misuse the term CIM for marketing purposes (Kletti, 2007).

In the 1990s, the far reaching vision of CIM was replaced by integrated data collection systems that concentrated on defined functional scopes, e.g. production (esp. supervisory control and data acquisition technologies), personnel management (staff work time logging, access control, etc.) quality control (e.g. CAQ) or product data management (PDM) and later on product lifecycle management (PLM) (Eigner and Stelzer, 2009; Kent, 1998). Although this pragmatic approach was a step forward, it still fell short of achieving the degree of integration that was needed for lifecycle transparency. This was due to the fact, that the integration of product-orientated IT-systems (e.g. PLM) and transaction-orientated IT-systems (e.g. Customer Relationship Management (CRM)) was still insufficient (Lasi et al., 2010).

In addition to the three layers explained above, a fourth layer called Business Intelligence (BI) is relevant in this context. BI denotes integrated approaches to support decision-makers and is usually associated with data warehouse systems (DWHs) that provide an integrated, subject-orientated, time-variant and non-volatile repository for diverse analytic and reporting applications (e.g. for OLAP analysis, data mining, balanced scorecards etc.) (Inmon, 2005; Kimball and Ross, 2002; Atre and Moss, 2005; Baars and Kemper, 2008; Negash, 2004). Major contributors to the DWH concept are Inmon (Inmon 2005) and Kimball (Kimball and Ross 2002). While Inmon stands for a strongly centralized, application-independent approach, Kimball and Ross propose a more decentralized data management, which is held together semantically by the use of shared dimensions ("dimensional bus"). Following Inmon, providing near-time transactional data is one of the most significant modifications of the classical DWH concept (Inmon 1999). However, the motivation of building "Operational Data Stores" (ODS) is still the aspect of integrating transactional data from multiple sources (Kelley 2007). Therefore, the neglecting of engineering data is still a limitation of current BI concepts (Koch et al., 2010).

Current frameworks organize BI in several layers: the data provisioning layer (extraction, transformation and loading (ETL)), the data storage layer (data warehouse), the logic layer and the access layer (Baars and Kemper, 2008; Jarke et al, 2003; Turban et al., 2005) (cf. Figure 3). ETL processes extract data from several sources, transform them syntactically and semantically, and load them into data warehouse systems (Inmon 2005). The data storage layer contains one or more data stores. The data stores are sometimes separated due to different data scopes, e.g. financial data warehouses and customer orientated data warehouses, or divergent requirements like timeliness, e.g. ODS (Kimball and Ross 2002; Jukic 2006). Core data warehouses are typically not used as direct sources for analysis systems (Baars and Kemper, 2008; Inmon, 2005). Multi-dimensionally modeled data marts in combination with a core data warehouse are known as the "hub-and-spoke approach" (Ariyachandra and Watson, 2006). The logic layer focuses on data analysis systems like data mining and OLAP (Baars and

Kemper, 2008). Within the data access layer all relevant components and functions are presented to the user in an integrated and personalized manner (Baars and Kemper, 2008).

USE CASE BASED INFORMATION DEMAND OF KNOWLEDGE ENGINEERS

As mentioned above, the role of the KE was identified as an important decision-maker in the context of the product lifecycle in literature as well as in practice. As also mentioned above, the tasks as well as the information demand of KEs are just vaguely described in literature. Therefore, the information demand for this role was explored empirically as follows: First the tasks of the role were identified. Next, the decisions within the tasks were derived and in a last step, the necessary information demand, based on the decisions, was determined. In a next step, the information demand was mapped to the information supply, which means to the actual data sources. The resulting use case for the role KE is depicted in Figure 2 and explained in the following section.

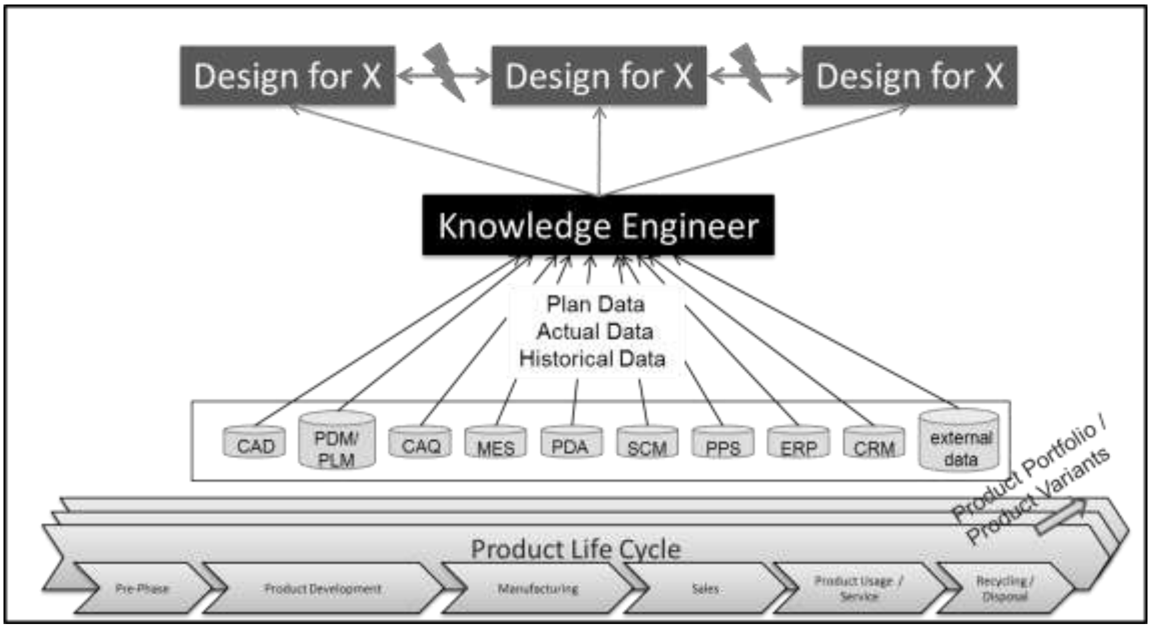

Figure 2: Use Case Knowledge Engineer

The role of the KE can be detected/observed in several companies. When asking experts from the task force of knowledge-based engineering within the Association of German Engineers (VDI), the KE is identified as common in industrial companies of all sizes. The use case is primarily based on two interviews with KEs in different companies (one of them is the head of a KE team consisting of four members) and supplemented through several workshops on knowledge based engineering. The interviewed experts agreed to the statement, that the primary task of KEs is the acquisition and association of (fragmented) information to regulate construction, based on an as-complete-as-possible information view (Giannakakis and Vosniakos, 2008; Chatterjea, 2000; Röhner et al., 2011). However, the experts also mentioned, that the purpose of their job is to enable design for X. Thereby the experts claimed that their business strategy requires more than one design for X commitment, e.g. design for cost, design for quality and design for assembly. The difficulty of their job was described as follows: on the one hand, they have to collect data from different business units and data sources and put this fragmented and heterogeneous data together to valid information. On the other hand, the design for X commitments are very often conflicting. For example reaching a higher quality level (design for quality) requires a trade-off with the reduction of costs (design for cost). Therefore, the KEs have to figure out the impacts of changes across the commitments, based on historical data. In a next Q & A the experts explained, which data concerning the product lifecycle they actually retrieve from which data sources. A summarized overview looks like Figure 2 depicts:

- Actual geometric and feature data as well as a history of changes out of CAD systems (Note: All of the nine investigated businesses have more than one kind of CAD system in use. The KEs therefore mostly ask for printed drawings).
- Actual and historic assemblies, e.g. the reuse of parts, out of PDM/PLM systems.

- Quality data out of quality systems, documents, and spreadsheets (Note: quality-based key performance indicators (e.g. rework costs) are mostly manually calculated ex-post with spread sheet systems).
- Actual as well as historical manufacturing data like non-financial key performance indicators (e.g. timeliness) from different manufacturing sites, mostly extracted from MES (Note: This also includes data about factory/machine configurations).
- Actual as well as historical manufacturing data on an atomic level. Sometimes this data is provided through production data acquisition (PDA) systems.
- Plan data, actual data as well as historical data about suppliers and supply chain processes from SCM systems.
- Plan data, actual data as well as historical data about resources in production from PPS systems.
- Plan, actual as well as historic financial data (e.g. financial key performance indicators, budgeting, costing) from ERP systems.
- Data concerning customer satisfaction (e.g. complaints) from CRM systems.
- An increasingly important data source is the internet. Ideas or experience from customers captured in e.g. blogs, data about competitors or patent databases are just a sample of relevant external data.

Asked about the quantity of relevant data sources the answers varied between 15 and more than 100. As mentioned above, the manual retrieval and preparation of data in order to get information leads to “data collection teams” and requires a great and complex effort. Asked about the degree of satisfaction with the quality of information (not data!), both KEs mentioned, that the type of information (plan, actual, historic) as well as their nature (itemization, correctness, completeness, and timeliness) (Wang and Strong, 1996; Koch et al., 2011) were incomplete and insufficient.

Summarizing the use case KE, the investigated decision-makers need information out of several lifecycle phases. Those have to be retrieved from a whole bunch of heterogeneous data sources and logically and semantically prepared. This is associated with a great effort, and the degree of satisfaction with the provided information is currently low.

ENHANCED BUSINESS INTELLIGENCE BASED CONCEPT

The presented results of this research depict that - as a matter of fact - industrial businesses lack concepts that enable KEs to make decisions and anticipate their impacts, based on satisfying information. Therefore, a concept was developed, which is based on established BI infrastructures (cf. chapter 2) and presented in Figure 3. The concept includes technologies and procedures to extract technical data out of CAx systems and a framework of an enhanced BI architecture. Therefore, the technologies and procedures (data provisioning layer) and second the data store layer of the enhanced framework are introduced first.

One fundamental pillar of this concept is the extraction of analyzable semantic feature objects out of digital product models. As shown in chapter 2, products are completely described by technical feature objects in several views. Therefore, all feature elements are extracted from the digital product models for analytic purposes for defined periods (e.g. on a weekly basis) or at special events (e.g. modification of parts) (Lasi, 2009). It is one of the challenges, that common ETL tools are unable to extract feature elements out of digital product models. Part of the research therefore was the identification of engineering tools, which are able to read and write feature elements within DMUs and export them into XML-based files. In a next step, the feature elements can be transformed and loaded into a DWH infrastructure.

To be able to conduct various kinds of analyses, the product data has to be stored in the data storage layer. Because of the entirely different scope of technical feature data compared to transactional data, the data storage layer is enhanced by an additional data store called product-orientated data warehouse (pDWH). The pDWH is therefore an integrated, subject-orientated, time-variant, and non-volatile repository of product features. The logical link between the transactional and the product-orientated data are keys, based on the bill of material (BOM). Hence, the multidimensionally modeled feature objects are prepared to an analyzable level and linked with economic data. It is thus possible to combine information from product features with the traditional dimensions of managerial analysis, in order to identify impacts of design-orientated decisions on product lifecycle within the logic layer of the BI framework.

At the access layer KEs are therefore in the position to get

- an extended decision support with different time and object horizons and
- to disclose feature interdependencies in the whole product lifecycle.

First feedback from practitioners received by interviewing experts shows that enterprises see crucial advancement to increase their innovative abilities by realizing this generic concept. In further research activities, the approach has to be concretized by means of real product and corporate scenarios in order to ensure a successful implementation of the concept.

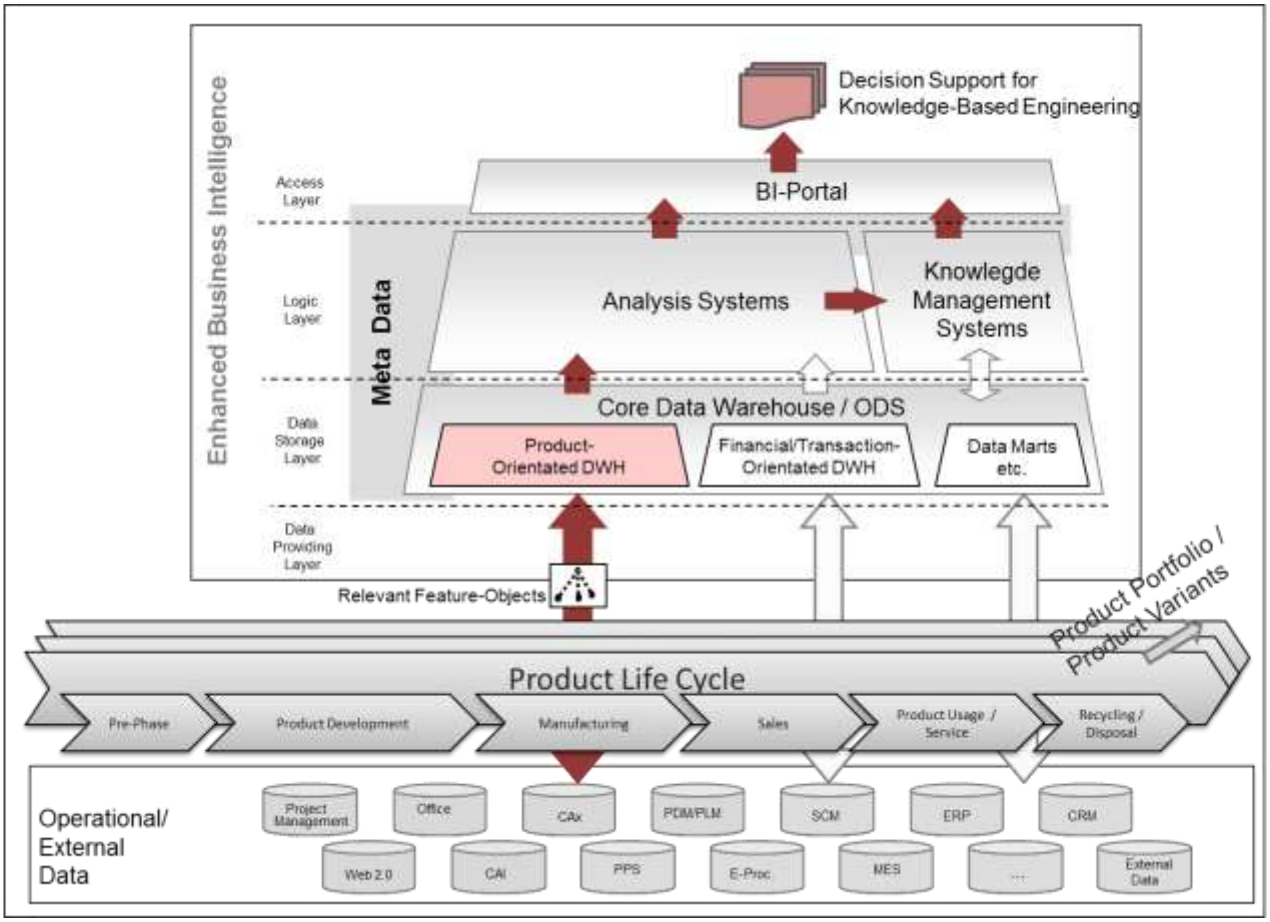

Figure 3: Conceptual Framework, based on Kemper et al., 2010

RESULTS AND LIMITATIONS OF THE RESEARCH

Yet, there are no existing concepts to analyze DMUs and further technical data sources, relating to consequences on the product lifecycle and product variants including managerial key figures. Based on an action design research process, the information demand of lifecycle-orientated decision-makers was explored and verified with the aid of a multilevel research including expert interviews and use cases. Also an enhanced BI concept was developed and discussed with experts based on the insights of the presented use case. It is assumed that a considerable practical benefit can be verified at least in some fields of application due to received feedback about the concept. But it also has to be acknowledged that there are some limitations: the research focuses on industrial businesses. Because of the chosen methodology, the sample of the empirical research is limited to a few businesses. It has to be mentioned that the expected results have to be tested in further businesses to be able to derive general findings. Another limitation is that in this research the development and manufacturing of physical goods is under consideration. So far it is not part of the research to focus on non-physical goods like services. The research therefore aims at testing the technical feasibility of the concept within different industry sectors by prototypical realizations. For the fields in which a prototypical realization is successful, software producers from the field of BI and CAD/PDM can be gained as cooperation partners.

REMARK

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REFERENCES

1. Ariyachandra, T. and Watson, J. (2006) Which Data Warehouse Architecture is the Most Successful, in *Business Intelligence Journal*, Vol. 11(1), 2–4.
2. Atre, S. and Moss, S. T. (2005) Business Intelligence Roadmap – The Complete Project Lifecycle for Decision Support Applications, Wiley, Boston (MA).
3. Baars, H. and Kemper, H.-G. (2008) Management Support with Structured and Unstructured Data: An Integrated Business Intelligence Framework, in *Information Systems Management*, Vol. 25 No. 2, 132-148.
4. Chatterjea, K. (2000) Knowledge Management: The most likely prime-over for the next decade, in *Towards a knowledge-driven marine industry*. Singapore, 1-7.
5. Ehrlenspiel, K. (2007) Integrierte Produktentwicklung, 3rd. Edition, Hanser Verlag, Munich and Vienna.
6. Eigner, M. and Stelzer, R. (2009) Product Lifecycle Management, 2nd Edition, Springer, Heidelberg, London and New York.
7. Giannakakis, T. and Vosniakos, G. C. (2008) Sheet metal cutting and piercing operations planning and tools configuration by an expert system, in *The International Journal of Advanced Manufacturing Technology*, Vol. 36, No. 7-8, 658-670.
8. Hossain, L., Patrick, J. D. and Rashid, M. A. (2002) Enterprise Resource Planning: Global Opportunities & Challenges, IGP, London.
9. Inmon, W. H. (1999) Building the operational data store, Wiley, New York.
10. Inmon, W. H. (2005) Building the data warehouse, Wiley, New York.
11. Jarke, M., Lenzerini, M., Vassiliou, Y. and Vassiliadis, P. (2003) Fundamentals of data warehouses, Springer, Berlin and Heidelberg.
12. Jukic, N. (2006) Data Marts and Data Warehouse, in *Studies in Computational Intelligence*, Vol.29, 75-150.
13. Kebede, G. (2010) Knowledge management: An information science perspective, in *International Journal of Information Management*, Vol. 30, Issue 5, 416-424.
14. Kemper, H. G. Baars, H. and Mehanna, W. (2010) Business Intelligence – Grundlagen und praktische Anwendungen, Vieweg and Teubner, Wiesbaden.
15. Kendal, S. (2007) in: Creen, M. (2007) *An Introduction to Knowledge Engineering*, Springer, London.
16. Kent, A. (1998) Encyclopedia of Library and Information Science, Vol. 63, CRC Press LLC, New York.
17. Kimball, R. and Ross, M. (2002) The data warehouse toolkit: the complete guide to dimensional modeling, Wiley, New York, Weinheim.
18. Kletti, J. (2007) Manufacturing Execution System: MES, Springer, Berlin and Heidelberg.
19. Koch, M., Baars, H., Lasi, H. and Kemper, H.-G. (2010) Manufacturing Execution Systems and Business Intelligence for Production Environments, in *Proceedings of the 16th Americas Conference on Information Systems (AMCIS)*, Lima.
20. Koch, M., Lasi, H. and Kemper, H.-G. (2011) Informationsmanagement in der Produktion - Empirische Ableitung eines Konzepts zur Ermittlung produktionsspezifischer Informationsbedarfe, in *Proceedings of the 10th International Conference on Wirtschaftsinformatik 2011*, Zurich.
21. Lasi, H. (2009) Aufbau eines IT-basierten Integrationskonzepts zur Unterstützung von Produktentwicklungs- und Produktionsprozessen, Eul, Lohmar-Köln.
22. Lasi, H., Hollstein, P. and Kemper, H.-G. (2010) Heterogeneous IT landscapes in innovation processes - an empirical analyses of integration approaches, in *Proceedings of the International Conference Information Systems (IADIS)*, Porto.
23. Lindemann, U. (2006) Methodische Entwicklung technischer Produkte: Methoden flexibel und situationsgerecht anwenden, Springer, Berlin.
24. Mayring, P. (2001) Kombination und Integration qualitativer und quantitativer Analyse, Forum Qualitative Sozialforschung / Forum Qualitative Social Research, 2(1), Art. 6, http://nbn-resolving.de/urn:nbn:de:0114-fqs010162, 2012-04-19.

25. McClellan, M. (1997) Applying Manufacturing Execution Systems, CRC Press LLC, Boca Raton (Fl).
26. Molloy, O., Tilley, S. and Warman, E. (1998) Design for Manufacturing and Assembly: Concepts, architectures and implementation, Chapman & Hall, London, New York et al.
27. Monk, F. E. and Wagner B. J. (2007) Concepts in Enterprise Resource Planning, 3rd Edition, Course Technology Cenage Learning, Boston (MA).
28. Negash, S. (2004) Business Intelligence, in *Communications of the Association for Information Systems*, Vol. 13, 77-195.
29. Österle, H., Becker, J., Frank, U., Hess, T., Karagiannis, D., Krcmar, H., Loos, P., Mertens, P., Oberweis, A. and Sinz, E. J. (2011) Memorandum on design-oriented information systems research, in *European Journal of Information Systems*, Vol.20, 7-10.
30. Ophey, L. (2005) Entwicklungsmanagement: Methoden in der Produktentwicklung, Springer, Berlin and Heidelberg.
31. Ovtcharova, J., A Framework for Feature-Based Product Design: Fundamental Principles, System concepts, Applications, VDI Verlag, Darmstadt.
32. Röhner, S., Breitsprecher, T. and Wartzack, S. (2011) Acquisition of design-relevant knowledge within the development of sheet-bulk metal forming, in *Proceedings of the International Conference on Engineering Design, ICED11*, Denmark.
33. Rudolph, F.-N. and Dietrich, J. (2006) Marktstudie: Praktischer Einsatz von CAD und EDM/PDM-Systemen, in *CAD-CAM Report*, Part I: No. 3, 58-63, Part II: No. 5, 58-61 and Part III: No. 6, 52-55, Dressler Verlag, Heidelberg.
34. Schreiber, G. (2008) Knowledge Engineering, in: van Harmelen, F., Lifschitz, V., and Porter, B., (2008) *Handbook of Knowledge Representation,* Elsevier Science, Amsterdam.
35. Sein, M. K., Henfridsson, O., Purao, S., Rossi, M. and Lindgren, R. (2011) Action Design Research, in *MIS Quarterly*, Vol. 35, Issue1, 37-56.
36. Shah, J. J. and Mäntylä, M. (1995) Parametric and Feature-Based CAD/CAM: Concepts, Techniques and Applications, John Wiley & Sons, INC., New York, Chichester et al.
37. Shaw, M. and Gaines, B. (1983) A Computer Aid to Knowledge Engineering, http://pages.cpsc.ucalgary.ca/~gaines/reports/KBS/BCSES83/BCSES83.pdf, 2012-04-19.
38. Turban, E., Aronson, J. E. and Liang, T.-P. (2005) Decision Support Systems and Intelligent Systems, 7th Edition, Pearson Prentice Hall, New Jersey.
39. VDI (2003) Information technology in product development, Feature Technology, VDI-Verlag, Düsseldorf.
40. VDI (2007) VDI 5600: Manufacturing Execution Systems, VDI Verlag, Düsseldorf.
41. Wang, R. Y. and Strong, D. M. (1996) Beyond Accuracy: What Data Quality Means to Data Consumers, in *Journal of Management Information Systems*, Vol.12, No.4, 5-34.
42. Weber, P. (2003) Digital Mock-up im Maschinenbau, Shaker Verlag, Aachen.
43. Zins, C. (2007) Conceptual approaches for defining data, information and knowledge, in *Journal of the American Society for Information Science and Technology*, Vol. 58(4), 479–493.