Extended Abstract - Decision Support for Operational Excellence in Manufacturing Systems

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1. SHORT ABSTRACT

In order to remain competitive in the digital transformed economic world, the perfect match of supply and demand through supply chain and operations management is of essential importance. Flexibility, quality, costs and customer satisfaction are of major interest for companies. Programs aimed at improving these factors are often launched under the label "Operational Excellence" (OPEX), which literally means "excellent operational performance" [Dahm and Brückner 2014]. The pursuit of operational excellence contributes significantly to the success of companies [Issar and Navon 2016] and is intended to secure long-term survival [Dahm and Brückner 2014]. The aim of this work is to evaluate how decision support systems can help to achieve operational excellence. For this purpose, literature was analyzed to derive requirements for decision support via an OPEX framework in manufacturing systems.

General Terms: Decision Support Systems, Operations Management

Additional Key Words and Phrases: OPEX, Business Manufacturing Intelligence, P&OM

2. INTRODUCTION

Nowadays, companies use elements of different management systems and concepts simultaneously. These management systems provide fundamental insights for Operational Excellence. The main challenge is to combine these systems to gain the ability to react better and faster to market volatility including quick response times to emerging customer requirements and the adaption of new technologies. Operational Excellence (OPEX) is achieved through continuous adaptation and optimization of processes [Gleich 2008] and illustrates a collective concept for various management approaches to align all business processes to customer requirements, quality and efficiency [Dahm and Brückner 2014]. Gleich et al. [Gleich 2008] define Operational Excellence as the dynamic ability to realize effective and efficient core processes of the value chain through the integrative use and design of technological, cultural and organizational factors on the basis of the strategy. In this work, the OPEX framework is considered as an information platform that integrates current systems used in the production environment and summarizes the data and information from these various systems collected in the supply chain process. Moreover, this paper provides an overview of an OPEX framework. Thus, the OPEX framework is assigned to the the category of Manufacturing Intelligence Systems. The aim of this work was to identify requirements for operational excellence applications in the manufacturing industry. A literature review was conducted to identify grounded literature within this topic. Therefore we observed relevant topics of "Operational Excellence", "Performance Measurement", "Manufacturing Execution Systems", Business Intelligence" and "Manufacturing Intelligence" within the meta-database Web of Science.

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3. OPEX DSS

The use of an OPEX decision support system can enable production control by quickly summarizing the essential information and conducting a wide range of analyses. A continuous analysis and improvement of the operational performance requires continuous monitoring of critical activities and the use of appropriate indicators [Issar and Navon 2016]. These key performance indicators are intended to help identify gaps between expectation and performance and to subsequently develop appropriate actions [Wouters and Wilderom 2008]. An example of a key performance indicator for operational excellence is the overall equipment effectiveness, consisting of the factors availability, performance and quality of manufacturing processes [Kemper et al. 2004].

Despite large quantities of operational data, companies face the challenge to derive useful information from this data. Business Intelligence systems (BIS) are expected to close this gap [Zeng et al. 2012]. BIS have the goal to improve decision-making "quality" through faster availability and higher data quality [Negash 2004]. The data which create the basis for BIS are gathered from various sources, such as Enterprise Resource Planning (ERP) or Manufacturing Execution Systems (MES), which are of different quality or exist in different formats. ERP is the integrated management of core business processes and MES provides traceability and enables the control of multiple elements of the production process to support the decision making process in manufacturing. The integration of this data is therefore a major challenge for BI systems and as the storage of large amounts of data becomes increasingly favorable, companies collect unstructured data in large quantities [Chaudhuri et al. 2011]. Business intelligence systems are intended to support the decision-making process by integrating these increasing volumes of unstructured data from internal and external sources [Isik et al. 2011]. Intelligent decision-making is one of the current keywords in this research field and is interrelated to modern business development. The potential of big data and advanced artificial intelligence offers new insights for innovations on Decision Support Systems (DSS) and for decision-making in the form of more objective and evidence-based smart decisions [Abbasi et al. 2016; Zhou et al. 2015]. The main impact and key aspect of these intelligent systems is an improved method of data analysis. The mere collection, storage and unregulated use of data has no direct impact on decision-making so far [Babiceanu and Seker 2016]. DSS research and development will benefit from progress in huge data bases, artificial intelligence and human-machine interactions [Power 2008]. In the case of the Industry 4.0 paradigm, the massive increase of data allows the optimization and improvement of models to enhance error analysis and the prediction of specific situations to set up counteractive measures [Andreadis et al. 2014]. Decisions made to optimize efficiency and effectiveness of manufacturing systems are reaching from the strategic level to tactical and operational production scheduling and control. Automating these decisions by using innovative algorithms and intelligent software applications based on the knowledge in the field of production and operations management, the performance of a manufacturing system can be improved [Felsberger et al. 2016].

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REFERENCES

Ahmed Abbasi, Suprateek Sarker, and RH Chiang. 2016. Big data research in information systems: Toward an inclusive research agenda. *Journal of the Association for Information Systems* 17, 2 (2016), 3.

Georgios Andreadis, Paraskevi Klazoglou, Kyriaki Niotaki, and Konstantin-Dionysios Bouzakis. 2014. Classification and review of multi-agents systems in the manufacturing section. *Procedia Engineering* 69 (2014), 282–290.

Radu F Babiceanu and Remzi Seker. 2016. Big Data and virtualization for manufacturing cyber-physical systems: A survey of the current status and future outlook. *Computers in Industry* 81 (2016), 128–137.

Surajit Chaudhuri, Umeshwar Dayal, and Vivek Narasayya. 2011. An overview of business intelligence technology. *Commun. ACM* 54, 8 (2011), 88–98.

Markus H Dahm and Aaron D Brückner. 2014. *Operational Excellence mittels Transformation Management: Nachhaltige Veränderung im Unternehmen sicherstellen–Ein Praxisratgeber*. Springer-Verlag.

Andreas Felsberger, Bernhard Oberegger, and Gerald Reiner. 2016. A Review of Decision Support Systems for Manufacturing Systems.. In *SAMI@ iKNOW*.

Ronald Gleich. 2008. *Operational excellence: innovative Ansätze und best practices in der produzierenden Industrie*. Haufe-Lexware.

Oyku Isik, Mary C Jones, and Anna Sidorova. 2011. Business intelligence (BI) success and the role of BI capabilities. *Intelligent systems in accounting, finance and management* 18, 4 (2011), 161–176.

Gilad Issar and Liat Ramati Navon. 2016. *Operational Excellence: A Concise Guide to Basic Concepts and Their Application*. Springer.

Hans-Georg Kemper, Walid Mehanna, and Carsten Unger. 2004. Business Intelligence–Grundlagen und praktische Anwendungen. *Vieweg, Wiesbaden* (2004).

Solomon Negash. 2004. Business intelligence. *The communications of the Association for Information Systems* 13, 1 (2004), 54.

Daniel J Power. 2008. Decision support systems: a historical overview. In *Handbook on Decision Support Systems 1*. Springer, 121–140.

Marc Wouters and Celeste Wilderom. 2008. Developing performance-measurement systems as enabling formalization: A longitudinal field study of a logistics department. *Accounting, Organizations and Society* 33, 4 (2008), 488–516.

Li Zeng, Ling Li, and Lian Duan. 2012. Business intelligence in enterprise computing environment. *Information Technology and Management* 13, 4 (2012), 297–310.

Hong Zhou, Christopher Noble, and Julie Cotter. 2015. A Big Data Based Intelligent Decision Support System for Sustainable Regional Development. In *2015 IEEE International Conference on Smart City/SocialCom/SustainCom (SmartCity)*. IEEE, 822–826.