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IFAC-PapersOnLine 48-3 (2015) 277–282

# Modelling Knowledge about Data Analysis Processes in Manufacturing

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**Abstract:** In industry 4.0, analytics and business intelligence (BI) are of particular importance to increase productivity, quality, and flexibility. It is necessary to make right and quick decisions for effective and efficient problem solving and process improvements. Modern technologies allow to collect a large amount of data that can be analysed. Heterogeneity and complexity of industrial environments require considerable expert knowledge to perform meaningful and useful data analysis. BI analysis graphs represent expert knowledge about analysis processes. This knowledge can be modelled pro-actively at schema level and used at instance level. Analysis situations can be considered as multi-dimensional queries and represent nodes of a BI analysis graph. An arc between two nodes is a relationship between two analysis situations describing the difference of both. It represents a navigation step, e.g., an online analytical processing (OLAP) operation, of the analysis process. We demonstrate BI analysis graphs by a use case originated from manufacturing of brushes. Complex analysis paths, e.g., to analyse substitute material in the case of delayed delivery, are modelled by BI analysis graphs and can be used multiple times (also by non-experts). Reinvention of analysis knowledge is prevented – right and quick decisions for finding effective and efficient problem solutions can be made.



*Keywords:* decision making, knowledge representation, data models, process models, manufacturing, industry 4.0, data warehouses, business intelligence

## 1. INTRODUCTION

In many areas, business analysts need to explore a large amount of data to answer management questions or questions of other stakeholders. In most cases the data is heterogeneous and considerable expert knowledge is required to perform meaningful and useful data analysis. Based on the result of data analysis, strategic decisions (e.g., decision whether or not to outsource the production of a whole product line) or operative actions (e.g., ordering appropriate substitute material for production, if there is a serious delayed delivery of planned material) are made depending on the given analysis goal. General contributions to the integration of various decision levels in manufacturing companies can be found in Gerber et al. (2012).

Business intelligence (BI) and analytics give a wide range of opportunities for comprehensive data analyses. Data is collected in data warehouses, organized in multi-dimensional cubes, and queried by online analytical processing (OLAP) operations. Whereas it is common to model "static" knowledge about the underlying data, e.g., as a dimension fact model (DFM), see Golfarelli et al. (1998), there are no appropriate means for modelling "dynamic" knowledge about analysis processes – such as, e.g., it can be found analogously in business process modelling notation (BPMN), see Silver (2011).

Industry 4.0 — an initiative of the German government — has become a new catchword emphasizing a "new industrial revolution" that automates customization of products on demand. Whereas in conventional production systems large quantities of a small range of products are manufactured, in industry 4.0 companies have to produce large quantities of a wide range of items with many options of individual customer configurations (mass customization). Production systems are coped with massive order-related manufacturing. With respect to these trends, smart factories and internet of things are visions that become reality, see Zühlke (2009). Dealing with big data issues for rapid decision making to improve productivity rises new challenges for companies, see Lee et al. (2014). In this context, analytics and business intelligence are of particular importance to increase productivity, quality, and flexibility. Right and quick decision making is necessary to guaranty effective and efficient problem solutions and process improvements. Data exploration is one of the key factors necessary for this endeavour. Heterogeneity and complexity of industrial environments issues a challenge to business analysts – considerable expert knowledge about data analysis processes in industrial environments is required.

To overcome these analysis requirements for industry 4.0, data must be integrated quickly into data warehouses and actions, as a consequence of the analysis result, should be executed automatically. Near real-time data warehouses

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Peer review under responsibility of International Federation of Automatic Control.
10.1016/j.ifacol.2015.06.094

set the focus to fast data integration, see Bruckner et al. (2002). Active data warehouses offer support to automate the routine elements of decision tasks by extending conventional data warehouse architecture with analysis rules, see Thalhammer et al. (2001). Analysis and judgement rules can be extended for ontology-driven comparative data analysis, see Steiner et al. (to appear in 2015).

Another crucial point for a successful analysis environment in manufacturing is the provision of expert knowledge and its flexible application. E.g., in the case of analysing substitute material, an analyst must have knowledge about material properties, about its usage within the production process, and about customers' requirements. Knowledge about data is made visible by elaborating conceptual models, e.g., dimension fact models. Business and technical terms are documented in business glossaries. The meaning of measures is described by mappings that relate original attributes of data sources to measures used for analysis. In contrast to these modelling and documentation support there exists no adequate means to model analysis processes itself, although these contain tacit valuable expert knowledge. A business analyst performs an analysis and evaluates the results that again induces a subsequent analysis, and so on. The difference between two analysis situations can be considered as an application of the analyst's expertise, or, in other words, navigation from one analysis situation to another one represents knowledge.

To achieve this type of knowledge integration, analysis processes should be modelled *pro-actively* to provide analysis guidance. Operational business processes are characterized by online transaction processing (OLTP) allowing a high degree of automation. In contrast, analysis processes can be considered as semi-routine processes comprising routine and non-routine elements. In analysis processes query execution and user interaction about how to proceed in the process (depending on the analysis situation) alternate frequently. Whereas other approaches about analysis processes focuses on evaluation of analysis situations' instances — see Romero et al. (2011), Giacometti et al. (2009), and Jerbi et al. (2009) — our approach sets priorities to pro-active modelling at schema level.

The focus of our approach lies on preparation for decision-making. The aim is to prepare decision-relevant data for management, e.g., required in emergency meetings. A business analyst searches for opportunities and impacts to support decision-making. To support the business analyst we provide more than fixed guided reports. By *pro-active modelling*, analysis processes can be flexibly defined, adapted, and subsequently executed. The business analyst gets suitable analysis guidance.

In this paper we show how knowledge about data analysis processes can be modelled *pro-actively* and used in the field of manufacturing. The approach is based on BI analysis graphs, see Neuböck et al. (2012) – our previous work focused on the instance level of analysis situations and not on modelling analysis situation schemas pro-actively. A BI analysis graph consists of analysis situations as nodes representing multi-dimensional queries and navigation operations (e.g., OLAP operations) as arcs representing relationships between analysis situations (the difference of two analysis situations). In the paper in hand we show

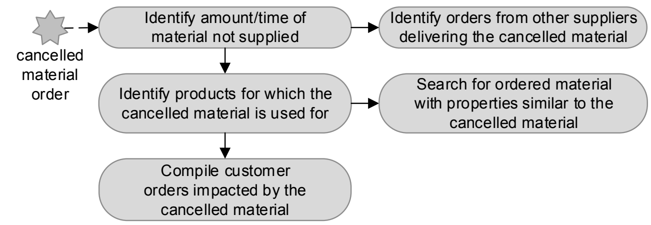


Fig. 1. Analysis graph (undetailed view)

how knowledge about analysis processes can be modelled at schema level (modelling) and used at instance level (analysing). The approach is demonstrated by a use case from the manufacturing area (production of various types of brushes with a high level of customization). It gives an understanding of how complex analysis paths can be modelled and used multiple times (also by non-experts; preventing reinvention). Right and quick decisions can be made to solve acute issues or to enforce effective and efficient process improvements.

Section 2 introduces the manufacturing use case. Section 3 presents the schema of a single analysis situation and shows how an analysis situation is instantiated. Analysis graph schemas are described in section 4 starting with the schema of a single navigation operation. Linking a set of analysis situations schemas by navigation operations returns the schema of an analysis graph. Section 5 shows the use of analysis graphs. A business analyst traverses analysis situations including backtracking. Finally, section 6 concludes our presentation with an outlook.

## 2. USE CASE

Our use case falls into the field of manufacturing brushes of various types. It comes from our Austrian business partner KOTI Kobra — a member of the European company group KOTI. To satisfy customers' requirements, the company has to offer both large scale production and strong customization leading up in an extreme case to a batch size of one. The focus lies on an order-related production process. Manufacturing of brushes covers a wide application range, i.e., everything that consists of a body material and bristles can be considered as a brush. Industrial and technical brushes, strip and sealing brushes, work tool brushes, sweeping and cleaning brushes, runway brushes, hygiene brushes, or entrance brush mats are important brush applications. Brushes are produced for various markets, e.g., automotive, airport and winter equipment, chemical industry, electronics, food and beverage industry, etc. Various production parameters are important for customization: base types of brushes (strip brush, roller brush, brush discs), body and bristle material (e.g., with respect to temperature resistance, lifetime, mechanical load, etc.), number and ordering of drill holes for bristles, colour, etc.

KOTI Kobra is faced with analysis tasks for solving strategic and operational issues. Here we demonstrate an analysis process that is triggered by a cancelled material order. In this case the situation and the courses of actions must be analysed and relevant information has to be gathered (preparation stage for decision making). The result of this analysis process can be used in an emergency meeting of the management as a well-founded basis for