A Mobile Dashboard for Analytics-based Information Provisioning on the Shop Floor

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Abstract: Today's turbulent global environment requires agility and flexibility of manufacturing companies to stay competitive. Thus, employees have to monitor their performance continuously and react quickly to turbulences which demands real-time information provisioning across all hierarchy levels. However, existing manufacturing IT systems, e.g., Manufacturing Execution Systems (MES), do hardly address information needs of individual employees on the shop floor. Besides, they do not exploit advanced analytics to generate novel insights for process optimization. To address these issues, the Operational Process Dashboard for Manufacturing (OPDM) is presented, a mobile data-mining-based dashboard for workers and supervisors on the shop floor. It enables proactive optimization by providing analytical information anywhere and anytime in the factory. In this paper, first, user groups and conceptual dashboard services are defined. Then, IT design issues of a mobile shop floor application on top of the Advanced Manufacturing Analytics Platform are investigated in order to realize the OPDM. This comprises the evaluation of different types of mobile devices, the development of an appropriate context model and the investigation of security issues. Finally, an evaluation in an automotive industry case is presented using a prototype in order to demonstrate the benefits of the OPDM for data-driven process improvement and agility in manufacturing.

Keywords: Dashboard; Cockpit; Process Optimization; Data Analytics; Business Intelligence; Data Mining

1 Introduction

Nowadays, manufacturing companies have to face intense competition in a globalized and highly turbulent environment. Ever shorter product lifecycles, rapidly changing customer needs and erupting market structures necessitate agile and flexible as well as continuously optimized company structures and processes (Westkämper 2009). The successful realization of agility-oriented management concepts such as the Stuttgart Enterprise Model (Westkämper, Hummel, and Rönnecke 2005) require comprehensive real-time information provisioning and transparency across all hierarchy levels, from the shop floor level to the enterprise control level. Workers have to be able to monitor their current performance, recognize problems quickly and react immediately to turbulent situations in order to avoid uncoordinated waiting times and costly communication (Bracht, Hackenberg, and Bierwirth 2011). For this purpose, data on the current status of manufacturing operations on the shop floor has to be aggregated, enriched and analysed in order to generate insights for process optimization and feed them back to the different hierarchy levels in a data-driven improvement cycle.

For example, if a certain combination of machine settings and input materials in a manufacturing step leads to quality problems in subsequent steps very likely, workers and supervisors should be warned proactively during process execution and action recommendations should be provided on how to avoid the problem. For this purpose, not only metrics-based performance data about the manufacturing process is necessary but advanced data analytics are needed enabling predictive optimization. In addition, employees have to be able to access information on the process status, on work instructions and on improvement suggestions anytime and anywhere on the factory shop floor in order to flexibly react to such changes.

However, existing manufacturing IT systems, e.g., Enterprise Resource Planning (ERP) or Manufacturing Execution Systems (MES) (Kletti 2007), are coined by the following three major insufficiencies which considerably limit flexibility and data-driven process optimization on the shop floor:

1. They are primarily designed for the enterprise control level and the manufacturing control level and do not address information needs of individual employees on the shop floor.
2. They do not exploit advanced data analytics, e.g., data mining techniques, to extract knowledge from the huge amounts of data generated during process execution and control.
3. They do hardly provide mobile and situation-aware information, e.g., by using mobile devices such as smartphones and tablet PCs.

To address these issues, the Operational Process Dashboard for Manufacturing (OPDM) is presented in this paper, a mobile and analytics-based dashboard for workers and supervisors on the shop floor in discrete manufacturing. It enables proactive process optimization and responsiveness on the shop floor by providing analytical process information and services, e.g., current metric values and data-mining-based root cause analyses, ubiquitously and near-real-time across the entire factory. Thereby, the OPDM holistically addresses the whole range of process-oriented information needs, namely process context, process performance, process knowledge and process communication, in a situation-aware manner.

The remainder of this paper is organized as follows: In Section 2, the most significant related work with respect to dashboards in manufacturing is categorized. Next, user groups of the OPDM as well as conceptual dashboard services are defined in Section 3. In Section 4, the requirements of the OPDM are investigated from the point of view of a Business Intelligence application and the Advanced Manufacturing Analytics (AdMA) Platform (Gröger et al. 2012) is presented as a technical basis for the OPDM. Section 5 focuses on general design issues of a mobile shop floor application for smartphones and tablet PCs on top of the AdMA platform in order to realize the OPDM. To this end, different types of mobiles devices, context management issues as well as security issues are investigated. The application of the OPDM in an automotive industry case as well as evaluation issues are comprehensively covered by Section 7. This includes real-world application scenarios and details on data mining techniques and data structures. Finally, Section 8 concludes the paper and highlights future work.

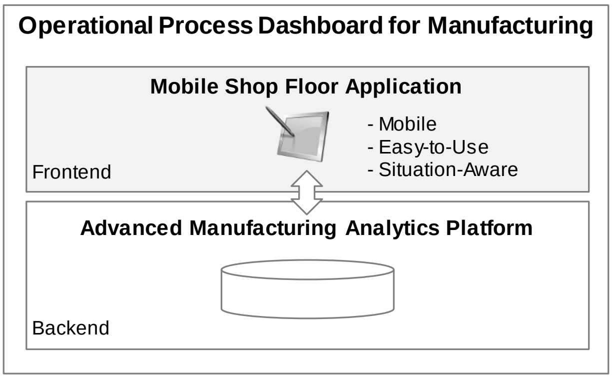

Figure 1: Building blocks of the OPDM.

This paper results from the research project Advanced Manufacturing Analytics (Gröger 2015) and specifically builds on the authors' previous work (Gröger et al. 2013a) which provides the basic concept and the requirements of the OPDM covered by the Sections 2, 3 and 4.1. Taking this as a starting point, the paper at hand addresses the realization challenge of the OPDM and focuses on the development of a mobile shop floor application and the evaluation of the entire OPDM (see Figure 1). The main contributions can be summarized as follows:

- A *conceptual analysis of the OPDM from the point of view of a Business Intelligence application is conducted* and the *AdMA platform is investigated as a technical ba*sis for the realization of the OPDM. This reveals the need for a mobile shop floor application on top of the AdMA platform as shown in Figure 1 (see Sections 4.2-4.4).
- General *IT design issues of a mobile shop floor application are investigated* to enable mobile, easy-to-use and situation-aware access to analytical optimization services on the shop floor. This comprises the *evaluation of different types of mobile devices*, especially tablet PCs (see Section 5.1), the *development of an appropriate context model* and the *investigation of localization techniques* suited for the shop floor (see Section 5.2). Besides, to address security issues, *concepts for data security in mobile applications* are studied (see Section 5.3).
- A *comprehensive evaluation of the entire OPDM* is conducted. It comprises both a *case-based evaluation* of the OPDM in an automotive industry case (see Sections 6.1-6.4) and a *comparative evaluation* with existing approaches (see Section 6.5). The evaluation highlights the technical feasibility and applicability of the OPDM and demonstrates the benefits of mobile and analytics-based information provisioning for continuous data-driven process improvement and agility in manufacturing (see Section 6.6).

2 Information Provisioning and Dashboards in Manufacturing

In this section, existing manufacturing dashboard concepts in terms of IT tools for information provisioning in manufacturing are structured. Thereby both, stationary and mobile dashboard realizations with a focus on mobile apps are taken into account. The latter refer to applications on touchscreen-based consumer devices, especially smartphones and tablet PCs, as defined in (Gröger et al. 2013b). First, the term 'dashboard' is defined, then existing dashboard approaches are categorised, and finally, the concept of the OPDM is differentiated.

In general, the term dashboard is inspired by dashboards in automobiles and aircrafts. Digital dashboards refer to dashboards in the area of Business Intelligence whereas no common, exact definition of the term exists (Adam and Pomerol 2008). In literature two types of definitions can be found: In a stricter sense, the term refers to tools for the graphical visualization of key performance indicators (KPIs) complemented by reporting functions for top managers, synonymously often called management cockpits (Rainer and Cegielski 2011). In a broader sense, digital dashboards are intuitive and easy-to-use front ends for monitoring, analysing and optimizing critical business activities by enabling users on all hierarchy levels to improve their decisions (Eckerson 2011; Malik 2005). In this paper, *the term dashboard always denotes a digital dashboard in a broader sense* focusing services and contents provided by the dashboard to the user.

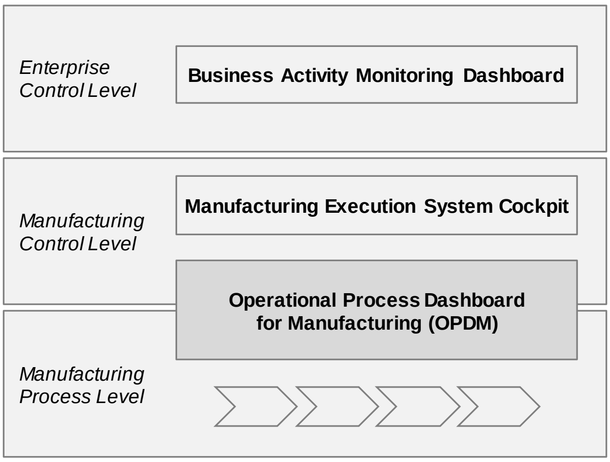

Figure 2. Classification of dashboard concepts (Gröger et al. 2013a).

Based on a literature review, major existing dashboard concepts in the context of manufacturing were identified. As shown in Figure 2, these dashboards can be classified according to the organizational level, that is, the hierarchy level the dashboard's services are designed for. It is based on a simplified version of the hierarchy model of manufacturing (International Society of Automation 2000) with the enterprise control level, comprising business-related activities such as production planning, the manufacturing control level, comprising the management of single manufacturing process executions, as well as the manufacturing process level, comprising the physical process on the shop floor. In this paper, the *term 'manufacturing process'* refers to all steps and resources from the creation of the production order until the finishing of a part or product as defined in the work plan. Moreover, the *term 'business process'* is used in the context of this work in order to refer to all other types of processes in a company, e.g., procurement processes or after sales processes.

Business Activity Monitoring (BAM) (McCoy 2002) and related dashboards focus on the real-time monitoring and analysis of critical business processes to identify irregularities during process execution and react promptly (Muehlen and Shapiro 2010). These dashboards are used on the enterprise control level and provide KPI monitoring and alerting. They are typically implemented in company-specific variants on top of ERP or workflow management systems using business intelligence and data warehousing platforms (Kemper, Baars, and Mehanna 2010). Traditional BAM realizations focus on stationary access, e.g., using browser-based frontends, whereas recently mobile apps are becoming more and more popular to provide current KPI information on-the-go (Airinei and Homocianu 2010).

MES cockpits are dashboards for manufacturing operations management used by production supervisors on the manufacturing control level (Kletti 2007). They are part of MES and support detailed scheduling, process monitoring as well as resource management. Regarding analytics, control panels are mainly based on simple statistics and reporting with basic alerting services. Control panels are typically realized on fixed work stations whereas recently MES vendors begin to port selected functions to mobile apps for the shop floor, e.g., OpsTrakker Mobile App (Enhanced Information Solutions 2014) and HYDRA Smart MES Apps (MPDV 2014).

Regarding *dashboards for the shop floor,* an initial approach named 'Visualization System for Operational Logistics' is presented in (Bracht, Hackenberg, and Bierwirth 2011). It includes a dashboard for the real-time visualization of process performance information, mainly KPIs, for shop floor workers in logistics and is implemented as a mobile app on a tablet PC. With respect to standard software solutions, SAP provides the Production Operator Dashboard (SAP 2012) as a dashboard for workers. It provides a web-browser-based frontend and mainly focuses on data acquisition as well as presentation of work instructions at stationary work places.

With respect to *mobile apps for the shop floor in general*, a comprehensive analysis is presented in (Gröger et al. 2013a). According to that, there are currently only rudimentary approaches focusing on isolated process aspects, e.g., apps for quality management such as SAP Quality Issue Mobile (SAP 2014) to track quality problems.

The OPDM significantly differs from these existing approaches, since a holistic mobile dashboard for shop floor workers and supervisors is provided. It goes beyond simple metrics-based performance information by providing data-mining-driven services and holistically addresses the whole range of process-oriented information needs.

3 User Groups and Dashboard Services

In this section, the user groups of the OPDM are described and corresponding conceptual dashboard services provided for these user groups are defined. The OPDM is designed for two major user groups, namely *workers* and *supervisors* on the shop floor. In the following, the term 'employee' is used to refer to both user groups. *Workers* comprise all employees who are directly involved in the execution of a manufacturing process, e.g., by controlling machines. *Supervisors* are responsible for the execution and control of a certain manufacturing process (or selected parts) and the corresponding group of workers and thus have a more aggregated view on manufacturing operations.

The dashboard services are grouped by the four process-oriented information needs for employees on the shop floor, namely *process context*, *process performance*, *process knowledge* and *process communication*. The following gives an overview of the dashboard services on a conceptual level. Special emphasis is put on services for process performance as these services are concerned with data analytics. To illustrate the concepts, a screenshot-based impression for an example OPDM for the mass manufacturing of steel springs in the automotive industry is given (see case example in Section 6). A further discussion of information needs and corresponding dashboard services can be found in the authors' previous work (Gröger et al. 2013a).

3.1 Process Context

Process context refers to information about both the context of the overall process, e.g., information about the goods to be produced, and the context of the particular process step a worker participates in, e.g., information about subsequent steps. On this basis, the worker grasps at a glance the current situation beyond his local work place. For supervisors, an overview of the whole process with all process steps is provided, which highlights currently failures and problems. In this way, the supervisor gets a quick impression about the overall state of the process.

3.2 Process Performance

In general, process performance refers to information about the technical and managerial performance of the process. It is based on set of business-critical metrics, that is, KPIs such as cycle time, to operationalize the effectiveness and efficiency of manufacturing operations, both on a process-wide and an employee-specific level (see Figure 3).

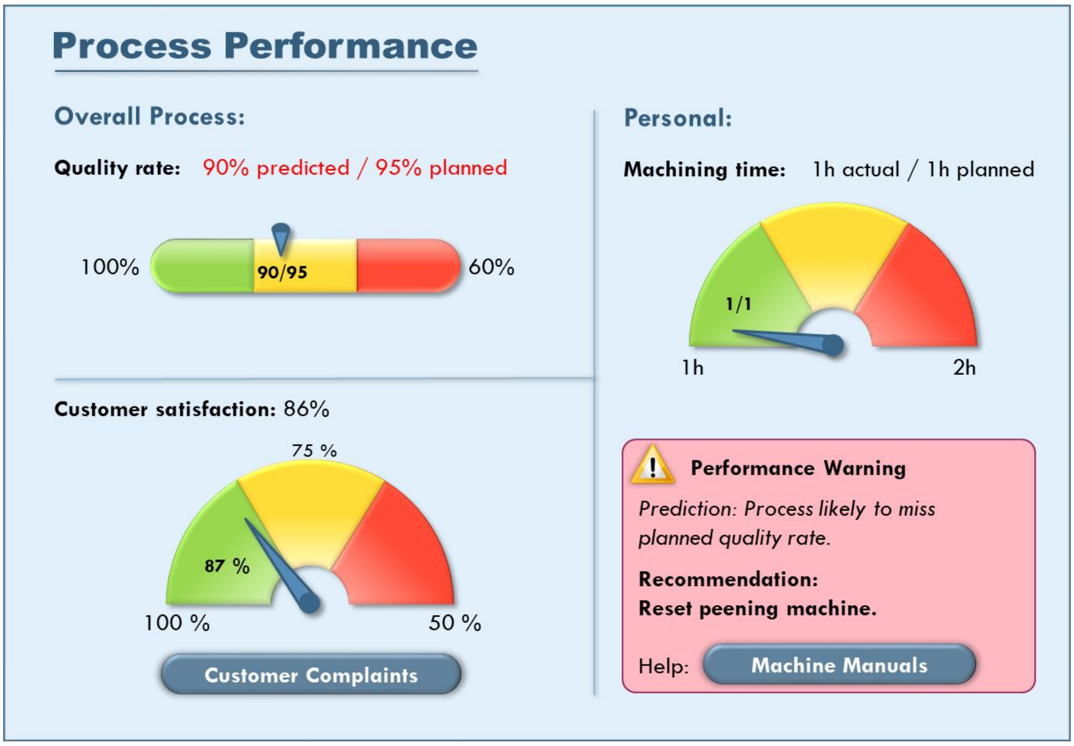

Figure 3. Screenshot of OPDM's process performance component (Gröger et al. 2013a; adapted from Procedia CIRP Vol. 7, © 2013 with permission from Elsevier).

In addition to descriptive KPI visualizations and statistics, predictive and prescriptive capabilities are provided by the OPDM to enable proactive and anticipatory acting of employees. This feature goes significantly beyond traditional BAM and control panel approaches. Metric-oriented predictions as presented in (Gröger, Niedermann, and Mitschang 2012) enable the forecasting of KPI values across the overall process based on data mining techniques If a process-wide KPI such as cycle time or quality rate is likely to exceed or fall below a certain threshold, all employees are warned during process execution and can take necessary measures. Moreover, a prescriptive analytics approach as described in (Gröger, Schwarz, and Mitschang 2014a) is provided, which proactively generates action recommendations on how to avoid the predicted KPI deviation, e.g., resetting a machine to avoid quality problems. This is based on data mining techniques to automatically identify improvement patterns in data on past process executions which prevented the metric deviation. In the same way, metric-oriented root cause analysis (Gröger, Niedermann, and Mitschang 2012) facilitates the identification of influence factors of KPI deviations across the entire manufacturing process, e.g., to identify reasons for high reject levels. It is particularly tailored for supervisors and exploits data mining techniques (see Section 6.3.2 for details on data mining techniques and data structures). These advanced analytics concepts leverage the huge amounts of data generated during process execution and control by extracting valuable knowledge for continuous process improvement.

3.3 Process Knowledge

Process knowledge comprises information on process instructions and process improvement to support organizational learning (see Figure 4).

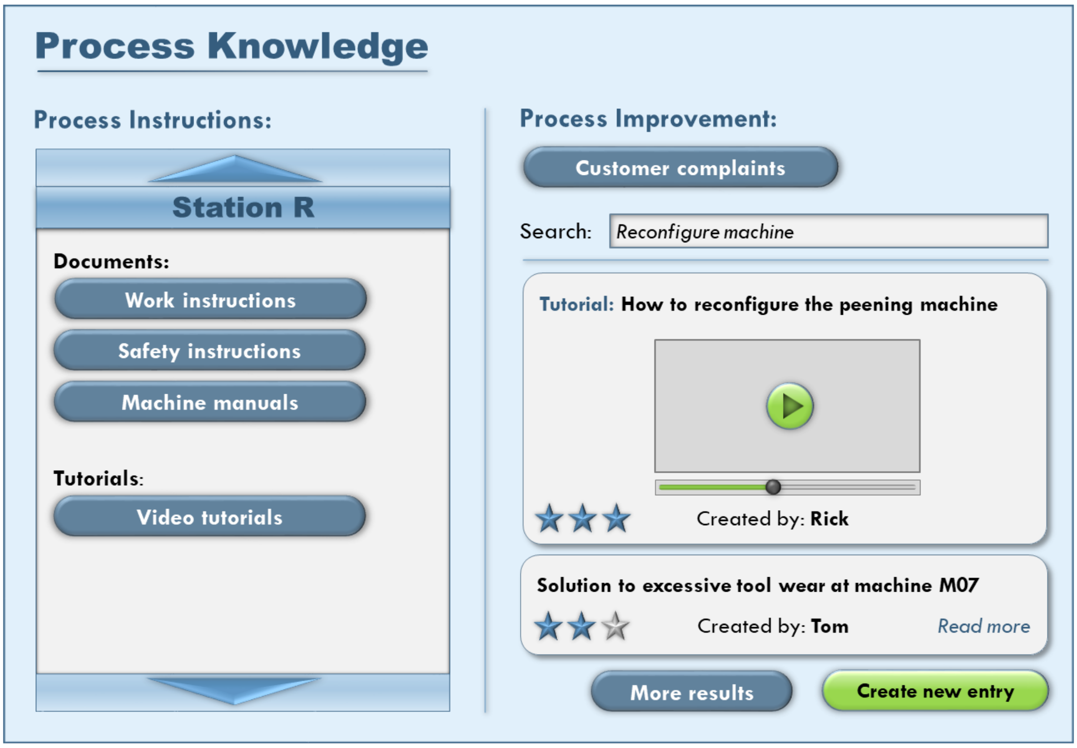

Figure 4. Screenshot of OPDM's process knowledge component (Gröger et al. 2013a; adapted from Procedia CIRP Vol. 7, © 2013 with permission from Elsevier).

Regarding interactive process instructions, there are not only traditional textual work instructions but additional photos and videos to enable fast introduction of new workers. In addition, there is a knowledge management component for process improvement. It represents a systematic solution for the creation, evaluation, sharing and application of suggestions for continuous improvements and problem tickets. These suggestions respectively tickets are created by workers and supervisors using text memos, photos, audio recordings or videos. This enables a community-driven improvement process integrating the valuable shop floor knowledge and hands-on experience of all employees on the shop floor.

3.4 Process Communication

Process communication refers to the exchange of information between different process participants to supports seamless interaction of employees, e.g., in case of exceptional situations. For this purpose, a component for asynchronous message exchange using text and audio messages as well as a real-time video conference component are provided. In contrast to process knowledge information, exchanged messages are only temporarily relevant and expire at some point in time, e.g., at the end of the current work shift. Process communication is designed to be simple and easy-to-use to encourage and foster information exchange on the shop floor.

4 Requirements and Technical Basis

From an IT point of view, the OPDM constitutes a Business Intelligence application (Kemper, Baars, and Mehanna 2010) as it requires components for data provisioning, data analytics as well as presentation. Section 4.1 defines the technical requirements of the OPDM and Section 4.2 presents the AdMA platform as a Business Intelligence platform and a technical basis for the realization of the OPDM. Finally, the AdMA platform is evaluated with respect to the requirements of the OPDM and necessary extensions, especially a mobile shop floor application, are identified in a gap analysis in Section 4.3.

4.1 Requirements Analysis

In the following, technical requirements of the OPDM are analysed considering each architectural layer of a Business Intelligence application, i.e., considering *data provisioning*, *data analytics and result sharing* as well as *presentation*.

Regarding the *data provisioning layer*, the OPDM requires not only data about the manufacturing process itself, e.g., the current cycle time, but additional operational data describing the subjects in the process, e. g., details about participating employees or machines. Thus, a *holistic data warehouse* integrating process manufacturing data and operational manufacturing data is a core requirement. In order to feed the OPDM with up-to-date information, *data provisioning has to be done in near-real-time*. That is, data changes in the source systems have to be immediately propagated to the holistic warehouse.

With respect to the data analytics and result sharing layer the OPDM requires both statistics and reporting concepts and data mining techniques for predictive and prescriptive issues. Moreover, a component for storing and sharing of content items is necessary to realize the OPDM areas process knowledge and process communication. In addition, a component for audio- and video-based communication is required to realize the conference system for process communication.

In view of the *presentation layer*, the user interface of the OPDM has to be *intuitive and easy-to-use*. Moreover, the services have to be presented in a *situation-aware* manner to realize a personalized and individualized information provisioning based on the current context of the user. Finally, a *flexible mobile usage* of the OPDM is necessary, as individual employees may change locations and walk through the factory, especially supervisors.

4.2 The Advanced Manufacturing Analytics Platform as a Business Intelligence Platform for Manufacturing

The AdMA platform (Gröger et al. 2012) is a Business Intelligence platform for data-mining-driven manufacturing process optimization. The conceptual architecture of the AdMA platform comprises three integrated layers as shown in Figure 5, namely the *data integration layer*, the *process analytics layer* and the *process optimization layer*, which are shortly presented in the following.

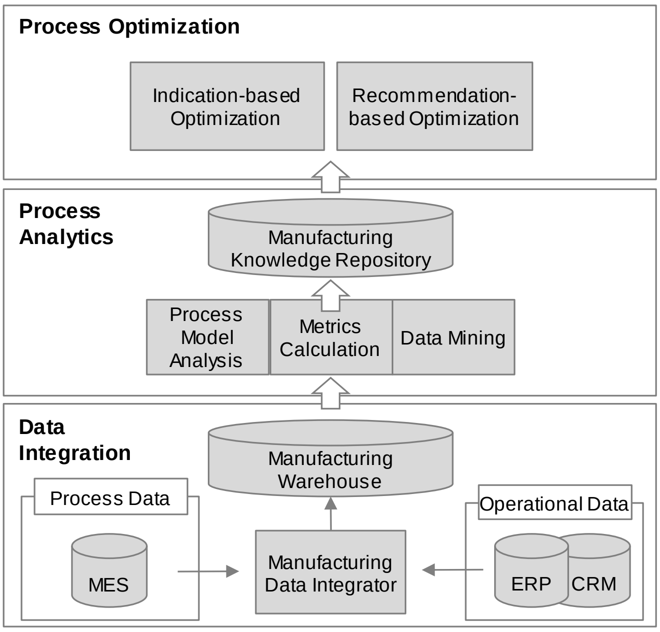

Figure 5. Conceptual architecture of the Advanced Manufacturing Analytics Platform.

On the *data integration layer*, the *Manufacturing Data Integrator* consolidates process manufacturing data and operational manufacturing data in a holistic process warehouse, the *Manufacturing Warehouse* (Gröger, Schwarz, and Mitschang 2014b).

The process *analytics layer* comprises various analytic techniques, especially *process model analysis*, *metrics calculation* and *data mining*, on top of the Manufacturing Warehouse in order to generate insights for process optimization and stores them in the *Manufacturing Knowledge Repository* (Gröger, Schwarz, and Mitschang 2014b). Details on the data model of the Manufacturing Knowledge Repository are presented in Section 6.2.2.

The Manufacturing Knowledge Repository and the Manufacturing Warehouse are based on a *generic manufacturing process meta model* (Gröger, Schwarz, and Mitschang 2014b). The meta model defines general constructs of discrete manufacturing processes, e.g., process steps and resources, and ensures the universal applicability of the AdMA platform independent of individual manufacturing processes.

The *process optimization layer* comprises optimization services that use and combine insights provided by the Manufacturing Knowledge Repository. *Indication-based optimization* (Gröger, Niedermann, and Mitschang 2012) uses preconfigured data mining models for root cause analyses and predictions. *Recommendation-based optimization* (Gröger, Schwarz, and Mitschang 2014a) generates concrete action recommendations for process improvement. Details on the data structures and the employed data mining techniques for the optimization services are provided in Section 6.3.2.

4.3 Gap Analysis

In the following, a gap analysis is presented analysing how the requirements of the OPDM are met by the AdMA platform (see Table 1).

Table 1. Gap analysis: OPDM requirements met by the AdMA platform.

			Advanced Manufacturing Analytics Platform
OPDM Requirements	Presentation	Easy-to-Use and Intuitive	*Gap: Mobile Shop Floor Application*
		Situation-aware	
		Flexible Mobile Access	
	Data Analytics	Metrics Calculation, Data Mining	✔
		Storing and Sharing of Content Items	✔
		Audio- and Video-based Communication	*Gap: Communication Middleware*
	Data Provisioning	Holistic Data Warehouse	✔
		Near-real-time Data Provisioning	✔

✔ Requirement met by the Advanced Manufacturing Analytics Platform

With respect to *data provisioning*, the AdMA platform fully meets the requirements of the OPDM. The Manufacturing Warehouse provides a holistic data basis integrating operational data and process data and the Manufacturing Data Integrator facilitates rapid data provisioning by exploiting near-real-time ETL concepts.

Regarding *data analytics and result sharing*, metrics calculation and data mining techniques constitute the core of the AdMA platform. Both are provided as generic components on the process analytics layer and used by predefined optimization services on the process optimization layer. The Manufacturing Knowledge Repository facilitates the storing of content, e.g., text messages, videos and documents, and integrates them with structured data from the Manufacturing Warehouse. However, components for audio- and video-based communication are not included in the AdMA platform as it does not focus on synchronous communication issues. This gap of a communication middleware can be addressed by the integration of existing conference systems in the AdMA platform, e.g., Microsoft Skype[1] , which are provided for a wide range of mobile and stationary devices. Hence, it does not constitute a major obstacle for the realization of the OPDM and is therefore not further addressed in this paper.

Presentation issues are not addressed in the architecture of the AdMA platform as the focus is on generic middleware functions for data analytics. Thus, there is a significant gap in order to realize the OPDM using the AdMA platform. To fill this gap, a *mobile shop floor application* is required which facilitates mobile, easy-to-use and situation-aware access to the AdMA platform.

4.4 Conclusion

All in all, the AdMA platform represents a suitable technical basis for the OPDM as it constitutes a generic Business Intelligence platform for manufacturing. To bridge the gap between the

[1] http://www.skype.com

user and the AdMA platform, a mobile shop floor application is needed. That is, the AdMA layers for data integration, process analytics and process optimization constitute the backend which is accessed by a mobile frontend (see Figure 6), whose conceptual design is in the focus of the following section.

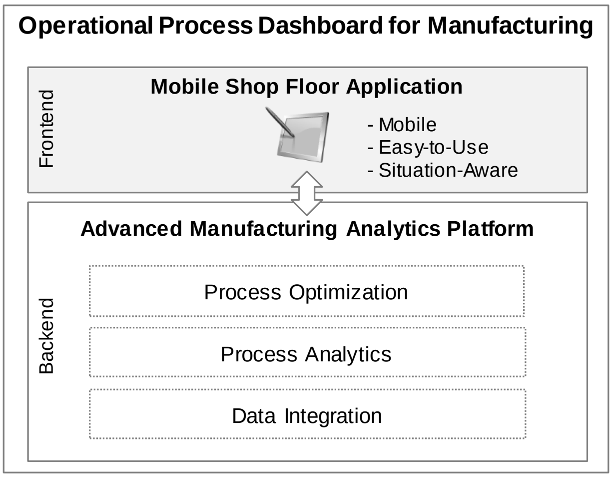

Figure 6. AdMA platform as technical basis for the OPDM.

5 Design Issues of a Mobile Shop Floor Application

In this section, the conceptual IT design issues of a mobile shop floor application are discussed enabling mobile, easy-to-use and situation-aware access to analytical optimization services on the shop floor. First, *types of mobile devices are investigated* in order to provide easy-to-use and mobile user access (see Section 5.1). On this basis, *context and location* aspects are analysed in Section 5.2 in order to realize situation-aware information provisioning based on the context of the user. Finally, the use of mobile devices for the access of business critical data rise *security issues*, which are discussed in Section 5.3.

5.1 Types of Mobile Devices

In general, there are two major types of mobile devices to support mobility in business processes as discussed in (Hoos et al. 2014), namely *notebooks* as well as *mobile touch-based devices*. *Notebooks* refer to laptops and netbooks with operating systems of stationary PCs, e.g., Microsoft Windows. *Mobile touch-based devices*, especially smartphones and tablet PCs, employ a touchscreen-based user interface and are based on specific mobile operating systems, e.g., Google Android or Apple iOS. In this work, applications on mobile touch-based devices are called ‘mobile apps’.

Table 2. Evaluation of mobile device types for the OPDM.

	Notebooks	Mobile Touch-based Devices
Computing Power	+	
Mobility & Handling		+
Input & Output Capabilities	+	
Sensor Technologies		+

As shown in Table 2, the mobile device types are evaluated with respect to *computing power*, *mobility and handling*, *input and output capabilities* as well as provided *sensor technologies* (Gröger 2015).

Notebooks provide *computing power* almost comparable to PCs as they are based on similar CPUs. In contrast, mobile touch-based devices are coined by reduced computing power because they employ low-energy CPUs. However, they are significantly more *handy and mobile*. They are specifically designed for an always-on usage, e.g., there is no time-consuming boot procedure, and they can be used anywhere, even on the go (Gröger et al. 2013b). With respect to *input and output capabilities*, notebooks provide both more powerful output capabilities due to larger screens and multimodal input capabilities. In contrast, mobile touch-based devices focus on the displaying of contents with comparably smaller screens and only limited data input using touchscreen keypads. In contrast to notebooks, mobile touch-based devices are equipped with a huge variety of *sensor technologies*, especially Global Positioning System (GPS), digital compass, acceleration sensors and gyroscope.

All in all, this work focuses on mobile touch-based devices, especially smartphones and tablet PCs, to realize the OPDM as they are significantly more handy and mobile than notebooks and thus enable information provisioning anywhere and anytime on the factory shop floor as required by the OPDM. Moreover, the wide range of sensor technologies facilitates the capturing of the environmental conditions and context information of the user in order to realize a situation-aware information presentation. The reduced computing power does not constitute an obstacle as computing-intensive tasks, e.g., data mining calculations, can be processed in a performant backend system. To cope with the reduced input and output facilities, the corresponding mobile app has to be consequently tailored towards the screen size and touchscreen-based usage.

5.2 Context and Location

In order to provide the dashboard services of the OPDM in a situation-aware manner, context information is necessary (Tarasewich 2003). That is, a context model defining relevant context categories is needed to make the AdMA platform a context-aware information system. The context information is then used in two general ways for the OPDM (Cheverst et al. 2001):

- *Simplifying the user interface* by presenting only information relevant to the current context of the user, e.g., to present current warnings only for the machine the supervisors stands in front of.
- *Reducing data input efforts* of the user by prepopulating input fields with context information, e.g., current noise level and location.

In the following, a high level context model for the AdMA platform is introduced in Section

5.2.1 comprising five context categories. A description of how context data is provided for each category is given in Section 5.2.2. Subsequently, several localization issues to provide location context data are discussed. It is important to remark that – to ease the definition and implementation of the context model – complex existing factory data models like (Lucke, Constantinescu, and Westkämper 2008) are *not* adapted but an AdMA-specific model is desigend which leverages the huge amounts of context-related information already provided by the Manufacturing Warehouse and the Manufacturing Knowledge Repository.

5.2.1 Context Model

The starting point for the AdMA context model constitutes the model described in (Schmidt et al. 1999) as it takes a generic and user-driven view on context. It comprises three context categories, namely *self*, *activity* and *environment*. *Self* refers to the user, *activity* to the user's task and *environment* to social or physical aspects of the environment. These three context categories provide a general structure for context and have to be adapted and detailed for a concrete application domain, in this case the OPDM, as follows.

With respect to the OPDM (see Figure 7), the *user* category refers to the individual worker or supervisor using the dashboard including details on his role and organizational assignment in the company. The *process* category refers to the process step respectively the manufacturing process the worker or the supervisor is responsible for including all process-related information, e.g., the current state of the entire process. This represents the process context as defined in Section 3.1. The environment is decomposed into two context categories as described in (Schmidt, Beigl, and Gellersen 1999), namely the *location* of the user and *physical conditions* at the location such as temperature or brightness. Besides, *time* is considered as additional context category to represent temporal issues as explained in (Tarasewich 2003).

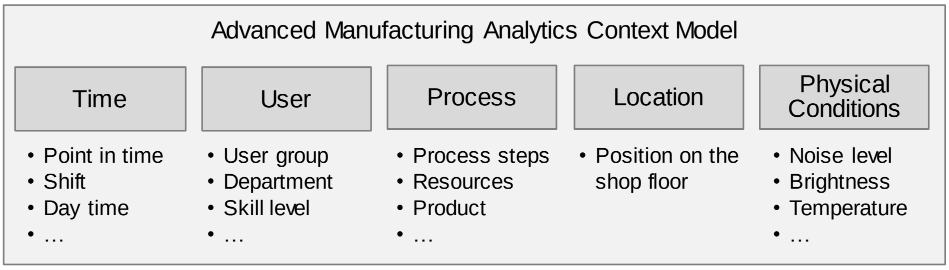

Figure 7. AdMA context model.

Thus, the AdMA context model comprises five context categories as shown in Figure 7, namely *time*, *user*, *process*, *location* and *physical conditions*. The following provides a description which context features in terms of attributes make up each context category and how concrete context data for these attributes is provided.

- The *time category* is modelled according to the time dimension of the Manufacturing Warehouse data model (see [Gröger, Schwarz, and Mitschang 2014b]). It comprises not only the current point in time but additional information on shifts, day time, season etc. The concrete time is then provided by the mobile device and constitutes a fact in the multidimensional data model. On this basis, the corresponding values for the related attributes, e.g., shifts, are derived from instance data in the time dimension of the Manufacturing Warehouse.

- The *user category* is made up of personal and organizational employee attributes as defined in the employee dimension of the Manufacturing Warehouse data model, e.g., department, skill level and user group. The individual user is then determined by his OPDM login at the mobile device and the related user attributes are given by warehouse instance data.
- The *process category* refers to a holistic view on the manufacturing process, its steps and underlying resources from a design-time and a run-time point of view as represented in the process meta model of the Manufacturing Knowledge Repository (see [Gröger, Schwarz, and Mitschang 2014b]). Hence, the structure and the current state of the process are represented. Corresponding context data is then provided by instance data in the repository.
- The *location* of the user refers to his position on the shop floor. Thereby, there is no need for an absolute position down to the last meter but for the position of the user with respect to the manufacturing process, e.g., the workplace he works at or the machine he stands in front of. The position has to be determined by a suitable localization technique using the mobile device (see Section 5.2.2).
- *Physical conditions* comprise the whole range of sensor data attributes provided by the mobile device (see Section 5.1), e.g., noise level or temperature.

All in all, the context model combines context-related information from the Manufacturing Warehouse and the Manufacturing Knowledge Repository with sensor data from the mobile device to realize situation-aware information provisioning. At this, the reuse of model data and instance data from the Manufacturing Warehouse and the Manufacturing Knowledge Repository significantly eases the implementation of the context model.

5.2.2 Localization Concept

To provide location data for the context model, a suitable localization technique has to be selected. Its conceptual design is discussed in the following.

With respect to localization on the factory shop floor, traditional GPS concepts cannot be employed due to missing satellite reception (Renso et al. 2008). Meanwhile, two major concepts for localization on the shop floor have been established and are investigated in the following, namely *Wi-Fi positioning* and *tag-based positioning* (Renso et al. 2008; Lucke et al. 2008; Gröger 2015).

- *Wi-Fi positioning* makes use of a network of wireless access points installed on the shop floor. Localization is done by measuring the distance of a mobile device as a Wi-Fi client to at least three access point using trilateration. The resulting position values are then to be mapped to positions on the shop floor. This enables accurate positioning on up to a few meters (Renso et al. 2008).
- *Tag-based positioning* exploits tags and sensors of mobile touch-based devices, that is, scanners such as cameras and corresponding tags such as Quick Response (QR) codes. These tags are linked with predefined locations on the shop floor, e.g., machines, following (Lucke et al. 2008).

Regarding Wi-Fi positioning, no additional hardware installation has to be done on the shop floor as the OPDM requires wireless access per se. In contrast, all relevant locations have to be equipped with tags in advance to make use of them for tag-based positioning. Besides, the tag-based approach does not provide accurate positioning in the stricter sense but rather the recording of the last location whose tag was scanned. Yet, factory layout modifications, e.g., rearranging machines, require a recalibration of wireless signals and a remapping of locations whereas tags remain untouched. With respect to the privacy of the user, Wi-Fi positioning poses the risk of continuously tracking the user's location on the shop floor without his knowledge (Lucke et al. 2008). In contrast, tag-based positioning hampers employee tracking since the user has to actively scan tags, at least when using QR codes.

For the OPDM, no accurate positioning down to the last meter is needed, that is, recording the location by scanning tags is sufficient. Hence, tag-based positioning is the best approach to realize the OPDM because it enables a flexible handling of factory layout changes and supports employee privacy control. To realize the tag-based approach in the AdMA platform, a central issue is the linking of tags and locations.

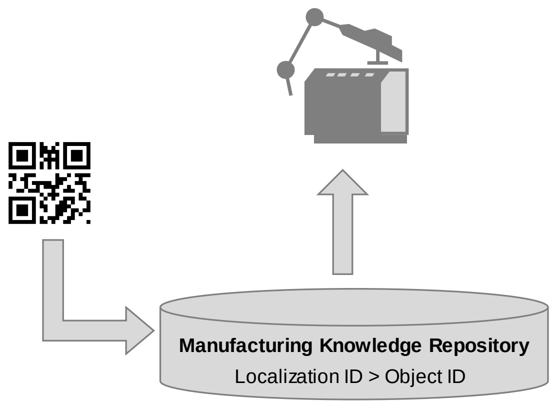

Figure 8. Tag-based positioning approach for the OPDM.

For this purpose, the factory layout which is already partly represented in the Manufacturing Knowledge Repository is used (see Figure 8). Each process step is associated with the spatial hierarchy of workplaces, areas and sites it belongs to. In addition, resources like machines and production aids are associated with process steps, as well. Consequently, physical workplaces and resources are equipped with tags that comprise a unique localization identifier in terms of a surrogate key for their logical representative in the Manufacturing Knowledge Repository. On this basis, the surrogate keys of the tags are linked with the identifiers of the logical objects in the repository. In this way, factory layout changes, which are reproduced in the Manufacturing Knowledge Repository, do not lead to changes of existing tags as their surrogate keys stay the same.

5.3 Security

The OPDM is based on business-critical data, especially manufacturing performance data in the Manufacturing Warehouse and the Manufacturing Knowledge Repository, which is of vital importance for the competitiveness of the company. This sensitive data has to be secured even in cases of loss or theft of mobile devices. Thus, security issues play an important role for the realization of the OPDM in a real-world case. Thereby, a wide range of topics has to be considered, from concepts for the remote wipe of data on mobile devices to enhanced wireless security. In the following, a coarse-grained overview of major *data security issues* related to mobile data access is given.

Regarding *data security in mobile environments*, there are three major components that have to be secured to prevent unauthorized data access as analysed in (Gröger et al. 2013b), namely the *backend system* comprising the AdMA layers described in Section 4.2, the *mobile device* itself, and the wireless *communication channel* between the backend and the mobile device (see Figure 9). In the following, major security concepts for these components are highlighted.

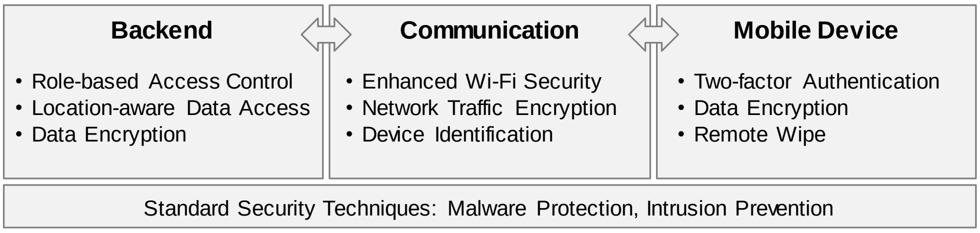

Figure 9. Overview of data security concepts for the OPDM.

Considering the *backend*, mobile access to the optimization services and the underlying data of the Manufacturing Warehouse and the Manufacturing Knowledge Repository has to be restricted according to the user group as well as the process responsibilities of the OPDM user. For instance, a worker is only allowed to access data on process steps, he participates in, and supervisors are only provided with data on the manufacturing process they are responsible for. For this purpose, *role-based access control* (Ahn and Sandhu 2000) concepts provide a suitable approach to restrict data access according to the user's role. With respect to context data, these concepts can be extended to include location data in order to grant access according to the role and the location of the user. In addition, the data in the backend has to be secured to prevent physical data access, e.g., using disk encryption.

The *wireless communication channel* connects the mobile devices with the backend system. Regarding data security, *data encryption* and *identification of backend and mobile device* are major issues which have to be addressed on the level of the network and the level of the mobile application. At this, Wi-Fi technologies are typically used for wireless communication. On the network level, traditional Wi-Fi encryption standards such as WPA2 have to be extended with concepts such as SecureArray (Xiong and Jamieson 2013) to protect them against spoofing attacks. On the level of the mobile application, established concepts for network traffic encryption, especially Transportation Layer Security, have to be applied. Thereby, client certificates and server certificates have to be employed consequently to identify backend and mobile device and avoid man-in-the-middle attacks.

Considering the *mobile device*, there are two major data security aspects, *user authentication* and *data protection in case of loss or theft* of the device. For user authentication, multi-factor authentication concepts have to be applied (Mansoor 2013). That is, additional credentials beyond username and password are used to strengthen authentication. Regarding data protection on the mobile device, in general, data storage on the device itself should be minimized to reduce the amount data that may 'get lost' in case of a loss of the device. In addition, the data which is stored on the device has to be encrypted. Moreover, remote wipe technologies have to be employed to facilitate the deletion of critical data over the air in case of a loss of a device (Mansoor 2013).

6 Application in the Automotive Industry and Evaluation

This section focuses on evaluation issues and provides (1) a case-based evaluation of the OPDM in an automotive industry case using a prototypical implementation and (2) a comparative evaluation of the OPDM with existing approaches. The prototype is presented in Section 6.1 and the case example is detailed in Section 6.2 including the concrete manufacturing process and the data model of the Manufacturing Knowledge Repository. The case-based evaluation comprises both carrying out typical real-world application scenarios in the case example (see Section 6.3) as well as evaluating the technical feasibility of the OPDM based on performance measurements (see Section 6.4). The goal of the case-based evaluation is to show that the OPDM is able to realize analytics-based and situation-aware information provisioning for a concrete manufacturing process. In addition, the qualitative comparison in Section 6.5 evaluates the OPDM with respect to existing approaches. Finally, Section 6.6 sums up the evaluation results and highlights the benefits of the OPDM.

6.1 Prototypical Implementation

The prototype of the OPDM comprises the AdMA backend as well as the mobile shop floor application. Hence, the prototype extends existing implementations of the AdMA backend, especially (Gröger, Schwarz, and Mitschang 2014b, 2014a), and was used in (Gröger and Stach 2014) as part of a demonstration track.

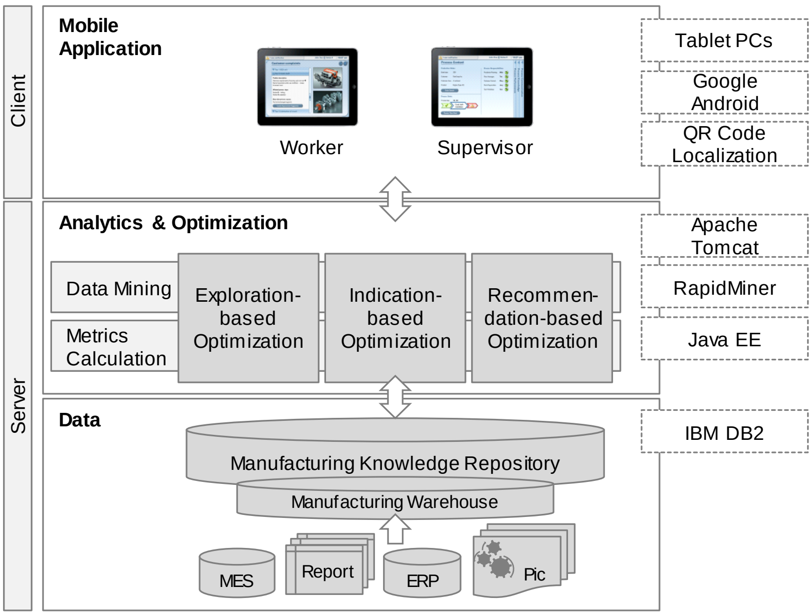

Figure 10. Technical architecture of the prototype.

The prototypical implementation is based on a client-server architecture with the server comprising the AdMA backend and the client implementing the mobile shop floor application using mobile touch-based devices, especially tablet PCs. The resulting technical architecture of the prototype is shown in Figure 10 and is made up of three integrated layers, the *data layer*, the *analytics & optimization layer* as well as the *mobile application layer*, which are detailed in the following.

The *data layer* comprises the *Manufacturing Knowledge Repository* and the *Manufacturing Warehouse*, which are implemented as one shared relational database using *IBM DB2*[2]. To store unstructured data on insights, advanced features of relational database management systems are exploited, especially *XML and large object processing facilities*. Details on the data model of the Manufacturing Knowledge Repository are presented in Section 6.2.2.

The *analytics & optimization layer* comprises generic analytics components for *metrics calculation* and *data mining* on top of the Manufacturing Knowledge Repository in order to realize the optimization services for *exploration-based*, *indication-based* and *recommendation-based optimization*. Exploration-based optimization is implemented as a new AdMA component to enable both direct querying of repository contents, e.g., to view all KPIs associated with a process step, as well as uploading of new contents, e.g., photos or videos taken by the mobile device. The optimization services access data in the repository and feed analysis results, e.g., data mining models as XML files, back into the repository to enable their reuse. The entire layer is realized as a *Java EE application* running on an *Apache Tomcat Application Server*[3] and access the repository using *SQL*. For data mining tasks, *RapidMiner*[4] is used as a prebuilt data mining tool. Details on the data structures and the employed data mining techniques for the optimization services are given in Section 6.3.2.

For the *mobile application layer*, *tablet PCs* for workers and supervisors are favoured to enable clear visualization beyond small smartphones displays. Considering the selection of a mobile platform, the choice fell on *Google Android*[5] because a wide range of devices from various hardware vendors is provided and it constitutes the only open source platform among the market-leading mobile platforms (these are: Google Android, Apple iOS, Microsoft Windows and RIM Blackberry) according to (IDC 2013). This enables a more flexible development as details of the underlying operating system can be investigated and adapted if necessary. The OPDM app itself is implemented as a *native app* in order to exploit sensor data for situation-aware information provisioning which is currently not fully supported by web apps (Clevenger 2011). Thereby, the app acts as a frontend to the AdMA's optimization services by triggering service executions, e.g., starting a root cause analysis. Regarding context and localization, *QR codes* are used for tagged-based positioning. The context model implemented in the app *realizes all five context categories* (see Section 5.2.1) whereas the focus is on noise level detection as a typical sensor for physical conditions. The implementation of security issues is only basically addressed in the current prototype. At the moment, a role-based access concept is used which separates access for workers and supervisors based on username-password combinations.

6.2 Case Example in the Automotive Industry

The case-based evaluation focuses on the application of the prototype in an example case in the automotive industry. As a concrete manufacturing process, the mass manufacturing of steel springs for car motors (Erlach 2011) is selected since it constitutes a highly automated and standardised process favouring comprehensive production data acquisitioning and manufacturing IT support. These are core requirements for an application of the OPDM in order to ensure

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[2] http://www-01.ibm.com/software/data/db2/

[3] http://tomcat.apache.org

[4] http://www.rapidminer.com

[5] http://www.android.com

the availability of a critical amount of source data, especially from MES and ERP systems. In the following, the manufacturing process is analysed in Section 6.2.1 and the data model of the Manufacturing Knowledge Repository for the implementation of the manufacturing process is described in Section 6.2.2.

6.2.1 Manufacturing Process

For the application of the prototype, a simplified version of the process is used which comprises four sequential steps for a batch-oriented manufacturing of steel springs. These steps are winding, tempering, shot peening and testing of springs, including corresponding machines, especially winding automates, tempering furnaces and blasting systems (see Figure 11). Machines are controlled by workers which take part in each manufacturing step, too. For the sake of simplicity, the focus of this paper is not on transportation steps and warehousing steps. The input material for winding is steel wire and batches of steel springs are the final output after the testing step.

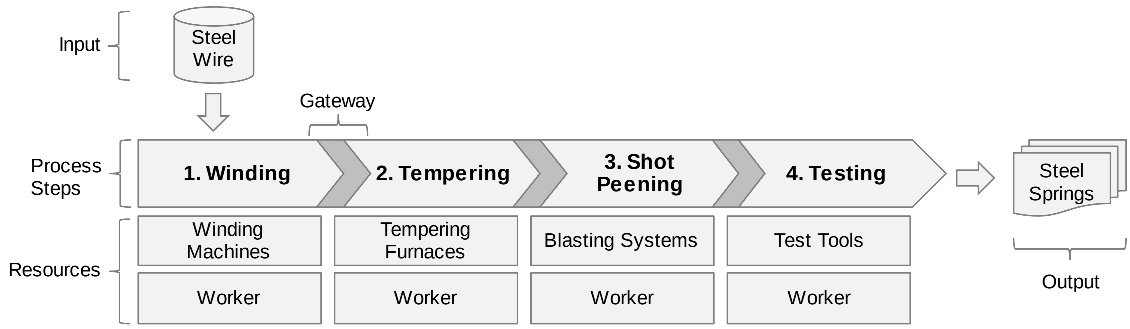

Figure 11. Model of the steel spring manufacturing process.

In order to implement the manufacturing process in the Manufacturing Knowledge Repository, the process is modelled according to the meta model of the AdMA platform (see Section 4.2). The manufacturing process is represented as a series of three manufacturing steps (winding, tempering, shot peening) and one testing step coupled by sequence gateways (see Figure 11). On the basis of this initial design-time model, the model is refined with respect to run-time aspects, especially data gathered during process execution. Therefore, typical process data attributes recorded in each process step, especially considering machine settings are investigated. For instance, winding speed and bending moment for winding or average temperature and duration of tempering. In addition, operational data attributes on process subjects are defined, e.g., master data on machines and employees. This comprehensive process model is implemented in the Manufacturing Knowledge Repository as explained in the following.

6.2.2 Data Model of the Manufacturing Knowledge Repository

The data model of the Manufacturing Knowledge Repository comprises two parts, a multidimensional warehouse model as well as an insight model (see Figure 12). In the following, an overview of the data model is given. Concrete data structures are presented as part of the application scenarios in the following sections. More details on the data model can be found in (Gröger, Schwarz, and Mitschang 2014b).

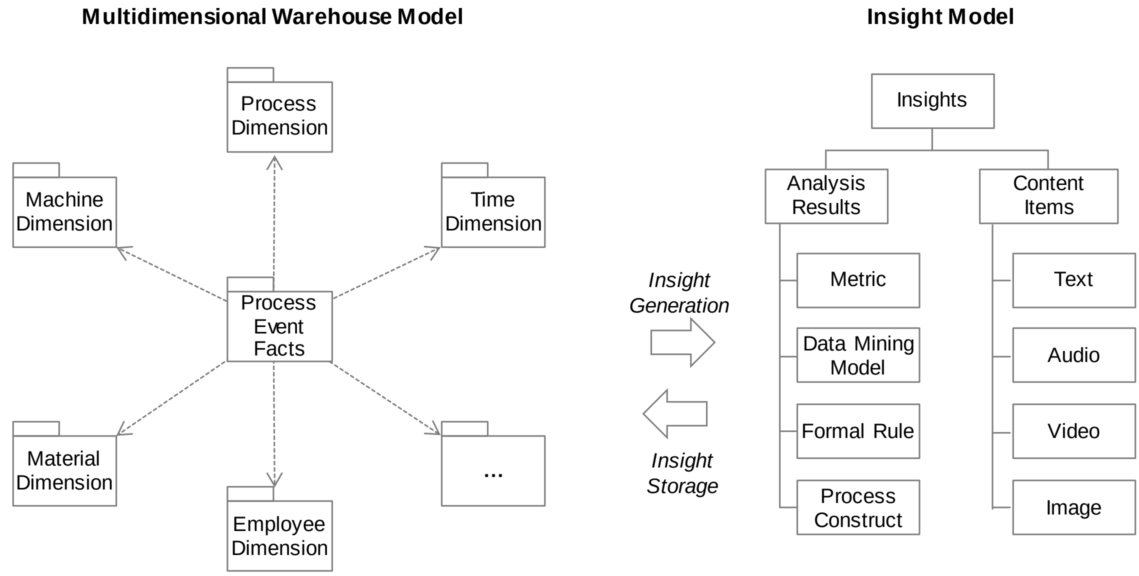

Figure 12. Overview of the Data Model of the Manufacturing Knowledge Repository.

The *multidimensional warehouse model* implements manufacturing processes according to the process meta model of the AdMA platform. It is comprised of thirteen generic dimensions and focuses on process events as central facts. In the case example, an event may refer to the start of a machine belonging to a certain process step. Dimensions represent analysis perspectives on these facts and encompass two types, flow dimensions as well as context dimensions. Flow dimensions describe the process flow over time and refer to the name of an event, the time it occurs and the process it belongs to. Context dimensions provide additional information on the context of an event and are based on identifiers included in the event, e.g., the machine used. Example context dimensions refer to machines, employees, production aids and materials used in a process step including details such as machine settings and material attributes. The warehouse model enables the integrated storage of huge amounts of process execution data as a basis for *insight generation*, especially data mining. For this purpose, it is implemented as a relational snowflake schema.

According to the *insight model*, insights refer to analysis results generated from warehouse data as well as content. Thus, insights represent knowledge items managed by the Manufacturing Knowledge Repository. *Content* comprises text documents, audio and video recordings as well as images like in Content Management Systems. In the case example, content especially refers to digital machine manuals and failure reports as well as photos of quality issues on the shop floor. For instance, a machine manual may detail the procedure for resetting a certain type of machine. *Analysis results* comprise data mining models like decision trees as well as metrics like cycle time and quality rate. Moreover, there are formal rules in terms of if-then relations. For *insight storage*, analysis results are represented as XML objects. In particular, data mining models are stored using the XML-based Predictive Model Markup Language[6]. Content items are represented as binary large objects. In this way, insights can be stored in the relational database and they can be linked with the relational warehouse schema, e.g., using foreign key relationships.

[6] http://www.dmg.org/v4-1/GeneralStructure.html

This results in a link-based approach for the flexible ad-hoc integration of warehouse data and insights. At this, there is no need for the costly construction and maintenance of a global schema like an ontology which specifies the sub structure of content items or analysis results. Instead, insights can be flexibly stored and linked with process constructs in the warehouse model to enable a process-oriented browsing and management of insights, e.g., to access all metrics and text documents associated with a certain machine or a specific manufacturing process. In other words, no knowledge formalization technique such as OWL is used since the focus is on a flexible and schema-less linking approach.

In the case example, process execution data on up to 100,000 process executions is generated to populate the warehouse model with instance data and calculate corresponding metric values for KPIs like quality rate. Moreover, content items are generated, especially machine manuals and failure reports including photos as PDF and JPEG files. This data basis constitutes the foundation for the realization of application scenarios as described in the following section.

6.3 Application Scenario in the Case Example

In order to evaluate analytics-based and situation-aware information provisioning by the OPDM, typical real-world application scenarios for the case example are defined based on (Gröger and Stach 2014; Gröger, Schwarz, and Mitschang 2014a). The scenarios make use of various dashboard services and combine context-related data from the Manufacturing Knowledge Repository and the mobile device according to the context model designed in Section 5.2.1. The scenarios put special emphasis on dashboard services for process performance to illustrate the usage of data mining techniques on top of the Manufacturing Knowledge Repository. In the following, a scenario is presented which addresses shop floor workers and focuses on recommendation-based optimization. It specifically targets a worker who is responsible for shot peening of springs in the third step of the steel spring manufacturing process. First, interaction steps with the OPDM are described from a user point of view (see Section 7.3.1). Second, data structures and data mining techniques for the optimization services used in the scenario are detailed (see Section 7.3.2).

6.3.1 Interaction Steps

1. Having logged in at the OPDM, the worker scans the QR code at the blasting system he works at. In this way, context-related information regarding the user, the process and the location is fused according to the context model in Section 5.2.1. Hence, the worker is registered for the corresponding manufacturing process step and the current state of the entire process is shown by OPDM's process context component (see Section 3.1). Then, the worker begins with the processing of the first batch of steel springs.
2. Using recommendation-based optimization, the worker is warned by OPDM's process performance component (see Section 3.2), that the quality rate of the next batch of steel springs is predicted to fall below a threshold of 95% at the end of the process. Thus, the OPDM presents a recommendation on how to proactively avoid the metric deviation. That is, the worker is advised to do a reset of the machine before processing the next batch.
3. The worker is unsure how to reconfigure the machine properly. Thus, he browses work instructions and machine manuals associated with his process step in the process knowledge component of the OPDM (see Section 3.3) in order to find additional infor-

mation on the machine settings. Finally, he succeeds in doing the reset and processes the following batch.

4. Based on the microphone sensor of the OPDM's tablet PC, the worker is warned that the current noise level at his workplace exceeds a certain threshold. Then, a corresponding problem ticket is automatically created and augmented by context data on the current process, the user and the noise level in OPDM's process knowledge component (see Section 3.3). The ticket is stored in the Manufacturing Knowledge Repository and posted to all workers who participate in the process as well as to the supervisor.
5. Another worker responds to the ticket on his OPDM and explains the reason for the excessive noise level by an unplanned machine maintenance. Moreover, he makes use of text messages to quickly inform his colleagues using OPDM's process communication component (see Section 3.4).

6.3.2 Data Structures and Data Mining Techniques for Recommendation-based Optimization

In the above scenario, recommendation-based optimization is based on the prescriptive analytics approach described in (Gröger, Schwarz, and Mitschang 2014a). In the following, an overview of the underlying data structures and data mining techniques is given in view of the application scenario.

Recommendation-based optimization is comprised of two major components, namely *real-time prediction* and *recommendation generation*. Both components make use of data provided by the multidimensional warehouse model (see Section 6.2.2). This data is denormalized as input for data mining (see Table 3 which includes the running process instance i400). Each row comprises all data of one instance of the manufacturing process which corresponds to the execution of one production order. The data includes operational data and process data, for example, attributes on machine settings and employees. Moreover, the categorized metric value with the labels 'OK' and 'NotOK' is added for completed process instances. In the application scenario, the metric quality rate is categorized as 'OK' if its value is equal or larger than 95% otherwise it is categorized as 'NotOK'. During the execution of a process instance, real-time prediction is executed after the completion of each process step to predict whether the metric value will be 'NotOK' at the end of the process instance. In case of a negative prediction, recommendation generation is executed to proactively derive a recommendation on how to avoid the predicted metric overrun.

Table 3. Denormalized data structure for recommendation-based optimization (Gröger, Schwarz, and Mitschang 2014a; adapted from Lecture Notes in Business Information Processing Vol. 176, © 2014 with permission from Springer).

Process Instance ID	Step1 Machine ID	Step1 Winding Speed	Step1 Empl ID	Step1 Empl Qualific	Step2 Machine ID	Step2 Tempering Temperature	Step3 Machine ID	Step3 Peening Reset	Step3 Peening Duration	…	Metric
i100	M12	120	E331	6	M23	290	M33	1	23		OK
i200	M12	135	E332	2	M23	291	M33	0	28		NotOK
i300	M12	135	E321	1	M23	290	M34	0	29		NotOK
i400	M12	121	E321	1	M23	285					
…			…	…							…

Input data for real-time prediction after completion of step 2 (Step1 Machine ID to Step2 Tempering Temperature)

Input data for recommendation generation for step 3 (Step3 Machine ID to Step3 Peening Duration)

Real-time prediction is based on decision tree induction as data mining technique to predict the nominal metric label because decision trees enable an intuitive interpretation of the prediction model due to their graphical representation. Training data for decision tree induction comprises all attributes of completed process steps of the running process instance as well as the metric label (in the scenario, steps one and two are completed in running instance i400, see Table 3). The data of the running process instance is then applied to the trained decision tree for prediction (see Figure 13). In the case example, the robust C4.5 algorithm (Quinlan 1993) is used for decision tree induction and binary trees are generated to ease understandability.

Process Instance ID	Step1 Machine ID	Step1 Winding Speed	Step1 Empl ID	Step1 Empl Qualific	Step2 Machine ID	Step2 Tempering Temperature
i400	M12	121	E321	1	M23	285

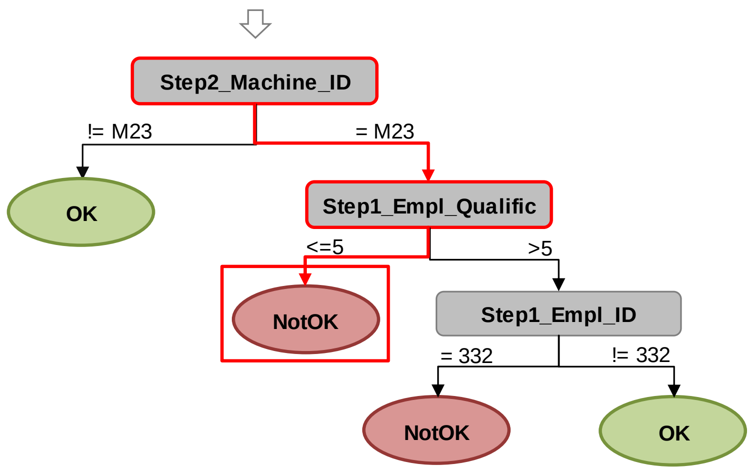

Figure 13. Decision tree for real-time prediction of process instance i400.

Recommendation generation derives an action recommendation using decision tree induction and scoring of decision rules. That is, there is no predefined knowledge base with cases or formal rules like in expert systems, which statically defines recommendations. Instead, recommendations are generated in a fully data-driven manner analysing historic process execution data. First, decision rules are generated based on a decision tree. Second, the decision rules are scored to select the best rule for the final recommendation and present it to the user.

Training data for decision tree induction comprises all attributes of the process step for which the recommendation is generated, e.g., step three in the scenario, including the metric label (see Table 3). Again, the C4.5 algorithm is used for binary decision tree induction as explained above. On this basis, each path from the root node of the resulting decision tree to a leaf node with the label OK represents a rule for a potential recommendation because the corresponding combination of attributes proved to avoid the metric deviation in past process executions. Each decision rule is then scored with a scoring function to select the rule with the highest score for the final recommendation (see Figure 14). The scoring function uses several metrics such as misclassification rate and length of a rule and is detailed in (Gröger, Schwarz, and Mitschang 2014a).

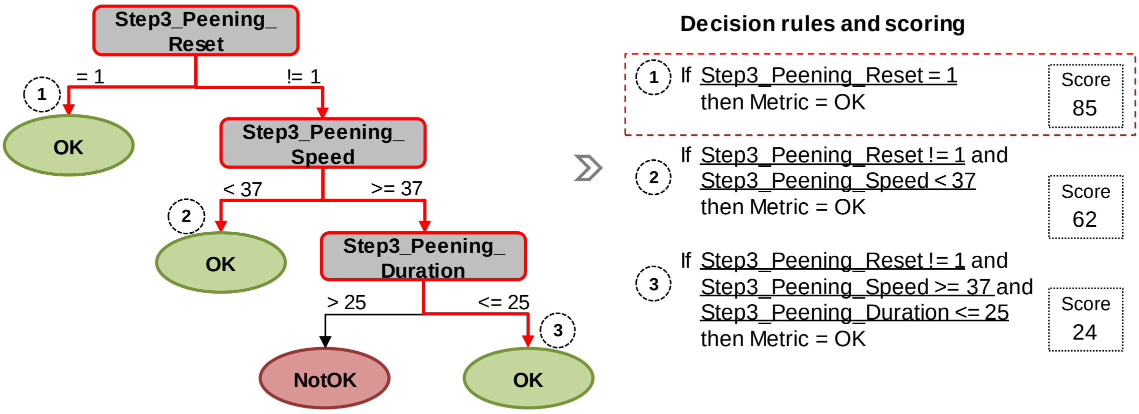

Figure 14. Decision rules and scoring for recommendation generation for process step three (Gröger, Schwarz, and Mitschang 2014a; adapted from Lecture Notes in Business Information Processing Vol. 176, © 2014 with permission from Springer).

In the application scenario, three decision rules are derived from the decision tree and scored according to Figure 14. The best scored rule results in the recommendation to do a reset of the machine before peening in order to avoid the metric deviation.

6.4 Evaluation of Technical Feasibility

To evaluate the technical feasibility of the prototype in the above case example, all major dashboard services were executed repeatedly for both workers and supervisors (e.g., generation of improvement suggestions, execution of root cause analyses etc.) in the areas of process context, process performance and process knowledge as defined in Sections 3.1-3.3 (backend test system: Microsoft Windows Server 2008 R2, Intel Core i7-2620M@2,7 GHz, 8 GB RAM, 512 GB HDD). Thereby, the dashboard services were used directly from the OPDM app on the tablet PC to take the perspective of a corresponding end user (tablet PC test system: Asus TF300T, Android 4.2). Considering process context and process knowledge, browsing and uploading of arbitrary contents in the Manufacturing Knowledge Repository were done in an interactive manner because they are mainly based on SQL commands. For instance, improvement suggestions were generated and metrics of single process steps were viewed. Regarding process performance, indication-based optimization and recommendation-based optimization are performance-critical tasks for the backend system as they involve decision tree induction on up to 100,000 process instances comprising all attributes across the entire manufacturing process. Summing up the performance results, one can state that the actual decision tree induction for these analytics tasks was typically done in less than one minute on average taking the above data basis. However, it took several minutes to prepare data for decision tree induction due to a high number of complex joins for data denormalization. Yet, there is a comprehensive potential for performance enhancements in the backend of the prototype, e.g., regarding the use of suitable server hardware such as SSDs, as the focus of this first technical proof of concept was on feasibility not on pure performance.

6.5 Comparative Evaluation

To evaluate the OPDM with respect to existing dashboard concepts in manufacturing (see Section 2), a qualitative comparison against defined criteria is presented in the following. For the comparison, the focus particularly lies on existing dashboards and mobile apps for workers on the shop floor. Hence, *mobile MES apps* for the shop floor – especially HYDRA Smart MES Apps (MPDV 2014) and OpsTrakker Mobile App (Enhanced Information Solutions 2014) – the *Visualization System for Operational Logistics (ViSOL)* (Bracht, Hackenberg, and Bierwirth 2011) as well as the *SAP Production Operator Dashboard (SAPOD)* (SAP 2012) are chosen because they are most closely related to the OPDM.

These approaches are compared with respect to four criteria C_i (see Table 4): (C1) whether they address all major process-oriented information needs (see Section 3) to enable *holistic information provisioning* on the shop floor; (C2) whether they support manual *shop floor data acquisitioning* by workers; (C3) whether they provide *advanced analytics* beyond simple descriptive metric visualizations and statistics; (C4) whether they combine context-related data to provide *situation-aware* information.

Table 4. Comparative evaluation of the OPDM with related approaches.

		OPDM	Mobile MES Apps	ViSOL	SAPOD
C1	Holistic Information Provisioning	+	○	-	○
C2	Shop Floor Data Aquisitioning	○	+	-	+
C3	Advanced Analytics	+	-	○	-
C4	Situation Awareness	+	○	+	○

+/○/- Approach fully/partially/does not meet(s) criterion

Regarding information provisioning (C1), mobile MES apps and SAPOD provide a variety of information for shop floor workers addressing process context, process performance and process knowledge. For instance, the current state of the manufacturing process, basic KPIs as well as work instructions are available. However, process communication as well as management of improvement suggestions are missing in contrast to the OPDM. ViSOL mainly focuses on situation-aware KPI monitoring for workers in logistics and thus concentrates on process performance.

Shop floor data acquisitioning by workers (C2) is out of scope of the ViSOL. The OPDM provides only rudimentary means for manual data acquisitioning using improvement suggestions and problem tickets (see Section 3.3) because comprehensive automatic machine data acquisitioning is assumed. In contrast, mobile MES apps as well as SAPOD support manual data acquisition by workers, e.g., to record quality test results.

With respect to analytics (C3), mobile MES apps as well as SAPOD are based on classical descriptive KPI visualizations, statistics and reporting. ViSOL mainly focuses on KPIs, too, but presents an initial idea for forecasting KPIs such as inventory level using simulation techniques. In contrast, the OPDM provides advanced analytics for indication-based and recommendation-based optimization using data mining techniques. These optimization services take a holistic view on the entire manufacturing process comprised of operational data and process data as provided by the Manufacturing Knowledge Repository and the Manufacturing Warehouse. That is, in contrast to existing data mining approaches in manufacturing such as (Harding et al. 2006; Polczynski and Kochanski 2010), data on all process steps and resources across the overall process is exploited, e.g., taking into account machine settings, input material details and employee information. In addition, existing data mining approaches focus on prediction and root cause analysis whereas the OPDM prescriptively generates concrete action recommendations. A detailed analysis of existing data mining approaches in manufacturing can be found in (Gröger, Niedermann, and Mitschang 2012; Gröger, Schwarz, and Mitschang 2014a).

ViSOL and the OPDM exploit context data on all categories of the context model (see Section 5.2.1) as they are natively designed as situation-aware applications (C4). For instance, ViSOL presents current metric values for the worker according to the manufacturing process, his local position and his role. In contrast, mobile MES apps as well as SAPOD only rudimentarily make use of context data on the manufacturing process and the user without exploiting physical conditions or the local position of the user on the shop floor.

6.6 Evaluation Results and Benefits

The case-based evaluation highlights the technical feasibility and applicability of the OPDM in an example case, the manufacturing of steel springs in the automotive industry. Based on the AdMA backend – comprising the Manufacturing Warehouse, the Manufacturing Knowledge Repository and data-mining-based optimization services – it was demonstrated by a typical real-world application scenario that the OPDM realizes mobile and situation-aware information provisioning on the factory shop floor using tablet PCs. In particular, the scenario showed that the OPDM is able to combine dashboard services for the whole range of process-oriented information needs, e.g., process performance and process knowledge, and enables proactive process optimization using data-mining-based recommendations. Regarding technical performance, especially performance of data preparation procedures for data mining, there is room for improvements using optimized server hardware for the backend beyond the test system presented in this paper.

The comparative evaluation of the OPDM with existing approaches underlines that the OPDM goes significantly beyond typical mobile MES apps and operator dashboards. The OPDM exploits data mining techniques and addresses the whole range of information needs on the shop floor in a situation-aware manner. In particular, the data-mining-based generation of action recommendations during process execution represents a novelty in manufacturing.

On the basis of these evaluation results, the key benefits of the OPDM for manufacturing can be summarized as follows:

- The OPDM significantly *enhances the transparency and agility of manufacturing operations* by targeted, holistic and near-real-time information provisioning for both workers and supervisors regarding process context, process performance, process knowledge and process communication. In this way, workers and supervisors are aware of the current situation on the entire shop floor at any time and can immediately react to turbulences, e.g. the sudden break down of machine, avoiding uncoordinated waiting times and costly communication.

- The OPDM *enables data-driven manufacturing process optimization* using data-mining-based optimization services. In particular, recommendation-based optimization enables proactive optimization by dynamically generating action recommendations on the basis of historic process execution data. That is, potential KPI deviations can be counteracted before they become reality by learning from past process executions. In contrast to model-driven process optimization, e.g. using simulation, there is no need for the costly and complex manual construction of formal models, such as simulation models or rule bases. In fact, analysis models, e.g., decision trees for recommendation generation, are dynamically derived from data providing novel insights for optimization.
- The OPDM *stimulates knowledge management on the shop floor* by reducing the barriers for knowledge acquisition and knowledge sharing. New knowledge can be easily codified right on the shop floor by creating multimedia problem tickets and improvement suggestions using the OPDM app on mobile touch-based devices, especially tablet PCs. Codified knowledge is then stored in the Manufacturing Knowledge Repository and can be easily viewed, edited and complemented by other users enabling shared usage.

7 Conclusion and Future Work

In this paper, the Operational Process Dashboard for Manufacturing (OPDM) was presented constituting a mobile and analytics-based dashboard for workers and supervisors on the shop floor in discrete manufacturing. In particular, conceptual IT design issues of a mobile shop floor application on top of the Advanced Manufacturing Analytics Platform were investigated including the evaluation of different types of mobile devices, the development of an appropriate context model and the study of security issues. Besides, a comprehensive evaluation of the entire OPDM in an automotive industry case was presented.

The case-based evaluation of the OPDM underlines the feasibility and applicability of the OPDM in a real-world case and emphasizes the benefits of analytics-based and situation-aware information provisioning on the shop floor, that are (1) enhancing transparency and agility of manufacturing operations, (2) enabling data-driven manufacturing process optimization and (3) stimulating knowledge management on the shop floor.

With respect to future work, there are two major aspects: First, a systematic selection procedure has to be developed to identify characteristics of manufacturing processes which favour a successful usage of the OPDM. This comprises organizational aspects, e.g., the type of production, as well as technical aspects, especially characteristics of the underlying data acquisition infrastructure in the factory to provide source data for the OPDM. Second, privacy aspects have to be investigated. The storage and analysis of personal employee data in the backend as well as the use of context data on the mobile device rise privacy issues as they facilitate employee tracking and profiling. Thus, concepts such as privacy-aware context and location management (Stach and Mitschang 2013) have to be examined.

All in all, the OPDM highlights the importance of comprehensive data management and data analytics on the shop floor as well as user-centric and situation-aware presentation of the resulting information which are both central aspects of the smart factory. The overall goal is to leverage the huge amounts of data to significantly enhance performance and agility of manufacturing operations.

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