Supporting Manufacturing Design by Analytics

Continuous Collaborative Process Improvement enabled by the Advanced Manufacturing Analytics Platform

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***Abstract*—The manufacturing industry is faced with global competition making efficient, effective and continuously improved manufacturing processes a critical success factor. Yet, media discontinuities, the use of isolated analysis methods on local data sets as well as missing means for sharing analysis results cause a collaborative gap in Manufacturing Process Management that prohibits continuous process improvement. To address this challenge, this paper proposes the Advanced Manufacturing Analytics (AdMA) Platform that bridges the gap by integrating operational and process manufacturing data, defining a repository for analysis results and providing indication-based and pattern-based optimization techniques. Both the conceptual architecture underlying the platform as well as its current implementation are presented in this paper.**

Keywords: Analytics, Data Mining, Process Management, Manufacturing, Process Optimization

I. Introduction

A. Motivation

Globalization confronts manufacturers with steadily increasing competition. Not only product quality and variety, but flexibility, short lead times and a high adherence to delivery dates have become critical success factors [1]. Efficient, effective and continuously improved manufacturing processes are therefore a key source of competitive advantage [2].

Business Intelligence (BI) technology and its application in the service industry clearly shows the benefit of applying detailed analytics to improve workflow-based business processes [3], [4]. The gained insights support the participating process engineers to cooperatively optimize the existing process landscape.

In general, we can observe various levels of analytics:

- Traditional BI applications [5] based on operational data, in particular on financial metrics,
- Business Process Intelligence (BPI) applications [6] focusing on process data, especially on workflow audit data, and
- Holistic BI applications that integrate both process data and operational data to generate deep insights.

On any of these levels, the focus of previous work was on the service industry and the analysis of workflow-based business processes. Other important business areas, e. g., the manufacturing industry, have not been addressed so far. The latter is characterized by a comparably low degree of standardisation regarding process modelling and process execution techniques. In addition, manufacturing processes are significantly more complex than workflow-based business processes, involving a variety of heterogeneous resources and activities and requiring elaborate planning methods [7]. Hence, existing workflow-oriented BI approaches cannot simply be applied to manufacturing.

The field of Manufacturing Process Management seems to be a beneficial area for applying a manufacturing-specific holistic BI approach: The high volume of process data recorded by Manufacturing Execution Systems (MES) [8] favours the integration with operational data, e. g., from Enterprise Resource Planning (ERP) and Computer Aided Planning (CAP) systems [9]. This enables continuous collaborative process improvement.

B. The Gap in Manufacturing Process Management

Manufacturing Process Management comprises the design, implementation, execution and analysis of manufacturing processes as shown in Fig. 1.

Roughly speaking, product planning and design focuses on what product to manufacture, production planning and scheduling decides when to manufacture it, and Manufacturing Process Management defines how to manufacture the product [10]. Typically, the different sub processes are supported by heterogeneous IT systems and conducted by teams of various disciplines [11], [7].

- Computer Aided Design (CAD) systems are used by product developers for product planning and design.
- ERP systems are at the core of production planning and scheduling. They are used by production schedulers.
- Production engineers use CAP systems for process planning, design and implementation.

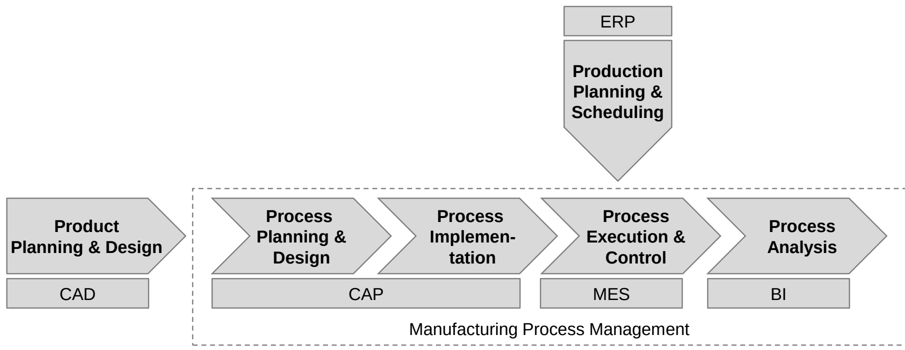

Figure 1. Classical view of Manufacturing Process Management and corresponding sub processes

- MES are used for process execution and control by production supervisors.
- Process analysis is done ex-post with various BI applications by managerial process controllers.

This brings about media discontinuities and the use of isolated analysis methods and terminologies on local data sets in each sub process. Furthermore, the sharing and combination of analysis results is significantly limited. Consequently, industry practice shows scarce information flow esp. between process analysis and process redesign, leading to a collaborative gap that prohibits continuous process improvement (see Fig. 2).

In this paper, we present the Advanced Manufacturing Analytics (AdMA) Platform as an enabler for continuous collaborative process improvement based on advanced analytics. The remainder is organized as follows: In Section II, we structure previous work in the BI context and present the Deep Business Optimization Platform as the central conceptual starting point. Moreover, we examine existing approaches of analytics in manufacturing practice. In Section III, we present the AdMA Platform as a transfer of the Deep Business Optimization Platform framework to the context of manufacturing and depict its architecture. In addition, we point out details about the development. We conclude in Section IV and highlight future work.

II. Previous Work

A. Levels of Analytics

Fig. 3 structures the various levels of analytics according to their data basis and the time horizon of their application. Analytics can be based on operational data or process data [12]. Operational data is subject-oriented and represents data of traditional data warehouses, e. g., sales data. Process data is flow-oriented and comprises execution data and process model data. Moreover, analytics can be applied after the execution of the activity that has to be analyzed (ex-post), during its execution (real-time) and before its execution (ex-ante).

Traditional BI applications are solely based on operational data and perform ex-post analysis. BPI applications use process data, whereat ex-post, real-time and ex-ante applications exist. Business Activity Monitoring (BAM) [13] is an example for a real-time BPI application, process simulation is applied ex-ante [3] and process mining comprises concepts for all time horizons [14]. Finally, holistic BI applications like the Deep Business Optimization Platform [15] integrate both operational and process data in all time horizons to find a broader range of optimization opportunities.

B. The Deep Business Optimization Platform

The Deep Business Optimization Platform (dBOP) [15] is a framework and a platform for the optimization of workflow-based processes. As a holistic BI application it constitutes the conceptual starting point for the AdMA Platform. The dBOP enables ex-post, real-time and ex-ante process optimization based on a data warehouse integrating operational and process data. Optimization is conducted using optimization patterns, i. e., formalized best practice techniques for the optimization of processes. Fig. 4 shows dBOP's conceptual high level architecture consisting of three integrated layers.

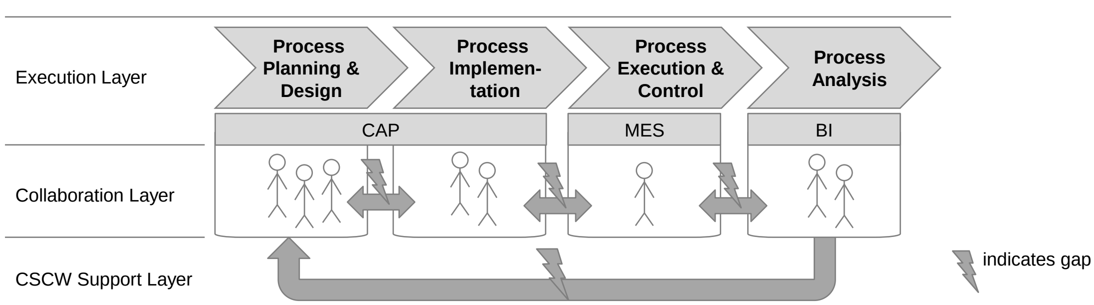

Figure 2. The collaborative gap in Manufacturing Process Management

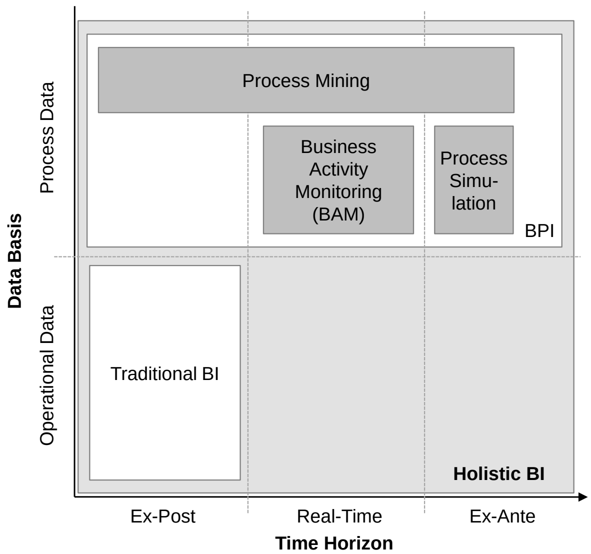

Figure 3. Classification of analytics

The *Data Integration layer* matches process and operational data to store it in an integrated process-centric data warehouse. Process data originates from Business Process Management System (BPMS) systems, esp. audit trails, [16] and operational data is taken from sources like ERP systems. To link operational data and process events a framework for automatic, semi-automatic and manual matching is provided. The aim is to integrate all data pertaining to process performance by abstracting from various heterogeneous source systems.

The *Process Analytics layer* extracts insights from the Integrated Data Warehouse, i. e., analysis results that can be transformed into concrete process optimizations. Predefined data mining models complemented by metric calculation and graph analysis are used on this layer. Data mining models comprise, e. g., association rules and decision trees [17]. Metric calculation focuses on the computation of metrics for process controlling, e. g., process costs or resource utilization. Graph analysis is based on an analysis of the process model itself. The Process Insight Repository [18] stores all process insights to enable their reuse, sharing and combination playing the role of a knowledge management component [19].

The *Process Optimization layer* conducts the actual process optimization using insights from the Process Insight Repository encapsulated in optimization patterns [20]. Optimization patterns are based on analytics, esp. data mining techniques. One pattern for example describes the optimal selection of resources for a process step using multiple regression. In a regression model, resource attributes like the experience of an employee are linked with performance indicators, e. g., the duration of an activity, to predict the likely performance and select the best resource available. Patterns can be applied ex-ante in the a priori design, real-time during the execution and ex-post in the a posteriori analysis of the process. The optimized process model is then deployed to the BPMS to close the optimization cycle.

The dBOP focuses on workflow-based business processes and makes use of standardized workflow-specific process modelling and process execution techniques, esp. the Business Process Model and Notation (BPMN) [21] and the Business Process Execution Language (BPEL) [22]. However, manufacturing processes are significantly more complex than workflow-based business processes, involving a variety of heterogeneous resources and activities [7]. In addition, there is no industry-wide standard for modelling and specifying manufacturing processes. Thus, process planning and process execution systems use proprietary event models and process data formats. Moreover, analysis and optimization of manufacturing processes require specific metrics, e. g Overall Equipment Efficiency (OEE), and suitable optimization patterns. These factors prevent a direct application of the dBOP in manufacturing and necessitate the modification and extension of the dBOP concepts.

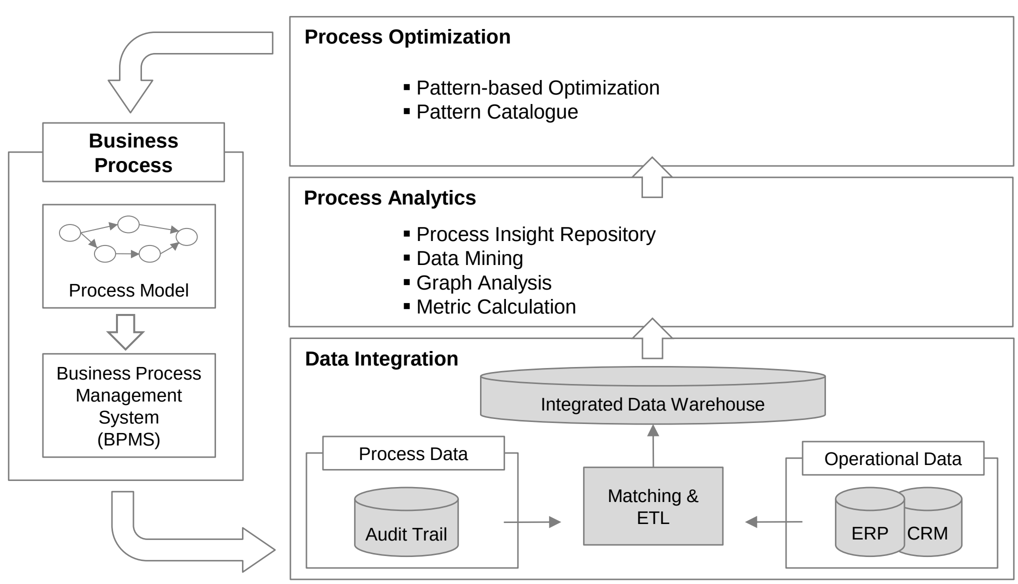

Figure 4. Conceptual architecture of the Deep Business Optimization Platform

C. Analytics in Manufacturing

Looking at the literature and conducting industry interviews, we currently know of essentially two types of widespread manufacturing analytics in industry practice:

- Pre-packaged dashboard applications, often called control panels, based on standardized metrics with simple reporting and statistics functions [23], [8].
- Custom traditional BI applications, partly built on data warehouses, mainly focusing on spreadsheet-based OLAP and reporting functions [24].

Pre-packed dashboard applications are typically part of MES or supplementary products and employed real-time during process execution and control. Custom manufacturing BI applications are usually used ex-post during process analysis. Both types miss a holistic view integrating operational and process data. Moreover, they do not make use of advanced analytics techniques, especially data mining to automatically extract valuable patterns from data. Most importantly, there is neither a concept for systematically storing and sharing analysis results, nor a technique for transforming them into concrete process optimizations. These factors considerably limit a continuous collaborative process improvement.

III. The Advanced Manufacturing Analytics Platform

A. Overview

The AdMA platform is a holistic BI application for the analysis and optimization of manufacturing processes based on advanced analytics to enable a continuous collaborative process improvement. It transfers the dBOP framework to the context of manufacturing by adapting and extending its core concepts. Fig. 5 shows the AdMA-enabled manufacturing optimization cycle. The collaborative gap sketched in Section I.B is bridged by the following four means:

- Integrating all data pertaining to the design, implementation, execution and analysis of the manufacturing process to perform holistic analytics.
- Systematically storing all analysis results in a central repository to enable their sharing, combination and reuse.
- Transforming analysis results into process improvements using indication-based and pattern-based optimization.
- Providing optimization functionality in all sub processes, i. e., during process design and implementation (ex-ante), process execution (real-time) as well as during process analysis and redesign (ex-post).

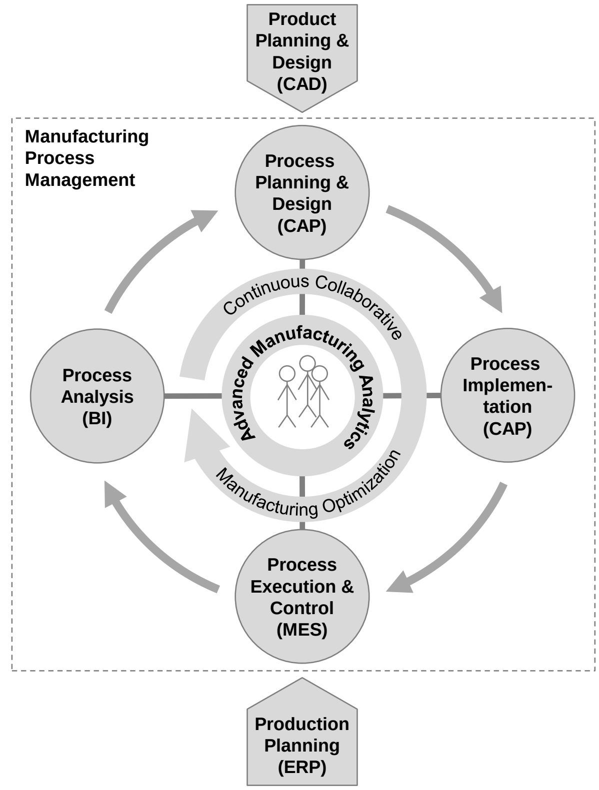

Figure 5. The Advanced Manufacturing Analytics approach

B. Architecture

Fig. 6 outlines the conceptual architecture of the AdMA Platform in analogy to the dBOP. It consists of three layers showing manufacturing-specific extensions and modifications.

The *Data Integration layer* integrates process manufacturing data and operational manufacturing data in a holistic process-centric data warehouse, the Manufacturing Warehouse. Process data comprises execution data, i. e., events recorded by MES based on machine data collection and production data acquisition. Operational data mainly encompasses CAD, CAP and ERP data. The Manufacturing Warehouse, the Manufacturing Data Integrator as well as the Process Insight Repository deal with steps and events in manufacturing processes. As a conceptual basis, we developed a generalized manufacturing process metamodel that defines essential concepts and their relationships relevant to the execution of manufacturing processes, e. g., process steps and different types of resources. This metamodel is based on a holistic view integrating process and operational aspects independent of their actual data source. In addition, we defined a unified event model in terms of a state machine with the main states and transitions of a manufacturing process step to derive events relevant for data warehousing.

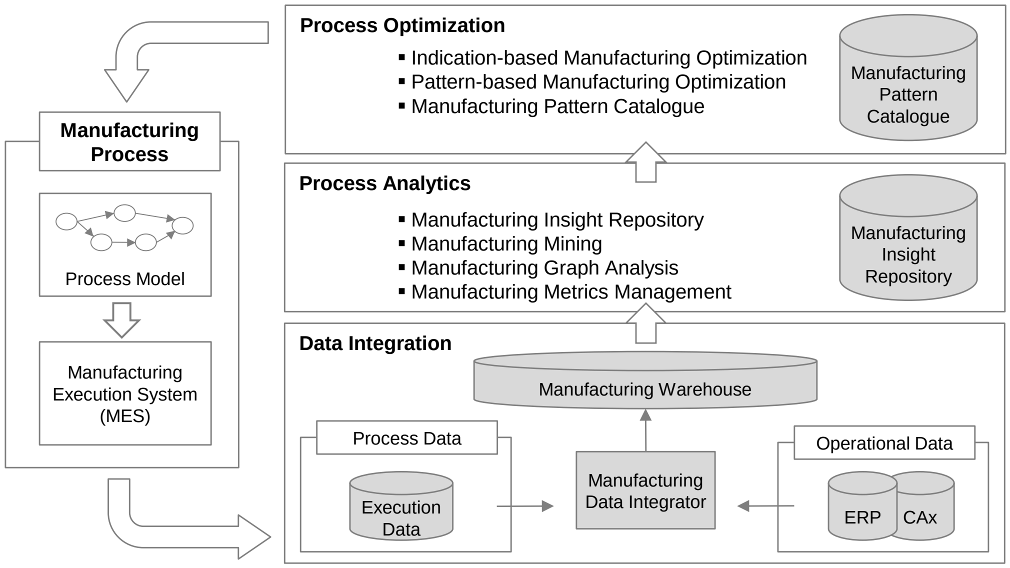

Figure 6. Conceptual architecture of the Advanced Manufacturing Analytics Platform

The *Process Analytics layer* combines three techniques to generate process insights and stores them in the Manufacturing Insight Repository. Manufacturing Graph Analysis conducts a static analysis of the manufacturing process model to identify process constructs relevant for optimization. The analysis of dependencies between process steps may for instance reveal options for parallelisation. The graph analysis is based on the manufacturing process metamodel and takes into account manufacturing-specific process characteristics, e. g., spatial attributes. Manufacturing Metrics Management comprises the definition, calculation and administration of manufacturing-specific metrics, e. g., First Pass Yield. Most importantly, the Manufacturing Mining component conducts adjusted data mining tasks, i. e., data preparation and pattern detection. It takes into account the Manufacturing Warehouse schema and transforms the data as needed by the selected data mining technique, for instance the generation of decision trees. The Manufacturing Insight Repository systematically stores all analysis results, e. g., data mining models and calculated metrics, to enable their reuse, combination and sharing. For that purpose it links them with the corresponding process constructs. Hence, analysis results are treated as supplements of a process model stored in the Manufacturing Insight Repository. An example is a decision tree, which is generated for a root cause analysis of metric deviations of a selected process. Thus, the Manufacturing Insight Repository has to be based on the manufacturing process metamodel as well.

The *Process Optimization layer* comprises components that use and combine insights from the Manufacturing Insight Repository to support the actual process improvement. Indication-based Manufacturing Optimization uses preconfigured data mining models supplemented by metrics to explain and predict certain process attributes. Consequently, hints respectively indications are presented to the user that enable him to infer corresponding process improvements. An example is the root cause analysis of metric deviations using decision trees. It allows to identify circumstances under which a selected process exceeds, e g., its cycle time. Possible reasons could be the use of special machines or manufacturing aids. Pattern-based Manufacturing Optimization goes beyond that and proposes concrete process modifications that are applicable for a given process to achieve a defined goal, e. g., to speed up the process. It uses specific optimization patterns stored in the Manufacturing Pattern Catalogue. These patterns describe optimization options like the parallelization of sequential activities.

C. *Development*

As the dBOP has successfully been developed and is currently used, both the implementation as well as the gained experiences define the starting point for the realization of the AdMA Platform. To specify the initial scope of development, we talked to manufacturing companies on their MES execution data and possible analytics. Based on these discussions, we decided to set two foci:

- Considering the data integration layer, we came up with a standardized process-oriented data warehouse model for the Manufacturing Warehouse integrating operational and process data.
- For analytics and optimization we agreed on investigating classical data mining techniques for Indication-based Manufacturing Optimization.

The resulting technical architecture of the current prototype consists of three layers shown in Fig. 7. The *Data Integration layer* comprises the Manufacturing Warehouse. It is built on IBM DB2 and contains a relational implementation of the multidimensional Manufacturing Warehouse schema. The multidimensional schema is deduced from the process metamodel and the event model to cover all aspects of a manufacturing process. It takes an activity-centric perspective on manufacturing processes with process step executions being the central facts. Dimensions are, amongst others, machines and manufacturing aids used in process steps, processed material and participating employees.

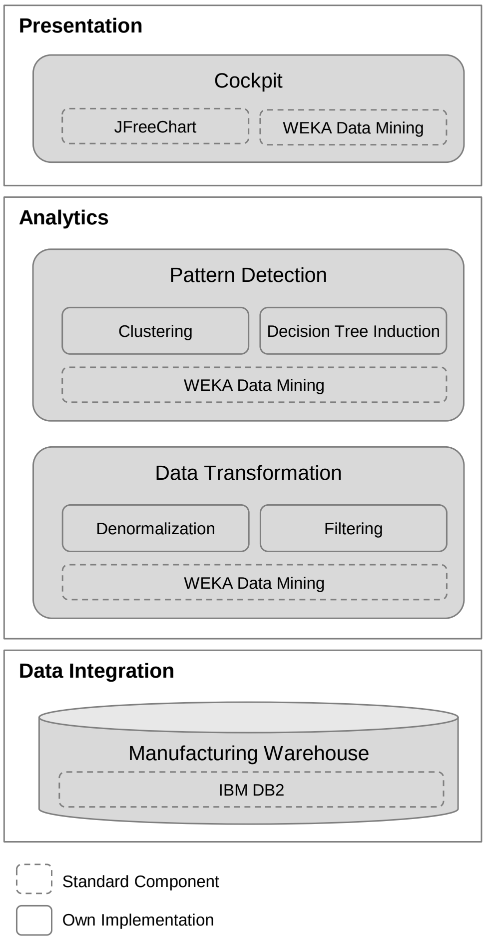

Figure 7. Technical architecture of the current prototype

Furthermore, we identified elementary manufacturing metrics related to process steps, e. g., the number of rejects, as the basis for calculating typical aggregated metrics, like First Pass Yield, used in industry practice [25]. For test purposes, we used synthetic data to populate the warehouse.

The *Analytics layer* focuses on data mining. Based on literature analysis [26] and industry interviews, we developed concrete data mining use cases for Indication-based Manufacturing Optimization and implemented the following two functionalities on top of the data warehouse.

- The so called metric-oriented root cause analysis identifies circumstances under which a certain metric of a selected process falls into a defined range. It uses decision trees and user-defined categorized metrics.
- The structure analysis is based on clustering and lets the user cluster instances of a selected process to identify exceptional or typical process executions.

The necessary data mining techniques are implemented in Java using the WEKA data mining framework [27]. As Fig. 7 shows, Data Transformation comprises the denormalization and filtering of data to prepare it for clustering and decision tree induction. The whole data pertaining to a process instance, e. g., all employed machines and participating employees, have

Process_ Instance_ ID	Step_1_ Machine_1_ ID	Step_1_ Machine_1_ Age	Step_1_ Empl_1_ ID	Step_1_ Empl_1_ Group	Step_2_ Machine_1_ ID	…	LeadTime
P1	M1	1	E10	G1	M34		OK
P2	M2	6	E10	G1	M34		TooHigh
P3	M7	5	E10	G1	M34		TooHigh
P4	M3	3	E10	G1	M34		OK
P5	M4	8	E10	G1	M34		TooHigh
…							

Figure 8. Exemplary denormalized input data for root cause analysis

to be denormalized to get one tuple per process instance as input for the data mining algorithms. Filtering alludes to the filtering of relevant attributes using standard WEKA filters. Pattern Detection is based on standard data mining algorithms for decision tree induction and clustering. The former uses WEKA's implementation of the C4.5 algorithm and the latter is based on WEKA's k-means clustering.

Fig. 8 shows an exemplary excerpt of denormalized input data for decision tree induction, i. e., training data for a metric-oriented root cause analysis of lead times. Every row comprises denormalized data concerning one process instance with the attribute "LeadTime" as class label. Amongst others, machines and employees taking part in production steps as well as corresponding additional information like machine age and employee group are used for decision tree induction. An exemplary resulting decision rule presenting an indication for process improvement could be: when the first machine employed in production step 1 is older than 3 years, lead times are typically too high.

The *Presentation layer* implements the GUI. It is shaped as a simple cockpit with graphical indicators for metric representation using JFreeChart. Users can select a metric for a specific process and start the corresponding root cause analysis or structure analysis. Decision tree visualization is done with the WEKA-provided tree visualizer.

IV. Conclusion and Future Work

This paper has demonstrated that media discontinuities, the use of isolated analysis methods on local data sets as well as missing means for sharing and reuse of analysis results cause a collaborative gap in Manufacturing Process Management that prohibits continuous process improvement. To address this challenge, we have introduced our Advanced Manufacturing Analytics (AdMA) Platform as a transfer of the workflow-oriented Deep Business Process Optimization Platform (dBOP) to the context of manufacturing.

The AdMA Platform is a holistic BI application and bridges the collaborative gap by four means:

- Integrating operational and process manufacturing data in a process-oriented data warehouse.
- Storing analysis results in a repository for reuse and sharing.

- Transforming analysis results into process improvements using indication-based and pattern-based optimization.
- Providing optimization functionality in all sub processes of Manufacturing Process Management, i. e., during the design, implementation, execution and analysis of manufacturing processes.

We have sketched the conceptual architecture and the current prototypical implementation of the AdMA Platform. The latter focuses on the Manufacturing Warehouse and indication-based optimization using classical data mining techniques, in particular decision tree induction and clustering.

In our future work, we plan to develop a detailed schema for the Manufacturing Insight Repository as an extension of dBOP's Process Insight Repository. Furthermore, we are going to design manufacturing-specific optimization patterns to enable pattern-based optimization - a completely new approach in manufacturing. Besides, we are currently extending our platform implementation, e.g., by realizing the Manufacturing Data Integrator in order to use authentic manufacturing data.

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