Warehousing Manufacturing Data

A Holistic Process Warehouse for Advanced Manufacturing Analytics

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Abstract. Strong competition in the manufacturing industry makes efficient and effective manufacturing processes a critical success factor. However, existing warehousing and analytics approaches in manufacturing are coined by substantial shortcomings, significantly preventing comprehensive process improvement. Especially, they miss a holistic data base integrating operational and process data, e. g., from Manufacturing Execution and Enterprise Resource Planning systems. To address this challenge, we introduce the Manufacturing Warehouse, a concept for a holistic manufacturing-specific process warehouse as central part of the overall Advanced Manufacturing Analytics Platform. We define a manufacturing process meta model and deduce a universal warehouse model. In addition, we develop a procedure for its instantiation and the integration of concrete source data. Finally, we describe a first proof of concept based on a prototypical implementation.

Keywords: Data Warehouse, Manufacturing, Process Optimization, Analytics, Business Intelligence, Data Integration

1 Introduction

1.1 Motivation

The manufacturing industry is faced with strong global competition. Apart from product quality and pricing, flexibility, short lead times and a high adherence to delivery dates have become critical success factors [1]. Efficient, effective and continuously improved manufacturing processes thus play a central role in a comprehensive competitive strategy [2].

Both in research and in industry, Business Intelligence (BI) technology is recognized as an enabler for analytics-based optimization of business activities as well as decision support. It has repeatedly proven its potential in the service industry for the improvement of workflow-based business processes [3], [4].

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With respect to BI approaches in manufacturing, we currently know of essentially two types wide-spread in industry: Pre-packaged dashboard applications, typically part of Manufacturing Execution systems (MES), based on standardized metrics with simple reporting functions [5] as well as custom BI applications, partly built on data warehouses, mainly focusing on spreadsheet-based Online Analytical Processing (OLAP) and reporting functions [6].

Several decisive insufficiencies of these approaches significantly prevent comprehensive process optimization in manufacturing: Most importantly, they miss a holistic process view integrating operational data and process data, e. g., from MES and Enterprise Resource Planning (ERP) systems, to find a broader range of optimization opportunities. Moreover, they do not make use of advanced analytics techniques, esp. data mining, to automatically identify hidden data patterns for process improvement. To overcome these deficiencies, in our overall work we develop the Advanced Manufacturing Analytics (AdMA) Platform as a novel approach for data-driven manufacturing process optimization. In this article, we focus on the central component of the AdMA Platform, the Manufacturing Warehouse, a manufacturing-specific holistic process warehouse.

The remainder is organized as follows: First, we introduce the AdMA Platform and structure related work for process warehousing and data integration in Section 2. Next, we define analytic requirements and potential data sources for the Manufacturing Warehouse in Section 3. Based on a manufacturing process meta model, described in Section 4, we develop a standardized warehouse model as well as a procedure for its instantiation and the integration of concrete data in Section 5. Our prototypical implementation and a first proof of concept are presented in Section 6. We conclude in Section 7 and highlight future work.

1.2 The Advanced Manufacturing Analytics Platform

The Advanced Manufacturing Analytics Platform, introduced in [7], is an integrated BI platform for manufacturing process optimization. It is based on a transfer of concepts of the Deep Business Optimization Platform [3], [8-10] to manufacturing with its conceptual architecture comprising the following components (see Fig. 1).

The *manufacturing process* is typically deployed on an MES and corresponding execution data is generated during process execution. Process data and additional operational data are integrated in the *Manufacturing Warehouse*, the focal point of this article. It is provisioned by the *Manufacturing Data Integrator*, which matches process and operational data. In general, operational data is subject-oriented and represents data of traditional data warehouses, e. g., financial data. Process data is flow-oriented and comprises execution data, i. e., events recorded during process execution, and process model data [9].

Process Analytics comprises different analysis methods, esp. data mining techniques and metrics calculation, to generate insights with the *Manufacturing Insight Repository* serving as a central component for the sharing of analysis results.

Indication-based Manufacturing Optimization uses pre-configured data mining models to explain and predict process characteristics.

Pattern-based Manufacturing Optimization goes beyond that and proposes concrete process modifications using optimization patterns. Both focus on the overall manufacturing process from the creation of the production order until the finishing of the product including all process steps and resources. They are further detailed and differentiated from existing data mining approaches in manufacturing in [11].

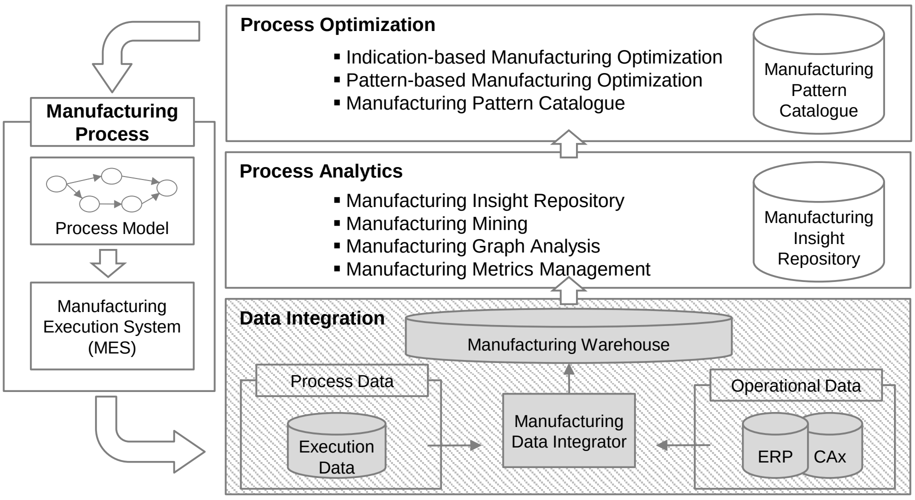

Fig. 1. Conceptual architecture of the Advanced Manufacturing Analytics Platform with the focus of this article marked in grey

The AdMA Platform can be seen as an application of process mining [12] to manufacturing whereas it focuses on the enhancement of process models, not on the classic process mining disciplines, i. e., discovery and conformance of process models. In contrast to traditional enhancement concepts, we use not only process data but also operational data in combination with novel analytical approaches, esp. indication-based and pattern-based optimization.

2 Related Work

For the discussion of related work, we distinguish between work referring to warehousing and analysing business processes as well as work related to data integration aspects.

Concepts and techniques for warehousing and analysing business processes are discussed in the area of Business Process Intelligence (BPI) [13]. BPI primarily focuses on workflow-based business processes and related process modelling and process execution concepts. Thus, traditional process warehouse concepts like [14], [15] are based on audit trail data of Workflow Management systems and corresponding meta models like [16]. Next-generation process warehouse approaches – we call them holistic process warehouses – try to enrich process data with additional operational data to realize corresponding holistic BI applications. Initial holistic process warehouse concepts are proposed in [17], [18]. The only fully developed holistic process warehouse, we know of, is the integrated data warehouse of the Deep Business Optimization Platform (dBOP) [8], [19] focusing on workflows.

Yet, workflow-oriented approaches cannot simply be applied to manufacturing for several reasons. First, manufacturing processes are significantly more complex than workflow-based business processes, involving a variety of heterogeneous resources and activities [20]. In addition, process planning and process execution systems in manufacturing use proprietary event models and process data formats. Moreover, processes optimization requires specific metrics and suitable optimization patterns. Based on these constitutive differences, we take the dBOP process warehouse as a starting point to develop a manufacturing-specific holistic process warehouse.

Considering existing manufacturing-specific process warehousing approaches, an initial traditional process warehouse for manufacturing is modelled in [21]. It defines five rudimentary dimensions and a few basic metrics to analyse processes at the level of the whole process. With respect to standardized data warehouse implementations in industry practice, the SAP Business Content as part of the SAP NetWeaver Business Intelligence Platform [22] provides a variety of manufacturing-specific metrics and multi-dimensional data models, called InfoCubes. Yet, it misses a consequent integration of process and operational data in a holistic approach.

Regarding data integration aspects, traditional warehousing concepts are based on Extraction, Transformation and Load (ETL) processes for materialized data integration [23], [24]. A holistic process warehouse requires an extended ETL approach based on the matching of operational and process data [25]. The foundations are general concepts for schema matching and integration [26], [27] that have to be adapted to the specific semantics of process data. [28], [19] present a framework and a tool for matching process and operational data based on workflow standards, esp. BPEL. Taking these concepts as a basis, we develop a procedure for manufacturing-specific matching and ETL that is able to cope with heterogeneous event models and source formats of various data acquisition systems.

3 Requirements and Data Sources

3.1 Analytic Requirements

From a business perspective, there are two central preconditions for efficient and effective manufacturing processes, namely process transparency and process responsiveness [5]. The former alludes to the availability of integrated up-to-date information about currently running processes and their status as well as details about the performance and weaknesses of completed processes, always with respect to the whole process and all participating resources. Transparency is necessary for responsiveness, referring to the ability to quickly realize potentials for improvement and react to changing environmental conditions. The analytic requirements for the Manufacturing Warehouse and the corresponding data integration concepts have to implement these preconditions and realize the vision of the AdMA Platform to provide a standardized integrated BI platform for the holistic data-driven optimization of manufacturing processes. Hence, the following analytic core requirements result:

- Holistic data base: Holistic process optimization requires the integration of all data pertaining to process performance, i. e., operational and process data related to a manufacturing process have to be consolidated and integrated.
- Standardization and Flexibility: To realize pre-defined optimization services a standardized and generalized data model is necessary. As manufacturing processes and data sources are extremely heterogeneous in industry practice, both the data model and the integration concepts should be flexible enough to be adapted to conditions of different manufacturing companies.
- Real-time capability: Both data integration and analytics have to work (near-) real-time to provide the user with up-to-date information about processes in progress.
- Historization: All integrated data have to be historized to analyse process performance over time.

3.2 Data Sources in Manufacturing

To structure potential data sources for the Manufacturing Warehouse we refer to a simplified version of the ISA hierarchy model of manufacturing [29]. We distinguish the following three levels on top of the actual manufacturing process:

The *Business Planning and Logistics* level comprises business-related activities, esp. product and process planning using Computer Aided Design (CAD) and Computer Aided Planning (CAP) systems. Moreover, production planning and scheduling typically supported by ERP systems is carried out on this level as well as Customer Relationship Management (CRM).

The level for *Manufacturing Operations Management* contains all activities to coordinate the execution of manufacturing processes and related resources. Typical IT systems are Production Data Acquisition (PDA) systems for the recording of process execution data as well as Computer Aided Quality (CAQ) systems. MES are the central IT systems for Manufacturing Operations Management integrating and extending PDA and CAQ functionalities. They connect the business level with the actual process by transforming production plans into concrete process executions and reporting results [5].

The *Automation* level comprises all activities for the direct technical monitoring and control of the actual process. At this level, Computer Aided Manufacturing (CAM) systems are used.

On this basis, the central data sources for the Manufacturing Warehouse can be defined: Process execution data is provided by MES, PDA and CAQ systems whereat process model data is supposed to be contained in MES, ERP as well as CAP systems. Operational data, esp. master data concerning product and customer information as well as production plans, is provided by ERP, CRM and CAD systems.

4 Manufacturing Meta Models

4.1 Motivation

To specify a standardized and universal data model, we follow a top-down development approach independent of syntax and semantics of concrete data sources. In order to define generalized information needs for the analysis of manufacturing processes, we develop both conceptual manufacturing meta models and a catalogue of basic manufacturing-specific metrics. In this section, we focus on the meta models, esp. the manufacturing process meta model (MPMM).

The MPMM provides a unified and technology-independent definition of essential concepts and their relationships relevant to the execution of manufacturing processes, e. g., process steps and different types of resources. It is based on a holistic view integrating process and operational aspects independent of the actual data source. Hence, the MPMM represents the basis for the selection of central analysis objects and related entities, i. e., facts and dimensions in the multi-dimensional warehouse scheme.

We complement the MPMM with a conceptual manufacturing event meta model (MEMM) in terms of a state machine with the main states and state transitions of a manufacturing process step, e. g., start, pause and completion of a step. Thus, the MEMM defines requirements for necessary process execution data, i. e., events that have to be provided by corresponding process data sources, e. g., MES. Moreover, it supports the definition of event-based facts in the Manufacturing Warehouse. Due to space restrictions, we do not go into detail on the MEMM in this article.

Both the MPMM and the MEMM abstract proprietary meta models used in data sources, esp. PDA systems and MES, to establish a common and consistent understanding of manufacturing processes and related events for data integration and analytics.

4.2 Manufacturing Process Meta Model

We conducted literature analyses to define a comprehensive meta model for manufacturing processes esp. adapted to the needs of serial and mass manufacturers. It takes a static perspective and models concepts relevant for the execution of a single process instance, i. e., it adopts a run-time not a built-time point of view and doesn't differentiate between process model and process instance. We took generic manufacturing meta models, esp. [21], [29], [30], as a starting point to concretize and extend them with respect to factors influencing the four basic target and analysis dimensions of manufacturing, i. e., time, cost, quality and flexibility [31]. Moreover, for an initial evaluation and refinement of the model, we did industry interviews with manufacturing consultants.

Fig. 2 shows a simplified excerpt of the MPMM as a UML class diagram. A *manufacturing process* consists of *production steps* and is linked with a *production order* defining, e. g., the batch size to be produced. A production order is associated with a *customer*, who can be internal or external, as well as with the *product* that is going to be produced as an output of the process. There are different types of production steps, esp. the actual *manufacturing steps* as well as *transportation steps*. Manufacturing steps refer to the manufacturing and assembly of parts, whereat transportation steps comprise the transportation of parts between different manufacturing steps, e. g., by pallet transporters. In each manufacturing step *scrap quantity* and *yield* of parts can be measured.

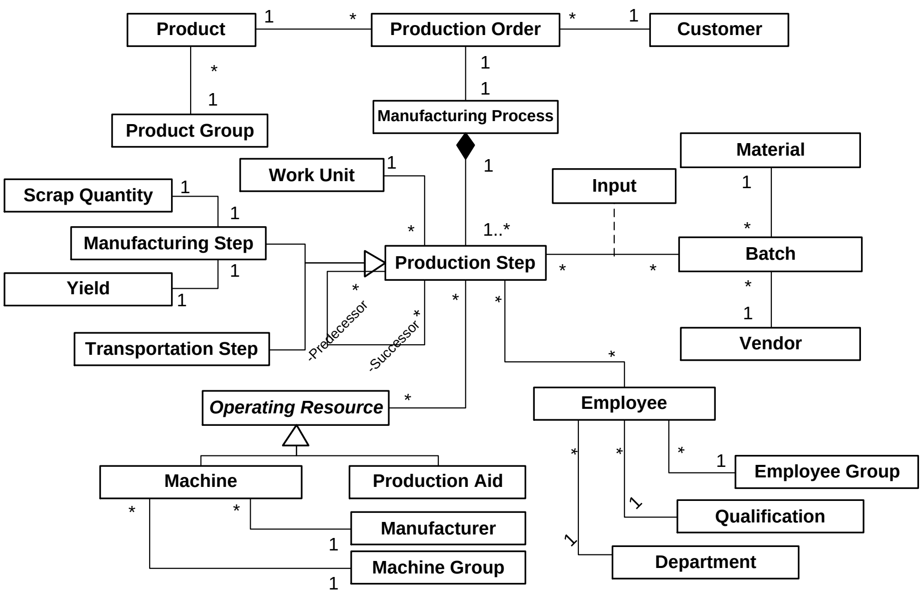

Fig. 2. Excerpt of the Manufacturing Process Meta Model (MPMM)

Regarding spatial aspects, a *work unit* and a corresponding hierarchy of areas and sites can be assigned to a production step. Moreover, a production step can have several *successors* and *predecessors* in a process execution. Resources used and processed in production steps are *employees*, i. e., production workers, *operating resources*, i. e., *machines* and *production aids*, like tools, as well as *material*. All resources can be described by various additional information like *vendors* of material or *manufacturers* of machines. For the sake of simplicity, we omit many details of the MPMM full version, esp. the modelling of operating supply items, environmental emissions or failures of production steps.

5 Manufacturing Warehouse

5.1 Conceptual Warehouse Model

To define a standardized conceptual warehouse model, i. e., a multi-dimensional scheme of the Manufacturing Warehouse, we first describe the generic structure of facts and dimensions of a holistic process warehouse. Next, we develop the actual warehouse model based on the above MPMM.

The generic structure represents a framework for the instantiation of the standardized model in individual cases based on available source data. This is necessary as concrete process and operational data sources vary significantly in existing manufacturing environments. For example, in an energy-intensive manufacturing process power consumption is relevant and recorded. In contrast, in another case CO2 emissions are logged. Hence, different warehouse models result which mainly differ by the dimensions describing the process.

In general, a limited number of process-oriented information is obligatory to define an activity-centric model for a holistic process warehouse. According to [32] we assume that each event during process execution occurs in a certain point of time, is associated with the instance of a single process step, thus is related to a single process instance, and provides a description about itself. Moreover, it provides various information about its context, i. e., links to objects relevant for the corresponding event. E. g., the start event provides information about machines used in the step. Hence, facts at lowest level of granularity are events with the obligatory dimensions “Time”, “Process” and “Event”. These dimensions are called flow dimensions as they describe the process flow over time. Context information provided by events, e. g., identifiers for material or machines, is the basis for additional dimensions, so called context dimensions. Flow and context dimensions result from process data and are enriched with supplementary operational data forming additional hierarchy levels, so called operational sub dimensions. It has to be remarked that events as central facts have no quantitative characteristics like metrics in traditional data warehouses. Hence, to ease analytics, so called derived, i. e., aggregated, facts are defined at the level of process steps and whole processes comprising basic process-oriented metrics, e. g., cycle time, which may already be computed during ETL. Although it extends the data volume of the warehouse, we decide to model event facts in addition to derived facts as they define the entire scope of process information available, thus enabling flexibility regarding previously unknown information needs. Finally, a fact constellation scheme with shared dimensions results as a generic structure for a holistic process warehouse.

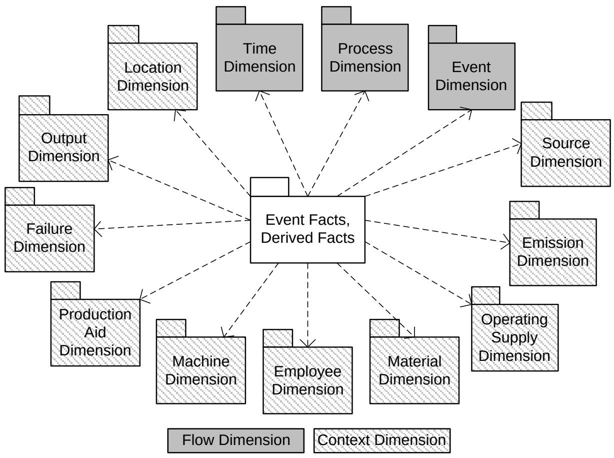

Fig. 3. Conceptual Model of the Manufacturing Warehouse

On the basis of this generic structure we define the standardized model of the Manufacturing Warehouse (see Fig. 3) using the MPMM as well as a set of basic manufacturing metrics related to process steps and whole processes operationalising the four manufacturing target dimensions cost, quality, time and flexibility. We defined ten standardized context dimensions in addition to the obligatory flow dimensions *"Time"*, *"Process"* and *"Event"*.

Fig. 3 shows a simplified version of the model in a multi-dimensional UML [33] package diagram. The *source dimension* refers to the technical source of an event, e. g., a certain machine. *Emissions* comprise environmental pollution like the generation of CO2 or waste. *Material* refers to input that becomes part of the product to be manufactured, whereat *operating supply* items like oil or electricity are consumed during manufacturing. The *output dimension* refers to yield and scrap quantity and the *failure dimension* comprises failures occurred during process execution.

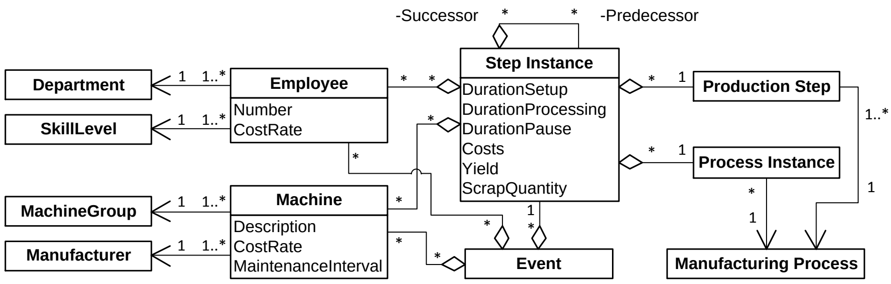

Fig. 4. Excerpt of the detailed Manufacturing Warehouse model

For illustrative purposes, an excerpt of a detailed model of the machine, employee and process dimension is shown in Fig. 4. According to the MPMM, a process comprises steps, whereat steps and processes are instantiated for process execution. Events provide context information about employees and machines and refer to a specified step instance. Derived facts are defined at process step level, e. g., duration for setup or costs of a step, with machines and employees taking part in a step.

5.2 Warehouse Instantiation and Data Integration

As mentioned in Section 2, we need an extended ETL approach for the integration of concrete source data in the Manufacturing Warehouse. Moreover, our standardized warehouse model has to be instantiated in each individual case as mentioned in Section 5.1. Hence, in the following, we provide a coarse-grained overview about the major steps of our integrated procedure for both warehouse instantiation and the integration of source data (see Fig. 5).

Instantiation focuses on the tailoring of the standardized warehouse model to available data sources in an individual case. Integration aims at determining matches between source data and warehouse model to define necessary ETL processes. Our concept relies on the ontology-based annotation [34] of both available process source data, i. e., concrete event logs esp. from PDA systems and MES, and standardized dimensions of the warehouse model. Therefore, we refer to an adapted version of the manufacturing-specific domain ontology in [35]. To enrich process data with operational data, we first match process data with the standardized warehouse model and then match operational data with the resulting selected warehouse dimensions.

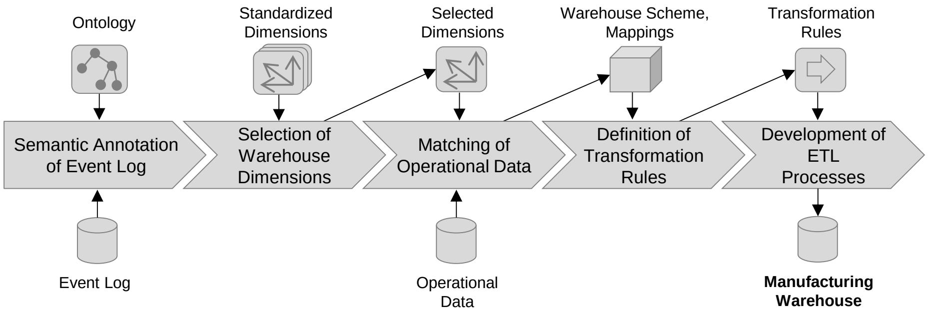

Fig. 5. Procedure for warehouse instantiation and data integration

The essential steps of our procedure are sketched in Fig. 5. First, all attributes of a given event log are annotated using the ontology to infer corresponding standardized context and process dimensions. For example, an event log containing the attributes “TimeStamp”, “EventName”, “MachineNumber” and “EmployeeNumber” is annotated. Thus, the process dimensions “Event” and “Time” as well as the two context dimensions “Machine” and “Employee”, resp. the corresponding dimensional attributes, result. Next, the selected dimensions are enriched with available operational data, e. g. from ERP or CRM systems, defining operational sub dimensions. Hence, matching mechanisms are employed to map given operational attributes to dimensional attributes of the standardized warehouse model. In this context, various traditional schema matching techniques [26] or ontology-based methods may be used. E. g., master data of machines and employees, like names and cost rates, are matched. Thus, the complete instantiated model of the Manufacturing Warehouse is based on concrete source data.

Finally, transformation rules are defined to realize all identified mappings. For example, transformations to convert proprietary event names or adjust different currencies are created. These transformation rules are the basis for the development of the corresponding ETL processes populating the warehouse and calculating standardized facts, i. e., metrics.

6 Prototypical Implementation and First Proof of Concept

Our current prototypical implementation comprises a first relational version of the Manufacturing Warehouse, basic data transformation and data mining functionalities as well as a dashboard-oriented GUI and is described in [7]. In addition, we developed universal process-centric data mining use cases for Indication-based Manufacturing Optimization (IbMO) presented in [11]. We are currently realizing the above instantiation and integration procedure in the Manufacturing Data Integrator, too. In the following, we demonstrate that the Manufacturing Warehouse in combination with IbMO enables the generation of novel insights for process improvement beyond traditional process warehousing approaches.

In a first proof of concept we implemented the so called metric-oriented root cause analysis as an IbMO explication use case designed for production managers [11]. It aims at explaining categorized metrics of process instances, e. g., lead time, by providing comprehensible explication models, namely decision trees. E. g., reasons for excessive lead times can be identified. Moreover, we developed a sample scenario for a manufacturing process, the production of steel springs for the automotive industry, and generated corresponding data to load the Manufacturing Warehouse. On this basis, we conducted metric-oriented root cause analyses on lead times. The latter are categorized as "OK" or "too high" in our proof of concept. Two exemplary decision rules, that are based on the decision tree depicted in Fig. 6, are:

- If the *first machine* in *production step 1* was maintained more than *15 days ago* and *vendor V7* delivered the *material* processed in *step 3*, then *lead time* is typically too high.
- If the former isn't the case but the *skill level of the first employee* in *step 2* is lower than *level 4* and *machine M2* is used, then *lead time* is typically too high.

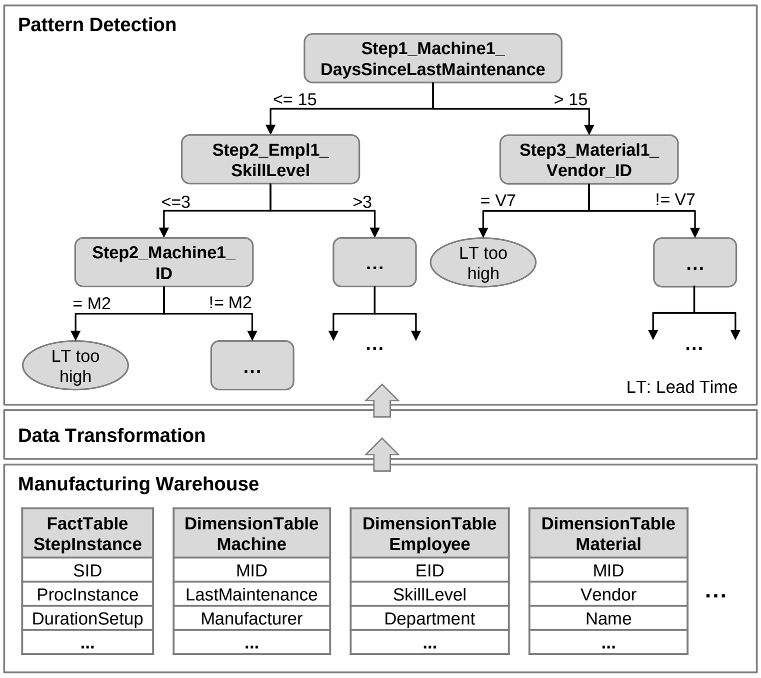

Fig. 6. Functional components of the prototype

These decision rules represent valid indications for concrete process improvements, e. g., to enhance training for employees engaged in step 2 or improve maintenance schedules for machines used in step 1. They demonstrate the fundamental feasibility and usefulness of the Manufacturing Warehouse in combination with suitable analytics. Based on the integration of operational and process data, the Manufacturing Warehouse enables the cross-correlation of all relevant aspects pertaining to process performance, e. g., machine- product-, material-, and employee-oriented aspects, in order to generate novel insights for process optimization. In contrast, typical traditional process warehouses are not aware of operational aspects like additional information on vendors of input material or employee training. In general, the universal holistic data model of the Manufacturing Warehouse can be used as a basis for various holistic analytics, ranging from holistic OLAP and reporting concepts to data mining-driven approaches like IbMO and pattern-based optimization.

Fig. 6 shows the exemplary decision tree from which the above listed decision rules were deduced from as well as the necessary functional components of our prototype for metric-oriented root cause analyses. On top of the *Manufacturing Warehouse*, *data transformation* is concerned with data denormalization and data filtering which prepare data for *pattern detection*, i. e., decision tree induction. The relational structure of the warehouse is deduced from the above conceptual model. Further technical details about the prototype are given in [7], [11].

7 Conclusion and Future Work

In this article we presented the Manufacturing Warehouse, a concept for a holistic manufacturing-specific process warehouse as central part of the overall Advanced Manufacturing Analytics Platform. It integrates operational and process data in a standardized multidimensional warehouse and is based on a generalized manufacturing process meta model. In addition, we introduced a procedure for warehouse instantiation and the integration of concrete source data.

To demonstrate the usefulness and feasibility of the Manufacturing Warehouse, we described a first proof of concept comprising a process-centric data mining use case for Indication-based Manufacturing Optimization on top of the warehouse.

In our future work, we plan to investigate application scenarios in discussion with industry partners comprising typical MES and ERP systems to further validate and extend the Manufacturing Warehouse. Moreover, we are going to refine it with respect to the implementation of pattern-based optimization in manufacturing.

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