A Process Model for Establishment of Knowledge-Based Online Control of Enterprise Processes in Manufacturing

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***Abstract* - Today's enterprises are operating in a complex and volatile business environment. To address this situation, enterprises endeavor to realize horizontal and vertical integration of enterprise processes (i.e., business and manufacturing processes) leading to a real-time enterprise. Research has been carried out in integrating data generated from automation devices in (milli) seconds and transactional data from business applications, referring to long time horizons (e.g., days). However, this integrated data is not used extensively for online control of enterprise processes. Therefore to overcome this issue, a process model is presented for identification and assimilation of knowledge. This process model comprises four steps: (i) analysis and (re-) design of enterprise processes to be controlled, (ii) creation of enterprise data model and data flow diagrams for automation devices and business applications, (iii) (offline) knowledge identification based on knowledge discovery in databases process, and (iv) online monitoring and control of enterprise processes using complex event processing. The envisaged process model is a prerequisite for implementation of IT-framework used for online monitoring and control of enterprise processes. Both, the process model and the corresponding IT-framework have been implemented and validated in a casting enterprise.**

Keywords - enterprise integration, knowledge discovery in databases, data mining, online control, complex event processing.

I. INTRODUCTION

The business environment of an enterprise has become complex, volatile and mainly driven by uncertainties [1]. In addition, pressure on an enterprise to manufacture components with high quality, reduced lead time and low cost has been intensified. As a consequence, relevant enterprise (value creation) processes (i.e., business and manufacturing processes) have to be flexible, adaptable and controlled online. In this regard, the integration of enterprise processes in horizontal and vertical direction of an enterprise has become indispensable. Available enterprise application integration (EAI) systems can be used to horizontally integrate existing business applications like enterprise resource planning (ERP) systems, supply chain management (SCM) systems, and customer relationship management (CRM) systems [2]. Along with this horizontal integration, vertical integration of different enterprise levels can be seen as a prerequisite for establishing online control of enterprise processes [3], and the vision of a real-time enterprise (RTE) [4][5].

According to German standard VDI 5600 [6], an enterprise can be classified into different manufacturing execution system (MES) levels as illustrated in Figure 1: (i) enterprise control level, (ii) manufacturing control level, and (iii) manufacturing level. VDI 5600 focuses on the problems and benefits related to MES. Similarly, standards like IEC 62264 [7] are available and emphasis on realization of MES. In the current contribution, various terminologies are based on VDI 5600.

At enterprise control level, business processes are performed to achieve the enterprise's long term strategies. Thus, business processes can be designed, configured, enacted, and analyzed applying four steps of a business process management (BPM) life cycle: (i) business process design, (ii) business process configuration, (iii) business process enactment, and (iv) business process diagnosis [8][9]. Process-aware information systems (PAIS) like workflow management systems (WMS) are in charge to invoke business applications (e.g., ERP system) and (web) services along a workflow execution (i.e., automation of a business process) to fulfill certain enterprise's strategic objectives [8][9]. During business process enactment at enterprise control level, planned performance values (i.e., TO-BE values) are generated offline (i.e., in months or weeks) and further, these values are transactional [10].

On the contrary, manufacturing processes are employed to accomplish the objectives set at the enterprise control

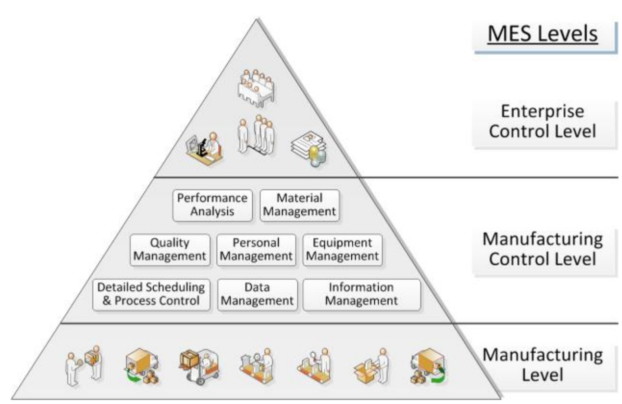

Figure 1. Enterprise levels as defined in VDI 5600 [6].

level. Automation devices are available at manufacturing level to execute manufacturing processes. Enormous amount of data (e.g., sensor data) is generated by these devices during execution of manufacturing processes in real-time (i.e., seconds or milliseconds). In addition, operators provide necessary data related to automation devices or orders like pre-defined reasons for a resource breakdown, order details during start of order execution, and so forth. Overall, these values (i.e., AS-IS values) indicate the actual performance at the manufacturing level.

MES solutions and business process applications are available to achieve computerized and automated vertical integration at certain MES levels [11]. However, major problems still remain open with respect to the interface between the enterprise control level and the manufacturing level [12]. More precisely, the realization of enterprise-wide multi-loop control within and across all levels from enterprise control level to manufacturing level is not adequately achieved [10][12]. Also, inadequate vertical integration hinders the establishment of enterprise-wide knowledge and learning cycles [13]. First, data from different MES levels is not adequately integrated and thus, it cannot be exploited to identify new knowledge. Second, if any new knowledge has been derived, it is not incorporated in online control of enterprise processes. As a consequence, concepts of RTE: sense-and-respond and learn-and-adapt are integrated insufficiently into enterprise processes [14].

The current contribution is based on the IT-framework for digital enterprise integration [13], and presents a methodology for identification and assimilation of knowledge for online control of enterprise processes in manufacturing. State-of-the-art on enterprise integration (EI), monitoring and control of enterprise processes, and data mining in manufacturing is summarized in Section II. A novel methodology is elaborated in Section III to establish enterprise-wide knowledge and learning cycles for online control of enterprise processes. Section IV describes an industrial case study. Finally, conclusion and future work are discussed in Section V.

II. STATE-OF-THE-ART

The methodology elaborated in Section III is based on various concepts like EI and data mining. Therefore, the current section summarizes state-of-the-art research in the area of EI, enterprise data model, identification of knowledge, and utilization of knowledge for online monitoring and control of enterprise processes.

Around the mid 1990's, several EI reference architectures (e.g., CIMOSA, PERA, ARIS and GRAI/GIM) were available to guide the design and implementation of an integrated enterprise [15]. However, these reference architectures were different in terms of their theoretical background [15], and enterprise understanding, modeling approaches, and purposes [16]. Hence, GERAM - generalized enterprise reference architecture and methodology has been developed to address these differences [17]. Aforementioned reference architectures have contributed in defining GERAM and later, it was standardized as ISO 15704 - requirements for enterprise reference architecture and methodologies [18].

The reference architectures mentioned above do not reveal how to realize them in terms of technologies. Apart from enterprise reference architectures, several software vendors have developed MES solutions to bridge the vertical integration gap between MES levels, like MES-HYDRA [11]. But also with MES, the exchange of data between MES levels is done manually or at most semi-automatically due to inflexible and proprietary interfaces [12][19].

An agent-based production monitoring and control system (PMC) based on the JADE framework was elaborated [20]. The PMC Provis.Agent integrates various IT-systems and machine control devices, and establishes the use of information between various systems (e.g., for visualization). Also, NIIIP-SMART architecture provides horizontal and vertical integration, and interoperation utilizing workflow, enterprise rules, agents and STEP [21].

Service orientation (especially by means of web and grid service technology and their corresponding standards) has been used for EAI [22]. In service oriented architecture (SOA), business applications offer their functionalities as services. These services can be loosely coupled and orchestrated to complex workflows. Because of the loosely coupled structure, the realized IT-architecture is flexible and adaptable. Hence, European-funded projects SIRENA [23] and SOCRADES [24] aim to exploit this SOA paradigm to seamlessly integrate heterogeneous resources located at manufacturing level with business applications at enterprise control level. In this regard, a prototype for vertical integration of SOA-ready devices with SAP MII was presented [5]. Unlike the predominant request-reply communication approach of traditional SOA, an enterprise has to react to events online, and hence, necessitates implementation of publish-subscribe mechanism [25]. However, this doesn't make SOA obsolete as SOA and event processing are complementary concepts for achieving modularity, loose-coupling, and flexibility [26].

Enterprise data model is necessary to enable EI, i.e. to relate TO-BE and AS-IS values from different MES levels. IEC 62264-2 [7] describes models and terminologies that enable to implement enterprise control between enterprise control level and manufacturing control level. Further, this standard can be augmented with various technical models like DIN EN 61512-2 [27]. An MES database structure for system integration was analyzed with respect to resource, system plans, system status and system configurations [28]. A factory data model was defined to represent strategic intent, capability, organization structure and behavior of an enterprise [29]. This factory data model consists of strategy, facility, process, resource, token and flow classes. The token classes represent physical flow of material (e.g., work piece, invoice). Flow classes represent links to token classes and process classes.

Knowledge is embedded into enterprise processes by enterprise members (i.e., know-who) in form of know-what, know-why, and know-how [30]. However, this knowledge is tacit and context-specific. This knowledge is externalized by enterprise members and can be expressed by means of enterprise process data (i.e., TO-BE values). These process data are updated online during execution of enterprise processes in terms of feedbacks (i.e., AS IS values). TO-BE and AS-IS values from different MES levels are integrated for online control of enterprise processes [13][31]. These integrated values are stored in a relational database as historical data, which is periodically exploited in offline processes to calculate key performance indicators (KPIs) and overall equipment effectiveness (OEE), among others.

Extensive research has been carried out to convert tacit knowledge embedded in processes into explicit knowledge using analytical methods (e.g., data mining), but this research focuses mostly on transactional data (e.g., finance, sales) at the enterprise control level (e.g., [32]). Around 7% of data mining methods are utilized to address problems in manufacturing [33]. This limited usage of data mining in manufacturing enterprises originated in the perception of relatively high efforts to achieve EI [33]. Nonetheless, data mining methods have been used in manufacturing domains like manufacturing system, and maintenance [34][35].

A decision making process related to enterprise process control can be a complex task spread across different MES levels, and depends upon the quantity and quality of information. In this regard, a framework for organizing and applying knowledge for decision making in manufacturing and service applications was elaborated [36]. The decision making process was supported with the knowledge derived using data mining algorithms.

European-funded project K-NET (sub-project of Future Internet Enterprise Systems (FInES) cluster) has presented an approach at a conceptual level to enhance, monitor and reuse of knowledge in a networked enterprise [37]. In addition, an enterprise modeling and integration framework was presented based on knowledge discovery in databases (KDD) by extending the views of CIMOSA i.e., adding knowledge and mining views [38]. In most of the enterprises, explicit knowledge is codified as rules managed in rule-based systems (RBS) [39].

RBS like Drools Expert [40] are often lacking in taking temporal and causal relations between events into account. As a consequence, research attempts are been made to employ the externalized knowledge for creating event patterns utilized in a complex event processing (CEP) engine. Unified event management architecture was conceptualized to deal with primitive and complex events for monitoring and control of manufacturing processes [41]. Nonetheless, the architecture is positioned at manufacturing control level and integrates real-time data from manufacturing level but neglects to integrate transactional data from enterprise control level. Further, architecture for an extensible event-driven manufacturing system was elaborated [42]. This architecture was built on a MES solution with a tight integration with enterprise control level and manufacturing level, and utilized CEP engine to manage events triggered in manufacturing level. However, the presented approach does not address knowledge identification required to define event patterns.

System Insights provides an open source framework for online monitoring and analysis of manufacturing enterprises [43]. The framework constitutes following components - data delivery, data collection, and data analysis. Data delivery from different devices is achieved through MTConnect standard and MTConnect data bus. Data is stored in (high speed) databases using functionality of data collection. For control of enterprise processes, data analysis is performed online utilizing the services of EsperTech [44] or Drools Fusion [45] CEP engines. Also, the stored data is utilized offline to calculate various metrics.

III. METHODOLOGY

An IT-framework for digital enterprise integration was articulated [13][31]. This framework utilizes tracking objects along with a RBS. However to consider the temporal and causal relations between events triggered across various MES levels, it is essential to replace RBS with state-of-the-art CEP engine. On basis of this framework, a methodology

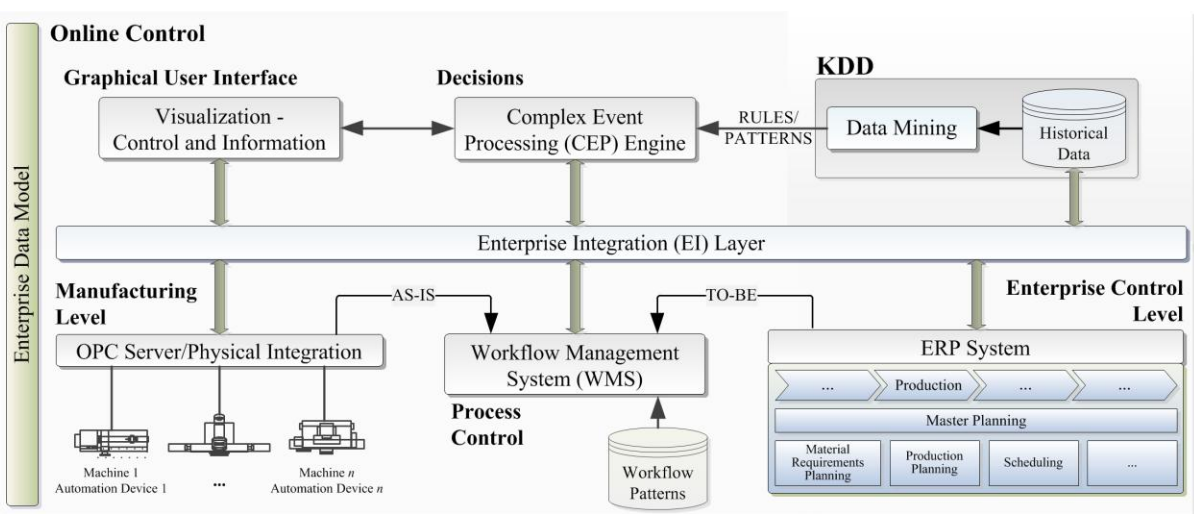

Figure 2. IT-framework for digital enterprise integration (adapted from [13]).

is elaborated for identification and assimilation of knowledge for online control of enterprise processes. This methodology encompasses following components: (i) enterprise process analysis, (ii) enterprise data model and data flow diagram, (iii) knowledge identification, and (iv) assimilation of knowledge for online control of enterprise processes. In the following subsections, the aforesaid IT-framework is introduced in brief and further, the components of the methodology are elaborated.

A. *Overview of IT-Framework for Digital Enterprise Integration*

An architectural overview of the IT-framework for digital enterprise integration is illustrated in Figure 2. In addition, flow of process data and control data between various components of this IT-framework is depicted in Figure 3. The IT-framework is based on available standards (e.g., ISO 15704 [18], IEC 62264 [7]), technologies and paradigms (e.g., SOA paradigm) and involves various IT-systems (e.g., ERP system). Enterprise processes are instantiated from predefined workflow patterns (see Step 1 in Figure 3) and are supplied with necessary planned performance or process values (i.e., TO-BE values) from business applications like ERP systems (see Figure 2 and Step 2 in Figure 3). Business applications or at least their crucial functionality in a certain context (e.g., accessing planned performance values) are made available as services within an SOA.

As one of the purposes of the IT-framework is online control of enterprise processes, publish-subscribe mechanism usually applied in event-driven architectures (EDA) is implemented. EI layer subscribes to the events triggered by manufacturing resources (i.e., automation devices) at the manufacturing level. Three-tier architecture for physical integration has been implemented to collect data from these manufacturing resources and forward the collected data to all

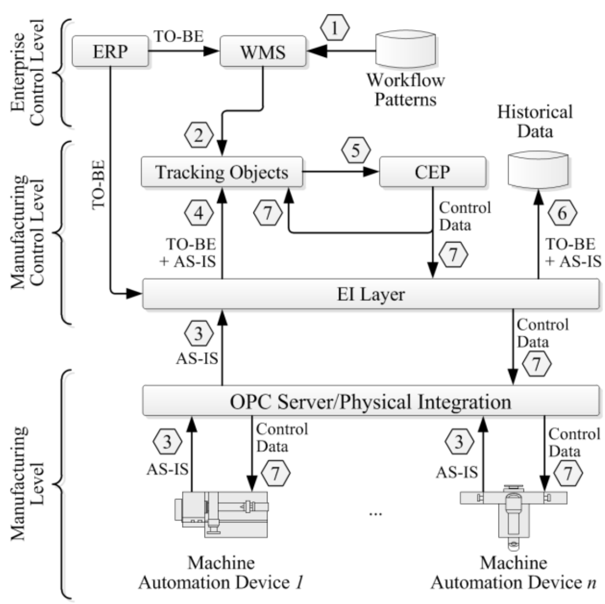

Figure 3. Flow of process data and control data in IT-framework for digital enterprise integration.

the subscribers, here EI layer (see Step 3 in Figure 3 and [13]). The received real-time data from the manufacturing level denotes actual achieved performance (i.e., AS-IS values). Planned performance values from enterprise control level (e.g., ERP system) together with actual achieved performance values from manufacturing level are integrated according to an enterprise data model, and stored in relational database as historical data (see Step 6 in Figure 3).

The digital enterprise integration framework was further enhanced for online monitoring and control of enterprise processes using tracking objects [31]. Tracking objects represent control-relevant objects like orders, products and resources, and are instantiated simultaneously with a corresponding workflow instance in a WMS (see Step 2 in Figure 3). These objects are updated during enterprise process execution with the values acquired from different MES levels (see Step 4 in Figure 3). The changes in tracking objects' status can be analyzed online by a RBS (e.g., Drools Expert) [31]. However, the usage of RBS implicates the lack of taking temporal and causal relations between events into account. In addition, it is remarkable that only a few WMS support the collection and interpretation of real-time data [8][9]. Hence, the usage of a CEP engine (e.g., EsperTech [44]) instead of RBS is necessary. Here, the CEP engine is in charge of continuously analyzing tracking objects and dispatching control data to required MES levels (see Step 7 in Figure 3).

In addition to the control of enterprise processes employing CEP engine, the historical data is periodically utilized offline to calculate KPIs and OEE. However, historical data is seldom exploited to identify new knowledge and further this identified knowledge is not utilized for online monitoring and control of enterprise processes. To overcome the aforesaid drawbacks, a methodology is elaborated to identify and assimilate knowledge for online monitoring and control of enterprise processes.

B. *Methodology for Knowledge Identification and Assimilation in Manufacturing*

An overview of the process model towards the realization of digital enterprise integration has been depicted in Figure 4. This process model consists of four process steps, which are unique to a particular enterprise. The process model can be put into practice by means of implementing the aforementioned IT-framework. These process steps need not necessarily be performed sequentially and further, individual process steps can be carried out from time to time to enhance enterprise (value creation) processes.

Prior to the implementation of the IT-framework for digital enterprise integration (see Section III.A), it is essential to analyze and (re-) design the enterprise processes as it is in the case of BPM life cycle [8][9] (see Step I in Figure 4). An enterprise data model based on industrial standards (e.g., IEC 62264 [7]) and enlarged with technical models (e.g., DIN EN 61512-2 [27]) is in charge of relating AS-IS and TO-BE values from different MES levels (see Step II in Figure 4). Also, data flow diagrams (DFDs) can be created to reveal the interdependencies between business

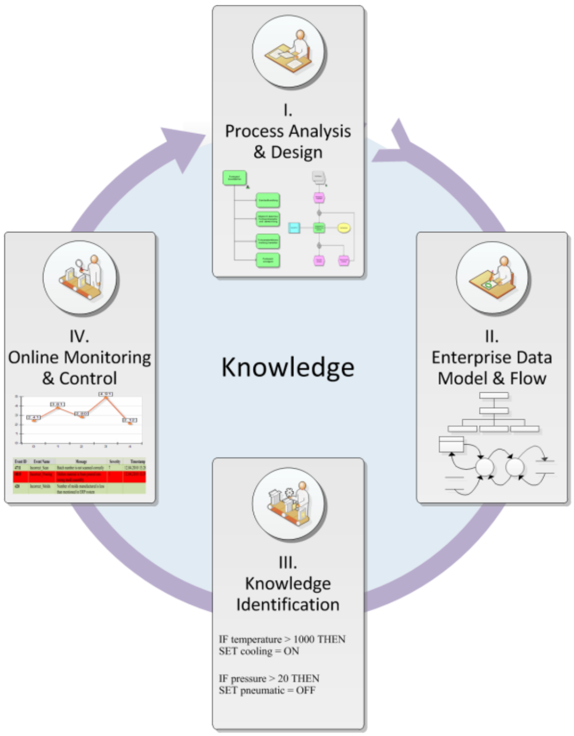

Figure 4. Process model towards the realization of knowledge-based online control of enterprise processes.

applications and resources, and associated events triggered at various MES levels.

Knowledge is embedded in enterprise process data (e.g., pressure, temperature) generated before and during execution of these processes i.e., TO-BE and AS-IS values. These process data is mapped onto the aforementioned enterprise data model and stored in a relational database as historical data. Subsequently, offline KDD process can be employed on the historical data to identify new knowledge (see Step III in Figure 4). Applying repeated and time-consuming database queries executed on the integrated database are not useful for online control of enterprise processes [46]. Instead, event streams (i.e., TO-BE and AS-IS values) created during process execution need to be analyzed and processed online using a CEP engine (see Step IV in Figure 4). Here, the externalized knowledge can be codified as event patterns and event pattern rules, and these event patterns can be used for detection of complex events in event streams. Along with this detection of complex events, event processing can be employed for online control of enterprise processes. In following subsections, each of the process steps will be elaborated.

1) Enterprise Process Analysis and (Re-) Design

Enterprise process analysis and (re-) design is part of enterprise reference architectures (e.g., ARIS [47]) and business process reengineering (BPR) [48]. BPR can be described using four main phases: (i) identification of critical enterprise processes, (ii) review, update and analysis of enterprise processes (AS-IS analysis), (iii) (re-) design of enterprise processes based on AS-IS analysis, and (iv) implementation of (re-) designed enterprise processes.

Comprehension of enterprise processes and their integration within an enterprise's organizational structure is crucial for the implementation of online enterprise process control strategies. Hence, process analysis and (re-) design incorporates enterprise's organizational structure as well as its process-oriented organization.

The activities and functions of an enterprise process are executed by various resources (e.g., IT-systems), which are in charge of an enterprise's organizational unit. Thus, the organizational units can be organized and modeled using organizational charts. In addition, functions and activities of an enterprise process take several kinds of inputs. These can be data (e.g., printed documents) but also intangible inputs like implicit knowledge of enterprise members. In summary, each function of an enterprise process can be linked with an organizational unit, various inputs and outputs. Further, the functions are orchestrated to enterprise processes using logical connectors like 'and', 'or', and 'exclusive or'.

Several modeling languages and methodologies are available to model enterprise processes like event-based process chain (EPC) and business process modeling language (BPML). Apart from these modeling languages that focus on tangible inputs and outputs (e.g., data and documents), knowledge management description language (KMDL) can be employed to describe knowledge intensive processes, i.e., creation, use and necessity of knowledge along enterprise processes [49].

2) Enterprise Data Model and Data Flow Diagram

Today's business applications and automation devices are complex, and several inputs are required by these systems to define enterprise processes. In addition, enormous amount of data is generated by the automation devices in real-time denoting information like feedbacks, product positions and alerts. For online monitoring and control of these enterprise processes, it is essential to analyze the business applications and automation devices, and their corresponding processes to identify critical control-related process parameters. In this regard, enterprise data modeling is an essential step to establish important control-relevant parameters. It influences the quality of information that is necessary to execute enterprise processes, achieve EI, and enhance online monitoring and control of enterprise processes.

IEC 62264-2 describes models and terminologies that enable to implement enterprise-wide control between enterprise control level and manufacturing control level [7]. An enterprise data model based on IEC 62264-2 can be further augmented with technical models depending on the type of manufacturing process, like DIN EN 61512-2 (for batch manufacturing, [27]) and DIN 8582 (for metal forming processes, [50]). Overall, IEC 62264-2 facilitates to exchange structured data between business applications and manufacturing resources.

Besides the static structure of an enterprise data model, DFDs reveal the interdependencies between processes' systems and manufacturing resources, either in isolation or in combination [51]. Further, DFDs identify the flow of data, describing the dynamic behavior of enterprise processes. Process data is generated and manipulated by several resources during process execution. The DFDs can be employed to expose the relationships between various IT-systems and resources. As the number of systems and resources has been increased in industrial scenarios, DFDs are usually organized in a hierarchy of DFDs. Coarse-grained DFD can depict an overview of the shop floor and its resources while a certain DFD is been created with regard to a certain enterprise (sub-) process.

3) Knowledge Identification

Knowledge can be defined from different perspectives. In the current research context, following definition is adapted: "Data is raw numbers and facts, information is processed data, and knowledge is authenticated information" [39]. As mentioned earlier, knowledge is embedded into enterprise processes as process data. This knowledge is enriched and enlarged during execution of enterprise processes (e.g., feedbacks). Further, integrated enterprise process data (i.e., TO-BE and AS-IS values) is stored as historical data based on the aforementioned enterprise data model.

Historical data can be also exploited to derive new knowledge, which can be utilized in online monitoring and control of enterprise processes. Hence, knowledge identification can be performed utilizing KDD process, defined as a "process of mapping low-level data into other forms that might be more compact or abstract or useful" [52]. KDD process is depicted in Figure 5. Input to KDD process is historical data and outputs are patterns, subjected to certain defined quality known as interestingness measures [53]. These interestingness measures can be objective measures based on the statistical strengths or properties of the discovered patterns and subjective measures, which are derived from the user's beliefs or expectations [53]. A pattern is an abstract representation of a subset of data and needs to be evaluated by domain experts to identify knowledge. KDD process consists of several steps (see Figure 5), which are elaborated in the following paragraphs.

Understanding of manufacturing domain in concern is indispensable for successful employment of KDD process. This can be carried out as described in process analysis and (re-) design, and enterprise data model and DFDs (see Step I and II in Figure 4). Major activities of manufacturing

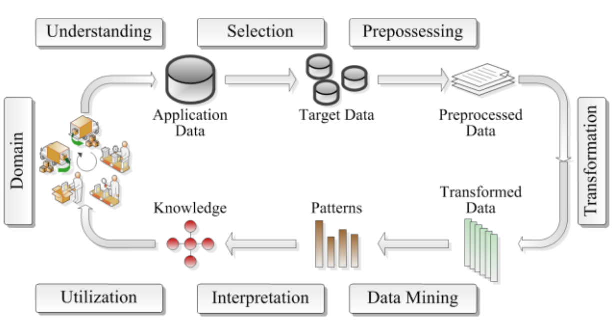

Figure 5. Knowledge discovery in databases (KDD) process (adapted from [51]).

enterprises are production, maintenance, quality and inventory [7], and consequently, define the goals of the KDD process. Depending upon the goals of the KDD process, specific data (target data) is selected from the historical data on which patterns will be searched.

However, historical data might be inaccurate due to various reasons and thus influencing the identified knowledge. During data acquisition process, data is collected from operators through console, and analog equipments and digital measuring devices through programming logic controllers (PLCs) (see Figure 2). In the aforementioned IT-framework, AS-IS values are made available to enterprise integration layer through object linking and embedding (OLE) for process control (OPC) severs (see Figure 2 and Step 3 in Figure 3). Data collected consists of noise or inaccuracies or missing values, which makes searching of patterns complicated [54]. This might be due to limitations of measuring instruments, typing errors of operator or errors in logic of PLCs. To overcome these inaccuracies, it is necessary to study and understand the domain, as described in Step I in Figure 4. Understanding of domain along with the enterprise data model will help to identify suitable statistical methods to remove noise, strategy to fill the missing values and deletion of duplicate data. Also periodically, data collection can be enhanced by verifying the collected data from manufacturing resources in coordination with the operators. Overall, cleaning and pre-processing activities are carried out on the selected data for further processing.

Only subset of pre-processed data is required for achieving the aforementioned goals of KDD process [55]. Hence, transformation of data involves reducing number of parameters in the target data or representing the target data in a more general or acceptable format. Filter and wrapper approaches can be employed to reduce number of parameters [56]. In addition, understanding of manufacturing processes, operations, and constraints will aid in transformation process supported with enterprise data model and DFDs.

Data mining is a particular sub-process in KDD process. It is based on proven techniques like machine learning, pattern recognition, statistics, artificial intelligence, knowledge acquisition, data visualization, and high performance computing [57]. Data mining consists of three steps: (i) selection of data mining method, (ii) determination of appropriate data mining algorithms, and (iii) employing these algorithms for pattern search.

Data mining methods have to be chosen in accordance to the goals of KDD process as they determine the type of knowledge to be mined i.e., concept description, classification, association, clustering and prediction [34]. Since the goal in current research is to enhance online monitoring and control of enterprise processes, knowledge to support decision making processes needs to be identified. In this regard, classification and regression methods can be engaged to determine new knowledge. Classification is a method to categorize a new instance of data into one of several predefined classes [52][54]. It consists of two steps [34]: (i) construction of a (classification) model based on the analysis of database tuples (i.e., a training set) described by attributes and (ii) usage of this constructed (classification) model for classification of new data instances. In contrary, regression is a function that maps data to a real-valued prediction variable.

According to previously selected data mining methods (e.g., classification), data mining algorithms have to be selected to search for patterns. For example, decision trees, decision rules, inductive logic programming and rough set methods can be utilized to determine rules [36]. Finally, the previously selected data mining methods and algorithms are employed to discover patterns.

Discovered patterns can be sufficient large or it might be necessary to select a subset of discovered patterns [56]. Consequently, to enhance the quality of discovered patterns, measure of interestingness can include both subjective and objective approaches [56]. A discovered pattern can be interpreted using structured interviews with domain experts. If necessary, all or selected steps of KDD process need to be repeated in order to obtain more suitable knowledge. If sufficient integrated data is not available to carry out KDD process, structured interviews with domain experts can be conducted to identify initial knowledge. Later, acquired historical data can be exploited employing the aforementioned KDD process to enhance and enlarge the knowledge base.

4) Knowledge-Based Online Control of Enterprise Processes

Historical data can be employed to identify new knowledge as described in Section III.B.3. This identified knowledge can be used for control of enterprise processes by directly accessing the aforementioned historical data. However, repeated and time-consuming database queries [46] (e.g., applying ex-post online analytical processing (OLAP) queries) result in offline control of enterprise processes. Consequently, real-time data should be processed online (i.e., near real-time) for control of enterprise processes utilizing previously identified knowledge, tracking objects and CEP engine as depicted in Figure 2 and Figure 3.

Tracking objects are representatives of process entities (e.g., products, orders, resources) of a particular enterprise process. A tracking object is instantiated simultaneously with a workflow in a WMS specifying a process route (see Step 1 in Figure 3) and associated planned performance values (i.e., TO-BE values). During execution of enterprise processes, AS-IS values from manufacturing level are made available in OPC servers and simultaneously forwarded to EI layer utilizing publish-subscribe mechanism (see Step 3 in Figure 3). These AS-IS values are integrated with corresponding TO-BE values from ERP system obtained using request-reply mechanism.

EI layer manages the integrated process data simultaneously in numerous ways. First, tracking objects are updated with corresponding integrated process data (see Step 4 in Figure 3) and thereby, tracking objects contain up-to-date status information of an actual enterprise entity within an enterprise process. Second, integrated process data is delivered to all subscribed clients with graphical user interface (GUI) for online monitoring of enterprise processes (see Figure 2). Finally, integrated process data is stored in a relational database as historical data for offline analysis (see Figure 2 and Step 6 in Figure 3). Tracking objects are constantly analyzed at manufacturing control level and utilized for online control of enterprise processes using CEP engine with the objective to enhance major activities of manufacturing enterprises i.e., production, maintenance, quality and inventory (see Step. 5 in Figure 3). Subsequently, CEP engine is in charge of dispatching control data to manufacturing resources (see Step 7 in Figure 3), and at the same time updating tracking objects with control data. In the following paragraphs, CEP and assimilation of previously identified knowledge is elaborated.

An event is characterized by its event source (e.g., a certain automation device), event type, event attribute (i.e., data) and timestamp or time interval [58] and additionally, event sink (e.g., operator, plant manager) as depicted in Figure 6. As mentioned previously, events are triggered across different MES levels during execution of enterprise processes and form an event cloud [43][58]. Events can be classified as simple or composite events based upon their level of abstraction. Simple events are triggered across different MES levels and do not have any abstraction. Hence, a simple event does not provide sufficient information for online control of enterprise processes [41]. For instance, a simple event is triggered whenever a lower mold is produced by a molding machine.

On contrary, a composite event with higher abstraction can be described with an event pattern based on simple events [41][59]. For example, a complex event is triggered whenever total of number of molds produced for a given order exceeds the required quantity specified in the order. Further, higher abstraction events can be derived from composite events as depicted in Figure 7. In summary, a composite event can be "created by combining base events using a specific set of event constructors such as disjunction, conjunction, sequence, etc" [58]. Finally, an event stream is a "linearly ordered sequence of events", which are ordered by arrival time or bounded by a certain time interval [58]. Here, event streams are composed of simple events denoting tracking objects created or updated during process execution.

An event pattern is a "template containing event templates, relational operators and variables" [58]. Relationships between different (simple and composite) events can be basic, temporal and spatial [43] or logical, temporal and causal [41][60]. Simple events are created at a

```
<event>
  <event_id>1234</event_id>
  <event_name>MOLD NUMBER</event_name>
  <event_type>MACHINE</event_type>
  <event_time>12:23:45.11</event_time>
  <event_data>234309</event_data>
  <event_causality>-</event_causality>
  <event_source>MOLDING 1</event_source>
  <event_sink>PLANT MANAGER</event_sink>
</event>
```

Figure 6. Simple event description in an XML format.

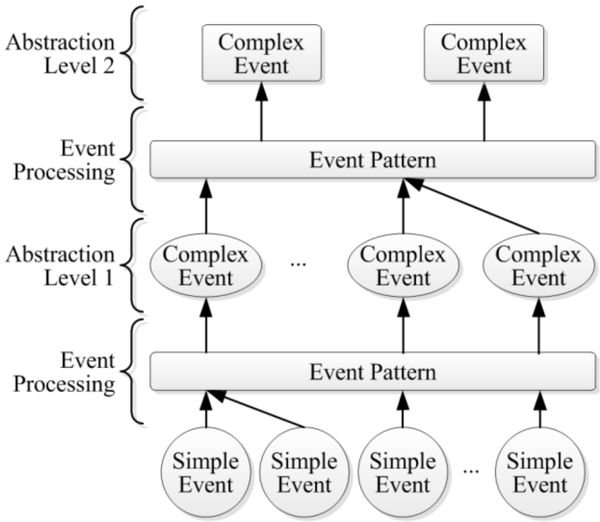

Figure 7. Hierarchical event abstraction (adapted from [58]).

certain period in time i.e., have an associated event timestamp. However, enterprise members from enterprise control level and manufacturing control level are interested in aggregated events for online monitoring and control of products, orders, or resources [41][60]. To enable aggregation of events, it is necessary to utilize temporal event patterns and hence, support time interval with sliding time boundary [41][60], as depicted in Figure 8. Temporal event patterns include overlap, coincides, contains and before or after event patterns [43]. Further, operators (e.g., concatenation, sequence) associated with temporal event patterns can be identified [41].

CEP can be defined as "computing that performs operations on complex events, including reading, creating, transforming or abstracting them" [58][60]. The main purpose of the CEP engine is to control enterprise processes based on a continuous analysis of events streams (i.e., tracking objects). As described before, tracking objects contain up-to-date status information of an enterprise process entity. On update with the new incoming integrated data, tracking objects are analyzed within the CEP engine as shown in Step 5 in Figure 3. Event patterns expressed by an event processing language (EPL) are used within the CEP engine, which is capable to analyze logical, temporal, and

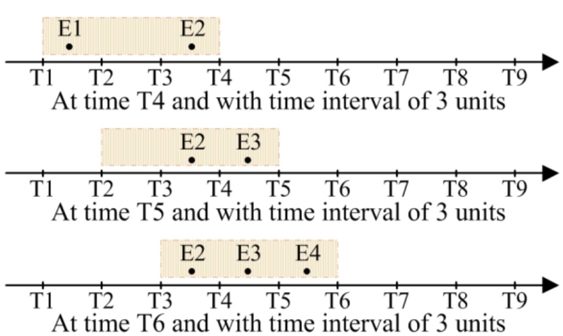

Figure 8. Processing of temporal events using sliding time boundary.

causal event patterns. Further, event pattern rules (i.e., reactive rules) define how the CEP engine reacts to the occurrence of a certain event pattern [59]. An example of an event pattern and event pattern rule is shown in Table I, based on [59]. Hence, the incoming events are analyzed using event pattern rules and necessary control data is dispatched. In addition, suitable events with higher abstractions are created and appended to the already existing event cloud for future event processing.

TABLE I. EVENT PATTERN AND EVENT PATTERN RULE

Element	Declarations
Variables	Order O, Order.Quantity Q, MoldList LM, MoldList.Count C, Mold M, Mold.Order M_O
Event types	MoldProduced(Order O, Mold M) Produce(Order O)
Pattern	MoldProduced (O, M)
Context test	C < Q
Action	Create Produce(O)

In order to effectively monitor and control the enterprise processes, it is essential to identify and characterize events. Previously identified knowledge can be assimilated by creating event patterns and event pattern rules codified as EPL statements. In addition, structured interviews with the domain experts can be utilized to enhance and enlarge event patterns and corresponding event pattern rules. Finally, event patterns and event pattern rules can be made persistent in a centralized database. Enterprise members or decision makers are not interested in all the events. Hence, event sinks or event consumers can be configured by enterprise members' roles (e.g., supervisor, plant manager) and their corresponding privileges (e.g., defined in a lightweight directory access protocol (LDAP) server). Therefore, an event configuration, part of client's GUI provides the necessary functionality to define and configure events and event patterns.

There are two implementations on how the CEP engine influences or controls the actual enterprise processes. First, the CEP engine uses interfaces and services provided by the EI layer (see Figure 2) to automatically dispatch control commands. Second, before manipulating enterprise processes, CEP engine exposes envisaged decision as a suggestion to clients with GUI. Here, an enterprise member accepts or declines the proposition. Obviously, human interaction is used in cases where enterprise members should take liability. However, access to the aforementioned functionality of dispatching control data depends upon the enterprise members' roles and their corresponding privileges.

IV. INDUSTRIAL CASE STUDY

The IT-framework as well as the corresponding process model for enabling digital enterprise integration and achieving online control of enterprise processes elaborated in Section III can be put into practice in different types of manufacturing, especially in batch manufacturing (e.g.,

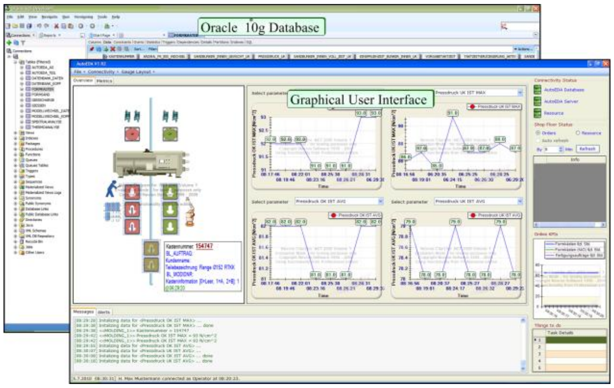

Figure 9. Software screenshots of implemented IT-framework for enabling enterprise integration and control of enterprise processes.

casting processes) and discrete manufacturing (e.g., sheet metal forming processes). Here, an attempt is made to realize the framework for casting processes with special purpose resources. To efficiently utilize these capital-intensive resources, online monitoring and control of enterprise processes is mandatory. The IT-framework has been implemented using Microsoft™ Visual Studio IDE and .NET framework 3.5. Different screenshots of the implemented IT-framework, stacked one over other, are displayed in Figure 9.

Enterprise processes have been analyzed and modeled using ARIS (utilizing EPC and Entity-Relationship-Model) [47]. IEC 62264-2 [7] and DIN 61512-2 [27] have been adapted to create an enterprise data model. In addition, DFDs were created to reveal interdependencies, and dynamic behavior between various automation devices and business applications.

Data is acquired from different automation devices and made available as OPC items in OPC servers (see Figure 2). This data is forwarded to EI layer. Here, the data is mapped onto the enterprise data model and integrated with TO-BE values from ERP system. EI layer manages the integrated data in numerous ways. First, integrated data is delivered to all clients with GUI for online monitoring of enterprise processes. The subscription of clients to process data is realized through a windows communication foundation (WCF) interface. Delivered data is displayed online by the clients using visual elements like charts and gauges. Second, integrated values are stored in an Oracle® 10g database for offline process analysis (see Figure 10). Client's GUI provides interfaces to track products, orders and resources using request-reply mechanism (i.e., accessing historical data). Finally, tracking objects containing integrated data are processed in EsperTech CEP engine [44] for online control of enterprise processes, especially with the objective to enhance productivity.

Casting process consists of following sub-processes: molding to manufacture molds, melting of raw material (e.g., aluminum), pouring of molten material, cooling and finishing (e.g., cutting, grinding, reaming). Molding machine in consideration is capable of producing upper and lower molds at high production rate and influences upstream as

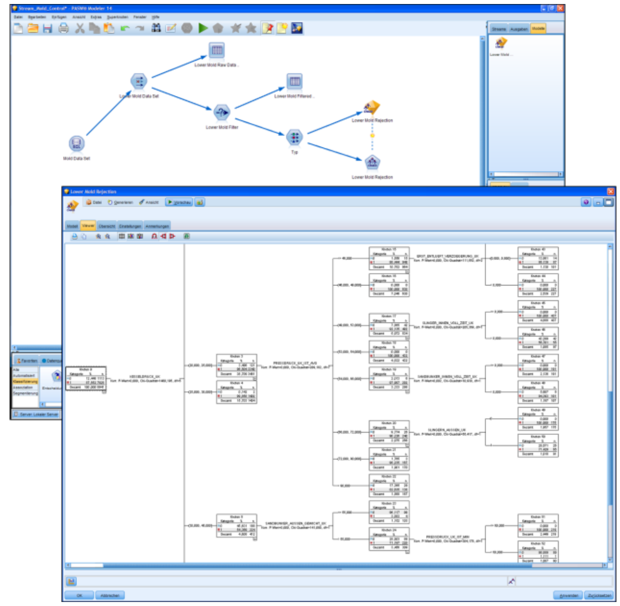

Figure 10. IBM® SPSS® Modeler Professional screenshots.

well as downstream processes. Therefore, goal of the KDD process is to enhance productivity of molding process by reducing number of rejects. Thus, enhancing productivity and reducing wastage (i.e., sand, molten material). Numerous applications are available to support steps of KDD process as illustrated in Figure 5. Here, IBM® SPSS® Modeler Professional [61] has been chosen.

At start of KDD process, a suitable data set has been selected from Oracle® 10g database for utilizing in SPSS® Modeler as illustrated in Figure 10. Here, data set containing mold details is selected, with 14891 rows. Further, each mold detail is associated with 459 attributes, stored in different database tables. Molding machine simultaneously produces lower and upper molds, and here, lower mold details are considered for further analysis. Hence, structured interviews with domain experts were carried out to identify the attributes of lower mold. Therefore, only 39 attributes of lower mold are retained and extraneous attributes are discarded in SPSS® Modeler. Still, reduced data set might contain erroneous data, unexpected situations or many unrelated parameters. SPSS® Modeler provides different graphical tools (e.g., histogram, distribution) to analyze and identify aforementioned causes from the data set. Also, filtering expressions are utilized to clean the data set. After these preprocessing and transformation, data set contains 12799 rows.

Classification algorithms like Chi-square Automatic Interaction Detectors (CHAID) algorithm provided by SPSS® Modeler are used to construct decision trees. Suitable target attribute (e.g., mold quality – good or bad) is selected. Remaining 38 attributes are chosen as input parameters. After executing the CHAID algorithm, a decision tree is created with depth of decision tree equal to 4 and 12 predictors (e.g., pressure). These determined patterns contained in decision tree are validated and refined by domain experts, i.e., using subjective interestingness

```
insert into AlarmEvent
select ProductionRessourceName,
ProductionProcessDataName, ProductionProcessData,
'Pressure is too high' as AlarmMessage from
ProcessDataEvent(ProductionRessourceName='MOLDING_1'
and ProductionProcessDataName='Pressure').win:length(2)
having avg(cast(ProductionProcessData, double)) >
cast(22.5, double)
```

Figure 11. Event pattern codified as an EPL statement in EsperTech.

measure. Further, validated patterns are utilized in creating event patterns and event pattern rules codified in EPL statements as shown in Figure 11. For instance, creation of an alarm event by analyzing applied mold pressure on last two molding machine's simple events. These EPL statements can be managed by domain experts with suitable privileges via a client's GUI and stored in an EPL database.

V. CONCLUSION AND FUTURE WORK

Today's enterprise environment is complex, volatile and driven by uncertainties, forcing enterprises to become more flexible and adaptable. Consequently, enterprises endeavor to overcome the aforesaid challenges by enhancing the online monitoring and control of their enterprise processes. This can be achieved by integrating the enterprise along horizontal and vertical direction. As a consequence, transactional data from enterprise control level and real-time data from manufacturing level have to be integrated and stored as historical data in relational database. However, these historical data is not used extensively for identification of knowledge and subsequently, identified knowledge is not used in the control of enterprise processes.

In the current contribution, a process model for identifying and assimilating knowledge for online control of enterprise processes has been presented. This process model consists of four components: (i) enterprise process analysis, (ii) enterprise data model and DFDs, (iii) knowledge identification, and (iv) assimilation of identified knowledge for online control of enterprise processes. These process steps need not necessarily be performed sequentially and individual process steps can be carried out from time to time to enhance enterprise value creation processes.

Enterprise processes are analyzed and modeled following the ARIS approach. Available standards were adapted to derive the enterprise data model. Analyzed enterprise processes assisted in creating DFDs revealing interdependencies between various automation devices and business applications. Real-time data from manufacturing level and transactional data from enterprise control level are integrated based on enterprise data model and stored in an Oracle® 10g database. Also, integrated data was displayed to enterprise members using charts and gauges. Knowledge was identified using IBM® SPSS® Modeler Professional. Further, the identified knowledge was assimilated for online control of enterprise processes using EsperTech CEP engine.

Currently, the framework has been used in an enterprise for online monitoring and control of batch manufacturing (i.e., casting processes). Future implementation is planned for discrete manufacturing processes i.e., for an automotive sheet metal component supplier.

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REFERENCES

[1] M. Grauer, D. Metz, S. S. Karadgi, and W. Schäfer, "Identification and Assimilation of Knowledge for Real-Time Control of Enterprise Processes in Manufacturing," Proc. 2nd Int'l Conf. on Information, Process and Knowledge Management (eKNOW 2010), Feb. 2010, pp. 13-16, doi: 10.1109/eKNOW.2010.14.

[2] D. Linthicum, Enterprise Application Integration, Addison-Wesley Longman, Amsterdam, 2000.

[3] J. Lee, K. Siau, and S. Hong, "Enterprise Integration with ERP and EAI," Comm. of the ACM, vol. 46, no. 2, Feb. 2003, pp. 54-60.

[4] A. Drobik, M. Raskino, D. Flint, T. Austin, N. MacDonald, and K. McGee, The Gartner Definition of Real-Time Enterprise, tech. report, Gartner Inc., 2002.

[5] S. Karnouskos, D. Guinard, D. Savio, P. Spiess, O. Baecker, V. Trifa, and L. de Souza, "Towards the Real-Time Enterprise: Service-based Integration of Heterogeneous SOA-ready Industrial Devices with Enterprise Applications," Proc. 13th IFAC Symp. on Information Control Problems in Manufacturing (INCOM '09), June 2009, pp. 2127-2132.

[6] VDI 5600, Manufacturing Execution System (MES) - VDI 5600 Part 1, Verein Deutscher Ingenieure (VDI), 2007.

[7] IEC 62264, Enterprise-control system integration, All Parts.

[8] W. M. P. van der Aalst, A. H. M. ter Hofstede, and M. Weske, "Business Process Management: A Survey," Proc. 1st Int'l Conf. on Business Process Management, Springer-Verlag, Berlin, LNCS 2678, 2003, pp. 1-12.

[9] M. Weske, W. M. P. van der Aalst, and H. M. W. Verbeek, "Advances in Business Process Management," Data & Knowledge Eng., vol. 50, no. 1, July 2004, pp. 1-8, doi:10.1016/j.datak.2004.01.001.

[10] A. Kjaer, "The Integration of Business and Production Processes," IEEE Control Systems Magazine, vol. 23, no. 6, 2003, pp. 50-58.

[11] J. Kletti, Ed., Manufacturing Execution System – MES, Springer, Berlin, 2007.

[12] H. Panetto and A. Molina, "Enterprise Integration and Interoperability in Manufacturing Systems: Trends and Issues," Computers in Industry, vol. 59, no. 7, Sept. 2008, pp. 641-646, doi: 10.1016/j.compind.2007.12.010.

[13] M. Grauer, D. Metz, S. Karadgi, W. Schäfer, and J. W. Reichwald, "Towards an IT-Framework for Digital Enterprise Integration", Proc. 6th Int'l Conf. on Digital Enterprise Technology (DET 2009), AISC, vol. 66, Springer, Berlin, Dec. 2009, pp. 1467-1482, doi: 10.1007/978-3-642-10430-5_111.

[14] C. Meyer, "Keeping Pace with Accelerating Enterprise", CIO Insight, Nov. 2002; http://www.cioinsight.com/c/a/Expert-Voices/Expert-Voice-Christopher-Meyer-on-the-Accelerating-Enterprise/, 25.12.2010.

[15] A. Chen and F. Vernadat, "Standards on Enterprise Integration and Engineering - State of the Art," Int'l J. of Computer Integrated

Manufacturing, vol. 17, no. 3, Apr. 2004, pp. 235-253, doi: 10.1080/09511920310001607087.

[16] S. Aier, C. Riege, and R. Winter, "Enterprise Architecture - Literature Overview and Current Practices," Wirtschaftsinformatik, vol. 50, no. 4, 2008, pp. 292-304 (in German).

[17] P. Bernus and L. Nemes, "The Contribution of the Generalised Enterprise Reference Architecture to Consensus in the Area of Enterprise Integration," Proc. of ICEIMT97, K. Kosanke and J. Nell, Eds., Springer, 1997, pp. 175-189.

[18] ISO 15704, Requirements for Enterprise Reference Architecture and Methodologies, ISO 15704:2000/Amd 1:2005, 2005.

[19] S. Karnouskos, O. Baecker, L. de Souza, and P. Spiess, "Integration of SOA-ready Networked Embedded Devices in Enterprise Systems via a Cross-layered Web Service Infrastructure," Proc. 12th IEEE Int'l Conf. on Emerging Technology and Factory Automation, Sept. 2007, pp. 293-300.

[20] O. Sauer and G. Sutschet, "Agent-Based Control", Computing & Control Eng. J., vol. 17, no. 3, June 2006, pp. 32-37, doi:10.1049/cce:20060305.

[21] C. Gilman, M. Aparicio, J. Barry, T. Durniak, H. Lam, and R. Ramnath, "Integration of Design and Manufacturing in a Virtual Enterprise Using Enterprise Rules, Intelligent Agents, STEP and Workflow," Proc SPIE Int'l Symp. on Intelligent Systems & Advanced Manufacturing , 1997, pp. 160-171.

[22] D. Linthicum, Next Generation Application Integration: From Simple Information to Web Services, Addison-Wesley Professional, Amsterdam, 2003.

[23] H. Bohn, A. Bobek, and F. Golatowski, "SIRENA - Service Infrastructure for Real-Time Embedded Networked Devices: A Service Oriented Framework for Different Domains," Proc. Mobile Comm. and Learning Technologies, Apr. 2006.

[24] L. M. S. de Souza, P. Spiess, D. Guinard, M. Köhler, S. Karnouskos, and D. Savio, "SOCRADES: A Web Service Based Shop Floor Integration Infrastructure," Internet of Things, C. Floerkemeier, M. Langheinrich, E. Fleisch, F. Mattern, and S. Sarma, Eds., Springer, Berlin, LNCS 4952, 2008, pp. 50-67.

[25] R. Schulte, A Real-Time Enterprise is Event-Driven, tech. report, Gartner Inc., 2002.

[26] S. T. Yuan and M. R. Lu, "A Value-Centric Event Driven Model and Architecture: A Case Study of Adaptive Complement of SOA for Distributed Care Service Delivery", Expert Systems with Applications, vol. 36, no. 2, Mar. 2009, 3671-3694.

[27] DIN EN 61512-2, Batch Control - Part 2: Data Structures and Guidelines for Languages, Ref. Nr. DIN EN 61512-2:2003-10, 2003.

[28] B. Zhou, S. Wang, and L. Xi, "Data Model Design for Manufacturing Execution System," J. of Manufacturing Technology Management, vol. 16, no. 8, 2005, pp 909-935.

[29] J. A. Harding, B. Yu, and K. Popplewell, "Information Modelling: An Integration of Views of a Manufacturing Enterprise," Int'l J. of Production Research, vol. 37, no. 12, Aug. 1999, pp 2777-2782.

[30] W. M. Cheung and P. G. Maropoulos, "A Novel Knowledge Management Methodology to Support Collaborative Product Development," Digital Enterprise Technology - Perspectives and Future Challenges, P. F. Cunha and P. G. Maropoulos, Eds., Springer, June 2007, pp. 201-208.

[31] M. Grauer, S. S. Karadgi, D. Metz, and W. Schäfer, "An Approach for Real-Time Control of Enterprise Processes in Manufacturing using a Rule-Based System," Proc. Multikonferenz Wirtschaftsinformatik, Feb. 2010, pp. 1511-1522.

[32] C. Groba, I. Braun, T. Springer, and M. Wollschlaeger, "A Service Oriented Approach for Increasing Flexibility in Manufacturing," Proc. 7th IEEE Int'l Workshop on Factory Communication Systems, Communication in Automation (WFCS 2008), Dresden, May 2008, pp. 415-422.

[33] H. Kuntze, T. Bernard, G. Bonn, and C. Frey, "Entscheidungsunterstützung im Produktionsumfeld mit Data-Mining-Werkzeugen," VDI/VDE-Gesellschaft Mess- und Automatisierungstechnik (GMA): AUTOMATION 2008 Lösungen für die Zukunft, June 2008 (in German).

[34] A. Choudhary, J. Harding, and M. Tiwari, "Data Mining in Manufacturing: A Review Based on the Kind of Knowledge," J. of Intelligent Manufacturing, vol. 20, no. 5, Oct. 2009, pp. 501-521, doi: 10.1007/s10845-008-0145-x.

[35] J. Harding, M. Shahbaz, Srinivas, and A Kusiak, "Data Mining in Manufacturing: A Review," J. of Manufacturing Science and Engineering, vol. 128, no. 4, Nov. 2006, pp. 969-976, doi:10.1115/1.2194554.

[36] A. Kusiak, "Data Mining: Manufacturing and Service Applications," Int'l J. of Production Ressearch, vol. 44, nos. 18-19, Sept./Oct. 2006, pp. 4175-4191, doi:10.1080/00207540600632216.

[37] E. Mazharsolook, S. Scholze, S. Ziplies, R. Neves-Silva, and K. Ning, "Enhancing Networked Enterprise Management of Knowledge and Social Interactions," J. of Computing in Systems and Eng., vol. 10, no. 4, 2009, pp. 176-184.

[38] E. Neaga and J. Harding, "An Enterprise Modelling and Integration Framework Based on Knowledge Discovery and Data Mining," Int'l J. of Production Research, vol. 43, no. 6, Mar. 2005, pp. 1089-1108, doi: 10.1080/00207540412331322939.

[39] M. Alaavi and D. E. Leidner, "Review: Knowledge Management and Knowledge Management Systems: Conceptual Foundations and Research Issues," MIS Quarterly, vol. 25, no. 1, Mar. 2005, pp. 107-136.

[40] Drools Expert, http://www.jboss.org/drools/, 25.12.2010.

[41] K. Walzer, J. Rode, D. Wünsch, and M. Groch, "Event-Driven Manufacturing: Unified management of Primitive and Complex Events for Manufacturing and Control", IEEE Int'l Workshop on Factory Communication Systems, 2008.

[42] Y. H. Zhang, Q. Y. Dai, and R. Y. Zhong, "An Extensible Event-Driven Manufacturing Management with Complex Event Processing Approach", Int'l J. of Control and Automation, vol. 2, no. 3, Sept. 2009, pp. 1-12.

[43] A. Vijayaraghavan, "MTConnect for Realtime Monitoring and Analysis of Manufacturing Enterprises," Dec. 2009; http://www.systeminsights.com/, 25.12.2010.

[44] EsperTech, http://www.espertech.com/, 25.12.2010.

[45] Drools Fusion, http://www.jboss.org/drools/, 25.12.2010.

[46] M. Cammert, C. Heinz, J. Krämer, T. Riemenschneider, M. Schwarzkopf, B. Seeger, and A. Zeiss, "Stream Processing in Production-to-Business Software," Proc. of the IEEE Int. Conf. on Data Eng., pp. 168-169, 2006.

[47] A. Scheer, Business Process Engineering. Reference Model for Industrial Enterprise, 2nd Edition, Springer, 1994.

[48] M. Hammer and J. Champy, Reengineering the Corporation: A Manifesto for Business Revolution, Harper Business, 1994.

[49] N. Gronau and E. Weber, "Management of Knowledge Intensive Business Processes," In: J. Desel, B. Pernici, and M. Weske, Eds., BPM 2004, Springer, 2004, pp. 163-178.

[50] DIN 8582, Manufacturing Processes Forming - Classification, Subdivision, Terms and Definitions, Alphabetical Index, 2003.

[51] K. Kendall and J. Kendall, Systems Analysis and Design, 6th Edition, Prentice Hall, 2004.

[52] U. Fayyad, G. Piatetsky-Shapiro, and P. Smyth, "From Data Mining to Knowledge Discovery in Databases," AI Magazine, vol. 17, Fall 1996, pp. 37-54.

[53] K. McGarry, "A Survey of Interestingness Measures for Knowledge Discovery," The Knowledge Engineering Review, vol. 20, no. 1, 2005, pp. 39-61, doi: 10.1017/S0269888905000408.

[54] D. T. Pham and A. A. Afify, "Machine–Learning Techniques and their Applications in Manufacturing," Proc. IMechE Part B: J. of Eng. Manufacture, vol. 219, no. 5, 2005, pp. 395-412, doi: 10.1243/095440505X32274.

[55] M. Shahbaz, Srinivas, J. A. Harding, and M. Turner, “Product Design and Manufacturing Process Improvement using Association Rules,” Proc. IMechE Part B: J. of Eng. Manufacture, vol. 220, no. 2, 2006, pp. 243-254, doi: 10.1243/095440506X78183.

[56] A. A. Freitas, “A Survey of Evolutionary Algorithms for Data Mining and Knowledge Discovery,” Advances in Evolutionary Computing: Theory and Applications, Springer-Verlag, Newyork, 2003, pp. 819-845.

[57] J. Han and M. Kamber, Data Mining - Concepts and Techniques, Morgan Kaufmann, London, 2001.

[58] D. Luckham and R. Schulte, Eds., Event Processing Glossary - Version 1.1, Event Processing Technical Society, 2008.

[59] D. Luckham, The Power of Events: An Introduction to Complex Event Processing in Distributed Enterprise Systems, Addison-Wesley, Munich, 2007.

[60] K. Walzer, A. Schill, and A. Löser, “Temporal Constraints for Rule-Based Event Processing”, Proc. ACM first Ph.D. workshop in CIKM, Nov. 2007, pp. 93-100.

[61] IBM SPSS Modeler Professional, http://www.spss.com/, 25.12.2010.