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RESEARCH PAPER

Prescriptive Control of Business Processes

New Potentials Through Predictive Analytics of Big Data in the Process Manufacturing Industry

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Abstract This paper proposes a concept for a prescriptive control of business processes by using event-based process predictions. In this regard, it explores new potentials through the application of predictive analytics to big data while focusing on production planning and control in the context of the process manufacturing industry. This type of industry is an adequate application domain for the conceived concept, since it features several characteristics that are opposed to conventional industries such as assembling ones. These specifics include divergent and cyclic material flows, high diversity in end products' qualities, as well as non-linear production processes that are not fully controllable. Based on a case study of a German steel producing company – a typical example of the process industry – the work at hand outlines which data becomes available when using state-of-the-art sensor technology and thus providing the required basis to realize the proposed concept. However, a consideration of the data size reveals that dedicated methods of big data analytics are required to tap the full potential of this data. Consequently, the paper derives seven requirements that need to be addressed for a successful implementation of the concept. Additionally, the paper proposes a generic architecture of prescriptive enterprise systems. This architecture comprises five building blocks of a system that is capable to detect complex event patterns within a multi-sensor environment, to correlate them with historical data and to calculate predictions that are finally used to recommend the best course of action during process execution in order to minimize or maximize certain key performance indicators.

Keywords Predictive analytics · Complex event processing · Prescriptive analytics · Event-driven business process management · Big data · Process industry

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1 Introduction

1.1 The Vision of the Predictive Enterprise

Driven by globalization, competing markets and fast-changing customer requirements, economic conditions are rapidly changing. In response to this pressure, companies are compelled to react to threats and opportunities in a timely manner. Thus, continuously monitoring and optimizing business processes towards current business situations is a prerequisite to remain competitive. However, a merely type-based analysis of business processes is no longer sufficient. Instead, each process instance needs to be adapted and optimized considering its individual business situation. The growing digitalization of the real world, in the age of the Internet of Things (IoT), allows for unprecedented insights into current process and context situations (Wortmann and Flüchter 2015).

In future, companies that are capable of analyzing their business operations based on the rapidly growing mass of data, of predicting the best proceeding process sequence, and proactively controlling their processes based on this knowledge will be a decisive step ahead of their competitors. This kind of company sketches the vision of a "Predictive Enterprise" as the next stage in the evolution of real-time enterprises within the age of data as a crucial competitive asset (Lundberg 2006).

1.2 Motivation and Problem Statement

The vision described above is not sufficiently implemented in today's corporate practice. The potential of data, which can already be collected, is not fully exploited in terms of business process analytics. Especially traditional industries, such as steel manufacturing, have not tapped the full benefits of advancements in sensing technologies and systems integration that enable fine-grained insights into manufacturing operations (Unni 2012). This, however, would contribute to cost savings, productivity and product quality improvements as well as to a timely discovery of defects within process executions. According to forecasts of business analysts, companies are going to face existential difficulties if problems in business process executions remain undiscovered or are not anticipated in time (Pettey and Goasduff 2011). To exploit the potential of data, myriads of internal and external events originating from business processes need to be analyzed, forming increasingly masses of data (Dhar et al. 2014). Thus, research faces the challenge of developing appropriate analytical methods and software systems that are able to detect and predict decisive events from collected data in a timely manner. Taking a look at experimental research gives an idea of the basic ability of envisioned future enterprise software. In experiments, the particle accelerator Large Hadron Collider at the nuclear research center CERN generates up to 40 million events per second resulting in 1 petabyte of data (Blue Yonder 2013). Currently, data storage of this scale is technically not feasible. Therefore, intelligent algorithms executed on clusters of supercomputers filter these tremendous event streams to track down the extremely rare – approximately one in ten million – but crucial events.

Likewise in business context, enormous quantities of captured low level events (such as single sensor signals) need to be transferred into business value (such as an early discovery of machinery failures or breakdowns). This is done by filtering event streams to detect meaningful patterns that indicate important situations with a decisive impact on the efficiency of business processes (Luckham 2012). With Complex Event Processing (CEP) the required technology that enables the real-time detection of complex event patterns has been available for years. CEP is considered to be an important driver to further advance the domain of BPM (Dixon and Jones 2011). Within the last decade, this has motivated numerous research efforts coining the term Event-Driven Business Process Management (ED-BPM) (Krumeich et al. 2014d).

1.3 Contribution, Previous Research and Research Method

Considering existing ED-BPM research, predictive analytics are rarely applied to CEP. First Event-driven Predictive Analytics (EDPA) approaches are almost exclusively used for monitoring purposes in the ED-BPM domain. Concepts and implementations incorporating both aspects especially aiming at a proactive control of business processes are missing (Krumeich et al. 2014d). However, EDPA yields considerable potentials in terms of computing situation-aware predictions of individual business process instances (Janiesch et al. 2012; Redlich and Gilani 2012) which is indispensable to take the next steps towards the envisaged goal.

To address this research gap, we conceived the concept of event-based process predictions (cf. Krumeich et al. 2014b). By means of further investigation, we revealed requirements for enterprise systems that implements those predictions. The first version of this investigation was introduced in Krumeich et al. (2014a). On that base, we conceived a system architecture. This architecture identifies the technological functional building blocks to construct an event-based process prediction system (cf. Krumeich et al. 2014c). In parallel, we on a conceptual level investigated the potentials for planning and controlling of manufacturing processes, in particular in the process industry. This work was presented in Krumeich et al. (2014e).

The paper at hand finally brings together our previous research and incorporates a consistent concept on prescriptive control of business processes in process industry. Here, we extend and detail our previous results conceiving a profound componentized scheme of a prescriptive control of business processes using event-based process predictions. In this regard, this paper applies a design-oriented research method following the guidelines proposed by Hevner et al. (2004). As the underlying artifact, the aforementioned concept is conceived in Sect. 3 (Guideline 1) and its implementability sketched in Sect. 5 (Guideline 4). The relevance for constructing the underlying artifact as well as the related research gap was pointed out in the introductory section (Guideline 2). To comply with Guideline 3, the paper applies two evaluation methods: a motivating scenario that describes the artifact's utility in general from a descriptive point of view (cf. Sect. 3.1) and a revelatory, single case study (cf. Sect. 4.4) that employs the methodology proposed by Benbasat et al. (1987).

The steel bar production line at one of the largest steel-producing companies in Germany was chosen as the subject of analysis. The two research questions which are set for the case study are “What type of data is currently available in industry processes using state-of-the-art sensor technology to realize event-based process predictions?” and “Why is it a ‘Big Data’ challenge to analyze this data appropriately?” The results of the case study are considered to be generalizable to other process manufacturing enterprises. Since the chosen research design is a single-case study, it is particularly appropriate to revelatory cases (Darke et al. 1998), as it is for concepts addressing prescriptive analytics (Jarke 2014) as a relatively new phenomenon in information systems research.

The case study data was collected and analyzed by the central department of information and communication technology of the chosen company. As data selection methods, interview techniques were applied and physical artifacts – sensor networks – were investigated. The data, which can already be collected by applied sensor networks, provides the required data foundation to put the concept into practice; however, to tap into the full potential of this data dedicated methods of big data analytics are required. Hence, the paper derives seven requirements that need to be addressed for a successful implementation and proposes a generic architecture of prescriptive enterprise systems (cf. Sect. 5).

Following the principle of design as an iterative process (*Guideline 6*), the refined concept is based on previously published work and incorporates feedback from several workshop and conference presentations (cf. Krumeich et al. 2014a, b, c, e). *Guideline 5* was accomplished by outlining the applied research methodology in this section. Last but not least, the submission of this paper aims at fulfilling *Guideline 7*, the dissemination of research results.

2 From Sensor Data to Business Value

2.1 Technological Progress Towards the Internet of Things and Industry 4.0

In Enterprise Resource Planning (ERP), forecast-based methods for determining independent requirements have been used for years (Kurbel 2005). Yet a forecast-based control of manufacturing processes cannot be attested. This is because determining forecasts always entails a certain inaccuracy. In the past, data measured in manufacturing processes covered operational context situations rather inadequately. This led to imprecise forecasts. In general, the larger the quantity and higher the level of detail of available process observations, the more accurate a process prediction will be (Dhar 2013). To be more specific, the accuracy of predictions increases by the square root of the number of independent observations (Jarke 2014). While, in principle, it was possible to expand and detail databases, the related process of data gathering proved to be too complex, too expensive and not accomplishable in a timely manner. Hence, processes had been forecasted by using basic statistical functions. Consequently, for determining likelihoods of process outcomes and process sequences, mean and median values, standard deviation and so forth were computed. However, this approach of descriptive analytics neither takes into account nor reflects the current process and context situation in which a specific manufacturing process instance takes place.

However, recent technological progress in the fields of IoT and Cyber-physical Systems make it possible to equip production processes with sensors in a relatively cost-neutral way (Lasi et al. 2014). This allows the measurement of internal and external process parameters in a previously unprecedented level of detail. As a result, real-time information availability, especially in manufacturing operations, has reached a new dimension (Bruns and Dunkel 2010). This paradigm shift is referred to as “Industry 4.0” (Kagermann et al. 2011). Being predominantly used as a term in the German-speaking area, the thus envisioned fourth industrial revolution was picked up by the German Federal Ministry of Education and Research and has been integrated as a cornerstone into the “High-Tech Strategy 2020” pursued by the German government (Lasi et al. 2014). Eventually, this technological progress will enable the establishment and continuous enrichment of databases containing sufficient manufacturing data in order to compute highly accurate process predictions possessing the capability to control processes.

Nevertheless, most manufacturing companies still perform insufficient predictive analytics on the sensor data that can already be collected – even though the increased implementation of predictive analytics would positively influence their economic and ecological performance (Unni 2012). This is in contrast to industries such as insurance or banking that have fully implemented predictive analytics in their business models (Minelli et al. 2013).

2.2 Event Processing and Complex Event Detection

As a technological basis to make use of fine-grained data originating from myriads of physical and virtual sensors measuring parameters along manufacturing processes, a timely analysis is essential. A common approach to analyze sensor data, of which each singular data point can be considered as an event, is to aggregate them to complex event patterns that indicate important situations with a crucial impact on the efficiency of processes (cf. Fig. 1) (Bruns and Dunkel 2010).

In this regard, Complex Event Processing has emerged as a novel event processing technology in addition to

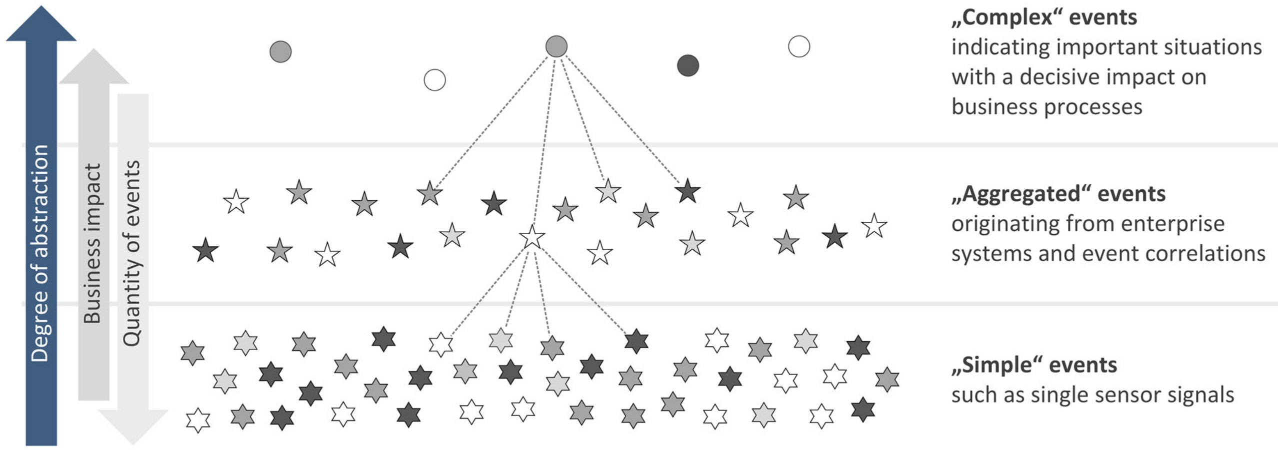


Fig. 1 Derivation of aggregated and complex events through abstraction mechanisms (based on Bruns and Dunkel 2010)

approaches such as simple event processing and event stream processing. CEP systems enable to determine potential threats and recognize opportunities in multitudes of event streams within real-time. Alongside being researched intensively as a specific research domain, successful industry applications of CEP can be found in fraud detection within banking and finance. Contrary to the manufacturing industry, it has been possible to examine financial transaction processes at a fine-grained level by means of information technology for some years (von Ammon et al. 2010). Further fields of application include logistics and supply chain processes, financial investment, traffic tracking, social sensing and so forth (Aggarwal 2012).

Complex event patterns represent templates which specify certain event combinations. They can be classified into various categories such as temporal, spatial, spatial–temporal, trend, modal and basic patterns with each category including various subcategories (Etzion and Niblett 2011). These so-called event patterns can be provided by experts or be automatically derived using machine learning algorithms. The actual detection of event patterns within continuous event streams are realized through predetermined queries. They are enabled by query processing techniques that are more evolved and differ from approaches applied within classical database analysis.

To describe event patterns and rules, special Event Pattern Languages (EPL) are used. Yet there is no language standard, which results in diverse competing approaches (Bruns and Dunkel 2010; Eckert and Bry 2009; Etzion and Niblett 2011): datastream-oriented languages building upon the Structured Query Language (SQL), production rules or rule-based languages applying Event-Condition-Action (ECA) principles originating from the Business Rule Management (BRM), as well as imperative script languages.

Event Processing Agents (EPA) are provided with the required knowledge about possible event types and their dependencies by means of event models. In contrast, declarative event rules specify event patterns and associated actions that should be started after the event detection.

To improve the performance of CEP systems, it is possible to combine multiple EPAs within a so-called Event Processing Network (EPN) (Etzion and Niblett 2011; Luckham 2002). Each participating agent may adopt a different task such as the processing of deducted events.

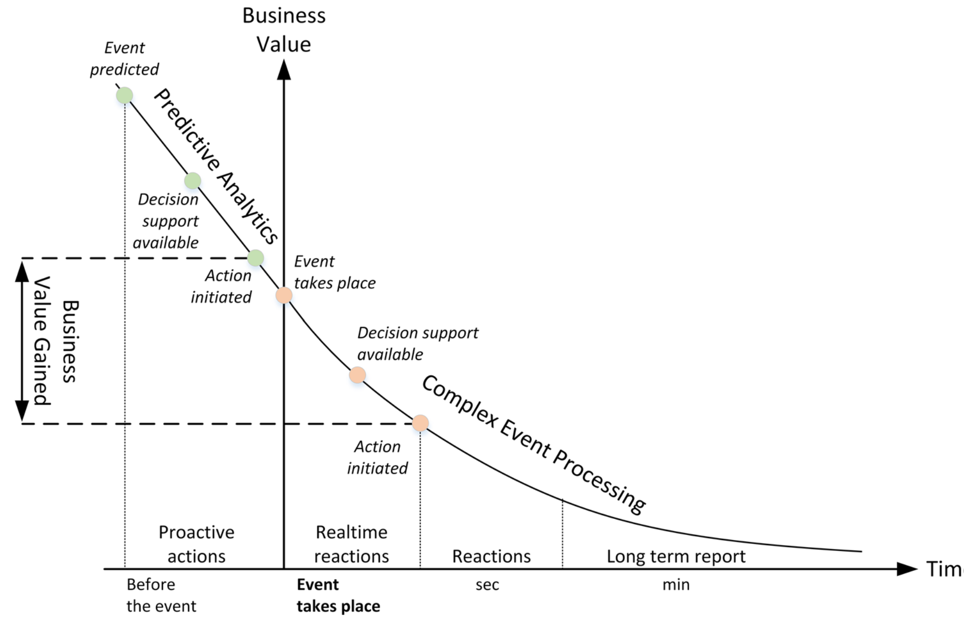
CEP is increasingly incorporated with other technologies, namely Business Process Management (BPM). The purpose of such an integration lays in the potential usage of real-time information gained from distributed systems and sensor networks for monitoring, controlling and eventually optimizing business processes. In this regard, ED-BPM makes it possible to initiate new process instances, to stop running ones and to influence their behavior based on recognized event correlations originating from massive streams of (sensor) data (Krumeich et al. 2014d).

2.3 Event-Driven Predictive Analytics

The temporal distance between the occurrence of a complex event pattern and the initiation of corresponding actions means a potential loss of business value in terms of information disadvantage (cf. Fig. 2). Thus, a timely detection and handling of complex event patterns is crucial and consequently an inherent feature of CEP.

This means, the earlier complex events are detected and processed or even emerging ones can be predicted through predictive analytics, the more valuable it is to have

Fig. 2 Business value gained through event prediction and proactive actions (based on Schwegmann et al. 2013 and Fülöp et al. 2012)



knowledge about them. This can be exemplified by an obvious example: consider a hurricane as a complex event whose occurrence is predicted (cf. “Event predicted” in Fig. 2) and corresponding actions like evacuation processes are initiated. It is obvious that the earlier the hurricane is predicted rather than reactively detected, the more valuable this information is (cf. Fülöp et al. 2012; “Business Value Gained” in Fig. 2).

By applying data mining techniques on historical event data, prediction models can be trained, which can again be used to make predictions of the occurrence of specific complex events during runtime (Engel and Etzion 2011; Engel et al. 2012; Fülöp et al. 2012). This requires the storage of historical events and event streams which is conventionally not within the scope of event processing engines (Bruns and Dunkel 2010); hence, this must be addressed by additionally connected databases or the respective operative systems.

By applying EDPA, it is possible to promptly enact countermeasures to looming events which is crucial for business processes (Redlich and Gilani 2012; Schwegmann et al. 2013). Whereas in its simplest form EDPA may only serve as a basis for enhanced monitoring purposes, the integration of EDPA with the actual business process execution control is conceivable. This can be considered as a revolutionary step, since it enables enterprises proactive process adaptions (Krumeich et al. 2014d).

2.4 Condition-Based Maintenance

One of the first generally known industry applications that, in principle, incorporate present process states and events into forecasts, can be found under the heading Condition-based Maintenance (CBM). CBM diagnoses failures within machine components or predicts the time by which failure may occur. This will result in a maintenance service, ideally with a minimized temporal distance between the service intervention and the estimation of the actual machine failure. Machine components can then be proactively repaired, overhauled or replaced, depending on the condition of the component, availability of spare parts and other variables (Veldman et al. 2011). Here, sensor technology and the thus acquired machine data aid in the effort to detect and classify errors, so that equipment problems can be identified, diagnosed and solved before a failure actually occurs (Heng et al. 2009). In order to predict the machine behavior, either physics-based or data-driven models are used. The latter are mostly used where collecting data appears to be easier than creating complex physical models. The paper at hand follows this basic idea.

The literature provides various CBM approaches which particularly focus on the process industry (cf. Sect. 4). For example, Goode et al. (2000) present a machine service life prediction for major facilities in hot rolling mills. Yam et al. (2001) have developed a so-called “Intelligent Predictive Decision Support System” for power plants that performs intelligent condition-based fault diagnosis and is capable of trend forecasting machinery degradation. Jardine et al. (2006) present a comprehensive analysis of existing diagnostic and prognostic approaches for use in the CBM. They consider the trend towards a correlation and fusion of different sensor data as decisive for the development of next-generation systems. Veldman et al. (2011), however, criticize the strong focus on diagnosis instead of prognosis. So far, prognosis systems have not been sufficiently developed and used in practice. As a cause, they particularly consider the complexity of the corresponding prediction models and the yet insufficient availability of operational and reliable data.

Beyond CBM there are other approaches for a forecast-based quality assessment of intermediate products, especially in process manufacturing with continuous rolling mill processes as an example (Konrad et al. 2012). As a result, these findings should enable an intelligent production control.

The objective of the paper at hand is it to apply the basic idea behind CBM to the general planning and control of business processes using event-based process predictions.

3 Conceiving a Prescriptive Process Control Using Event-Based Process Predictions

3.1 Motivating Scenario

To exemplify shortcomings in utilizing conventional techniques of descriptive analytics and to outline advantages of a prescriptive control of business processes by combining predictive analytics and CEP techniques, this section will illustrate a process example. The scenario is motivated by the sample presented in Krumeich et al. (2014e).

3.1.1 Shortcomings in Utilizing Conventional Techniques

In this motivating scenario, a steel manufacturing company handles two customer orders for which a production planning has to be carried out. Additionally, the concerning manufacturing processes have to be controlled. The first order requires final products of type D with a quality of at least 90 quality units (QU); the second order for the same type of product requires only a quality of at least 70 QU.

Assuming the underlying manufacturing process A, as it is depicted in Fig. 3a, conventional descriptive approaches would calculate a probability of 80 % that the production will result in final products of type D with material properties of 95 and 80 QU (cf. the characteristics of analytical manufacturing processes in Sect. 4). Hence, both customer orders could be satisfied and the production plan would assume the further processing of intermediate products C, which result in a quality of 90 QU. Based on these assumptions, the timing of underlying customer orders as well as machine allocations will be planned accordingly.

In addition to the manufacturing process A, the manufacturing process B permits to make final products of type D out of intermediate products C (cf. Fig. 3b). This manufacturing variant is particularly suitable if resulting intermediate products C (e.g., originating from process A) do not satisfy the required quality threshold of 90 QU that is required for their further processing within production step A.3a to final products D of at least 80 QU. However, this alternative in manufacturing final products D consumes more time and considerably greater amounts of material. Moreover, the resulting final products D within this production line only meet the required quality criteria in 25 % of all cases. In the statistically more likely case (75 %), products with 70 QU will be manufactured, thus only satisfying the second customer order. In this worst case, partial quantities of final products must be disposed of separately or they need to be returned to manufacturing process A (e.g., in steelmaking by melting them down again).

Traditional descriptive approaches would assume the production sequence as outlined above with a probability of 80 % (cf. "A.1 → A.2 → A.3a" in Fig. 3a). Consequently, the reasoning is wrong in almost a quarter of all instances. This would lead to final products that are not suitable without additional expense (cf. "A.1 → A.2 → A.3b" in Fig. 3a). Therefore, the use of descriptive analytics proves to be insufficient to control individual process instances, since it may lead to rather incorrect production planning due to its insufficient means of considering the contextual situation during the process execution.

3.1.2 Stronger Situation-Awareness through Predictive Process Analytics

If the considered manufacturing processes are equipped with appropriate sensors, a database can be built up that incorporates diverse situations of production and corresponding manufacturing context patterns. This database can then be used to build up prediction models that can be correlated with current process situations detected via CEP techniques. Hence, in the outlined scenario, a significantly more accurate prediction could be computed when knowing about situations X and Y (cf. Fig. 3). This is possible, since the production plan would not build on type-based descriptive analytics, but rather on instance-related predictive analytics capturing the current process and event situation.

This means for the underlying scenario: if for instance a complex event pattern is detected (e.g., certain qualities of input raw materials, machine variances, or participating employees) after completing or during production step A.1 within manufacturing process A, this particular situation can be correlated with the underlying prediction model. The resulting process forecast will then either strengthen the probability of process variant A or, in contrast, predict the statistical exception (e.g., "A.1 → A.2 → A.3b" as in

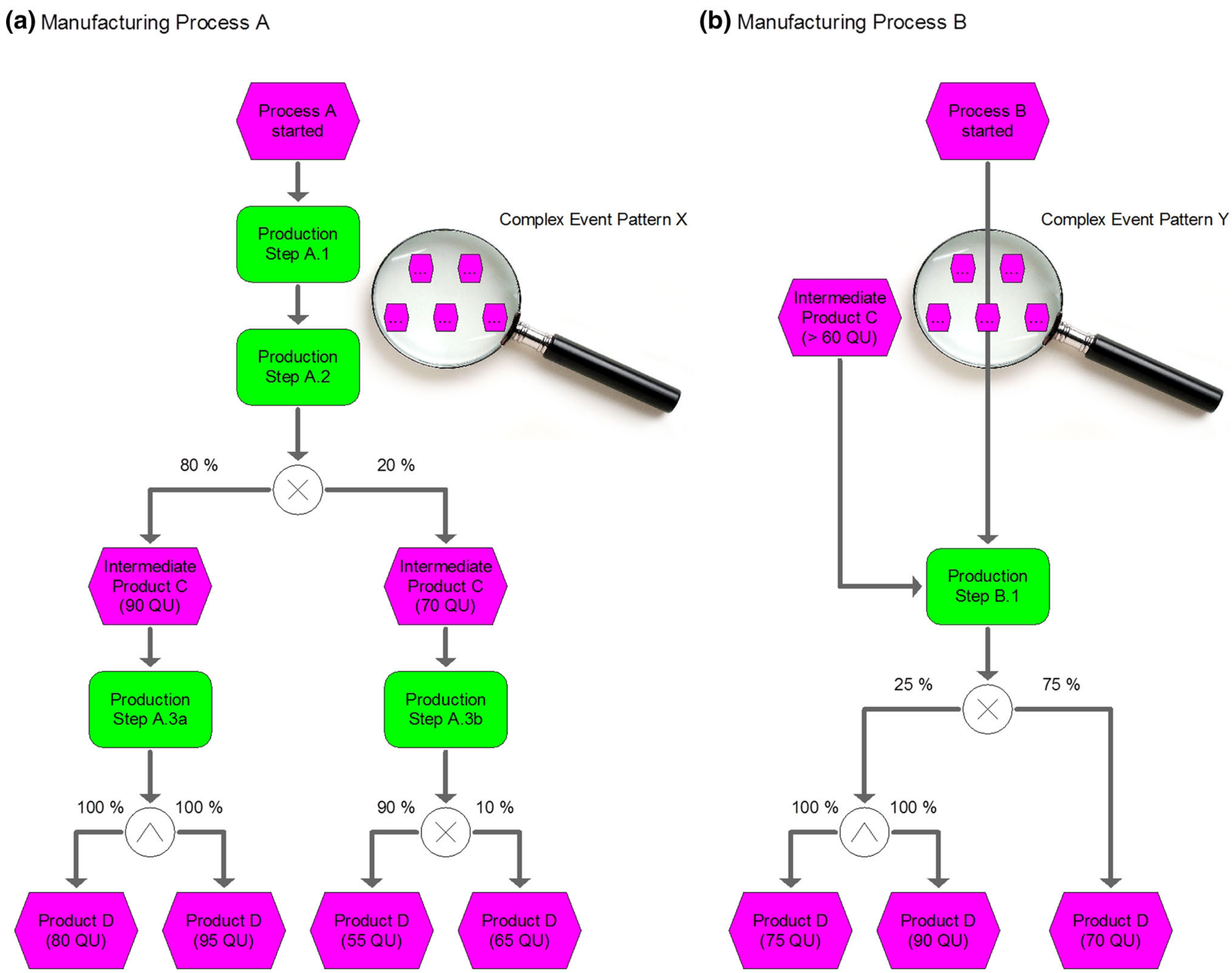


Fig. 3 Assumed manufacturing processes of the motivating scenario

only 20 % of all instances). Considering the latter, intermediate products C with a quality of 70 QU will result with high probability. For their further processing to product D, a resulting quality of 65 QU is predicted. According to this, it will not be possible to satisfy both customer orders as initially planned. Based on the determined qualities of intermediate products C as well as other process parameters, in accordance with the detected situation Y, the prediction will be that the further processing in manufacturing process B will significantly contribute to the statistical unlikely product D that is of sufficient quality to satisfy both customer orders (likelihood of 25 % for resulting products D with qualities of 75 and 90 QU, cf. Fig. 3b).

This exemplifies that by incorporating process and event parameters, the further sequence of a process could be predicted with considerably higher precision. Hence, the production can be planned more precisely and be proactively controlled. For instance, certain setup procedures for starting manufacturing process B may already be performed in parallel to the running process step A.2 within production process A. Stretched production time, increased material requirements as well as personnel and equipment utilization could be scheduled earlier or examined for the computation of possible alternatives.

3.2 From Descriptive to Prescriptive Process Analytics

At this point, the three different perspectives on business process analytics should be defined and compared (for the following cf. Akerkar 2013; Evans and Lindner 2012; Gröger et al. 2014; Jarke 2014).

Descriptive process analytics focuses on a type-based, mostly ex-post analysis of business processes. Such approaches typically fulfill reporting and dashboarding functionalities and are the most common type of analytics. By computing different statistical functions on historic, but increasingly also real-time process data, they help to answer questions such as “How has a process performed in the past?” or “What is the current performance of a process like?” Business process intelligence systems typically feature a broad range of descriptive analytics capabilities and help to understand and analyze the performance of business processes.

Predictive process analytics, on the other hand, differs from traditional descriptive approaches, since it strives to predict future process conditions based on analyzing historical process executions, e.g., through machine learning. The underlying objective is to detect certain rules and patterns, based on which forecasts of (running) process instances can be computed while considering current context information (cf. Schwegmann et al. 2013 for a related approach). In this regard, questions such as “When will this process instance end?” or “What will be the cycling time when executing a certain process sequence?” are considered.

On top of that, prescriptive process analytics, as the third stage of business process analytics, uses the trained prediction models to forecast process executions. Based on that, it recommends the best course of action in order to minimize or maximize certain key performance indicators (KPI) (cf. Gröger et al. 2014 for a related approach). In this respect, it helps to answer question like “What is the best execution sequence for the currently running process in order to minimize the overall resource consumption?” Thus, prescriptive analytics contribute to a proactive control of business processes.

3.3 Concept of Prescriptive Control of Business Processes

This section proposes the concept of prescriptive control of business processes by using event-based process predictions. To realize a prescriptive control of business processes, the subsequently outlined concept consists of four core components: component one serves to map complex event patterns and prediction targets in process models. The second component detects specified event patterns within running process instances by using methods of CEP. In case a complex event pattern has occurred, a prediction of the running instance considering the current process situation is triggered in component three. The prediction results are used within component four to simulate and optimize specified key performance indicators (KPI) based on a given optimization function. The computed results are used to support process owners’ decisions according to the principles of prescriptive analytics. After the components of the concept have been outlined, a high-level technical realization of event-driven process predictions will be sketched.

3.3.1 Component 1: Process Blueprints Containing Complex Event Patterns

The foundation of the concept is based on blueprints of process models that are instantiated in process engines (cf. Fig. 4, 1). These models can be extracted from completed process instantiations according to the principles of process mining (van der Aalst et al. 2012). Yet, to realize event-based process predictions, it is not the foremost challenge to mine and store intra-process related data, like cycling times of single process steps, but in particular cross-process related event situations with a decisive impact on the process execution. These situations, represented as complex event patterns, should be embedded into process models and should also feed into CEP engines as technical specifications, such as queries (cf. component 2). Complex events can be part of decision rules, i.e., of primary structural respectively control-specific nature; on the other hand, the presence of specific patterns can have significant influence on fluctuations of process KPIs. The mapping of such information into process models is only to a limited extent possible with current modeling techniques (Vidačković 2014). To address this research gap, some first approaches explicitly seek a graphical solution for the specification of CEP event patterns, e.g., Vidačković (2014) proposes an extension to the Business Process Modeling Notation (BPMN) 2.0 and Krumeich et al. (2015b) suggest an extension to the Event-Driven Process Chain (EPC) modeling notation.

Furthermore, there is a need for embedding prediction targets into process models, i.e., specific process parameters, such as cycle times, likelihoods of specific events occurring, as well as execution probabilities of certain process branches. Based on such predicted values, proactive decisions can be made without the necessity to wait for actually resulting values. Without doubt, there is a certain divergence between prediction targets and actual prediction potential in terms of prediction accuracy rates awarded to available process data sets (Dhar 2013). Whereas prediction targets are requested and accordingly specified by domain experts and owners of processes, prediction potentials are analyzed by data scientists (Buhl et al. 2013; Dhar 2013; Kowalczyk and Buxmann 2014; Viaene 2013). As already mentioned in Sect. 2, the accuracy of predictions increases by the square root of the number of independent observations (Jarke 2014). In this regard, technological progress in sensor technology as well as the increasing digitalization of physical goods triggers the possibility of grasping contextual data in an unprecedented fine-grained manner. On the other hand, this mass of potential information makes great demands on the analytical power in the context of big data (cf. Sect. 4).

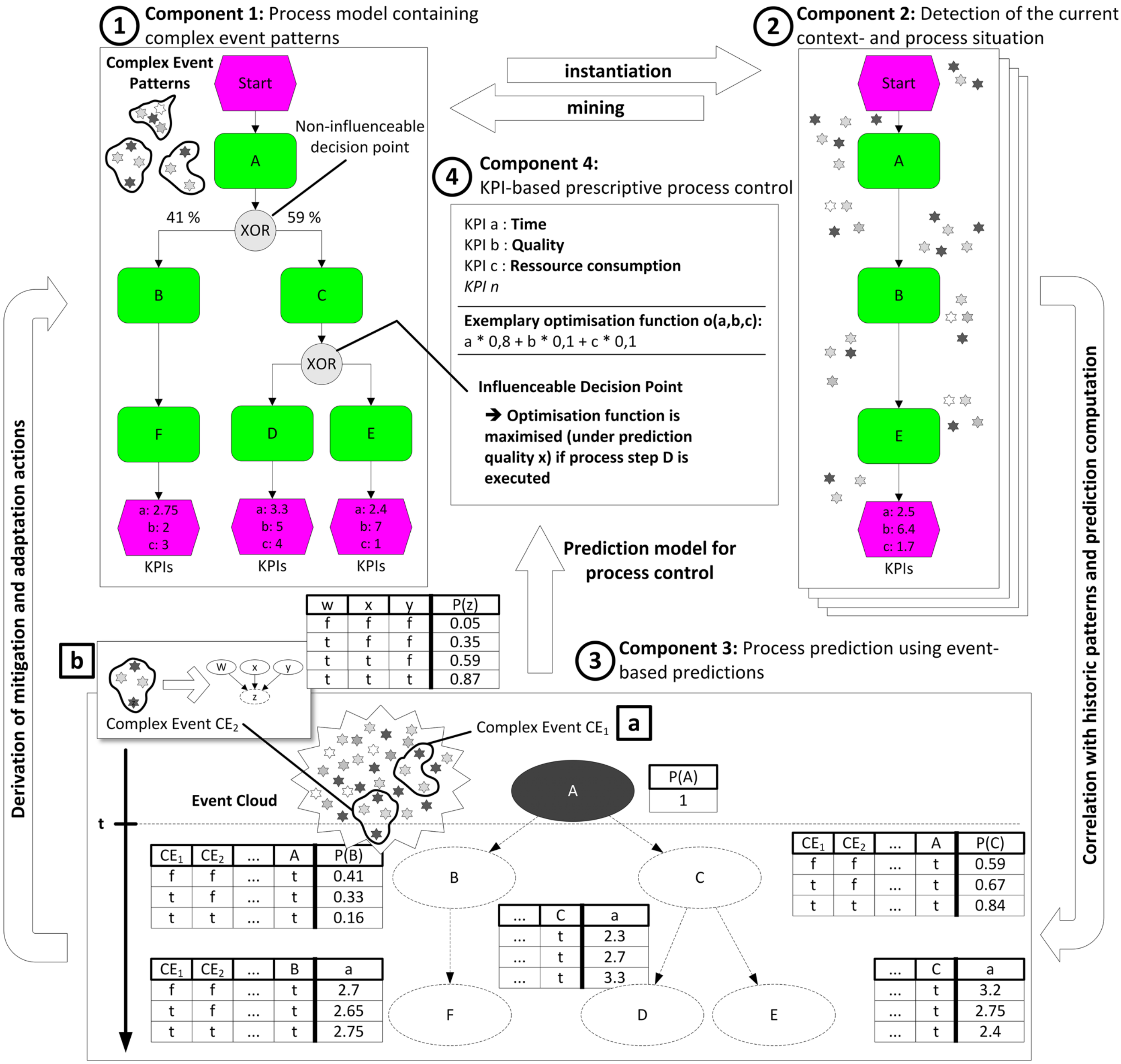


Fig. 4 Interactions of the four components for a prescriptive control of business processes based on event-based process predictions

3.3.2 *Component 2: Induction of Complex Event Patterns and Their Detection in Process Instantiations*

To automatically identify event patterns influencing process outcomes, different algorithms of pattern matching and recognition can be applied (Widder et al. 2007). They determine the significance of certain events influencing the likelihood of executing different process branches or consuming more or less resources as well as longer or faster cycle times. However, utilizing such machine learning approaches, like rule induction, for cluster detection has not been sufficiently analyzed in research and industry (Metz et al. 2012; cf. Margara et al. 2014; Mehdiyev et al. 2015a, b, 2016 for first approaches). These clusters reflect so called complex events yielding a higher significance in affecting process outcomes. Hence, only the concurrent (non-)occurrence of multiple atomic events represents a significant situation for process executions. As a result, these mined complex event patterns need to be stored with their respective process blueprints to be used in process instantiations (cf. Fig. 4, 2). They do not occur in each process execution, but need to be detected using means of CEP. Such detection of a complex event is based on event patterns and rules described by dedicated Event Pattern

Languages (EPL). Here, data-stream oriented languages, rule-based languages and imperative script languages can be distinguished (Krumeich et al. 2014d).

3.3.3 Component 3: Process Forecasting Using Event-Based Process Predictions

As a result of detecting current process and context situations as complex events via component 2, they can be matched with the underlying process model and its inherently stored history of process instances. This makes it possible to compute prediction models for the further proceeding of the process as well as determined prediction targets, often represented as KPI. Due to the situation-awareness of predictive analytics, this kind of forecast calculation enjoys significant advantages over conventional BPI and PPM methods, which frequently compute mean values over all process instances (Schlegel et al. 2013). Even if they can be drilled down to certain properties, these approaches always possess the risk of falling short considering a specific, perhaps exceptional situation; hence, a situation-aware control of process instances cannot be realized.

Figure 4, 1 exemplifies certain likelihoods within a running process instance on the basis of mean values originating from historical process executions. Accordingly, with a probability of 59 %, process step "C" as well as the associated KPI will result after the first (non-influenceable) decision point (regarding non-influenceable decision points cf. Sect. 4.1 on analytical material flows and non-linear production outputs in process industries). Even though this probability is accurate on average, the currently given process situation could include an exceptional case – especially in case the probability exhibits a high variance. Event-driven process predictions mitigate this shortcoming through a specific consideration of the current process and context situation. In case Complex Event CE_1 is detected (cf. Fig. 4, 3a), the probability for P(C) evolves towards 0.67.

As a matter of fact, predictive analytics itself can be applied to derive forecasts of the occurrence of specific complex events (Engel et al. 2012; Fülöp et al. 2012; Krumeich et al. 2015a). As depicted in Fig. 4, 3b, the likelihood of the occurrence of event z – as an atomic event – can be predicted based on already detected process and context events, e.g., w, x and y. In case w, x and y have occurred, the probability of z has been computed to $P(z) = 0.87$. This number may exceed a certain predefined threshold to trigger z as a predicted event. In this case, the corresponding complex event CE_2 will be detected by CEP and associated actions will be proactively initiated. Of course, this example abstracts from different characteristics of composite events that make them complex, such as temporal or spatial properties.

The prediction of CE_2 might significantly influence the prognosis of the ongoing process progress as well as resulting KPIs. The conditional probabilities depicted as a Bayesian network in Fig. 4, 3 show that the probability for $P(C \mid CE_1$ and $CE_2)$ increases to 0.84 and KPI a (time consumption) will be significantly different in case complex event CE_2 takes place and process step "D" or "E" will be processes. Actually the applied prediction approach will not compute a probability mass function for the associated KPIs, but rather a probability density function.

3.3.4 Component 4: Prescriptive Process Control

Through utilizing event-based process predictions, the process execution can eventually be proactively controlled based on desired KPIs. In more detail, an optimization function *o(a, b, c,)* must be defined based on a weighting of the considered KPIs (Fig. 4, 4). On this foundation, the further (most optimal) process sequence can be computed and used for a prescriptive process control. In the present scenario, the assumption that the predicted complex event CE_2 is going to occur would suggest to perform step "D"after completing "C". To consider the average would in contrast suggest to perform "E" (cf. $a = 3.3$ vs. $a = 2.4$ since *o(a, b, c)* should be maximized and b and c can be considered as constant). Hence, the decision between step "D" and "E" is influenceable. In this case, machineries used in step "D" can already be started to be instantly ready as soon as "C" is completed. This finally realizes a prescriptive control of business processes (cf. Sect. 4.3 for a consideration of the state-of-the-art of planning and control systems in process industry).

3.3.5 Technical Realization of Event-Based Process Predictions

To realize event-based process predictions from a technical perspective, i.e., to incorporate the increasingly large amounts of events, a powerful event processing technology is needed in the first place. In this respect, a CEP engine is considered as the basic enabler for a real-time analysis of event streams (cf. Fig. 5, 1). The required knowledge about possible event types and their dependencies is provided to Event Processing Agents (EPA) by means of event models (cf. Fig. 5, 1).

After detecting aggregated or complex events (cf. Sect. 2.2), certain procedures can be initiated within connected Event Handler, such as prediction or process engines (cf. Fig. 5, 2, 3). By utilizing predictive analytics on event streams, the likelihood of occurrence of complex events, of

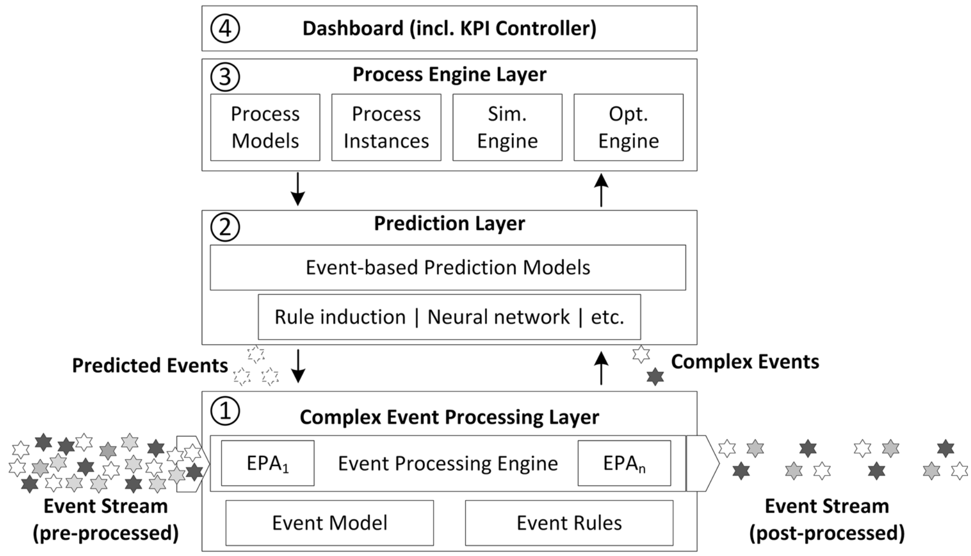


Fig. 5 Prescriptive control of business processes using event-based process predictions

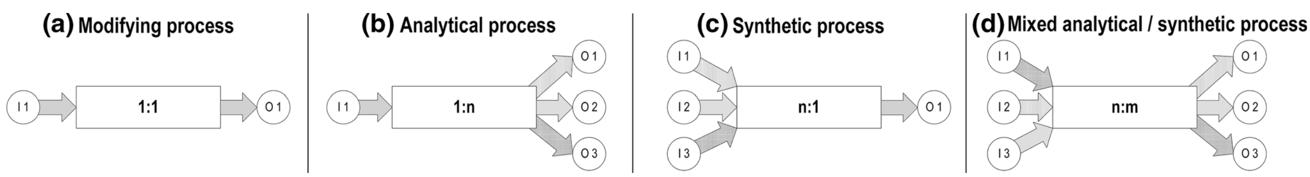


Fig. 6 Different forms of material transformation in manufacturing processes (Loos 1997)

which only a subset has already occurred, can be forecasted (cf. Engel et al. 2012; Fülöp et al. 2012). This results in predicted events that feed back into the CEP engine (cf. Fig. 5, 2), which in turn triggers actions within the connected event handler such as a process engine (cf. Fig. 5, 3). Via process simulation and optimization algorithms, the prediction knowledge will be used to calculate an optimized process execution sequence according to KPIs provided by process managers in a dashboard layer (cf. Fig. 5, 4). Since the detected complex event has not fully occurred so far, but relies on certain predicted events, the initiated action in the process engine can be considered as proactive. Either the actual occurrence of the predicted complex event, in case it was not mitigated through proactive actions, or the absence of the predicted event has to feed back into the prediction engine, in order to constantly train the underlying prediction models.

4 Production Planning and Control in the Steel Industry – Characteristics and Case Study

4.1 Characteristics of the Process Industry

Manufacturing processes are classified by numerous criteria that may appear in a variety of combinations. One example is the differentiation of production processes regarding their relation to specific branches of industry. This is conducted by using several industry taxonomies (e.g., International Standard Industrial Classification of All Economic Activities by the United Nations 2008).

Besides such rather general characteristics, manufacturing processes are also classified regarding their transformation of underlying products and materials (cf. Fig. 6). In this regard, synthetic and analytic processes, mixed transformation forms as well as purely modifying processes are differentiated (Riebel 1963, p. 57). Whereas synthetic processes synthesize quantities of inputs into one output (n:1 relation); analytical processes, on the other hand, process single inputs into several separated outputs (1:n relation).

Synthetic processes are characteristic for discrete manufacturing processes, as they can be found, for example, in the automobile assembly. In contrast, analytical material transformations are inherently featured in process manufacturing, as in the chemical and the steel producing industry. In discrete manufacturing, input and/or output factors are quantifiable, whereas companies processing materials such as gases or liquids are allocated to the process manufacturing industry or process industry respectively.

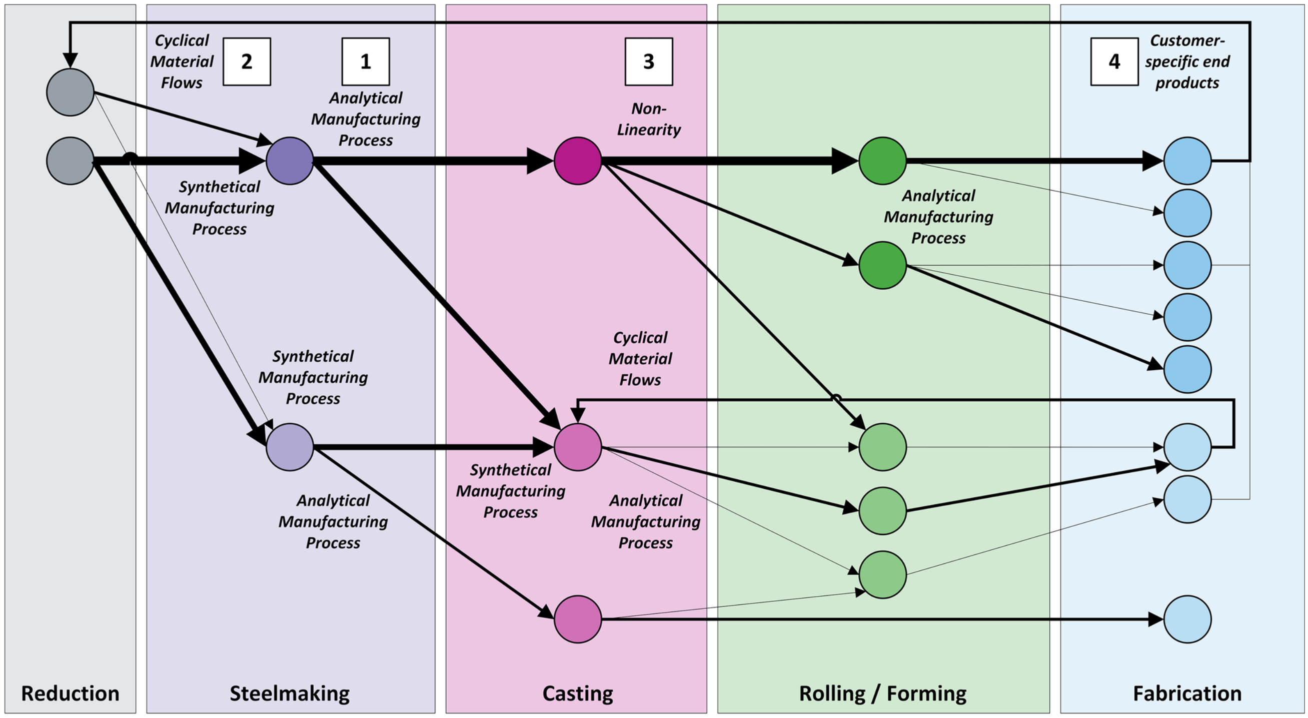


Fig. 7 Schematic representation of steel production processes and their characteristics (based on Allwood and Cullen 2011)

A closer look at process industries reveals several interesting specifics. These are outlined in the following with a dedicated focus on steel manufacturing, which is a typical example of the process industry. Figure 7 illustrates the usual process sequence within steel production and points out the inherent industry characteristics.

4.1.1 *Divergent/Analytical Material Flows*

Caused by the characteristics of analytical processes, various types of co- and by-products as well as waste originate while producing the actual main product (cf. Fig. 7, 1).

These additional products can be differentiated into cost and revenue-neutral, cost-generating but revenue-neutral, and revenue-generating ones (Loos 1997, p. 41). From a production logistics point of view, revenue-generating co-products are of the greatest interest as they can be further processed and used in succeeding processing steps.

Production processes commonly feature multiple steps covering a mixture of synthetic and analytical processes. In process industries, divergent material flows can particularly be found at earlier production steps, while in later steps syntactical processes are more common (May 1996).

4.1.2 *Production Cycles*

Resulting co- and by-products, but also waste, are often cyclically added to manufacturing processes or are continuously required for additional production lines (cf. Fig. 7, 2). These cyclical relations between output and input factors are diametrically opposed to traditional manufacturing industries, e.g., the automotive industry as a typical assembly industry (Rapp 2002).

4.1.3 *Non-Linear Production Outputs and Non-Controllable Production Deviations*

Both main products as well as co- and by-products originating from analytical processes often differ in terms of quantity and quality, i.e., do not follow a linear production function (cf. Fig. 7, 3). This means that increasing the number of inputs will not result in an equally increasing amount of produced outputs. However, quantity and quality have to be considered in the ongoing production planning and control (Hahn and Lassmann 1999). These fluctuations have different reasons: varying qualities of raw materials, external influences such as temperature or pressure, as well as internal influences such as reaction rates e.g. in the chemical industry (Rapp 2002; Scheer 1998).

4.1.4 *Customer-Specific End Products*

A look at steel manufacturing companies reveals that resulting main products are tremendously customer-specific, specifically in terms of their levels of quality (cf. Fig. 7, 4); standard products only rarely exist. This clearly contrasts with discrete manufacturing. Even though, for example, in the automotive industry, complexity is given due to the wide range of variations, there is no heterogeneity in terms of the actual quality of products that can be measured and the process sequences controlled accordingly.

4.2 Challenges in Production Planning and Control

As a result of these characteristics, production planning and control within the process industry is an adequate domain for the application of the concept presented in Sect. 3. This is mainly due to the need of process manufacturing companies to analyze and control each of their process instances individually, since customer orders require diverse and individual material properties and qualities as well as production processes are non-linearity.

This can be illustrated by an example: a standard process in steel making may include the steps peeling, furnace treatment, and finally cutting the steel into bars; however, the raw steel cannot go through those steps if a sensor network detects a curving, as an example of a production deviation. In this case, this intermediate either needs to be post-processed in a dressing and straightening machine to comply with quality requirements, or the processing of the intermediate can continue for another customer with lower quality demands. Therefore the production planning for this process instance is obsolete and needs to be re-initiated in order to meet quality promises to and deadlines of all customers, e.g., the steel bars need to be inserted into the normal process flow after conducting ad-hoc processing step. Since production planning systems frequently compute an almost full capacity for the following days in batch mode, a simple insertion of a process instance into the running production flow may contradict the planned execution.

Even though such deviations are unavoidable since production in process industries is not fully controllable (May 1996, p. 38; Scheer 1998, p. 398), influencing factors – such as varying material properties of cast iron or deviations from nominal values of employed production facilities – are more and more detectable via modern sensor networks. Consequently, impending deviations within production can be predicted, and thus, corresponding countermeasures, such as a proactive re-scheduling, may be initiated before deviations occur.

Due to the common absence of such a predictive process control, produced goods partly need to be considered as steel scrap and have to be melted down again – with all corresponding economic and ecological consequences. In this regard, Allwood and Cullen (2011) found that in 2008, from a globally required amount 1040 million tons of steel products, 334 million tons were discarded as waste, which is a ratio of one to three. This waste is reintroduced to the production cycle together with scrap metal which is however also needed to a certain ratio as cooling scrap to stabilize the temperature of liquid steel (cf. Fig. 7, 2). Nevertheless, more than two thirds of the steel scrap is only recognized as such and discarded as waste in the later stages of production, meaning that these 236 million tons are run through the entire production process. This emphasizes the potential of a predictive planning and control of production processes, especially within the process industry.

4.3 State of the Art of Production Planning and Control Systems

Production planning and control systems are usually divided into three system classes that are hierarchically related to each other (Shobrys and White 2002). At the top level, planning systems support the management with a planning horizon of several weeks or months. Mid-level scheduling systems efficiently distribute activities on the available production machinery over a time scale of days to weeks. Below this operating level process control systems manage the real-time execution of the respective production machine.

In the field of process control systems, so-called Model Predictive Control (MPC) is considered to be an important achievement (Chan et al. 2014). MPC was developed in the late 1970s and since then has constantly evolved (Camacho and Bordons 2007). However, MPC does not describe a special regulatory procedure, but rather a wide range of control methods that use a physical model of the controlled process to predict its future behavior depending on possible control signals. Thus, control signals for achieving optimal process results can be calculated for upcoming time periods. A disadvantage is the relatively high computational effort, though attempts to reduce efforts by applying approximation are being made (Graichen et al. 2010). MPC approaches are often used in engineering processes that are common for the process industry. For example, consider the contributions of Niamsuwan et al. (2014) – for controlling milk pasteurization processes –, Chan et al. (2014) – in the field of power plant processes –, and Kittisupakorn et al. (2009) – for steel pickling processes.

Before a process can be regulated, scheduling systems forecast which jobs should be processed at what time, in what sequence, and on which machine. A recently published article by Harjunkoski et al. (2014) provides a comprehensive overview of existing scheduling algorithms that have been developed specifically for the process industry. Accordingly, scheduling procedures range from computer-aided manual schedule generation (e.g., by using interactive Gantt charts) and extend to expert systems, mathematical programming methods, heuristics, and artificial intelligence up to stochastic optimization approaches.

In the field of artificial intelligence, a review of literature reveals various approaches of so-called multi-agent systems that have also been applied within the industry. For instance, Fischer et al. (2004) developed a multi-agent system for steel production. It uses a distributed planning and scheduling algorithm, in which each production unit acts as an agent, and thus independently calculates a set of possible solutions. Finally, another agent performs the overall optimization. The real-time system monitors the planned execution, identifies potential problems, and suggests how to resolve them. Jacobi et al. (2007) developed this system called MasDISPO further and recapped the lessons learned from the productive use in a steelmaking company. However, the system does not reveal forecast functions. Another example of an agent-based production system is provided by Elghoneimy and Gruver (2011), who focus on wood product manufacturing.

Before scheduling, a system-wide planning needs to be performed. For example, modern data mining approaches are used to gather implicit knowledge from complex production data and consequently generate planning rules. This forms the basis of so-called knowledge-based production planning systems. For this purpose, Rainer (2013) developed a process model and demonstrated its use with a case study from the production of semi-finished aluminum.

Focusing on the process industry, i.e., more precisely, steelmaking and continuous casting, Zhu et al. (2010) provide a novel optimization model to improve the efficiency and performance in production planning. Their optimization model is coupled with a simulation model and provides an online evaluation and adaptation of the production schedule. A detailed review of scientific literature on simulation techniques regarding different domains has been presented by Jahangirian et al. (2010), who compared almost 300 different approaches.

The mutual integration of the three described system classes is crucial to the successful operational use. With regard to this question and by dedicatedly looking at the process industry, Loos and Allweyer (1998) presented principles and concepts to achieve a comprehensive integration.

Thus, production in process manufacturing industries is neither characterized by strong linearity (as in discrete manufacturing), nor is the quality of resulting co-products easily detectable or even deterministic, e.g., based on bills of materials. Manufacturing processes can thus be considered as strongly interweaved (Loos 1997). From an information systems' point of view, the optimization of production processes in process manufacturing can consequently be considered as particularly challenging (Loos 1997). Hence, choosing this type of manufacturing as the underlying object of investigation proves to be particularly appropriate for using event-based predictions for a prescriptive process control (cf. motivating scenario in Sect. 3.1). However, to do so, a foundation of data must exist in order to be able to generally compute forecasts with high accuracy. To outline what type and size of data is currently available in process manufacturing industries using state-of-the-art sensor technology, the following section will present a case study of the steel bar production at one of Germany's largest steel manufacturers (cf. Krumeich et al. 2014a, b, c, e).

4.4 Case Study: Manufacturing Processes in Steel Bar Production

The following case study analyzes a segment of the production processes at one of Germany's largest steel manufacturers (for an overview of steel producers in Germany, see Statista 2015) and discusses some of the current challenges that the company is facing in controlling its production process in a proactive manner. The data sketched in this study was collected and evaluated by the department for process control computer applications of the chosen company.

In the considered production branch half a million tons of steel are produced annually. To meet customer-specific quality standards for the various end products, the manufacturer has implemented extensive quality tests within the production line. These tests include diameter controls with laser, surface testing by magnetic particle testing, checks for internal steel errors by ultrasound, and a variety of temperature and vibration measurements.

All these measurements continuously generate sensor data at the lowest system level (L1). Furthermore, additional sensor systems are installed in production (ambient and positioning sensors) to monitor the control of steel bars via a material flow tracking system (L2-system level). Based on this basic data and the available customer orders, a rough timetable is calculated by means of production planning and monitoring systems (L3 to L4 system level). In this regard, the international standard IEC 62264 (International Electrotechnical Commission 2013) provides a differentiation of system levels within enterprise systems.

Currently, the sensor networks that are integrated into the production processes are continuously providing too much data to be entirely appropriately processed. The employed information and control systems as well as the analysis techniques available on the market are not capable to monitor and control the entire production processes in a proactive manner. Thus, no future states and events, such as looming production deviations, can be predicted on time. Hence, control production process control is instead executed in a reactive way.

In the following, sample data obtained from the applied sensor networks are described using the big data characteristics in accordance with the classification of the German

Association for Information Technology, Telecommunications and New Media (BITKOM 2012). If the entire sensor networks within the production process are considered – which would be necessary for a comprehensive production planning and control on an L3-/L4-systems' level –, the Big Data challenge will multiply.

4.4.1 Volume

An example from the sensor network illustrates the immense amount of data (volume) that is associated with monitoring the production process. In the rolling mills 31 and 32, there are two optical surface test sensors that can continuously provide real-time data for the detection of surface defects during the rolling process. This makes it possible to take into account the varying customer demands for a particular surface quality. The plant already implements an error detection (using a detector) and a classification of the error types (using a classifier). This optical test sensor generates annually about 400 terabyte of video data for each rolling mill, which corresponds to a data rate of one gigabyte per minute. Currently it is only possible to realize a sporadic reactive analysis of this data. The preferred option of linking it with context data originating from other sensor networks and systems settled on levels L2 and L3 is currently not possible in real-time due to the volume of the data that is to be analyzed. Although these systems can in principle detect problems in batch mode, this detection is too slow to be able to react on time and avoid production deviations.

4.4.2 Variety

While this is merely an example of very large amount of data from individual sensors in one segment of the production, another example shows the high data diversity (variety) that is continuously generated by various sensor networks throughout the production line. This places high demands on an analysis according to big data principles. The further processing of steel bars already provides half a million of sensor data records per month, which reflects in detail the context situation of this production area. This corresponds to a sampling frequency of about five seconds for a record size of several megabytes. Although the data size of these real-time sensor data streams is considered to be relatively small from an isolated point of view, for a comprehensive analysis across all production areas and a correlation with prediction models, conventional methods quickly reach their limits. Within the next months, the sensor performance at this point will have improved so that over 1.5 million sensor data records will be available on level L1 and L2 every month. In accordance with the principle of CEP, however, only the identification of relevant event patterns within this flood of homogeneous and heterogeneous data sets will detect production deviations on time. At this point, the basic claim of a scalable solution becomes obvious, as the equipped sensor network should be extendable in a flexible way, and at the same time analyses and predictions should be performable in the required time scale. Within the next three years, the company is additionally planning to increase its sensor coverage in this section to generate an output of more than five million data records, which corresponds to a sampling rate of two data sets per second.

4.4.3 Velocity/Analytics

Thus, in terms of analyzing this large and diverse data, the responding time is crucial, since velocity is a decisive competitive factor in analytics (velocity/analytics). Classic reporting or batch processing would definitely be too slow, so that so-called high velocity technologies must be performed in near-real-time analyses. For the purposes of the outlined vision of predictive enterprises, it is also crucial to conduct accurate forecasts of the process sequences. Each day, an average of one terabyte of video data is recorded in a single subsection of the plant. However, a pure video analysis method is not sufficient for predictive analytics. In the existing system, it has been shown that only a few production deviations could be detected by this classical approach. In addition, there is no feedback for a proactive process optimization. Therefore, process data need to be included in the model formation and forecasting. Here, as outlined, over one million data sets will occur in the coming months. For analyzing the dependencies between process and video data, data from a longer period must be used for model training. In this case, the data volume may rapidly exceed 50 terabytes. For a real-time adaptive prediction, on average one-tenth of the data should be used. At present, however, such a number of data can hardly be processed in real-time. A direct compression of the data is impossible because of its variety to be considered.

Due to this big data problem, the current production process is a long way from an envisioned optimum with regards to a proactive control. Technically, the company could integrate additional sensors into its production processes to achieve an even more fine-grained monitoring; however, current analytical methods take too long to complete an analysis and to gain an economic benefit from this.

5 Architecture Proposal for Prescriptive Enterprise Systems

In this section, seven requirements that need to be fulfilled in order to systematically implement a prescriptive control of business processes are illustrated. The requirements were motivated by the research in Krumeich et al. (2014c) and were derived from the analysis of the case study conducted in Sect. 4. After this, a corresponding system architecture is proposed (cf. Krumeich et al. 2014e), which emphasizes the outlined requirements, and may serve as a blueprint for prescriptive enterprise systems.

5.1 Requirement Analysis

As the case study analysis revealed, the overall challenge of computing accurate predictions has shifted from being able to capture process and context situations – as the baseline for deriving forecasts – to being able to manage and adequately consider this huge quantity of data. In addition, the case study illustrated that the masses of data are progressively growing – which is accompanied with general expectations (Dhar 2013) – resulting in the necessity of possessing a scalable platform for integrating sensor technology. This leads to the first requirement of a system architecture.

Requirement 1 Providing scalable means for extending sensor networks throughout production processes and storing the masses of data in descriptive process and context models.

In addition to collecting and storing process data in historical description models – as a knowledge base for process predictions –, it is compulsory to investigate current real-time conditions of processes through analyzing their current events and context situations. Due to the wide variety of heterogeneous sensors which are used in enterprises, this particularly is a challenge of big data analytics in terms of data variety (cf. case study analysis in Sect. 4.4). To address this, these streams of atomic data have to be searched for patterns in real-time, e.g., by CEP technologies.

Requirement 2 Providing means for detecting and filtering complex events within tremendous streams of sensor data.

Such CEP permits to correlate current conditions with historical ones as the baseline for deriving event-based predictions. Through this correlation, event-based forecast models can be derived and constantly adapted. As a technical infrastructure, a platform must be available which combines a batch-oriented analysis with that of a distributed stream mining analysis. Whereas batch-oriented methods are important for training prediction models, stream-oriented ones are compulsory for the actual real-time analysis of incoming data streams. In particular for the automatic analysis of image and video sensors – as outlined in the case study –, dedicated algorithms need to be available in order to derive structured information from unstructured data. The necessity to realize a real-time correlation of complex events with historical process data leads to the third requirements.

Requirement 3 Providing capabilities for real-time data analyses to correlate and analyze data collections and streams that can be classified as "big" in terms of high volume, high variety and high velocity.

Based on such correlations, prediction models comprising forecasts of the future progress of business processes can be computed, which allows for a proactive reaction to predicted problems. Several prediction techniques and algorithms can be applied, all of which have to be capable of processing big data and have to cope with real-time requirements, which is another challenge in terms of big data analytics. In this regard, sophisticated CEP techniques are required to predict likelihoods of the occurrence of future atomic events that will eventually trigger complex ones. These probability assumptions will realize a predictive complex event detection.

Requirement 4 Deriving and continuously adapting (event-based) prediction models.

Based on event-based prediction models, forecasts of substantially higher accuracy can be computed, since predictions are not purely based on stochastics. Instead, the actual current state is decisive for the computation. Hence, process progressions can be forecasted and certain deviations from planned and required process execution objectives can be proactively detected leading to corresponding system responses.

Requirement 5 Creating alerts as responses to predicted deviations from planned process objectives based on calculated forecasts.

Within computed prediction models, not only one single possible future process progress will be forecasted, but multiple ones whose occurrences are depended on both non-influenceable events and influenceable actions. Thus, recommendations or automatic decisions and actions should be provided to positively influence and control the outcome of business processes in accordance with specific process objectives. This will make it possible to realize a proactive incident management in contrast to a reactive incident handling as a prerequisite of a predictive enterprise.

Requirement 6 Deriving recommendation and automatic decisions for mitigation actions.

As a result of intelligent algorithms it should further be determined whether changes enacted within one process instance – as a response to detected deviations, defects and problems – will impact other running instances that in turn will affect recommendations and automatic actions. These automatic or manually triggered actions based on real-time event-based predictions eventually realize an intelligent

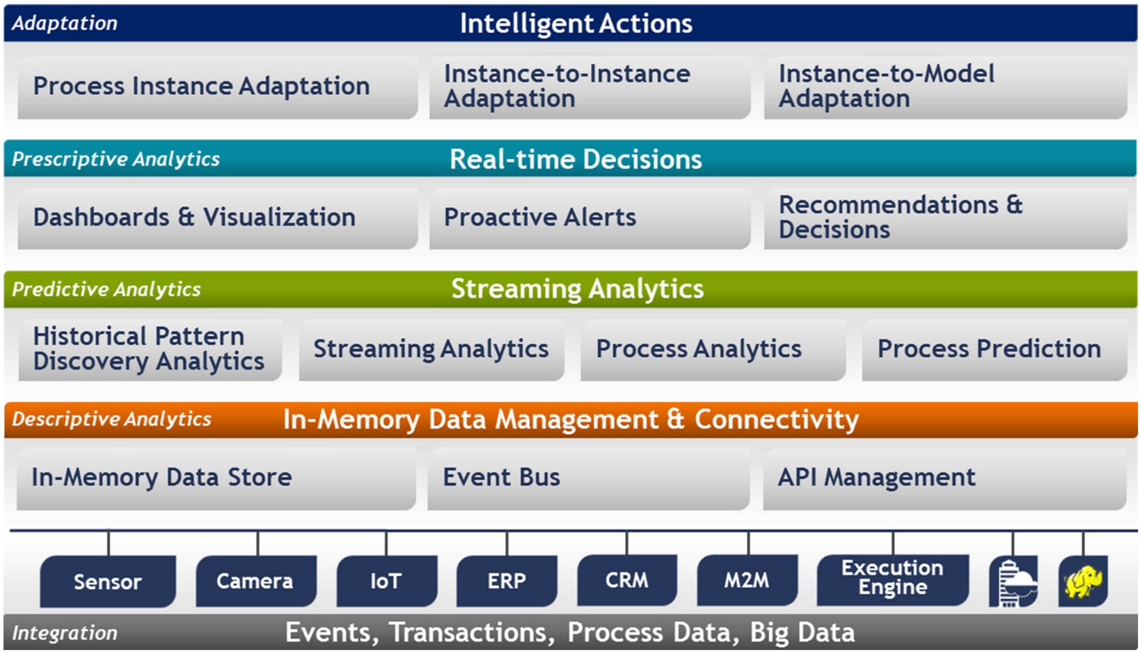


Fig. 8 Layers and functional building blocks of a prescriptive enterprise systems' architecture (Krumeich et al. 2014e)

proactive process planning and control and thus the vision of a predictive enterprise.

Requirement 7 Enacting sophisticated proactive process adaptations on the basis of computed recommendations and decisions.

5.2 Architecture Proposal

This section outlines a functional description of components required for realizing a prescriptive control of business processes (cf. Fig. 8).

On the basis of the previously derived requirements, the architecture comprises three inherent layers that are typically considered within analytical processes of big data (Akerkar 2013): a descriptive (cf. Requirements 2, 3), a predictive (cf. requirement 4) and a prescriptive layer (cf. Requirements 5, 6). On top of these, an adaptation layer (cf. Requirement 7) allows for intelligent actions incorporated into business process engines as responses to prescriptive decisions. As the architecture's baseline, an integration layer (cf. Requirement 1) realizes the system's physical interweaving into production process and facilities.

5.2.1 Integration Layer: Events, Transactions, Process Data, Big Data

The foundation of this system is a solid integration platform that connects the system to a company's existing IT infrastructure. In an Industry 4.0 context additional adapters for sensor and IoT object integration are required. Due to the wide variety of heterogeneous sensors which are used throughout enterprises, an initial classification is required, which can be realized via ontology-based enterprise models. The use of ontologies realizes the semantic interoperability of context data and thus in principle enables an automated analysis.

5.2.2 Descriptive Analytics Layer: In-Memory Data Management and Connectivity

Due to the high volume of data and the velocity in which it is generated, an in-memory data management platform is utilized, allowing for distributed in-memory data management with extremely low, predictable latency and fast data access (microseconds) for real-time data handling. An in-memory data store will act as a central point of coordination, aggregation and distribution. Besides data management, events such as alerts or system messages are communicated by using an event bus by means of which components can publish and to which they can subscribe. To manage the diverse data sources and connected enterprise systems, an API management component is introduced.

5.2.3 Predictive Analytics Layer: Streaming Analytics

Real-time data accessible via the in-memory data management platform can be preprocessed. In particular for the intelligent evaluation of image and video sensors as outlined in the case study, special algorithms have to be developed in order to derive structured information from unstructured multimedia data. The results are fed back to the in-memory data store. The aggregated data is used for both ex-post and ex-ante analysis. From an ex-post point of view, historic data can be analyzed for pattern detection and correlated with respective business process behaviors. Based on these patterns, real-time event detection, such as deviations of production progress from an expected state, can be learned, optimized and applied to monitor real-time data streams. Here, an extension of the sub group search for distributed stream analysis could be developed. This technique is suitable to recognize the deviation from the normal state as well as to generate predictions. Furthermore, modern Bayesian approaches could be combined with it, which are specifically optimized for large amounts of data. Data analysis components can communicate detected patterns to the event bus on which a complex event processing engine (CEP) is operating to correlate business process relevant events from data analysis results. These can then be used for process prediction.

5.2.4 *Prescriptive Analytics Layer: Real-Time Decision Making*

In order to enable process owners to make qualified real-time decisions, all relevant data needs to be aggregated and visualized appropriately. Here, dashboarding functionalities similar to current business activity management solutions can be applied. In addition, process owners must be notified proactively if a decision is required or when a deviation from the current state of a process instance is detected. Besides pure visualization and notification, a recommendation is generated based on historic process analysis. To understand why a recommendation was made, drill-down functionalities allow to navigate to previous process instance information and enable process users to make qualified decisions.

5.2.5 *Adaptation Layer: Intelligent Actions*

Based on the data gathered and the resulting process prediction, business processes can either be adapted on an instance base (process instance adaptation) by adjusting the current process execution, or by optimizing the entire process type (instance-to-model). However, adaptations in a process instance can lead to necessary adaptations in other correlated process instances such as supporting or following processes (instance-to-instance). Here, the process owner is also supported. Once the adaptations have been decided on, a governance process ensures a consistent transition of changes back into the process execution system(s).

6 Conclusion and Outlook

In order to keep up with increasing market demands in global competition, companies are forced to dynamically adapt each business process instance by considering its individual business situation. Companies that have the capability of analyzing the current state of their business processes, forecasting their most optimal further sequence and proactively controlling them based on this knowledge will be a decisive step ahead of their competitors. Such a company sketches the vision of a predictive enterprise in the age of data as a decisive competitive asset. Thus, research faces the challenge of developing appropriate analytical methods and software systems that are able to detect and predict decisive events from collected data in a timely manner.

This paper explored new potentials through the application of predictive analytics on big data. Thus, it proposed a concept for the prescriptive control of business processes by using event-based process predictions. Nowadays, finance and insurance companies are no longer the only enterprises with fine-grained insights into their business processes. More particularly, industries with a dedicated focus on physical objects, like the manufacturing ones, have reached new dimensions in data sensing through technological advancements resulting from the rise of the IoT.

In this regard, this paper focused on production planning and control in the context of process manufacturing, which includes several key industries not only in Germany, but also worldwide. Based on a case study of a German steel producing company, the paper outlined which data becomes available when using state-of-the-art sensor technology. This will be the foundation to realize the concept that was proposed by the paper. However, a consideration of the data size revealed that dedicated methods of big data analytics would be required to tap the full potential of already available data. Consequently, the paper derived seven requirements that need to be addressed for a successful implementation of the concept and additionally proposed a generic architecture of prescriptive enterprise systems.

Whereas the paper sketched how large quantities of low level data can be transferred into business value, the paper abstracted from more technical implementation details required to analyze these masses of data. In the ongoing research project iPRODICT, an interdisciplinary team of researchers and industry experts explore the technical realization of the proposed concept (cf. Acknowledgements).

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