Anticipation-driven Architecture for Proactive Enterprise Decision Making

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Abstract. In this paper we present a visionary approach about a new architecture for supporting proactive decision making in enterprises. We argue that a cognitive approach of continuous situation awareness can enable capabilities of proactive enterprise intelligence and propose a conceptual architecture outlining the main conceptual blocks and their role in the realization of the proactive enterprise. The presented approach provides the technological foundation and can be taken as a blueprint for the further development of a reference architecture for proactive enterprise applications. We illustrate how the proposed architecture supports decision-making ahead of time on the basis of real-time observations and anticipation of future undesired events by presenting a practical application in the oil and gas industry.

Keywords: proactivity, predictive analytics, enterprise, decision-making, event-driven computing, condition-based maintenance.

1 Introduction & Motivation

Today's enterprises are facing increasing pressure due to globalization, uncertainties, and increased regulations, among others. These pressures are forcing the companies to manage production at the margins of performance, achieving better control through the whole of the production process. As an example companies need to know what goods are in transit, what is about to enter the warehouse, what is being shipped from suppliers, in order to dynamically route goods in-transit.

To cope with these challenges in general, dynamic business networks need to enhance their monitoring capabilities within the network and across different levels. To achieve this, real time monitoring can be used and such kind of real-time monitoring have been already implemented in many enterprises in the form of extensive sensor/IoT- systems. Indeed, sensing enterprises are a reality, starting from manufacturers that can sense some deviations from the production plan as soon as

they appear, till large logistics networks that sense delays about the delivery time in real-time. The main driving concept in sensing enterprises is events and correspondingly, the event-driven architecture (EDA) is underlying their realization.

However, event monitoring, is only the first, crucial step to manage problems in complex, dynamic systems. Next step is enabling that event monitoring copes with the scale and dynamics of the business context (internal and external). Indeed, change is constant, therefore monitoring solutions must also change so they can adapt and stay relevant. For example, changes in the business performances should be registered as soon as they happen and taken as new monitoring goals.

This kind of dynamic monitoring is the basis for the new level of (sensing) performance observing that is not only sensing the problems, but also sensing that the problem might appear, i.e. focusing on a proactive approach. Indeed, observing a delay is very useful information, but anticipating that there will be a delay is far more important from the business point of view. Moreover, such anticipation will lead to the possibility to act ahead of time, i.e. to be proactive in resolving problems before they appear or realizing opportunities before they become evident for the entire business community and be able to recover and support continuity. This ability to support continuity in operations at the margins is called resilience [1], and is a key strategy in today's and future industrial operation. From the architecture point of view this requires reorientation from events as changes that happened in time to anticipation as prediction that something will happen in near future.

In this paper we present a visionary approach about anticipation-driven sensing and decision-making that will enable the transition from sensing to proactive enterprise. One of the main novelties is the treatment of anticipation as the first class citizens in our approach: it supports the whole life-cycle of the anticipation, from sensing/generating anticipations till validating the reactions (proactions) based on them. We argue that a cognitive approach of continuous situation awareness can enable capabilities of proactive enterprise intelligence and propose a conceptual architecture for proactive enterprises systems. We present an application scenario for proactive decision-making in the area of condition-based maintenance.

The rest of the paper is organized as follows. Section 2 discusses our vision for the proactive enterprise, while Section 3 outlines the proposed approach for realizing such a vision. Section 4 presents our proposed architecture and Section 5 an envisaged scenario where proactivity can be injected in enterprise decision-making. Section 6 discussed related work, while Section 7 concludes the paper.

2 Vision

Our vision for the proactive enterprise compared to the current reality of sensing enterprise is illustrated in Figure 1. Sensing enterprises are operating on the surface of the possibilities (the tip of the iceberg), whereas a deeper diving into the endless wealth of opportunities is required in order to enable the transition to the proactive enterprise. Consequently, like the events are driving reactivity in the sensing enterprise, anticipations (predictions) are driving proactivity in proactive enterprise leading to increased situation awareness capabilities even ahead of time (cf. Figure 1). This requires new methods and technologies that are responsible for dealing with anticipations, which are part of the novel anticipation-driven architecture: Anticipation-driven Architecture for Proactive Enterprise Decision Making 123

- Anticipation based on Big data Exploiting the power of big enterprise data, by sensing the whole business ecosystem: shifting relevant business context from internal processes to the ecosystem
- Anticipation-based Actions Extracting the actionable meaning from data, by applying advanced big data predictive analytics: shifting the processing capabilities from real-time into ahead-of-time processing
- Anticipation-driven Optimization Increasing the strategic value of data analysis for decision making, by dynamically adapting patterns of interest found in real-time big data streams and enabling proactive decisions: shifting decision making focus from early warnings into business optimization

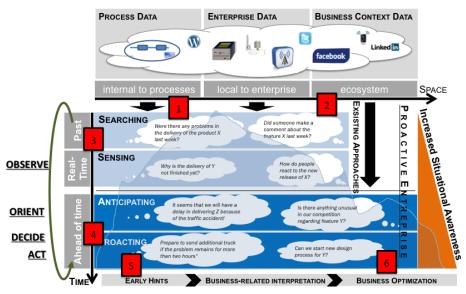


Figure 1: From Sensing till Proacting. (1-> 2, Space axis: From Processes to the Business Ecosystem; 3-> 4, Time axis: From Real-time to Ahead of Time Processing; 5 -> 6: Decision Making: From Early Hints to Business Optimization)

This will lead to a new class of enterprise systems, proactive and resilient enterprises, that will be continuously aware of that what "might happen" in the relevant business context and optimize their behavior to achieve what "should be the best action" even during stress and balancing on demanding margins. Proactive enterprise systems will be able to suggest early on to the decision makers the most appropriate process adjustments to avoid singular system behavior and optimize its performance.

This paper introduces a novel architecture for realizing proactive enterprise, encompassing anticipations as the first class citizens and driver of the processing. The architecture is based on the Observe, Orient, Decide, Act (OODA) loop of situational awareness that has been recognized as one of main models for the big data supply chain [2] - the key for continuous situational awareness. This model sees decision-

making occurring in a recurring cycle of unfolding interaction with the environment, oriented via cues inherent in tradition, experience and analysis. These cues inform hypotheses about the current and emerging situation that, in turn, drive actions that test hypotheses.

The first step towards continuous situation-aware proactivity is to enable comprehensive observing of the relevant enterprise context/ecosystem through the design and development of a smart sensing system able to cope with a huge amount of heterogeneous (big data) in real-time, focusing on predictive sensing (sensing early warnings - anticipations). Next, semantic understanding of acquired data in near real time should be enabled (orient) by designing and developing an efficient management framework for dynamic (proactive) and context-aware anticipation and detection of the situations of interest on the basis of complex and predictive data analysis algorithms and event-detection. This will provide the basis for supporting making decisions and actions ahead of time through designing and developing mechanisms for the proactive recommendations based on the dynamic situational awareness and the predictive data analysis. An example of this dynamic mechanism is the use of proactive indicators to support resilience. Finally, proactive handling that will result in sustainable business improvements should be ensured, through designing and developing methods for defining and dynamic monitoring of KPIs and corresponding adaptation of the whole OODA cycle, closing the feedback loop and leading to the continual proactive business optimization. Figure 1 illustrates how our approach for realizing the OODA loop can be seen in the context of the proactive enterprise vision.

3 Conceptual Architecture

Based on the proposed continuous situational awareness approach presented above, we outline the main conceptual blocks and their roles in the realization of the proactive enterprise platform, an anticipation-based platform for integrating heterogeneous real-time and dynamic streams created by hardware sensors, software and external data used in enterprises. The proposed conceptual architecture is strongly oriented on the OODA loop and combines services of smart sensing, anticipation management, incremental proactivity and proactivity management (see Figure 2).

Smart sensing services include adapters, pub-sub middleware and the Scalable Event Storage. <u>Adapters</u> enable communication with all necessary enterprise information sources such as hardware sensors (which might include vibration and temperature sensors, environmental sensors), software sensors from ERP and other enterprise systems and external business context data. <u>Pub-sub middleware</u> is realized as an event cloud, a scalable, P2P based repository that delivers RDF events to the requesting parties (subscribers) and ensures the decoupling between components so that the system can scale very easily. <u>The Scalable Event Storage</u> enables semantic enrichment with background knowledge of real-time streams and allows storage of events (in the form of RDF triplets) received from adapters for historical and statistical purposes. It supports synchronous and asynchronous queries expressed in a subset of the SPARQL language and accessible through corresponding APIs.

Services for anticipation management will enable the generation of real-time, data-driven predictions, as well as the discovery of unusual situations, based on events delivered by storage. Novel <u>predictive analytics services</u> will be realized as

intelligent services on the top of probabilistic stream processing technologies. The <u>Complex Event Processing (CEP)</u> component has the role of dynamic definition and detection of complex events and reasoning over events, supplied by Event Storage. Complex Event Patterns can be defined and deployed dynamically or produced by offline analytics. CEP allows goal-driven identification of relevant situations of interest and leverages detection of anomalies in real-time providing the basis for proactive actions.

Incremental proactivity service subscribes for predicted situations of interest (pub/sub communication) and generates corresponding proactive recommendations, by taking into account business context. It couples dynamic and uncertain decision making methods and decision theoretic optimization models and proactively recommends actions and activation time maximizing the utility for the enterprise, while considering several criteria such as cost, time and safety.

Proactivity Management deals with defining and dynamic monitoring of KPIs and corresponding adaptation of the whole OODA cycle, closing the feedback loop and leading to the continual proactive business optimization.

By taking into account the complexity of the business environment the modern enterprise is working in (Big Data, Dynamic Context, Critical Decision Making), we argue that this architecture, by assuming that it will be validated through use cases, can be taken as a blueprint for further development of a reference architecture for Proactive enterprises.

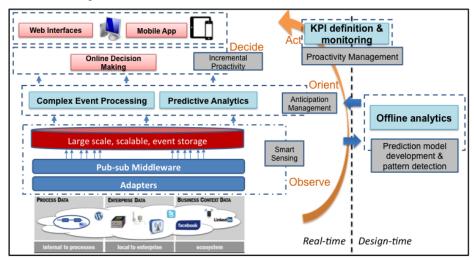


Figure 2: Conceptual Architecture

4 Envisaged Scenario & System Walkthrough

In this section we present a practical application of the proposed framework for anticipation-driven sensing and proactive decision-making, in the oil and gas industry. We describe the practical role and use of the proposed framework focusing on how it can support decision-making ahead of time on the basis of real-time observations,

predictions and anticipation of future undesired events, through an indicative scenario of proactive condition-based maintenance (CBM).

CBM in the oil and gas industry employs various monitoring means to detect deterioration and failure in some critical drilling equipment. Equipment failure situations can be forecasted/anticipated based on observations of events related to this equipment or the surrounding environment; e.g monitoring engine temperature indicators, monitoring electric indicators (measuring change in the engine's electric properties) and performing oil analysis [3]. In reality, several different patterns will imply various failure distributions; for the sake of the example, we will focus on thermal indicators, adopting the approach presented in [4]. More specifically, in this scenario we focus on the gearbox drilling equipment and consider as indicators the rotation speed of the drilling machine's gearbox.

We distinguish between two different types of operations performed by components of the proposed framework in order to support anticipation management; offline and online operations performed at design time and real-time, respectively. At <u>design-time</u> the **offline analytics** component extracts from historical data of oil temperature, RPM events and gearbox equipment failure, the distributions associated with gearbox breakdown along with their relation to monitored indicators and builds a breakdown prediction model that will enable the generation/detection of the anticipation of interests. Moreover, it identifies which complex event patterns indicate that a drilling gearbox equipment failure starts to occur, on the basis of historical data, and communicates the identified pattern to CEP for real time monitoring.

At <u>real-time</u>, the **CEP** component detects a complex pattern of simple oil temperature and RPM events characterized by an abnormal oil temperature rise (10% above normal) measured over 30% of the drilling period when drilling RPM exceeds a threshold, caused by abnormal friction losses in the drilling gearbox during drilling. This pattern, learned at the offline phase, is a strong indication that a gearbox equipment failure starts to occur. Based on the pattern detected by CEP in real-time, the **online predictive analytics** component analyzes the current trend of oil temperature and RPM increases and drops for the most recent events and predicts (anticipates) the occurrence of a future gearbox break down along with the associated probability distribution function, based on trend analysis and the breakdown prediction model learned at the offline phase.

Based on the predicted probability distribution for the occurrence of a future gearbox breakdown, the **online decision-making** component provides proactive recommendations of actions that either mitigate (i.e. reduce the probability of occurrence) or completely eliminate the future gearbox breakdown, along with the recommended activation time. This component applies dynamic and uncertain decision making methods and decision theoretic optimization models that minimize cost or maximize the utility for the oil drilling company. Examples of actions aiming to optimize the maintenance policy according to cost criteria may be a) to take the equipment down for full maintenance - an action that completely eliminates the predicted gearbox breakdown - or perform less costly actions that only reduce the probability of failure such as b) perform lubrication of metal parts, or c) shift drilling to lower pressure mode. Actions could also be related to resource management and organization of the resources needed to rectify the gearbox failure in case it occurs.

The business added value of anticipation-driven proactive decision-making in this scenario is huge. With a typical day rate for a modern oil rig being around USD 500 000, reducing undesired downtime, with its associated high cost (one hour of saved downtime is typically worth USD 20 000) is of outmost importance in the oil drilling industry. Therefore, we expect that the proposed framework, which is able to provide early notifications about equipment problems and proactive recommendations about optimal decisions on the basis of utility, cost and other factors, will allow proactive enterprises in the oil and gas industry to gain a strong competitive advantage based on reduced downtimes and optimized performance.

5 Related Work

Although the idea of proactive computing may seem simple, the quantity and quality of proactive applications is rather modest. Proactive applications have been developed in an ad-hoc manner for several years; applications regarding proactive decision-making include network management [5], supply chain management [6] scheduling of manufacturing systems [7] and maintenance [8].

Especially maintenance has gathered significant research interest. Although there is not a complete agreement in the literature about the classification of maintenance types, they can generally be divided to three categories: breakdown maintenance which takes places when a failure occurs, time-based preventive maintenance which sets certain activities when a defined period of time passes and Condition Based Maintenance (CBM) which recommends actions according to the health state of the manufacturing system [9]. In CBM, real-time proactive decision support becomes significant because a maintenance strategy, usually based on a prognosis model, needs to be implemented [8]. Several techniques have been developed within the framework of CBM by utilizing OR, AI, multiple criteria methods and several statistical techniques accompanied with the appropriate architecture [10].

Despite these applications, the lack of a generic paradigm to develop proactive event-driven applications makes it difficult for this capability to spread. Because of its nature, proactive computing requires an integration of various technologies for sensing, real-time processing and decision-making. The approach presented in this paper provides the technological foundation and can be taken as a blueprint for the further development of a reference architecture for proactive enterprise applications. With respect to the maintenance domain, which is the application domain of the presented envisaged scenario, our approach goes beyond time-based preventive maintenance by extending stochastic preventive maintenance methods [11] and integrating them in an innovative anticipation-driven ICT architecture.

6 Conclusions and Future Work

We argue that the proposed architecture for anticipation-driven decision-making is the ultimate basis for realizing proactive enterprise. This has several implications for practitioners. They need to be prepared both in technical terms and from a cognitive perspective to take advantage of the novel business intelligence capabilities that will be provided. On the one hand they need to design and implement physical (such as smart sensors and actuators, location-aware sensors, cyber-physical systems) and

virtual sensors (such as agents in customer transaction and relationship systems) in virtually every aspect of their enterprise that has an impact on the end result.

Regarding future work, we aim to follow a multi-aspect approach for validating the main facets of the proposed research. We will pursue validation in diverse enterprise settings with different technical constraints and user requirements so that the impact is leveraged. Validation will be performed on a technical level (covering system-related metrics such as performance) and on a business level, covering the benefits for end-users of the proposed system. Specifically, on the business perspective, validation will be focused based on performance in terms of decreased maintenance costs and equipment deterioration and increased reliability. On the other hand, domain experts will validate the results based on factors which are usually hard to measure such as increase in safety, decrease of environmental impact and the added value of the proactive business intelligence capabilities provided. Validation of the approach will be performed in the context of the ongoing FP7 project ProaSense in two main use cases: proactive manufacturing in the area of production of lighting equipment, and proactive maintenance within the oil and gas sector.

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