A Framework for Integrated Proactive Maintenance Decision Making and Supplier Selection

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Abstract. The increasing use of sensors in manufacturing enterprises has led to the need for real-time data-driven information systems capable of processing huge amounts of data in order to provide meaningful insights about the actual and the predicted business performance. We propose a framework for real-time, event-driven proactive supplier selection driven by Condition Based Maintenance (CBM). The proposed framework was tested in a real in automotive lighting equipment scenario.

Keywords: Condition Based Maintenance, supplier selection, proactive computing, event processing.

1 Introduction

The emergence of the Internet of Things (IoT) enhances the extensive use of sensors generating huge amounts of data and consequently the need of real-time data-driven information systems in order not only to react on actual problems but also to provide meaningful insights about potential future undesired events or opportunities [1]. This proactive approach can significantly enforce decision making processes in the context of various manufacturing operations and functions of manufacturing enterprises, such as maintenance and purchasing. Since manufacturing companies need to work with different suppliers of maintenance spare parts, the purchasing department can play a key role in cost reduction and risk optimization as well as in empowering the suppliers for improved quality, response time and reliability of supplies deliveries [2]. In this sense, the strategic process of supplier management is replacing the function of purchasing [2] involving a smaller numbers of highly qualified buyers, decentralized control of non-value adding items and greater planning activity horizons. Consequently, supplier selection becomes one of the most important operations of supply chain management, since it should split the order quantities among suppliers for creating a constant environment of competitiveness [2]. Our approach utilizes the proactive event-driven computing principles, the Condition Based Maintenance (CBM) concept and the purchasing management theory in order to form a framework for real-time, event-driven proactive supplier selection. The rest of the paper is organized as follows. Section 2 discusses the literature review. Section 3 presents the proposed framework, while Section 4 describes the implemented system. Section 5 presents its application in real industrial environment, Section 6 shows the comparative and sensitivity analysis and Section 7 concludes the paper and discusses the future work.

2 Literature Review

2.1 Proactive Event-driven Computing and Condition-Based Maintenance

The use of sensors in enterprises enhances the IoT paradigm and leads to the development of event-driven information systems capable of processing sensor-generated data in complex, dynamic environments. Therefore, there is the capability to decide and act ahead of time, in a proactive way [1]. Proactivity refers to the ability to avoid or mitigate the impact of future undesired events, or to exploit future opportunities, by applying real-time prediction and automated decision making technologies [1]. Several works in the past have spotted proactivity as the next evolutionary step in event processing systems [1,3] and proactive computing in different application domains has started to emerge. The manufacturing domain has not exploited its capabilities in a real-time streaming environment in order to facilitate proactive decision making [1]. In the manufacturing domain, maintenance is related to all the industrial operations and focuses not only on avoiding the manufacturing failures but also on improving the whole business performance. CBM incorporates condition monitoring, enabled by manufacturing sensors, for identifying and predicting the health state of a manufacturing system in order to better support decision making process [4].

2.2 Purchasing Management

In manufacturing enterprises, procurement deals not only with the raw materials required for the production process, but also with spare parts needed for maintenance. Therefore, the supplier relationship strategy should be aligned with the equipment maintenance strategy. Since the supplier selection process occupies a large amount of resources, companies expect to conclude in high value contracts. However, prices of spare parts and raw materials are subjected to fluctuations with uncertain trends, making procurement, and especially supplier relationship management, a key element of business performance [2]. Suppliers' prices affect long-term business profitability, business reputation and output product's price, thus suppliers' prices prediction algorithms and autonomous interacting software agents have gathered an increased interest during the last years [5]. At the same time, procurement management should ensure reliability and quality of supplies in conjunction with the transaction costs and risks in a dynamic uncertain environment [2]. Procurement management driven by CBM can be benefit from lean manufacturing in order to eliminate operation's wastes during the production process [6]. Cooperating with one outsourced supplier may cause significant problems [6], so having more choices of suppliers that produce and deliver the same components can lead to less future risks and costs [2].

3 The Proposed Framework

The proposed framework, built on the CBM concept [4] and on a real-time architecture for proactive decision making [1], covers the whole prediction lifecycle from sensing till automated proactive decision making and monitoring. The framework consists of a user interaction, a real-time processing and a data layer, as shown in Fig. 1. The user interaction layer supports the configuration of the architecture and the visualization of appropriate information through a GUI. The real-time processing layer is based on the "Detect- Derive- Decide- Do" (4D) model of situational awareness in sensor-based real-time intelligent systems [7] and consists of two information processing pipelines working in parallel but at different timestamps (asynchronous processing). These two pipelines are represented by two components: a maintenance and a supplier selection component. The framework does the mapping of the 4D phases to CBM and supplier selection phases and extends previous research works by utilizing the proactivity principles, the event processing technologies and the recent advances in maintenance and logistics management. The maintenance component implements the CBM steps for diagnosis, prognosis, action recommendation and action implementation, while the supplier selection component consists of an indicator detection, a prices prediction, a supplier recommendation and purchasing. The services in each phase for each component are described below.

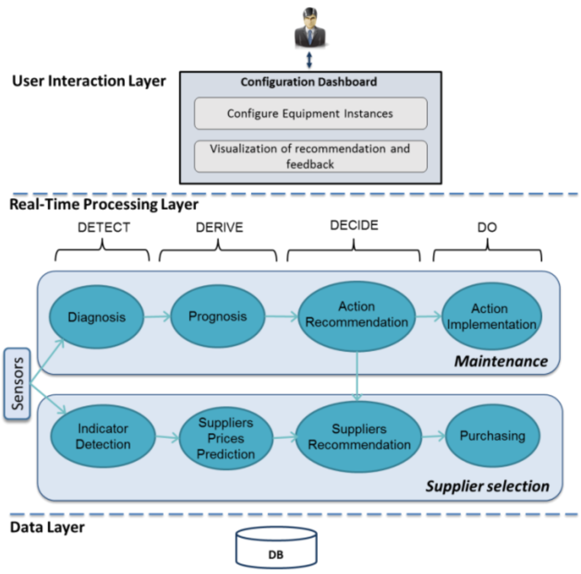

Fig. 1. The proposed framework for real-time, event-driven proactive supplier selection in manufacturing enterprises.

Detect: This phase deals with sensing, data collection and acquisition in order to discover unusual situations on the basis of complex enriched events identified by a Complex Event Processing (CEP) service. In the maintenance component, the CEP engine deals with the detection of an abnormal behaviour of the equipment on the basis of hardware sensor data (e.g. manufacturing sensors). The supplier selection component deals with the detection of indicators (causes) that suppliers' prices are to increase (e.g. the start of a negotiation process after an invitation to bid) on the basis of software sensor data (e.g. ERP system containing data collected through Electronic Data Interchange (EDI) from suppliers with a strategic partnership).
Derive: This phase deals with a predictive analytics service, which enables the generation of real-time, event-driven predictions of future undesired events, i.e. failures. Predictions are triggered on the basis of unusual situations identified by the Detect phase. In the maintenance component, it deals with the development of a prognostic model about a future failure in order to predict the Probability Distribution Function (PDF) of the failure occurrence. In the supplier selection component, this phase deals with the prediction of suppliers' prices on the basis of the associated detection event throughout a decision horizon (e.g. until next planned maintenance).
Decide: This phase includes a decision management service that provides proactive recommendations on the basis of the prediction events generated by the Derive phase. In the maintenance component, it deals with uncertain decision making ahead of time, e.g. about the optimal time for a maintenance action implementation along with the optimal time of ordering the required spare parts Just-In-Time. This recommendation feeds as input into the supplier selection component that provides recommendations about the optimal portfolio of suppliers given the purchasing budget at the recommended future ordering time so that the expected losses are minimized. The use of a portfolio optimization approach supports the allocation of scarce resources in the manufacturing enterprise to different supplier relationships and thus, the minimization of supply-related risks. Since information processing is asynchronous, the suppliers' recommendation part of supplier selection component receives and stores the most recent update of the suppliers' prices predictions in order to use it when the action recommendation part of maintenance component triggers the supplier recommendation part of supplier selection component.
Do: This phase deals with the continuous monitoring and the actual implementation of the recommended actions in order to adapt the whole 4D cycle of the operational system closing the feedback loop and leading to the continuous proactive business performance optimization. The feedback gathered from the Do phase is transferred to all the previous phases for both components according to which one corresponds. In the maintenance component, feedback is collected through hardware sensors and measuring devices and deals with the actual complex pattern that would led to failure, the actual time of the failure occurrence (if it finally occurs) as well as the actual maintenance and inventory costs during the action implementation. Then, the previous phases are updated offline accordingly. In the supplier selection component, feedback is collected through software sensors (e.g. ERP) and deals with the actual cause that led to prices fluctuations, the actual prices fluctuations in the course of time and

the actual suppliers' prices at the time of spare parts ordering. Then, the previous phases are updated offline accordingly.

4 The Implemented System

Based on the framework, we developed an information system. The User Interaction Layer has been implemented as a web-based application using web2py, while the real-time processing layer as a Storm topology. For each consisting module, we integrated existing systems, we embedded modifications of existing algorithms and we developed new models as explained below.

Detect: In this phase, we used an existing tool called "StreamPipes", which defines and executes stream processing pipelines consisting of multiple heterogeneous runtime implementations [8]. It is used in both components with a different formulation. In the maintenance management component, it is used for the detection of abnormal equipment behavior on the basis of manufacturing sensor observations that may be causes of a future failure (e.g. temperature, vibration, etc.). In the supplier selection module, it is used for the detection of indicators for a possible future prices change on the basis of observations of changes in the ERP system due to EDI (e.g. start of negotiation process, change in profitability of suppliers, etc.).

Derive: In this phase, the maintenance component was implemented by integrating an existing system called "StreamStory" [9], which allows the simultaneous analysis of multiple data streams by their modelling as hierarchical Markovian model on the basis of complex event patterns. Then, it provides predictions about the PDF of future failures (prognostic information). As far as the supplier selection component is concerned, we embedded a modification of an existing algorithm for suppliers' prices prediction using Artificial Neural Networks (ANN) [5] so that it becomes dynamic [7] and event-driven in order to utilize the detected indicators of the previous phase. Its output is the prediction of suppliers' prices throughout a decision horizon, sent and stored in the suppliers recommendation part of supplier selection component.

Decide: In this phase, both the maintenance and the supplier selection components were implemented in a tool for proactive decision making which incorporates a joint predictive maintenance and spare parts inventory optimization method for providing a recommendation about the optimal time of applying a maintenance action and the optimal time of ordering the required spare parts [10]. This output triggers the suppliers' recommendation part of the supplier selection component and is used along with the stored suppliers' prices prediction event as input to a Markowitz Portfolio Theory (MPT)-based optimization algorithm [11] where the assets correspond to suppliers. Thus, MPT method is applied on the basis of the recommended optimal ordering time and the predictions for the suppliers' future prices in order to enable the purchasing department to decide in advance what proportion of the procurement budget should be spent to each supplier. The MPT algorithm is solved using convex optimization [12] because it is a complex problem with bounds, constraints and a Lagrange multiplier.

Do: In this phase, we used a tool for monitoring and updating the input parameters of the joint decision model (e.g. actual costs) by using a Sensor- Enabled Feedback mechanism (SEF) [13] for both the maintenance and supplier selection components.

5 Application in Industrial Environment

We validated our proposed framework by deploying the aforementioned system in a manufacturing company in the area of automotive lighting equipment production. However, due to the lack of prices-related data and historical portfolios, we also used simulation based on prior expert knowledge. The manufacturing process deals with the production of the headlamps' components. Until now, the company conducted time-based maintenance by cleaning the moulding machine from dust and replacing the moulds once per month. Its aim is to turn into CBM by adapting at the same time its spare parts ordering policy according to the 'just-in-time' concept and by deciding proactively about the portfolio of its suppliers. After implementing the aforementioned system, the manufacturing company started a negotiation process with its 4 suppliers. This information along with suppliers-related data (inventory level, scheduled production plan, capacity, etc.) is continuously updated in ERP through EDI. At some time, an abnormal equipment behavior was identified and the implemented system followed the process described in Table 1.

Table 1. Inputs and outputs of each 4D phase for the current scenario

4D model		Maintenance	Supplier Selection
Detect	**Input**	Dust levels, environmental sensors (temperature, humidity)	Negotiation process start, 4 suppliers, bid prices, suppliers-related data, economic environment (e.g. taxes)
	Output	Complex pattern about an abnormal equipment behavior	Complex pattern about a possible future price change
Derive	**Input**	Complex pattern about an abnormal equipment behavior	Complex pattern about a possible future price change
	Output	Exponential PDF of cover lens scrap rate exceeding 25% with $\lambda = 1$ / time-to-failure (12 days)	Prices prediction until the next planned maintenance (Fig. 2)
Decide	**Input**	Exponential PDF of scrap rate exceeding 25% with $\lambda = 1 / 12$	Prices prediction till next planned maintenance, Recommended time for ordering
	Output	Recommendation to conduct maintenance in 3.5 days and to order the associated spare parts, i.e. moulds, in 1.3 days (Fig. 4)	'Markowitz bullet' and its 'efficient frontier' (through the simulation of mean returns and volatility for 100 portfolios) (Fig. 3), The optimal portfolio of suppliers (Table 2)
Do	**Input**	Recommended times for maintenance and ordering	The optimal portfolio of suppliers
	Output	Cost monitoring and update	Cost monitoring and update

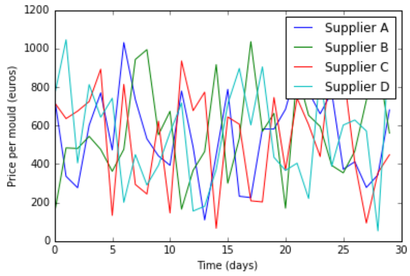

Fig. 2. The prices prediction in the course of time until the decision horizon.

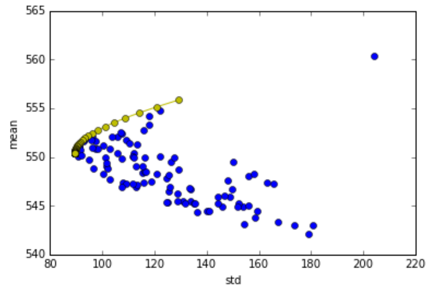

Fig. 3. The Markowitz bullet and its Efficient Frontier for the portfolios.

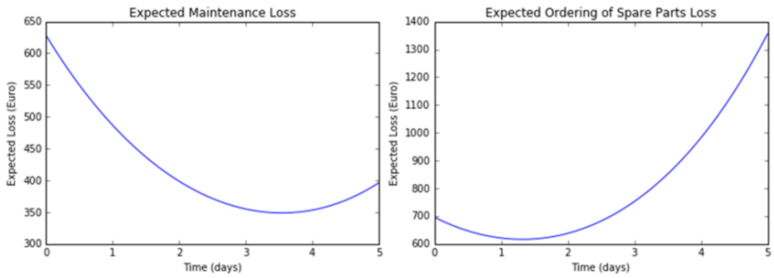

Fig. 4. The expected maintenance and ordering of spare parts loss functions.

Table 2. The optimal portfolio of suppliers.

Supplier A	Supplier B	Supplier C	Supplier D
0.14	0.38	0.26	0.22

6 Comparative and Sensitivity Analysis

We compared our approach with two scenarios under several executions: a reactive scenario, having no prediction (with corrective actions and emergency spare parts ordering when the failure occurs) and one where there is a prediction algorithm but not automated decision making. In the first case, corrective maintenance actions last more than predictive ones due to the lack of root causes knowledge, while emergency, unplanned ordering of spare parts requires a longer lead time and leads to a penalty cost due to unplanned distribution. In the second case, due to the failure prediction, either corrective actions are implemented when the failure actually occurs (with the previously referred costs and lead time), or immediate preventive actions are applied, according to a cost-benefit analysis. These results are shown in Table 3.

Table 3. Results of comparative and sensitivity analysis.

Approach	Maintenance Cost	Inventory Cost	Supplies Cost	Total Cost
No prediction	1,466 ± 58	1,013 ± 27	1,195 ± 34	3,674 ± 119
Only prediction	1,355 ± 112	905 ± 89	1,069 ± 121	3,329 ± 322
Proposed Approach	823 ± 46	708 ± 38	802 ± 44	2,333 ± 128

7 Conclusions and Future Work

We presented a framework for real-time, event-driven proactive supplier selection driven by CBM. An information system was developed and validated in industrial environment in the area of automotive lighting equipment. The evaluation results showed that our approach reduces the costs related to maintenance, inventory and supply of spare parts by enabling the transformation of the company's maintenance and purchasing strategy from reactive to proactive. Regarding our future work, we aim to develop more advanced visualization techniques and to add a context-awareness mechanism integrated with the whole 4D cycle.

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