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Using immune designed ontologies to monitor disruptions in manufacturing systems

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ABSTRACT

Manufacturing systems are subject to several kinds of disruptions and risks, which may break the continuity of workflows, disturb pre-set organization, and prevent the production system from reaching its expected levels of performance. Several approaches were proposed to deal with manufacturing system disruptions and risks. Unfortunately, most of them focus more on explaining the causes of the disruption/risk, rather than on determining disruption/risk effects on workflows, pre-set organization and expected performance. Existing approaches usually operate off-line, thus missing current and accurate data about plant activities and changing conditions. Most of them do not offer concepts that allow the design of computerized tools dedicated to disruption/risk monitoring and control. In this paper, we rely on biological immunity to guide the design of a knowledge-based approach, and to use it to monitor disruptions and risks in manufacturing systems. The suggested approach involves functions specifically dedicated to deal with a variety of disruptions and risks, such as detection, identification of consequences and reaction to disruptions. This architecture is intended to be embedded within industrial information and decision support systems, such as ERP (« Enterprise Resource Planning ») and MES (« Manufacturing Execution System »). A prototype implementation using ontologies and multi-agent systems shows the relevance of the suggested approach in monitoring disruptions and risks. A simplified example from the steel industry illustrates the kind of support that can be provided to decision makers.

1. Introduction

Production systems are subject to several kinds of disruptions, which are undesirable events that usually occur in an unexpected manner (e.g. machine failures, product or process related quality problems, inventory shortages, etc.). Such events lead to detrimental consequences, including direct impacts and probable downstream effects, usually called production system risks. Disruptions and risks may break the continuity of workflows, disturb pre-set organization, and prevent the production system from reaching its expected levels of performance. Thus, detecting disruptions on-line, and identifying their risky consequences timely are important tasks that enable advised decision-making and reaction.

A lot of research has been conducted to deal with disruptions and risks in industrial and manufacturing organizations [1–3]. Unfortunately, many of the suggested approaches usually consider disruptions and risks according to separate business process viewpoints and interests (e.g. production, quality or maintenance), using specific tools and in isolation, i.e. through separate functional teams. Such approaches, like Reliability-Centered Maintenance [4], Condition-Based Maintenance [5] or else Statistical Process Control [6], focus more on predicting a disruption or a risk and on interpreting its symptoms or explaining its causes, rather than on determining disruption/risk effects on interrelated workflows and business processes, pre-set organization and expected performance. Hadidi et al. [7] highlight the importance and necessity to design multidisciplinary, integrated and interoperable approaches to handle disruptions and risks in production organizations in a more comprehensive way. Pandey et al. [8] highlight the importance and necessity to design approaches that analyze the impacts of a disruption/risk on interrelated business processes and workflows, and that enable an advised decision-making process, i.e. one that

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considers such impacts in a comprehensive way when establishing reaction decisions. Churliov et al. [9] emphasize "*the progress toward an integrated risk-aware approach for process management is still in its infancy*".

Interdependency, interrelation and interaction between production, maintenance and quality policies has resulted in a considerable amount of interest in developing combined models that take into consideration all or more than one of these three aspects to improve the overall system performance and responsiveness to disruptions and risks [7,8]. For example, some authors looked for joint inventory control (buffer sizing) and maintenance schemes to overcome shortages and prevent production interruption due to unexpected machine breakdowns [10–13]. Some other authors integrated preventive maintenance concerns in scheduling schemes, such as [14] and Kuo and Chang [15], who proposed models for scheduling jobs with machine unavailability due to maintenance operations. Pahl et al. [16] and Karmakar and Choudhuri [17] are among researchers who proposed joint optimal inventory and quality control policies. Other researchers focused on joint product quality, process quality and equipment maintenance policies [18]. Integrated production, maintenance and quality models were also studied [8,19,20].

Unfortunately, existing combined/integrated approaches rely on a preventive and off-line philosophy that seeks to anticipate disruptions and risks by finding decisions that prevent or at least reduce the probability of their occurrence and the extent of their impact. Such approaches usually rely on static mathematical models that either optimize structural components of a production system (e.g. production buffers to alleviate part of a disruption/risk), or establish robust schedules that represent acceptable trade-offs between several business process interests. Musulin et al. [21] highlight the need for dynamic, reactive and on-line approaches that meet current and accurate data about plant activities and changing conditions and that enable decision making in a timely manner in order to handle disruptions and risks. To bridge this gap, several monitoring and control approaches, based on multi-agent [22–24], holonic [25,26] and bionic [27] paradigms were suggested. Recent trends in monitoring and control are mainly directed toward designing and developing model driven and knowledge based approaches [28], evolvable and self-organized approaches [26], as well as autonomic manufacturing execution systems [29]. Fernandez et al. [28] provide a classification and an analysis of monitoring approaches based on three criteria, namely their prediction ability (reactive/predictive), the sources of observed events (orders/resources), and the generality of approaches considering their ability to use different monitoring models that belong to different application domains. Although existing approaches offer promising directions to monitor and control manufacturing systems based on a reactive philosophy, more investigation effort is still needed to design and develop interoperable, interactive and integrated tools that are able to deal with disruptions and risks in a more generic way [29]. Marhavilas et al. [2] compared 18 qualitative, quantitative, and hybrid risk analysis and assessment techniques. They found that only five techniques offer the possibility of incorporation in databases, and only six techniques offer the possibility of incorporation in computer automated toolkits. Consequently, there is still a need for approaches that offer concepts and mechanisms that facilitate the design of computerized toolkits able to be integrated within enterprise data management systems.

Recently, biological immunity inspired the design of a promising integrated and generic framework to manage disruptions and risks in manufacturing systems [30–33]. However, these works focused on designing the general conceptual framework [31–33] and suggesting methodological guidelines [30] to apply immune concepts and mechanisms to solve manufacturing problems. They did not focus on showing the detailed design of immune based ontologies, demonstrating their usage to achieve functions specifically dedicated to deal with a variety of disruptions and risks (such as detecting disturbances, identifying risks and suggesting control decisions), and discussing their integration and compliance with existing industrial information systems and business process legacy software. In this paper, we provide the detailed design of an immune based ontology and show how to use it as a tool to detect disruptions, identify risky consequences and suggest reaction decisions in manufacturing systems. We show that the suggested tool is an on-line and dynamic tool that contributes to design integrated and reactive knowledge based approaches for disruption and risk management. Therefore, the paper is structured as follows: Section 2 overviews the main features and principles of the biological immune system and surveys existing artificial immune system applications that are closely related to the topic. Section 3 discusses the reasons that motivate the use of ontologies as a tool to handle disruptions and risks. Section 4 introduces our case study. Section 5 details the design of the suggested immune based ontology and Section 6 shows how to use it as a tool to detect disruptions, identify risky consequences and suggest reaction decisions in manufacturing systems. Section 7 provides a discussion of the main advantages and limitations of the suggested approach. Section 8 concludes the paper and opens several future research directions.

2. Biological and artificial immunity

Biological immunity is an integrated system that relies on a reduced but powerful set of concepts and mechanisms that are very effective and efficient in protecting host organisms against a wide variety of disease causing elements. In the following subsections, we first introduce the main biological immune system (BIS) concepts and mechanisms. Then, we overview adaptations of biological immunity, called artificial immune systems (AIS), to address manufacturing system related applications.

2.1. Overview of biological immunity

In the biological world, *pathogens* are disease-causing elements that proliferate within a body and attack its cells and tissues by spreading their toxic substances. Among these substances, *antigens* are molecules that are present at the surface of a pathogen and that represent its specific characterizing features. To defend its host organism, the BIS relies on many types of immune cells – including *Antigen Presenting Cells* (APC), *Natural Killer (NK) cells*, *B cells*, *T cells* – to fight and eliminate those pathogens and antigens [34,35].

Immune cells have surface receptors that are able to discriminate what belongs to the body, also called *Self*, from what is foreign to the body, also called *Non-Self*. *Self* corresponds to a set of features that are present at the surface of body cells and that characterize the membership of each cell to the body. *Non-Self* corresponds to any set of features that are different from *Self* and that are present at the surface of pathogens. Therefore, any single feature in the set of *Non-Self* is an *antigen*. This *Self/Non-Self discrimination principle* enables the BIS to detect the presence of pathogens in the body. The receptors at the surface of immune cells exclusively detect Non-Self patterns. In real world applications, this principle inspired the design and development of *positive detection algorithms* applied to detect machine and process anomalies, including errors, faults and failures (cf. Section 2.2.1.1).

To learn how to discriminate *Self* from *Non-Self*, the BIS relies on the *negative selection principle*. During their early life, newly created immune cells are confronted to elements of *Self*. Any immune cell that matches (attaches to) *Self* is eliminated. Only those immune cells that do not match *Self* are kept. In real world