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The Adapter module: A building block for Self-Learning Production Systems

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ABSTRACT

The manufacturing companies of today have changed radically over the course of the last 20 years and this trend certainly will continue. The increasing demand and the intense competition in market sharing are radically changing the way production systems are designed and products are manufactured pushing, in this way, the emergence of new manufacturing technologies and/or paradigms. This scenario encourages manufacturing companies to invest in new and more integrated monitoring and control solutions in order to optimize more and more their production processes to enable a faster fault detection, reducing down-times during production while improving system performances and throughput along time. In accordance with these needs, the research done under the scope of Self-Learning Production Systems (SLPS) tries to enhance the control together with other manufacturing activities (e.g. energy saving, maintenance, lifecycle optimization, etc.). The key assumption is that the integration of context awareness and data mining techniques with traditional monitoring and control solutions will reduce maintenance problems, production line downtimes and manufacturing operational costs while guaranteeing a more efficient management of the manufacturing resources.

1. Introduction

As in other domains, production market has deeply felt the effects of globalization on all its different layers [1,2]. The increasing demand for new, high quality and highly customized products at low cost and with minimum time-to-market delay is radically changing the way production systems are designed and deployed. This trend implies a change in production strategies in order to achieve the so-called Manufacture-to-Order paradigm [3]. To do that, production companies are demanding for more and more innovative production systems that are able to produce as many product variations as quickly as possible with reduced costs and high quality.

As stated in [4], most manufacturing companies operate in an extremely dynamic environment characterized by unpredictable real-time events inside and outside the company such as market variations and changes in demand, machine failures, and due date changes. The new manufacturing systems are requested to be capable to adapt to meet rapidly changing requirements in an efficient and effective way. To achieve this goal, modern production companies need to take into account not only production control and execution processes but also associated secondary processes in a fully integrated approach. As discussed in [5], secondary processes, such as maintenance, energy saving, lifecycle optimization of manufacturing process parameters and/or allocation of manufacturing resources, have always been very important for industrial production systems. However, they are typically detached from the core monitoring and control system, implying poor machine performance and higher lifecycle production costs. An integrated approach merging the main production processes with the named secondary processes will enhance the efficiency of production as well as of maintenance and optimization tasks during production systems lifecycle [6]. Therefore, a rational way to attain this goal is to embed self-learning skills into monitoring and control solutions for manufacturing production systems improving system capabilities in terms of reconfiguration, monitoring of equipment performance degradation, optimization of control parameters and operation management, sustainability, etc. In this scenario, a Self-Learning Production Systems (SLPS) will be able to both control the production process and constantly monitor all the processes related to it, extracting the particular system context and adapting all the production parameters such as machine configurations, and production strategies if a context change is perceived.

This paper presents the research and developments related to the Adapter proposed architecture in the scope of the integration of SLPSs supported by the use of Service-Oriented Architecture (SOA)

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principles and technology. Pushing SOA into production control and monitoring levels is becoming increasingly appealing since it leads to the usage of a service-based communications infrastructure to build an unified solution transparently compliant along enterprise ICT levels [7,8]. The Adapter is the component responsible for starting an Adaptation Process whenever a change in the actual production system context is perceived. The use of machine learning techniques along production system lifecycle ensures that the Adapter naturally calculates the adaptation that best fits the current context based on context data. The reminder of this paper is organized as follows: Section 2 presents these and other adjacent concepts that are used as the foundation of current proposed solution; Section 3 presents the SLPS architecture followed by this work; Section 4 focuses on the Self-Learning Adapter (commonly referred simply as the Adapter) generic architecture, on its new Proactive behavior component and on the aspects related with the Adaptation Process; Section 5 presents an application used for testing and validating the proposed architecture; finally, Section 6 presents the main conclusions and possible future work.

2. Supporting concepts

2.1. Context awareness

Context awareness is widely applied in modern ICT solutions for developing pervasive computing applications that are characterized by flexibility, adaptability and are capable of acting autonomously [9]. A context-aware system/application is capable to extract, interpret and use context information to adapt its functionalities and behavior to cope with the current context [10]. The development of such kind of systems/applications is inherently complex and extremely dependent on the information extracted. As a matter of fact, context information is typically gathered from a variety of sources that differ in quality of information they produce and are usually failure prone [11]. According to [9], the complexity of engineering context-aware systems/applications can be reduced by using infrastructure capable of gathering, managing and provisioning context information to the applications that require it. To do this an appropriate infrastructure is needed to provide support for most of the tasks involved in dealing with contexts. Moreover such infrastructure requires a well-defined context model to represent, manipulate and access context information [12]. Different approaches to context modeling has been developed using the most disparate technologies such as Markup Scheme Models that rely on the use of the Extensible Markup Language (XML) or Graphical Models that made extensive use of Unified Modeling Language (UML) and Object-Role Modeling (ORM). A comprehensive overview on the context modeling approaches can be found in [13]. Despite the distinct modeling techniques, the ontology based context modeling is the most investigated one. Ontology provides a formal, explicit and shared conceptualization of a domain that can be communicated between people and remote heterogeneous computing systems [14]. Hence, ontologies can be used to create a formal description of a certain domain (i.e. manufacturing production system) [15]. The ontological description can be then processed by reasoning mechanisms in order to deduce and infer new knowledge from the extracted raw information. The exploitation of reasoning mechanisms, relying on inherent features of the ontological model, allows the verification of the extracted information and eventually solve the inconsistencies that could appear due to imperfect input [16].

In the context of this paper, ontologies are used in order to build a reliable and easy-to-share description of the particular manufacturing environment. This description will be then explored to adapt the behavior of the production system.

2.2. Data mining in manufacturing

Modern manufacturing enterprises are characterized by a deep dissemination of databases aiming to guarantee that all the information produced during the production activities is stored and available inside the enterprise. However, although a huge amount of data is typically collected by several systems, at the moment there is no efficient and productive method for data processing [17]. Therefore, information storing is sterile if not supported by tools and techniques allowing to extract knowledge from data. As Harding told in his work [18]: "the advancements in information technology (IT), data acquisition systems, and storage technology as well as the development in machine learning tools, algorithms and methodologies have solicited the research community to move toward discovering knowledge from databases (KDD)". The process of extracting knowledge from large quantities of data is also known as *data mining* [19,20]. The discovered knowledge can be used for classification tasks, modeling tasks, and to make prediction about future evolution of the analyzed variables. The application of data mining techniques to manufacturing began in the 1990s [21–23]. Data mining can be applied at different areas in manufacturing such as quality control, fault detection, scheduling and decision support. However, there are areas where these techniques are not exhaustively explored such as manufacturing shop floor monitoring and control. To enhance the usage of data mining in industrial context the development of a standard methodology for industrial applications of data mining is necessary for allowing reliability and repeatability of data mining processes. The Cross Industry Standard Process for Data Mining (CRISP-DM) project [24] is an effort in this direction.

Despite the existence of standard processes for data mining and valid solutions for manufacturing [25–27], most of the applications for industry are stand-alone, one-of-a-kind and not fully integrated applications inside enterprise reference architectures. The huge amount of data stored in databases during production operations represents a great source of potentially new information. This information needs to be explored to enhance fundamental manufacturing activities such as lifecycle optimization of process parameters. The literature review shows several applications in this direction confirming from one side an exponential growth of data mining application but from the other side the lack of a generic holistic approach and design methodology as well as a reference architecture.

2.2.1. Integrated data mining

Manufacturing enterprises can benefits from the application of data mining techniques to solve problems and/or to analyze and forecast relevant variables of a production system. The output of a data mining process can be easily used during the strategic planning of manufacturing resources. However, nowadays there is an important need to apply more and more data mining techniques for diagnosing and solving online manufacturing problems [28]. To do that, integrated data mining architecture and approaches can be used to allow the utilization of the huge amount of manufacturing data obtained from the process. The design and implementation of methodologies and concepts that integrate data mining techniques provides a mechanism to ensure production system evolvability along time, in the sense that the outcome of such solutions can be used to deliver additional productivity gains to a manufacturing process extending the reach of the traditional automation system beyond the world of process control.

2.3. Scheduling in flexible manufacturing systems

A Flexible Manufacturing System (FMS) is constituted by several manufacturing high-specialized machines together with