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A virtual factory approach for in-situ simulation to support production and maintenance planning

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Structured methodologies and tools for the tailored design of factories are more and more adopted by suppliers of manufacturing systems but usually discontinued after the design phase. The use of an ontology-based virtual factory, continuously synchronised with the real plant, is proposed to guarantee digital continuity and enable in-situ simulation during the operating phase of a factory. This digital counterpart of the system can be used for integrated shop-floor simulations to assess future impact of production and maintenance planning decisions. An industrial application is provided in the context of roll shops, i.e., systems devoted to the grinding of cylinders for rolling mills.

1. Introduction

The design of a manufacturing system is a complex engineering problem requiring the joint use of multiple structured methodologies and tools [1]. These tools, exploited during the design phase [2], are typically discontinued as soon as the installation of the manufacturing system enters the operation phase. However, their residual value could be high if they were integrated in a Virtual Factory environment to support:

- the performance evaluation of a factory starting from a specific state to compare different management decisions [3].
- possible reconfigurations of the system [4]. This scenario is becoming more and more relevant given the short product lifecycles and, thus, the need of adapting an existing manufacturing system to the production of new part types.
- the ramp-up phase of production systems, often due to the fact that system integrators usually evaluate the performance of a factory design grounding on incomplete models and data (maintenance policies, failures modes and operating conditions are typically not available at the design phase).

The focus of this paper is on the first item in the list, proposing the application of an ontology-based virtual factory approach to evaluate the impact of planning and maintenance decisions during the operation phase of a manufacturing system. This goal can be achieved via in-situ simulation by exploiting and adapting the set of tools available at the design phase. However, these tools require a digital model of the factory continuously synchronised with the real one. This demands the integration of various monitoring and planning tools modelling and storing the evolution of the system and its current status. The availability of these data in a shared format and location enables the initialization of in-situ simulation tools to rapidly assess the impact of decisions to be taken in a short-term horizon.

The implementation of in-situ simulation entails a wide range of scientific problems to be tackled. Firstly, a smooth model initialization is poorly supported in almost all of the commercial discrete simulation software tools. A second one is the integration of multiple and heterogeneous sets of data and tools into a unique and coherent scheme. Nevertheless, overcoming these technical limitations opens the way to significant benefits from the industrial point of view. In fact, the availability of rich data sets and the use of engineering tools in the every-day life of a production system is neither frequent nor smooth. These tools could clearly provide a much more structured approach to take decisions in a complex environment and, consequently, a potential improvement of the factory performance.

Section 2 gives a review of virtual factory approaches and their role in coupling digital and real factories for production and maintenance management. Section 3 outlines the proposed methodology, specifically the representation of production system history and how multiple histories from different sources can be merged achieving digital continuity. Section 4 provides the framework scheme for digital continuity and in-situ simulation applied to a reference case. Section 5 describes the implementation in a real industrial environment and Section 6 provides a summary and outlook for further developments.

2. Literature Review

The main benefits coming from Virtual Manufacturing and Virtual Factory consist in a multi-layered integration of the information related to: (1) various activities along the factory and product lifecycle; (2) hardware, software, and human resources; (3) real world and virtual world [5]. Through this effort, modelling and simulation approaches can be extensively used to support and speed-up the decision process, not only in the design stage but also for management decisions [3]. In particular, the close relationship between production and maintenance planning often requires these sets of decisions to be jointly taken. More generally, the need to consider production, maintenance and the quality from an overall point of view has been highlighted in [6].

This class of integrated approaches is typically limited by the lack of updated information on the status of the system and could benefit from the availability of a virtual factory model to support them. However, the continuous upgrade, update and maintenance of Virtual Factory models and tools along the factory lifecycle has to face practical problems that hinder the usage of approaches typical of the design phase also during the operations of a factory. Indeed, simulation tools are usually developed and used by experienced operators (mainly machine tool builders and system integrators, given their specific expertise and frequency of needing to solve this type of problem) and rarely transferred to the customer (i.e. the owner of a factory). In addition, these models are usually not updated, thus failing to guarantee the digital continuity. Nevertheless, the realization of a full-scale Virtual Factory is still far from being reached both on academic and commercial sides. Enabling technologies are being investigated by academics to fulfil the concepts sketched by the early literature works, while large ICT market players propose software suites that still lack full integration and/or are not affordable for a large share of industrial companies.

The exploitation of a digital model of a factory, coupled with a continuous synchronisation of the information coming from the real system, has been previously addressed in [7]. The authors proposed the use of a simulation model that can be initialized to match the real state of the manufacturing system under study. The authors identified the following problems to be tackled: (i) the acquisition and validation of the input data, (ii) the responsiveness of the analysis and (iii) the capability of creating a snapshot of the real system to initialize the simulation model. In particular, the first and third points highlight a data synchronisation and consistency problem between the real and the virtual environment.

Indeed, the generation and management of digital factory data is a key problem of Virtual Factory approaches. Several authors addressed the need of relying on data schemas in compliance with existing standards like STEP [8]. The Core Manufacturing Simulation Data (CMSD) initiative [9] proposed by NIST is one of the efforts towards integrating the real data coming from the shop-floor with simulation tools. Recently, the attention has been also focused on the use of ontologies to meet the goals of modelling, meta-modelling and interoperability [10] between the digital tools in the Virtual Factory context to guarantee a proper digital continuity [11][12]. The key advantages of an ontology-based approach include (i) the exploitation of semantic web technologies in terms of interoperability, data distribution, extensibility of the data model, querying, and reasoning; (ii) the re-use of general purpose software implementations for data storage, consistency checking and knowledge inference.

The typical obstacles in the implementation of digital continuity are highlighted in [7]: (i) the matching of the data structures of ERP and MES databases with the data needed for the analysis, (ii) the difficulty of coping with an enormous amount of data coming from the real plant to get aggregate values suitable for the analysis. These key problems can be addressed by adopting an ontology-based approach [12] to support the factory design phase. Herein, this approach is further developed by extending the ontological data model to represent the continuous evolution of factory objects during the operation phase of a plant. The need of acting at different levels of detail is also considered and managed through a multi-scale representation of the data.

3. Modelling the history of factory objects

A unifying modelling of the evolution of the objects in a factory (i.e. products, processes and production resources) has to cope with a wide range of heterogeneous data and levels of detail. These streams of data (*histories*) come from different sources, e.g., monitoring systems (i.e. a *real* history), production-planning methods (i.e. a *planned* history), performance evaluation tools (i.e. a *simulated* history). Data relate to both physical characteristics (e.g. the placement of an object) and abstract properties (e.g. state transitions) and the *dynamic* evolution of the factory objects must be coherent with their *static* representation. To meet these requirements, an OWL (Web Ontology Language) ontology data model [13], based on the standard Industry Foundation Classes (IFC), has been extended with additional classes, as sketched in Figure 1, where the novel classes have a grey background.

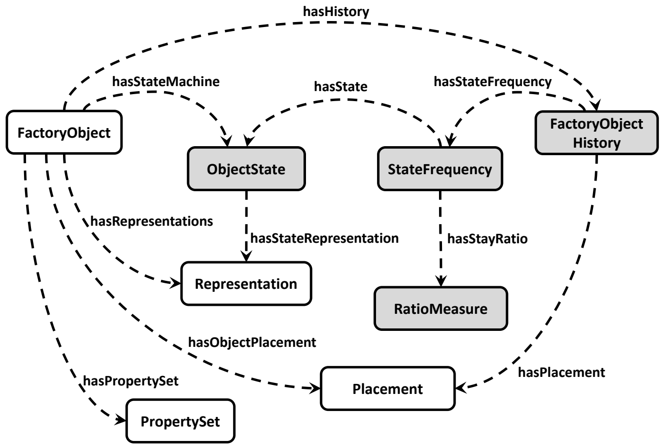

Figure 1. Simplified fragment of the ontology-based data model. Boxes represent OWL classes, whereas arcs represent property restrictions (*universal quantification*).

The generic factory object (*FactoryObject* class) is characterized by its placement, geometrical representation and property sets, but also by its *finite state machine.* Each state (*ObjectState* class) composing the finite state machine can be associated with a specific representation of the object. According to the different specialization of the *FactoryObject* (e.g. machine tools, transporters, workpieces, etc.), specific subclasses of the *ObjectState* class are provided. For instance, a machine tool will be linked to instances belonging to classes representing the *idle*, *working* and *failed* states.

A *FactoryObject* can be linked to as many as necessary instances of *FactoryObjectHistory* to describe its history. A piece of history can be decomposed both time-wise (i.e. defining sub-intervals) and hierarchically (i.e. decomposed into the history of its object components). The first option entails the capability of formalizing detailed and specific history data coming from a real monitoring system, while the second allows to model the history of an object aggregating the histories of its components (e.g., a workstation is failed if some of its components are failed).

A *FactoryObjectHistory* is characterized by the start and end time of the corresponding time interval. However, a detailed record of the evolution of factory objects along the time is not always available. Data coming from performance evaluation approaches (e.g., mathematical methods) typically provide a performance measure only in terms of aggregate indicators (e.g. mean and variance). To manage these heterogeneous cases, since the factory object behaviour can be described by a set of possible states, the class *StateFrequency* was introduced to define the fraction of the time interval spent in a specific state together with other statistics. This modelling pattern applies to both aggregate intervals (where more than one state may have a frequency greater than zero) and detailed intervals (where only one state has a frequency equal to 100% in the considered time span). Finally, the history of a product can be associated with a placement in the space, to represent movements and trajectories with the desired level of detail. The placement can also be defined in relation to another object (e.g., a workpiece on an AGV transporter), linking histories of different objects and providing a concise representation for the routing.

Also the class *FactoryObjectHistory* can be specialized according to the characteristics of the corresponding factory object, e.g., a history interval of a buffer is characterized by the buffer level and/or by a descriptive statistics representing the observations of the buffer level during that time interval. Figure 1 shows the links between object state and object history to unify data coming from different sources and related to different time spans in a single representation of the production system evolution.

4. Digital continuity and in-situ simulation

The history model of factory objects can be exploited to guarantee the digital continuity between the real factory and its virtual model. Historical data can be collected and stored in a distributed way, while keeping an overall coherence thanks to the virtual factory model. This entails the modelling of the evolution of a system in time by joining together portions of the history generated by different sources, e.g. the monitoring of the physical system, a planned set of events (e.g., a production plan) or forecasts of external factors (see Figure 2).

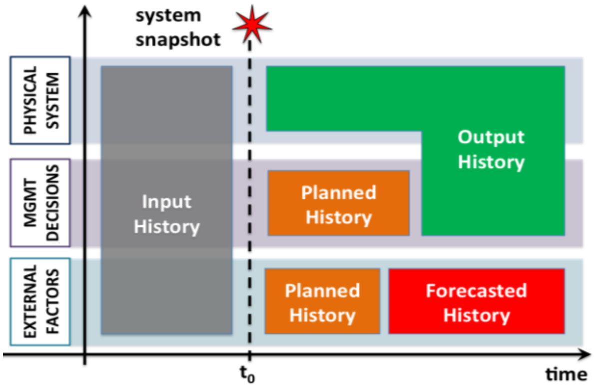

Figure 2. Framework for digital continuity and in-situ simulation.

This schema paves the way to in-situ simulation approaches, through the seamless integration of simulation tools and the real environment. As shown in Figure 2, a snapshot of the current state of the system (condensed in a *input history*), together with a set of *planned* and *forecasted histories*, can be used to feed a simulation model and get a simulated history of the evolution of the system (*output history*). This approach provides the capability of a fast assessment of the impact of decisions grounding on the current state of the whole factory and is specifically relevant for short-term management decisions, e.g., production planning and maintenance planning.

Depending on the envisioned application, different data sources must be elaborated and aggregated in the shared semantic repository. A highly detailed history is necessary for all the physical factory objects if the goal is to run a virtual reality animation of the factory. On the contrary, only the most recent history of the system is necessary if the goal is to warm-start a Discrete Event Simulation (DES). Herein, the latter scenario is considered, aiming at demonstrating the use of this approach to support production and maintenance planning in a flow line with five process steps processing a single part type (see Figure 3). The first and last stations are manual, whereas the other ones are automatic. The third station consists of two parallel machines. The flow line is balanced and the automatic stations are characterized also by their failure modes. Inter-operational buffers separate the stations.

A Virtual Factory model is implemented for the considered flow line together with a configurable DES model. Since the connection with a real plant is not available in this case, the data generated by a previous simulation are used to mimic the behaviour of the real plant. The input history of the system consists in the snapshot of the objects in it (i.e. position of the parts in-progress; status of the automatic stations) and event-related information about the recent past (i.e. time when the parts in-progress entered the buffer/workstation where they are placed). The goal of in-situ simulation is assessing the impact of management decisions, specifically different maintenance and loading policies, on the short-term performance of the production line. The automatic stations must undergo a preventive maintenance whose duration is three hours. Four different schedules are considered for the maintenance operations (1, 2, 3, 4) and two policies (A, B) defining the workload balancing for the two parallel machines in the third station of the line. External factors are taken into consideration in terms of parts arriving from the previous manufacturing stage.

Figure 3. 3D virtual reality representation of the test case.

The combined maintenance and loading policies were simulated using 40 replicates, 24-hour long, initializing the simulation model with two different input histories (*h1*, *h2*) representing different states in the system in terms of number of in-process parts, their location in the system, and state of the machines. Arena by Rockwell Automation was used but, since it does not provide a built-in warm-start function, the initialization of the model was done through a specific software connector presented in [13]. The response of the experiments is the throughput (TH) of the flow line measured in parts per day.

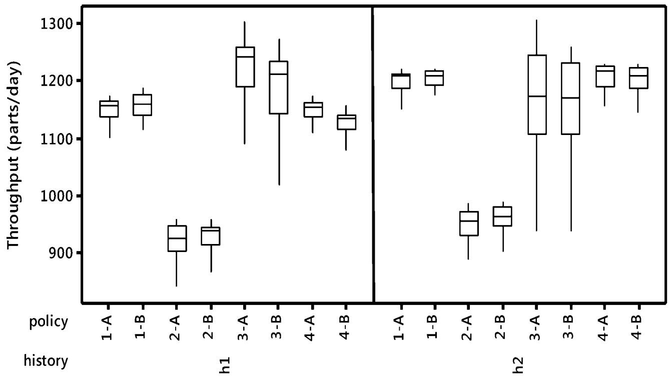

Figure 4. Boxplot of the throughput of the flow line.

Figure 4 shows the boxplot of TH. Starting from status *h1*, the highest average TH is given by the combined policy *3-A* (i.e. maintenance policy 3, loading policy A), whose TH is 32% higher than the policy with the lowest average TH (i.e. policy *2-A)*. However, it can be noticed that the policy *3-A* has a higher variance compared to other ones (e.g. policy *1-B)* and the best solution should be chosen taking in consideration a trade-off between the average TH and its variance. The maintenance policy influences TH more than the loading policy since it is not possible to implement very different policies in a flow line with only one parallel station. Starting from *h2* a rank reversal of the policies takes place: policies *1-B* and *4-A* show the highest average TH with a low variance as well. Policy *3-A*, performing well with input history *h1*, is even worse than policies *1-A* and *4-B*.

Hence, the initial status of the system can significantly impact on the performance of a management policy and the proposed in-situ simulation approach can support the selection of proper management decisions accordingly.

Finally, in-situ simulation entails a paradigm change since the traditional *warm-up* identification and elimination phase is replaced by the *warm-start* initialization of the model. Short simulation runs are executed to assess the impact of a decision in the short term and statistical relevance is achieved through multiple replicates. Referring to the previous experiments, each simulation run took less than five seconds, thus confirming the viability of the in-situ simulation approach as a support for taking management decisions.

5. Application case: roll shop

The application case relates to the production and maintenance planning of a *roll shop,* devoted to the grinding of cylinders for rolling mills. Exhausted cylinders, whose surface has been damaged during the rolling process, are changed frequently (from two hours up to 30 minutes). Cylinders are cooled (only for hot rolling process) and the bearings could be taken apart before the grinding. Different machines are used for the different class of cylinders (working, intermediate and backup rolls) according to their dimensions. Grinding machines for backup rolls have a higher power and can also process other types of cylinders after a setup. Cylinders, weighing from 10 to 100 tons, are moved using overhead and semi-gantry cranes that are significantly stressed and require frequent inspection and preventive maintenance (wire rope inspection and substitution, hook inspection, etc.), keeping the crane inactive for about a week. Hence, maintenance and production must be carefully planned, taking into consideration the stock of processed cylinders, the status of the system and the replacement schedule of the rolling mill.

Figure 5. A 3D virtual reality representation of the roll shop.

A Virtual Factory approach was implemented to support the integrated design of a roll shop defining the layout in a virtual reality environment (Figure 5) and evaluating its performance through a customizable DES model. In relation to Figure 2, the physical system is the roll shop whose simulation model is initialized with data automatically acquired from the shared data repository. Management decisions address the workload assignment to the machines, while external factors are the schedule of the replacement of cylinders in the mill. A static schedule is adopted, even if a different simulator could be used to model the rolling mill, jointly running multiple interacting simulation models [14]. In the specific case, the roll shop serves two rolling mills: a *tandem mill* and a *steckel mill*. The adoption of a maintenance policy (M_1), operating opportunistic maintenance in relation to the replacement schedule of the mill, is analysed against the one currently used (M_0). Also a loading policy (S_1), tuning the priority rules and the setup plan of the machines according to the scheduled stops of the mill, was considered against the old one (S_0). The combinations (M_0, S_0) and (M_1, S_1) were evaluated through the in-situ simulation approach taking as starting point the status of machines and transporters, the position of cylinders and cranes, the scheduled setup of the machines. The analysis was useful to suggest the adoption of the policy (M_1, S_1), guaranteeing service levels comparable with the others but a lower average flow time of the cylinders (-1.5% for tandem, -3.1% for steckel rolls) as shown in Table 1, providing an earlier availability in case of unexpected replacement (damaged cylinders, opportunistic replacement, etc.).

Table 1
Results for the roll shop application case.

Policy	(M_0, S_0)		(M_1, S_1)	
BUR Roll Type	**Tandem**	**Steckel**	**Tandem**	**Steckel**
N. in the system	16	8	16	8
Avg Flow Time [h]	919.38	1280.27	905.40	1240.74
Min Flow Time [h]	458.12	1141.86	502.04	1144.67
Max Flow Time [h]	1202.97	1450.21	1209.43	1342.33

6. Conclusions

An ontology-based virtual factory model, synchronised with the real plant, was considered to enable in-situ simulation in support of maintenance and production planning and tested in two application cases. Further developments will address the lack of built-in warm-start functionality in commercial DES software packages, the difficulty in modelling and simulating real management policies and exploiting the approach to also tackle other decisions related to the ramp-up phase, e.g. aiming at prioritizing a set of possible actions, or to the reconfiguration phase, e.g. scheduling the list of reconfigurations,

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