A Digital Twin Modular Framework for Reconfigurable Manufacturing Systems

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Abstract. The emergence of Industry 4.0 and its related technologies transformed modern manufacturing environment by making them more intelligent. This is associated with the fast evolution of data acquisition technologies and the enormous amount of generated data. Among these modern manufacturing environment, Reconfigurable Manufacturing System (RMS) is a concept able to cope with the current market conditions, characterized by an increasingly personalized and volatile demand. At the same time, Digital Twin (DT) emerged as a new concept. DT represents a new data-driven vision that combines real time data analytics, optimization and simulation. When managing modern and complex manufacturing systems, DT provides new insights and potentials in decision-making process support. In this context, this paper is an attempt to present an integrated RMS digital twin (RMS-DT) modular framework. RMS-DT is a model that can represent the system state at any moment in time while allowing a holistic system visibility to improve its performances and enable flexible decision-making. The paper is concluded with a discussion, future challenges and perspectives in order to enhance the proposed RMS digital twin framework.

Keywords: Digital Twin · Reconfigurable Manufacturing System · Modular Framework · RMS digital twin

1 Introduction

The current markets are characterized by an increasingly personalized and volatile demand. As a result, companies are seeking for responsiveness and customization. Thus, many research attempt to provide new solutions in order to achieve the aforementioned challenges. In this regard, Reconfigurable Manufacturing System (RMS) is considered as one of the most suitable solution. Such system was proposed by Koren *et al.* [13]. The differences of this system from all other concepts of manufacturing systems are presented in [6]. RMS is characterized by reconfigurability *i.e.* the ability to quickly change and reorient components (hardware and/or software) easily to adjust production (in terms of functionality and capacity) in response to abrupt changes. This is possible thanks to reconfigurable machine tools (RMT) that are a major components of RMS. Such machines have a modular structure allowing to be reconfigured in order to fulfill different functionalities and capacities.

RMS is a part of the industry 4.0 [3]. The latter is driven by the rapid evolution of information, data acquisition and communication technologies, which are the main foundation of the so-called smart factory. This is achievable due to digitalization, where all components of an industry are linked and can communicate in real time. In this context, Digital Twin (DT) appeared as a concept that benefits from these technologies to achieve intelligent manufacturing [22]. Indeed, it provides a high-fidelity virtual representation of a physical system. DT comprises two main parts (physical and virtual) with real data transmission between them. DT will process, analyze and evaluate the enormous amount of collected data (Real-time/offline), allowing a better system transparency. As a result, a wide range of information can be collected and used for many applications, such as tracking the state of the system, making predictions, diagnosis, simulation and optimization of the system (e.g. planning, scheduling, configuration/reconfiguration selection, etc.).

In a reconfigurable environment, where unpredictable changes in demand and flexibility are challenging, a DT may prove to be very useful in a decision-making process at all levels. In fact, designing and selecting an RMS configuration is shown to be complex [14], since the number of configurations grow significantly with the number of RMTs. Thus, a DT can help to achieve a flexible decision-making process (*e.g.* choosing an appropriate configuration based on real time, predicted and historical data). The DT applications are various and have proven to be very useful in a manufacturing context. However, few research works consider both RMS and DT [22]. Moreover, to the best of our knowledge, the software reconfiguration part of the RMS reconfigurability characteristic is rarely treated by researchers. In this regard, this paper is an attempt to present a generic and modular framework that integrates both RMS and DT concepts. This latter includes the software reconfiguration part through a "plug & play" type of software as module components. Furthermore, the idea is to shed light on the considerable gap in this matter and rise attentions to the importance of research around it.

2 Related works

RMS literature covers various areas like system design, process planning, scheduling and reconfigurable control as demonstrated by several state of the arts reviews in recent years [2–4]. Moreover, Industry 4.0 covers a lot of new emerging concepts and technologies [16]. However, this section will only focus on a small portion of these fields that includes respectively: RMS design, digitalization (digital twin) and how it is integrated in RMS.

One of the major issues found through the RMS literature is RMS design. The objective is to use their core characteristic (i.e. reconfigurability) to design responsive systems. RMS design problems are more complex, this is due to the fact that these systems are characterized by dynamic capacities to change and to integrate change. Besides, RMS properties, including reconfigurability, emerge after the deployment of the manufacturing system [1, 9]. RMS focuses on scalability and responsiveness, supported by adding or removing functionalities. This allows these systems to be easily scalable to maintain the life cycle of the manufacturing system itself. Thus, to meet these requirements with these properties, reconfigurability must be incorporated into system design from the outset in order to have the best responsiveness when facing changes [14]. Hence, all system components as well as its different levels must be considered and prepared for change. This kind of perspective of the system (on the production and on the design problem) is favored by reconfigurability [8].

Reconfigurability represents a non-functional requirement of the system, linked to its long-term behavior [1]. This implies that classical approaches, which consider only the immediate requirements of the system will not necessarily lead to dynamically changeable systems. Besides, instead of achieving the objectives of reconfigurability, they cause the designed system to quickly become obsolete when facing market variations. Furthermore, for a system to be easily reconfigurable, certain characteristics must be fulfilled such as modularity, integrability, convertibility, diagnosability, customization and scalability [7, 13], as well as automatibility [19, 20]. Based on the previous statements, we see that there is a need to adapt existing approaches and/or develop new design methodologies to design systems with dynamic capacity for change by including the essential parameters of reconfigurability. These methodologies must consider reconfigurability as a dynamic property of the manufacturing system. Thus, a key characteristic towards industry 4.0 is the development of changeable and reconfigurable manufacturing systems.

Industry 4.0 affects the different performance dimensions of a production system, thus it must be considered as factor when designing RMS. The latter needs to be responsive to adapt quickly to changing conditions. This becomes possible in the context of industry 4.0 thanks to digital twin emergence [10]. [21] stressed that the realisation of industry 4.0 is hindered by the lack of powerful tools especially formal methods and systems methods. Authors continue to show the unpreparedness to support digital transformation by current infrastructures and the need of new ones. To tackle that, they argued that there is a need to develop digital twin with added-value decision-making services. The concept of DT has been expanded from product to manufacturing system [5, 17, 18]. In this context, [22] conducted a systematic study on the related research and application of DT. Authors underlined that most DT research lacks referable application cases and are considered in theoretical stage. They also argued that there is a lack of clearness of the proposed application methods and application framework. Based on that, authors proposed an application framework of DT for product lifecycle management. In a reconfigurable environment, [15] proposed a rapid reconfiguration of automated manufacturing system using a novel digital twin-driven approach. The authors attempted to find an optimal reconfiguration solution through a bi-level programming model of upper-level productivity rebalancing and lower-level reconfiguration cost.

RMS reconfiguration complexity increases remarkably when considering both machine-level and system-level (in both hardware and software) [12]. Thus, the number of configurations grow significantly with the number of RMTs. This makes the process of designing then selecting a RMS configuration very complex [14]. Developing comprehensive approaches seems to be very difficult due to the huge variety of possible manufacturing tasks. As a result, integrating digital twin within RMS could be more efficient. This is due to the fact that DT can be oriented to focus on specific problems like diagnosability, predictive maintenance, training, reconfiguration selection or scheduling, etc. Moreover, DT can optimize all activities within the system due to its comprehensive and real-time control of information flow. However, to the best of our knowledge, research work are focusing more on specific parts of DT applications and little research work considered the benefits of a global framework integrating digital twin within RMS while considering its core characteristics as well as software reconfiguration. In this context, our paper presents a first attempt to fill this gap. The goal is to profit from the digital twin concept and propose a modular framework that can be used to ensure an easy reconfiguration of the software part of the RMS by adding new software blocks (e.g. simulation, control...) as needed when needed in "plug & play" manner, which will eventually help in a better selection and gives a better insight and a flexible decision-making process (e.g. hardware reconfiguration).

3 RMS-DT modular framework

In this section, we present the proposed RMS-DT modular framework for a digital twin within RMS (Fig. 1), explain its various blocks/modules as well as the information flow. The proposed framework, which focuses on the virtual space, is based on broad interpretation of the DT concept. Thus, we did not focus on all the possible technologies related to/can be used within industry 4.0. DT core components are physical space, virtual space, and the data/information flow between them. Nevertheless, this paper focuses only on the virtual space. Our RMS-DT framework is modular and describes the process of the virtual modeling and the construction idea for application subsystems of DT. It is introduced to solve amongst other, complex reconfiguration problems. As the number of machine (RMTs) increases, RMS configurations number increases faster than a natural exponential function [14]. In this regard, RMS-DT represent an attempt to tackle the complexity of reconfiguration problems in a reconfigurable environment.

Using the RMS-DT framework, this problem can be solved following two step process. The first step considers executing reconfiguration experiments on high-fidelity virtual space of the RMS-DT. Moreover, the Real-time data flow between the two spaces (physical and virtual) is seamless. This creates and favors high-fidelity conditions that helps to explore all the possible reconfigurations, optimize, simulate and evaluate them on the virtual space. In a second step, the

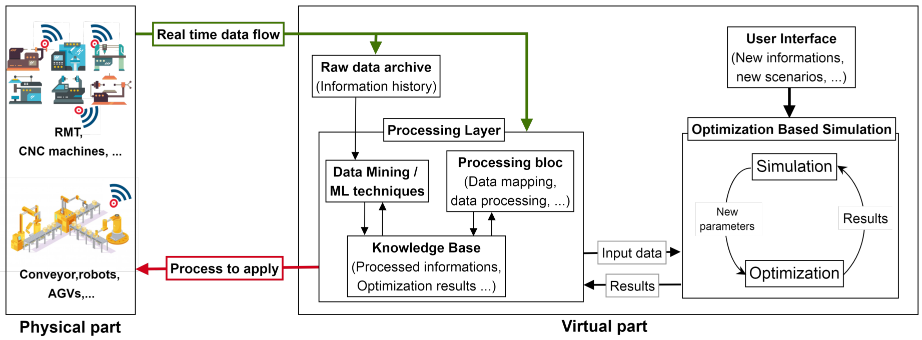

Fig. 1. RMS-DT framework

feedback from the virtual space (e.g. optimized production, best reconfiguration, maintenance...) can be used to apply efficiently on the physical space.

The objective of the RMS-DT modular structure is to ensure an easy reconfiguration of the software (adding, modifying and/or removing blocks/modules) in a "plug & play" manner. This makes the framework extensible and adaptable to different needs by integrating new technologies or adapting/developing new behaviours/tasks. For example the "Optimization based simulation" module can be replaced by a solver intended for other tasks like finding the best maintenance strategy instead of finding "the best reconfiguration".

To ensure high-fidelity conditions for solving the problem, the data collected from the physical part —using data acquisition technologies like sensors for example— is transmitted in real-time to the virtual part (green arrow in Fig.1). Data is collected from different sources (manufacturing systems, machines, AGVs, PLCs,etc). The real-time raw information collected will then be redirected to two modules (i) *"Raw data archive"* and (ii) *"Processing layer"*.

The **"Raw data archive"** module will simply store the data as it is collected from the physical space. This raw data archive can be used later as historical data, which can be an input for the *"Data Mining/Machine Learning (ML) techniques"* module that will be detailed hereafter.

The **"Processing layer"** module connects information flow between physical space and virtual space through information mapping, processing and storing. The data interaction within this module allows the interoperation of both spaces(physical and virtual). This module comprises three main function modules that are respectively:

– **The "Processing bloc" module**: This module is responsible for processing, mapping and analysing real-time data from the physical space. First, the raw data is processed through cleaning (*e.g.* rule based), structuring and clustering. The clean data is mapped to match and extract the needs of the decision-maker patterns,decision variables, and information. The resulted

data is then analyzed and compared with data stored in the *"Knowledge base"* module. After the comparison we are left with two scenarios:
   1. The processed information does not exist in the knowledge base. In this case, the data is stored in the Knowledge base and then redirected to the *"Optimization based simulation"* module to find a new solution corresponding to the new data.
   2. The knowledge base already has this data. In this case, the corresponding solution to apply is fetched and redirected to the physical space.
- **The "Knowledge base" module**: Stores data from both spaces (physical and virtual). All data stored is considered as processed data. That means the data is coming from the *"processing bloc"* module or it represent new data from the *"Data mining/Machine Learning (ML)"*. The physical space data comprises (but not limited to) equipment data (capacity, functionality, reconfigurations, tools, ...), workshop environment data,production data, etc. For virtual space data we can find (also not limited to) decision data, simulation/optimization evaluation results, and prediction data and new inferred models or patterns, etc.
- **The "Data Mining/Machine Learning (ML)" module**: Its role is to infer/find new patterns and correlations between various collected information collected/stored within both the *"Knowledge base"* module and the *"Raw data archive"* module

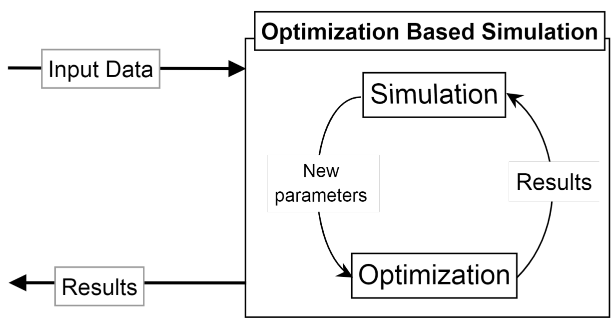

Fig. 2. Optimization based Simulation module

Once the real-time data flow treated by the *"processing layer* and redirected to the **"Optimization based simulation"** module (Fig.2), the latter will try to find the best solution. This Module follow a looped two step process. First, the optimization of an objective function subject to constraints —as defined by the decision-maker or a team of experts— is conducted. Then, a stochastic simulation is used to evaluate the optimization results as well as the objective(s) function(s) and its respective constraints. The process is then repeated until fulfilling a stop criteria (e.g. a time limit, stable solutions,...).

The *"Optimization based simulation"* module can also be used directly in asynchronous mode to the physical space through the **"User interface"**. This latter offer to the user (e.g. decision-maker) the possibility to test and evaluate new scenarios or introduce new parameters of the production process/system. The goal is to get insights about them and to predict, control, and optimize the system in exploitation in its environment.

4 Conclusion and perspectives

In this paper, a framework, which describes the use of the digital twin (DT) in an RMS is provided. The framework shows how a DT can be used to achieve the needed RMS flexibility and responsiveness during its operating phase by providing a flexible decision-making process. This is done by continuously collecting real time data from the RMS components. Subsequently, these are stored, processed and analyzed by using information analytic, simulation and optimization module blocs. Based on this, DT can quickly provide critical decisions such as the appropriate RMS configuration to efficiently cope with sudden changes. Due to space limitations, we do not provide in details how the data are collected and exchanged between the RMS and the DT. Instead, we only focus on the virtual part.

For future research perspectives, a comprehensive framework, which includes not only the virtual part, but also a detailed descriptions of the physical part and the connection protocols between them will be provided. More, we are looking forward to develop an online optimization based simulation approach for RMS configuration selection based on what have been done in [11]. This will constitute a first step towards achieving the proposed framework. Accordingly, a DT can be used in an RMS context to achieve diagnosability, which is a core characteristic of such systems and is defined as the ability of an RMS to be easily diagnosed. To the best of our knowledge, few papers study this feature. Since DT offers system transparency and real time feedback, this can be used to detect and prevent root causes of machine and system failures. Finally, an interesting work direction is to study how other RMS characteristics can be integrated using this RMS-DT as well as its general use towards Industry 4.0.

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