Global Resources Management

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Contributor: Leonilde R. Varela , Justyna Trojanowska , Maria Manuela Cruz-Cunha , Miguel Ângelo Pereira , Goran D. Putnik , José M. Machado

Global resources management intersects with collaboration and Industry 4.0 paradigms, namely for collaboratively managing cyber-physical systems. Only organizations that cooperate with their business partners, along with their suppliers and remaining stakeholders, including their clients, will be able to permit and promote the much-needed endowing of agility, effectiveness, and efficiency in their management processes. For that, suitable decision-making paradigms, along with underlying approaches, will be needed, in order to properly fulfil current companies' decision requirements and practices.

global resources management dynamic distributed integrated intelligent predictive parallel real time

1. Introduction

Global resources management (GRM) requires the application of management processes and approaches of a more or less widened set of companies and stakeholders that interact for solving some shared problem, usually intending to reach some common goal, besides their own objectives and priorities.

Collaborative networks (CN), and global or group decision-making approaches (GDMA) are fundamental for enabling and promoting the interaction and sharing of knowledge among two or more collaborating entities [1][2][3][4][5]. Moreover, independently of sharing or not having the same goal, and/or resources, usually, interplaying entities do fall into some kind of business environment, for instance in the context of distributed or extended manufacturing systems (EMS) or agile/virtual enterprises (A/VE) [6][7][8].

In the current complex and turbulent manufacturing environments [9], such as EMS or A/VE, it is fundamental to make use of CN and GDMA, in order to fulfil the requisites imposed by Industry 4.0 (I4.0) [10], and to solve the shared management problems, for instance, related to manufacturing planning and scheduling, occurring either in more traditional or in EMS or A/VE manufacturing environments or in cyber-physical production systems (CP[P]S) [11][12][13][14], thus, usually requiring some combination of management paradigms and approaches (P&A) for solving complex and distributed manufacturing scheduling (DMS) problems.

A DMS problem [7][15], is one typical example of the need for using CN and GDMA for solving the scheduling problem among a set of participating companies, which may or may not further share manufacturing resources and be geographically dispersed, tending to be quite complex combinatorial optimization problems [5][15].

The use of GDMA is fundamental to enable the resolution of DMS problems, among others, occurring in the scope of GRM, based on a proper approaches, methods, and techniques, along with the use of appropriate communication networks among the set of interacting entities or companies.

Besides distributed scheduling, other important issues do occur in the scope of GRM, namely related to dynamically changing production conditions and customers' order requisites, in real-time, along with the need for integrating varying kind of other management issues, besides scheduling ones, related, for instance, to maintenance management, among others, that do also influence the whole global management process and increase its complexity [16][17].

Thus, it turns out to be imperative to make use of appropriate decision support (DS) approaches and tools, which, enable dynamic and agile DS, namely through the use of multicriteria decision making (MCDM) methods and models [15], along with intelligent and/or predictive DS algorithms and systems [18][19], besides other approaches and technologies, for instance to permit parallel programming [20]. This last one can further benefit from different kind of I4.0 technology, namely from the use of high-performance computing (HPC) [20].

Thus, this entry intends to contribute to the synthesis of the main research and findings about GRM-P&A, during the last decade, by highlighting the importance of supporting I4.0 technology, and to enable answering the following research question: "What are the main decision support paradigms and approaches underlying global resources management in the current digitalization era to promote collaboration among entities or companies?".

Moreover, both GRM-P&A and I4.0 together, can be seen as collaborative decision-making processes and practices that are currently fundamental to enable and promote decision-making in and between companies and their stakeholders, namely in the context of CPPS, and to permit to reach the endowing of agility, effectiveness, and efficiency of their management processes.

The synthesis and detailed analysis performed in this entry through the application of a systematic literature review (SLR) enabled us to identify a varying set of GRM-P&A that enable supporting companies to properly address their daily management decision-making processes.

Moreover, it was possible to identify a set of main GRM paradigms that were encompassed in a proposed collaborative management (CM) framework, in the I4.0 context. The proposed framework is, thus, intended to enable solving more or less complex GRM problems, namely in EME or A/VE, or in the context of cyber-physical production systems (CPPS) [10][17], which play a very important role nowadays in the I4.0 era. This proposed framework integrates dynamic, distributed, integrated, intelligent, predictive, parallel, and real-time-based approaches, for fulfilling the requirements underlying the resolution of the GRM problems that may occur nowadays in different kind of manufacturing environments.

These manufacturing environments may vary from more classical or centralized manufacturing environments up to fully distributed and decentralized ones. Moreover, the proposed CM framework is a novel contribution, as, as to the knowledge, there is not yet any such kind of contribution available in the literature. Thus, some more specific ones are made, regarding the resolution of some kind of problem occurring in a more or less concrete manufacturing environment or application scenario are usually being explored, and/or based on a reduced combination of management paradigms and underlying approaches. Instead, by considering the proposed CM framework, different kind of management P&A can be combined, along with varying types of underlying methods/algorithms, and corresponding problem-solving tools or platforms, for solving a GRM problem. Therefore, different combinations of appropriate methods and techniques, varying from applying pure mathematical optimization methods to the use of diverse types of metaheuristics, among other AI approaches, e.g., machine learning or multi-agent systems (MAS), just to mention a few, may be applied for solving the GRM problems, among others [5][7][18][19][21].

This entry is organized as follows.GRM-P&A, along with some applications from the literature, is summarized. The SLR methodology used is summarily described. The main literature review results reached are presented and analyzed, based on the main decision-making paradigms identified. These are further correlated, based on the information made available through the main set of papers that were deeply analyzed, and that make use of two or more GRM paradigms identified through the SLR carried out. The proposed CM framework is presented and summarily discussed in order to highlight its importance in the I4.0 context.

2. Global Resources Management in the Industry 4.0

The I4.0 concept is based on digital transformation in traditional production and management methods with the introduction of information technology; it is, according to the definition of Deloitte in 2014 [22], composed of four fundamental characteristics, namely vertical and horizontal integration, end-to-end technology, and orchestration of the value chain by people, which assumes a central role and importance currently [23][24], namely for enabling collaboration.

The systems that exist in a factory environment can be integrated at five levels. The integration of operational data with business data can be aligned using the ANSI, ISA-95 ISO, and IEC-62246 standards “Enterprise-Control System Integration” (ISA-95) [25]. This standard establishes the terminological and functional basis, good practices, workflows, data flows, and alignment between business systems, e.g., ERP, and operational control systems, e.g., MES, SCADA (and IoT and CPS middleware) [25][26][27].

Global value chain networks are optimized networks that provide real-time information about geographically dispersed factories, facilitating global management and optimization through extended and globally distributed resource markets [28][29]. This exchange of information and resources increases transparency between factories and business partners, and promotes a high level of integration, interoperability, flexibility, distributivity, agility, virtuality, and agility to respond quickly to varying kinds of requests about specific issues, problems, or failures [28][30][31].

The shared information ranges from inbound logistics to storage, production, marketing, sales, and outbound logistics and businesses. In this sense, the history of each product or raw material is recorded and can be accessed through the factory system, and the state of the situation can be shared with other factories, ensuring constant traceability (a concept known as “product memory”) [32].

It is in the layer of actuators and sensors that a large part of the factory information, namely from the factory floor, is located. This very low-level information is then used by other systems (as suggested in ANSI/ISA-95) [25][33].

In this sense, the use of protocols adopted worldwide, such as MQTT, CoAP (constrained application protocol), AMQP (advanced message queuing protocol), HTTP/2 (updated version of hypertext transfer protocol), IPv6 (Internet protocol version 6), or 6LoWPAN (IPv6 over low-power wireless personal area networks) is an accepted and appropriate practice for implementing I4.0 technology [24][34][35][36].

Despite being a relatively recent concept, efforts to standardize it have already been made in the current digitalization era, which allowed for the emergence of a reference architecture. This architecture was presented by the Industrial Internet Consortium (IIC), and it is called the industrial Internet reference architecture (IIC, 2017) [26][35][37]. Present in this architecture are concepts related to an industrial Internet environment and its interconnections from four perspectives, namely business, use, functionality, and implementation [26][35].

The industrial Internet reference architecture (IIRA) integrates a security policy for manufacturing infrastructures, hardware, software, and communication across the four perspectives presented in [26][35]. Another equivalent initiative is called the reference architecture model Industry 4.0 (RAMI4.0), referenced in [24]. This architecture defines hierarchies for the development of a unified model of all components of the I4.0 concept present in the value chain. These hierarchies refer to the business, functional, information, communication, integration, and asset layers [24].

In this work the main focus consists on studying the state of the art research about GRM, and its relation with collaboration theory and practice, in the current I4.0, along with the analysis of expected benefits that can arise from the combined application of management paradigms, along with different types of solving approaches, methods, and algorithms, varying from more or less pure mathematical or optimization methods up to diverse kind of methods, such as those based on AI, for solving management problems in different production environments. These manufacturing environments can vary from more classical ones up to more recent cyber-physical and/or extended, complex, and agile or virtual manufacturing environments.

To this end, some relevant and more or less recent GRM paradigms and underlying approaches and systems from the literature are now briefly referred to, in order to better contextualize the work carried out in the scope of the I4.0 context and associated collaborative processes and practices, which is intended to be a novel contribution, as no similar work was identified through the literature analysis performed.

In the I4.0 context, one typical example of GRM is distributed manufacturing scheduling (DMS), which is characterized by a set of tasks that have to be chained in order to obtain a coordinated workflow among the dispersed manufacturing resources. This chaining process results in a more or less complex production program through the allocation and sequencing of the tasks on the corresponding production resources, which has to satisfy a set of constraints related either to the production resources itself and/or to the tasks, in order to reach some simple or combined or complex goal.

Currently, due to the globalization, DMS plays a crucial role, and diverse approaches have been proposed to accomplish it; a very popular one is based on a multi-agent systems (MAS), through the use of appropriate architectures and protocols [38].

One such contribution concerning DMS is mentioned in [15], which is considered to be necessary in the current global production environments. Another example is presented in [15] about an approach for dynamic DMS, supported by a dynamic multicriteria decision model (DMCDM), and by further integrating strategies that enable trade-offs between diverse kind of performance measures. Moreover, there are many different kind of approaches, algorithms, tools, or systems and platforms to support GRM or, more precisely, global manufacturing scheduling, that can be further implemented. These vary from purely centralized up to fully decentralized architectures, for instance for further integrating other management functions, besides manufacturing scheduling, such as process planning, batching, system balancing, and layout definitions, namely referred to in the following sources [7][12][39][40].

In [41] a simulation model is proposed that implements a dynamic scheduling scheme to generate training scheduling examples, considered by the authors to be good schedules. Their search training was performed by using a proposed genetic algorithm, along with a tolerance-based learning algorithm requiring the acquisition of general scheduling rules from the scheduling training examples, and further adapting to new perceived examples, enabling knowledge modification. According to the authors, their experimental results showed that the dynamic scheme meaningfully outperformed a static one when integrating a simple dispatching rule for performing the distributed scheduling.

In [42] an agent-based approach is proposed for distributed manufacturing programming, which enables companies to solve a global combinatorial optimization schedule, by integrating a jobs process plan in a distributed production environment. Their approach was adapted from a particle swarm optimization (PSO) algorithm, through which the agents move towards a schedule to find a best global makespan.

Saeidlou et al. in 2019 [43] propose a cooperative system to perform distributed manufacturing scheduling, based on a set of rules considered to be most relevant, which are integrated through their proposed cooperative system, through an agent-based decision support system that, according to the authors, enables them to find near-optimal solutions within a reasonable computational time.

Zhang et al. in 2019 [44] put forward an optimization algorithm centered on a discrete fruit fly optimization algorithm (DFOA), integrating an evolutionary optimization model for costs minimization, namely energy consumption, for scheduling jobs in a distributed manufacturing system that comprises multiple factories, each one integrating a flow shop with blocking constraints. According to the authors, their proposed approach outperforms some well-known precision and convergence algorithms.

Wang, Ghenniwa, and Shen in 2008 [45] present a real-time distributed shop floor scheduling approach, based on an agent-based service-oriented architecture, through which the shop floor is modelled as a group of flexible manufacturing systems in the form of multiple work cells. In this proposal, the authors perform the distributed scheduling process through a local dynamic scheduling approach, by the interaction of a scheduling agent, a real-time control agent, and resource agents, based on web services, for a proper integration.

Mishra et al. in 2016 [46] describe a cloud-based multi-agent architecture for distributed manufacturing units' operational planning and scheduling. Their proposed system is self-reactive, integrated, dynamic, and autonomous, in order to assist manufacturing industry in establishing real-time information sharing among autonomous agents, clients, suppliers, and the manufacturing units, which is illustrated through a case study.

In [47] an integrated brainstorm optimization algorithm is put forward by the authors for distributed production, through the use of a stochastic multi-objective model. The distributed manufacturing environment consists of a set of independent flow shops with different quantities of machines. They conclude that their proposed approach can achieve satisfactory performance when compared with two other multi-objective algorithms from the literature, based on the experimental results obtained.

Mao, Li, Guo, and Wu in 2020 [48] researched cooperative planning and symmetric scheduling on parallel shipbuilding projects in the context of an open distributed manufacturing environment. To this end, the authors propose an assistant decision-making approach to support task dispatching and multi party collaboration in order to achieve better-distributed resource utilization, further helping project managers in controlling the shipbuilding practice, based on negotiation through an iterative combination auction (ICA) method for solving integrated project planning and scheduling. The authors present a demonstrative example to show the efficacy and reasonableness of their proposed approach.

Lou, Ong, and Nee in 2010 [6] put forward a distributed programming method supported by multi-agents for assigning tasks to machines, for being applied through a dynamic formation of virtual job-shops to satisfy manufacturing requisites, further based on market mechanisms, as well as a distributed scheduling approach based on negotiation among participating entities.

Cheng, Bi, Tao, and Ji in 2020 [49] propose what they call a hyper network-based manufacturing service for distributed scheduling and cooperative production in smart systems, through the use of cloud services, along with real-time data, as collaborative services. Their proposed approach is further based on graph coloring and an artificial bee colony algorithm for solving the scheduling problem. The authors state that three sets of tests were performed and discussed in terms of three scenarios of distributed cooperative manufacturing processes, through a private, public, and hybrid cloud-based model.

In the concrete context of CPS, some further interesting contributions did arise. In Kim et al. in 2013 [50] a parallel programming approach is applied for analyzing a self-driving car case study.

In 2019, Nouiri, Trentesaux, and Bekrar put forward an integrated energy efficient programming approach for production systems based on a collaboration process between cyber-physical and energy systems.

Putnik and Ferreira in 2019 [10] proposed an Industry 4.0 meta-model, which enables businesses to integrate models and tools in cyber-physical manufacturing systems.

Tan et al. in 2019 [51] presented an integrated approach to model, plan, and schedule operations on a shopfloor assembly system characterized by dynamic cyber-physical cooperation, which was analyzed through a smart industrial robot production case study.

Another interesting contribution is referred to in [52] about a decision-making model for supporting dynamic programming in cyber-physical production systems by using digital twins technology.

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