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Review

Global Resources Management: A Systematic Review and Framework Proposal for Collaborative Management of CPPS

Leonilde R. Varela [1,2,*], Justyna Trojanowska [3], Maria Manuela Cruz-Cunha [4], Miguel Ângelo Pereira [1], Goran D. Putnik [1] and José M. Machado [5,6]

1 Department of Production and Systems, School of Engineering, University of Minho, 4804-533 Guimarães, Portugal
2 ALGORITMI Research Centre/LASI, University of Minho, 4804-533 Guimarães, Portugal
3 Department of Production Engineering, Faculty of Mechanical Engineering, Poznan University of Technology, 60-965 Poznań, Poland
4 School of Technology, Polytechnic Institute of Cávado and Ave, 4750-810 Barcelos, Portugal
5 Department of Mechanical Engineering, School of Engineering, University of Minho, 4804-533 Guimarães, Portugal
6 Metrics Research Centre, University of Minho, 4804-533 Guimarães, Portugal
* Correspondence: leonilde@dps.uminho.pt

Abstract: Nowadays, 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. The main purpose of this paper is to show that this can be achieved by applying combined global resources management paradigms and approaches, to reach collaboration further supported by recent technology made available through Industry 4.0. In doing so, the interaction of companies and stakeholders, supported by appropriate networks, along with varying kind of other communication and problem-solving technology, will enable them to promote and reinforce interoperation to reach the best-suited management decisions, by considering each ones' objectives and priorities, along with common goals. To this end, in this paper, a systematic literature review methodology is used to synthetize the main contributions about the relation of these domains. The study carried out and the results obtained permitted us to realize that dynamic, integrated, distributed, parallel, intelligent, predictive, and real-time-based decision paradigms are of the upmost importance currently, but are still just scarcely being combined, which is suggested though its encompassing through a proposed collaborative management framework that is recommended to be applied, either in industry or academia, to improve global resources management processes and practices.

Keywords: global resources management; dynamic; distributed integrated; intelligent; predictive; parallel; real-time; collaborative management; Industry 4.0; cyber-physical production systems

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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 [1–5]. 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) [6–8].

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) [11–14], 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 paper 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 paper 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 our 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 our 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 paper is organized as follows. In Section 2, GRM-P&A, along with some applications from the literature, is summarized. The SLR methodology used is summarily described in Section 3. In Section 4, 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. In Section 5, the proposed CM framework is presented and summarily discussed in order to highlight its importance in the I4.0 context. Section 6 briefly presents the conclusions and some insights about future work.

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) [25–27].

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 [24,34–36].

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.

3. Research Methodology

In this work was performed a literature review that aims to analyze the literature about GRM-P&A, and its contextualization in the I4.0 context, along with its relation with collaborative decision-making processes and practices, between industrial companies and their main stakeholders, that may include not just varying set of business partners, but further be extensible to suppliers and clients, interconnected through CN, in a more traditional context, or extended and distributed through A/VE or in CPPS. This study was carried out by using a SLR, thus, following a methodical behavior [53], for properly identifying this field's conceptual and practical content, and for contributing to the focused theory development [54].

The SLR methodology applied in this work includes five stages to enable it to properly explore the joint analysis of the main contributions about GRM-P&A in the I4.0 context, and its relation to collaboration processes and practices, as is now exposed.

Stage 1—research scope identification.

The research scope was identified through the definition of an intended main research question for identifying the following: "What are the main paradigms and approaches underlying GRM, in the I4.0, to enable collaborative processes and practices among companies and associated stakeholders?"

Stage 2—topics' definition.

In order to properly reach relevant contributions to be further analyzed, the main topics that were defined are grouped in three main sets of key words to further direct the search process, as shown in Table 1.

The first group (G1) is related with collaborative processes and practices, because collaboration, along with more or less closely related terms, consists of the main keywords to be explored through the study conducted in the context of global resources management. The second group (G2) is related to GRM paradigms and approaches and, thus, a list of main terms that are being explored regarding management in the current digitalization era were included in this group. Finally, the third group (G3) is related to Industry 4.0 itself, by including some similar terms and expressions related to the underlying CPPS.

Table 1. Main groups of key words used in the search process.

GK1	GK2	GK3
Global	Dynamic	Industry 4.0
Collaborative	Decentralized	Industrie 4.0
Cooperative	Distributed	I4.0
Concurrent	Integrated	Digitalization
Networked	Artificial	Cyber-physical System
B2B	Smart	Manufacturing
P2P	Intelligent	Production
End-to-end	Predictive	Process
Point-to-point	Real-time	Business
Group	Parallel	Resource
Shared	Learning	Machine
Joint	Management	Operator
Open	Planning	User
Cloud	Programming	Human
Innovative	Scheduling	

Stage 3—literature search.

The search was carried out in a reference database called "b-on" (www.b-on.pt, accessed on 12 September 2022), which is a large database that consists of a collection of several important databases, available for a large number of diverse Portuguese and international research and technological institutions that allows access to the main international scientific bibliographic resources. The literature search process was, thus, carried out based on a search string that was formed by using the 'and' logical operator for linking the three groups of key words and the 'or' operator to process the key words in each group. Only recent publications, between 2011 and 2021, were considered, and a total set of 1276 were reached.

This set of publications were next subject to an exclusion process, by using refined criteria, in order not to include publications that were not written in English language, as well as the ones that were not peer reviewed, and those that did not have full text available. Moreover, the publications that did not arise from international scientific conferences or journals, and from well-known editors, e.g., Springer, Elsevier, Taylor & Francis, John Wiley and Sons, Kluwer Academic Publisher, IEEE, or MDPI, were also excluded, resulting in a total of 715 publications to be subsequently analyzed.

Next, as the inclusion criteria definition, attention was given to publications really falling in the scope of the focused domain, about the industrial context, specifically manufacturing and/or management domains, by further screening the publications' abstracts and keywords, as well as their titles, along with the source of the publication, in order to consider only the publications that exactly fit the purpose of this study, and were relevant ones. As such, it was necessary that the publication had a focus, at least to some minimal extent, on some more or less closely related aspect regarding the collaboration paradigm, along with a focus on some issues related to GRM in manufacturing context, and underlying scientific domains, besides its relation or contextualization in the I4.0 era. After this analysis a subset of 168 publications were considered for further analysis.

Stage 4—publications analysis, synthesis, and further discussion.

The set of most relevant publications reached in Stage 3 was further analyzed to retrieve general meta-data about the main key words underlying the corresponding contributions, regarding GRM-P&A, collaboration, and I4.0 aspects, to synthetize the main information about the evolution of these joint subjects during the last decade.

Next, a new analysis over this set or papers was carried out, in order to reach the topmost relevant publications in the focused domain, that did in fact use terms related to GRM paradigms and approaches, along with collaboration and I4.0 issues, in the body of the paper, besides its reference in the title, abstract and/or key words or by just sporadically mentioning terms in the text, without any further analysis. This refined analysis led to a subset of 49 publications that were further explored, being subject to a deeper analysis. This set of topmost relevant and closely related publications were, thus, referenced and analyzed in Sections 4 and 5, to uncover results and realizations about the current status of the studied scientific domain, and to further identify research gaps for suggested future developments.

Stage 5—synthesis of future working plans and research questions.

Besides the central research question about using GRM in the Industry 4.0 era to enable collaboration, other additional sub-questions that further arose were as follows:

- What does GRM bring that is new, and what doors does it open in the I4.0 era?
- Does I4.0 promote or improve GRM, along with collaborative processes and practices?

This study has a broad spectrum, which does limit the possibility of the current work to properly detail all the issues underlying both sub-questions mentioned above, an to address issues about all relations between GRM and the I4.0 context, which aim to further reach or accomplish collaboration through additional development. The broad spectrum makes a deep analysis and study of the interactions of these domains—for instance, in the focused engineering and collaboration context—difficult, and this is required in order to further enhance the industrial understandings on the importance today of the underlying communication and interaction needed to properly accomplish collaborative manufacturing management processes and practices. More specifically, this is important in the general management sense, and more concretely regarding the underlying planning and scheduling scope is essential.

Figure 1 synthesizes the main five aspects underlying the SLR performed in this study to further clarify the used methodology.

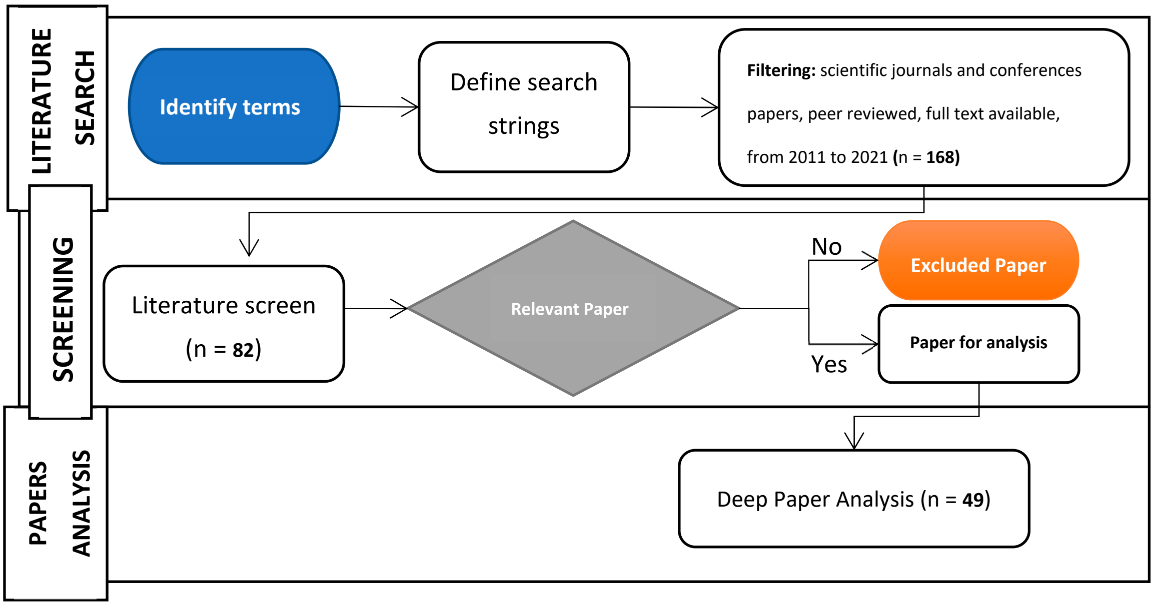

Figure 1. Applied SLR methodology.

Several contributions have already been put forward, for instance, regarding the more technical aspects underlying the I4.0 context, that can promote or enhance GRM issues in and between collaborating companies, and its inherent business and management models, namely [55–59], among others, which will be further synthetized and analyzed in the next sections.

4. Literature Search Results Analysis

In this study, the approximately 49 publications achieved were analyzed, which corresponded to the set of the most relevant ones, once they had satisfied the whole set of exclusion and inclusion criteria defined in the used SLR process, as previously presented. Thus, this main publication set will be subject to a deeper analysis and discussion.

The set of the most relevant publications was reached by using the b-on platform at UMinho. This kind of platform was chosen as it permits access to the full content of a widened collection of scientific works published in high-quality sources, for instance in journals, and in the proceeding books of international conferences, indexed in relevant scientific databases, such as the Web of Science, Scopus, Science Direct, and IEEE.

The search process was carried out by using the three groups of keywords (Group 1, Group 2, and Group 3) previously expressed in Table 1.

Figure 2 shows the total amount of works obtained regarding the focused management paradigms between 2011 and 2021. As can be seen in Figure 2, the GRM paradigm that occurred the most was the integrated one, followed by the real-time one. Thereafter, the distributed paradigm appears to be highly relevant, followed narrowly by the intelligent or predictive paradigm, and next by the dynamic paradigm. A less expressive relevance does appear with the parallel paradigm, although it is revealing and increasing tendency, as shown in Figure 3.

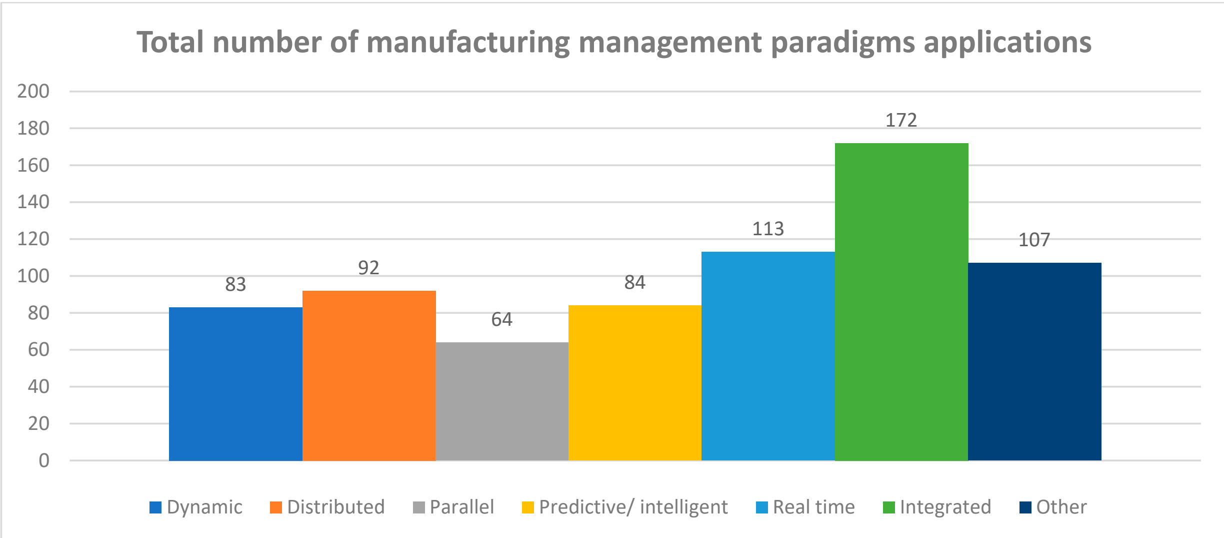

Figure 2. Total amount of publications about management paradigms from 2011 to 2021.

Figure 3 expresses the progression of the GRM paradigms during the last decade. It is, thus, also perceptible through Figure 3 that the integrated and the real-time paradigms are among the ones most widely being applied, and continue growing, as also happens, in general, with the remaining ones. This growing trend in the paradigms reveals its positive impact in the current digitalization era, namely in the GRM scope.

Moreover, the distributed and the predictive/intelligent paradigms are also receiving increased attention lately, being particularly visible, and followed by the dynamic and the parallel management ones. The last, the parallel paradigm, is the one that has been less explored during the last decade, although it is one of those that is currently experiencing a higher application increase. Furthermore, other management strategies have also been explored, namely related with concurrent engineering applications [60,61].

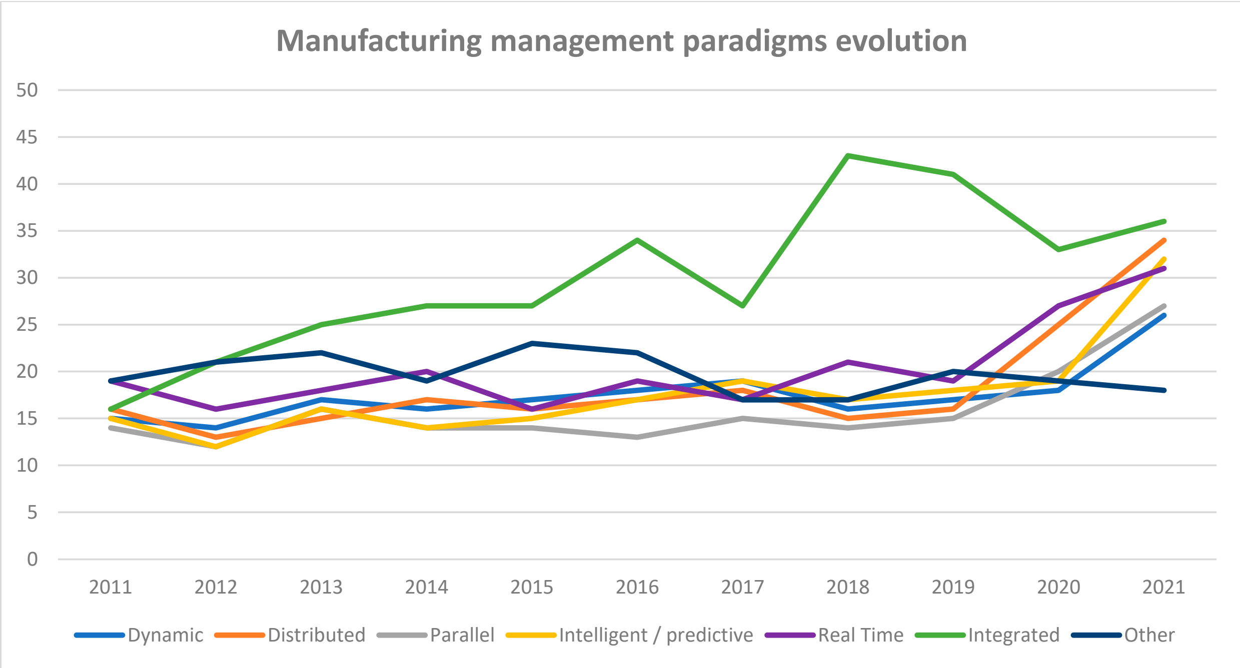

Figure 3. Progression of the number of publications about manufacturing management paradigms from 2011 to 2021.

5. Collaborative Management Framework and Results Discussion

5.1. Proposed Collaborative Framework

In this section, a framework about GRM is put forward, which hereafter will be named as collaborative management (CM), in the I4.0 context, and which resulted from the SLR carried out, in addition to the co-authors' own knowledge in the focused scientific domain, as can be seen, for instance, in [18–21,29,32,40,62–65].

The proposed CM framework is considered to be of the utmost importance currently in the I4.0 era, as includes a set of the six main identified management paradigms from the literature, as follows: integrated, dynamic, intelligent/predictive, distributed, parallel, and real-time management (Figure 4).

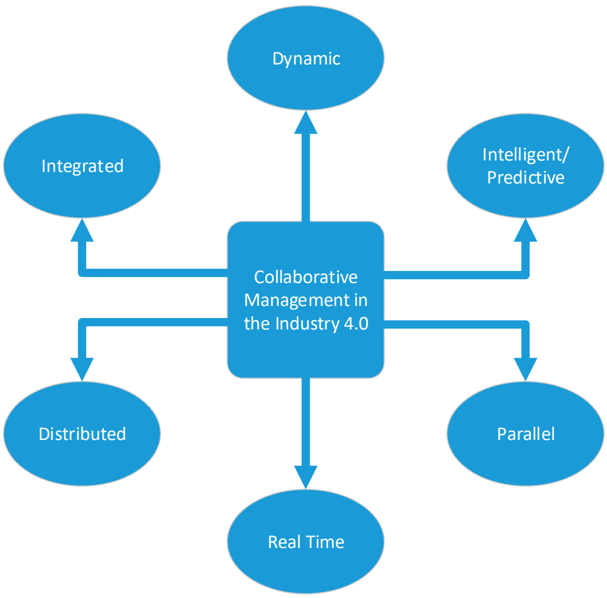

Figure 4. Proposed collaborative management framework.

5.2. Results Analysis and Discussion

The content of the set of the 49 most relevant selected publications from the last decade found in the literature was deeply analyzed to further explore the proposed CM framework, integrating the set of 6 main management paradigms identified, as is summarized in Table 2. In this table these most relevant publications in the studied scientific domain are, thus, analyzed, in order to realize to what extend they focus on two or more of the set of six identified CM paradigms and underlying approaches.

Table 2. Collaborative management paradigms used on the deeply analyzed publications.

Global Resources Management Paradigm	**Dynamic**	**Intelligent/Predictive**	**Distributed**	**Parallel**	**Integrated**	**Real-Time**	**Total n° of Combina-tions**
Research Publications							
Alves, Putnik, and Varela (2021) [14]	X					X	**2**
Azevedo, Varela, and Pereira (2021) [18]	X	X					**2**
Cardin et al. (2017) [66]		X			X		**2**
Chen, Fang, and Tang (2020) [67]	X		X			X	**3**
Coelho and Silva (2021) [68]	X	X		X		X	**4**
D'Aniello, Falco, and Mastrandrea (2021) [69]	X	X	X				**3**
Delaram and Valilai (2018) [70]			X		X		**2**
Demoly et al. (2013) [60]			X		X		**2**
Dogan and Birant (2021) [71]		X			X	X	**3**
Deshpande (2018) [61]	X		X		X		**3**
Ebufegha and Li (2021) [72]	X	X	X			X	**4**
Ferreirinha et al. (2019) [64]	X	X					**2**
Fernandez-Viagas and Framinan (2021) [73]	X	X			X	X	**4**
Frazzon et al. (2018) [74]			X		X		**2**
Fu, Wang, and Huang (2019) [47]			X		X		**2**
Gahm et al. (2016) [75]	X				X		**2**
Ghaleb, Taghipour, & Zolfagharinia (2020) [76]	X	X				X	**3**
Hofer et al. (2020) [77]	X	X				X	**3**
Hsu and Yang (2016) [78]	X				X	X	**3**
Hsu, Wang, and Chu (2018) [79]			X		X	X	**3**
Jimenez, Bekrar, Trentesaux, Leitão (2016) [80]	X	X	X		X		**4**
Kalinowski, Krenczyk, & Grabowik (2013) [81]		X				X	**2**
Kim et al. (2013) [50]		X		X			**2**
Kocsi, Matonya, Pusztai, and Budai (2020) [82]		X				X	**2**
Laili, Lin, and Tang (2020) [83]	X		X		X	X	**4**
Liu, Zhang, Zhang, Tao, and Wang (2019) [84]	X	X	X				**3**
Lohmer and Lasch (2021) [85]		X	X		X	X	**4**
Lopes et al. (2022) [20]	X			X			**2**
Leusin et al. (2018) [86]	X	X			X		**3**
Low and Chang (2013) [11]	X				X		**2**
Mao et al. (2020) [48]			X		X		**2**
Modekurthy, Saifullah, and Madria (2021) [87]			X		X	X	**3**
Moon and Park (2014) [88]		X	X				**2**
Morariu et al. (2020) [89]	X	X			X	X	**4**
Nouiri, Trentesaux, and Bekrar (2019) [90]		X	X		X		**3**
Rahman, Janardhanan, and Nielsen (2019) [91]		X			X	X	**3**
Rohaninejad et al. (2021) [92]		X		X	X		**3**

Table 2. *Cont.*

Rossit et al. (2021) [93]		X			X	X	**3**
Saboor et al. (2019) [94]	X				X	X	**3**
Sahu et al. (2018) [55]		X	X		X		**3**
Sobaszek, Gola, and Świć (2017) [95]		X			X		**2**
Sousa and Oliveira (2020) [96]		X	X		X		**3**
Tan, Tong, Wu, and Li (2019) [51]	X	X			X	X	**4**
Tighazoui, Sauvey, and Sauer (2021) [97]	X	X			X		**3**
Vafaei et al. (2019) [29]	X		X				**2**
Varela et al. (2021) [65]		X	X		X	X	**4**
Villalonga et al. (2021) [52]	X	X			X	X	**4**
Wang et al. (2017) [98]		X	X		X		**3**
Wenzelburger and Allgöwer (2021) [99]	X	X			X		**3**
Yang and Takakuwa (2017) [100]	X	X				X	**3**

According to the study carried out, it is understandable that the CM paradigms are, to some extent, being combined. A frequent arrangement of the real-time and the dynamic, as well as with the distributed and/or with the intelligent or predictive management paradigms, is also noticeable.

Moreover, the simulation technique is also being considerably used nowadays as a CM method, and is also being combined with other technologies and approaches, namely with digital twins, and with the dynamic management paradigm, as well as other AI-based approaches, including different types of metaheuristics and multi-agent systems (MAS).

The cloud and MAS technology is also frequently being used with along with metaheuristics, and with distributed, parallel, and real-time management paradigms.

Moreover, other AI-based methods, for instance based on blockchain, smart contracts, fuzzy logic, holons, and machines of deep learning approaches, are also being frequently used, namely in association with distributed, parallel, predictive, and real-time management paradigms, along with other approaches for enabling big data processing and analysis from the data science domain, for instance regarding the application of intelligent and predictive management paradigms.

The rolling horizon is another frequently used approach, which is further being analyzed in the scope of real-time management. Additionally, there are other kinds of methods that are being explored in the actual digitalization age, for instance to permit other kind of cooperative management approaches, namely regarding manufacturing scheduling through stakeholders to reach improved solutions. Some well-known examples include the use of group decision-making models, as well as game theory, chaos and complexity analysis, and other negotiation-based management methodologies. Such kinds of approaches are frequently used in dynamic, distributed, and agile or virtual systems or in EME [1,2,9,28,62,90,101].

The deep analysis of the publications summarized in Table 2 does further enable us to recognize that around three out of the whole set of six management paradigms are being combined. Therefore, an additional effort will be needed to properly tackle collaborative management among companies and remaining stakeholders, to reach improved decision-making processes and practices by increasing the combination of global management paradigms and underlying problem-solving approaches.

The six management paradigms underlying the proposed collaborative management framework are further synthetized in Table 3, along with the main underlying characteristics and supporting bibliography, in order to provide further insights and directions regarding global manufacturing management research and practice in companies.

Table 3. Main characteristics underlying the proposed six management paradigms.

Management Paradigm	Main Characteristics	References
Dynamic	Adapts to changing manufacturing conditions	[11,14,18,20,29,51,52,61,64,67–69,72,73,75–78,80,83,86,86,89,94,97,99,100]
Distributed	Decomposes complex management problems	[29,47,48,55,60,61,65,67,69,70,72,74,79,80,83,85–88,90,96,98]
Intelligent/predictive	Processes big data in complex and highly demanding and uncertain manufacturing environments	[18,50–52,55,64–66,68,69,71–73,76,77,80–82,85,86,86,88–93,95–100]
Parallel	Decentralizes the resolution of management problems	[20,48,50,68]
Integrated	Tackles the combined resolution of different management functions	[11,48,51,52,55,60,61,65,66,70,73,74,78–80,83,85–87,89–99]
Real-time	Enables businesses to capture, process, and analyze manufacturing and management data in due course	[14,47,51,52,65,67,68,72,73,75–79,81–83,85,87,89,91–94,100]

The dynamic management paradigm is mainly characterized by the possibility of quickly adapting to changing manufacturing management conditions by adapting the corresponding management approaches and solving methods [14,29,30,51,64,94].

The distributed management paradigm is well-suited for permitting the decomposition of management problems, which may arise in the scope of extended, agile, and virtual production systems, usually characterized by higher levels of complexity associated with its underlying networked organization [7,40,43,44,46,96,102].

The intelligent and predictive management paradigm is currently a main issue in the I4.0 context, and underlying CPPS, supported by AI-based approaches, plays an important role in promoting the resolution of management problems through the use of different kind of methods and techniques that further enable us to predict data and manufacturing conditions, by exploring high volumes of varying kind of dynamically emerging data [12,18,19,66,95].

The parallel management paradigm is particularly well suited for solving 'heavy' or complex management problems through a decentralized solving methodology through which two or more entities collaborate in its resolution. The use of HPC is nowadays recommended in the I4.0 context, mainly when in presence of big data and by further making use of compound management methods, which is quite typical in the resolution of manufacturing scheduling problems, particularly those occurring in distributed and extended manufacturing environments and which may further include CPS [20,48].

The integrated management paradigm allows the integration of two or more management functions, for instance, regarding process planning and scheduling, batching and scheduling, scheduling and manufacturing layout arranging, scheduling and maintenance management, and scheduling and supply chain management, among other combinations, to mention just a few of the most frequently used ones [11,47,65,74,83].

The real-time management paradigm is also one of the most popular ones in the I4.0 context, as it enables businesses to acquire, process and analyze data in a dynamic and agile way from the manufacturing environment up to the management level through the use of appropriate technological support, based on suitable middleware, including smart objects and associated devices [14,45,81].

The proposed collaborative management framework, integrating the six main global resources management dimensions through the underlying management paradigms, consists of original input, as the co-authors did not come across any more or less closely related work mentioning the combined use of this whole set of management paradigms either in academia or industry, as previously shown through the compiled information in Table 2. Therefore, regarding the whole and diversified set of benefits expected through its use, further developments regarding the combination of the underlying six management paradigms is highly recommended, as each one enables us to tackle specific main issues in the context of GRM, being considered to be of highest relevance in the current Industry 4.0 era.

6. Conclusions

In this paper, the main results about global resources management paradigms were synthetized and analyzed, in the scope of the I4.0 era, and a collaborative management framework was proposed, which includes six paradigms concerning integrated, dynamic, intelligent/predictive, distributed, parallel, and real-time management.

The proposed framework is aimed at supporting proper collaborative management processes and practices by encompassing, as much as possible, the underlying paradigms according to specific needs of each company and associated stakeholders, in order to reach joint and enhanced decisions once around three are jointly explored. Such aims or objectives will greatly depend on the underlying manufacturing environment, which may vary from more simple, classical, or more traditional, and centralized ones up to more complex, cyber-physical, distributed, extended, and agile or virtual enterprises. These varying kinds of manufacturing environments, for instance more complex and dynamic ones, along with their underlying management strategies, assume a primer importance nowadays, in the I4.0 era, namely in the context of cyber-physical systems, as was highlighted in this paper. It is, thus, envisioned that the proposed full joint exploration of the set of six management paradigms identified will be of the upmost importance, namely in managing such complex and highly demanding manufacturing environments as currently exist. This expectation is based on the capability of a dynamic adaptation to changing manufacturing conditions, to the decomposition or distribution and decentralization of the resolution of complex management problems, and also on the focus on different management functions through real-time-based big data acquisition, processing, and analysis in highly demanding and uncertain manufacturing environments. This is an original work, as opposed to current studies, as it permits broader and deeper insights about currently considered fundamental decision-making paradigms and underlying approaches, which are, thus, suggested to be further explored and combined, to enable to businesses to properly support manufacturing management, to carry it out in a collaborative manner, and to further support and promote the current Industry 4.0 technology. However, some limitations are expected to occur, related to the joint exploration of different kinds of management paradigms, due to the underlying highly-demanding knowledge and technology for permitting a full exploration of its joint application, along with associated problem-solving approaches. Thus, additional future work is suggested, namely for finding out some promising technologies for enabling the proper application of the proposed collaborative management framework in real industrial and academic scenarios, through the combined use of its six management paradigms, along with suitable approaches and tools for permitting prosperous and true innovation and company development in the current digitalization era.

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