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Collaborative Networks, Decision Systems, Web Applications and Services for Supporting Engineering and Production Management

Edited by
Leonilde Varela and Goran D. Putnik

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About the Editors

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Leonilde Varela is Assistant Professor at Department of Production and Systems, and an integrated member of the Algoritmi Research Centre, at University of Minho, Portugal, were she received her Ph.D. in Industrial Engineering and Management in 2007, and has worked since 1994, in teaching, researching, in addition to collaborating in management tasks, namely regarding the coordination of the industrial management and systems subgroup in which she has integrated since 1994, and coordinated from 2012 to 2021. She has also integrated the steering committee of the master's course in Systems Engineering, between 2016 and 2019, and currently, since 2021, she is the director of the Quality Engineering and Management master course. Her main research interests are in Manufacturing Management, Collaborative Management, Production Planning and Control, Optimization, Artificial Intelligence (AI), Meta-heuristics, Scheduling, Web based Systems, Services and technologies, mainly for supporting Engineering and Production Management, Collaborative Networks, Decision Making Models, Methods and Systems, and Virtual, Distributed and Networked Enterprises. She has published more than 200 refereed scientific papers in international conferences and in international scientific books and journals, conference proceeding books, indexed in the Web of Science and/or in the Scopus data bases, and other books. She coordinates several research projects, namely with financial support from the national Foundation for Science and Technology, along with Ph.D. and M.Sc. projects, in the area of Production and Systems Engineering, namely concerning the development of collaborative management models, methods, and tools, varying from more traditional decision support approaches to advanced intelligent systems and web-based platforms. She is a member of several international institutions and research groups, such as the Machine Intelligence Research Labs, Scientific Network for Innovation and Research Excellence (MirLabs), in the Euro Working Group of Decision Support Systems, in the Institute of Electrical and Electronics Engineers, in the Industrial Engineering Network, and in the Institute of Industrial and Systems Engineers, having served as organizing and publication or scientific chair, in many international conferences.

Goran D. Putnik

Goran D. Putnik was born in Belgrade, Serbia, in 1954. He received the B.S. and M.S. degrees in production engineering from the Faculty of Mechanical Engineering, University of Belgrade, and the DrSci (Ph.D.) in mechanical engineering from University of Belgrade, in 1993. After graduation, he joined the Motor Industry Rakovica, Belgrade, Serbia, and 3 years later joined the Department of Production Engineering at Faculty of Mechanical Engineering, University of Belgrade as Assistant Researcher. In 1993, he joined the University of Minho, Portugal, where he is currently Full Professor in the Department of Production and Systems Engineering, School of Engineering. His research and teaching interests are in the areas of production systems, languages, automata theory and production systems formal theory, and chaos and complexity management in organizations. He is the author of 13 books, more than 250 articles, and coordinator of a number of international projects. He is member of the IFIP WG 5.5—"COoperation infrastructure for Virtual Enterprises and electronic business—COVE", and of the International Academy for Production Engineering—CIRP, Paris.

Preface to "Collaborative Networks, Decision Systems, Web Applications and Services for Supporting Engineering and Production Management"

This book addresses collaborative networks, decision systems, web applications and services for supporting engineering and production management, along with other social oriented services.

The main scope and purpose consists on presenting a general overview of some main issues related to collaborative approaches and practices, aiming at raising awareness about the importance of collaboration not just in engineering and manufacturing and management contexts, but also in other areas, namely in social science's domain, along with computer science and science and technology, in general.

The main motivation underlying the publication of this book is to provide a summarized set of representative work regarding the application of methodologies, approaches, tools and systems that enable us to put into practice collaboration among different kind of entities, varying from human- to machine-centered focus, and occurring in different kinds of industrial and social contexts.

This book is not just recommended to all readers that intend to achieve or clarify the importance of collaboration, but also to provide some concrete illustrative examples of its application domains.

The editors thank the important contribution provided by the following list of the co-authors that did enable the publication of this book, and to the fundamental support of the underlying institutions, namely regarding financial entities.

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Editorial

Collaborative and Intelligent Networks and Decision Systems and Services for Supporting Engineering and Production Management

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Collaborative networks and systems (CNS) have received much attention in recent decades to reach a competitive advantage. Many contributions have arisen from the industrial context to service-oriented companies, for instance, in the scope of artificial intelligence. Therefore, many contributions have been put forward related to collaborative and intelligent networks and systems [1–7].

Despite the wide range of existing work in this area, however, it continues to be imperative for companies to understand and anticipate the importance of CNS in manufacturing to enable them to reach a competitive advantage in the current global market and Industry 4.0-oriented manufacturing scenario [8,9].

These main topics strengthen the specific characteristics of CN through collaboration to deliver products and services; decentralize decision-making; and achieve inter- and intra-organizational integration to meet imposed performance requirements in competitive global markets [10–12].

Moreover, in the context of CNS, normalization is a crucial step in all decision models to produce comparable and dimensionless data from heterogeneous data [5]. Therefore, it is of upmost importance to use appropriate data-normalization techniques for each application scenario, for instance, according to the kind of multicriteria or multiobjective optimization methods or algorithms used for networked supply and operations management [2,5,13]. This is even more important in the upcoming increasingly digital era of I4.0, along with the perceived need for big data processing in terms of the need for the vertical and horizontal integration of data and manufacturing processes [6,10,14,15].

This Special Issue intends to contribute to collaborative and intelligent networks and systems supporting engineering and production management, as well as fill the gap in theories and practical applications supporting industrial companies through suitable methods and solutions.

Collaborative Engineering (CE) assumes an important role in Industry 4.0 (or I4.0) [16,17], namely, in the context of Collaborative Networks (CN), which includes a diverse set of companies, business partners, suppliers, and other stakeholders, including customers [7,18,19]. These entities are thus connected and communicate to enable CE practices and accomplish Collaborative Manufacturing and Management (CollM&M). CollM&M further implies sharing something between these entities, including some tangible or intangible asset, e.g., manufacturing resources and/or management information [7]. By doing so, the collaborating entities envision the co-creation of a product and/or service [6,7], for which I4.0's technologies are of utmost importance to enable and promote such joint practices, which include human–human, human–machine, and machine–machine interactions [6,12,20].

The widened set of I4.0 technologies permits the development and application of a varying range of management paradigms, approaches, and methods through the use of appropriate and diverse types of supporting tools, systems, and platforms [6,8,9,11,12,20–24], including:

- Collaboration strategies;
- Learning organizations principles;
- Chaos and complexity management;
- Game theory models and approaches for supporting production management;
- Blockchain technology applied to manufacturing and management;
- Intelligent models, methods, and tools;
- Dynamic and real-time-based decision-support approaches;
- Decentralized and distributed decision-support networks and models;
- Social-network-based models, methods, and tools;
- Hybrid intelligent decision-support and recommendation systems;
- Multiagents models, systems, and platforms;
- Machine- and deep-learning-based approaches and systems;
- Bio-inspired models and algorithms applications;
- Negotiation and group-decision-making approaches;
- Multicriteria and multiobjective models;
- Uncertainty treatment methods and tools;
- Data-normalization and data-fusion methods, techniques, and systems;
- Data analytics for manufacturing systems and management processes;
- Cloud computing, manufacturing, and big data processing approaches and tools;
- Learning and data mining and other data-science-oriented approaches and systems;
- Data visualization models and tools for promoting and supporting digital, intelligent smart factory, and cyber–physical production systems;
- Real-time machine- and process-monitoring, diagnostics, and prognostics methods and tools;
- Real-time management methods, tools, and platforms;
- Manufacturing execution systems;
- Open-source software applications for digital or cyber manufacturing;
- Internet of Things and associated models, devices, means and tools for cyber manufacturing and management.

The accomplishment this widened set of approaches, methods, tools, systems, and platforms implies the use of appropriate CollM&M paradigms, which are related to dynamic, distributed, integrated, intelligent/predictive, parallel, and real-time-based contributions [6,24–28].

Moreover, CollM&M has to ensure the fulfillment of an appropriate set of varying objectives or performance measures, which include companies' internal and external goals, and are frequently contradicting, thus further requiring the application of multicriteria and/or multiobjective and intelligent optimization methods, along with data acquisition, normalization techniques, and tools, to enable further incomplete and uncertain data processing, visualization, and analysis [2,5,13,25,29].

The cyber–physical (production) systems (C[P]PS) and smart factories, based on intelligent sensing systems, open and networked and distributed manufacturing systems, along with virtual organizations and extended manufacturing environments, play a fundamental role in I4.0 [22,24,29,30]. In such advanced manufacturing systems (AMS), integration, distributivity, virtuality, agility, servitization, digitalization, and decentralization are major issues for reaching suitable collaborative processes and practices in the I4.0. In this regard, the (Industrial) Internet of Things ((I)IoT), along with smart and ubiquitous networks based on cloud technology, enable large and complex networks and their digitalization [2–4,6,10,14] to carry out CollM&M [7]. In this regard, decisions and related actions must be taken promptly and be further supported by appropriate data-visualization systems [6,14,15,31,32].

Cloud-based M&M technology is, therefore, fundamental to enabling enhanced interoperability and collaborative practices (Varela et al., 2019c; Ferreira et al., 2022). Moreover, horizontal and vertical integration between companies, business partners, factories, suppliers, other stakeholders, and clients is fundamental in I4.0 [2,10,13,14,32,33].

Exponential technology, along with advanced processes, high-performance computing, and disruptive technologies (e.g., automation and robotics, autonomous and collaborative robots, advanced mechatronics, micro- and nano-manufacturing, and supercomputing) are key enablers for proper M&M in I4.0 [6,7,12,32,33].

Moreover, advanced interfaces, virtual, augmented, and mixed reality technology, along with simulation and digital twins, further promote and enhance CollM&M among collaborating entities. These technologies enable advanced and integrated decision-support systems (DSS) and databases (DB), along with knowledge engineering and knowledge bases (KB), automatic data acquisition, and a semantic web for enhancing collaboration [7].

In addition, data science, along with business intelligence, big data processing, and data analytics, are essential pillars of I4.0 supporting CollM&M practices [6,7].

All these issues are crucial for enabling advanced, integrated, and intelligent supply networks, projects, businesses, and their interoperable and fully supported implementation, to reach M&M while ensuring high-quality product development and M&M practices based on appropriate standards, means, and communication devices and protocols, to fully ensure appropriate extended supply network management strategies [5,8,10,15,32–34].

This Special Issue aims to provide new insights regarding CollM&M models and practices, aligned with the contemporary needs regarding the capability of co-creation actions supported by I4.0 technology [7].

In this regard, each of the six selected papers of this Special Issue makes a novel contribution to this purpose.

Pombo et al. present expectations and limitations of cyber–physical systems (CPS) for advanced manufacturing in the scope of the grinding industry. In their work, the authors refer to the importance of grinding technology in the manufacturing of high-added-value precision parts, accounting for approximately 20 to 25% of the whole machining costs in the industrialized world and relying heavily on the experience and knowledge of the operatives. Thus, the authors conclude that suitable approaches are needed to overcome these issues, and digital twin technology is promising in this regard by contributing to the reduction and possibly even the elimination of unnecessary trial-and-error strategies through intensive collaboration between all the involved agents from the university to the industry. The authors highlight the successful implementation of this technique in developing new and more realistic models for predicting wheel wear.

Miranda et al. propose a system model for offline seismic event detection in Colombia. The authors put forward an integrated model that includes five sub-models and is based on a machine-learning approach, and they highlight its suitability for identifying P-wave windows in historical records that permit detect seismic events. Their proposed model permits seeking, gathering, and storing seismic data, along with data reading, analysis, sampling, and classification. The authors further provide some recommendations regarding their model's implementation in developing a seismic-event detection system.

Samala et al. put forward a systematic literature review (SLR) about investigating degradation and upgradation models for flexible unit systems. In their work, the authors research the so-called flexible unit systems (FUS) in the current I4.0 era and the context of descriptive, predictive, and prescriptive analysis, aiming at integrating distributed and digitalized systems. The authors highlight that the existing literature mostly focuses individually on the descriptive, predictive, and prescriptive analysis paradigms. Moreover, the authors also claim that the literature is unclear about the integration of degradation and upgradation models for FUS. Thus, the authors carried out an SLR, through which it was possible to identify five main issues about degradation—residual life distribution, workload adjustment strategy, upgradation, and predictive maintenance—as major performance measures to investigate the performance of the FUS. In this study, it was understood that the degradation rate would affect the life and production rate of different configurations of FUS. Moreover, it was possible to realize that the considered upgradation model and predictive maintenance, along with advanced analytics procedures of the manufacturing systems, are valuable and enable the systems to run with higher production rates while increasing the life of systems. Moreover, it was also possible to explore three research objectives related to system configuration flexibility to improve the proposed FUS and identify further research opportunities in this field.

Carchiolo et al. focus on co-authorship networks analysis to discover collaboration patterns among Italian researchers. Through their study about the analysis of behaviors of a large community of researchers and their correlations between the underlying environments, the authors determined a set of grouping rules by law or specific institutional policies that enabled conclusions about their performance and, importantly, affecting metrics to evaluate the quality of their research carried out. To this end, the coauthors created a procedure to craft a large dataset of Italian academic researchers by considering a set of performance indices and co-authorship information. Through their study, the authors could automate the association of profiles and the mapping of publications to reduce the use of computational resources. Moreover, the authors presented several examples of how the information extracted from the datasets can help better understand the dynamics influencing scientific performances.

Fior, Cagliero, and Garza refer in their work to leveraging explainable AI to support cryptocurrency. The authors clarify that this research area has been attracting the attention of many researchers and continues to be a very important research focus for private and professional traders and investors. They further mention that forecasting financial markets can be properly approached by using algorithmic trading systems based on AI models, which are becoming more and more developed. Moreover, the authors state that such approaches usually suffer from a lack of transparency, thus hindering domain experts from directly monitoring the fundamentals behind market movements. Additionally, they mention that this is particularly critical for cryptocurrency investors because studying the main factors influencing cryptocurrency prices, including the characteristics of the blockchain infrastructure, is crucial for driving experts' decisions. Thus, in their paper, the authors propose a new visual analytics tool to support domain experts in explaining AI-based cryptocurrency trading systems. To further describe the rationale behind AI models, their proposed approach exploits an established method, the SHapley Additive exPlanations, which, according to their results, allows experts to identify the most discriminating features and provides them with an interactive and easy-to-use graphical interface.

Orlova approached design technology and AI-based decision-making models for digital twin engineering. This study proposes comprehensive technology (methodological approach) for digital twin design to accelerate its engineering. The author clarifies that this kind of technology consists of design steps, methods, and models and provides systems synthesis of digital twins for a complex system (object or process) operating under uncertainty that can reconfigure in response to internal faults or environment changes and perform preventive maintenance. The author mentions that the proposed technology structure was developed based on a simulation model using situational "what-if" analysis and based on fuzzy logic methods. The author applied this technology to develop a digital twin prototype for a device at a creation life cycle stage to reduce the consequences of unpredicted and undesirable states. Through the study, it was possible to realize unforeseen problems and device faults during its further operation. According to the author, the proposed model identifies a situation as a combination of failure factors of the internal and external environment and provides an appropriate decision about actions with the device. Further, the authors mention that the practical significance of the research is the developed decision support model, which is the basis for control systems to solve problems related to monitoring the current state of technical devices (instruments, equipment) and supporting adequate decisions to eliminate their dysfunctions.

Undertaking this Special Issue, "Collaborative and Intelligent Networks and Decision Systems and Services for Supporting Engineering and Production Management", was a challenging and rewarding task for the Editors. The diversity of the manuscripts demonstrates the broad scope and relevance of the research theme in fostering performance and transformation for achieving collaborative practices in I4.0.

List of Contributions:

1. Pombo, I., Godino, L., Sánchez, J.A., and Lizarralde, R. (2020). Expectations and limitations of Cyber-Physical Systems (CPS) for Advanced Manufacturing: A View from the Grinding Industry.
2. Miranda, J., Flórez, A., Ospina, G., Gamboa, C., Flórez, C., Altuve, M. (2020). Proposal for a System Model for Offline Seismic Event Detection in Colombia.
3. Samala, T., Manupati, V.K., Varela, M.L.R., and Putnik, G. (2021). Investigation of Degradation and Upgradation Models for Flexible Unit Systems: A Systematic Literature Review.
4. Carchiolo, V., Grassia, M., Malgeri, M., and Mangioni, G. (2022). Co-Authorship Networks Analysis to Discover Collaboration Patterns among Italian Researchers.
5. Fior, J., Cagliero, L., and Garza, P. (2022). Leveraging Explainable AI to Support Cryptocurrency Investors.
6. Orlova, E.V. (2022). Design Technology and AI-Based Decision Making Model for Digital Twin Engineering.

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Review

Investigation of Degradation and Upgradation Models for Flexible Unit Systems: A Systematic Literature Review

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Abstract: Research on flexible unit systems (FUS) with the context of descriptive, predictive, and prescriptive analysis have remarkably progressed in recent times, being now reinforced in the current Industry 4.0 era with the increased focus on integration of distributed and digitalized systems. In the existing literature, most of the work focused on the individual contributions of the above mentioned three analyses. Moreover, the current literature is unclear with respect to the integration of degradation and upgradation models for FUS. In this paper, a systematic literature review on degradation, residual life distribution, workload adjustment strategy, upgradation, and predictive maintenance as major performance measures to investigate the performance of the FUS has been considered. In order to identify the key issues and research gaps in the existing literature, the 59 most relevant papers from 2009 to 2020 have been sorted and analyzed. Finally, we identify promising research opportunities that could expand the scope and depth of FUS.

Keywords: flexible unit systems; degradation; residual life distribution; workload strategy; upgradation; predictive maintenance

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1. Introduction

Recently, the manufacturing systems domain underwent a paradigm shift by introducing several key enabling technologies as a requirement of Industry 4.0 [1]. Keeping in mind clients' customized requirements and global manufacturers' personalized production, the current production and process capabilities need to be transformed. For example, recent requirements such as shorter product life cycles, high production rates, jobs complexity, quality products, and cost effectiveness are the most significant factors for any manufacturing industry [2]. Considering all the foregoing requirements, and, in addition, according with the current market demand and society requests, there is a need to enhance the system's capabilities by maintaining it under control from system breakdowns and several external forces that have not been considered as a highest priority in the past decade. To accomplish these challenges, there is a need for high machine availability, flexibility, configurability, and accessibility of manufacturing processes, as mentioned in [3–9]), along with another interesting contribution for emphasizing the necessity of increasing the level of flexibility of manufacturing systems, which can be seen in https://publications.muet.edu.pk/index.php/muetrj (accessed on 23 January 2021). However, various manufacturing systems available to fulfil the above-mentioned requirements have costs affairs and high maintenance. In this review paper, we introduced a special kind of configuration: i.e., flexible unit systems (FUS) with one degree of flexibility, two degrees of flexibility, semi flexibility, and highly flexible configurations, where the reconfiguration and upgradation of unit (machine) systems are easily achieved [10,11].

The common factors from different studies that affect FUS are identified as degradation rate, residual life distribution, workload strategy, upgradation, and predictive maintenance.

To improve the health status of the system and to make the manufacturing functions effective and efficient, system-level health monitoring is new thinking to which nowadays researchers are paying attention. Therefore, the degradation rate at the system level is of the highest priority. Studies have shown that manufacturing systems are subjected to degradation both with age and usage, including wear, cracking, and fatigue, among others; whereas the residual life of a machine was characterized as remaining useful till its level of degradation arrives at a predefined failure threshold [12]. Real-time production data from complex systems produce a huge variety and volume of data. Handling this kind of data-intensive system with conventional statistical tools may be insufficient when firms seek to strategically conceal the data [13]. Hence, there is a need for advanced analytics such as descriptive, predictive, and prescriptive analytics to analyze the machine's historical data to improve the efficiency of the system by knowing the health condition at every stage.

Given this scenario, towards summarizing the status of present research and to stimulate the future investigations, the main aim of this paper is to carry out a Systematic Literature Review (SLR) with respect to the degradation and upgradation models for FUS. Hence, a review of manufacturing systems in the context of three analytics has been considered, particularly with flexibility as a key common word. The analysis of the reviewed literature enabled us to develop a comprehensive conceptualization as shown in (Figure 1). It is the conceptualization that was used to classify the findings and it was also referenced for future research.

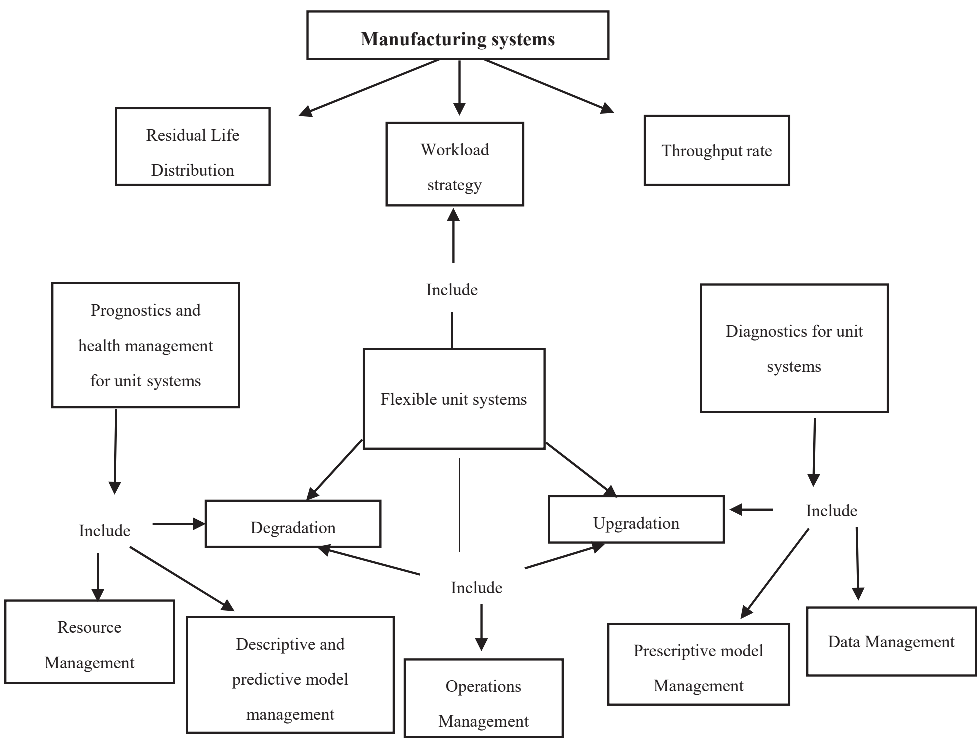


Figure 1. Framework addressing the topics affecting flexible unit systems (FUS).

The paper is structured as follows. In Section 2, a detailed research methodology is used, which follows SLR's five-step approach. Effectiveness of degradation and upgradation models on the FUS and findings have been presented in Section 3. Discussion and

Future research agenda is explained in Section 4. Conclusions and future work directions are pointed out in Section 5.

2. Research Methodology

This research followed the SLR as a basic scientific activity that delivers a clear and comprehensive overview compared to descriptive literature reviews. The formation of a basic framework for an in-depth analysis and a scientific process can be possible by using this SLR. The systematic literature followed a sequence of five steps, as mentioned in [10], which are as follows.

(1) Formation of questions;
(2) Finding the studies;
(3) Study preference and evaluation;
(4) Investigation and combination;
(5) Reporting and using the results.

Step 1. Formation of questions:

Research Question 1. What is the role of degradation, residual life distribution, workload strategy, upgradation, and predictive maintenance on flexible unit systems?

Research Question 2. How to integrate the degradation and upgradation models to the flexible unit systems?

Step 2. Finding the studies:

This step concerns how to find and choose the bibliographic database or search engine, and additionally the search strings. The research questions have been considered in this search for literature reviews. Following similar literature reviews [14–16] and three bibliographic databases, i.e., Web of Science, Scopus, and Science Direct, a remarkable quantity of published literature on degradation rate, residual life distribution, workload strategy, upgradation, and predictive maintenance, including very relevant and important journals in this area, has been considered. Additionally, also considered were advanced analytics, like descriptive, predictive, and prescriptive ones, to analyze the machine's historical data for improving the efficiency of the system.

Tables 1–3 show the search strings searched in the data bases and the results obtained using the three mentioned databases. However, sorting the selected research articles and selecting the publication title between 2009–2020 shows 603 articles for the search string "Flexible unit systems" (or) "Flexible machine systems" and "Degradation" (or) "Degradation rate", 167 articles for the search string "Flexible unit systems" (or) "Flexible machine systems" and "Residual Life Distribution" (or) "Residual life", 140 articles for the search string "Flexible unit systems" (or) "Flexible machine systems" and "workload strategy" (or) "workload adjustment", 104 articles for the search string "Flexible unit systems" (or) "Flexible machine systems" and "Upgradation", and 243 articles for the search string "Flexible unit systems" (or) "Flexible machine systems" and "Predictive Maintenance", respectively.

Table 1. Search string and number of results from Web of Science.

Search String	Search Field	Date of Search	No. of Results
"Flexible unit systems" (or) "Flexible machine systems" and "Degradation" (or) "Degradation Rate"	Topic	11 August 2020	273
"Flexible unit systems" (or) "Flexible machine systems" and "Residual Life" (or) "Residual Life Distribution"	Topic	11 August 2020	34
"Flexible unit systems" (or) "Flexible machine systems" and "Workload strategy" (or) "Workload adjustment"	Topic	11 August 2020	42
"Flexible unit systems" (or) "Flexible machine systems" and "Upgradation"	Topic	11 August 2020	2
"Flexible unit systems" (or) "Flexible machine systems" and "Predictive Maintenance"	Topic	11 August 2020	41

Table 2. Search string and number of results from Scopus.

Search String	Search Field	Date of Search	No. of Results
"Flexible unit systems" (or) "Flexible machine systems" and "Degradation" (or) "Degradation Rate"	Article title, abstract, keywords	4 September 2020	178
"Flexible unit systems" (or) "Flexible machine systems" and "Residual life" (or) "Residual life Distribution"	Article title, abstract, keywords	4 September 2020	9
"Flexible unit systems" (or) "Flexible machine systems" and "Workload strategy" (or) "Workload adjustment"	Article title, abstract, keywords	4 September 2020	14
"Flexible unit systems" (or) "Flexible machine systems" and "Upgradation"	Article title, abstract, keywords	4 September 2020	1
"Flexible unit systems" (or) "Flexible machine systems" and "Predictive Maintenance"	Article title, abstract, keywords	4 September 2020	9

Table 3. Search string and Number of Results from Science direct.

Search String	Date of Search	No. of Results
"Flexible unit systems" (or) "Flexible machine systems" and "Degradation" (or) "Degradation Rate"	18 September 2020	152
"Flexible unit systems" (or) "Flexible machine systems" and "Residual life" (or) "Residual life Distribution"	18 September 2020	124
"Flexible unit systems" (or) "Flexible machine systems" and "Workload strategy" (or) "Workload adjustment"	18 September 2020	84
"Flexible unit systems" (or) "Flexible machine systems" and "Upgradation"	18 September 2020	101
"Flexible unit systems" (or) "Flexible machine systems" and "Predictive Maintenance"	18 September 2020	193

Step 3. Study preference and Evaluation:

In this step, filtering criteria were explicated, to choose only relevant studies to add in the review, in which the studies actually addressed the research questions. From 1995 to 2008, articles were excluded because they were just consigned to the small percentage of the examples. 11 years (2009–2020) of related studies were performed to focus on recent studies, methodologies, and technologies. The article journals of document type were sorted from the search results and the best articles distributed in peer-reviewed journals in English were contemplated. Colicchia et al. [17] argue that restricting the search to peer-reviewed journals enables one to reach better results due to the rigorous reviewing processes inherent to such articles before their publication.

This exercise reduces the number of journal articles to 198. After checking the duplicates (initially in each search string and after, taking into consideration all search strings set together), titles and abstracts of the selected journal articles were analyzed for relevance, which enabled us to further reduce the number of articles to 106. Articles qualified for review had to fulfil the five major criteria: (i) articles related to finding the Degradation level of manufacturing systems, (ii) articles related to finding the residual life of manufacturing systems, (iii) articles related to adjustment strategy of workload to reduce the degradation level of manufacturing systems, (iv) articles related to upgradation of manufacturing systems, and (v) articles focused on predictive maintenance of manufacturing systems. At this step, the number of articles for investigation was 106. At last, a more examined analysis of the 66 articles was made with the full gratified review.

Step 4. Investigation and Combination:

In this step, the content of each paper was analyzed to identify the key issues. Through full-content review, different articles were excluded, which were not as per the specified research focus of this study. In this way, the number of definite articles for the investigation was reduced to 59, as recorded in Table 4.

Table 4. Summary of articles preferences and evaluation.

Bibliographic Database Analysis	Search 1	Search 2	Search 3	Search 4	Search 5	Total
Web of Sciences	273	34	42	2	41	392
Scopus	178	9	14	1	9	211
Science Direct	152	124	84	101	193	654
	Inclusion/Exclusion criteria of Web of Sciences					
Date Range	193	29	26	1	28	277
Document Type	191	29	26	1	28	275
Research Area	175	26	23	1	26	251
Language	174	26	22	1	26	249
	Inclusion/Exclusion criteria of Scopus					
Date Range	155	9	11	1	6	182
Document Type	130	6	7	1	6	150
Research Area	109	6	6	1	6	128
Language	96	6	6	1	6	115
After checking the duplicates (in each search)	113	22	36	3	24	198
After checking the duplicates (in all search)	106					
Analysis of (Abstract and Title)	66					
After a detailed article analysis	59					

Step 5. Reporting and using the results:

The data contained in 59 articles were summarized, then prepared with connected categories, for example, methodologies used in their research and various key findings. Table 5 shows the list of journals related to the number of articles published as well as the year of publication. *Reliability Engineering and Systems Safety*, *International Journal of Advanced Manufacturing Technology*, *IIE Transactions on Automation Science and Engineering*, *Journal of Intelligent Manufacturing*, *IFAC online*, *CIRP Annals: Manufacturing Technology*, and *IEEE Transactions on Reliability* contributed to 55% of the total articles published related to factors (degradation, residual life distribution, workload strategy, upgradation, and predictive maintenance) related to manufacturing systems. Other journals like the *Journal of Computers & Industrial Engineering*, *IEEE Transactions*, *Journal of Manufacturing Systems*, *Procedia Manufacturing*, *European Journal of Operations Research*, and a few other journals contributed to 45% of the total journal articles published related to factors affecting manufacturing systems.

Table 5. List of journals related to the parameters related to the flexible unit systems.

Sl. No.	Name of the Journal	Number of Articles	Year of Publishing
1	Reliability Engineering and Systems Safety	5	2012,14,17,19
2	IEEE Transactions on Automation Science and Engineering	4	2015,16
3	International Journal Advanced Manufacturing Technology	3	2015,18
4	IEEE Transactions on Reliability	3	2014,15,17
5	CIRP Annals: Manufacturing Technology	3	2017,19
6	Journal of Intelligent Manufacturing	3	2009,2014
7	IFAC online	3	2017,19
8	Journal of Manufacturing Systems	2	2018
9	International Journal of Production Research	2	2015,17
10	IIE Transactions	2	2014,15
11	Procedia Manufacturing	2	2017
12	Computers & Industrial Engineering	2	2017,19
13	IEEE Transactions on Power Systems	2	2015
14	IEEE Systems Journal	2	2019
15	European Journal of Operation Research	2	2018
16	Journal of Precision Engineering and Manufacturing Technology	1	2009
17	Materials Today: Proceedings	1	2018
18	International Journal of Productivity and Quality Management	1	2016

3. Findings

The relevant data were collected and studies arranged dependent on five factors, mentioned in the research methodology. The detailed description of these five factors and their relevance under study is as follows.

3.1. Prognostics and Health Management (PHM) for Unit Systems

In recent years, PHM has emerged as an essential approach in the global competitive market, achieving advantages over others by improving system maintainability and reliability. However, the application of PHM to flexible unit systems is a challenging task as systems are more complex. Specifically, small and medium-sized ventures experienced difficulty in applying PHM, because of the lack of resources and time for research and development.

Shin et al. [18] explored how the Prognostics method is an intelligent answer for enhancing the availability of unit systems and fault prognosis to evaluate residual life. A PHM model for manufacturing systems integrated with different online sensors with different flexible structures has been developed by [19], and Hao et al. [12] proposed a contemporary sign partition as well as prognostics structure for multi-section systems with non-resolute segment signals, and Fang et al. [20] developed a prognostic procedure that uses multi-stream signals for predicting the residual life of partially degraded manufacturing systems.

3.1.1. Throughput Rate

The throughput rate is significant for the design and the activity of manufacturing systems. A remarkable quantity of throughput rate related research has been developed to estimate the throughput of manufacturing systems by creating analytical methods with various unreliable machines. Hao et al. [12] characterized the "throughput rate" of a manufacturing system, which is equivalent to summing up all the workloads from each unit. Table 6 shows the literature related to degradation of manufacturing systems. In FUS, this performance measure is considered one of the important expected outputs due to its direct relevance for capacity. For example, if a FUS consists of three different machines with different capacities, then the maximum throughput is considered as the summation of all three machines. If the expected demand is less than the capacity of the system, the throughput rate is equal to the demand, otherwise the throughput rate is equal to the total capacity.

Table 6. Literature review on degradation rate related to flexible unit systems.

Literature Review on Degradation Rate in the Context of Flexible Unit Systems		
Sl. No.	**References**	**Findings**
1	[21]	The machine's degradation was analyzed in view of an impact on machine performance and product quality utilized as the performance index.
2	[22]	A new degradation model, "Transformed Inverse Gaussian process", has been presented in this paper.
3	[23]	Shows that it can be conceivable to make robust reconfigurable manufacturing systems by taking the degradation of modules.
4	[12]	The multistage manufacturing measures have been utilized to focus on modelling the interconnection between product quality degradation and tool wear.
5	[24]	Addresses the issues of maintenance, joint production, for an untrustworthy production system subjected to degradation.
6	[22]	Researches Inverse Gaussian models for degradation investigation, with constant monotonic degradation rates also mentioned.
7	[25]	Introduces a degradation modelling system for assessing and updating the RLDs of partially degraded segments using an FPT approach.
8	[26]	Works on the availability of machines as well as random failure rate to fulfil economically a random demand under certain constraints.
9	[27]	Describes linear-quadratic stochastic production planning issues so as to fulfil a random demand.

3.1.2. Degradation

Degradation is a stochastic process, which will occur through random shocks and also through the components being worn in manufacturing processes. Degradation rate plays a significant role in the life of FUS because the impact of the degradation process on different types of manufacturing systems are observed on the failure severity. A Degraded machine impacts on the nature of the parts manufactured where the defectives rely upon the production rate, as has been mentioned in [28]. Zied et al. [27] worked on the degradation of the unit as stated by the rate of production. Hajej et al. [26] explained that their examination is to investigate the impact of the production rate on the degradation level and machine availability. Through this diverse literature, it was shown that the degradation process was grouped in two ways, i.e., continuous degradation and discrete degradation.

Zhenggeng et al. [21] explained about multiple degradation methods, which involve continuous degradation, as well as that discrete degradations have been modelled through various stochastic processes, for example, Markov renewal and gamma processes. Zhang et al. [29] proposed that the conventional Wiener process-dependent degradation is an important degradation model technique for manufacturing systems. With this, the past research on the degradation of manufacturing systems showed that efforts have been made to characterize the relation between degradation rate and workload adjustment strategy by using a Bayesian approach to find the residual life distribution literature, as is mentioned below in Table 7.

Table 7. Literature review on residual life distribution related to flexible unit systems.

Literature Review on Residual Life Distribution in the Context of Flexible Unit Systems		
Sl. No.	**References**	**Findings**
1	[30]	To predict the Residual Life under time differing conditions, the degradation rate changing and unexpected signal bounds at condition change points have been proposed.
2	[29]	In this paper, an attempt was made to audit and sum up the ongoing demonstrating improvements of Wiener process models for assessing the Residual life.
3	[31]	A data-driven technique for Residual life expectation depends on a Bayesian approach that has been proposed.
4	[32]	In this paper, remaining useful life prediction of slightly degraded parts with co-dependent degradation processes have been shown.
5	[33]	Describes the fundamental steps needed to execute the Prognostics and Health Management System, so that the remaining useful life of CNC milling cutters can be predicted.

3.1.3. Residual Life Distribution

A machine's or a component's residual life estimation during its operation based on its present condition is very important in order to find its health condition. Li et al. [30] proposed a remaining useful life prediction by introducing the degradation rate changing to transition function, and it jumps the degradation signals towards the measurement function. For example, in the manufacturing industry, the usage of a prognostic health management system for deciding the residual life of a milling cutter in a high-speed milling machine depends on externally measured conditions, as has been mentioned in [33].

Bian et al. [32] introduced how prediction of the life of a complex manufacturing system needs an exact estimation of degradation conditions of its constituent parts as well as an adequate understanding of how these stages progress in the future. Si et al. [34] proposed s degradation method to anticipate the remaining useful life of machines utilizing a recursive channel calculation. Zhang et al. [29] surveyed modelling improvements of the Wiener process strategies for degradation information examination, remaining useful life estimation as their implementation in the empirics of the health management of manufacturing systems. Mosallam et al. [31] presented two stages of an information-driven strategy for remaining useful life prediction. It is noted that based on the residual life of a manufacturing unit, a workload adjustment strategy will be helpful to maintain the production rate mentioned in Hao et al. [12]. The various literature related to workload strategy has been mentioned below in Table 8.

Table 8. Literature review on workload strategy related to flexible unit systems.

Literature Review on Workload Strategy in the Context of Flexible Unit Systems		
Sl. No	**References**	**Findings**
1	[35]	Investigates the effects of various workload strategy methodologies on manufacturing system performance by a mathematical study.
2	[36]	A workload adjustment has been proposed to find the extreme workload to the remaining working units to fulfil the manufacturing prerequisites.
3	[37]	Focuses on the dynamic workload adjustment to manage the degradation of all the units in a compound system.
4	[38]	Works on dynamic workload adjustment strategy to control the degradation of units.

3.1.4. Workload Strategy

A dynamic workload adjustment technique has been proposed by [36] to locate the most extreme workload machinery. In their work, the highest degraded machines were identified to satisfy the production necessities on parallel configurations. With various benchmark instances, simulation tests have been conducted to assess the degradation rate. Li et al. [35] explored the effects of various workload adjustment methodologies on a system agent-based simulation approach. To prevent the overlap of machine failure within a period of time, Hao et al. [39] developed a method to control the degradation and predicted failure time of each machine by adjusting the workload. Similarly, the allocation of buffer capacity is especially important in order to obtain an acceptable throughput and work-in-progress, as mentioned in [40].

3.1.5. Descriptive and Predictive Model Management

The arrangement of the present smart manufacturing systems is subjected to the capacity for (a) sensibly modelling the production system, (b) predictable plant information, (c) solving issues proficiently with computational attempts, and (d) including feedback to raise the decision-making on top of time. Hence, enabling descriptive and predictive analytics for the estimation of manufacturing systems performance is a greater concern in the current information and digital age.

3.1.6. Resource Management

Resource management is the way towards planning, scheduling, and allocating resources in the best possible way. More observation is on future manufacturing, where resource management is a greater concern and it must handle more proficiently. Particularly different manufacturing, as well as automotive industries, are advancing towards utilization of resources to improve proficiency and profitability without trading off the current manufacturing capacity. De Ryck et al. [41] proposed a methodology that makes resource management in automated guided vehicle systems more effective. The resource management aims at providing robust strategies in manufacturing systems to accomplish the resource allocation and to solve related issues, for example, resource levelling, and production layout adjustment in production planning.

3.2. Diagnostics for Unit Systems

Present manufacturing systems are outfitted with different sensors that provide continuous checking and diagnosis, but sensors cannot be equipped across all the parts in the manufacturing system due to big data challenges. These outcomes in non-observable parts limit our capacity to help successful and continuous real-time monitoring and fault diagnosis activities. The exact diagnosis is the most significant step because the fault is the primary cause of a manufacturing system's failure in the fault treatment. Among a wide range of possible faults in a manufacturing system, operative faults occur most often (about 70%). Djelloul et al. [42] solved maintenance optimization issues in manufacturing systems by considering the diagnosis and suggested a hybrid neural network technique focusing on developing a diagnosis system. Qin et al. [43] proposed that a fault identification, as well as a diagnostic module, is depicted dependent on an internal programmable logical controller. Generally, manufacturing industries have a large number of machines with different old programmable logic controllers that can benefit from an upgrade to new technology. The literature related to the upgradation of manufacturing equipment is mentioned below in Table 9.

Table 9. Literature review on upgradation related to flexible unit systems.

Literature Review on Upgradation in the Context of Flexible Machine Systems		
Sl. No.	**References**	**Findings**
1	[44]	Introduces a plan for usage of a data preparing kit that will upgrade a manufacturing machine allowing it to coordinate into an industry 4.0 environment.
2	[45]	Explains that the traditional manufacturing industry upgrading is partially important in this trend.
3	[46]	Explores the situation of a system upgrade, both electronics and mechanical, which requires extensive software modifications.
4	[47]	Considers the problems of selecting and upgrading equipment for creating and upgrading production systems on facilities with discrete manufacturing.

3.2.1. Upgradation

According to [48], there are four motivations for the upgradation of manufacturing equipment. They are support, cost performance, reliability, and need for change. Pavlov et al. [47] considered the issues of choosing and upgrading equipment for making and upgrading manufacturing systems on facilities with discrete manufacturing. An example has been taken and it solved an excess of ten equipment choice test issues for the plan and upgrade of manufacturing systems. Garcia-Garza et al. [44] present a strategy to identify and upgrade a data preparation unit to make it viable with an extensive system as it advances into an Industry 4.0 condition.

Grohn et al. [46] investigated the upgradation of a production system model with mechanical capacities, and the experimental study incorporates changing of a mechanical plant and relocation of computerization system programming to another, more distributed machinery configuration. Xingyu et al. [23] present a reconfigurable manufacturing systems decision-making model to ideally decide and alter operational activities continuously considering demand fulfilling, system health, and maintenance cost. Furthermore, predictive maintenance will help to maintain the system's health in an efficient way. The literature related to predictive maintenance of the flexible unit systems is mentioned below in Table 10.

Table 10. Literature review on predictive maintenance related to flexible unit systems.

Literature Review on Predictive Maintenance in the Context of Flexible Unit Systems		
Sl. No.	**References**	**Findings**
1	[49]	A general framework has been developed and that has been applied to manufacturing tools by using predictive maintenance.
2	[50]	Conducts a study of the predictive maintenance on industrial equipment.
3	[19]	Presents a prognostic method that uses sensor degradation data for calculating the time to failure of machines, with maintenance policy.
4	[51]	Develops a cutting tool wears monitoring and predictive maintenance system.
5	[20]	Proposes a multisensor prognostic method, that uses multistream signs to anticipate the Remaining Useful Life of partially degraded systems.
6	[52]	The proposal focuses on predictive maintenance of manufacturing systems and tools.
7	[53]	Introduces the predictive maintenance system, and joints product quality as well as mission reliability imperatives.
8	[54]	An extended model with a system that connects a low-level execution condition monitoring information.
9	[55]	Presents the design and implementation of a conductance sensor for micromachining processes.
10	[56]	A sensory updated degradation-based maintenance has been presented to assess the predictive maintenance by using residual life distributions.

3.2.2. Predictive Maintenance

Nowadays, predictive maintenance is considered as the key point for many manufacturing industries because of a major part of the operational cost and system failure impacts on product quality and equipment availability. Menezes et al. [55] explained that predictive maintenance considers close past information for predicting future tendencies, biases, behaviors, etc. through correlation. He et al. [53] introduced that predictive maintenance is an analytic technique to eliminate prospective failures and improve the mission dependability of production systems. Consequently, a coordinated predictive maintenance procedure considering item degree and mission dependability state was proposed from reasoning of prediction and manufacturing. Spendla et al. [52] proposal focused on predictive maintenance of manufacturing systems to improve the production process quality.

Dong et al. [19] have attempted to work on a flexible structure of a versatile manufacturing system to satisfy different needs and item varieties and to build up a PHM structure for assembling with different online sensors and flexible structures utilizing different sensors-based degradation data for registering and predicting each machine's time to failure. For example, Traini et al. [49] discussed the execution of predictive maintenance of milling cutting tool information, and the collection as validation of a structure, and [56,57] presented a model-driven approach using embedded artificial intelligence strategies by the development and implementation of a quality monitoring framework, and also presented a sensory system for high precision monitoring, applicable to all machining and milling operations on conductive materials. Kevin et al. [58] proposed a sensory updated degradation based predictive maintenance strategy. Their proposed maintenance strategy used degradation methods that combine part-specific continuous degradation data obtained during activity to predict the remaining useful life distribution. Yildirim et al. [54] expanded an adaptive predictive generator maintenance model that has been presented. From the different literature, on predictive maintenance, it can be concluded that the predictive maintenance of the machines allows extending of the machine's life and the lowering of maintenance costs by addressing the problems before they cause machine failures.

3.2.3. Data Management

The need for more flexible and efficient data management in manufacturing systems is necessary to secure the maximum productivity for many manufacturing organizations. The systems require precise and current information as ongoing activity to meet users' expectations. For example, information and communication technology take part in a significant role in the factors of Industry 4.0, and data management becomes a major problem for different types of manufacturing systems. The related literature, such as Song et al. [59], focused on data management that explains the defective data generated by the unsuitable operation of cyber components of a manufacturing cyber-physical system. Similarly, Liu et al. [60] proposed an application of a Digital Twin technology in the manufacturing area to show a significant effect in enabling the manufacturing data management.

3.2.4. Prescriptive Model Management

The prescriptive maintenance empowers manufacturers to resolve their own maintenance needs without the need for a vast array of experts, as mentioned by Brian Brinkmann. Menezes et al [55] explained that prescriptive analytics finds the best route to operate (outputs) in the view of given information and models (inputs). Similarly, Lepenioti et al. [61] said that prescriptive analytics tries to locate the best action for the future in the manufacturing industry and it is frequently considered as the subsequent stage towards improving data analytics maturity for business execution improvement. Moreover, prescriptive analytic strategies, such as decision optimization, can handle profoundly complex issues running from hundreds to a large number of limitations that would never be analyzed manually, and Matyas et al. [62] proposed a prescriptive maintenance methodology for manufacturing systems analysis, as well as simulation tools, that have been utilized to analyze past data, i.e., machine failure data and product quality data, to guarantee a high level of process flexibility and the quality of the product.

3.2.5. Operations Management

The job of operations management is to oversee the process of converting resources into goods and services. Hashemi-Petroodi et al. [63] focused on the challenges of the interactions between machine robots and humans in order to find the effective contributions of operation management's methods to improve the working condition of hybrid manufacturing systems. Kozjek et al. [64] research focused on investigating manufacturing data collected from a manufacturing system during various operations conducted in an engineer-to-order enterprise, and developed tools for scheduling of operations.

4. Discussion and Future Research Agenda

This paper presents the SLR using different articles to discuss degradation and upgradation models for flexible unit systems life. Some significant issues from the review are talked about in this section. Moreover, there is an opportunity to identify the number of research gaps, with suggestions for future work. The discussion follows the conceptualization that appeared in Figure 1. First, the 5 keywords that have been taken into consideration are (1) Degradation, (2) Residual life distribution, (3) Workload adjustment, (4) Upgradation, and (5) Predictive Maintenance. The keywords have helped us to find related journal articles by searching in the three databases in the selected research area. Authors such as [43,65,66] discussed different analytic techniques, for example, descriptive, predictive, and prescriptive, to analyze manufacturing data for achieving competitive benefits for the manufacturing industries.

Authors Hao et al. [12], Ben-Salem et al. [24], Peng et al. [67], Bian et al. [68], and Hajej et al. [26] worked on the degradation of different configurations, for example, series and parallel configuration manufacturing systems. Zhenggeng et al. [21] worked on degradation models and various stochastic processes like gamma process and Markov renewal process to find the degradation rate of manufacturing equipment. Zhang et al. [29] proposed conventional Wiener process-based degradation as one of the most important degradation model techniques among different degradation techniques. Naipeng et al. [30], Das et al [33], Si et al. [34], Zhang et al. [29], and Bian et al. [32] worked on finding the relationship between degradation rate and the residual life of a machine. The prediction of the manufacturing unit's residual life will be helpful to reduce the degradation rate by adjusting the workload to maintain the maximum production rate.

Adam Robinson [48], Pavlov et al. [47], Garcia-Garza et al. [44], Grohn et al. [46], Du et al. [45], Menezes et al. [55], and Dong et al. [19] investigated upgradation of a manufacturing system, which will help to enhance the performance and reliability of manufacturing equipment. Spendla et al. [52], Dong et al. [19], Fang et al. [20], and Kaiser et al. [69] present the predictive maintenance of machines using sensors degradation data for calculating the time to failure of various machines. Traini et al. [49], Zhang et al. [50], and He et al. [53] worked on predictive maintenance analytics by considering recent past data to eliminate prospective failures and also to improve the mission dependability of production systems.

4.1. Research Opportunity 1: How Can Residual Life Be Predicted in FUS to Improve Systems Efficiency

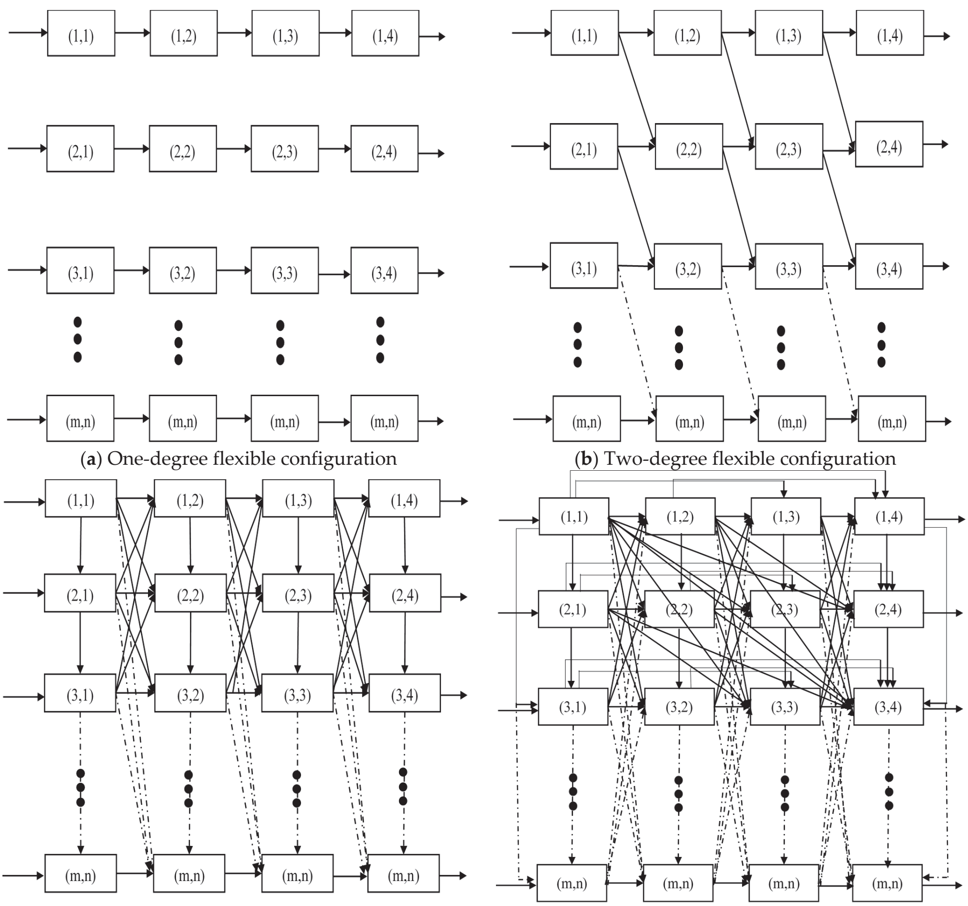
Degradation is an unavoidable characteristic, which it requires the utmost attention to pursue. However, a lot of literature is already available to handle the degradation rate at the component level. A limited number of papers (Hao et al. [12]; Manupati et al.) [38] have considered system level degradation, especially in the manufacturing systems context. A recent paradigm shift has forced the use of the Internet of Things (IoT) in almost every stage of the product life cycle. In addition, process industries have highly benefitted from the key technologies that emerged from this shift (Varela et al., [70] Varela and Ribeiro,) [71]. To make these processes effective and efficient, system-level health monitoring is a new thinking among researchers paying attention to these issues. To improve the health status of the system, an individual system's degradation rate needs to be decreased, which in turn improves the residual life of the machine. Here, the residual life of a machine was characterized as remaining useful time till its level of degradation arrives at a predefined failure threshold. The degradation and residual life follow different distributions depending on the order requirement and system status. Hence, this is a challenging work one can take into consideration to explore further.

4.2. Research Opportunity 2: How to Deal with Heterogeneous Data Obtained from Various Sensory Sources for Predicting the Degradation Rate of FUS?

Heterogeneous data includes multiple internal and external databases generated from different sources obtained in various dimensions (Varela and Silva, 2008 [72], Zhang and Gregorie, 2016) [73]. Real-time production data from complex systems produce a huge variety and volume of data. Handling these kinds of data-intensive systems with conventional statistical tools may be insufficient when firms seek to strategically conceal the data [13,74–76]; Hence, to handle the heterogeneous data in FUS and predict the degradation rate, improving the residual life advanced analytics is essential. This area opens wider challenges for the researchers to explore.

4.3. Research Opportunity 3: How to Develop FUS for Real-Life Problems?

In this section, we propose four different configurations derived from the real-life examples: i.e., one degree, two degree, semi-flexible, and fully flexible, shown in Figure 2a–d. Where one degree configuration is represented, it handles the requirements to process it in sequential order. The open braces (1, 1) represent the position and stage of the machine, e.g., (1, 4) in Figure 2a. Consequently, for two degrees of flexibility, the configuration is shown in Figure 2b, through which, after the jobs arrived and processed in the first machine are chosen for the next operation to process on the second machine, it has a flexibility of alternative machines available in the second position at the second stage. Hence, it has position flexibility, routing flexibility, and machine flexibility to execute the operations. Figure 2c,d represents the semi-flexible and fully flexible unit system, wherein in the semi-flexible configurations, the second operation can be processed on more than 2 machines unlike the restrictions presented in the previous systems. In the fully-flexible systems, the machines have the flexibility to process any operation at a time.



(**a**) One-degree flexible configuration (**b**) Two-degree flexible configuration

(**c**) Semi-flexible configuration (**d**) fully flexible configuration

Figure 2. Flexible unit system with different configurations.

5. Conclusions

A significant amount of literature related to manufacturing systems has been made available during the last decade to conduct various investigations. However, regardless of growing interest in these investigations, the existing literature does not bring clarity on the degradation and upgradation strategies, and models on recently emerging FUS. Despite the availability of many manufacturing systems, the arrangement of machines according to demand is of crucial importance, along with the capability of simultaneously adjusting the machines with different flexibilities to compensate the workload, and, in turn, for reducing the degradation of the system. Moreover, an integrated approach using predictive, prescriptive, and descriptive analytics and the parameters required to understand the performance of the system in line with the mentioned advanced analytics are also not much explored. To overcome this gap, this paper presented a systematic literature survey on the proposed FUS to identify the key factors that greatly affect system performance.

The review of this study was conducted based on SLR, and 59 articles were deeply analyzed after removing the duplicates. In this paper, from the observations, five key parameters, i.e., degradation, residual life distribution, workload strategy, upgradation, and predictive maintenance, were identified and their individual contributions were analyzed in the context of FUS. From this study, it is understood that the degradation rate will affect the life and production rate of different configurations of FUS. Moreover, the upgradation model and predictive maintenance, along with advanced analytics procedures of the manufacturing systems, are valuable and enable the systems to run with higher production rate, while increasing the life of a system. Furthermore, this study analyzed different existing research and established three research objectives to explore and improve the proposed FUS. The authors hope that this research can serve as a guideline for more research and discussion of FUS towards degradation and upgradation models.

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Design Technology and AI-Based Decision Making Model for Digital Twin Engineering

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Abstract: This research considers the problem of digital twin engineering in organizational and technical systems. The theoretical and methodological basis is a fundamental scientific work in the field of digital twins engineering and applied models. We use methods of a system approach, statistical analysis, operational research and artificial intelligence. The study proposes a comprehensive technology (methodological approach) for digital twin design in order to accelerate its engineering. This technology consists of design steps, methods and models, and provides systems synthesis of digital twins for a complex system (object or process) operating under uncertainty and that is able to reconfigure in response to internal faults or environment changes and perform preventive maintenance. In the technology structure, we develop a simulation model using situational "what-if" analysis and based on fuzzy logic methods. We apply this technology to develop the digital twin prototype for a device at the creation life cycle stage in order to reduce the consequences of unpredicted and undesirable states. We study possible unforeseen problems and device faults during its further operation. The model identifies a situation as a combination of failure factors of the internal and external environment and provides an appropriate decision about actions with the device. The practical significance of the research is the developed decision support model, which is the basis for control systems to solve problems related to monitoring the current state of technical devices (instruments, equipment) and to support adequate decisions to eliminate their dysfunctions.

Keywords: digital twin; methods for modeling digital twins; system design of digital twins; artificial intelligence methods

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1. Introduction

Under the fourth industrial revolution, the driver of innovative development in high-tech enterprises is the technology of a "digital twin" (DT), or a virtual replica of a cyber-physical system, a virtual prototype of real processes or products. DTs, and more generally, computer-aided design and simulation technologies, are intended to meet the great challenge of creating complex engineering structures and technical systems that are optimal by the setting of conflicting performance criteria. The potential benefits of DT include the ability to perform what-if analyses and provide decision support by fast-verifying designs and digital tests used in changing the product, process or its components. DT applications contribute to the growth in the competitiveness of manufactured products by enhancing the market processes by reducing the time for product development, testing and implementation.

However, the organizational and methodological maintenance for DT development is still not fully developed from the point of the monitoring and coordination of physical objects. Such a methodology requires a systematic approach for an object's design taking into account various aspects—functions performed, including the identification and solution of operational problems, complexity, purpose, life cycle stages and other object features.

The aim of this paper is to develop organizational and methodological maintenance for organizational and technical systems with a DT design, which provides a systematic synthesis of design stages, tools (methods and models) and results aimed at accelerated DT engineering. To achieve the goal, the following problems are solved:

1. Generalization of approaches and methods for the modeling and designing of organizational and technical systems' DT.
2. Development of the system model and technology for setting up organizational and technical systems' DT design process.
3. Within the framework of DT model suggestions, development of the decision support model for diagnosing a device's technical conditions and making decisions to eliminate its malfunctions based on artificial intelligence and fuzzy logic methods.

This article is organized as follows. The second chapter examines and critically summarizes methods for modeling digital twins. The advantages and disadvantages of the methods are described, and the scope of their applicability is determined. The third chapter presents the developed methodology for systems engineering and technology for the designing of organizational and technical systems' DTs. The fourth chapter reflects a numerical example of the implementation of the developed technology and considers the digital twin of a medical device. The fifth chapter is devoted to the decision making model based on the fuzzy logic method, which is part of the digital twin. The results obtained by the model are discussed. The conclusions give the main results of the study and outline their theoretical and practical significance.

2. Literature Review

There are three groups of approaches and methods used for DT designs:

- modeling methods based on the mathematical modeling of physical processes (structural models) (Simulation-Based DT) [1–5];
- modeling methods based on data (Data-based DT) [6,7];
- hybrid methods (Hybrid DT) [8–11].

Features of the above methods are given in Table 1, which summarizes modeling approaches by certain characteristics.

Table 1. Comparative analysis of the models for DTs of organizational and technical system designs.

Feature	Modeling Approach		
	Mathematical Modeling	**Data-Based Modeling**	**Hybrid Modeling**
Object (system) description	Describes the laws of functioning of an object (process) and its connection with the external environment. The system behavior is modeled, causal relationships and patterns are identified.	It is built on the basis of available empirical data using machine learning tools. The modeling problem is reduced to model parameters selection and some function composition	It is built on the basis of the functioning regularities and is adjusted with empirical data
Modeling principle	White box model, cause-and-effect modeling	Black box model, correlation modeling	The gray box model
Simulation and design direction	Top down	Bottom up	Top down, bottom up
Description of information certainty	Information uncertainty is controlled by input data and accuracy of modeling. Description—deterministic, stochastic	Probabilistic description of information based on data distributions in training samples	Deterministic, stochastic
Modeling methods	Numerical methods, methods of operations research, methods of simulation and situational modeling	Statistical methods, extrapolation methods, machine learning methods, big data analytics methods	Interdisciplinary models

Table 1. *Cont.*

Feature	Modeling Approach		
	Mathematical Modeling	**Data-Based Modeling**	**Hybrid Modeling**
Predictive capability	Prediction in wide ranges of parameter values described by the model	Difficulty in predicting rare events as well as in conditions of incomplete data and noisy information, as well as outside of training samples	High predictive ability within regular/ emergency situations
Priority approach to decision making and management	Decision making is based on an analysis of the overall performance (efficiency) of the system. Management decisions based on the solution of inverse problems	Decision making is based on the analysis of monitoring data and diagnostics. Management decisions are based on prediction and the solving of direct problems	Solving both direct and inverse control problems
Type of control system	Deviation control, adaptive control	Deviation control, adaptive control	Deviation control taking into account weak environmental signals; reflective control
System life cycle stage	All stages	Exploitation	Growth, stability
Operation scheme	Numerical simulation + sensors→ Data acquisition→IIoT platform	Sensors + IIoT platform→ data collection→data analytics	Mathematical Modeling + Sensors→ Data Acquisition→ IIoT-platform→analytics
Tools	Matlab Simulink, ANSYS, AnyLogic, Ithink etc.	R, Python, Statictica. GPSS etc.	Interdisciplinary Platforms

A generalized modeling method is the mathematical modeling of the physics (functioning principles) of an object/process. The physical model provides for the computer modeling of physical processes as well as a description of their functioning and relationships with the external environment. The construction of such models in practice is associated with the mathematical programming methods (operations research) [12], and simulation modeling based on its various paradigms and approaches—system-dynamic, discrete-event or agent-based modeling [13].

Mathematical modeling is a key component of the digital transformation. To create models that are used to create system models, the DT can use the results of detailed three-dimensional numerical calculations performed using interdisciplinary CAE solvers. Depending on the purpose, mathematical models can be descriptive or optimizing. The purpose of descriptive models is to establish the laws of change in model parameters. The optimization model provides a search for the function's extreme value under restrictions using numerical methods. Depending on the certainty of the initial information degree and taking into account the time factor, linear, non-linear, stochastic programming, game-theoretic and fuzzy logic methods can be used.

Simulation models as a subclass of mathematical models are divided into static and dynamic; deterministic and stochastic; discrete and continuous. In continuous simulation models the variables change continuously, the state of the simulated system changes as a continuous function of time, and as a rule, this change is described by systems of differential equations. In discrete simulation models, variables change discretely at certain moments in simulation time. The dynamics of discrete models are a process of transitioning from the moment of the next event to the moment of the next event.

Data-driven modeling includes data mining, artificial intelligence, big data and advanced analytic methods. Each of these methods imposes special requirements on the necessary computing resources. For example, data mining methods require large-scale storage with high bandwidth for collecting and accessing analytical data, as well as a high scalability for the computing system for processing them; machine learning methods require nodes with installed graphics accelerators.

Models based on data mining are used to discover knowledge in the data previously unknown, non-trivial, or practically useful and open to interpretation, necessary for making strategically important decisions. Artificial intelligence and machine learning are effectively used in digital warehouse forecasting. The use of these methods makes it possible to achieve a level of predictive accuracy higher than that based on traditional simulation methods [13].

The use of "big data" has its limitations, associated with incomplete or noisy data, and difficulties in predicting rare events. Extrapolation methods do not allow for such predictions. For some products, sensors are expensive to install and maintain, sensors are prone to errors, failures can give incorrect readings, and the results can overwhelm users with redundant information.

Without a structural (mathematical, physical) model, it is difficult to determine the areas of technical devices where it is advisable to locate sensors. Collecting raw data from sensors is only part of the modeling process. At the stage when the inverse problem appears, that is, when it is necessary to restore the picture of what is happening on the basis of data received from sensors without a mathematical model, this problem turns out to be intractable, since most of the collected data are unusable "garbage", of which it is very difficult to select a meaningful part that adequately describes the object (process).

At the same time, the mathematical modeling of objects (processes) in combination with data-based models provides more opportunities for forecasting than models based only on machine learning technologies. Data-driven modeling can be applied at the operational stage of an object's (product) life cycle, when it is possible to obtain feedback from it. Mathematical models based on physical processes are more promising for problems with a situational analysis and for decision making under "what-if?" condition analysis. In addition, hybrid models can be used in non-recurring situations where there are not enough data to apply statistical methods.

On the basis of the additional information obtained during the operation stage, the level of adequacy of the hybrid model increases, that is, the DT is trained and makes it possible to further predict the level of possible deviations from normal modes and damage to equipment, or evaluate its residual life [10].

It should be noted that at different stages of DT design, there is a different amount of data about object. At the development stage, there are no data from a real object, since there is no physical product (product) itself, and data about an object can only be obtained on the basis of modeling physical processes that determine the creation and functioning of a future product. As product data accumulate, the latter can increasingly be used to build analytical models. A mathematical model based on physical processes can be created before the stage of creating a real object, and can predict its behavior over a wide range when the boundary conditions of the numerical simulation problem change.

A DT with a high level of adequacy should combine both physical process models and data-driven models. Smart digital twins with intelligent controls should combine both of these approaches, enhancing the benefits of each of them.

The use and scope of digital twins is very wide. They are used not only in heavy engineering [14–16], in the automotive industry [17] and building [18], in the field of nuclear energy [19], in the aerospace [20,21] and oil and gas industries [22], in architectural design and creating smart cities [23], and agriculture, but they are also used to improve operational efficiency in the production of consumer goods [5], the accuracy of diagnostics and decision making in healthcare [24], to attract customers and customize services in the financial sector [25] and in retail [26], for organizing logistics processes and supply chains [27], and in regional and municipal management [28,29].

Demand for and the range of application of DTs is expanding. Since their development and implementation are based on a number of rapidly developing technologies, the development of digital storage directly depends on the growth of the capabilities of these technologies. This is due to:

- The development of quantum technologies and the increase in the speed of computing systems [30,31]. If general-purpose quantum computing is ever realized, there would be a qualitative leap in the speed of hardware systems. This will make it possible to perform numerical analyses based on already existing (and more complex) models in a time acceptable for the operational interaction of a physical object and its digital copy. Today, companies are working to develop and use quantum algorithms to model complex physical processes. The transition to such technologies will speed up the solution of problems based on numerical modeling, providing for the required accuracy of algorithms under the conditions of the available computing resources (problems of multi-parameter optimization, etc.);

- The development of 5G and 6G technologies [32–34]. These technologies have higher throughput, lower latency, and lower battery consumption of IoT sensors. This provides an increase in the speed of signal transmissions between the physical object and its DT. The use of 5G networks will make it possible to construct virtual reality services as part of digital twins and make available the virtual verification and validation of finished products.
- The development of strong artificial intelligence technology [35,36] will make it possible to build a data center in which the role of a person in making managerial decisions will be minimized. DTs will be able to provide decision making autonomously, coordinate these decisions with other DTs, and perform self-testing and diagnostics with subsequent troubleshooting. Such decision support systems based on digital data will ensure the adoption of complex decisions in aggressive and dangerous environments without the presence of a person.

3. Methodology for Systems Engineering and Technology for Digital Twin Design

Following [37], and dividing the behavior types of a real system into Predicted Desirable (PD), Predicted Undesirable (PU), Unpredicted Desirable (UD), and Unpredicted Undesirable (UU), in this work, we build a Digital Twin Prototype that describes the prototypical physical artifact. It contains the necessary components to describe and produce a physical version that twins the virtual version. We consider the “create” life cycle stage of the system (physical object). At the create life cycle stage of the system, the problem is to foresee its possible states and develop a decision support system to neutralize the consequences of unforeseen events.

While the traditional approaches have been to verify and validate the requirements, or the predicted desirable (PD), and to eliminate the problems and failures, or the predicted undesirable (PU), the Digital Twin prototype can help to identify and eliminate the unpredicted undesirable (UU) states. This problem is solved on the basis of changing the simulation parameters within the possible range, and investigates a variety of different situations; it is possible to explore the variety of behavioral patterns of the system that can lead to serious catastrophic problems. Such modeling will allow for designing the physical object in a virtual space with a number of possibilities, and will significantly reduce the consequences of UUs.

The purpose is to develop an approach for digital twin engineering of a physical object (device) that will minimize undesirable unpredictable behavior. This will mitigate or eliminate the negative consequences of such risks. To do this, we propose the following methodology.

The process of DT construction is a multi-stage process and consists of the design and engineering stage, digital modeling and technological testing (Figure 1). In this paper, we consider only the first stage of design and engineering.

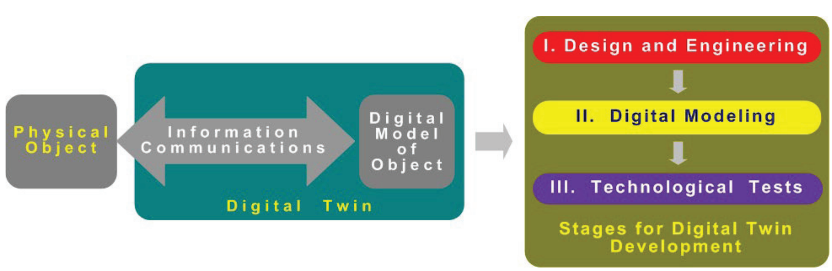

Figure 1. Digital twin and stages for its development.

DT is defined as a system consisting of a physical object digital model and two-way information links with the physical object or its components. DT is based on a digital model in the form of mathematical and computer models, as well as documents that describe the structure, functionality and behavior of a newly developed or operated product (object) at various stages of its life cycle, for which, based on the results of digital or other tests, an assessment of compliance with the requirements for the product was carried out. In this case, a digital model is created using computer simulation software and describes the structure, functions and behavior of the product being developed. The content and functionality of the digital model depends on the stage of the product's life cycle. The conformity assessment of a digital product model generally includes verification and validation procedures for mathematical and computer models. A computer model is implemented in a computing environment and is a collection of data and program code required to work with data. The computer model is based on a mathematical model, that is, a model in which information about the modeling object is presented in a formalized form.

The organizational requirements to create a digital twin include the use of a software and technological platform for digital twins, which should include: (a) computer modeling software controls; (b) project management tools: (c) tools for collecting, processing, analyzing, visualizing, cataloging, storing, transferring computer models and computer simulation results; (d) means of tracking all changes in design, technological solutions and modifications of computer models, and options for engineering calculations; (e) means of reporting results; (f) means of data protection and organization of joint work of project participants in accordance with access rights; (g) computer simulation tools for planning the usage of an object (product) for its intended purpose; (h) maintenance and repair support.

The organizational and methodological support of DT is not fully developed in terms of the coordination of modeling and management processes including structural, functional and informational modeling. To fill this gap, we propose to form a work plan by its stages like triads: problem–content–results. These require a systems approach and design for all life cycle stages of a physical object, including the identification and solution of emerging problems in the process of its operation.

We develop the following technology, which provides organizational and methodological support for the development and operation of DT for the organizational and technical system and is presented in Figure 2. The proposed technology combines the stages of its design, methods and models, and provides for the accelerated engineering of DT.

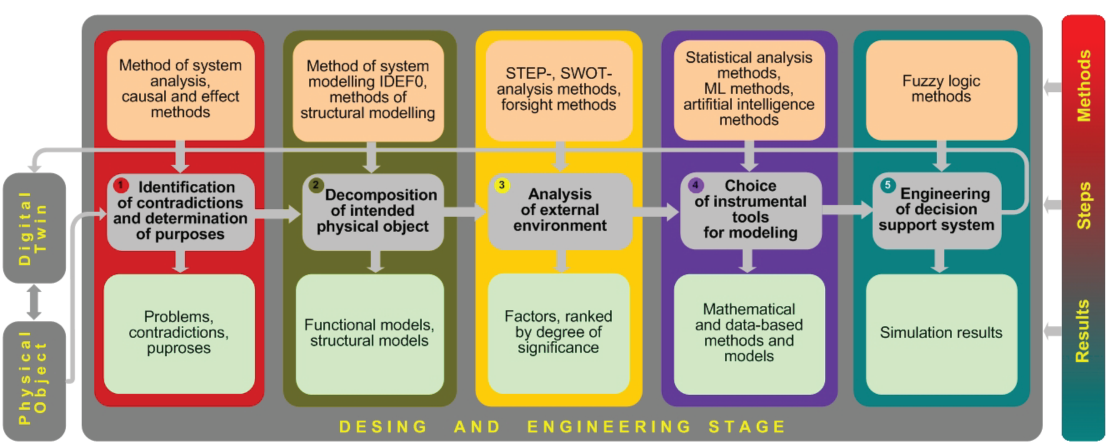

Figure 2. Technology for digital twin development (stage "Design and Engineering").

The proposed technology allows, firstly, to carry out a system analysis of a physical object, taking into account the uncertainty of the external environment on the basis of heterogeneous tools for qualitative and quantitative analysis. Secondly, it forms an adequate mathematical model of the physical object, taking into account the results of the conceptualization stage, and develops a computer model and implements a test of it. Thirdly, it can be the basis for DT engineering and forming a decision support system.

The operational scheme of the proposed technology consists of five steps. First, it is necessary to identify the problems and describe the contradictions that arise in the development and implementation of digital twins in the industry. Next, we should determine the goals of the DT implementation, set problems based on the goal and describe the project. At the second step, the decomposition (scanning) of physical object takes place. The functions and properties as well as the technical parameters of the considered system (equipment, device) are described. Further, its structural and functional model is built. The third step is devoted to the analysis of the external environment of the functioning of the technical system. Using STEP (Social–Technological–Economic–Political) and SWOT (Strengths–Weaknesses–Opportunities–Threats) analysis, we determine important internal and external factors and expertly evaluate their impact on the effectiveness of DT. At the fourth step, mathematical and computer modeling tools and methods for DT designing are chosen. In addition, a decision support system is being built based on the selected mathematical model, and simulation experiments are being carried out.

4. Empirical Results

As an example of the implementation of the proposed technical device at the creation life cycle stage—a neonatal intensive care incubator with microprocessor controls for monitoring the parameters of temperature, oxygen concentration, air humidity, temperature and body weight is considered. Application of the technology is described by the steps defined in Figure 2.

Step 1. The incubator is designed for the nursing and intensive care of newborns, including premature babies with critically low weight (from 500 g). The incubator provides an adjustable heat supply, the required air humidity and oxygen concentration in the children's module, and body weight control.

Step 2. First, we form the structural and functional models of the device. The block diagram is shown in Figure 3 and consists of a sensor system, control system, temperature control system and oxygen supply. The observed parameters of the device are: (a) air temperature; (b) skin temperature; (c) relative air humidity; (d) oxygen concentration; (e) body weight.

The construction of a functional model allows for clearly fixing what processes are carried out—what information objects are used when performing functions of various levels of detail. The model shows the areas of responsibility of the process executors and the course of the process itself, the relationships between processes and the results. The functional model is the basis for identifying problems and weaknesses in the operation of the device.

The functional model of the incubator is formed on the basis of the notation of system modeling of business process IDEF0. Figure 4 shows the first level of decomposition and reflects the main functions.

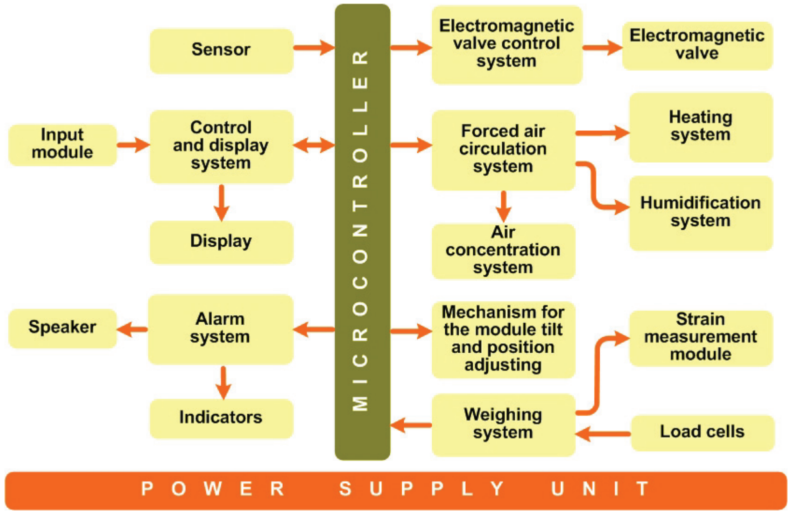

Figure 3. Block diagram for the technical device.

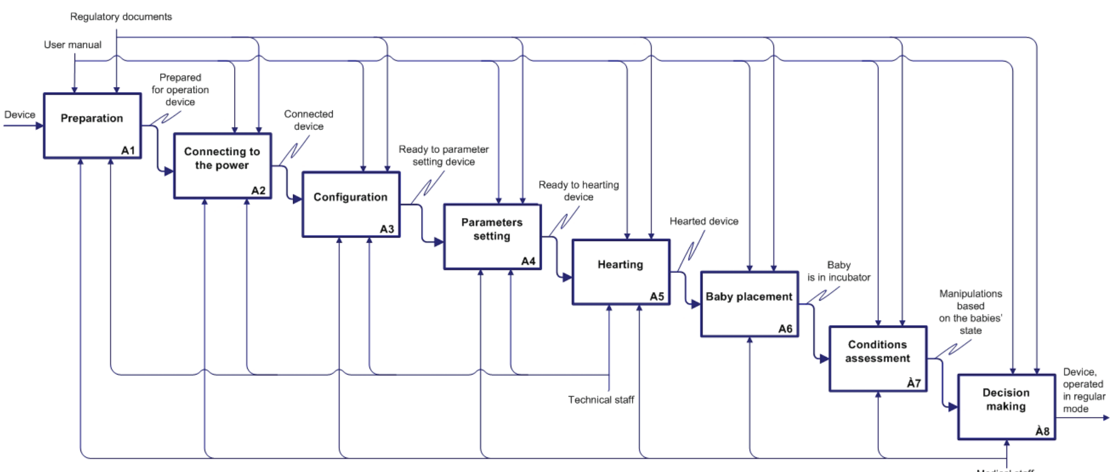

Figure 4. Functional diagram for the device's operation (first decomposition level).

Step 3. At the next step, the diagram of cause-and-effect factor relationships is formed to identify possible causes of failures. Based on a qualitative analysis of similar devices of this class [38], it can be assumed that the following six factors are the main sources of incubator malfunction: (1) medical personnel; (2) technical staff; (3) external environment; (4) sensor system; (5) control system; (6) power system. The diagram shows the decomposition of these factors in the form of problems that, acting in isolation or together, can lead to incubator failure (Figure 5).

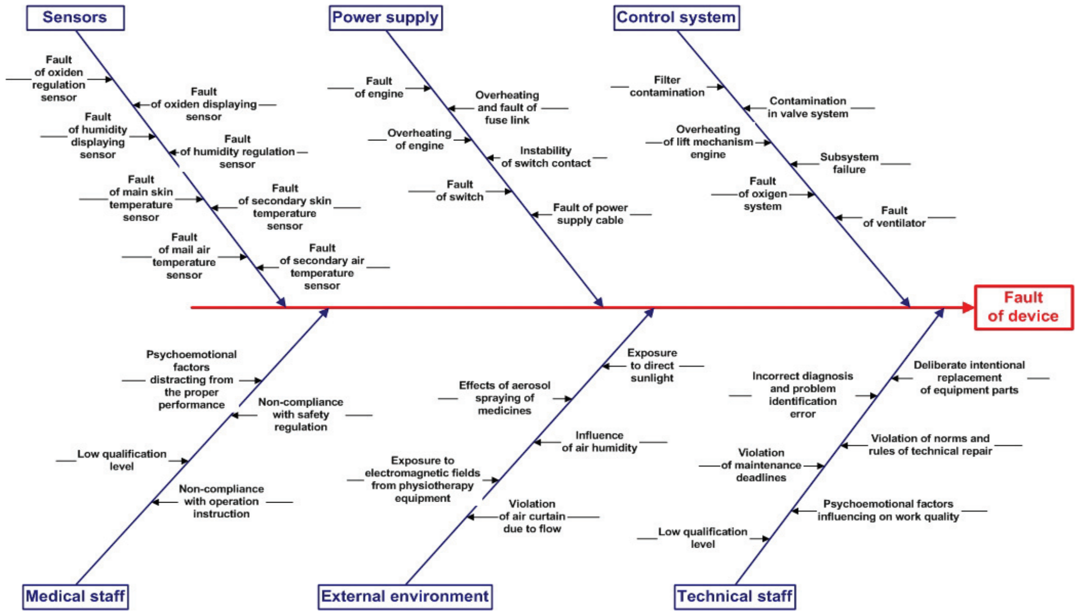

Figure 5. Diagram of cause-and-effect factor relationships for the appearance of possible malfunctions.

Decision Support Model for Diagnosing the Technical Condition of Equipment Based on Fuzzy Logic Methods

Steps 4, 5. Identified problems and possible causes of equipment failure show that a number of factors and causes are described not in quantitative, but in qualitative form. Therefore, a decision support system should use possibilities to use different measurement scales of the simulated device properties. Problems of this type can be solved using artificial intelligence methods and fuzzy logic models [39–41].

The category of technical condition depends on many factors, both qualitative and quantitative. The developed model considers fault factors that are related to the internal technical condition of the device itself, that is, faults associated with the baby module engine, power cable, oxygen connection system, valve impeller system, humidity sensor, temperature sensor of the main and additional, etc.

The implementation of the fuzzy modeling process is carried out by using the Fuzzy Logic Toolbox module of the MATLAB software tool. Fuzzy inference is implemented based on the Mamdani algorithm.

To diagnose the technical condition of a device, its qualitative description is made using linguistic expressions (logical rules). Twenty-five input variables are used, reflecting the state of the equipment subsystems, determining one of the four possible decisions on the action with the equipment (output variable)—to take out of service, to repair, to conduct additional preparation for operation, to keep in service (Table 2).

Table 2. Description of input and output variables.

Indicator	Description	Values
	Input variables	
I_1	Adjusting height position of the baby unit	Impossible, possible
I_2	Adjusting oblique position of the baby unit	Impossible, possible
I_3	Baby module engine	Fault, overheat, serviceable

Table 2. *Cont.*

Indicator	Description	Values
I_4	Baby unit switch mechanism	Fault, correct
I_5	Position height mechanism of the baby module	Turns off, does not turn off
I_6	Air temperature under the hood	Low, normal, high
I_7	Filter	Dirty, clean
I_8	Filter installation time	More than three months, less than three months
I_9	Water in the tank of the humidifying system	Absent, present
I_{10}	Valve system	Dirty, clean
I_{11}	Indicator	Red, network, flicker
I_{12}	Power cable	Not attached, attached
I_{13}	Sound signal	3, 2, intermittent, continuous
I_{14}	Fan impeller	Installed wrong, installed correctly
I_{15}	Fan	Faulty, correct
I_{16}	Display humidity sensor	Faulty, correct
I_{17}	Regulating humidity sensor	Faulty, correct
I_{18}	Main skin temperature sensor	Fault, serviceable, not connected, connected
I_{19}	Secondary skin temperature sensor	Fault, serviceable, not connected, connected
I_{20}	Air oxygen concentration	Low, medium, high
I_{21}	Oxygen connection system	Fault, correct
I_{22}	Control system	Fault, good
I_{23}	Obsolescence	Absent, present
I_{24}	Physical deterioration	Not removable, removable
I_{25}	Fusible link	Burnt out, not burned out
	Output variable	
O_1	Technical condition and operation with device	To take out of service, to repair, to conduct additional preparation for operation, to keep in service

Linguistic variables and the range of their possible values are described in Table 3.

Table 3. Description of linguistic variables.

Indicator	Qualitative Meaning	Range of Linguistic Values
I_1, I_2, I_4, I_5, I_7, I_8, I_9, I_{10}, I_{12}, I_{14}, I_{15}, I_{16}, I_{17}, I_{21}, I_{22}, I_{23}, I_{25}	"Impossible", "Faulty", "Not turn off", "Dirty", "More than 3 months old", "Missing", "Not connected", "Installed incorrectly", "Cannot be repaired"	(0; 0.35; 0.7)
I_1, I_2, I_4, I_5, I_7, I_8, I_9, I_{10}, I_{12}, I_{14}, I_{15}, I_{16}, I_{17}, I_{21}, I_{22}, I_{23}, I_{25}	"Possible", "Serviceable", "Disconnecting", "Clean", "Less than 3 Months", "Present", "Attached", "Installed Properly", "Retiring"	(0.4; 0.7; 1)
I_3, I_6, I_{11}, $I_{20.}$	"Low", "Red", "Low", "Fault"	(0; 0.2; 0.4)
I_3, I_6, I_{11}, I_{20}	"Normal", "Network", "Medium", "Overheat"	(0.3; 0.5; 0.7)
I_3, I_6, I_{11}, I_{20}	"Increased", "High", "Central alarm", "Serviceability"	(0.6; 0.8; 1)
I_{13}, I_{18}, I_{19}, O_1	"Take it out of service", "Not operating"	(0; 0.175; 0.35)
I_{13}, I_{18}, I_{19}, O_1	"Repair", "Serviceable"	(0.2; 0.375; 0.55)
I_{13}, I_{18}, I_{19}, O_1	"Intermittent", "Perform additional preparation for operation", "Not connected"	(0.4; 0.575; 0.75)
I_{13}, I_{18}, I_{19}, O_1	"Continuous", "Keep in service", "Connected",	(0.65; 0.825; 1)

The accumulation of the conclusion according to all the rules is carried out using the operation of max-disjunction. The center of gravity method is used for defuzzification. By implementing a fuzzy inference system at the defuzzification stage, we obtain a decision about operation modes under conditions of known input data.

The rule base for making decisions on the technical condition and action with the device in the event of a malfunction is determined using a set of production rules of the “If-Then” type (selectively):

- If (I_1 is “possible”) and (I_2 is “possible”) and (I_3 is “serviceable”) and (I_4 is “faulty”) and (I_5 is “not turn off”) then (O_1 is “to repair”);
- If (I_1 is “possible”) and (I_2 is “possible”) and (I_3 is “serviceable”) and (I_4 is “serviceable”) and (I_5 is “not turn off”) then (O_1 is “to keep in service”);
- If (I_7 is “clean) and (I_9 is “present”) then (O_1 is “to keep in service”);
- If (I_{11} is “red”) and (I_{13} is “2”) and (I_{20} is “low”) and (I_{21} is “serviceable”) then (O_1 is “to repair”);
- If (I_{20} is “average”) and (I_{21} is “serviceable”) then (O_1 is “to keep in service”);
- If (I_{11} is “central alarm”) and (I_{13} is “3”) and (I_{20} is “medium”) and (I_{22} is “faulty”) then (O_1 is “to repair”);
- If (I_{23} is “present”) and (I_{24} is “non removable”) then (O_1 is “to take out of service”);
- If (I_{23} is “missing”) and (I_{24} is “non recoverable”) then (O_1 is “to take out of service”);
- If (I_1 is “not possible”) and (I_2 is “possible”) and (I_3 is “overheating”) and (I_4 is “correct”) and (I_5 is “shutdown”) then (O_1 is “to conduct additional preparation for operation”).

5. Discussion of Results

Using the developed technology and model, we conduct the situational “what-if” analysis, and identify a device’s technical conditions and its possible faults. The model delivers decisions in various situations, determined by a combination of input variables. We consider multivariate situations with different input factor combinations. The following types of situations are tested: (1) light network indicator is on, continuous signal sounds; (2) red alarm indicator flashes, signal “3” sounds; (3) baby module does not function. Results of the situational analysis are presented in Tables 4–6.

Table 4. Modeling results on Situation 1.

Situation 1: If Indicator is “Network” and Sound Signal is “Continuous” and . . .	**Input Variables**					**Output Variable O_1**
	I_{11}	**I_{13}**	**I_{12}**	**I_{25}**	**Others**	
1-1. Power cable is “not connected”	0.5	0.8	0.2	0.7	0.7	**0.59**
1-2. Power cable is “connected”	0.5	0.8	0.8	0.8	0.7	**0.92**
1-3. Fusible link is “burnt out”	0.5	0.8	0.1	0.35	0.7	**0.376**
1-4. Fusible link is “not burnt out”	0.5	0.8	0.9	0.2	0.7	**0.95**

Table 5. Modeling results on Situation 2.

Situation 2: If Indicator is “Flicker” and Sound Signal is “3” and . . .	**Input Variables**					**Output Variable O_1**
	I_{11}	**I_{13}**	**I_{12}**	**I_{25}**	**Others**	
2-1. Main skin temperature sensor is “not connected”, secondary skin temperature sensor is “connected”	0.1	0.3	0.5	0.8	0.6	**0.74**
2-2. Main skin temperature sensor is “connected”, secondary skin temperature sensor is “not connected”	0.1	0.3	0.9	0.6	0.6	**0.65**
2-3. Main skin temperature sensor is “not connected”, secondary skin temperature sensor is “not connected”	0.1	0.3	0.7	0.55	0.6	**0.574**
2-4. Main skin temperature sensor is “fault”, secondary skin temperature sensor is “fault”	0.1	0.3	0.1	0.2	0.6	**0.454**
2-5. Main skin temperature sensor is “serviceable”, secondary skin temperature sensor is “fault”	0.1	0.3	0.35	0.1	0.6	**0.89**
2-6. Main skin temperature sensor is “fault”, secondary skin temperature sensor is “serviceable”	0.1	0.3	0.3	0.4	0.6	**0.95**

Table 6. Modeling results on Situation 3.

Situation 3: Baby Module Does not Function	Input Variables						Output Variable O_1
	I_1	I_2	I_3	I_4	I_5	Others	
3-1. Position height mechanism of the baby module is "not turn off", baby unit switch mechanism is "fault", baby module engine is "serviceable"	1	1	0.7	0.2	0.4	0.5	**0.464**
3-2. Position height mechanism of the baby module is "not turn off", baby unit switch mechanism is "correct", baby module engine is "fault"	1	1	0.1	0.7	0.3	0.5	**0.52**
3-3. Position height mechanism of the baby module is "not turn off", baby unit switch mechanism is "fault", baby module engine is "fault"	1	1	0.3	0.5	0.2	0.5	**0.34**
3-4. Adjusting the height position of the baby unit is "impossible", baby module engine is "overheat"	0.25	1	0.5	0.9	1	0.5	**0.62**
3-5. Adjusting the height position of the baby unit is "impossible", baby module engine is "fault"	0.3	1	0.1	0.9	1	0.5	**0.376**
3-6. Adjusting the height position of the baby unit is "impossible", baby module engine is "serviceable"	0.1	1	0.8	0.9	1	0.5	**0.75**
3-7. Adjusting oblique position of the baby unit is "impossible", baby module engine is "fault"	1	0.5	0.2	1	0.8	0.5	**0.45**
3-8. Adjusting oblique position of the baby unit is "impossible", baby module engine is "overheat"	1	0.2	0.6	1	0.8	0.5	**0.68**
3-9. Adjusting oblique position of the baby unit is "impossible", baby module engine is "serviceable"	1	0.6	0.9	1	0.8	0.5	**0.7**

In the situation when the indicator is "network" and the sound signal is "continuous", a fusible link is "burnt out", and the appropriate decision made by model is "to repair". In the situation when the indicator is "flicker", the sound signal is "3" and the main skin temperature sensor is "connected", the secondary skin temperature sensor is "not connected", the decision is "to conduct additional preparation for operation". If the position height mechanism of the baby module is "not turn off", the baby unit switch mechanism is "fault", and the baby module engine is "fault", then the decision is "to take out of service".

The developed decision making model for eliminating device malfunctions as a part of its DT takes into account internal and external factors and allow for identifying the malfunction problem and suggesting the appropriate decision to provide a regular mode of device operation. In the framework of decision support systems of DT, the model provides a reduction in device downtime, reduced repair costs and improved operational efficiency.

6. Conclusions

The focus of this paper is the complex process of DT construction. In this study, we have given a comprehensive analysis of approaches and methods for organizational and technical systems' DT design. DT construction requires multi-stage technology, and consists of design and engineering stage, digital modeling and technological testing. In this paper, we consider the design and engineering stage.

The design and engineering stage is quite time consuming and includes steps to study object properties and its connections with the external environment, describe its structure and functioning, and identify possible problems in the process of functioning. In order to organize the work at this stage and describe the operation of the device, its structure and possible failures in the operation, this study proposes an approach to organizing the design process. As a numerical example, we use the device at the design stage of its life cycle; we study possible unforeseen problems during its further operation. Possible combinations of failure factors of the internal and external environment are modeled, and the model based on fuzzy rules is proposed for making management decisions in such situations.

It is shown that for complex organizational and technical systems functioning under uncertainty, there is no comprehensive and universal methodological approach for organizing a DT design and its accelerated engineering. We consider the digital twin prototype for a device in the creation life cycle in order to reduce the number and consequences of unpredicted undesirable states. The new theoretical results have been obtained over investigation:

1. The technology for organizing systems' DT design has been proposed. The technology differs from others in that it combines design stages, methods and models, and provides DT accelerated engineering.
2. The decision support model for diagnosing the technical condition of a technical device has been developed. The model is based on methods of situational analysis and fuzzy logic, and provides decision making under miscellaneous internal and external factors having a quantitative or qualitative nature. The model increases the accuracy and reliability of a decision support system and provides a synthesis of effective decisions in various situations and combinations of heterogeneous factors. Using observations of the object state, the model identifies, responds to changes and provides a basis for making decisions about future actions.

The practical importance of the developed technology and the model is that they are the foundation for decision support systems to observe the current state of technical devices (instruments, equipment) and to develop adequate decisions to eliminate its malfunctions.

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Expectations and limitations of Cyber-Physical Systems (CPS) for Advanced Manufacturing: A View from the Grinding Industry

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Abstract: Grinding is a critical technology in the manufacturing of high added-value precision parts, accounting for approximately 20–25% of all machining costs in the industrialized world. It is a commonly used process in the finishing of parts in numerous key industrial sectors such as transport (including the aeronautical, automotive and railway industries), and energy or biomedical industries. As in the case of many other manufacturing technologies, grinding relies heavily on the experience and knowledge of the operatives. For this reason, considerable efforts have been devoted to generating a systematic and sustainable approach that reduces and eventually eliminates costly trial-and-error strategies. The main contribution of this work is that, for the first time, a complete digital twin (DT) for the grinding industry is presented. The required flow of information between numerical simulations, advanced mechanical testing and industrial practice has been defined, thus producing a virtual mirror of the real process. The structure of the DT comprises four layers, which integrate: (1) scientific knowledge of the process (advanced process modeling and numerical simulation); (2) characterization of materials through specialized mechanical testing; (3) advanced sensing techniques, to provide feedback for process models; and (4) knowledge integration in a configurable open-source industrial tool. To this end, intensive collaboration between all the involved agents (from university to industry) is essential. One of the most remarkable results is the development of new and more realistic models for predicting wheel wear, which currently can only be known in industry through costly trial-and-error strategies. Also, current work is focused on the development of an intelligent grinding wheel, which will provide on-line information about process variables such as temperature and forces. This is a critical issue in the advance towards a zero-defect grinding process.

Keywords: cyber-physical systems; digital twin; advanced manufacturing; grinding process; grinding wheel

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1. Introduction and Literature Review

Digital solutions for improving the performance of high added-value manufacturing industries are paving the way towards the digitalization of industrial companies. Machine-tool manufacturers have taken the lead in the development of tools such as Celos or Savvy [1], which provide excellent platforms for digitalization. Digitalization of the manufacturing sector is running parallel to current societal and economic developments. In a survey conducted in 2020, Eurostat states that the manufacturing sector employed more than 28.5 million people in the EU in 2017 [2], with this sector occupying third place in the employment rankings [3]. CECIMO (The European Association of the Machine Tool Industries), in its annual survey on machine-tool production, states that since January 2017, industrial production has grown by 3.0% in the EU [4], emphasizing the importance of the manufacturing sector in current European society.

With regard to the development of manufacturing technologies in the EU, in a recent survey carried out in 2019 [5], it is stated that "the production processes will become increasingly digital and less mechanical", whilst also pointing out that "Digitisation is expanding possibilities to: design and test products or processes virtually (simulation); repair industrial apparatus remotely; and automate the constant fine-tuning of processes." A recent paper [6], studied in detail the main aspects and technologies that will enable this revolution, along with the main application domains.

The grinding process is key in the manufacturing of high added value parts in many industrial sectors such as aerospace, the automotive industry, and energy production [7]. Its characteristics make it the best choice when smooth tolerances and good surface quality must be achieved in difficult-to-machine materials. This fact is of critical importance in the previously mentioned industrial sectors in which new materials are being developed every day, and the precision requirements continue to become more demanding [8]. Thus, together with high-quality ground parts, the grinding process is required to be highly productive whilst also meeting sustainability demands [9].

Grinding will also play a leading role in facing some of the challenges related to the development of e-mobility (according to Bloomberg NEF, in 2040 there will be more electric vehicles than combustion vehicles), the need to expand aircraft fleets (which, according to the Aerospace and Defense Industries Association of Europe, is a sector that is expected to see considerable growth up until 2032) and the new challenges to be met in terms of ensuring clean and sustainable energy systems [10]. Grinding is adapting successfully to the current situation and, according to a recent report [11], the grinding wheel market is predicted to show an annual growth rate of around 2.83% until 2025, particularly in the niche market sectors such as those mentioned previously. This fact reflects the industrial importance of the process and highlights the necessity for industrial companies to optimize their grinding processes in order to be competitive in the 21st century global society. In spite of these encouraging data, it is important to note that the global situation of the industry is continuously changing [12] and that grinding technology must be prepared to be competitive within this framework.

Cyber-physical systems (CPS) will be critical for facing these new challenges. The digital twin (DT) concept is now key for optimizing capabilities of manufacturing processes. In [12], this concept is widely analyzed and applied to the manufacturing processes and it has been defined as "a mirror of the real world that provides a means of simulating, predicting and optimizing physical manufacturing systems and processes". Usually, the DT is thought to be the same as a model or a theoretical simulation of a given process, but it is, in fact, much more: A digital twin is a high-fidelity representation of the operational dynamics of its physical counterpart, enabled by almost real-time synchronization between the cyberspace and physical space [13]. In a recent work [14], a digital twin-based design platform was validated with a case study of the hollow glass smart manufacturing system. The application to lean production is addressed in [15], comparing the performance of three pull control strategies by simulation. In both cases results prove the efficiency of the approach. However, no references have been found to put the focus on the process itself, which is particularly critical in the case of the grinding industry.

The selection of the grinding process is based on the fact that it is one of the most complex machining processes, that involves a large number of variables that, to some extent, cannot be directly controlled. For instance, tool wear in milling or turning is a well-known fact, with good predictive models being currently available. It is also possible to know tool wear in turning or milling by using a pre-setting tool station. However, the mechanisms of wheel wear in grinding are extremely complex because of the composite nature of the grinding wheel. In fact, wheel wear is only indirectly known in grinding, because of its effect on part damage. Also, problems such as grinding burn (because of excessive contact temperatures) do not affect turning or milling. Many other aspects such as part finishing, spark-off operations, etc. can be also cited. In summary, grinding is more heavily based on experience than other machining processes, for which models are available; therefore, it is an optimal technology to test the impact of digital twins in the machining industry.

According to this, a number of elements must be included within a DT such as process modelling, the characterization of grinding wheel mechanical behavior, and process monitoring.

1.1. Process Modelling

Process modelling is a classic research topic. One of the most popular modelling areas concerns the thermal aspects of the grinding process due to their importance for impacting process performance. In the 1970s Malkin and Anderson [16] developed the first systematic analysis of the thermal elements of the grinding process, including simple analytical models based on classic heat conduction mathematical solutions. Several analytical developments were made by various authors such as Snoeys et al. [17], Lavine et al. [18,19], Ueda et al. [20], Rowe et al. [21,22], or even in the subsequent works of Malkin et al., summarized in [23]. The most recent research investigations into modelling the grinding process have usually been based on numerical methods because these have a greater capacity to represent reality in comparison with analytical approaches. In this case, these methods are not only focused on thermal issues [23,24], but also on the characterization of material removal mechanisms [25,26], dressing process performance [27] or methods to advance wheel surface modelling [28]. Doman et al. [29] conducted a complete review of the most recent advances in grinding modelling. Although not a very recent study, it perfectly summarizes the work that has been done, along with the work that needs to be carried out in the future. The development of sound models for the grinding process is of critical importance, because they allow a deeper understanding of the physical phenomena and the interactions among complex process variables. However, it is a fact that process models commonly fail when they are transferred to industrial workshops. In many cases, the causes for this situation is the complexity of the models (that limits their practical application) and the lack of actual real-time information of the machine and the process. Because of this, integration of such models in industrial practice requires a new and complete approach.

1.2. Wheel Characterization

When developing a theoretical model of a real phenomenon, one of the key issues is the characterization of the behavior of the modelled object. Classic models focus on the ground part and traditional metal characterization methods are employed to characterize both thermal and mechanical properties. Whilst this characterization is very useful for analyzing the influence of the process parameters on the ground part, on several occasions this information is shown to be insufficient, such as, for example, when wheel wear needs to be modelled or the behavior of a single abrasive grain must be reproduced. In spite of the importance of characterizing the grinding wheel mechanical behavior (e.g., for a wheel wear model) relatively few studies have addressed this issue. In regard to including material characteristics in the models, Young's modulus is used to characterize the elastic behavior of the wheel. This classic approach involves associating the hardness of the wheel with its Young's modulus [30]. However, classic studies suggest that this hypothesis is not completely correct [31] and using the same grade for different wheels can lead to variations in Young's modulus values. There is a lack of knowledge about this important issue in wheel modelling. Additionally, relatively few studies can be found regarding the fracture behavior of the grinding wheel. Given the nature of the grinding wheel structure, it should be regarded as a quasi-brittle material. In recent years, various research groups have focused their efforts on developing discrete element method (DEM) solutions to characterize the fracture behavior of these types of materials [32–34] Furthermore, in [35,36] the authors characterize the fracture behavior of the grinding wheel using a DEM model, they propose an experimental procedure for quantifying mechanical parameters (Brazilian test applied to grinding wheels) [35], and they describe tests for characterizing the grinding wheel material [36]. Unfortunately, this approach has not been validated for the classical problem of wheel wear. It is therefore not possible to know if the models developed for the bond material correctly represent the wear behavior of the wheel. Extensive work must still be done in this direction.

1.3. Process Monitoring

In the case of the grinding process, this is a complex issue due to the characteristics of the process, including accounting for the small contact area between the tool (grinding wheel) and the ground part, high temperature gradients in the contact region (103–104 K/s) [37], poor accessibility to the contact zone, and the large quantity of grinding fluid over the working zone [23]. The easiest parameter to be acquired is the power consumption of the grinding wheel spindle during the process. Although this is a very useful parameter, it only reveals a relatively limited amount of information about the process; thus additional sensors must be used in order to extract useful data from the process. In this regard, a number of attempts have been made to measure grinding temperatures, in both classic and new research works. In particular, the first attempts to measure temperatures with thermocouples were carried out in the 1950s [38], but until the 1990s no reliable data were extracted [39]. Later, several developments were reported in various studies [40,41]—every thermocouple solution presents an unsolvable problem, that is, the difficulty in following the high temperature gradients in the grinding zone. In [42] a state-of-the-art classification of the thermal measuring devices used and methods for material removal processes are presented. Considering these issues, a recent study by Urgoiti et al. [37] developed a new two-color pyrometer-based optical fiber system for measuring the temperature of the ground part. In [43] a new possibility was proposed for the in-process measurement of workpiece temperature in cylindrical grinding. This last work, together with [44], in which the authors propose wireless data transmission, could form the basis of future temperature acquisition devices. Whilst the reviewed studies indicate that considerable efforts have been made to accurately measure the grinding temperatures, there is no suitable technology for implementing this process in an industrial setting. The importance of this issue is shown in [45], where a complete review was carried out on the detection of grinding burn. Moreover, in their work, Teixeira et al. [46] propose an additional method for detecting thermal damage in ground parts, which reinforces the current need for thermal monitoring within the industry.

Another interesting parameter to be measured is wheel wear—traditionally defined by the G-ratio—which represents the volumetric wear of the grinding wheel compared with the amount of ground material. Although the information provided by this parameter is quite useful, again, additional information about the evolution of the grinding wheel surface characteristics is required for a full evaluation of the process performance. There have been considerable developments in recent years in optical devices and software analysis [47–50] for evaluating the evolution of wear flat, and usually the percentage of apparent wear flat area has been used as the wear parameter [23]. In [50] an example of an image analysis application for detecting abrasive grain wear flat was presented. Several attempts have been made to analyze the wear of new types of abrasives [51], which is a key issue in the profile of modern grinding processes [52]. According to the works analyzed, in-machine wheel wear measuring devices will be a fundamental aspect to be studied in future research works, particularly for heavy-duty profile ground parts such as those to be analyzed in this project proposal.

It is also important to analyze the dynamic control of the grinding process. The influence of the dynamic behavior on the quality of the ground part is quite important, since this is the main factor responsible for the appearance of leads and micro leads in the ground surface, or the presence of long wavelength surface marks. When analyzing dynamic behavior, the main problem to arise concerns the difficulty to position the accelerometers near to the grinding zone, which limits the possibility of achieving a highly accurate analysis, particularly when there is a need to analyze low amplitude vibratory phenomena. Several works can be found in the literature, particularly in relation to the avoidance of vibratory effects such as chatter [53–56] and the appearance of surface marks [56,57]. Accelerometers are still usually positioned relatively far away from the contact point between wheel and workpiece. Research work and technology development must be done to try to analyze displacement, velocity and acceleration as close as possible to the contact zone.

Finally, in the field of process monitoring, acoustic emission analysis is worth noting; it represents a powerful tool for extracting information about the performance of the process. In [58] a review was conducted of studies regarding acoustic emission during monitoring of the grinding process. Although this review is quite old, recently published works show that the use of acoustic emission in grinding is a very useful tool to monitor the state of wheel wear [58], dressing tool behavior [59] or the avoidance of thermal damage [60].

Analysis of the state-of-the-art and of the needs of the current grinding industry showed that DT technology could be a very powerful tool to analyze, design and optimize industrial grinding processes [12]. In [61], the authors made the first attempt to use a DT applied to the grinding process, which focused on minimizing the environmental impact of the process by analyzing the wheel dressing cycles. However, in this work there is not concern for critical issues such as wheel wear, occurrence of part damage because of grinding burns, etc. It is therefore, a very limited approach to the complex technology of grinding.

The main contribution of this work is that, for the first time, a complete digital twin (DT) for the grinding industry is presented. The required flow of information between numerical simulations, advanced mechanical testing and industrial practice has been defined, thus producing a virtual mirror of the real process. The underlying hypothesis is that process knowledge is distributed between very different agents (wheel manufacturer, machine-tool builders, end-users of the process, and fundamental research groups), and it is necessary to effectively share this knowledge. The aim is to produce a virtual mirror of the real process, integrating innovative monitoring systems (intelligent grinding wheel) and original theoretical and experimental approaches for the grinding processes. First, the local ecosystem in which the DT is being developed is presented. Section 3 presents the global structure of the DT. This structure integrates four different high-tech layers. Each layer is described in detail, and interactions between the layers are discussed. In this paper, an open platform is proposed that is capable of integrating the knowledge generated in the other layers, thus becoming the actual user interface of the DT.

2. A Local Ecosystem for a Viable DT for the Grinding Industry

The development of a transferable DT for industry can only be accomplished with the participation of all agents involved in the research, development and industrialization of the technology. This section describes the umbrella under which the concept of a DT for the grinding industry will be developed. The DT is being developed in the Basque Country under the initiative of the Basque Digital Innovation Hub (BDIH). The BDIH is a connected network of advanced manufacturing assets and services infrastructure available to companies for training, research, testing and validation. This initiative offers technological solutions, primarily for SMEs (Small and medium-sized enterprises), in order to meet the challenges of Industry 4.0. To this end, a digitally linked network is created, which consists of a public–private collaboration involving R&D infrastructures, pilot plants and specialized know-how in different areas of advanced manufacturing. The aims of the network are to develop R&D projects, the scaling of industrial projects, and the exhibition of cutting-edge technologies, whilst also serving as a resource for training and acceleration of start-ups.

The BDIH is divided into six work areas that are classified according to knowledge and technology, among which the Smart and Connected Machines—Digital Grinding Node is particularly noteworthy. Grinding is a critical manufacturing process which combines the technological complexity of the process with the high demand for quality and fine precision of the process. Moreover, grinding is usually the last process in the manufacturing chain, which ensures the final quality of the manufactured parts. In the Basque Country there are numerous companies that use the grinding process, along with many grinding machine manufacturers. Therefore, in research centers and universities, various research groups are focused on grinding, including the Grinding Process Research Group (UPV/EHU) and the

IDEKO technological center. In this sense, the mission of the Digital Grinding Node is to collect and coordinate the knowledge and assets of the main agents that develop their activity in the areas of knowledge associated with grinding. Thereby, the Digital Grinding Node forms a multidisciplinary distributed space in which Basque companies—particularly SMEs—can find solutions to their concerns and needs for knowledge; the companies can take advantage of numerous developments within the field of grinding that cover its multiple variants, including cylindrical, surface, centerless, vertical, and horizontal grinding, and different types of workpiece materials, grinding wheels, and coolants.

3. A Proposed Transferable DT for the Grinding Industry

Due to its heavy dependence on non-systematic knowledge, which means that the process relies on extensive trial-and-error strategies, the grinding sector needs to advance towards a complete, transferable and ready-to-use digital twin (DT) through the integration of advanced models of the grinding process, original simulative mechanical tests, and state-of-the-art process sensors.

Since at present grinding technology is linked to high-added value products and markets (e.g., the aerospace, automotive, and railway sectors), by achieving this goal grinding companies (machine-tool builders, wheel manufacturers and end-users of the process) will directly benefit from zero-defect production strategies and reduced setup times in a process that is highly dependent on trial-and-error experimental approaches.

The present work proposes a down-top approach composed of different layers of the DT. The underlying hypothesis is based on the fact that process knowledge is distributed between very different agents (wheel manufacturer, machine-tool builders, end-users of the process, and fundamental research groups), and it is necessary to effectively share this knowledge. The aim is to produce a virtual mirror of the real process, integrating innovative monitoring systems (intelligent grinding wheel) and original theoretical and experimental approaches to grinding processes. The structure of the DT is composed of four layers, which integrate: (1) scientific knowledge of the process (advanced process modeling and numerical simulation); (2) characterization of materials through specialized mechanical testing; (3) advanced sensing techniques, to provide feedback for the process models; and (4) knowledge integration in a configurable open-source industrial tool. Each layer is described in detail in the following paragraphs, while Figure 1 illustrates the general concept underlying the DT.

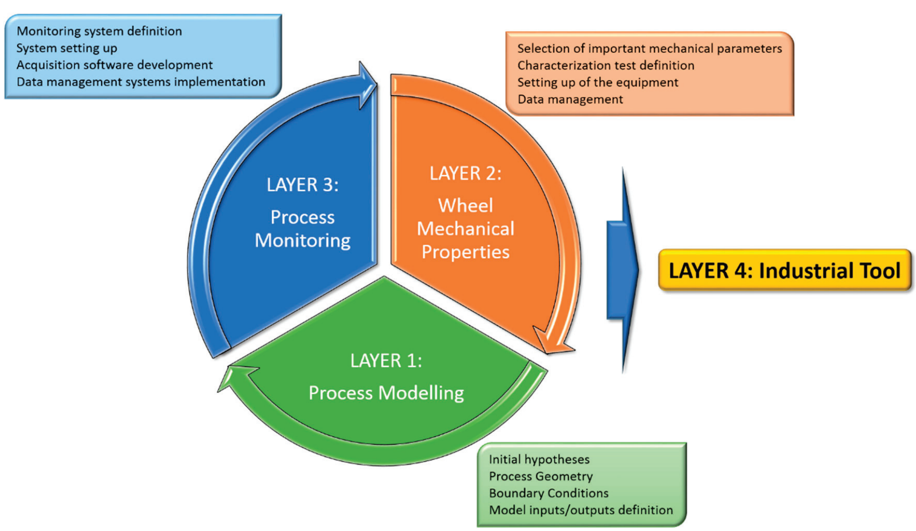

Figure 1. Structure and interaction between layers in the digital twin (DT) for the grinding industry.

3.1. Layer 1: Numerical Modeling of Mechanical Behavior of the Grinding Wheel Using Advanced Process Simulation

One of the main reasons for the lack of systematic knowledge about the behavior of the grinding process itself, and in particular, the behavior of the abrasive tool (the grinding wheel) lies in the fact that grinding wheels are manufactured by mixing abrasive and bonding agents along with certain other components. Since the specification is not fully standardized, and there are no standard mechanical tests for wheel characterization, the result is that it is very difficult to predict the behavior of a grinding wheel for a given part. Although general rules can be followed, the industrial practice of leading wheel manufacturers (Tyrolit, Saint-Gobain, etc.) for the optimum selection of a grinding wheel is absolutely dependent on each specific application. Due to this fact, wheel manufacturers are continuously developing new types of grinding wheels, mixing different grain shapes and sizes, inducing porosity in an artificial way or changing the bonding material properties in order to meet the requirements of new materials to be ground. The development of adequate grinding wheels is particularly important when profile wheels must be used. In this case, whilst it is possible to find not only an optimal material removal rate and good surface quality, it is also important to take into account minimum volumetric wear of the wheel in order to achieve optimal geometrical accuracy. Although this is one of the biggest challenges faced by the current industrial environment, very little information can be found in the scientific literature regarding the link between grinding wheel characteristics and performance. Consequently, in industrial practice, extensive trial-and-error experiments must be carried out in order to determine the optimum parameters for a given application.

In order to meet this challenge, scientific process models can be considered as the deepest layer of a DT of the process. As shown in the literature review, a number of different theoretical models of the process are available. Unfortunately, few of these can be generalized to industrial practice due to the unique specifications of each grinding wheel structure. Thus, a model of the process must consider the interactions between the different components of the grinding wheel, namely abrasive grits, bonding agents, and porosity, along with the interaction between the grinding wheel and the part to be machined.

In the present study, the discrete element method (DEM) has been selected as the optimum numerical tool for the modeling and simulation of the grinding process. DEM models allow for reproducing the granular structure of the grinding wheel and the mechanical behavior of the bonding bridges. Likewise, the development of cohesive beam models allows for the simulation of continuous bodies using DEM [62]. The mechanical properties of the bonding agent can be replicated at a microscopic level in such a way that the complete behavior of the wheel body can easily be reproduced, regardless of its composition. The interactions with the part material can also be modelled; by doing so, it is possible to predict critical process data such as the contact forces, temperatures and power consumption. The effect of wheel rotation can also be included in the model, which is an interesting contribution, particularly for high-speed grinding processes. These possibilities are supported by preliminary investigations conducted by our research group, such as those published in [63,64]. Nonetheless, intensive research is currently being carried out to optimize DEM models and their application to the DT of the grinding process. Figure 2 shows a DEM model of a high-performance alumina grinding wheel. This model is being developed in collaboration with the wheel manufacturer UNESA (Abrasivos UNESA, S.A.,Hernani, Spain) and the ENSAM of Bordeaux. In the present DEM model the real grinding process is modelled. To this end, not only real grinding parameters are considered, but also the composition of real grinding wheels. Firstly, a discrete grinding wheel is built in order to characterize the mechanical behavior of the wheel, especially the behavior of the bond. To this end the size of the discrete elements (DEs) are equal to the real abrasive grain, 350 μm. This hypothesis allows the isolation of a bond fracture from the other types of wheel wear. In order to minimize the computational cost of the model, instead of modelling the real grinding wheel, which has an actual diameter of 400 mm, a wheel with a reduced diameter of 30 mm is modelled. Likewise, the width and thickness are also reduced, and are modelled with a width of 5 mm and a wheel thickness of 10 mm. The modification of the external diameter of the grinding wheel also affects different process parameters, such as the grinding wheel speed or the contact length, therefore the corresponding parameter correlations are also performed. Moreover, the real contact length and the real contact time is considered in the DEM model, therefore, a specific workpiece shape is designed. Finally, the real force generated during grinding is introduced in the model with the aim of reproducing the mechanical behaviour of the grinding wheel during the grinding process.

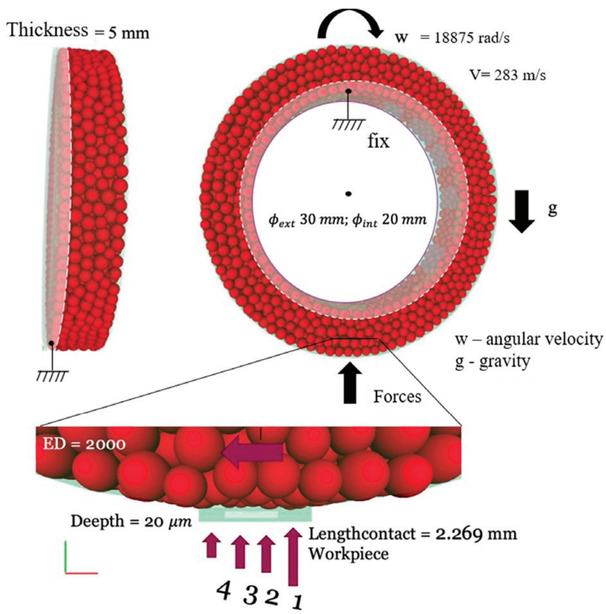

Figure 2. The discrete element method DEM model of a high-performance alumina grinding wheel.

Layer 1 only makes sense by interacting with the rest of the elements of the digital twin. Thus, mechanical characterization of the properties of both the bonding agent and the abrasive grits requires the development of advanced and specific mechanical tests for the wheel, which is considered a quasi-brittle material. Layer 2 focuses specifically on those tests (see below), and the knowledge generated in Layer 2 must immediately be made available to the DEM models that constitute Layer 1. Moreover, the model can also be fed with actual data inputs from the industrial process (see Layer 3 in this Section). Finally, the DT must address the classic problems of computationally heavy numerical models, which are barely applicable to production-oriented industrial workshops. The integration with Layer 4 is therefore a key issue for the DT.

3.2. Layer 2: Advanced Testing for Mechanical Characterization of Alumina Grinding Wheels

As previously mentioned, one of the drawbacks for mechanical characterization of grinding wheels is their composition. The wheels are composed of abrasive grains, bonding agents and pores, and each of these elements have different mechanical properties. Moreover, during grinding wheel manufacturing, high temperatures are reached, which also modifies the mechanical properties of the body. Whilst there are studies in the literature that have conducted in-depth analyses to determine the mechanical properties of abrasive grains, there is no consensus regarding the values of such properties. Moreover, the most recent trend has been to manufacture customized grinding wheels depending on the particular needs of each case. Thus, for each application, there are differences in abrasive and bonding materials and grain shape and wheel porosity, which hinders establishing a common characterization of grinding wheels. Therefore, following a review of the literature regarding the mechanical properties and behavior of grinding wheels and composites, it is concluded that the best option is to characterize the mechanical behavior of these grinding wheels as a concrete, and thus, quasi-brittle material.

Quasi-brittle materials show a nonlinear response, combining a moderate strain hardening (which is a characteristic of metallic materials) with sharp softening responses representative of brittle materials. With regard to the behavior of the wheel binder during grinding, among the various mechanical properties, particular attention is paid to the ultimate principal tensile strength σ_{max} which will be used as an input parameter in the DEM model proposed in Layer 1. Likewise, Young's modulus E and the Poisson coefficient ν are the two other input mechanical properties in the DEM model. The development of precise experimental methods for determining these variables also becomes a primary objective when developing the DT of the process. The behavior laws of the grinding wheel material, assumed to be a quasi-brittle material, must be determined by mechanical tests such as the Brazilian test, which is described in the following paragraphs.

In the reviewed literature, the Brazilian tests are carried out using a disk, as shown in Figure 3a. However, this specimen configuration does not take into account the shape of the grinding wheel, which has a central hole. Moreover, the shape of the specimen determines the beginning of crack propagation. Therefore, new specimens are designed and manufactured as shown in Figure 3b. The specimen presents a central hole and flat surfaces to secure the specimen and to impose the load.

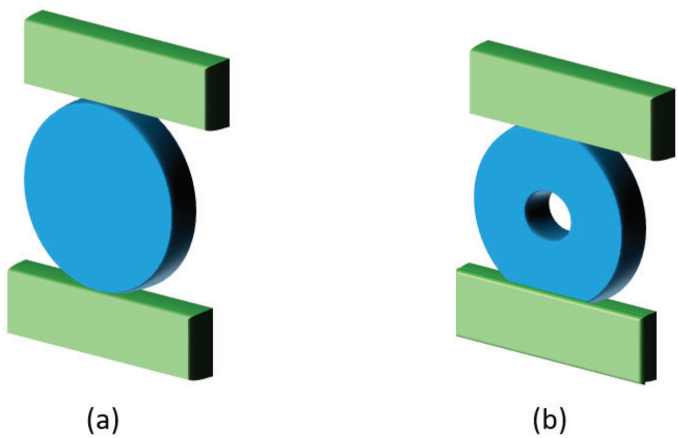

Figure 3. A disk specimen configuration used for (**a**) conventional Brazilian tests and (**b**) modified Brazilian tests.

The modified Brazilian tests need to include digital image correlation (DIC) analysis and fractography in order to thoroughly analyze crack propagation together with the quantification of ultimate principal tensile strength σ_{max}. The values of ultimate tensile strengths varied between 60 and 85 MPa for the different specimens that were tested. The values were archived, as this information is critical for feeding the DEM simulation model presented in Layer 1. The ultimate tensile strength determines the fracture of the bonding agent and thus the wear of the grinding wheel.

3.3. Layer 3: A New Generation of Grinding Process-Monitoring Systems: Intelligent Grinding Process

Numerical models (as described in Layer 1) and simulative testing (Layer 2) are fundamental for obtaining a better understanding of the grinding process. However, these are more strongly related to the scientific knowledge of the process and do not allow for efficiently considering a large number of weaker interactions related to actual machining. Some examples of these interactions in the grinding process include the influence of the workpiece holding, the effect of coolant flow, and the presence of vibrations. Eventually, extremely complex and heavy process models could incorporate these types of effects, but then the industrial applications would be even more limited. To solve this problem, a digital twin must be able to collect actual and in-process information about process variables and incorporate this information, in order to update existing models.

Due to the nature of the grinding process, current instrumentation is very limited. The interaction between wheel and workpiece occurs at very high contact speeds (in many cases, higher than 100 m/s), with extremely high local contact pressure (1–2 GPa), whilst generating local temperatures close to the melting temperature of the component material. In this case, temperature gradients are extremely steep, which makes the process of temperature measurement very difficult.

All these problems must be addressed by the DT of the grinding process. Intensive research work is being conducted to set up advanced instrumentation that can provide the existing models with useful information. Thus, power measurement has already been implemented in grinding machines, and the information collected was made available to the user through the GREAT software (see Layer 4). Since too high a contact temperature may ruin an expensive component, a sensorized grinding wheel is currently being developed for actual temperature measurement. This wheel will use two-color pyrometry and a wireless connection with Layer 4, so that the machine user can access real-time information about the effect of grinding temperatures on the component being manufactured. Sensors are also being developed to control the dynamic behavior of the wheel. In this case, the use of virtual sensors could represent a potentially interesting alternative if combined with artificial intelligence models from which useful indicators can be extracted. Finally, optical sensors for the control of wheel effective topography and contact conditions will also be integrated in Layer 3, including micro cameras and image recognition software to identify both volumetric wear and the appearance of wear flat in abrasive grains.

3.4. Layer 4: Grinding Research Assisting Tool (GREAT)

Computational models of the process, such as those described in Layer 1, provide a more in-depth understanding about the large number of interactions among process variables. However, these types of simulations are time-consuming, and usually require high-performance hardware to run and speed up the model computations. These factors drastically limit the industrial application of scientific models. Moreover, the use of platforms such as the previously mentioned GranOO (which is not a commercial software) requires trained and specialized researchers that can define the boundary conditions and simplify hypotheses. Clearly, this is not easily achievable in a machine-tool workshop.

With the aim of integrating all the developed knowledge within an instrument that can be used on the shop floor, an intuitive and easy-to-use software tool is being developed. The software, called GREAT (Grinding Research Assisting Tool, Figure 4) is already in its first version, and incorporates only a limited number of apps that help the user in the task of process optimization. The apps developed are listed here:

- Power acquisition
- Power analysis
- Specific energy analysis
- Power consumption predictor
- Grinding burn analysis
- Wheel-material data base
- Wheel wear measurement
- Dresser wear measurement

Figure 4. Layer 4: The Grinding Research Assisting Tool (GREAT).

GREAT is being developed in Python, and it is based on a simple user-interface that assists the user during grinding operations. In order to do so, the results obtained from numerical models developed in Layer 1 must be converted into a set of tables and equations that will be stored in the wheel–material database (see Figure 4). Data for the specific grinding wheel are fed from Layer 2. The reduced models are correlated with the current grinding operation through the interaction with Layer 3, since the GREAT software must be able to receive data from the different sensors implemented both on the machine and on the grinding wheel. Thus, at the current stage it is possible to integrate actual power consumption data (power acquisition module in Figure 4). Since the software is open and completely scalable, in the near future it is anticipated that data from temperature sensors, force gauges, accelerometers and other advanced instrumentation will be included. Moreover, one of the advantages of this software is the developed user-friendly interface, which is intuitive and easy to use. This feature makes GREAT a suitable tool for both industrial and academic environments.

It is worth noting that the DT is not a static concept. As new grinding apps are continuously optimized, they will be incorporated into the DT and updated in GREAT. In this regard, GREAT is also conceived as an open user interface. Existing knowledge will be presented in a user-friendly application, although the scientific fundamentals can be complex and deep, as explained in Layers 1 to 3. For instance, it is expected that new modules for wheel wear quantification (based on optical sensors to be developed in Layer 3), measurement of the mechanical properties of the wheel (to be developed in Layer 2), monitoring of dressing devices (to be developed in Layer 2), and others will become available and incorporated in the near future. Finally, the aim is to have a “cloud system” accessible to the end user via the internet so that they are able to receive assistance according to their particular needs.

4. Conclusions

This paper presents a general approach to the development of a digital twin that can be effectively applied in the grinding industry. In view of both the existing knowledge and advances in technology, the following conclusions can be drawn:

- If the DT is to be useful for industry whilst serving as a virtual mirror of the manufacturing process, interaction between industry, applied research and fundamental research is essential. This means that industrial companies, research centers and university groups must share knowledge, facilities and case studies for the application. The Digital Grinding Node, as part of the Basque Digital Innovation Hub, thus provides the optimum ecosystem for this development.

- The new approach to the DT for the grinding industry involves the interaction between four layers, namely process simulation, advanced testing of materials, state-of-the-art process monitoring and finally, an easy-to-use open interface that can be transferred to SMEs.
- Fundamental process simulation must go a step further and become a useful tool, not only for a better understanding of complex physical phenomena, but to reduce process setup times and to eliminate trial-and-error strategies typical of the manufacturing industries. For the DT of the grinding process presented in this paper, DEM modeling has been considered as the optimum simulation method, given the characteristics of the abrasive wheel material.
- Process simulation only becomes realistic when it is fed with actual and reliable data. Therefore, further efforts must be made within the fields of mechanical testing of grinding wheels and process monitoring using advanced sensors. Extensive research work will need to be devoted to both issues in the coming years.
- The proposed DT is not a closed tool, instead it is open so that it can incorporate new technologies for data acquisition and processing, new types of mechanical tests, and of course, new wheel materials and machine capabilities. Still, the proposal will be valid, because it incorporates the key factors for the grinding process.
- Finally, the knowledge developed must be effectively transferred to SMEs. Since heavy fundamental models, which involve the use of complex programs and costly hardware are not feasible for workshops, the development of easy-to-use applications for process optimization is of primary importance. In this paper, an open platform is proposed that is capable of integrating the knowledge generated in the other layers, thus becoming the actual user interface of the DT.

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Article

Leveraging Explainable AI to Support Cryptocurrency Investors

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Abstract: In the last decade, cryptocurrency trading has attracted the attention of private and professional traders and investors. To forecast the financial markets, algorithmic trading systems based on Artificial Intelligence (AI) models are becoming more and more established. However, they suffer from the lack of transparency, thus hindering domain experts from directly monitoring the fundamentals behind market movements. This is particularly critical for cryptocurrency investors, because the study of the main factors influencing cryptocurrency prices, including the characteristics of the blockchain infrastructure, is crucial for driving experts' decisions. This paper proposes a new visual analytics tool to support domain experts in the explanation of AI-based cryptocurrency trading systems. To describe the rationale behind AI models, it exploits an established method, namely SHapley Additive exPlanations, which allows experts to identify the most discriminating features and provides them with an interactive and easy-to-use graphical interface. The simulations carried out on 21 cryptocurrencies over a 8-year period demonstrate the usability of the proposed tool.

Keywords: quantitative trading; cryptocurrencies; blockchain

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1. Introduction

Cryptocurrencies are digital assets whose transfers and accounting are cryptographically estabilished through the blockchain [1]. Even though they are not backed by any physical asset, they have become popular financial assets for online trading. After bitcoin, which is the first and most famous cryptocurrency [2], many different cryptocurrencies have been created, thus increasing the options to invest in cryptoassets significantly.

Following the recent trends on algorithmic trading, many research efforts have been devoted to designing cryptocurrency trading systems based on Machine Learning (ML) and Artificial Intelligence (AI). Existing methods rely on algorithms that span from classical classification and regression methods (e.g., [3–7]) to Deep Learning architectures (e.g., [8–11]). The aim is to learn predictive models from historical data related to cryptocurrency assets (e.g., markets, blockchain-related data, news) and apply them to forecast the future price directions. A recent survey on cryptocurrency trading can be found in [12].

Although Machine Learning-based solutions have shown to achieve better performance than simpler heuristic methods [12], they suffer from the lack of transparency. In fact, most state-of-the-art classification models, including all the Neural Network-based approaches, are not explainable; i.e., domain experts cannot gain insights into the model decisions. Cryptocurrency markets can be influenced by a large variety of factors, including the underlying market trends, the characteristics of the blockchain, and the sentiment of financial investors on the virtual assets. This prompts the need for new approaches aimed at explaining ML reasoning in cryptocurrency trading.

This work focuses on leveraging an established eXplainable AI (XAI) method, namely SHapley Additive exPlanations (SHAP) [13], to provide domain experts with an effective visualization of the ML reasoning behind cryptocurrency trading. SHAP quantifies the contribution of different features on classifier predictions, thus highlighting the contribution of different factors to the decisions of the ML-based system. We aim at addressing the following research questions:

- **Q1**: What are the most discriminative features for cryptocurrency price prediction?
- **Q2**: How can cryptocurrency investors be provided with quantitative estimates of the influence of specific features and feature categories on machine learning-based cryptocurrency predictions?
- **Q3**: How can we evaluate the statistical dependency of the Machine Learning (ML) feature ranks returned by SHAP in different time periods and on different cryptocurrencies?

To address Q1, this paper explores a large variety of features computed on the daily price series of 21 different cryptocurrencies. The analyzed features are established for cryptocurrency trading [12] and encompass the price- and volume-related series, the technical indicators summarizing the momentum, volatility, and moving averages of the original price series, and the blockchain-related features. The latter are particularly relevant to the scope of the present study because they are peculiar to cryptoassets.

To address Q2, we use eXplainable AI methods based on the Shapley value [14] to provide cryptocurrency traders with evidence of the main factors influencing algorithmic trading. We present a new eXplainable AI tool for visualizing and monitoring the activities of Machine Learning-based systems, with particular attention paid to the blockchain-based features influencing the decision process.

To tackle Q3, we apply the Rank Biased Overlap similarity measure [15] to quantify the pairwise agreement between the top-10 features shortlisted by SHAP. We also performed the experiment using feature subcategories and categories rather than individual features.

The experiments carried out on a 8-year period produce the following main outcomes:

- **O1**: The high variability of the feature importance across different cryptocurrencies. This confirms the relevance of eXplainable AI solutions for cryptocurrency traders.
- **O2**: A visual eXplainable AI tool, namely Crytpocurrency-based Machine Learning Explainer (CryptoMLE, in short). Some practical examples of use of CryptoMLE are also presented.
- **O3**: The dependency among the feature ranks is weak, whereas those among feature subcategories and categories are stronger.

The paper is organized as follows: Section 2 overviews the related literature. Section 3 details the dataset employed in the study. Sections 4 and 5 introduce the fundamentals of Shapley values and SHAP and presents the Visual Analytics tool, based on SHAP, to support cryptocurrency investors' activities. Section 6 summarizes the main empirical results, whereas Sections 7 and 8, respectively, report a discussion of the main achievements and open issues and draw the conclusions of the present work.

2. Comparison with Prior Works

Table 1 summarizes the main characteristics of the existing approaches to eXplainable AI (XAI) in finance, including the Crytpocurrency-based Machine Learning Explainer (CryptoMLE) presented in this paper. We analyze the current and prior works under the following aspects:

1. The considered assets, which encompass specific stocks, cryptocurrencies, or a combination of the above (e.g., the stocks belonging to the Standard&Poor500 U.S. index).
2. The features under analysis, which describe the environmental and market characteristics considered by the classification models (including the blockchain-related features for cryptocurrency assets).
3. The availability of a user interface to support domain expert decisions.
4. The main model used to explain ML-based decisions (e.g., SHAP [13] for the proposed CryptoMLE tool).
5. The resolution of the analyzed data (typically, one sample per trading day).
6. The goal of the approach (e.g., support decision making with data-driven insights for CryptoMLE).

The main goal of this work is to present a visual analytics tool providing AI-based explanations for cryptocurrency investors. Notice that our goal is not to propose a new, more effective trading system but rather to provide experts with an interactive tool, based on XAI, to explain the decisions of algorithmic trading approaches and make appropriate decisions.

Similar to [16–18], CryptoMLE provides domain experts with a graphical interface. Unlike all the prior works on algorithmic trading, it also allows them to interactively collect, analyze, and compare data models trained in multiple time periods. Analogously to [18], CryptoMLE analyzes a large number of cryptocurrencies. Unlike [18], it also considers blockchain-related data.

CryptoMLE relies on SHAP [13], whereas other approaches (e.g., [17,19]) adopt simpler explainable models such as partitional clustering and decision tree, which are known to be less robust to noise and model bias than SHAP. The work recently proposed in [20] is, to the best of our knowledge, the first attempt to use SHAP in algorithmic trading. Unlike [20], this work (1) Addresses short-term cryptocurrency trading instead of long-term portfolio management. Hence, it compares the outcomes of classification models predicting next-day cryptocurrency price; (2) Presents a graphical tool for supporting decision making. It also allows experts to interact with the tool and gain insights into specific market trends; (3) Analyzes a significantly larger set of cryptocurrencies (21 vs. 8).

Table 1. Comparison with prior works. Legend: crypto = cryptocurrency/cryptocurrencies, BC = blockchain, MA = market data, V = Exchanged volumes, TA = technical analysis, B6 = CME Globex British Pound futures, SPF = S&P E-mini Futures.

			User Interface				
Paper	**Asset**	**Features**	**Graphical**	**Interactive**	**XAI Model**	**XAI Resolution**	**XAI Goal**
CryptoMLE	21 crypto	BC, MP, TA	Yes	Yes	SHAP [13]	Daily	Decision making
[21]	S&P index	MA	No	No	Ablation, permutation, added noise, integrated gradients [22]	Daily	XAI model comparison
[23]	CHES120 China	MA	No	No	Custom LightGBM-based model [24]	10 s, 30 s, 1 min ticks	Matching testing and real-trading performances
[20]	8 crypto	MA	No	No	SHAP [13]	Daily	Portfolio management approach for crypto
[19]	The BTC crypto	BC, MA	No	No	K-means clustering, decision tree classifier [25]	Daily	Valuation method for cryptocurrency markets
[16]	The ETH crypto	MA, TA	Yes	No	Adversarial Deep Neural Networks [26]	Daily	Display reversal patterns on candlestick charts [27]
[17]	The S&P stocks	MA, TA, News	Yes	No	decision tree classifier	Daily	Identify the most impactful words in business-specific stock market sectors
[18]	18 crypto	MA, Reddit	Yes	No	Ensemble methods, co-occurrence analyses [25]	Daily	Correlation analysis between crypto
[28]	B6, SPF	MA, V	No	No	Decision trees [25], SHAP [13]	Daily	Adapt market data to the Machine Learning pipeline.

3. Data Overview and Categorization

We collect historical data about the 21 most popular cryptocurrencies within the time period from 2011 to 2018 (For the cryptocurrencies whose year of introduction is after 2011, we gathered data from the date they became available.). In the experiments we sampled cryptocurrency data at a daily granularity. However, the performed analyses can be straightforwardly extended to finer or coarser aggregation levels.

We consider three main feature categories:

- The *Blockchain-related* (BC) features, which describe the underlying characteristics of the distributed ledger technology enabling each cryptocurrency [18].
- The *Market Data* (MD) features, which represent the main cryptocurrency Open–High–Low–Close–Volume (OHLCV) price series as well as a selection of summarized features derived from the candlestick chart [29].
- The *Technical Analysis* (TA) features, which include a variety of momentum indicators, volatility indices, and oscillators that are commonly used in Technical Analysis on both cryptocurrencies and regulated market assets [8].

The features are aggregated into the corresponding category and subcategory according to the hierarchy reported in Table 2. We considered a large variety of features among the most established for cryptocurrency trading (according to [12]). To foster the reproducibility of our work, both the analyzed dataset and the project code are publicly available for research purposes (https://dbdmg.polito.it/dbdmg_web/index.php/leveraging-explainable-ai-to-support-cryptocurrency-investors/, accessed on 1 August 2022). A detailed description of the dataset features is available at https://dbdmg.polito.it/dbdmg_web/wp-content/uploads/2022/08/features.xlsx, accessed on 1 August 2022.

Table 2. Categories and subcategories of the features present in the dataset.

Category	**Subcategory**	**Description**
Blockchain	Addresses	Metrics representing an index of network activity and interest.
	Economics	Metrics regarding the ratio of the USD network value divided by the adjusted transfer value (in USD).
	Exchange	Metrics representing the currency flow for known centralized exchange addresses for both deposits and withdrawals.
	Fees and Revenues	Metrics covering the network's efficiency in terms of transfer costs, representing fees for doing operations on the blockchain such as transactions and smart contract execution.
	Market	Metrics covering the economic aspects of cryptocurrency markets such as capitalization, BTC exchange price, ROI and volatility returns.
	Mining	Metrics representing protocol-specific parameters.
	Network Usage	Metrics covering blockchain activity in the form of mined block and their size.
	Supply	Metrics that aim to explain token supply and its distribution among wallets.
	Transactions	Metrics addressing transferred value and throughput of the network.
Market Data	Prices	Features directly derived from Open, High, Low, Close prices of the current timestamp.
	Volume	Features directly derived from the trading volume of the current timestamp.
	Volatility	Features directly derived from current volatility of the currency.
	History	Features derived from the historical time series of Open, High, Low, Close prices and Volume.
	Candlestick Analysis	Features concerning the analysis of the candlesticks shapes.

Table 2. *Cont.*

Category	Subcategory	Description
Technical Analysis	Trend Indicators	Trend-following indicators whose values help assess the direction and strength of established trends.
	Momentum Indicators	Indicators used to determine the strength or weakness of a stock's price.
	Volatility Indicators	Indicators measuring how far the security moves away from its mean price.
	Volume Indicators	Indicators representing a security's bull and bear power.

3.1. Blockchain-Related Features

We gathered BC features containing various specific properties of the enabling blockchain architecture, which are aggregated on a daily basis. The 30 features belonging to the BC category cover different aspects addressed by the following subcategories: *Address*, *Economics*, *Exchange*, *Fees and Revenues*, *Market*, *Mining*, and *Network Usage*. They are likely to show direct or indirect relations with the cryptocurrency bid and ask prices. Hence, they can be deemed relevant by the Machine Learning model to obtain accurate price predictions.

The high variability of the technologies enabling each cryptocurrency makes cross-cryptocurrency analyses of BC features particularly relevant to understand the rationale behind Machine Learning predictions. For example, the in-depth analysis of the blockchain supply and mining features can reveal an increasing/decreasing interest of the cryptocurrency investors in particular virtual assets.

3.2. Market Data Features

MD features characterize temporal trends in cryptocurrency prices [11]. The data we gathered include the raw Open–High–Low–Close–Volume (OHLCV) price series, the residuals from the Seasonal-Trend Decomposition using Loess (STL) [30], and the characteristics of the shapes of the candles in the candlestick chart [29].

3.3. Technical Analysis Features

Technical analysis provides a synthetic description of price- and volume-related trends [27]. They were derived from the historical price and volume series using the TA-Lib Python library (https://ta-lib.org/, accessed on 10 January 2022).

The TA feature category describes notable price-related properties of the cryptocurrency such as momentum, volatility, oversold/overbought conditions, etc. Recently, they have shown to be relevant to cryptocurrency trading as well [8].

4. SHapley Additive Explanation Values

SHapley Additive Explanation (SHAP, in short) [13] is a method to explain individual predictions. It is based on the Shapley value, whose applications to eXplainable AI rely on coalitional game theory [14].

4.1. The Shapley Value

Given a set of players $\mathcal{P} = \{P_1, P_2, \ldots, P_n\}$, a *player coalition* $\mathcal{C}$ is a $\mathcal{P}$'s subset cooperating to accomplish a specific task. The *utility* $\mathcal{U}(\mathcal{P})$ evaluates the payoff of the coalition for the task, whereas the *marginal utility* $\mathcal{U}(P_j)$ indicates the additional contribution provided by a new player P_j being added to the coalition $\mathcal{P}$, i.e.,

$$\mathcal{U}(P_j) = \mathcal{U}(\mathcal{P} \cup P_j) - \mathcal{U}(\mathcal{P})$$

The Shapley value [14] is the expectation of the marginal contribution $\mathcal{U}(P_j)$ in all possible coalitions.

$$\mathcal{SV}_i = \frac{1}{n} \sum_{\mathcal{S} \subseteq \mathcal{N} \setminus P_i} \frac{\mathcal{U}(\mathcal{P} \cup P_i) - \mathcal{U}(\mathcal{P})}{\binom{n-1}{|\mathcal{C}|}}$$

Computing the exact Shapley value entails enumerating all the possible coalitions, which is computationally prohibitive in real-world contexts.

4.2. Additive Feature Attribution Methods

Given a training dataset consisting of a set of features $\mathcal{F} = \{F_1, F_2, \ldots, F_n\}$, each value of an individual feature F_i acts as a player in a coalition. The number n of considered features can be interpreted as maximum coalition size.

Let f be a complex prediction model, trained on $\mathcal{F}$ instances. For the sake of simplicity, we assume the financial forecasting model f predicts the next-day closing price direction (i.e., *Uptrend* or *Downtrend*) of a specific cryptocurrency based on the past samples observed in the last W days (Hereafter, we will disregard the *Stationary* class (neither uptrend nor downtrend)).

We seek explanations of f clarifying the effects of features in $\mathcal{F}$. Specifically, we aim at explaining the prediction $f(x)$ of an instance x of $\mathcal{F}$ by computing the contribution of each individual feature.

Within this scope, the Shapley value of feature F_i indicates how to fairly distribute the *payout* among the features; i.e., it quantifies the effect of the individual feature F_i on the outcome of the prediction task. To generalize players as sets of feature values, we exploit the additive feature attribution method to linearly combine the individual Shapley values.

The explanation model g is defined as a linear combination of binary features associated with each feature F_i:

$$g(z') = \phi_0 + \sum_{i=1}^{n} \phi_i \cdot z'_i \,,\; z' \in 0,1^n$$

where z'_i is a binary variable denoting either the presence of a feature ($z'_i = 1$) or its absence ($z'_i = 0$). ϕ_i is the F_i's attribution value, which quantifies the effect of F_i on $f(x)$. The explanation model sums the effect of all individual feature attributions approximating the output.

4.3. The SHAP Explanation Model

In [13], Shapley values are leveraged to explain Machine Learning models by applying sampling approximations to the original Shapley expression. Specifically, it approximates the effect of removing a variable from the model by integrating over samples from the training dataset.

The key steps of the SHAP model generation are as follows:

1. Generate random sample coalitions z'' of $m < n$ features in $\mathcal{F}$, where $z'' \in 0,1^m$.
2. Sample coalitions to valid instances.
3. Train a regression model on the generated instances, whose target is the prediction for a coalition.

To move from coalitions of feature values to valid data instances (Step 2), instance values are taken from the instance x we want to explain for all features that are present in the coalition ($z'' = 1$), whereas the other features are randomly sampled from the training dataset instances for all the absent features ($z''_i = 0$).

The regression function (Step 3) corresponds to the weighted linear explanation model g previously defined according to the additive feature attribution method.

5. The CryptoMLE Tool

Receiving advice from algorithmic advisors is becoming more and more popular for financial analysts [31]. However, relying on sophisticated Machine Learning models trained on massive datasets is particularly risky in financial market forecasting, because the ML models often act as black boxes and domain experts are not keen to trust.

EXplainable AI models provide insights into ML algorithms by indicating which features are more important and how they could affect ML predictions [32]. They can return either local or global explanations. In the former case, the insight is about a particular instance x. The local model estimates the effect of the features in $\mathcal{F}$ on $f(x)$ [13]. Conversely, global models summarize the main patterns driving ML decisions (on whatever instance). In this work, we conveniently combine the local explanations of the cryptocurrency price predictions provided by SHAP to model the global influence on ML models of individual features, features subcategories and categories.

We present a visual eXplainable AI tool, namely Crytpocurrency-based Machine Learning Explainer (CryptoMLE, in short). It supports cryptocurrency traders and investors in monitoring the performance of quantitative Machine Learning-based cryptocurrency predictions. CryptoMLE consists of an interactive dashboard summarizing the main feature contributions to the ML price predictions.

A snapshot of the dashboard interface is depicted in Figure 1. The plot in the upper side of the dashboard shows the SHAP time series of the 10 most influential features in the prediction of class *uptrend*. The purpose is to explain how ML works within a restricted time period and how ML decisions vary over time. More specifically, a time series value sampled on day d consists of the mean Shapley value of a given feature F_i computed over the W days preceding d (Since historical data are collected at a daily granularity, each time point in the series corresponds to a distinct trading day.). The mean Shapley value of F_i indicates the effect of F_i on the ML model trained on d using a sliding window approach.

For example, according to the SHAP series plot in Figure 1, the MD feature *close_resid* appears to be the most influential one in the period between August 2017 and April 2018, whereas between May 2018 and December 2018, *Close_resid* and *High_resid* are joint winners. The SHAP series plot can be useful, for instance, for discretionary traders who need to select and monitor a relatively small subset of visual features.

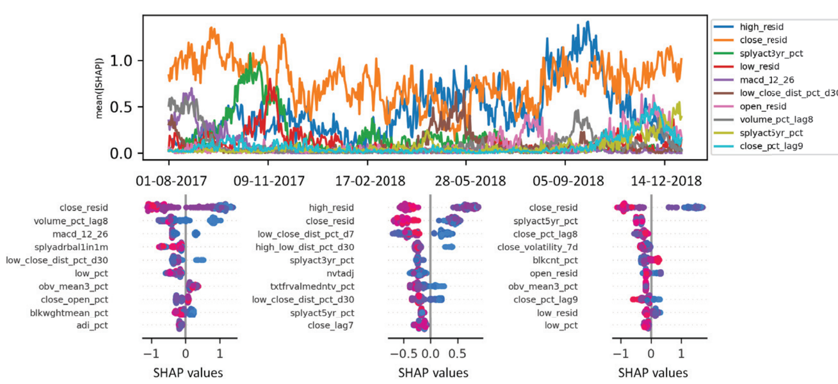

Figure 1. Interactive dashboard snapshot. Uptrend class. LTCUSD. Training window size $W = 90$.

The bee-swarm summary plots in the lower side of the dashboard snapshot are pop-up windows that analysts might activate when they are interested in gaining insights into the characteristics of the ML model trained on a particular day. It shows the Shapley values of all instances belonging to a training window of size W (i.e., W points per feature). For the sake of readability, only the top-10 features in order of decreasing Shapley value are visualized.

For example, according to the left hand-side bee-swarm summary plot in Figure 1, *close_resid*, *volume_pct_tag8 macd_12_26*, and *low_close_dist_pct_d30* are the only features obtaining a significant number of positive Shapley values during the training window from the beginning of February 2017 to the end of July 2017. Comparing different summary plots over time can be useful, for instance, for detecting temporal changes in the ML decisions. Traders can manually verify and possibly revise the current trading strategy based on the alarms triggered by the eXplainable AI tool.

To generate the plot, we apply the procedure described in Algorithm 1 considering one cryptocurrency at a time. First, the dataset D_c, containing the data of the cryptocurrency c, is split into train and test, and the feature importance scores are computed based on a general-purpose Machine Learning model trained on D_{train} (e.g., XGBoost [33]). Then, we generate a ranked feature list, based on the importance score, and tune the system hyper-parameters. This first phase aims at performing feature selection and parameter tuning before training the following models. To have up-to-date and contextualized models, one model is retrained for each test date/time-step t considering the latest W days preceding t, using the previously defined feature subset and hyperparameters; i.e., we employ a sliding window approach to train ML models tailored to the time-steps t. Finally, the trained ML models (one per test time-step) are analyzed to compute the SHAP series and the summary plots, thus enabling the visual exploration of the ML reasoning at different time points. The procedure is repeated for all cryptocurrencies of interest.

Algorithm 1: CryptoMLE: Procedure of dashboard generation for a cryptocurrency.

Input : $\mathbf{F}$: feature set;
$\mathbf{D_c}$: dataset associated with cryptocurrency c;
$\mathbf{W}$: sliding training window;
f_{pr}: chosen Machine Learning model for the prediction step;
f_{fs}: chosen Machine Learning model for the feature selection step;

output: $\mathbf{SH}$: time series of average Shapely values per-feature;
$\mathbf{BS}$: bee-swarm summary plots for each point of the test-set;

```
/* Train-test dataset split                                    */
D_train, D_test ← SplitDataset (D_c)
/* Feature selection                                           */
M_fs ← TrainFeatureSelectionModel (f_fs, D_train, F)
R ← FeatureImportanceRankingForModel (M_fs)
F_s ← SelectFeaturesFromRanking (R, F)
/* Hyper-parameters tuning                                     */
P ← TuneHyperparameters (f_pr, D_train, F_s)
/* Dashboard generation                                        */
foreach time-step t ∈ D_test do
    M_pr ← TrainPredictionModel (f_pr, D_(t−W,t), F_s, P)
    BS_t ← ProduceBeeswarmPlot (M_pr)
end
SH ← ProduceShapTimeSeries (BS_t)
return SH, BS_*
```

6. Experimental Results

In this section, we simulate a session of Machine Learning-based forecasting of 21 cryptocurrency prices explained by CryptoMLE.

The rest of the section is organized as follows.

- Section 6.1 clarifies the experimental settings and the reproducibility aspects.
- Section 6.2 reports the main findings related to Research Question 1, i.e., *What are the most discriminative features for cryptocurrency price prediction?* Empirical outcome *O1* compares the feature importance plots relative to different cryptocurrencies.

- Section 6.3 addresses the Research Question 2, i.e., *How to provide cryptocurrency investors with quantitative estimates of the influence of specific features and feature categories on Machine Learning-based cryptocurrency predictions?* The empirical outcome *O2* consists of a selection of SHAP series and bee-swarm summary plots highlighting interesting trends in the analyzed cryptocurrencies.
- Section 6.4 addresses the Research Question 3, i.e., *How can we evaluate the statistical dependence of the ML feature ranks returned by SHAP in different time periods and on different cryptocurrencies?* We address *O3* by evaluating the pairwise agreement between the shortlisted feature ranks using the Rank Biased Overlap similarity measure [15].

6.1. Experimental Design

In the following, we describe the hardware used to perform the experiments and the experimental settings to improve reproducibility.

Hardware settings. We run experiments in a single-node setting on an HPC facility. The node runs Ubuntu 20.04.2 LTS, with an 8 CPU threads Intel(R) Xeon(R) Gold 6140 CPU @ 2.30 GHz and 40 GB of RAM.

Experimental settings and reproducibility. The source data described in Section 3 and a detailed per-feature description are available for research purposes. We also release the guidelines for dashboard creation (again for research purposes only).

As a representative ML model for both classification and feature importance estimation, we used the XGBoost classifier available in the SK-Learn library [33]. It is both efficient and accurate. To run SHAP [13], we use the publicly available code released by the paper's authors.

6.2. Empirical Outcome O1: Feature Importance across Cryptocurrencies

The pie charts in Figures 2–5 show the feature importance scores (returned by the XGBoost ML model) computed over all cryptocurrencies (see Figure 2) and separately for BTCUSD, BCHUSD, and ETHUSD (see Figures 3–5). BTCUSD is, by far, the most famous cryptocurrency. BCHUSD is a fork of BTCUSD, whereas ETHUSD is another extremely popular cryptocurrency.

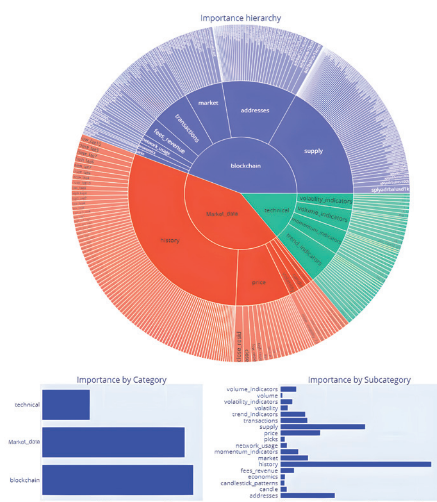

Figure 2. Hierarchical mean feature importance over all the analyzed cryptocurrencies.

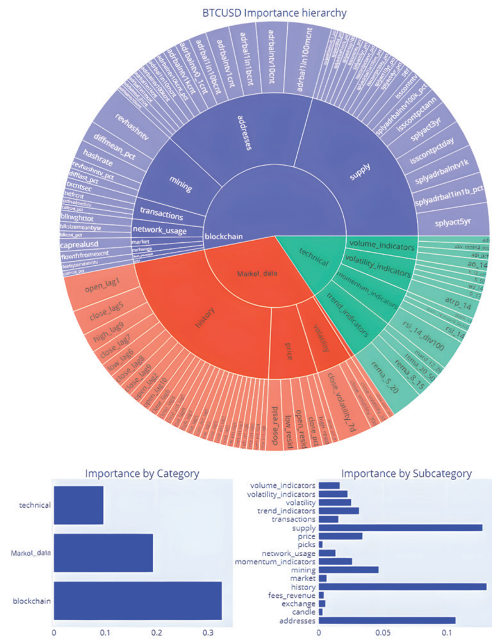

Figure 3. Hierarchical mean feature importance for BTCUSD.

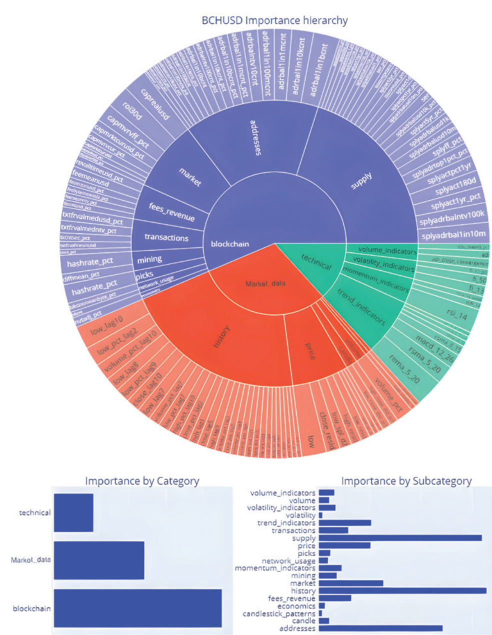

Figure 4. Hierarchical mean feature importance for BCHUSD.

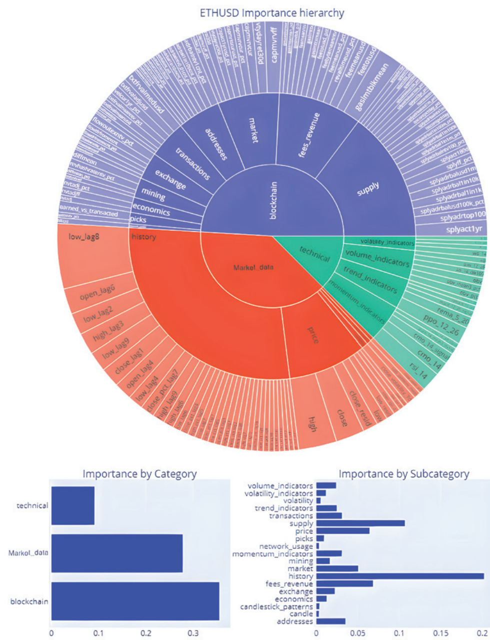

Figure 5. Hierarchical mean feature importance for ETHUSD.

The outermost circular crown of the pie chart in Figure 2 reports the average importance scores per feature by considering all cryptocurrencies. Specific price-related features, such as *close_resid* (i.e., the Seasonal-Trend decomposition using LOESS of the closing price series [30], have shown to be the most relevant to predict future cryptocurrency prices). However, the selected features are not the same for all cryptocurrencies and also include blockchain-related ones. For example, *hashrate_pct*, which indicates the amount of computational operations that a miner or the network of miners is capable of carrying out, is particularly relevant to BitCoin casH (BCH), which has been created to specifically address efficiency issues of the most established BTC cryptocurrency. Conversely, it is not relevant to Ethereum (ETH) because ETH is known to be weakly correlated to BTC.

To have a higher-level view of which features are more discriminating for a given cryptocurrency, we also aggregate the feature importance scores per subcategory and category (see the two inner crowns in Figure 2 and the bar charts). The most relevant features are those belonging to category *Blockchain* (average score 0.48), which is followed by *Market data* (0.46) and *Technical analysis* features (0.16). This means that to drive their investments, cryptocurrency traders should closely monitor blockchain-related features first rather than simply analyzing price-related features (e.g., moving averages, momentum [27]).

Focusing on the most influential subcategories, they encompass the properties of the supply chain, namely *Supply* (BC category), the historical cryptocurrency prices, i.e., *History* (MD category), and the blockchain network activity metrics, namely *Addresses* (BC category). It is worth noticing that restricting the in-depth analysis to these feature subsets allows experts to ignore almost 70% of the original features.

The variability in feature importance across different cryptocurrencies is also quite significant (see Figures 3–5). For example, for ETHUSD, the blockchain-related features turn out to be slightly less significant than for BTCUSD and BCHUSD, which is possibly due to the primary influence of the blockchain architecture on the price movements of the BiTCoin-related assets. Ethereum (ETH) is partly uncorrelated with BC and weakly dependent on blockchain-related properties such as hash rate and transaction counts.

6.3. Visual Explanations

We report the dashboard snapshots for three representative combinations of cryptocurrency and prediction class (see Figures 6–11).

From the line chart in the upper side of Figure 6, we can see how the average Shapley value changes over time for the top-10 most influential features for class Uptrend. Some features (e.g., *close_resid*) are always highly relevant regardless of the considered time period, whereas some others show variable influence. The latter can be dynamically included in the trading system models according to the feedback collected from the eXplainable AI tool. Moreover, traders can also use the provided information to assess the reliability of the performed predictions. If the features associated with the highest absolute Shapley values are, based on the prior knowledge of traders, remarkable features, traders will become more confident in the returned predictions and thus will likely use them in the design of the cryptocurrency trading strategy. In a nutshell, the visual explanation of CryptoMLE has a twofold aim: (1) understand the rationale behind ML decisions, and (2) discover potentially interesting (cryptocurrency-specific) patterns that are worth considering in the future trading activities.

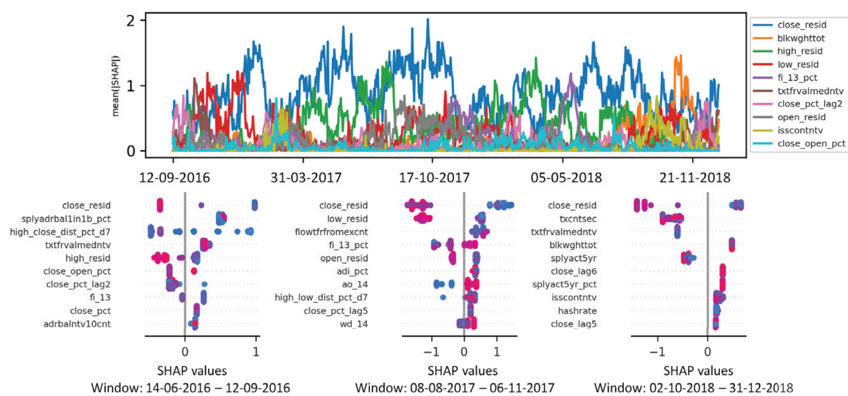

Figure 6. Interactive dashboard snapshot. Uptrend class. BTCUSD. Sliding training window size $W = 90$.

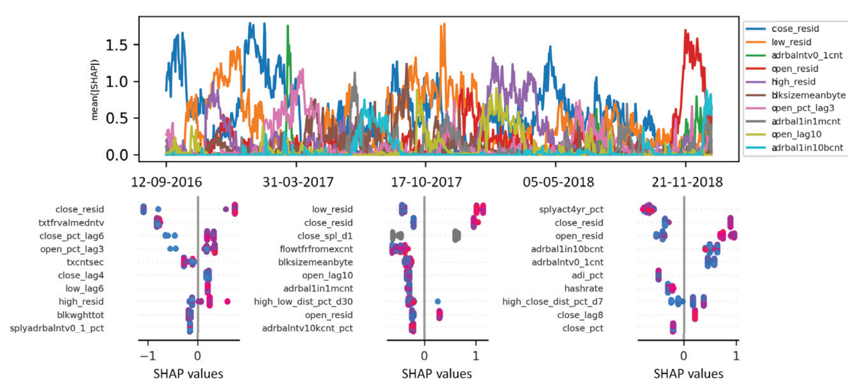

Figure 7. Interactive dashboard snapshot. Downtrend class. BTCUSD. Sliding training window size $W = 90$.

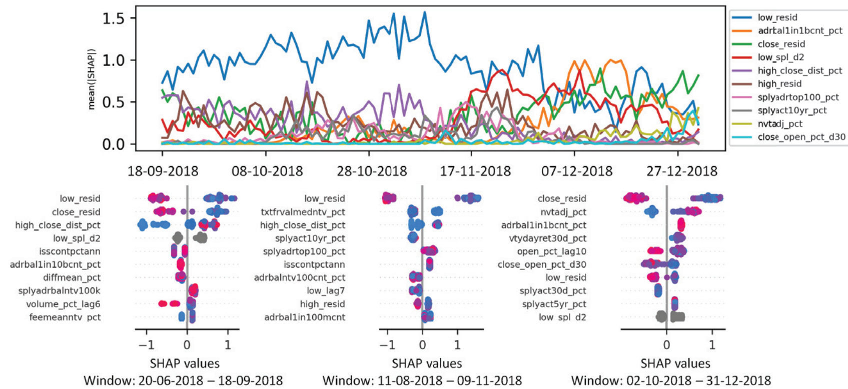

Figure 8. Interactive dashboard snapshot. Uptrend class. BCHUSD. Sliding training window size $W = 90$.

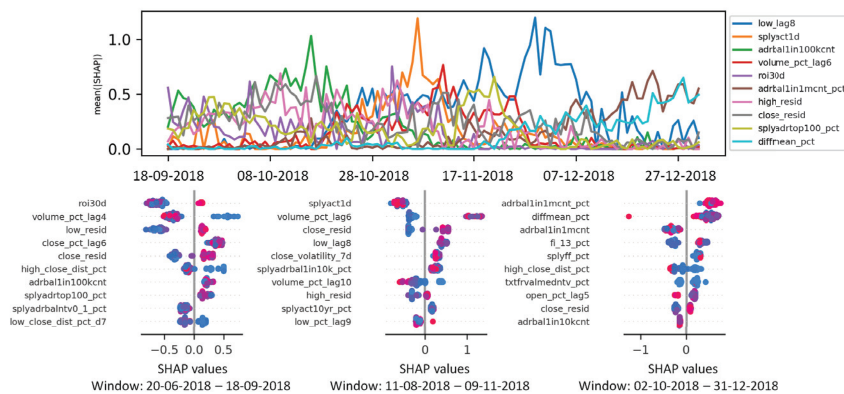

Figure 9. Interactive dashboard snapshot. Downtrend class. BCHUSD. Sliding training window size $W = 90$.

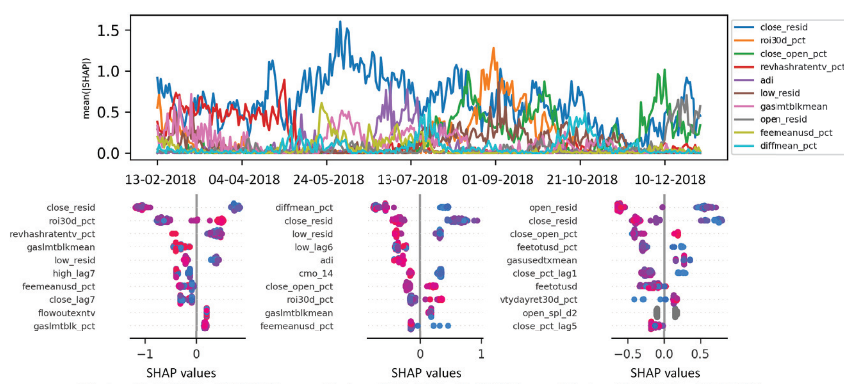

Figure 10. Interactive dashboard snapshot. Uptrend class. ETHUSD. Sliding training window size $W = 90$.

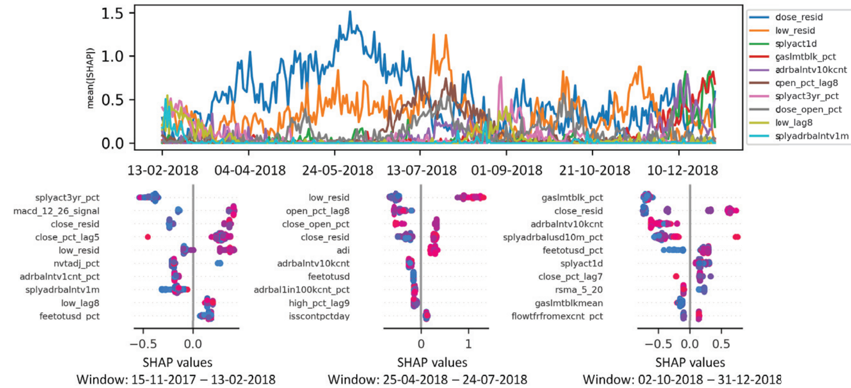

Figure 11. Interactive dashboard snapshot. Downtrend class. ETHUSD. Sliding training window size $W = 90$.

The charts in the bottom part of Figure 6 report the Shapley values computed for three representative windows of size W (i.e., the ones associated with the first, the middle, and last date of the considered evaluation period). Each chart reports, for the top-10 most influential features, the Shapley values associated with the predictions made within the considered time window (i.e., one point in the plot per prediction). The absolute Shapley value indicates the strength of the feature influences. Its sign indicates whether the value of the feature positively or negatively impacts on the prediction of the Uptrend label. If the Shapley values associated with a feature are close to -1 or 1, it means that the feature affects the prediction more significantly than the other ones. As for the SHAP series plot, the variability in the summary plots over time strongly depends on the underlying market conditions. For example, in the last quarter of 2018, AI model predictions turn out to be primarily influenced by the historical price series, whereas in the previous quarters of 2018, the influence of blockchain-related features is more evident. Based on these results, domain experts can investigate more in depth the reasons behind such a strategy change to judge the reliability of the algorithmic trading approach. More specifically, in the last quarter of 2018, all the BitCoin-related plunged, and such an evident market downtrend is prevailing for algorithmic trading systems.

Figure 7 reports a similar information but the class label Downtrend is considered, i.e., those charts try to explain which features impacted more on the prediction of the label Downtrend. Some features are relevant for the prediction of both class labels, whereas others are specific for each class.

Figures 8–9 and Figures 10–11 report similar pieces of information for BCHUSD and ETHUSD, respectively. We can notice that some of the top features are shared between BTCUSD and BCHUSD, whereas ETHUSD is more affected by other blockchain-related features. Most of the top features categories are shared among all the three considered features.

Tables 3 and 4 report the top-3 most influential features per cryptocurrency and class in terms of average Shapley value. The achieved results confirm that for most of the analyzed cryptocurrencies, the subcategories of the most influential features are independent of the predicted class label.

Table 3. Most influential features for class Uptrend.

Crypto	Top1_Feature	Top1_Subcategory	Top2_Feature	Top2_Subcategory	Top3_Feature	Top3_Subcategory
ADA	close_resid	market_data_prices	splyact180d_pct	blockchain_supply	adi_pct	technical_analysis_volume
BCH	close_resid	market_data_prices	nvtadj_pct	blockchain_economics	adrbal1in1bcnt_pct	blockchain_address
BNB	close_open_pct_d30	market_data_candlestick_analysis	splyadrbalntv100k	blockchain_supply	capact1yrusd	blockchain_market
BTC	close_resid	market_data_prices	txcntsec	blockchain_transactions	txtfrvalmedntv	blockchain_transactions
BTG	close_resid	market_data_prices	high_low_dist_pct_d7	market_data_candlestick_analysis	low_pct_lag4	market_data_history
DASH	close_resid	market_data_prices	adrbal1in1mcnt_pct	blockchain_address	low_pct_lag3	market_data_history
DOGE	close_open_pct_d30	market_data_candlestick_analysis	close_resid	market_data_prices	txtfrvalmedntv	blockchain_transactions
EOS	close_resid	market_data_prices	open_pct_lag6	market_data_history	low_pct_lag3	market_data_history
ETC	adrbalntv0_01cnt	blockchain_address	gaslmtblk	blockchain_fees	gaslmttx	blockchain_fees
ETH	open_resid	market_data_prices	close_resid	market_data_prices	close_open_pct	market_data_candlestick_analysis
LINK	txtfrcnt	blockchain_transactions	splyadrtop1pct_pct	blockchain_supply	caprealusd	blockchain_market
LTC	close_resid	market_data_prices	high_resid	market_data_prices	txtfrcnt	blockchain_transactions
NEO	adi_pct	technical_analysis_volume	close_resid	market_data_prices	txtfrcnt	blockchain_transactions
QTUM	low_resid	market_data_prices	volume_pct_lag9	market_data_history	open_pct_lag5	market_data_history
TRX	high_resid	market_data_prices	close_resid	market_data_prices	high_pct_lag8	market_data_history
WAVE	txcntsec	blockchain_transactions	low_resid	market_data_prices	adi	technical_analysis_volume
XEM	cmo_14	technical_analysis_momentum	high_pct_lag2	market_data_history	close_resid	market_data_prices
XMR	close_resid	market_data_prices	high_lag2	market_data_history	rema_8_15_pct	technical_analysis_trend
XRP	close_resid	market_data_prices	close_open_pct_d3	market_data_candlestick_analysis	close_pct_lag7	market_data_history
ZEC	high_resid	market_data_prices	close_resid	market_data_prices	close_pct_lag3	market_data_history
ZRX	txtfrvalmeanusd	blockchain_transactions	high_pct_lag2	market_data_history	txtfrvaladjntv_pct	blockchain_transactions

Table 4. Most influential features for class Downtrend.

Crypto	Top1_Feature	Top1_Subcategory	Top2_Feature	Top2_Subcategory	Top3_Feature	Top3_Subcategory
ADA	splyadrtop100_pct	blockchain_supply	splyact1yr_pct	blockchain_supply	close_resid	market_data_prices
BCH	adrbal1in1mcnt_pct	blockchain_address	diffmean_pct	blockchain_mining	adrbal1in1mcnt	blockchain_address
BNB	splyadrbalntylk_pct	blockchain_supply	splyadrbal1in1k_pct	blockchain_supply	low_close_dist_pct_d30	market_data_candlestick_analysis
BTC	splyact4yr_pct	blockchain_supply	close_resid	market_data_prices	open_resid	market_data_prices
BTG	close_resid	market_data_prices	low_resid	market_data_prices	txtfrvaladjusd	blockchain_transactions
DASH	close_resid	market_data_prices	isstotl_isstot365_pct	blockchain_supply	high_resid	market_data_prices
DOGE	volume_pct_lag3	market_data_history	high_resid	market_data_prices	txtfrvalmedntv	blockchain_transactions
EOS	close_pct_lag8	market_data_history	close_resid	market_data_prices	open_pct_lag4	market_data_history
ETC	close_resid	market_data_prices	splyactever_pct	blockchain_supply	nvtadj	blockchain_economics
ETH	gaslmtblk_pct	blockchain_fees	close_resid	market_data_prices	adrbalntv10kcnt	blockchain_address
LINK	high_close_dist_pct_d3	market_data_candlestick_analysis	splyadrbalusd1m	blockchain_supply	close_resid	market_data_prices
LTC	close_resid	market_data_prices	volume_pct_lag1	market_data_history	close_open_pct_d30	market_data_candlestick_analysis
NEO	close_resid	market_data_prices	low_pct_lag9	market_data_history	low_close_dist_pct	market_data_candlestick_analysis
QTUM	close_pct_lag10	market_data_history	low_resid	market_data_prices	open_lag9	market_data_history
TRX	fi_13_pct	technical_analysis_volatility	close_resid	market_data_prices	high_resid	market_data_prices
WAVE	close_pct_lag7	market_data_history	close_resid	market_data_prices	volume_pct_lag3	market_data_history
XEM	low_resid	market_data_prices	volume_pct_lag2	market_data_history	low_lag4	market_data_history
XMR	close_resid	market_data_prices	txcnt_pct	blockchain_transactions	close_volatility_7d	market_data_volatility
XRP	close_resid	market_data_prices	adrbalntv1mcnt_pct	blockchain_address	volume_pct_lag4	market_data_history
ZEC	close_resid	market_data_prices	close_pct_lag8	market_data_history	low_spl_d1	market_data_prices
ZRX	high_close_dist_pct_d3	market_data_candlestick_analysis	splyadrbal1in10k_pct	blockchain_supply	low_resid	market_data_prices

6.4. Statistical Dependence between Feature Ranked Lists

We evaluate the agreement between the feature ranked lists associated with the 21 cryptocurrencies using the Rank Biased Overlap similarity measure [15]. The goal is to verify whether ML predictions on different cryptocurrencies are influenced by the same features, feature subcategories, or categories.

Tables 5 and 6, respectively, report the pairwise similarity matrices for the classes Uptrend and Downtrend. They allow us to identify specific cryptocurrency clusters characterized by relatively high pairwise similarities. For instance, XMR and ZEC are highly similar, which is probably because they are both focused on privacy aspects.

Table 5. Pairwise similarity among cryptocurrencies. Class Uptrend.

	ADA	BCH	BNB	BTC	BTG	DASH	DOGE	EOS	ETC	ETH	LINK	LTC	NEO	QTUM	TRX	WAVE	XEM	XMR	XRP	ZEC	ZRX
ADA	1.00	0.84	0.98	0.84	0.89	0.94	0.94	0.72	0.80	0.78	0.68	0.94	0.85	0.72	0.76	0.90	0.81	0.90	0.88	0.91	0.86
BCH	0.84	1.00	0.85	1.00	0.74	0.89	0.84	0.61	0.66	0.94	0.84	0.84	0.69	0.61	0.59	0.74	0.63	0.71	0.77	0.81	0.78
BNB	0.98	0.85	1.00	0.85	0.90	0.96	0.96	0.74	0.82	0.80	0.70	0.96	0.84	0.74	0.78	0.88	0.79	0.88	0.89	0.93	0.87
BTC	0.84	1.00	0.85	1.00	0.74	0.89	0.84	0.61	0.66	0.94	0.84	0.84	0.69	0.61	0.59	0.74	0.63	0.71	0.77	0.81	0.78
BTG	0.89	0.74	0.90	0.74	1.00	0.84	0.91	0.83	0.65	0.79	0.52	0.91	0.79	0.83	0.87	0.79	0.83	0.96	0.96	0.94	0.76
DASH	0.94	0.89	0.96	0.89	0.84	1.00	0.95	0.77	0.76	0.84	0.74	0.95	0.80	0.77	0.75	0.84	0.73	0.82	0.87	0.92	0.89
DOGE	0.94	0.84	0.96	0.84	0.91	0.95	1.00	0.78	0.73	0.84	0.65	1.00	0.84	0.78	0.82	0.84	0.78	0.89	0.94	0.97	0.86
EOS	0.72	0.61	0.74	0.61	0.83	0.77	0.78	1.00	0.45	0.67	0.40	0.78	0.62	1.00	0.96	0.62	0.66	0.81	0.84	0.81	0.66
ETC	0.80	0.66	0.82	0.66	0.65	0.76	0.73	0.45	1.00	0.54	0.81	0.73	0.74	0.45	0.51	0.90	0.66	0.64	0.62	0.68	0.87
ETH	0.78	0.94	0.80	0.94	0.79	0.84	0.84	0.67	0.54	1.00	0.73	0.84	0.68	0.67	0.65	0.68	0.66	0.75	0.82	0.87	0.72
LINK	0.68	0.84	0.70	0.84	0.52	0.74	0.65	0.40	0.81	0.73	1.00	0.65	0.62	0.40	0.38	0.78	0.54	0.51	0.55	0.60	0.82
LTC	0.94	0.84	0.96	0.84	0.91	0.95	1.00	0.78	0.73	0.84	0.65	1.00	0.84	0.78	0.82	0.84	0.78	0.89	0.94	0.97	0.86
NEO	0.85	0.69	0.84	0.69	0.79	0.80	0.84	0.62	0.74	0.68	0.62	0.84	1.00	0.62	0.66	0.85	0.96	0.80	0.78	0.81	0.81
QTUM	0.72	0.61	0.74	0.61	0.83	0.77	0.78	1.00	0.45	0.67	0.40	0.78	0.62	1.00	0.96	0.62	0.66	0.81	0.84	0.81	0.66
TRX	0.76	0.59	0.78	0.59	0.87	0.75	0.82	0.96	0.51	0.65	0.38	0.82	0.66	0.96	1.00	0.66	0.70	0.85	0.88	0.84	0.67
WAVE	0.90	0.74	0.88	0.74	0.79	0.84	0.84	0.62	0.90	0.68	0.78	0.84	0.85	0.62	0.66	1.00	0.81	0.80	0.78	0.81	0.96
XEM	0.81	0.63	0.79	0.63	0.83	0.73	0.78	0.66	0.66	0.66	0.54	0.78	0.96	0.66	0.70	0.81	1.00	0.85	0.82	0.79	0.75
XMR	0.90	0.71	0.88	0.71	0.96	0.82	0.89	0.81	0.64	0.75	0.51	0.89	0.80	0.81	0.85	0.80	0.85	1.00	0.93	0.90	0.74
XRP	0.88	0.77	0.89	0.77	0.96	0.87	0.94	0.84	0.62	0.82	0.55	0.94	0.78	0.84	0.88	0.78	0.82	0.93	1.00	0.96	0.79
ZEC	0.91	0.81	0.93	0.81	0.94	0.92	0.97	0.81	0.68	0.87	0.60	0.97	0.81	0.81	0.84	0.81	0.79	0.90	0.96	1.00	0.83
ZRX	0.86	0.78	0.87	0.78	0.76	0.89	0.86	0.66	0.87	0.72	0.82	0.86	0.81	0.66	0.67	0.96	0.75	0.74	0.79	0.83	1.00

Table 6. Correlations among cryptocurrencies. Class Downtrend.

	ADA	BCH	BNB	BTC	BTG	DASH	DOGE	EOS	ETC	ETH	LINK	LTC	NEO	QTUM	TRX	WAVE	XEM	XMR	XRP	ZEC	ZRX
ADA	1.00	0.88	0.98	0.95	0.76	0.85	0.76	0.56	0.86	0.97	0.83	0.69	0.64	0.56	0.55	0.76	0.66	0.85	0.87	0.69	0.82
BCH	0.88	1.00	0.86	0.87	0.76	0.73	0.76	0.54	0.74	0.85	0.79	0.54	0.47	0.54	0.54	0.62	0.51	0.73	0.75	0.54	0.82
BNB	0.98	0.86	1.00	0.93	0.74	0.87	0.74	0.53	0.86	0.95	0.82	0.71	0.66	0.53	0.52	0.78	0.68	0.87	0.85	0.71	0.80
BTC	0.95	0.87	0.93	1.00	0.84	0.86	0.84	0.66	0.87	0.98	0.89	0.72	0.68	0.66	0.63	0.80	0.70	0.86	0.88	0.72	0.87
BTG	0.76	0.76	0.74	0.84	1.00	0.90	1.00	0.83	0.91	0.82	0.96	0.83	0.79	0.83	0.68	0.90	0.81	0.90	0.92	0.83	0.97
DASH	0.85	0.73	0.87	0.86	0.90	1.00	0.90	0.69	0.99	0.88	0.95	0.87	0.82	0.69	0.57	0.94	0.84	1.00	0.98	0.87	0.93
DOGE	0.76	0.76	0.74	0.84	1.00	0.90	1.00	0.83	0.91	0.82	0.96	0.83	0.79	0.83	0.68	0.90	0.81	0.90	0.92	0.83	0.97
EOS	0.56	0.54	0.53	0.66	0.83	0.69	0.83	1.00	0.71	0.62	0.78	0.64	0.66	1.00	0.84	0.75	0.65	0.69	0.72	0.64	0.80
ETC	0.86	0.74	0.86	0.87	0.91	0.99	0.91	0.71	1.00	0.89	0.95	0.86	0.81	0.71	0.58	0.93	0.83	0.99	0.99	0.86	0.94
ETH	0.97	0.85	0.95	0.98	0.82	0.88	0.82	0.62	0.89	1.00	0.86	0.75	0.70	0.62	0.59	0.82	0.72	0.88	0.90	0.75	0.85
LINK	0.83	0.79	0.82	0.89	0.96	0.95	0.96	0.78	0.95	0.86	1.00	0.81	0.77	0.78	0.65	0.89	0.79	0.95	0.96	0.81	0.99
LTC	0.69	0.54	0.71	0.72	0.83	0.87	0.83	0.64	0.86	0.75	0.81	1.00	0.95	0.64	0.48	0.92	0.98	0.87	0.85	1.00	0.80
NEO	0.64	0.47	0.66	0.68	0.79	0.82	0.79	0.66	0.81	0.70	0.77	0.95	1.00	0.66	0.50	0.88	0.98	0.82	0.80	0.95	0.76
QTUM	0.56	0.54	0.53	0.66	0.83	0.69	0.83	1.00	0.71	0.62	0.78	0.64	0.66	1.00	0.84	0.75	0.65	0.69	0.72	0.64	0.80
TRX	0.55	0.54	0.52	0.63	0.68	0.57	0.68	0.84	0.58	0.59	0.65	0.48	0.50	0.84	1.00	0.59	0.49	0.57	0.59	0.48	0.67
WAVE	0.76	0.62	0.78	0.80	0.90	0.94	0.90	0.75	0.93	0.82	0.89	0.92	0.88	0.75	0.59	1.00	0.90	0.94	0.92	0.92	0.87
XEM	0.66	0.51	0.68	0.70	0.81	0.84	0.81	0.65	0.83	0.72	0.79	0.98	0.98	0.65	0.49	0.90	1.00	0.84	0.82	0.98	0.78
XMR	0.85	0.73	0.87	0.86	0.90	1.00	0.90	0.69	0.99	0.88	0.95	0.87	0.82	0.69	0.57	0.94	0.84	1.00	0.98	0.87	0.93
XRP	0.87	0.75	0.85	0.88	0.92	0.98	0.92	0.72	0.99	0.90	0.96	0.85	0.80	0.72	0.59	0.92	0.82	0.98	1.00	0.85	0.95
ZEC	0.69	0.54	0.71	0.72	0.83	0.87	0.83	0.64	0.86	0.75	0.81	1.00	0.95	0.64	0.48	0.92	0.98	0.87	0.85	1.00	0.80
ZRX	0.82	0.82	0.80	0.87	0.97	0.93	0.97	0.80	0.94	0.85	0.99	0.80	0.76	0.80	0.67	0.87	0.78	0.93	0.95	0.80	1.00

We performed a further experiment to compare the list of categories of the features that are more relevant for predicting Uptrend or Downtrend. We considered three different windows/time periods (P1, P2, P3) to analyze also the impact of the time dimension. Table 7 reports the results. For each cryptocurrency, we report the computed correlations in P1, P2, and P3. For almost all cryptocurrencies, the correlation value is stable with respect to the time slot and is higher than 0.7. Hence, for almost all cryptocurrencies, the decision about the class label is based on the same categories of features independently of the predicted label.

Table 7. Uptrend/Downtrend correlations.

Crypto	P1	P2	P3
ADA	0.72	0.62	0.80
BCH	0.82	0.90	0.66
BNB	0.92	0.76	0.80
BTC	0.90	0.83	0.78
BTG	0.96	0.90	0.93
DASH	0.77	0.99	0.97
DOGE	0.87	0.75	0.99
EOS	0.91	1.00	0.93
ETC	0.77	0.65	0.74
ETH	0.69	0.81	0.75
LINK	0.82	0.78	0.71
LTC	0.83	0.94	0.84
NEO	0.94	0.64	0.64
QTUM	0.60	0.76	0.93
TRX	0.76	0.84	0.82
WAVE	0.89	0.75	0.76
XEM	0.59	0.82	0.67
XMR	0.95	0.98	0.79
XRP	0.80	0.82	0.86
ZEC	0.87	0.70	0.87
ZRX	0.59	0.89	0.87

7. Discussion

Explainability plays an important role in many Machine Learning-driven applications, including quantitative cryptocurrency trading. Despite their accuracy, ML models are deemed as not reliable enough, as domain experts do not trust the automated solutions. In the financial, in particular, a clear explanation of the rationale behind machine-driven decisions is deemed as unavoidable.

EXplainable AI opens the ML black boxes providing global or local explanations based on the underlying data features. Due to their high dimensionality and multi-faceted nature, cryptocurrencies are particularly suited to eXplainable AI. The main purposes are:

- The enhancement of existing crytpocurrency trading systems based on the collected feedback on the current market trends.
- The online support to discretionary traders, who commonly monitor the financial markets and execute trading operations in real time.

CryptoMLE is designed for supporting the monitoring of ML model performances on cryptocurrency markets. To enhance trading system strategies, CryptoMLE helps cryptocurrency investors verify the predictive rules inferred by the ML algorithms against the domain knowledge. To support online discretionary traders' activities, it shortlists the most influential cryptocurrency features that are worth monitoring. The SHAP series and the SHAP summary plots provide them with a simple, interactive environment to obtain actionable feedback based on the recent ML outcomes.

The main takeaways from the empirical outcomes can be summarized as follows:

- Feature relevance to cryptocurrency price forecasting is either *generalized*, i.e., valid for all cryptocurrencies independently of time periods and market conditions (e.g., for the *Close_rel* feature), or *selective*, i.e., valid only for a subset of features and for specific time periods. For the latter feature subset, CryptoMLE provides experts with an automated way to recognize them and leverage their predictive power for quantitative trading.
- Based on the prediction outcomes, the relevance of the individual features is highly variable (see the dashboard snapshots in Figures 6–11). To drive short-term cryptocurrency investments, it is crucial to monitor the most likely causes of market movements. For example, the percentage variations of the trading volume between current and previous days (namely *volume_pct**) appear to be relevant to predict BCHUSD variations (see Figure 9), whereas they are less influential in the prediction of other cryptocurrency prices.
- The influence of feature subcategories and categories is less sensitive to the market conditions, but they can be tailored to particular cryptocurrencies. For example, a cryptocurrency is more likely to be more influenced by BC features than others. This can be easily verified using CryptoMLE in real trading simulations.
- The discrepancies between the observed results among the target class (e.g., Uptrend, Downtrend) are often negligible. Therefore, traders relying on both long- and short-selling trading strategy can easily and quickly interact with CryptoMLE to gather all the required information.
- Simpler ML models analyzing only the prices of the target cryptocurrency assets appear to be suboptimal because, according to the achieved results, cryptocurrency prices are likely to be relevantly influenced by many other features (see, for instance, BCHUSD and ETHUSD). This confirms the utility of the CryptoMLE graphical interface, which provides human experts with a summary of the main feature contributions to the ML predictors.

8. Conclusions and Future Works

This paper introduced an eXplainable AI tool for cryptocurrency price forecasting. It presented a visual interface based on which domain experts can infer actionable dependencies among input data features and Machine Learning predictions. The interactive dashboard consists of an SHAP series plot, showing the temporal variation of the mean Shapley values associated with the most recent ML predictions, and a selection of pop-up summary plots, which are snapshots of the main features' influences at given time points. The empirical simulation, which was run on a 8-year period, showed the variability of the model explanations across 21 cryptocurrencies and three reference time periods in terms of selected features, feature subcategories and categories.

As future work, we plan to leverage the Shapley values in quantitative intraday trading. Specifically, we aim at dynamically adapt algorithmic decisions in crtyptocurrency trading based on the relevant feedback provided by domain experts through the graphical interface.

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Proposal for a System Model for Offline Seismic Event Detection in Colombia

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Abstract: This paper presents an integrated model for seismic events detection in Colombia using machine learning techniques. Machine learning is used to identify P-wave windows in historic records and hence detect seismic events. The proposed model has five modules that group the basic detection system procedures: the seeking, gathering, and storage seismic data module, the reading of seismic records module, the analysis of seismological stations module, the sample selection module, and the classification process module. An explanation of each module is given in conjunction with practical recommendations for its implementation. The resulting model allows understanding the integration of the phases required for the design and development of an offline seismic event detection system.

Keywords: seismic event detection; detection model; seismology; classification

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1. Introduction

Earthquakes have been one major concern to societies around the world. Earthquakes are a consequence of earth tectonics, which cause intercontinental plate drifts. Deformation energy is stored along the plates. Once one or more fault lines exhaust their elastic deformation capacity, rupture occurs and the stored energy is released as seismic waves, propagating along with the earth's crust. Depending on the amount of energy released and the depth of rupture, seismic waves can hit civil infrastructure, causing major impacts. Such events as in Sumatra (Indonesia, 2004), Haiti (2010), and Tohoku (Japan, 2011) are proof of how devastating can earthquakes be over human infrastructure and society as well. In Colombia, the Armenia earthquake (1999, Mw 6.2) is referenced as the worst seismic event for the country, which forced the government to call for an updating of the existing design and construction code. The resulting document was introduced into the Colombian legislation, making it a mandatory practice among civil infrastructure designers and constructors [1,2].

Earthquake engineering is a branch of engineering born to reduce the effects of earth seismicity. The approaches that earthquake engineering take can be seen from two perspectives: a study of the seismic phenomena and a study of the structural response after the seismic event. Research in earthquake engineering has increased in depth as new materials and computational power have been conceived. Simple techniques for the characterization of earthquake events can be used intensively in an attempt to formulate methodologies that provide people with a time frame to evacuate civil infrastructure during significant seismic events. However, current methodologies involving computational power deal with limitations in storage capacity (storage of seismic traces and raw data), processing capabilities (multichannel seismic acquisition), and lack of compatibility and integration of software resources, adding difficulties for the implementation of a successful seismic event detection technique [3–5].

Few academic research groups in Colombia, including the Colombian Geological Service, dedicate their efforts to boost techniques and methodologies focused on the seismic phenomena. Most of the research efforts aim toward a better understanding of both site seismic and structural responses, while some research has been carried on the understanding of local seismicity. Countries such as Mexico and Chile, both with similar seismic characteristics as Colombia, dedicate their research efforts to improve cities' structural resilience and to improve the social response during seismic events as well. The proposal of this research paper is a system model for offline seismic event detection in Colombia, where a set of integrated modules for reading and processing historical seismic raw data deals with the reduction of the computational costs for the successful detection of seismic events.

This article structures the proposal of a machine learning-based model for the detection of seismic events as follows: (a) problem statement (seismology and seismic data recording), (b) earthquake detection methodologies (traditional vs. current approaches), (c) seismic detection model proposal (model architecture and modules description), and (d) article conclusions.

2. Problem Statement

Countries over the Pacific coast of Southern America have a long history of catastrophic earthquake events. According to the US Geological Survey, five of the top 20 largest earthquake events occurred since the earlier 1900s, including the largest, have occurred along the fault line traced by the borders of the Nazca Plate that subducts below the South American Plate [6]. The tectonic environment in Colombia can be described by its two main fault zones: (a) Romeral zone (intraplate seismic zone that runs from north to south of the country's Pacific coast with an approximate length of 1200 km) and (b) the frontal fault of Eastern Cordillera (fault system that divides the Colombian Andean territory from its eastern great plains, most likely a southern border of the Caribbean Plate) [7]. One local seismic zone on the Colombian northeast of great activity is the Bucaramanga Seismic Nest, where at least eight events with a magnitude Mw > 4.7 occur each year [8].

Typical geological and seismic observation services such as SGC in Colombia provide seismic analysis in a two-stage fashion: first, by acquiring and storing seismic records (which can include up to three spatial components of accelerations, velocities, and ground displacements) and second, by performing seismic event recognition by looking for particular seismic characteristics within the stored data. Then, the geological service within a short time frame reports the occurrence of a seismic event, which is usually information that commonly contains the event magnitude and its approximate geolocation. [9–11]. This two-step procedure is complex, since it involves algorithms to read, synchronize, and process seismic data information. Geological services usually rely on black-box software that performs these tasks, closing the door to monitor sub-stages and therefore not letting the user integrate alternative algorithms that could eventually improve and/or fit specific site characteristics to the seismic data analysis sub-stage [12,13].

To establish methods for the detection and analysis of seismic events, the disposition of a set of historical seismic records that can be stored, read, and processed is essential to develop an accurate detection of future events (classic approach of learning from data). However, it is difficult to find a seismic dataset that fits the requirements for later processing stages, and when retrieved, the seismic files are not easy to interpret, as they include specific seismic parameters contained in legible formats that only specialized software such as SEISAN and SeisComP can process [14,15].

Moreover, several factors make an integral analysis of these Colombian historical records unfeasible: (a) limitations on the storage capacity, (b) limitations on the compatibility between current software resources, (c) limitations on the processing power required, (d) use of techniques that are not integrated within the detection models, and (e) low flexibility of the existing tools for modifications and adequations of storage and processing algorithms [16,17].

Furthermore, the online detection of coming earthquakes can be done by picking the seismic phases manually or by establishing a fixed-threshold approach; these techniques are statistically earthquake-proven for significant earthquakes and signals with low sampling rates and few numbers of components, given a higher signal-to-noise ratio. When high samples rates are considered from multiple three-dimensional seismological stations, the phases may be picked differently, introducing bias into the detection [18].

In this sense, a system model for offline seismic event detection for the Colombian region is proposed, which allows the identification of patterns and dynamics in historical records, using machine learning techniques.

The following sections present a theoretical basis and the description of the model for seismic event detection.

3. Earthquake Detection Methodologies

Seismic detection algorithms are used by public and/or private services dedicated to monitor and study seismic activity. Several agencies dedicate efforts to maintain an updated database of information that can help scientists and engineers analyze any activity that could represent a hazard to the infrastructure and population, including volcanic and seismic activities [19]. Data collected include ground motion records (accelerations, velocities, and/or displacements), which are used by detection algorithms as input data.

Several approaches have been conceived to perform seismic events detection. In the seismic signal, amplitude, shape, power, or several other time-domain characteristics can be used to formulate a detection procedure [19,20], depending on the desired purpose of the outcome. In practical terms, seismic signals are identified by monitoring isolated ground vibrations, which under changes in amplitude, frequency content, or motion direction indicate the arrival of seismic waves [20]. Current developments on earthquake signals monitoring aim to provide faster and more reliable detection algorithms for warning systems [21].

3.1. Traditional Approaches

Detection algorithms for earthquake detection assume that seismic signals correspond to ground vibrations isolated from human activity. Only stationary background noise is registered prior to earthquake waves' arrival. To automate the process of identifying the arrival of earthquake waves, specialized detection algorithms are required. These algorithms deal with the task of effectively discriminating background noise from seismic events, to avoid the recording of unnecessary data or the loss of actual seismic signals. Then, detection algorithms require having a high rate of positive event identification, which is easily achieved when strong motions occur (e.g., triggers such as signal's threshold can discriminate noise from strong seismic signals). However, if a seismic event is detected far from the causative fault, a decrease in the signal's amplitude can be expected, making it harder for the algorithm to perform a positive event detection.

The simplest approach for an earthquake detection system is a front detection system, which consists of the direct monitoring of a given seismic source. Monitoring the signal's amplitude allows a central managing system to perform pre-defined tasks such as shutting down the power on certain areas or generating alerts of populated areas far enough from the strong ground motion epicenter. Mexico's earthquake monitoring system (SASMEX) implements front detection for this purpose. The front detection approach requires the analysis of most of the seismic signal to validate the trigger, dismissing valuable time that can be used to alert a wider area in case of a strong ground motion event. To deal with this, further approaches attempt to wider the alert time window by analyzing a shorter segment of the seismic signal, requiring more elaborated metrics that can be positively correlated to a significant earthquake event. Some of those metrics include the average noise level, predominant signal period, or cumulative energy [22]. However, these algorithms have a high rate of false alarms when dealing with weak-motion earthquake events [23]. Detection triggers are also specialized to work with frequency-domain data. In this case, signal energy metrics are used as thresholds (e.g., average power). Transform methods such as Fourier or Walsh and signal filtering have been used to provide faster and more reliable detection algorithms [5]. Time-frequency domain techniques such as the wavelet transform have been used to track the initiation of ground motion [24,25]. A technique found more reliable and widely used is based on the short-time average through the long-time average ratio (STA/LTA). The technique is based on the fact that when seismic events occur, the current signal average (STA) is different from the long-term signal average (LTA) where no events occurred [5,26].

Figure 1 shows the implementation of the STA/LTA algorithm over a strong-motion record. The seismic record (top figure) shows the arrival of P-waves in the interval 5–10 s. P-waves (P for primary) travel across the earth's mantle in tension–compression mode. Rocks have their highest stiffness (force to deformation ratio) for compression forces, and thus, compression waves can travel the fastest across the earth's mantle, arriving at the surface prior to secondary waves. After 10 s, the seismogram on the top figure shows the strongest acceleration recorded by the seismic station for the event. Secondary and surface waves arrive at the seismic station seconds later than P-waves. Cities with poor seismic resilient infrastructure usually take the highest toll on human and economic losses when they experiment strong ground accelerations.

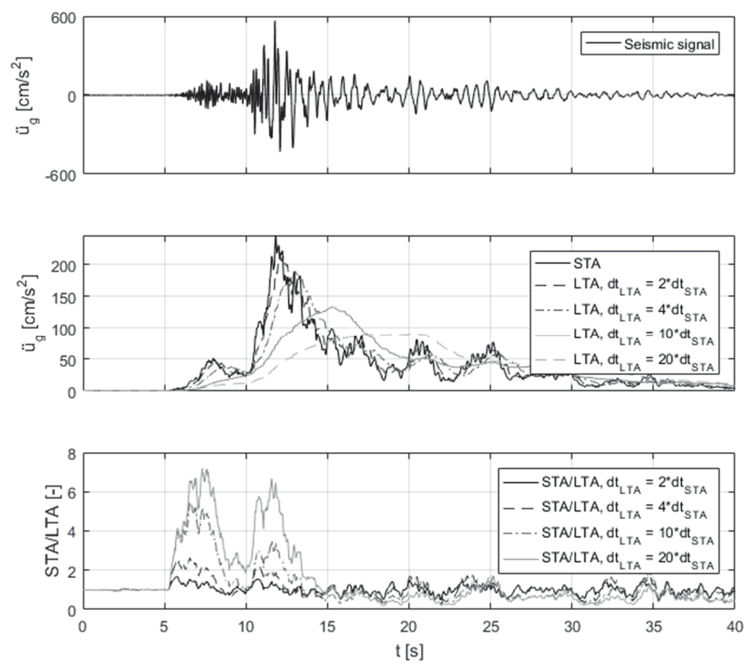

Figure 1. Short-time average through the long-time average ratio (STA/LTA) algorithm.

Figure 1 (middle) shows the STA and LTA parameters. It can be seen that the short-time average is useful to indicate the arrival of the seismic event as it suddenly arises from a very low value (assumed to be noise). The long-time average is less sensitive to the arrival of the seismic signal but keeps track of the signal's duration. The STA/LTA ratio (Figure 1, bottom) points out the location of the seismic event's start point, which is one of the most important features required by any detection methodology.

The STA/LTA algorithm has shown to be very effective due to its simplicity [5,27,28], but it requires the optimization of user-defined parameters to obtain a high rate of positive-event detection.

Parameters such as the sampling rate, detection threshold, or even, pre-event and post-event parameters are required to achieve a desired positive detection with the algorithm.

3.2. Current Approaches

Actual developments of detection algorithms take advantage of current technological advances that allow the capture, processing, and storage of data with high resolution. A large amount of available data today is used for advanced and still rarely used techniques: local similarity (quantifies consistency of data between neighboring stations) [29], probability (parameters such as distance to the seismogenic zone or signal phases are treated as random variables with an associated probability) [30], data mining (establishes a fingerprint of seismic waves for later comparison) [31], neural networks (neural network-based algorithms are trained to identify several characteristics of seismic waveforms) [19], and social sensing (based on trending hashtags or key words on social media, algorithms can trigger responses on alert systems) [32–34]. These approaches are all computational powerful and help identify waveforms on large historic seismic arrays that were not processed so far or that could have been processed by techniques with less accuracy. The cost of these techniques is the computational time. In terms of computational efficiency, the STA/LTA concept [26,35] arises as a traditional and yet highly efficient parameter for earthquake detection.

4. Seismic Detection Model Proposal

This research paper proposes the model presented in Figure 2—a set of modules in which seismic signals can be processed—from the seismic data collection to the detection mechanism expressed in the classification process module. The applicability of the model is directly related to the selection of the geographical zone whose seismicity is to be studied—in this case, the northeastern region of Colombian. The size of the study area, the rate of occurrence of events, and the homogeneity of the subsoil are some of the variables that directly influence the number of observations to be analyzed and the performance of each of the modules, which is why a careful selection of the region of interest must be first carried out. Applicability of the model on a different geographical region would require historic seismic arrays specific to the location.

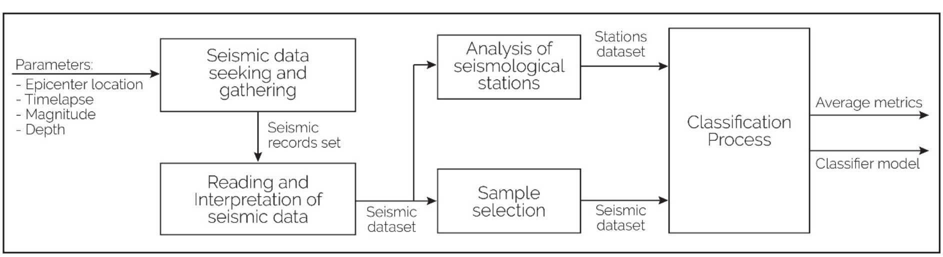

Figure 2. Model for offline seismic event detection.

The modules are described below as follows: Seismic data seeking and gathering, Reading and interpretation of the seismic data, Analysis of seismological stations, Sample selection, and Classification process.

4.1. Seismic Data Seeking and Gathering

To analyze seismic signals by algorithmic means, it is necessary to have a set of records that can be manipulated. In this first step, a download of the historical seismic records is made, filtering by the chosen region. A set of seismological records of each station is obtained.

Depending on the region of interest, it is possible to obtain seismological records through web services, such as the United States Geological Survey (USGS), the European-Mediterranean

Seismological Centre (EMSC), the National Earthquake Information Center (NEIC), the National Institute of Seismology, Volcanology, Meteorology, and Hydrology of Guatemala (INSIVUMEH), the Mexican National Seismological Service (SSN), the National Seismological Center of Chile (CSN), or the Colombian National Seismological Network (RSNC by its Spanish acronym), among others. These web services allow downloading data of seismic events one by one, although it is usually necessary to provide searching filters, generally concerning magnitudes, depths, and dates.

The seismic records are usually of public access, so it is possible to request the set of desired data directly to the seismology agency responsible for its storage. Another easier way to do this data-gathering process is to use automated interaction web tools to download the requested files, such as the creation of web snippets using the web-scraping technique, which allows interacting with the web resources of the web service. This technique is usually legally authorized by the RSNC and other services, since all the information downloaded is public access and no intromission for non-authorized domains or web resources is made. Although the scraping procedure is legally accepted, it is recommended to inform the geological services about this practice when executed.

The technological infrastructure needed to download and to store seismic files depends on the volume of data to be processed. In Colombia, the RSNC gathers the seismic records into two categories:

- Trace files (Waveforms), which contain the seismic samples taken by all seismological stations available around the region of interest.
- Parameter files (Sfiles), which provide detailed information about the seismic events, such as the longitude and latitude of the epicenter and the P-wave and the S-wave arrival times, among others.

The seismic traces recorded in the Waveform files are usually a large size because they record non-event samples that occur before and after the seismic event picking. Their content is dependent on the duration of the recorded earthquake. Each trace file can have a storage size from approximately 5 MB if it corresponds to a microseism that has been registered by one or few seismological stations, or a specific seismic event registered by a couple of stations, and up to approximately 120 MB, if it is registered by most seismological stations with a duration close to five to ten minutes. The RSNC registers up to 10,000 seismic events per year, with an average of 60 MB of storage per seismic record.

The seismic records may not be stored completely. The storage of all the records allows faster access for later processing stages; however, as has already been shown, the computational load applied to the data storage is high. On the other hand, storing portions of data that are processed and then erasing the unrequired portions, or processing the records one by one so that the results are stored and the records are erased are two recommended procedures to save storage space. Nevertheless, if the data are processed one by one, any subsequent processes to be done or corrections to previous processes will force to access the data sources again, which will hinder processing.

4.2. Reading and Interpretation of the Seismic Records

Once the seismic records are obtained, it is necessary to understand the format in which the data are presented, to establish the mechanisms by which they will be read. After reading the data, a sample selection is proposed, which depends on the characteristics found, and a set of memory instances that represent the trace files and read parameters is obtained as an output.

Among the most common international formats for the Sfiles [36] are HYPO71, HYPOINVERSE, and Nordic formats. The most used international formats for Waveform files are SEED, miniSEED, and SimpleASCII [37]. There are comprehensive seismological analysis tools capable of reading a wide range of formats of these two types of files, such as SEISAN and SeisComP. It is also possible to read the files through native programming languages or using libraries linked to these languages, such as SEISPP for C++ [38], Obspy for Python [39], or the open-source tools made available by the USGS for Java [40].

The implementation of specific architectures for reading multiple seismic records is of utmost importance. It is vital to analyze the computational capacity in terms of volatile memory, mainly by considering the techniques exposed and the data stored during the seeking and gathering of seismic records. Therefore, a sub-module can be incorporated for balancing the computational load, which includes techniques for transforming volatile information into non-volatile (hard disk storage), as well as considering parallel processing mechanisms to facilitate the processing of large sets of seismic records.

Additionally, it is pertinent to include file selection algorithms that can discard repeated files or easily identifiable irregularities in both parameter files and trace files to prevent their storage. This process is called data wrangling, in which a data-cleaning procedure is required. Among the irregularities found in the seismic records from the RSNC are inconsistencies in the format, absence of trace files that correspond to existing parameter files, lack of start and end times of the event in the records, as well as non-existent P-wave and S-wave arrival times in some of the records recorded by the seismological stations. A key process to clean the seismic data from the RSNC is shown in Figure 3.

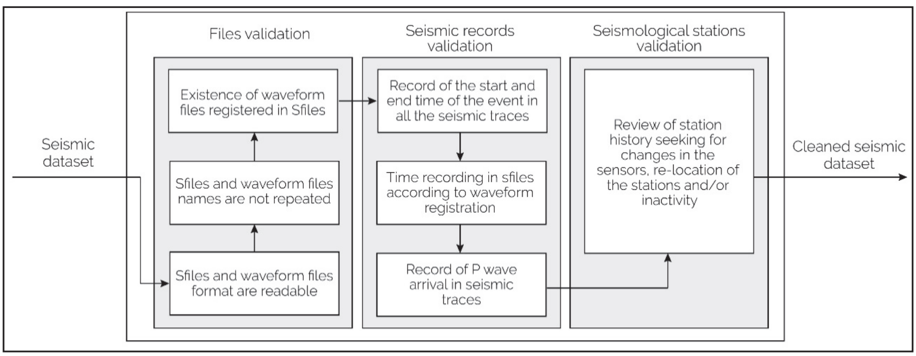

Figure 3. Seismic data cleaning process for RSNC files.

The data cleaning process is executed from three approaches: (1) the validation of the sought and gathered files, (2) the validation of the seismic samples in these files, and (3) the validation of the stations that register these samples.

In the first stage of this cleaning process in the file validation approach, it is checked that the sfile and waveform files can be read correctly for processing. First, if the files cannot be read, the inconvenience may be the source of the data. Secondly, it is verified that there are no repeated files, because the complexity of processing grows and there is no compensation to the investigation for processing the same data more than once. Third, it is verified that the general sfiles data files have a correct record of the corresponding waveform file. If in any of these stages there are inconsistencies, it is recommended that the file(s) are discarded, as they may create a bias in the general seismic analysis.

In the second stage of the cleaning process that focuses on the validation of the samples, it is convenient to check first if there is a record of the start and end time of the events that is homogeneous between each sfile and waveform files, secondly, that the P-waves have been recorded in both files.

Finally, in the third stage of the cleaning process, changes in the seismological station sensors, their relocation, or periods in which they have stopped operating must be considered. This permits the definition of a time interval in which the analysis will be executed, with the certainty that the dynamics of the waves will not be altered by external changes that do not concern the merely seismological field.

4.3. Analysis of Seismological Stations

Once the historical seismic archives are read, an analysis of the seismological stations that have recorded the events of interest is carried out, so that those that best represent the events and allow a reduction of the computational load in the processing of the data can be selected. The selected seismological stations are obtained as an output of this process.

Each seismic station provides a specific recording pattern that is dependent on several factors:

- The distance from the hypocenter and the epicenter (hypocenter and epicenter distances) to the geographic position of the station defines the amount of attenuation of the seismic wave.
- The geomorphology to which the seismic waves are exposed on the way to the station defines the propagation pattern and the attenuation of the seismic waves.
- The natural and artificial noise sources demean the seismic records due to the loss of quality regarding the content associated with seismic information, adding sources of information that concern other events that are not from a seismic nature.
- The technical parameters of the stations such as measurement channels, signal-to-noise ratio, analog-to-digital conversion, sampling rates, sensitivity, and dynamic range define how the seismic event is perceived from an analog source to a digital environment.

Then, these factors influence the composition and patterns of the traces that are transmitted to the monitoring site and stored for further offline processing. Each Colombian station records the seismic events individually by considering the named factors. The more stations that detect the event, the more data that can be transmitted, processed, and stored.

When a microseism occurs, usually few stations record it, since it can be a noise event due to a local disturbance on the surface or a seismic event of very low magnitude and/or considerable depth. In this case, the amount of data that contains useful information is not extensive and can be analyzed quickly and stored without major physical space costs.

However, when there are long-term, shallow, or large-scale seismic events that are perceived in various regions, the computational capacity for analysis and storage is high. Therefore, selecting a set of stations to analyze the traces that are recorded allows the dimensionality reduction of the data and reduction of the computational load.

Defining the stations to be studied is a process that requires a strong seismological criterion; however, the use of algorithms for statistical analysis facilitates the discernment between station selection criteria. For example, using libraries for the geographical mapping of stations and seismic epicenters, clustering and sampling the data exposed in the parameter files, among other procedures, allow contrasting the information stored and decide about the stations that best represent the events analyzed.

Figure 4 proposes a general procedure for the selection of the seismological stations used to identify the presence of seismic events in the Colombian monitored signals.

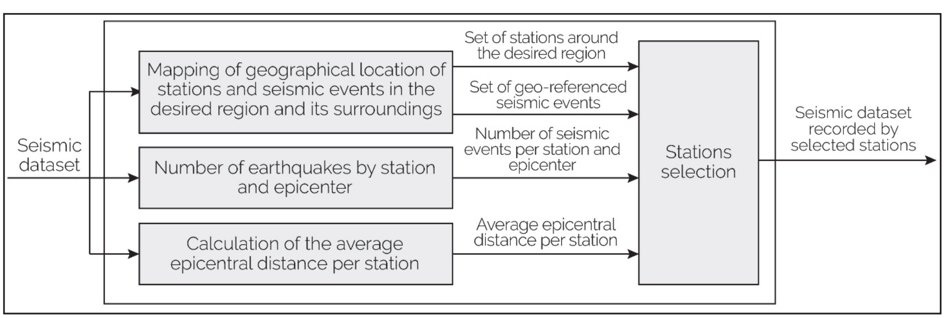

Figure 4. Seismological station selection process.

At first sight, it is necessary to identify the geo-referenced position of the stations, so that there is a spatial perspective of their distribution. Depending on the area under monitoring, the stations of interest will be those closer to this area. This is because the dynamics of local earthquakes are more marked and detectable than the dynamics of regional earthquakes and teleseisms, which have attenuated and difficult to model features. It is recommended that more than two stations be selected, as events that have a non-seismic nature can be detected as such if only the activity is monitored in one or two stations.

In the second stage, it becomes clear to calculate the identification rate of seismic events labeled by each station, according to the monitoring region. This supports the selection of the stations concerning their geo-referenced position, as it is an indicator of the proximity of the stations to the epicenters (epicentral distance) and the signal attenuation index when arriving at the stations.

The stations with the highest identification rate of seismic events must be checked against their epicentral distance. A good relationship for the choice, as the third stage in this process, is to select the stations that have identified the most earthquakes, with a short epicentral distance. It is advisable to include the processing capacity as a third attribute in the selection process, since an additional station can signify the processing of 210,000 additional samples, on average.

4.4. Sample Selection

The sample selection process can be carried out in parallel to the station analysis process, since these two processes are independent of each other. There are several factors to consider when selecting a Colombian seismic event sample, as it was shown in Section 4.2:

- Inconsistencies in the file formats: There are different formats in which a seismic file can be structured, as SEED and miniSEED. During the processing and storage stages, the data are susceptible to be modified or lost, since there are multiple sources of information. Sometimes, these modifications alter the file formats, making them inconsistent. The files that present inconsistencies in the format and cannot be read correctly must be discarded.
- Absence of trace files that correspond to SEED and SAC existing parameter files: As part of the data storage process, the seismic information extracted from the seismic events (Sfiles) and the seismic samples (Waveforms) are recorded in separate files, as described in previous sections. Some of them are stored as part of the dataset without being associated. In this way, cases in which seismic information is recorded and samples were lost and vice versa can be found. Those files where the description data do not correspond to the seismic traces must be discarded.
- Lack of start and end times and/or inexistence of P-wave and S-wave arrival times in the events recorded: when a seismic event is recorded, some variables are measured, among which are the start time and end time of the event and the P-wave and S-wave arrival times. These values are very important to train classification algorithms, as some specific samples can be extracted from the seismograms, knowing when the earthquake began and when it finished. Unfortunately, some files can be well stored but lacking one or more of these four key parameters. In this case, it should be analyzed whether it is possible to determine the start or end date of the event by processing the seismic traces. If this is not possible, the files must be discarded.

It is also important to consider the structural changes of the stations, such as changes in the sampling frequency, sensors, digitizers, and number of spatial components, among others. These variations, although some of them are subtle, represent substantial alterations in the seismic patterns that might not be detected, since the detecting algorithms learn from specific patterns shown in the learning stages.

The inconsistencies in the files may be a consequence of the wrong acquisition, processing, and storage processes that are sometimes attributable to the algorithms that execute those processes for the seismology entities of each region or country.

In Colombia, between 20% and 30% on average of the selected files within the initial population of seismic events are propense to be discarded due to these inconsistencies, although some regions that are affected by very strong seismic events have accurate and well-stored files [41]. Other less frequent irregularities that may occur are (a) recording of the seismic data from stations that are inactive, (b) recording of the seismic data from components that the seismological station does not have (e.g., the registration of three components for stations with monoaxial sensors), (c) recording seismic traces with a different sampling frequency from that described in the sensor datasheet, (d) recording of the seismic traces with different sampling frequencies among the components from the same station, either by components or by events, (e) the annotation of the P-wave in the traces is outside the measurement period of the seismic events, and (f) recording of all relevant seismic attributes described of the seismic signals with a magnitude of zero.

4.5. Classification Process

The analysis of seismological stations and sample selection processes provide the input datasets to the classification process, regarding seismological stations and seismic record datasets, respectively. With these inputs, the classification process implements supervised learning strategies using the selected seismological stations to detect the seismic event. The outputs of the classification process are (a) the average performance metrics of the classification approach and (b) the classification model, which is trained and validated, as described in Figure 5. The performance metrics are related to the ability of the classifier to differentiate between a seismic event and a non-seismic event, i.e., a binary classification, and the classification model corresponds to the implementation of the classifier, and it is able to classify new signals and provide the event detection output.

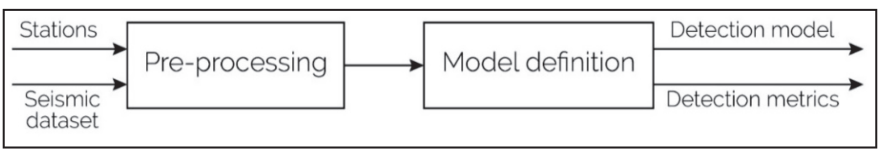

Figure 5. Block diagram of the classification process.

The identification and classification of seismic events can be done using different techniques, as described in Section 3. For instance, the phase picking of seismic waves is widely used for real-time monitoring, detection, and localization with the P-wave picking is the main method for detection in early warning systems. Several algorithms for P-wave picking have been proposed in the time-domain [42], whereas the STA/LTA and its variations are the most implemented algorithm in observation and detection networks [43]. In Colombia, the SeisComP3 software is currently used by the RSNC for the acquisition of seismic data from stations located throughout the national territory. With the STA/LTA-based AutoPick module, the P-wave is detected by a SeisComP3 implementation [44,45].

Traditional approaches such as STA/LTA are suitable options for the classification algorithm. Nevertheless, these approaches have limitations regarding their adaptability to the behavior of seismic waves [5,46,47]. As [48] state, the automatic picking of seismic waves can remove the ambiguity derived from the lack of synchronization between channels and signals proceeding from the seismological stations. Furthermore, [48–50] have shown that STA/LTA and cross-correlation approaches have a high rate of Types I and II errors (namely false negative and false positive) due to excessive noise that cannot be removed from the source and very low-frequency components that might not be enhanced. These factors can be handled accurately (as far as possible) using machine learning techniques.

Considering that the dynamic behavior of seismic signals recorded by sensors is subject to many factors that influence the signal, as denoted in Section 4.2, machine learning algorithms represent an appropriate alternative for the development of classification models, since they enable the abstraction of attributes associated with the signals, based on the modeling of large training datasets. Machine learning algorithms rely on the quantity and quality of data and, as described in Sections 3.2 and 4.1, current seismological services can provide huge amounts of data that can be processed to obtain datasets to classify seismic records such as the ones provided as output in the Sample Selection process.

As [51] state, machine learning algorithms are particularly well-used in seismology due to their facility to model complex relationships of a wide range of variables. Since the majority of tasks in this context are normally targeting classification problems, machine learning drives a well-structured solution, since it can build a predictive environment in which a model is trained over sample data and tested over unseen data, guaranteeing the generalization of the solution against the data and the context. Sometimes, this procedure can be harmful if there is not enough data to proceed with the training procedure or when the representative descriptors (features or covariates) are almost the same as the number of samples. In these cases, additional machine learning approaches can be implemented, such as feature selection using forward or backward procedures [52].

With the selection of a machine learning algorithm as the classification algorithm, the classification process can be configured with a set of subprocesses depending on the specific machine learning algorithm requirements, which may be feature-based or time-series-based. The proposed set of subprocesses for the classification process is shown in the subprocesses diagram of Figure 6. The sequence of subprocesses can fulfill the classification capabilities for attribute-based or time series machine learning algorithms.

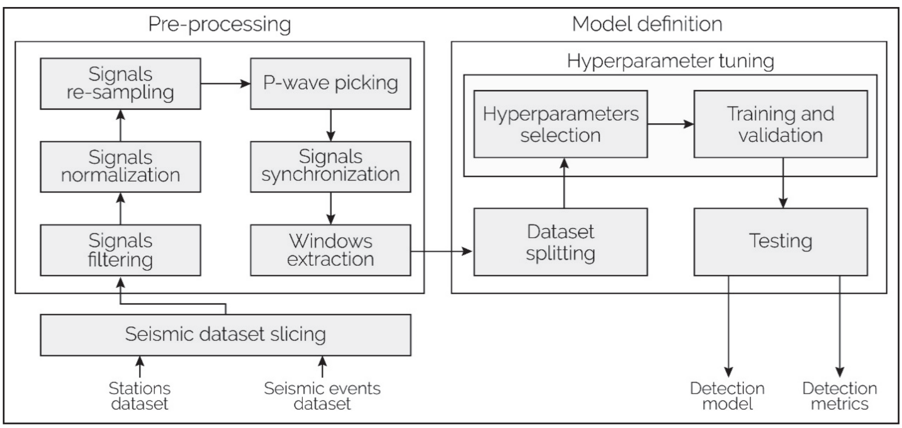

Figure 6. Classification process.

To set up the subprocesses, it is necessary to determine the number of classification models desired to represent the dynamics perceived by the stations. A single classification model might represent the events linking all the stations throughout a centralized fusion, or multiple classification models might correspond to each station separately throughout decentralized functions (such as the ones proposed by bagging techniques). In the case of decentralized fusion, each station has its classification model; hence, the Pre-processing and the Model definition stages need to be done separately for each selected station. The results provided by the per-station models can be composed into a combined result in the Testing subprocess using logical functions or more complex integration functions, producing a single classification model based on individual station analysis.

When the selected stations and the Seismic events dataset enter the classification process, the first subprocess that manipulates the datasets is the *Seismic dataset slicing* subprocess. This subprocess oversees linking the events to the selected stations and splits the Seismic events dataset into datasets per station if a decentralized schema is going to be used. In the *Pre-processing* stage, six subprocesses oversee formatting the dataset into a scheme ready to be used as input for a learning algorithm in the *Model definition* stage. Each subprocess in the *Pre-processing* stage is applied to every component that the signal may contain.

After the *Seismic dataset slicing*, the seismic signals associated with each event in the dataset are filtered in the *Signals filtering* subprocess. This subprocess considers the influence of noise sources that affect the seismic signals. The considered noise sources are the soil vibrations produced by natural causes and the instrumental noise associated with the measurement equipment hardware [41]. The filter choice is crucial for the classification model performance, since the quality of the signal depends largely on the quality of the filter; therefore, the ability of the learning algorithm to generalize P-wave dynamics relies on the filter. It is recommended to make a frequency analysis to obtain the frequency components of the signals and the noise. The suggested frequency band is between 1 and 12 Hz [53], and different filter techniques can be applied to this subprocess [54].

When the *Signals filtering* subprocess is performed successfully, the dataset is relocated to the *Signals normalization* subprocess, whose objective is to standardize the scale of the signals to the $[-1, 1]$ interval according to the minimum and maximum value of each signal and remove the direct current component that is commonly added by the instrumentation. Then, the normalized signals are re-sampled in the *Signals re-sampling* subprocess. The definition of a common sampling rate for the signals is necessary due to the variety of the sampling rates that the signals may have, which are the outcome of diverse sampling properties that the acquisition devices and the digitalization algorithms present in the seismological stations.

The seismic signals associated with each record are commonly signals that contain information before the arrival of the P-wave and after the arrival of the S wave. To focus on the P-wave dynamics, in the *P-wave picking* subprocess, the identification of the time where the P-wave arrived is performed. This picking time annotation is commonly found in the Sfiles. Then, in the *Signal synchronization* subprocess, the picking time obtained in the *P-wave picking* is used to determine the exact sample where the P-wave arrived, relying on the defined sampling rate used in the *Signals re-sampling* subprocess, and a standard amount of samples is selected for a homogeneous duration time for each signal component. Therefore, all the signals representing an event start at the same time according to their P-wave time and end at the same time depending on the selected duration time.

The last *Pre-processing* subprocess is the *Windows extraction* subprocess whose purpose is to extract segments from the signals where the P-wave dynamics are contained and segments where there is no P-wave. The window length in samples is subject to the P-wave picking time and the window duration. A 2-s window is a recommended length [55]. It is necessary to obtain non-P-wave windows as well, since the classification algorithm learns to distinguish between the attributes of a P-wave and the attributes of a non-P-wave signal. Therefore, it is recommended to have the same number of windows concerning P-waves and non-P-waves to avoid class imbalance issues. With the *Window extraction* subprocess, the dataset of filtered, re-sampled, and synchronized signals associated with the events turns into a windows dataset with two classes, P-wave and non-P-wave, which is a common approach for the binary classification of seismic events.

With the window dataset, it is possible to generate a feature dataset that is commonly used by some feature-oriented machine learning techniques. A feature is a description of a record; the seismic events can be statistically described in terms of time, frequency, and non-linearity, among others. The features selection has a huge impact on the classification model's metrics, since they define how the classification algorithm perceives the seismic events. Each event is represented by a set of features in a matrix, and each feature acts as an input to the classification algorithm.

The *Pre-processing* stage differs from feature-based learning algorithms and time-series learning algorithms. The *Signals filtering*, *Signals re-sampling*, and *Signals normalization* subprocesses may be skipped depending on the time series technique, and some extra processes must be carried out, such as checks for stationarity, correlation, and autocorrelation. It is necessary to indicate the location of the P-wave in the signals (*P-wave picking*) to synchronize the signal's arrival and duration throughout the dataset (*Signals synchronization*) and to determine the characteristics of the moving window (*Window extraction*).

The input dataset for a feature-based technique is a set of single values that describes the original P-waves and non-P-waves in the seismic signals. Among the most commonly used machine learning feature-based algorithms applied to P-wave detection are Hidden Markov Models [56], Bayesian Networks [57], Support Vector Machines [58–60], Logistic Regression [53,61,62] and Artificial Neural Networks (ANN) [41,53,63–67]. Conversely, the input dataset for a time-series technique is a set of signals split into P-wave signals and non-P-wave signals. Among the most used time-series forecasting techniques (TTF) for P-wave detection are Autoregressive Integrated Moving Average (ARIMA) [68], Seasonal ARIMA (SARIMA) [69], and ARIMA with Exogenous Regressors (ARIMAX) [70]. Some time-series forecasting recent methods used for P-wave detection include Pure Linear Neural Networks (PLNN) [71] and Polynomial Neural Networks (PNN) [72].

By following the suggested set of subprocesses and using a machine learning algorithm as the ones previously described, the classification process outputs a classification model and a set of metrics associated with that classification model. The produced model is suitable for performing the offline detection of seismic signals through the identification of P-waves. The mentioned metrics indicate the performance of the classification algorithm with the best set of hyperparameters scored on the test set records. The classification model, as denoted in the graph of the resulting classification model (Figure 7), can be interpreted as a system with testing preprocessed signals as the input to a function that contains the resultant algorithm responsible for the event detection. The output of this algorithm is a value that indicates whether the input signal contains a P-wave or not, in case of being a binary classification process.

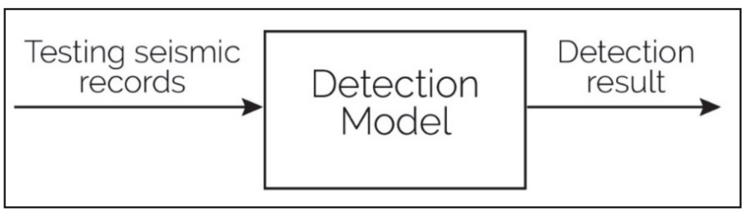

Figure 7. Classification model.

The classification model is the result of the System Model for Offline detection. It is recommended to generate several classification models by testing different approaches. In this sense, depending on the performance of the classification model reflected on the metrics, a change in the selection of classification process parameters, such as the filter type and length of the window, among others, may be considered to improve the classification performance. In the same way, other parameters that belong to macro processes, such as the number of stations in the Analysis of seismological stations or filtering the seismic records by magnitude range in Seismic data seeking and gathering, may have a huge influence on the classification performance.

Some studies have been carried out using the proposed System Model to perform the identification of P-waves in Colombia. In [41], a dataset of seismological records of events with epicenter in the department of Santander, Colombia between 2010 and 2017 was selected in the Seismic data seeking and gathering process. In the Reading and interpretation of the seismic records process, the records were described in the Nordic format. Then, in the Analysis of seismological stations, four stations were selected according to the epicenter distance. In the Sample Selection process, 20% of the downloaded records gathered were discarded due to inconsistencies in seismic attributes. Finally, in the Classification Process, the selected classification algorithm was logistic regression. The classification model was composed of four logistic regressors, one per each station, and a decentralized voting function that applied a logical function to the output of each regressor, to produce a binary output (P-wave or not P-wave). The obtained classification model produced an accuracy of 98.26% for the detection of the P-wave.

Similarly, in [41], the use of the System Model was applied to a dataset of events with an epicenter in Santander, using four stations. In the binary classification process, the selected classification algorithm was a feed-forward back-propagation Artificial Neural Network (ANN) after being cleaned and the missing values handled appropriately. Unlike the voting function applied in [53], the classification algorithm relied on the behavior associated with all the stations, which were analyzed as a group in a centralized function represented by the ANN. The degree of polarization, the ratio of vertical power to total power, skewness, and kurtosis of the three-component seismic data for each station were used as the selected features to feed the training process of the named ANN binary classifier. All the input features were extracted from observations whose classes were balanced and equally distributed in the datasets. With the described settings, the obtained classification model produces an accuracy of 99.24% for the detection of the P-wave.

5. Conclusions

The proposed five modules of the seismic detection model facilitated the comprehension of the integration of the phases of an offline detection system. A set of historical seismic records is first downloaded and read (depending on the format of the data). The data can be filtered to make it easy to process by the subsequent phases. A selection of seismological stations that recorded an event of interest may allow the reduction of the computational load. This selection can be made based on the distances, geomorphology, noise sources, and technical parameters of the stations. The identification of a seismic event is a binary classification task, i.e., the presence/absence of a P-wave on the seismic signal.

The proposed model allows specifying detection and classification tasks for seismic events, which is applicable to the Colombian region. However, it can be extrapolated to other regions, as the detailed procedures are general enough to be applied in the local seismological networks that have monitoring stations with data formats and equivalent measurements.

Author Contributions: J.M. and C.G. contributed to the design of the seismic detection model. A.F. and M.A. supervised the research activities, and then carried out the coordination activities and the analysis of results. G.O. and C.F. conceived and wrote the earthquake detection methodologies. J.M., A.F., G.O., C.G. and M.A. contributed to the final version of the manuscript. All authors have read and agreed to the published version of the manuscript.

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Conflicts of Interest: The authors declare no conflict of interest.

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future internet

Article

Co-Authorship Networks Analysis to Discover Collaboration Patterns among Italian Researchers

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Abstract: The study of the behaviors of large community of researchers and what correlations exist between their environment, such as grouping rules by law or specific institution policies, and their performance is an important topic since it affects the metrics used to evaluate the quality of the research. Moreover, in several countries, such as Italy, these metrics are also used to define the recruitment and funding policies. To effectively study these topics, we created a procedure that allow us to craft a large dataset of Italian Academic researchers, having the most important performance indices together with co-authorships information, mixing data extracted from the official list of academic researchers provided by Italian Ministry of University and Research and the Elsevier's Scopus database. In this paper, we discuss our approach to automate the process of correct association of profiles and the mapping of publications reducing the use of computational resources. We also present the characteristics of four datasets related to specific research fields defined by the Italian Ministry of University and Research used to group the Italian researchers. Then, we present several examples of how the information extracted from these datasets can help to achieve a better understanding of the dynamics influencing scientist performances.

Keywords: network sciences; social network; coauthorship networks

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1. Introduction

In the last years, the use of bibliometrics [1] gained greater and greater importance in the evaluation of researchers and scientific projects, and it is currently used in several countries (such as Italy) to rank researches and universities, and the attempts at performing this kind of quantitative analysis have often been referred to as "science of science" [2–4]. However, the use of citation indexes is quite old as witnessed by pioneering works of Garfield [5] in the 1950s, and de Solla Price [6]. Today, there are several metrics that tries to quantify the quality and impact of researchers [7–10]. On the other hand, co-authorship networks, i.e., networks where nodes represent scientists and a link between any couple of nodes means the corresponding researchers have co-authored at least a paper, have been extensively studied with the aim of understanding the collaboration patterns among scientists. To approach such a task there are many challenging issues as, for instance, data collection and filtering, definition of domain-specific metrics and algorithms, data visualization, and mining. Co-authorship networks have been widely explored from the perspective of complex networks [11,12], since such representation allows discovering structural and dynamic patterns of scientific collaborations, often hidden, or neglected in the bibliometric approach. Barabási et al. [13] and Newman [14,15] examined the "small-world" and "scale-free" features in the co-authorship networks using the datasets in the disciplines of mathematics, neuro-science, physics, biomedical studies, and computer science. Several works followed the path of these pioneering papers deepening the "scale-free" and "small-world" characteristics [16–18] or investigating the mechanisms for the evolution of the co-authorship networks [19–21].

The enrichment of co-authorship networks with bibliometrics indices allow studying the characteristics and dynamics of such complex networks. In this work, we discuss why and how we created a co-authorship dataset from the Italian academic context. In particular, each academic working in an Italian university belongs to an *academic discipline* (i.e., a grouping by topic imposed by law), which is also used for evaluation and career advancement, and we believe that this fact has a strong impact on both bibliometrics and how academic collaborations arise. Here, we selected four academic disciplines (Mathematical Analysis—MAT/05, Economics—SECS-P/01, Information Processing Systems—ING-INF/05, and Informatics—INF/01) that have almost the same number of researchers but cover different research topics. We built the dataset starting from the profile of Italian researchers and obtaining all the available bibliometrics querying the Scopus database, and we extracted all the bibliometrics up to end of 2021. This paper presents the details of the datasets crafting, such as mapping, solving ambiguity, etc., some preliminary analysis and, finally, a discussion about their characteristics.

The next section briefly summarizes the state-of-the-art, Section 3 deals with method and materials used to create datasets, while Section 4 presents the above-mentioned example and conclusions reports about results, open problems, and further development.

2. Related Works

Co-authorship networks have been of great interest for several decades [11,12] and have been one of the main topics in network science research. For instance, in the pioneering work [15], Newman constructed some networks in which nodes are scientists (extracted from bibliographic databases in biology, physics, and mathematics) and two nodes are connected by an edge if they have co-authored almost a paper. Such network were used to study collaboration patterns over time, and how they vary between subjects. Newman highlighted that *"the co-authorship network is as much a network depicting academic society as it is a network depicting the structure of our knowledge. Additionally, perhaps because of this, it has received far less attention than have citation networks"*. In [22] the authors presented a study showing how some topological features impact on some bibliographic indices using networks that encompass only a subset of Italian scientists.

In addition to the works already mentioned in the introduction that mainly focused on network topological properties, such as the "scale-free" and "small-world" properties, other authors used the co-authorship networks to evaluate the performance of a set of researchers. Hâncean et al. [23] exploited the co-authorship networks among the most productive European researchers, over a 12-year time window, looking at the impact of collaboration upon the citations aiming at discovering the best European researchers. Weihua et al. [1] examined the impact of early co-authorship on the careers of junior researchers in four specifics scientific. In [24], the authors explored the correlation between centrality metrics in co-authorship networks and Hirsch index [8] (H-index). In [25], the level of collaboration is evaluated through the definition of a specific centrality index called ϕ. Other authors examined the evolution over time of the co-authorship networks. For example, Parish et al. [26] studied the dynamics of productivity in different fields of scientific research while Xie [27] proposed a hyper-graph model for simulating the evolution of large co-authorship networks.

Of course, whatever is the goal of the study the starting point is always the choice of scientists to study and the construction of the network itself. It is straightforward that the number of scientists included, but also the set of features, the time interval and several other elements could influence the final results, therefore the method and sources selected are fundamental by themselves to guarantee meaningful results. The main contribute of this paper is the description of the strategies used to construct a dataset from which derive the co-authorship networks enriched by several well-established performance parameters. We also explain issues met during the setup, such as the presence of ambiguous or duplicated information, how to manage missing information, how to combine results and so on.

The source of bibliometrics information is the Elsevier's Scopus Database [28], while the scientists used as seeds was the Italian researchers belonging to official academic organizations. Although there are many other bibliographic databases available, such as Web Of Science (WoS) [29] and Google Scholar [30], we decide to use the Scopus Database since it is widely recognized in Italy, contains almost all publication types and is used as a reference for many Italian academic ranking by law. However, in literature can be found several examples where co-authorship networks are based on different data sources, such as [31] that extracts data from WoS.

Among the recent co-authorship networking available in the literature based on Scopus, Di Bella et al. [32] proposed a temporal analysis of the co-authorship network of Italian Institute of Technologies, and Pradhan et al. [33] evaluated the performance of some universities; both selected the authors (nodes of the network) according the authors' affiliation. Fujita and Vitevitch, in [34], quantified the extent to which Psychology is multidisciplinary, and how it changed over time using the tool provided by network science. They studied the citation network from all the articles published in journals identified by the Web of Science as Multidisciplinary-Psychology for each year from 2008 to 2018.

In our proposal the selection criteria are based on a classification, performed in Italy by law, that groups researchers belonging to public universities according to topics similarity called "Settori Scientifici Disciplinari" that can be translated in English in academic disciplines or specializations. The peculiarity of the proposed dataset is the extension of the network to direct collaborator and collaborators of collaborators outside the authors used as seed, since we believe that topological properties strongly depend on the full network. To the best of our knowledge, such kind of study has not been carried out so far.

3. Data Collection

The collection of meaningful and useful data is a task with many challenges. When dealing with collaborations among researchers, the key issues come from the multiple data sources and the data not being structured, which translates, for instance, into ambiguous names or duplicate author profiles. In this section, we introduce the data sources and the data-collection methodology used to build the collaboration networks.

3.1. Data Sources

The sources of data used to create the dataset are: the list of researchers employed in Italian public universities provided by Italian Ministry of University and Research (MUR) [35] and the well-known Elsevier's Scopus database. Data were collected at the end of 2021 and contains all records presents in Scopus and Ministry's list at the moment. In particular, the former—which is updated daily and provides the profile of the researchers that are employed in the Italian academia—are used as seed data, and the latter are used to retrieve all the researchers' publications and bibliometrics. As shown in Figure 1, reporting a slice of the data, the information is partially structured, all fields are in Italian language and some of them—such as department or structure—are in free form that do not allow to directly use them to query Scopus. To build a coherent dataset, we build a network starting from the (seed) researchers that belong to a given academic discipline, i.e., the group of people that belong to the research area, as defined by the Italian Law. Specifically, we selected the academic researchers belonging to MAT/05 "Mathematical Analysis" ("Analisi matematica"), SECS-P/01 "Economics" ("Economia politica"), ING-INF/05 "Information Processing Systems" ("Sistemi di elaborazione delle informazioni"), and INF/01 "Informatics" ("Informatica"). We selected these academic disciplines because they have a similar number of academics that allows performing a thorough analysis in a reasonable amount of time, they are all *scientific disciplines* and share some research topics, but are significantly different from each other. Moreover, the authors of this paper belong to one of them (ING-INF/05) and, thus, are aware of some of its dynamics, which can help in the analysis of the academics' habits. Of course, other academic disciplines share these characteristics and would allow to extend the dataset in the future.

Fascia	Cognome e Nome	Genere	Ateneo	Facoltà	S.C.	Struttura di afferenza	Servizio prestato in altro ateneo
Associato	[redacted]	M	Scuola Superiore Sant'Anna		09/H1	Istituto di Tecnologie della Comunicazione, dell'Informazione e della Percezione (TECIP)	
Ordinario	[redacted]	M	BOLOGNA		09/H1	Ingegneria dell'Energia Elettrica e dell'Informazione "Guglielmo Marconi"	
Ordinario	[redacted]	M	GENOVA		09/H1	Informatica, bioingegneria,robotica e ingegneria dei sistemi (DIBRIS)	
Associato	[redacted]	M	Politecnico di MILANO		09/H1	Elettronica, Informazione e Bioingegneria	
Associato confermato	[redacted]	F	PAVIA		09/H1	INGEGNERIA INDUSTRIALE E DELL'INFORMAZIONE	
Associato	[redacted]	M	"Ca' Foscari" VENEZIA		09/H1	Scienze Ambientali, Informatica e Statistica	
Associato	[redacted]	M	PARMA		09/H1	Ingegneria e Architettura	
Ordinario	[redacted]	M	Politecnico di MILANO		09/H1	Elettronica, Informazione e Bioingegneria	
Associato	[redacted]	F	Napoli Federico II		09/H1	Ingegneria Elettrica e delle Tecnologie dell'Informazione	

Figure 1. Excerpt of data as provided by MUR. Column labels are role, family and given name, gender, university, school, sector, department, or structure, and note about service.

The Elsevier's Scopus database, according to their fact sheet [28], holds more than 1.8 billion of cited references dating back to 1970, more than 17.6 million of author profiles, and more than 84 million of records. We queried the database using the provided APIs, which expose curated abstracts and citation data from all journals indexed by Scopus, in agreement to their policies [36,37].

3.2. Mapping and Ambiguity

Once chosen the academic disciplines and collected information from both sources we must combine them into a unique dataset that contains the information related to academic discipline and all bibliometrics. Unfortunately, no unique identifier, such as OrcID, is present in Ministry's list therefore the ambiguity must be resolved using the information related to affiliation (columns *Ateneo*, the University's name, and *Struttura di appartenenza*, the department). Moreover, the Scopus database is built from the information present in published papers and has multiple profiles for the same author (often already linked), homonyms and partial registrations (researchers registered with partial names or omitted information), and each of those issues can lead to the wrong network representation.

The Scopus Search API is organized into three clusters: Affiliation that has Affiliation Profile, Author that contains Author Profiles, and Scopus contains the abstracts and relevant metadata. Searching against Author cluster retrieves the following attributes useful to uniquely identify the author: "dc:identifier" that is the Scopus unique identifier associated with profile, "OrcID" if any, "surname", "given-name", and "affiliation" split into name, city and country. Despite the details of information given by the query, there are still some problems in mapping the data from the MUR's list to a unique Scopus profile. We report the most important ones in the following:

1. The surname and given-name in the Ministry list is always the legal name while the corresponding fields in Scopus may be abbreviated, misspelled, alias, reverted, and incomplete. For instance, Ministry List refer to "Michele Giuseppe Malgeri" while Scopus profile only contains "Michele Malgeri", some authors have more than one profile that often are not combined, sometimes surname and given-name are inverted, and, of course, several authors with same (or similar) names may exist.
2. The Ministry list affiliation reports the official name of the institution, meaning that the name is always in Italian, while Scopus often contains the abbreviations, acronyms, or the English translation of the University's name. Of course, again, misspelling and typos may be always present.
3. Spaces, stippling, national characters (e.g., the use of accented vocals).
4. Authors during their activity may change affiliation several times, therefore multiple profile could be present.

To face the problems connected with misspelling, stippling, and typos, before the processing each name is cleaned removing all punctuation, unnecessary spaces, and mapping national characters, if any, to a normalized form. Comparisons are performed using the Levenshtein distance [38]. The *prepare_queries* setups the set of queries using the author's surname and the shuffle of the given name (if more than one) and the initials of the name, for instance "Malgeri Michele Giuseppe", where the surname is "Malgeri", generates the queries listed in Listing 1:

Listing 1. List of queries generates by Malgeri Michele Giuseppe. If they fail third condition about affiliation is discarded and queries will be repeated.

```
AUTHLAST(Malgeri) and AUTHFIRST(M) and AFFIL(Università di Catania)
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We describe the algorithm used to search for the Scopus profile of Italian researchers from the Ministry's list in Algorithm 1. Please note that, for sake of simplicity, the algorithm does not include the use of the researcher's affiliation and the validation of data, which is performed when few matches are found.

Algorithm 1 Searching for a matching profile between Ministry's list and Scopus Authors' cluster.

procedure $search\_for\_author$(profile)
    $matches \leftarrow []$
    $queries \leftarrow prepare\_queries(profile)$
    for all $query \in queries$ **do**
        $result \leftarrow search\_against\_Author\_Cluster(query\_string)$
        if $surname == result.surname$ **then**
            $result.distance \leftarrow Levenshtein\_distance(profile.given\_name, result.given_name)$
            $append(match, result)$
        end if
    end for
    if $match \neq \emptyset$ *and* $min(distance) < threshold$ **then**
        $return(Found)$
    else
        $return(Failed)$
    end if
end procedure

Table 1 reports the dimension of data from Ministry's list and the relative consolidated data. Let us note that, by law, a researcher, at a given time, must belong to one academic discipline, therefore, we use that value from Ministry's list. The last column reports the percentage of authors that could not be associated to any Scopus profile either because of failed disambiguation or because the author is not even present in the database. Let us also note that, while it may be possible to recover some of the missed profiles, for instance by manually inserting the researcher's OrcID or Scopus identifier, we simply discard these few records since the error introduced not affect significantly the dataset being created.

Table 1. The results of searching and mapping.

Academic Discipline	Total in the SSD	Matched	% of Missed
MAT/05	723	679	6.08%
SECS-P/01	733	674	7.77%
ING-INF/05	843	785	5.75%
INF/01	1027	966	6.76%

3.3. Making the Coauthorship Network

After matching and recovering the profile of Italian academic researchers from the MUR's list, the next step is to retrieve the publication list of each of them and build the co-authorship networks. Specifically, we build a network for each of the "academic disciplines" (SSDs) under study, where nodes are researchers and links among them represent collaborations. More in detail, given two nodes u and v, the edge (u, v) represents the fact that researchers u and v have co-authored a paper. We enrich the networks with bibliometrics about the researchers (such as H-index, number of published documents, of citations and of co-authors, Years of activity, etc.) from the Scopus' database, and also associate the number of co-authored papers as the edge weight $w_{(u,v)}$.

Although the algorithm used to obtain the publications and build the networks is quite trivial, it must be optimized to reduce the number and the complexity of the queries to avoid filling the query quotas provided by Elsevier and avoid throttling. Please note that such queries were performed against the Scopus cluster instead of Scopus Author because the information about each publication is useful for further processing and verification. Let us also note that, to reduce the number of API calls, we query 25 documents with each call, and we cache result to avoid to repeat a query.

The algorithm, described in Algorithm 2, was executed three times to explore the co-authorship at different "depths", that is, the maximum number of hops from the seed nodes to explore:

1. Depth-zero: that is the co-authorship of Italian researchers only, i.e., it contains only vertices that belong to Ministry's list.
2. Depth-one: in this step we added only authors that have direct connections with Italian researchers.
3. Depth-two: starting from deep-two we also included the co-authors of co-authors ('two' means that we stopped the deep first search at the second step).

Of course, depth-two network contains depth-one that, in turn, contains depth-zero.

Algorithm 2 Deep first search of common publications.

```
procedure Create_Coauthorship(author_list)
    vertices ← []
    edges ← []
    for all author ∈ author_list do
        if author ∉ vertices then
            append(vertices, author)
        end if
        result ← search_against_Scopus_Cluster(authors)        ▷ search for all author's documents
        for all document ∈ result do
            for all coauthor ∈ extract_authors(result) do       ▷ extracts list of authors from result
                if (author, coauthor) ∉ edges then
                    append(edges, (author, coauthor))
                    weight((author, coauthor)) ← 1
                    append(document, setof_documents((author, coauthor)))
                else if document ∉ setof_documents((author, coauthor)) then
                    weight((author, coauthor)) = weight((author, coauthor)) + 1
                end if
            end for
        end for
    end for
end procedure
```

4. Inside the Data

In this section, we briefly analyze the topology of 12 networks (built as described in the previous section) and the bibliometrics of the authors, and highlight some characteristics of the collected samples.

4.1. Structure of the Networks

As detailed in the previous sections, we have built the co-authorship networks using the list of Italian academic researchers from four different "academic disciplines" as seeds: for each discipline, we build three subnetworks where we include all the researchers separated by up to one, two, or three degrees of collaborations. As shown in Table 2, reporting the number of nodes and edges of the three datasets, the networks built at different depths have different size. This is expected, since the networks may also include researchers from other institutions or countries. We also extract the Giant Connected Component (GCC, also known as Largest Connected Component, LCC) of the networks, i.e., the largest cluster of connected nodes, capturing the largest group of researchers that have a finite degree of separation from each other. The sizes of such components are shown in Table 3.

Table 2. Italian co-authorship networks size of the academic disciplines under analysis.

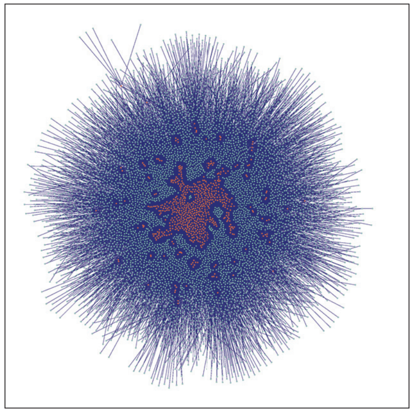
Academic Discipline	**Depth-Zero**		**Depth-One**		**Depth-Two**	
	Vertices	**Edges**	**Vertices**	**Edges**	**Vertices**	**Edges**
MAT/05	679	1990	7891	13,764	338,475	1,042,750
SECS-P/01	674	784	10,736	13,404	727,060	2,512,882
ING-INF/05	784	3759	46,879	84,127	1,900,424	6,897,383
INF/01	966	4327	43,339	78,283	1,824,553	6,666,596

Table 3. Giant Connected Components size of the Italian co-authorship networks of the academic disciplines under analysis.

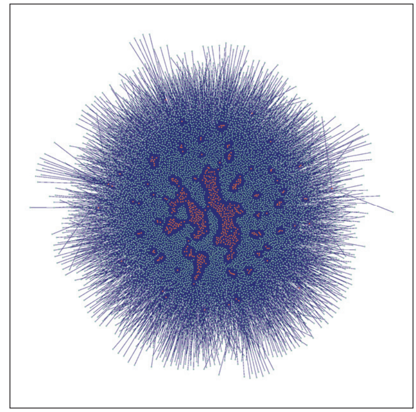
Academic Discipline	**Depth-Zero**		**Depth-One**		**Depth-Two**	
	Vertices	**Edges**	**Vertices**	**Edges**	**Vertices**	**Edges**
MAT/05	613	1970	7712	13,599	338,462	1,042,745
SECS-P/01	458	752	9309	12,042	727,028	2,512,863
ING-INF/05	758	3758	46,851	84,101	1,900,413	6,897,354
INF/01	929	4318	43,324	78,271	1,824,552	6,666,596

We also plot the GCC of the depth-one networks (for the sake of readability, as the larger networks would be unintelligible) in Figure 2 that highlights the Italian researchers. Let us note that the co-authorship networks of ING-INF/05 and INF/01 disciplines show similar collaboration patterns, which is expected considering the large overlap in research interests and topics between them.

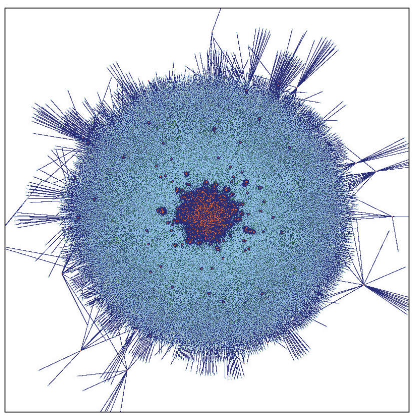
In Table 4, we report some topological characteristics of the depth-two networks, describing their size, edge density, and connection patterns. As the Reader may notice, although the computer science-related fields have comparable size, the networks show a very different number of nodes and edges among academic fields. On the other hand, the average degree, strength, and link weight are comparable. Another interesting difference among the disciplines is in the average local clustering coefficient and in the transitivity, which shows that the researchers in computer science-related fields are more prone to collaborate. We also compute the degree and strength assortativity, as defined in [39,40].



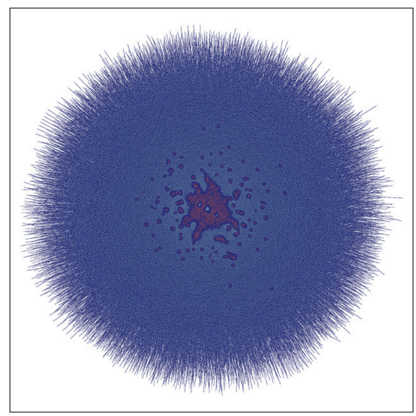
(**a**) MAT/05



(**b**) SECS-P/01



(**c**) ING-INF/05



(**d**) INF/01

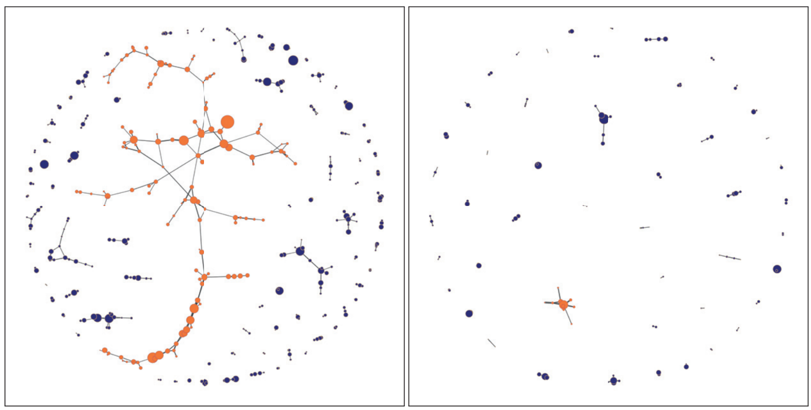
Figure 2. These figures highlight the core of co-authorship networks (orange/clear) with respect to direct coauthors (blue/darker).

Table 4. Characteristics of the Largest Connected Component of the Depth 1 networks.

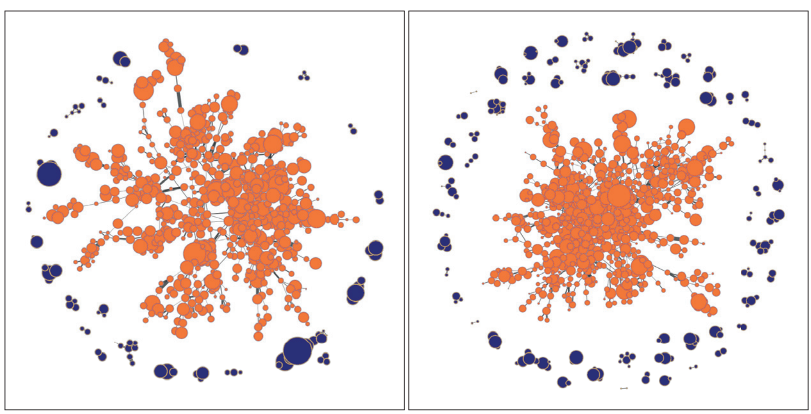
	SECS-P/01	MAT/05	ING-INF/05	INF/01
Number of edges	12,042	13,599	84,101	78,271
Number of nodes	9309	7712	46,851	43,324
Avg. degree	2.58717	3.52671	3.59015	3.61329
Density	0.00028	0.00046	0.00008	0.00008
Avg. link weight	2.12465	2.62593	2.91573	2.93882
Avg. strength	5.49683	9.26089	10.46791	10.61878
Avg. local clustering coefficient [11]	0.08487	0.23174	0.27827	0.26523
Transitivity [41]	0.00364	0.04231	0.01994	0.02194
Avg. k-core [42,43] number	0.09904	0.30368	0.09470	0.11534
Max k-core number [42,43]	3	6	17	8
Degree assortativity [39]	−0.05231	−0.13266	−0.12238	−0.12909
Strength assortativity [40]	−0.02465	−0.09091	−0.11980	−0.01308
Avg. Shortest Path Len.	6.25596	4.44838	3.86187	3.93791
Diameter	16	16	9	10

4.2. Bibliometrics

In this Subsection, we analyze the bibliometrics associated to the authors. Figure 3 represents the depth-0 networks with a node and edge size proportional to the author's H-index and number of coauthored publications, respectively. Such figures allow to appreciate that relevant nodes are often heavily connected, i.e., they are *hubs*, and also the different habits and policies of the academic disciplines is clearly show by this representation: researchers in the SECS-P/01 discipline collaborate with other Italian researchers belonging to the same discipline less than others, which also translates into a larger number of small Connected Components; MAT/05 shows a very small core with a sort of "tail", a chain of collaborations; INF/01 and ING-INF/05 exhibit a large core and a far denser collaboration network.



(**a**) MAT/05 (**b**) SECS-P/01



(**c**) ING-INF/05 (**d**) INF/01

Figure 3. Italian academics' co-authorship networks at depth-0. Vertices and edge widths are proportional to the author's H-index edge weights, respectively. The Giant Connected Component colored in orange/clear. For sake of readability, the nodes with degree $d_i < 5$ have been filtered out.

The distributions of the most relevant bibliometrics indices contained in the dataset are shown in Figure 4 with darker color standing for larger density. Again, a strong similarity can be observed between computer science-related fields, while the economics and mathematical analysis disciplines show different distributions. For instance, the H-index range is wider in the ING-INF/05 and INF/01 than the other disciplines, and the distribution is fat-tailed. Regarding the number of documents, of citations and of coauthors the distributions of INF/01 and SECS-P/01 show a very dense area around small value. On the other hand, number of years activity is similar across all disciplines.

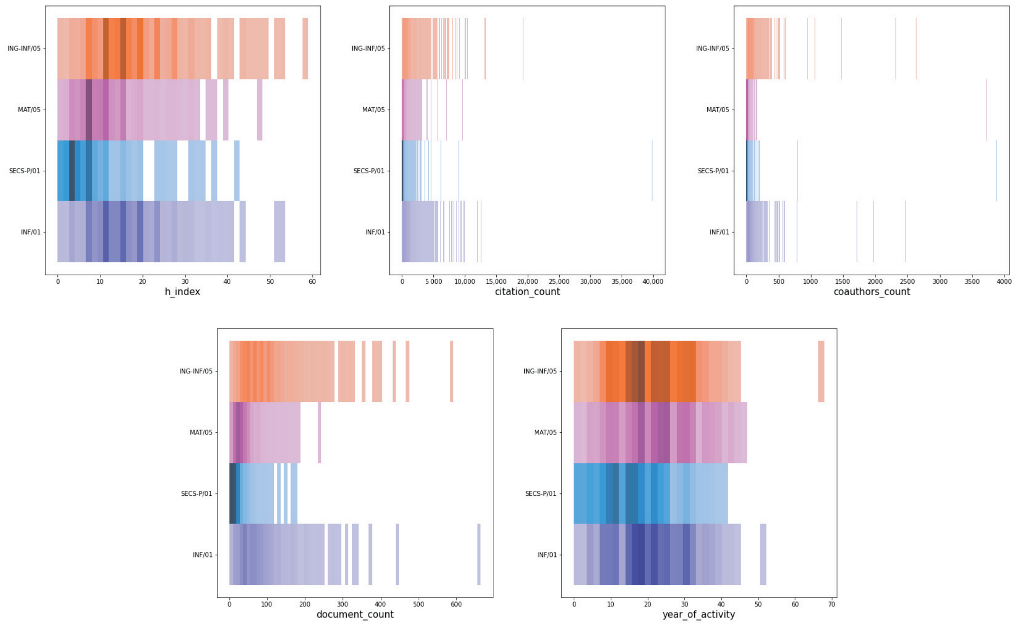
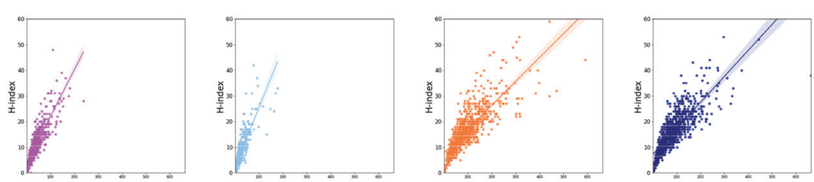
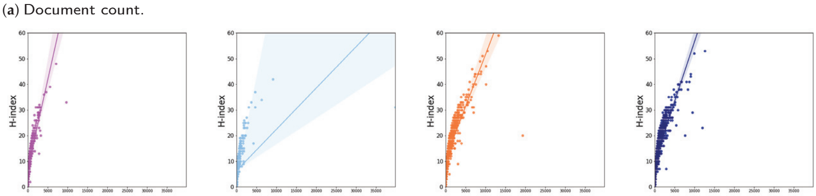


Figure 4. Distribution of some bibliometric indices in the academic disciplines.

Another interesting analysis that could be performed on the networks is related to the "Science of Success". Here, we show, in Figure 5, the correlation between H-index and some indices. More specifically, the figure plots the relation between H-index and the other features in the four dataset using a linear model regression and a confidence interval. Table 5 shows the Pearson product-moment correlation coefficient between H-index and the other features in the four dataset. Once again, the table highlights a very strong overlap of ING-INF/05 and INF/01 disciplines for all the bibliometric indices whilst the Pearson's correlation of SECS-P/01 is markedly different.

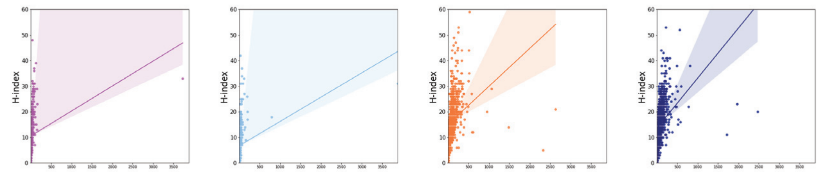


(**a**) Document count.

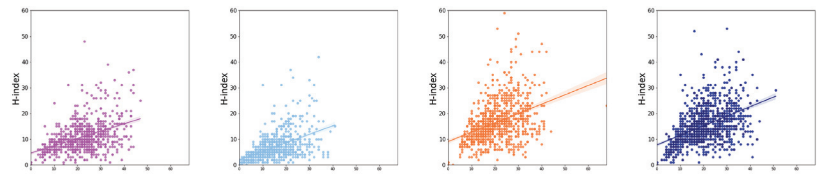


(**b**) Citation count.

Figure 5. *Cont.*



(**c**) Co-author count.



(**d**) Years of activity

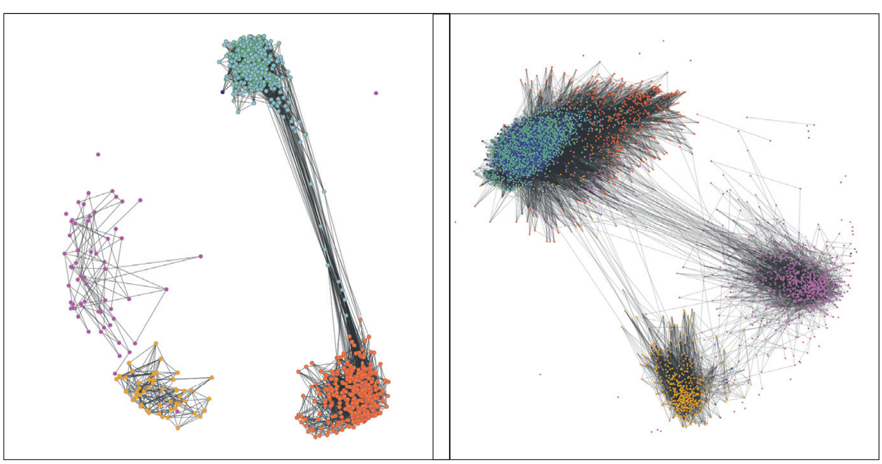
Figure 5. Correlation among H-index and bibliometric indices in the academic disciplines, from left to right academic disciplines are: MAT/05, SECS-P/01, ING-INF/05, and INF/01.

Table 5. Pearson's correlation among H-index and bibliometric indices in the academic disciplines.

Bibliometric Indices	ING-INF/05	MAT/05	SECS-P/01	INF/01
documents count	0.80	0.85	0.85	0.82
citations count	0.84	0.86	0.49	0.84
coauthors count	0.30	0.23	0.27	0.37
Year of activity	0.38	0.43	0.49	0.44

4.3. Multidisciplinarity

In this subsection, we aim at answering the following questions: *do researchers belonging to different academic disciplines work together?* and *does the grouping imposed by the Italian law affect the collaboration patterns among researchers?* To do so, we merge the networks of the different disciplines together and show the resulting networks in Figure 6.



(**a**) depth-zero. (**b**) depth-one.

Figure 6. Co-authorship network of the four academic disciplines (ING-INF/05 dark orange, INF/01 cyan, MAT/05 is orange, and SECS-P/01 is violet).

At first, we limit the analysis to the depth-zero networks Figure 6a, which only include Italian academic researchers. As shown in the plot, the number of collaborations across the disciplines under study is very low. More in detail, there is almost no cooperation between researchers in MAT/05, SECS-P/01, and the computer-science related ones, while researchers ING-INF/05 and INF/01 have coauthored more papers, which is expected since the strong overlap in the research topics [44]. We later extend the networks by including the direct coauthors, i.e., by merging the depth-one networks. The resulting network, depicted in Figure 6b, shows that there is some (indirect) collaboration among groups, and a very strong overlap in the groups of INF/01 and ING-INF/05. (Let us note that in depth-1 and depth-2 some authors can be coauthors of researchers belonging to different academic disciplines, so they are present in both networks; we represent them as blue points). By merging the networks at depth-two, the size of the largest cluster grows a lot, which shows that other researchers (e.g., researchers from the same field but working for private institutions or living abroad) bridge the various groups. Please note that we omit the resulting figure since the network would be too large and dense.

5. Conclusions

The collaboration patterns among researchers, and also their relation to higher performance metrics are widely investigated problems, with applications, for instance, in the science of success. In this work, we propose and briefly study a new dataset of collaboration among Italian academic researchers. In particular, we first describe the data-collection process, the challenges and the solution to various problems. Then, we build and analyze the collaboration networks, in search of the different characteristics of four different academic disciplines (groups of researchers defined by the Italian law), however we mainly focused on the approach to build the datasets giving some example of the analysis that could be completed leaving explanation of the results to further works. Our results show similar collaboration patterns among researchers of computer science-related fields (ING-INF/05 and INF/01) and, even if with a limited extent, collaborations among them. On the other hand, researchers from Economics (SECS-P/01) and Mathematical analysis (MAT/05), tend to collaborate less with other Italian colleagues.

5.1. Discussion

In this section we provide a brief discussion on contribution of this paper that mainly lies in the datasets and their features, the analysis of them have the purpose to inspire further researches aiming at both studying this specific co-authorship with a well established approach and to explore new approaches, such us the use of the network science tools, to understand hidden mechanism that drive the behavior of scientist communities.

The creation of new dataset represents an important contribution itself, however, it must cover a real world case that exploits some new characteristics and creation strategies to add to previous studies. The case described in this paper has the following peculiarities:

- The scientist community is stable and well-defined since it is defined by law;
- The four dataset share some characteristics (scientific/technical topics, publication areas) but have different publication policy (e.g., number of authors, type of contribution);
- The algorithm, as discussed, can be used to easily extract more academic disciplines in a reasonable time;
- Almost all problems dealing with ambiguity and wrong classification has been solved (the error are $\approx$5%, of course, the error can be reduced by human involvement, but it does not modify the structure of co-authorship network;

Measuring the performance of scientist using performance indices, such us bibliometrics, is widely debated but, since it is adopted by more and more institution any contribute that study the correlation between network structure and bibliometrics, if any, permit defining more correct policies (such as recruitment policies) or limit abuses (e.g., publishing “salami slices” with similar methods and slightly different results). However, the exploratory examples of analysis provided in this paper simply aim at validating the datasets and show its effectiveness in highlight specific characteristics.

5.2. Future Works and Limitations

Future works may involve enriching and improving the dataset, for instance, by extending the groups analyzed either to other academic disciplines or to more collaboration hops. Moreover, further analysis can be performed, for example, with data science and network science approaches. Finally, an attempt to explain both the internal behaviors and the difference among academic disciplines is a further step in the comprehension of some dynamics and could lead to understand why some people are more successful than others.

The dataset, since covers several years and long-lasting collaborations could be used to explore the trust relationship among scientists and the impacts of aging [45], or strategies and the cost to build strong communities [46].

The dataset proposed in this paper, as well as the proposed analysis, does not include any studies on the content of the co-authored paper and on the different contribution of each author (if any are documented). Some additional features, present in Scopus DB, such as abstracts and keywords using text analytic techniques [47], could allow searching for very similar publication, and, for instance, to evaluate the impact in bibliometrics but also in co-authorship. However, the dataset contains all information useful to enhance and complete the included information since it includes most of the unique key universally adopted (e.g., OrcID, Scopus-id) that can be used to query both Scopus itself and other archives.

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Data Availability Statement: The networks analyzed in this study were derived from Elsevier's Scopus DB and are available upon request.

Conflicts of Interest: The authors declare no conflict of interest.

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