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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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Citation: Samala, T.; Manupati, V.K.; Varela, M.L.R.; Putnik, G. Investigation of Degradation and Upgradation Models for Flexible Unit Systems: A Systematic Literature Review. *Future Internet* **2021**, *13*, 57. https://doi.org/10.3390/fi13030057

Academic Editor: Stefano Rinaldi

Received: 24 January 2021
Accepted: 19 February 2021
Published: 25 February 2021

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.

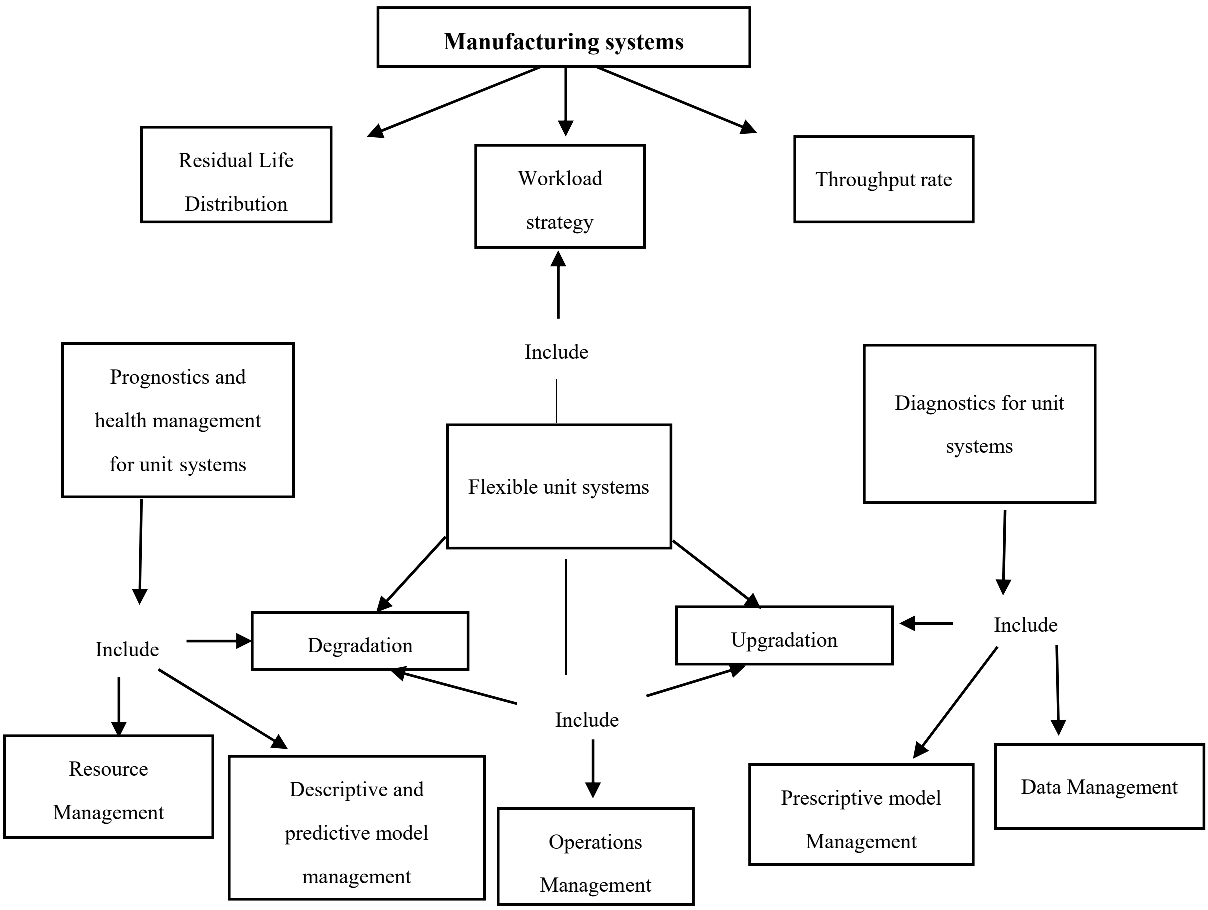

Figure 1. Framework addressing the topics affecting flexible unit systems (FUS).

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.

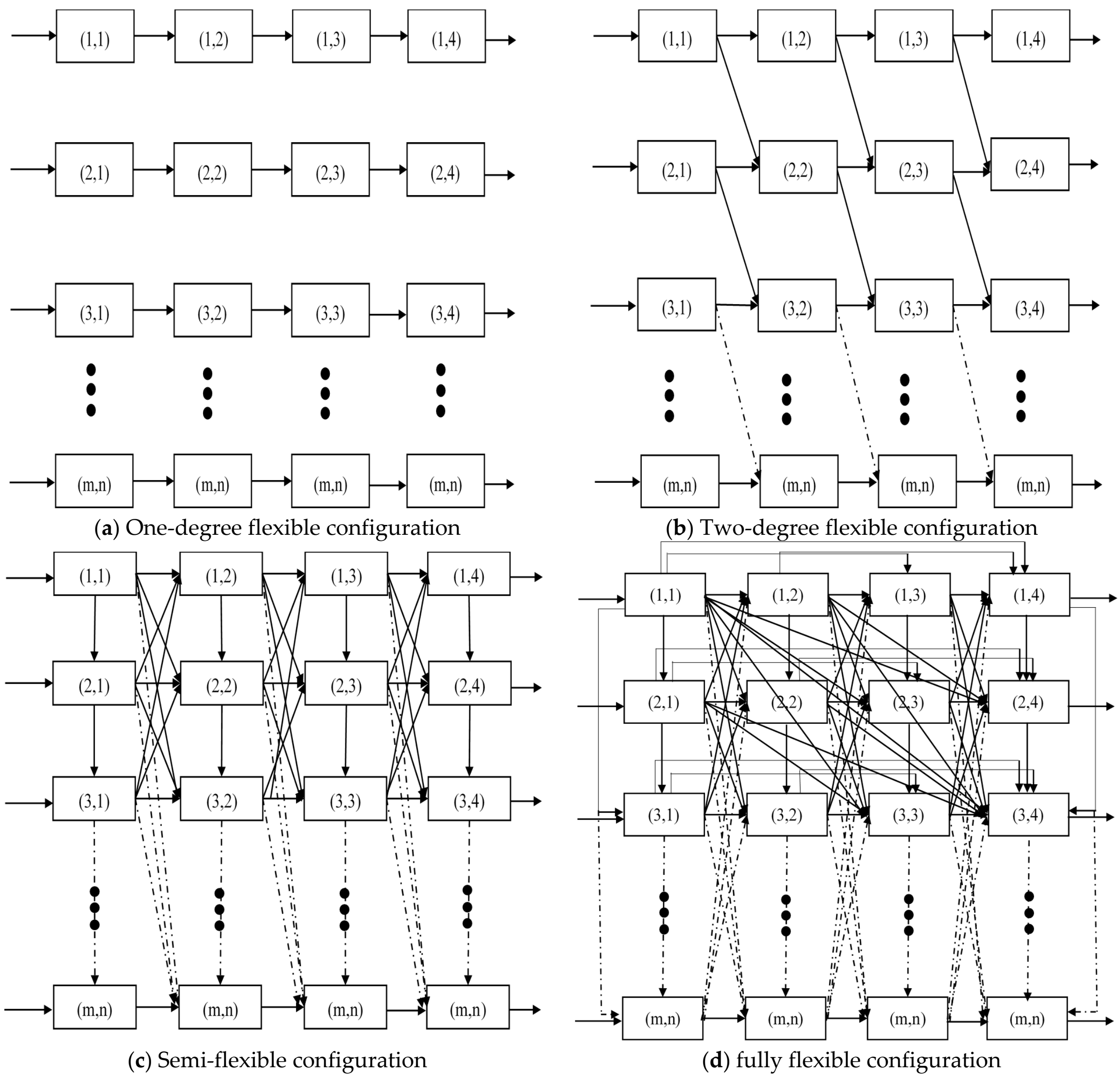

Figure 2. Flexible unit system with different configurations.

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.

Author Contributions: Conceptualization, V.K.M. and M.L.R.V.; methodology, V.K.M. and M.L.R.V.; investigation, T.S.; writing—original draft preparation, T.S.; writing—review and editing, T.S., V.K.M., and M.L.R.V.; visualization, T.S., V.K.M., and M.L.R.V.; supervision, G.P.; project administration, V.K.M. and G.P. and M.L.R.V.; funding acquisition, V.K.M. and G.P., and M.L.R.V. All authors have read and agreed to the published version of the manuscript.

Funding: The project is funded by the Department of Science and Technology, Science & Engineering Research Board (DST-SERB), Statutory Body Established through an Act of Parliament: SERB Act 2008, Government of India with Sanction Order No ECR/2016/001808, and also by FCT—Fundação para a Ciência e Tecnologia through the R&D Units Project Scope: UIDB/00319/2020.

Acknowledgments: We thank the Associate Editor and three anonymous referees for their thoughtful comments, which have greatly aided in the improvement of the manuscript. We also are grateful for the financial support of the Department of Science and Technology, Science & Engineering Research Board (DST-SERB), Statutory Body Established through an Act of Parliament: SERB Act 2008, Government of India with Sanction Order No ECR/2016/001808, and of the FCT—Fundação para a Ciência e Tecnologia through the R&D Units Project Scope: UIDB/00319/2020.

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

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