Predictive Manufacturing: Enabling Technologies, Frameworks and Applications

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Abstract. The impact of globalization and the recent advancements in Information and Communication Technologies has pushed the manufacturing sector towards a new transformation. Current manufacturers with the help of recent advances in Cloud Computing, Artificial Intelligence, and Internet of Things are moving towards a new intelligent system called Predictive Manufacturing Systems (PMS). These systems can be used in a wide array of applications, including proactive maintenance, improved quality control and higher performance. This paper provides an overview of the current trends in Predictive Manufacturing Systems in recent years. The paper discusses the developed frameworks, enabling technologies and various applications of Predictive Manufacturing Systems.

Keywords: Predictive manufacturing systems · Smart manufacturing · Artificial intelligence · Cloud computing · Internet of Things · Data analytics

1 Introduction

Smart Manufacturing
The need for mass customization and competition from emerging markets has pushed the manufacturers to shift towards a new manufacturing paradigm by utilizing the emerging technologies in computer engineering. This new manufacturing paradigm is called Smart Manufacturing. Smart manufacturing can be defined as "A set of manufacturing practices that use networked data and Information & Communication Technologies (ICTs) for governing manufacturing operations" [1].

Predictive Manufacturing Systems
In smart manufacturing, to have a competitive advantage in the market, many manufacturers have started to utilize the data generated from sensors and converted them into

The original version of this chapter was revised: this chapter was previously published non-open access. The correction to this chapter is available at
https://doi.org/10.1007/978-3-030-78288-7_36

L. M. Camarinha-Matos et al. (Eds.): DoCEIS 2021, IFIP AICT 626, pp. 51–61, 2021.
https://doi.org/10.1007/978-3-030-78288-7_5

useful information. This has led to the development of intelligent systems called "Predictive Manufacturing Systems (PMS)" which gives self-x capabilities (self-predicting, self-maintaining & self-learning) for manufacturers.

Need for this Work

In the last half decade, there were very limited reviews which gives a general overview of the current frameworks, technologies, and applications of a PMS. Nikolic et al. [2] presents the current trends in predictive manufacturing system but mainly focuses on the benefits and challenges. The authors provided very little information on the developed frameworks or applications of PMS. Other authors have tried to explain in detail specific areas which fall under PMS. Lee et al. [3] reviewed predictive manufacturing with focuses on maintenance. Peres et al. [4] focused on industrial artificial intelligence in industry 4.0. Few other reviews [5, 6] focuses on the application of big data for predictive manufacturing. Hence, there is a need for a review which focuses on the developed frameworks, enabling technologies and current application of PMS.

Aim of the Work

This work will act as the starting point in formulating the hypothesis for the PhD Dissertation of the first author whose tentative research question is, *"Which is an effective generic framework for the realization of a Predictive Manufacturing System (PMS) to improve the overall equipment effectiveness (OEE) in a smart manufacturing environment?"*.

We hope that our work helps in giving new researchers a brief overview of the current trends in predictive manufacturing. More specifically, with this work, we aim to give a concise view for researchers to understand the current frameworks, technologies, and applications of PMS. We also would like this work to act as a guide for manufacturers in implementing PMS for their specific requirements.

2 Relation to Applied Artificial Intelligence Systems

PMS utilizes the emerging technologies in computer engineering to provide an intelligent system for current manufacturing needs. In these emerging technologies Artificial Intelligence stand out as a promising technology for predictive manufacturing. As we will explain in later sections, many researchers have preferred to use Applied Artificial Intelligence System for predictive applications. These applications include Quality Control [7], performance [8], parameter estimation [9, 10], Planning & Scheduling [11, 12] and Maintenance [13]. According to our analyzes, around 40% of the publications in the last 5 years use machine learning techniques for predictive manufacturing. We believe that this trend will steadily increase in the coming years with more manufacturers implementing advance technologies like Internet of Things and Data Analysis for achieving competitive advantage. Hence, Applied Artificial Intelligence Systems will act as a very relevant and effective tool for the realization of PMS.

3 Adopted Methodology

To understand the current trends in PMS a structured literature review was carried out (Fig. 1). The first and the most important step is to identifies relevant research questions (RQ) which would satisfy the requirements of the review. The 3 Research Questions identified for this review paper are mentioned below,

RQ1: What are the various frameworks developed in recent years for the realization of PMS?
RQ2: What are the different technologies used for the development of PMS in recent years?
RQ3: What are the different areas of application of PMS in recent years?

Our review will answer these three research questions and analyze & Discuss their results.

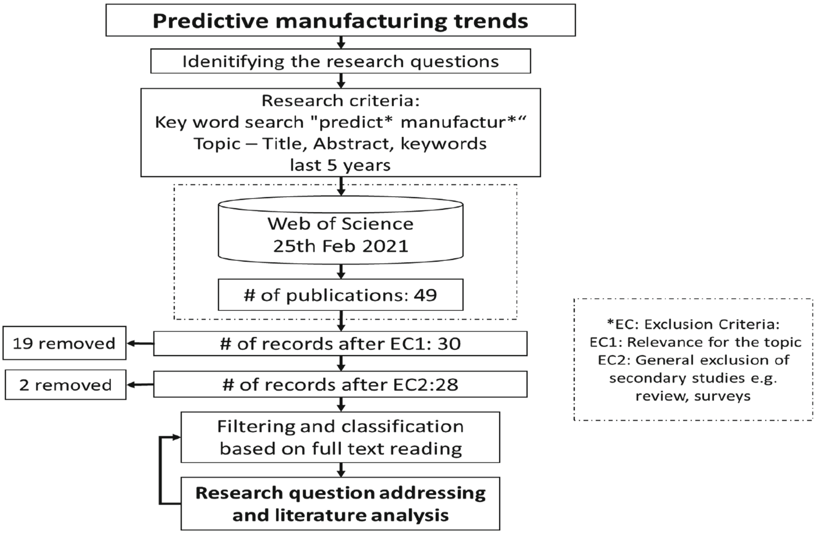

Fig. 1. Adapted methodology for literature analysis.

4 Results and Discussions

RQ1: What are the various frameworks developed in recent years for the realization of PMS?

The term "framework" is the context of this paper is a broad term which defines the basic structure or model underlying a system or concept. In the literature works presented here this is mentioned using different terminologies like architecture, structure, methodology, model etc. From the 28 research papers we reviewed, we found only 13 papers which describes a framework. Others are experimental work based on previously established framework. The brief overview of these papers is mentioned in Table 1. One paper (by Luter et al. [14]) was excluded from the table as the paper gives insight on a methodology to predict the manufacturer's viability to succeed. This paper does not fit the criteria of providing a solution for PMS.

Finding a common ground among these wide variety of frameworks is a tedious task, which show a greater challenge in creating a generic framework for PMS. We also

Table 1. Frameworks for realization of PMS.

Article	Framework	Significance
Majiwala, Parmar and Gandhi [6]	Data classification into different level of management Data optimized using lean principle	Decision trigger from different levels of management
Gyulai et al. [15]	Closed loop controller Data from MES* and ERP* to a Machine Learning engine	Real time prediction of lead time
Park et al. [16]	Multi- Entity Bayesian Networks model with at least three kinds of entities: System, item, and time	Introduce self-awareness capabilities
Cai, Guo and Lui [17]	Considering trajectory patterns and dataset equations followed by synthesizing for a result list	Predict the next location of the work-in-process
Kostolani, Murin and Kozak [18]	Node layer - sensor, production system, Augmented Reality Fog and Cloud layer	Rule based intelligent predictive maintenance control
Jin et al. [19]	5C Architecture - Connection, Conversion, Cyber, Cognition and Configuration Level	predict degradation of critical assets
Takada et al. [20]	Data Processing - formatting, analysis, enrichment and viewing Hybrid modeling - experience & statistical model	Solution for maintenance, enhanced efficiency, and quality
Peres et al. [21]	3 components - Cyber Physical Production System, Real time Data Analysis & Knowledge Management	Real time supervision for maintenance and quality control
Yang et al. [9]	Super-meta model - a composition of weighted individual models (like kriging, ANN*, polynomial regression)	Improve prediction accuracy without need for additional data
Fang et al. [11]	IoT based data collection, data pre-processing, input and output sequence generation, Parallel gated recurrent units model development	Near, mid and long-future bottleneck prediction and its shifting trends
Fang, Guo, Liao, Ramani et al. [12]	Stacking multiple symmetrical Neural Network with dropout and batch normalization layer to make outer layer as linear regression	Robust and accurate prediction of jobs remaining time

(*continued*)

Table 1. (*continued*)

Article	Framework	Significance
Kwon and Kim [22]	Control unit - sensor, equipment, actuator; Wireless/Wired sensor node & gateway; PC based measurement system	Real time production data acquisition for quality analysis

*Acronyms: ANN – Artificial Neural Network, MES – Manufacturing Execution System, ERP – Enterprise Resource Planning

noticed that only very few frameworks provide real-time prediction which show a need for greater focus on this area. Data collection, storage and analysis plays a vital role in all the frameworks and almost all frameworks require the need for the collection of historical data.

RQ2: What are the different technologies used for the development of PMS in recent years?
We categorize enabling technologies for Predictive Manufacturing applications into twelve dimensions, as shown in Fig. 2. Results of this question do not aim to provide a very strict statistical analysis but to offer a general vision of what scope of technologies and with what strength are supporting predictive manufacturing.

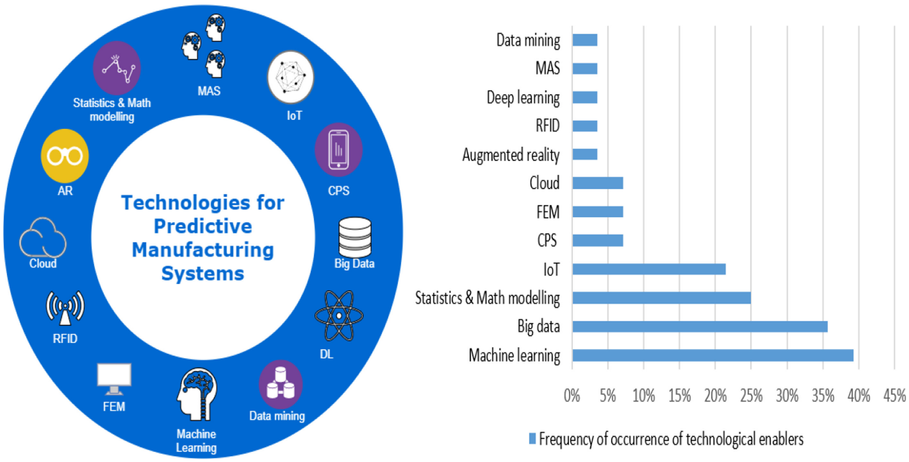

Fig. 2. Various technologies that support PMS.

No surprisingly, we found that **Machine Learning (ML)** algorithms are used more frequently (39%). ML provides mechanisms that utilize experience-based knowledge i.e., supervised and non-supervised techniques like lineal regression. Based on a pre-trained data set, ML allows production monitoring in non-linear environments in which historical data sets are used as a prediction input [23]. **Deep learning (DL)** as part of ML algorithms is less exploited (4%). We argue that such result implies the lack of computational efficiency and complexity of model representation [24]. Similarly, and to a lesser extent, **Data mining (DM)** (4%) promotes the extraction of useful knowledge from data sets. In general, DM is used to discover new patterns and for machine forecasting in presence of huge and raw data sets [25].

We should also highlight the presence of tools related to **statistics and mathematical modelling formulation** (25%). The model representation aims to develop mechanisms that can predict environmental variables on a prospective timeline and therefore recognize what variables may need assistance [26]. Despite promising ideas, it is our opinion that such approaches are less adopted due to high complexity in mathematical formulation. Conversely, ML and DL techniques hide all this complexity and thus promote a more straightforward methodology for manufacturing prediction.

Moving towards scalability and decentralization of manufacturing processes [4], **big data (35%)** and **cloud technologies (7%)** provide the necessary infrastructure for data storage, analysis, security and interoperability [12]. These technologies also act like data lakes or data warehouses to be used by ML and DL. Big Data predominantly uses either database like NoSQL or NewSQL or cloud storage (ex. cloud services from Amazon, Microsoft or Google). We state that the low percentage of cloud applications reflects the needed research effort for such technological integration especially due to the lack of real time communication and interoperability. At the same time, **multi-agent systems (MAS) (3%)** and despite not being highly considered in the set of papers, are a recognized technology for distributed applications. Agents can abstract resources which are distributed over the network and at the same time manage them, negotiate, monitor, predict and adapt to unforeseen events in real time [21].

The introduction of **internet of things (IoT)** technologies (21%) along with high interconnectivity, networking capability, sensors, **Cyber-physical systems (CPS)** (7%), **RFID** identifiers (3%) and human integration in the manufacturing supervision and control e.g., with augmented reality (**AR**) (3%), are gradually promoting manufacturing digitalization and creating intelligent machines and products. Thus, developing more awareness and supporting a holistic approach for PM applications.

Finally, we should also note the utilization of finite elements methods (**FEM**) as a mechanical alternative for PM. These methodologies have not been highly exploited in PM (7%). However, the combination of such classical methods with enabling technologies i.e., ML, DL, DM can support novel strategies for PM e.g. to predict and analyze quality of materials to capture defect behavior in finalized parts [27].

RQ3: What are the different areas of application of PMS?

This research question gives an overview of the different areas of application of PMS in the reviewed papers. The papers mentioning cost reduction as the application of PMS was ignored from this analysis as all applications directly or indirectly aims at cost reduction for the manufacturers. Figure 3 presents percentage distribution of each application compared to the number of publications. Others mentioned in Fig. 3 represents applications which are addressed in less than 5% of total publications. Some articles address more than one application. These articles are added more than once in different applications. The results shows that 70% of all application of PMS are in Quality Control, Planning & Scheduling and Maintenance. This shows strong focus of PMS research in the lower level of ISA 95 levels (International Society of Automation levels) and on real time predictions.

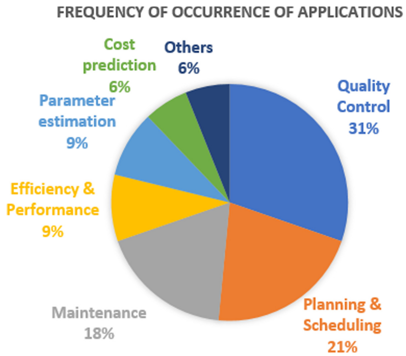

Fig. 3. Application of PMS in manufacturing.

Further Discussions – Towards a Generic Framework for PMS

When we combine the answers of individual research questions, we obtain further interesting results. We believe that these results can guide future researchers in developing a generic framework for PMS. Table 2 list the various technologies used for different manufacturing applications. We could notice that big data and machine learning techniques have been used for all the applications with just one exception (machine learning techniques were not used in cost prediction). This shows that a system developed with the combination of these two technologies might help in giving a solution for the realization of a generic framework. Further analyzing these technologies shows Neural Network as the most promising tool used compared to other machine learning tools.

Implementing the developed framework in multiple applications validates the claim of developing a generic framework for PMS. We found that, from the 13 frameworks described for the realization of a PMS only three frameworks have been utilized in more than one application. These three frameworks (See Table 1 for more details of the framework) and their applications are explained below,

1. Park et al. [16] developed a predictive situation awareness system using Multi- Entity Bayesian Networks model for production scheduling and quality control.
2. Peres et al. [21] used multi-agent system and machine learning for realizing a flexible and pluggable data analysis and real time supervision framework. The framework was used for predictive maintenance and Quality Assurance.
3. Monozukuri Navigation System [20] is the only framework in our analysis which applied it's framework in three different scenarios – Predictive Maintenance, Quality Control and efficiency. The System is developed using Big Data Analysis and Internet of Things.

Even if Parenti et al. [33] has applied their graphical method in three different applications namely, process planning, performance and cost prediction, they dint present a

Table 2. Technologies used for various application of PMS.

Application	Technologies used	References
Quality control	Statistics and Math modelling, ML, DL, Big Data, FEM, IoT, CPS, MAS	[7, 16, 20, 21, 22, 27, 28, 29, 30, 31]
Planning & Scheduling	ML, Statistics and Math modelling, RFID, IoT, Big data, DL, ML	[11, 12, 15, 16, 17, 32, 33]
Maintenance	IoT, AR, Cloud, IoT, Big data, MAS, ML, DL	[13, 18, 19, 20, 21, 34]
Efficiency & Performance	DL, IoT, Big data	[8, 20, 33]
Parameter estimation	Statistics and Math modelling, DL, Big data	[9, 10, 26]
Cost prediction	Statistics and Math modelling, Big data	[33, 35]

Acronyms: DL - Deep Learning, ML - Machine Learning, FEM - Finite Element Methods, IoT - Internet of Things, RFID - Radio frequency Identification, MAS - Multi-Agent Systems, CPS - Cyber Physical Systems.

novel framework for PMS. These results show that there are very few publications which have developed a framework for the full realization of PMS.

5 Conclusion

Some of the key takeaways from this review article are listed below,

- In recent years, only very few articles have developed a generic framework for the realization of a PMS. Only three works have validated their framework in more than one application.
- PMS technologies are highly constrained by real-time manufacturing expectations. Thus, most approaches rely on using AI technologies locally. We evidence this by the lack of adoption of cloud infrastructures. Therefore, it is not feasible to create interoperability that involve PMS with the manufacturing supply chain and that can integrate and optimize the process holistically. Further research should be conducted into increasing such technological real-time applicability.
- 70% of the applications of PMS are in Quality Control, Maintenance and Production Planning & Scheduling.
- Many researchers have used Neural Network models for wide variety of applications. This indicates that Neural Network techniques might be a promising tool for achieving an effective PMS.

Future research direction would focus on the use of AI technologies for the development of a generic PMS and validating them on various manufacturing applications.

Another research direction would be to use IoT and Edge-Fog-Cloud architecture for real time prediction - which lacks in current research works.

Acknowledgements. This project has received funding from the European Union's Horizon 2020 research and innovation programme under the Marie Skłodowska-Curie grant No. 814078. Partial support also comes from Fundação para a Ciência e Tecnologia through the program UIDB/00066/2020 (CTS- Center of Technology and Systems).

References

1. Mittal, S., Khan, M.A., Romero, D., Wuest, T.: Smart manufacturing: characteristics, technologies and enabling factors. Proc. Inst. Mech. Eng. Part B J. Eng. Manuf. **233**(5), 1342–1361 (2019). https://doi.org/10.1177/0954405417736547
2. Nikolic, B., Ignjatic, J., Suzic, N., Stevanov, B., Rikalovic, A.: Predictive manufacturing systems in industry 4.0: trends, benefits and challenges. In: International DAAAM Symposium, pp. 796–802 (2017). Ann. DAAAM Proc. https://doi.org/10.2507/28th.daaam.proceedings.112
3. Lee, J.: Intelligent Maintenance Systems and Predictive Manufacturing, November 2020. https://doi.org/10.1115/1.4047856
4. Peres, R.S., Jia, X., Lee, J., Sun, K., Colombo, A.W., Barata, J.: Industrial artificial intelligence in industry 4.0 -systematic review, challenges and outlook. IEEE Access **4**, 1–21 (2020). https://doi.org/10.1109/ACCESS.2020.3042874
5. Guha, S., Kumar, S.: Emergence of big data research in operations management, information systems, and healthcare: past contributions and future roadmap. Prod. Oper. Manag. **27**(9), 1724–1735 (2018). https://doi.org/10.1111/poms.12833
6. Majiwala, H., Parmar, D., Gandhi, P.: Leeway of lean concept to optimize big data in manufacturing industry: an exploratory review. In: Mishra, D., Yang, X.S., Unal, A. (eds.) Data Science and Big Data Analytics, Lecture Notes on Data Engineering and Communications Technologies, vol. 16. Springer, Singapore (2019). https://doi.org/10.1007/978-981-10-7641-1_16
7. Bai, Y., Sun, Z., Deng, J., Li, L., Long, J., Li, C.: Manufacturing quality prediction using intelligent learning approaches: a comparative study. Sustainability 10(1) (2017). https://doi.org/10.3390/su10010085
8. Tan, L.P., Wong, K.Y.: A neural network approach for predicting manufacturing performance using knowledge management metrics. Cybern. Syst. **48**(4), 348–364 (2017). https://doi.org/10.1080/01969722.2017.1285161
9. Yang, Z., Eddy, D., Krishnamurty, S., Grosse, I., Lu, Y.: A super-metamodeling framework to optimize system predictability, August 2018. https://doi.org/10.1115/detc2018-86055
10. Adesanya, A., Abdulkareem, A., Adesina, L.M.: Predicting extrusion process parameters in Nigeria cable manufacturing industry using artificial neural network. Heliyon **6**(7), e04289 (2020). https://doi.org/10.1016/j.heliyon.2020.e04289
11. Fang, W., Guo, Y., Liao, W., Huang, S., Yang, N., Liu, J.: A Parallel Gated Recurrent Units (P-GRUs) network for the shifting lateness bottleneck prediction in make-to-order production system. Comput. Ind. Eng. **140**, 106246 (2020). https://doi.org/10.1016/j.cie.2019.106246
12. Fang, W., Guo, Y., Liao, W., Ramani, K., Huang, S.: Big data driven jobs remaining time prediction in discrete manufacturing system: a deep learning-based approach. Int. J. Prod. Res. **58**(9), 2751–2766 (2020). https://doi.org/10.1080/00207543.2019.1602744

13. Ang, E.C.: Smart manufacturing with an artificial neural network to predict manufacturing healthiness. In: 2019 IEEE 15th International Colloquium on Signal Process, pp. 120–123 (2019)
14. Luter, N., et al.: An updated methodology to review developing-country vaccine manufacturer viability. Vaccine **35**(31), 3897–3903 (2017). https://doi.org/10.1016/j.vaccine.2017.04.087
15. Gyulai, D., Pfeiffer, A., Bergmann, J., Gallina, V.: Online lead time prediction supporting situation-aware production control. Procedia CIRP **78**, 190–195 (2018). https://doi.org/10.1016/j.procir.2018.09.071
16. Park, C.Y., Laskey, K.B., Salim, S., Lee, J.Y.: Predictive situation awareness model for smart manufacturing. In: 20th International Conference on Information Fusion, Fusion 2017 - Proceedings (2017). https://doi.org/10.23919/ICIF.2017.8009849
17. Cai, H., Guo, Y., Lu, K.: A location prediction method for work-in-process based on frequent trajectory patterns. Proc. Inst. Mech. Eng. Part B J. Eng. Manuf. **233**(1), 306–320 (2019). https://doi.org/10.1177/0954405417708222
18. Kostolani, M., Murin, J., Kozak, S.: Intelligent predictive maintenance control using augmented reality. In: Proceedings of 2019 22nd International Conference on Process Control, PC 2019, pp. 131–135 (2019). https://doi.org/10.1109/PC.2019.8815042
19. Jin, W., Liu, Z., Shi, Z., Jin, C., Lee, J.: CPS-enabled worry-free industrial applications. In: 2017 Prognostics and System Health Management Conference, PHM-Harbin 2017 - Proceedings, November 2017. https://doi.org/10.1109/PHM.2017.8079208
20. Takada, E., Kobayashi, T., Matsuoka, H., Soeda, T., Maida, M.: Monozukuri navigation system to deliver outstanding quality and efficiency. Fujitsu Sci. Tech. J. **53**(4), 70–76 (2017)
21. Peres, R.S., Dionisio Rocha, A., Leitao, P., Barata, J.: IDARTS – Towards intelligent data analysis and real-time supervision for industry 4.0. Comput. Ind. 101, 138–146 (2018). https://doi.org/10.1016/j.compind.2018.07.004
22. Kwon, Y.J., Kim, D.H.: IoT-based defect predictive manufacturing systems. In: 2017 International Conference on Information and Communication Technology Convergence, pp. 1067–1069 (2017). https://doi.org/10.1109/ICTC.2017.8190856
23. Liu, Y., Wang, L., Wang, Y., Wang, X.V., Zhang, L.: Multi-agent-based scheduling in cloud manufacturing with dynamic task arrivals. Procedia CIRP **72**, 953–960 (2018). https://doi.org/10.1016/j.procir.2018.03.138
24. Angelov, P., Sperduti, A.: Challenges in deep learning. In: ESANN 2016 - 24th European Symposium on Artificial Neural Networks, pp. 489–496 (2016)
25. Widmer, T., Klein, A., Wachter, P., Meyl, S.: Predicting material requirements in the automotive industry using data mining. In: Abramowicz, W., Corchuelo, R. (eds.) Business Information Systems, BIS 2019, Lecture Notes in Business Information Processing, vol. 354. Springer, Cham (2019). https://doi.org/10.1007/978-3-030-20482-2_13
26. Kumari, M., Kulkarni, M.S.: Single-measure and multi-measure approach of predictive manufacturing control: a comparative study. Comput. Ind. Eng. **127**, 182–195 (2019). https://doi.org/10.1016/j.cie.2018.12.018
27. Stavropoulos, P., Michail, C., Papacharalampopoulos, A.: Towards predicting manufacturing effect on hybrid part efficiency: An automotive case. Procedia CIRP **85**, 156–161 (2020). https://doi.org/10.1016/j.procir.2019.09.044
28. Dalia, F., Rauf, A., Schiøler, H., Kulahci, M., Zaki, M., Westermann-rasmussen, P.: Cost-sensitive learning classification strategy for predicting product failures. Expert Syst. Appl. **161**, 113653 (2020). https://doi.org/10.1016/j.eswa.2020.113653
29. Lin, H.K., Hsieh, C.H., Wei, N.C., Peng, Y.C.: Association rules mining in R for product performance management in industry 4.0. Procedia CIRP **83**, 699–704 (2019). https://doi.org/10.1016/j.procir.2019.04.099

30. Peres, R.S., Barata, J., Leitao, P., Garcia, G.: Multistage quality control using machine learning in the automotive industry. IEEE Access **7**, 79908–79916 (2019). https://doi.org/10.1109/ACCESS.2019.2923405
31. Dörr, D., et al.: A benchmark study of finite element codes for forming simulation of thermoplastic UD-tapes. Procedia CIRP **66**, 101–106 (2017). https://doi.org/10.1016/j.procir.2017.03.223
32. Gan, W., Lin, J.C.W., Chao, H.C., Vasilakos, A.V., Yu, P.S.: Utility-driven data analytics on uncertain data. IEEE Syst. J. **14**(3), 4442–4453 (2020). https://doi.org/10.1109/JSYST.2020.2979279
33. Parenti, P., Cacciatore, F., Ratti, A., Annoni, M.: A graphical method for performance mapping of machines and milling tools. Procedia Manuf. **26**, 1500–1508 (2018). https://doi.org/10.1016/j.promfg.2018.07.089
34. Rastegari, A., Archenti, A., Mobin, M.: Condition based maintenance of machine tools: vibration monitoring of spindle units. In: Proceedings of Annual Reliability and Maintainability Symposium, January 2017. https://doi.org/10.1109/RAM.2017.7889683
35. D'Urso, G., Quarto, M., Ravasio, C.: A model to predict manufacturing cost for micro-EDM drilling. Int. J. Adv. Manuf. Technol. **91**(5–8), 2843–2853 (2017). https://doi.org/10.1007/s00170-016-9950-0