Predictive Maintenance Solutions for SMEs

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Contributor: Sepideh Hassankhani Dolatabadi

Small- and medium-sized enterprises (SMEs) play an important role in the economy of societies. Although environmental factors, such as COVID-19, as well as non-environmental factors, such as equipment failure, make these industries more vulnerable, they can be minimized by better understanding the concerns and threats these industries face. Only a few SMEs have the capacity to implement the innovative manufacturing technologies of Industry 4.0.

predictive maintenance SMEs expectations requirements challenges

1. Introduction

Physical assets play a key role in fulfilling the needs of factories and companies. However, installation is highly automated and technically very complex, and, as a result, maintenance management has had to become more sophisticated to meet higher technical and commercial expectations. A wide variety of people work in very inefficient industrial environments [1] In addition, much research has been conducted on the maintenance of machine repairs over the past several decades, with studies on different phases of maintenance, including run-to-failure or corrective maintenance, preventive or scheduled maintenance, and predictive maintenance. The extant literature [1][2][3][4][5], reports significant results for the performance of different phases of maintenance.

Figure 1 [5] gives an overview of the maintenance types. There are several maintenance strategies that can be identified according to their roles. Companies have to decide what kind of strategy works for them. In the case of run-to-failure (RTF), companies risk the failure of systems because they did not maintain them in advance. Preventive maintenance (PvM) can cause inefficient replacement of parts, often before the end of their service life. Effective and reliable maintenance strategy should improve the conditions of the equipment, reduce unexpected system failures, and minimize maintenance costs while maximizing the working time of system components. Regarding these factors, the predictive maintenance (PdM) strategy stands out amongst the others because it optimizes the utilization of equipment, maximizes operation time of system component, and reduces risks from unexpected failures. PdM is related to the high degree of digitization and implementation of the industry 4.0 concept. Its advantages include maximizing the time of use and operation of equipment, delaying and/or reducing maintenance activities, and reducing material and labor costs [6].

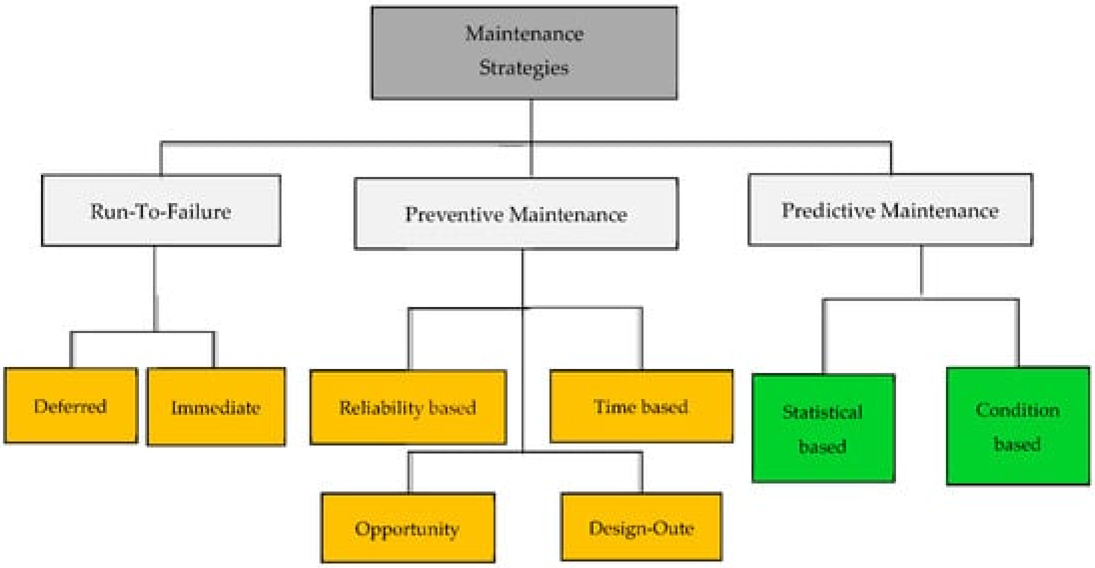

Figure 1. Classifications of maintenance strategies [5].

Currently, according to Baglee et al. [7], SMEs generally use preventive or reactive maintenance strategies. As mentioned in their work, preventive refers to scheduling maintenance processes irrespective of the current state of the machine, whereas reactive refers to maintenance activities due to a change of state or anomaly.

Industry 4.0 is mainly offered by larger companies, and small and medium-sized companies are at risk of not being able to exploit this enormous potential. However, micro-, small-, and medium-sized companies provide about 45% of the value added of production and about 59% of employment and can, therefore, be considered the backbone of the European economy. Therefore, Industry 4.0 concepts should not only be conceived of and implemented in larger companies but also, and arguably more importantly, implementation solutions, approaches, concepts, and technology solutions for efficient implementation should be provided for SMEs [8].

2. SME Challenges

Industry 4.0 is a challenge for businesses in general, and SMEs in particular. The concepts and compatibility of Industry 4.0 for SMEs are only partially realized. Smaller SMEs are at higher risks that they will not be reimbursed for investment into digitization—at least in the short term [9]. One of the likely reasons for this obstacle is that the main idea for many SMEs is to 'start from scratch'. However, SMEs often do not have a complete and correct assessment of their current state and lack an idea of the benefits of digitization in the future, which is another challenge [10]. Jerrentrup's [11] study provides a comprehensive map of the challenges facing small industries in the deployment of Industry 4.0. We divided the challenges of the digitalization process in SMEs into five main categories: systems, structure, orientation, culture, and resources, each of which can have an effect on the other groups. **Figure 2** shows examples of each the above groups.

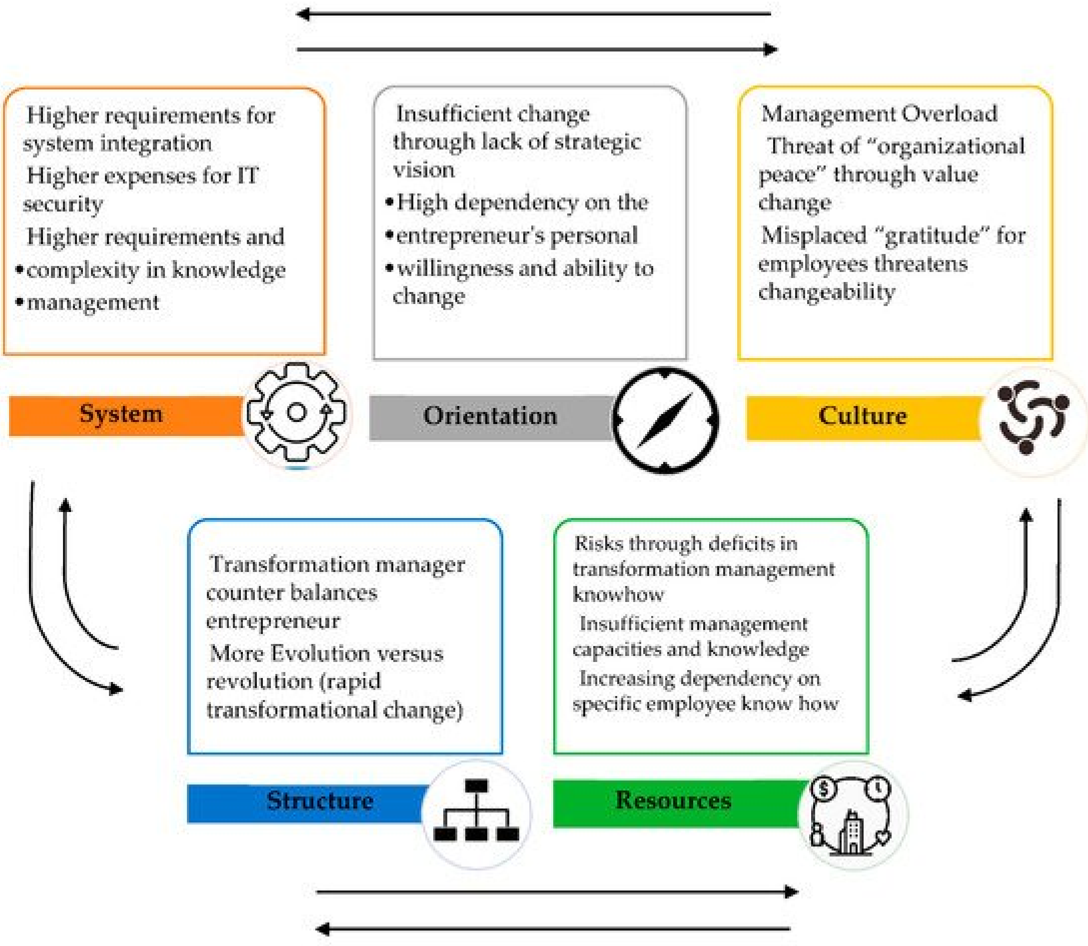

Figure 2. Challenges of the digitalization process in SMEs [11].

Other challenges discussed in the recent research, specifically on the subject of predictive maintenance, include investments and unclearly defined costs (based on a questionnaire in 2019 on Industry 4.0 regarding Serbian SMEs) [12], not enough opportunities for failure and small-sample learning tasks [13][14], a lack of highly qualified users [15], and the loss of specialists or the dependence of the system on them [16], forcing organizations to absorb increasingly more distant knowledge faster and with fewer opportunities for reuse [17]. This modeling and integration of large volumes of industrial data [18] are in contrast to small sample prediction problems [19]. Heinis et al. [20] completed an empirical study on 109 SMEs and large enterprises (LEs) in the electrical, metal, and machine industries which are located in Switzerland. Compared to SMEs, LEs showed higher levels of interest and engagement in IOT application development, such as PdM technologies. The limited human and financial resources, which prolong research and development activities, might explain this result.

In addition to the aforementioned, Kordon [21] emphasized that one of the biggest challenges is to achieve a smooth dialog between the two communities of business language and approach-specific language.

The environmental conditions of some industries also pose different challenges. Sezer et al. [22] faced sensor failure and high vibrations in sensitive environments, so there is a need to design highly durable and stable hardware as well as reliable prediction accuracy. Another example of this is the distance between the maintenance site and the relevant human sources. Actionable data may not be available at the right time and place or to the persons authorized to have access to it [23]. In addition, with the rapid spread of the Internet of Things, hackers can gain more access to wireless devices, e.g., sensors and cloud databases. The reliability of a complete system of sensors and cloud resources according to the importance of assets is high risk. Another problem is caused by the high heterogeneity of devices, which can cause a conflict with interoperability [24]. Although both Bluetooth and WLAN (wireless local area networks) are developing low-cost structures, so far, there are only very limited mechanisms to solve problems such as anti-interference, information security, and response times [25].

From a general point of view, Genenning [26] presented seven challenges for integrating an industrial cloud into the service systems of German small enterprises. These challenges, shown in **Table 1**, are divided into three categories: actors, information, and value proposition. See [26] for further details.

Table 1. Challenges of industrial cloud integration in service systems [26].

Actors	Interactions between the entities and stakeholders
	Adopt a philosophy in an integrated organization
	Adopt a strategy in an integrated organization
	Budget reclassification between units
Information	Acquire the required qualifications
Value Proposition	Requires a systematic process for service innovation by digital technology
	Implement a culture of failure in the organization

Finally, although PdM programs promise significant benefits, Adu-Amankwa et al. [23] mapped a summary of the additional responsibilities and challenges of PdM, including unreliable data or a calibration error, special training required and costs for system analysis, maintenance and security of data infrastructure, and significant investments in the acquisition cost.

3. Requirement

Considering the expectations and goals of small and medium industries in the establishment of Industry 4.0, especially predictive maintenance, there are also limitations and challenges. Thus, we attempted to clarify the key roles of different requirements of different projects for researchers and executive engineers.

Olanrewaju and Abdul-Aziz [27] considered maintenance management from a new perspective. From their perspective, maintenance management requires a multidisciplinary approach, including technological, engineering, economical, commercial, and social views. Precisely, maintenance is a business. The maintenance department should be considered as a business unit.

Matt et al. [8] presented an explorative set of hypotheses of the requirements for implementing Industry 4.0 concepts into logistics processes in SMEs around the world, including the Northeastern United States, Central Europe, and Northern Thailand. The statements were assigned to ten general thematic clusters, which would be more specific in an enterprise: leanness and agility, real-time status, digitization, connectivity and network tracking, PPC and WMS, culture and people, security and safety, ease of use, transportation, automation.

Deployment requirements can be divided into two groups: hardware and visible or software and invisible. Li et al. [13], Selvaraj et al. [28], and Sezer [22] all expressed that PLCs, sensors, open platform communications (OPC), the industrial Internet of Things (IIOT), and sense HAT are among the most important devices and hardware that could help SMEs in data acquisition.

Moreover, Dobrotvorskiy et al. [15] mentioned that unified information flows in the workspace require connecting to a large number of databases, a homogeneous information structure, and information support. In this way, all stakeholders, systems, and data should thus be integrated via incremental steps so that adjustments can be made quickly [29]. Mascoloc et al. [30] verified the effectiveness of the complete DynaWeb solution by integrating the technological and information technology strands into business industries. They demonstrated the integration of 25 DynaWeb hardware and software components as well as services. The requirements for oil sensors included a power source (220 V per sensor), a computer for data gathering, and a connection to the lubrication system. In addition, to measure the oil, an outlet and inlet were required to connect to the lubrication system. Hydraulic fittings were used to connect the sensors to the conditional random fields (CRFs) system. In this case, the bypass was the most difficult problem to solve, because the oil tank was not easily accessible.

As Cerquitelli et al. [31] pointed out, there is a need for a coherent architecture for the implementation of effective predictive maintenance. The following functionalities are required to implement the platform and arrange an integrated architecture: communication broker, edge gateway, orchestration and registry, data storage, predictive analytics service, visualization, and scheduling. Based on all these architectural elements, we were able to develop a fog computing solution.

Finally, Yang [32] pointed out the significance of data collection through measurement parameters. He states that in order to monitor the performance of a system, it is essential to determine which system parameters should be measured, how to obtain these values and store them. They can be obtained by direct or indirect measurements. Some commonly used parameters in processing plants, depending on the type, are summarized as follows: flow rate, pressure, temperature, concentration, and liquid level.

4. Summary of Studies and RQ Answers

The three significant elements of this study, that is, stakeholder expectations, project implementation requirements, and the challenges faced by small- and medium-sized industries for predictive maintenance are based on the steps of PdM and are outlined in **Figure 3**. According to the PdM process, which includes the necessary phases for data production, preparation, analysis, validation, and visualization [33], data in the area of maintenance can be generated or extracted and then refined and validated.

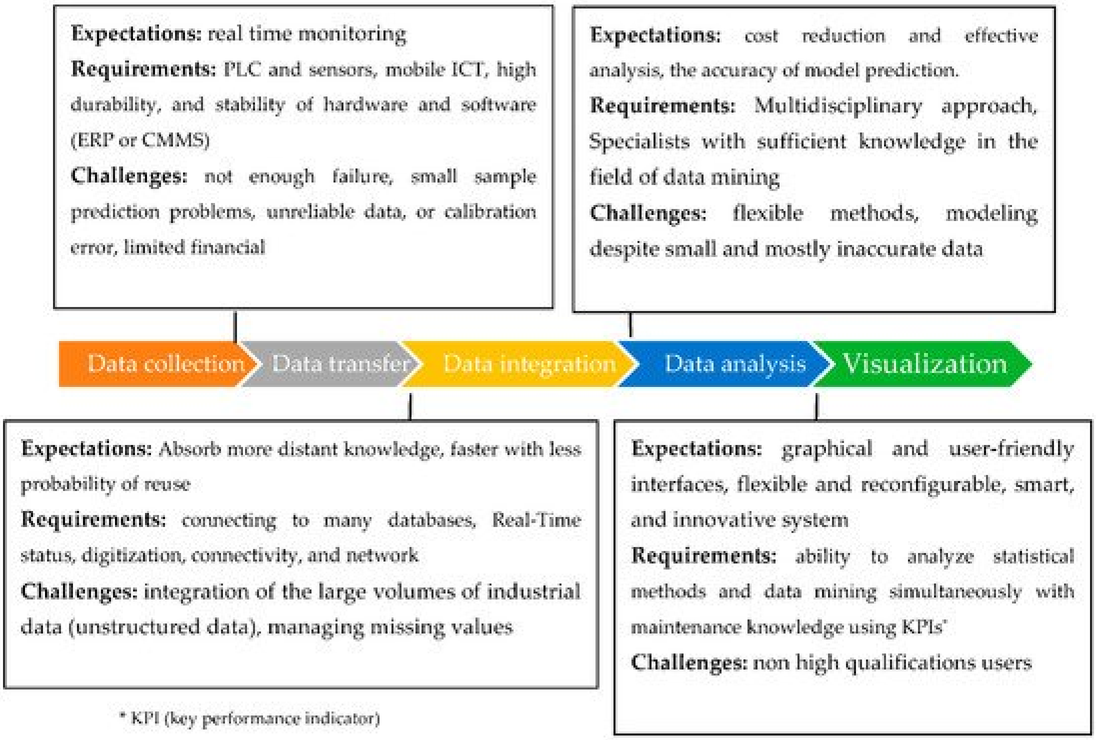

Figure 3. Expectations, requirements, and challenges in the field of predictive maintenance based on implementation phases.

The steps are summarized as follows:

- Data collection: To obtain relevant data and manage its content. Data can be collected from a variety of sources, including sensors, RFID tags, people, and so on.
- Data transfer: The collected data need to be transferred without affecting their content. Data are transferred from the source to the data management system.
- Data integration: Combining data from different sources in a data warehouse using methods that ensure its quality.
- Data analysis: Data analysis and extract information and knowledge to support decision making by managers.
- Visualization: By visualizing the information required by the users or decision makers. Visualization can be statistical or reporting.

References

1. Pintelon, L.; Parodi-Herz, A. Complex System Maintenance Handbook; Springer: Berlin, Germany, 2008.
2. Al-Turki, U.M.; Ayar, T.; Yilbas, B.S.; Sahin, A.Z. Integrated Maintenance Planning in Manufacturing Systems; SpringerBriefs in Applied Sciences and Technology no. 9783319062891; Springer: Berlin, Germany, 2014; pp. i–iv.
3. Susto, G.A.; Pampuri, S.; Schirru, A.; Beghi, A. Optimal Tuning of Epitaxy Pyrometers a Predictive Maintenance System for Silicon. In Proceedings of the 2012 SEMI Advanced Semiconductor Manufacturing Conference, Saratoga Springs, NY, USA, 15–17 May 2012; pp. 294–299.
4. Susto, G.A.; Beghi, A.; De Luca, C. A Predictive Maintenance System for Epitaxy Processes Based on Filtering and Prediction Techniques. IEEE Trans. Semicond. Manuf. 2012, 25, 638–649.
5. Wang, K.-S.; Li, Z.; Braaten, J.; Yu, Q. Interpretation and compensation of backlash error data in machine centers for intelligent predictive maintenance using ANNs. Adv. Manuf. 2015, 3, 97–104.
6. Kumar, A.; Chinnam, R.B.; Tseng, F. An HMM and polynomial regression based approach for remaining useful life and health state estimation of cutting tools. Comput. Ind. Eng. 2019, 128, 1008–1014.
7. Baglee, D.; Knowles, M. Maintenance strategy development within SMEs: The development of an integrated approach. Control Cybern. 2010, 39, 275–303.
8. Matt, D.T.; Modrák, V.; Zsifkovits, H. Industry 4.0 for SMEs: Challenges, Opportunities and Requirements; Springer International Publishing: Cham, Switzerland, 2020.
9. Gualtieri, L.; Palomba, I.; Wehrle, E.J.; Vidoni, R. The Opportunities and Challenges of SME Manufacturing Automation: Safety and Ergonomics in Human–Robot Collaboration. In BT—Industry 4.0 for SMEs: Challenges, Opportunities and Requirements; Palgrave Macmillan: London, UK, 2020.
10. Jantunen, E.; Emmanouilidis, C.; Arnaiz, A.; Gilabert, E. Economical and technological prospects for e-maintenance. Int. J. Syst. Assur. Eng. Manag. 2010, 1, 201–209.
11. Jerrentrup, R. Digital Transformation in SMEs—Lean Management + Industry 4.0; Springer Fachmedien: Wiesbaden, Germany, 2020.
12. Majstorović, V.D.; Mitrović, R.M.; Mišković, Ž.Z. Assessing industry 4.0 readiness in manufacturing companies from Serbia. In Lecture Notes in Mechanical Engineering; Springer: Berlin, Germany, 2020; pp. 69–79.
13. Li, B.-R.; Wang, Y.; Dai, G.-H.; Wang, K.-S. Framework and case study of cognitive maintenance in Industry 4.0. Front. Inf. Technol. Electron. Eng. 2019, 20, 1493–1504.
14. Xiong, S.; Liu, Y.; Fang, J.; Dai, J.; Luo, L.; Jiang, X. Incipient Fault Identification in Power Distribution Systems via Human-Level Concept Learning. IEEE Trans. Smart Grid 2020, 11,

5239–5248.

15. Dobrotvorskiy, Y.; Basova, S.; Dobrovolska, L.; Sokol, Y.; Kazantsev, N. Big Challenges of Small Manufacturing Enterprises in Industry 4.0; Springer International Publishing: Cham, Switzerland, 2020; Volume 1.
16. Starr, A.; Al-Najjar, B.; Holmberg, K.; Jantunen, E.; Bellew, J.; Albarbar, A. Maintenance today and future trends. In E-Maintenance; Springer: Berlin, Germany, 2010; pp. 5–37.
17. Thalmann, S.; Schäper, S. Localizing knowledge in networks of SMEs—Implication of proximities on the IT support. In Knowledge Management in Digital Change; Springer: Berlin, Germany, 2018; pp. 189–206.
18. Hern, E.; Rodr, S.; Mart, T.S.; Gonz, A. Machine Learning Predictive Model; Springer: Berlin, Germany, 2015; Volume 1, pp. 501–510.
19. Xu, X. Combination Prediction Method of Power Transformers Based on Feature Gas Arrangement Diagram and Grey Model. In Proceedings of the 2018 IEEE Conference on Electrical Insulation and Dielectric Phenomena (CEIDP), Cancun, Mexico, 21–24 October 2018; pp. 406–409.
20. Heinis, T.B.; Hilario, J.; Meboldt, M. Empirical study on innovation motivators and inhibitors of Internet of Things applications for industrial manufacturing enterprises. J. Innov. Entrep. 2018, 7, 10.
21. Kordon, A.K. Business problems dependent on data. In Applying Data Science; Springer: Berlin, Germany, 2020; pp. 39–67.
22. Sezer, E.; Romero, D.; Guedea, F.; MacChi, M.; Emmanouilidis, C. An industry 4.0-enabled low cost pre-dictive maintenance approach for SMEs: A use case applied to a CNC Turning Centre. In Proceedings of the 2018 IEEE International Conference on Engineering, Technology and Innovation (ICE/ITMC), Stuttgart, Germany, 17–20 June 2018; pp. 1–8.
23. Campos, J.; Jantunen, E.; Baglee, D.; Gilabert, E.; Fumagalli, L.; Emmanouilidis, C. The use of mobile tech-nologies and their economic benefits in maintenance. In Proceedings of the 10th World Congress on Engineering Asset Management (WCEAM 2015), Tampere, Finland, 28–30 September 2015; Lecture Notes in Mechanical Engineering; Springer: Berlin, Germany, 2016; pp. 113–119.
24. Jantunen, E.; Baglee, D.; Campos, D.; Sharma, P. Digitalisation of Maintenance. In Proceedings of the 2nd International Conference on System Reliability and Safety (ICSRS), Milan, Italy, 20–22 December 2017; pp. 343–347.
25. Wang, X.; Gao, L. 5G Communication Technology in Industry 4.0. In When 5G Meets Industry; Springer: Berlin, Germany, 2020; pp. 75–96.

26. Genennig, S.M. Realizing Digitization-Enabled Innovation; Springer Gabler: Wiesbaden, Germany, 2020.
27. Adu-Amankwa, K.; Attia, A.K.; Janardhanan, M.N.; Patel, I. A predictive maintenance cost model for CNC SMEs in the era of industry 4.0. Int. J. Adv. Manuf. Technol. 2019, 104, 3567–3587.
28. Olanrewaju, A.L.; Abdul-Aziz, A.R. Building Maintenance Processes and Practices: The Case of a Fast Developing Country; Springer: Berlin, Germany, 2015.
29. Selvaraj, H.; Zydek, D.; Chmaj, G. Virtual Enterprise Process Monitoring an Approach. In Advances in Intelligent Systems and Computing; Springer: Berlin, Germany, 2015; Volume 366, p. V.
30. Hasselbring, W.; Henning, S.; Latte, B.; Möbius, A.; Richter, T.; Schalk, S.; Wojcieszak, M. Industrial DevOps. In Proceedings of the 2019 IEEE International Conference on Software Architecture Companion (ICSA-C), Hamburg, Germany, 25–26 March 2019; pp. 123–126.
31. Mascolo, J.; Nilsson, P.; Iung, B.; Levrat, E.; Voisin, A.; Krommenacker, N.; Garramiola, F.; Bellew, J. Industrial demonstrations of E-maintenance solutions. In E-Maintenance; Springer: Berlin, Germany, 2010; pp. 391–474.
32. Cerquitelli, T.; Bowden, D.; Marguglio, A.; Morabito, L.; Napione, C.; Panicucci, S.; Nikolakis, N.; Makris, S.; Coppo, G.; Andolina, S.; et al. A fog computing approach for predictive maintenance. In Lecture Notes in Business Information Processing; Springer International Publishing: Cham, Switzerland, 2019; Volume 349.
33. Yang, S.H. Remote Control Performance Monitoring and Maintenance over the Internet; Advances in Industrial Control no. 9781849963589; Springer: Berlin, Germany, 2011; pp. 147–167.
34. Aljumaili, M.; Wandt, K.; Karim, R.; Tretten, P. eMaintenance ontologies for data quality support. J. Qual. Maint. Eng. 2015, 21, 358–374.