Internet of Things and Artificial Intelligence applied to predictive maintenance in Industry 4.0: A systematic literature review

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Abstract
The technological advancements in Industry 4.0, specifically in the areas of Industrial Internet of Things (IIoT) and Artificial Intelligence (AI) enables a series of enhancements in production management. The development of Big Data, Fog & Cloud Computing and Neural Networks have made Predictive Maintenance (PdM) an area of interest as it has been able to effectively transform and adapt to machine conditions. This paper presents a systemic literature review of the state of the art in AI and IIoT regarding PdM to serve as a basis for future work in the area. The relevance of this subject is still high, as seen by the number of publications in the last two years, however there are still several relevant research challenges to be addressed, in particular to achieve an adaptable and homogeneous PdM model.

Keywords
Artificial Intelligence (AI), Industrial Internet of Things (IIoT), Industry 4.0, Internet of Things (IoT), Predictive Maintenance (PdM)

1. Introduction
Industry 4.0 and its pillar technologies, namely, Internet of Things (IoT), Big Data and Artificial Intelligence (AI) – especially, Neural Networks – are changing the original industrial automation approach (Dalzochio et al., 2020). Such changes in manufacturing are leveraged by the analysis of data collected through innumerous sensors distributed in the fabric production plants. Predictive Maintenance (PdM) is among the possibilities offered by this scenario.

The main idea in PdM is to anticipate failures just before they occur avoiding unscheduled machine stops and production halt while maximizing equipment life usage (Rieger et al., 2019). To make these predictions, real time data must be stored an analyzed taking into consideration different aspects and effects of the collected signals. In this context, AI, and, especially, Neural Networks with Deep Learning techniques and processing algorithms, have the capacity of turning Big Data into actual information that can be used to make decisions.

However, with benefits also comes challenges to the implementation of these new technologies. Now industries need to deal with a much more dynamic environment and many of them are not ready to deal with this scenario notably when it comes to handle Big Data. In order to Big Data positively impacts productivity it is of paramount importance to choose and apply the right AI strategies.

Aiming to contribute in this direction, this paper provides a systematic literature review of Industrial IoT (IIoT) and AI applied in PdM. Recent work covering the most recent techniques in AI on IIoT data, specifically those that produce predictive analysis using Neural Networks to maintenance were prioritized. The progress of the positive impact of AI on IIoT applications in Industry 4.0 is discussed from three perspectives: i) how AI advancements have increased the applications of IIoT; ii) the relation between PdM and IIoT and the relationship between PdM and AI; and iii) works that exploit all the three areas: PdM, AI, and IIoT.

1.1 Objectives

The main objective of this paper is to perform a systematic literature review to answer the following research question:

How AI technologies enhances and allows IIoT applications in Industry 4.0, especially for PdM?

To achieve this goal an emphasis was made on reviewing the state-of-the-art of the technologies and their characteristics and methods instead of the individual results presented by the authors.

2. Methods

Initially the research string and databases to carry out this study needed to be defined. Google Scholar was chosen as the search mechanism because it indexes several databases such as IEEE, Springer, and SCOPUS and performs a free search in publications title and texts. The next step was to define the search query. After combining the Keywords and other words that represent the research question detailed in Section 1.1, the final search equation was defined:

$$(\text{"industry 4.0"} \textbf{ OR } \text{"intelligent factory"} \textbf{ OR } \text{"smart factory"} \textbf{ OR } \text{"smart manufacturing"}) \textbf{ AND } (\text{"industrial internet of things"} \textbf{ OR } \text{"IIoT"}) \textbf{ AND } (\text{"artificial inteligence"} \textbf{ OR } \text{"AI"}) \textbf{ AND } (\text{"model"} \textbf{ OR } \text{"method"}) \textbf{ AND } (\textbf{monitor} * \textbf{ OR predict} *) \textbf{ AND } (\text{"neural networks"})$$

The search was performed in 12/24/2020 and yielded 926 results that were then filtered by the criteria listed in Table 1. The Keywords IoT, IIoT, IA and PdM were used for the final filters due to the objectives of this paper.

Table 1 – Systematic Review Filters

Criteria	Articles Remaining
Initial Search	926
Publication Year (2019 or 2020)	747
Remove duplicated articles	711
Remove Books, Thesis and Technical papers	577
Remove non-English written articles	544
Paper Title do not contain Keywords	172
Paper has at least two Keywords	49
Abstracts Analysis	33

The criteria presented on Table 1 was based on the work of Zonta et al. (2020). For the last criteria (abstract analysis) the authors read the abstracts of the 49 remaining papers and cast a vote to include or reject it. Papers which received the majority of the votes were included in this study.

3. Data Collection

Table 2 lists the 33 papers selected for this systematic literature review after the steps described in Section 2:

Table 2 – Systematic Literature Review Selected Papers

Author(s)	**Title**	**Year**
Bellavista et al.	Machine Learning for Predictive Diagnostics at the Edge: an IIoT Practical Example	2020
Burkhardt et al.	The Symbiosis of Distributed Ledger and Machine Learning as a Relevance for Autonomy in the Internet of Things	2019
Burresi et al.	Machine Learning at the Edge: a few applicative cases of Novelty Detection on IIoT gateways	2019

Cakir et al.	The experimental application of popular machine learning algorithms on predictive maintenance and the design of IIoT based condition monitoring system	2020
Calabrese et al.	An Event Based Machine Learning Framework for Predictive Maintenance in Industry 4.0	2019
Cardoso & Ferreira	Application of Predictive Maintenance Concepts Using Artificial Intelligence Tools	2020
Cavalieri & Salafia	A Model for Predictive Maintenance Based on Asset Administration Shell	2020
Cerquitelli et al.	A Fog Computing Approach for Predictive Maintenance	2019
Christou et al.	Predictive and Explainable Machine Learning for Industrial Internet of Things Applications	2020
Dalzochio et al.	Machine learning and reasoning for predictive maintenance in Industry 4.0: Current status and challenges	2020
Ghahramani et al.	AI-based modeling and data-driven evaluation for smart manufacturing processes	2020
Gupta et al.	Economic IoT strategy: the future technology for health monitoring and diagnostic of agriculture vehicles	2020
Hansen & Bøgh	Artificial intelligence and internet of things in small and medium-sized enterprises: A survey	2020
Khan & Al-Badi	Open Source Machine Learning Frameworks for Industrial Internet of Things	2020
Kharchenko et al.	Combination of digital twin and artificial intelligence in manufacturing using industrial IoT	2020
Lee et al.	Intelligent Maintenance Systems and Predictive Manufacturing	2020
Liulys	Machine learning application in predictive maintenance	2019
Ma et al	Artificial Intelligence powered Internet of Things and smart public service	2019
Magaia et al	Industrial Internet of Things Security enhanced with Deep Learning Approaches for Smart Cities	2020
Martins et al.	Modeling system based on machine learning approaches for predictive maintenance applications	2020
Naren & Subhashini	Comparison of deep learning models for predictive maintenance	2020
Perico & Mattioli	Empowering process and control in lean 4.0 with artificial intelligence	2020
Radanliev et al	Design of a dynamic and self-adapting system, supported with artificial intelligence, machine learning and real-time intelligence for predictive cyber risk analytics	2020
Rastogi et al.	Predictive Maintenance for SME in Industry 4.0	2020
Rieger et al	Fast Predictive Maintenance in Industrial Internet of Things (IIoT) with Deep Learning (DL): A Review.	2019
Ruiz-Sarmiento et al.	A predictive model for the maintenance of industrial machinery in the context of industry 4.0	2020
Stracener et al.	The Internet of Things Grows Artificial Intelligence and Data Sciences	2019
Trakadas et al	An Artificial Intelligence-Based Collaboration Approach in Industrial IoT Manufacturing: Key Concepts, Architectural Extensions and Potential Applications	2020
Wu	Cloud-Edge Orchestration for the Internet-of-Things: Architecture and AI-Powered Data Processing	2020
Yu et al.	A global manufacturing big data ecosystem for fault detection in predictive maintenance	2019
Zhang & Tao	Empowering Things with Intelligence: A Survey of the Progress, Challenges, and Opportunities in Artificial Intelligence of Things	2020
Zheng et al.	Advancing from Predictive Maintenance to Intelligent Maintenance with AI and IIoT	2020
Zonta et al.	Predictive maintenance in the Industry 4.0: A systematic literature review	2020

With information from the metadata of the articles, it was possible to generate Figures 1 and 2 to verify all terms related to Industry 4.0 and PdM. The three most frequent terms are IoT, AI and Machine learning in which they represent more than 58% of the keyword density map followed by PdM with 11%. Such a result is expected given the PdM-based search equation (discussed in section 2), in addition to the strong adoption of AI techniques in industry 4.0. Figure 3 illustrates another interesting aspect, there were a variety of sources for the papers with IEEE being the most frequent one.

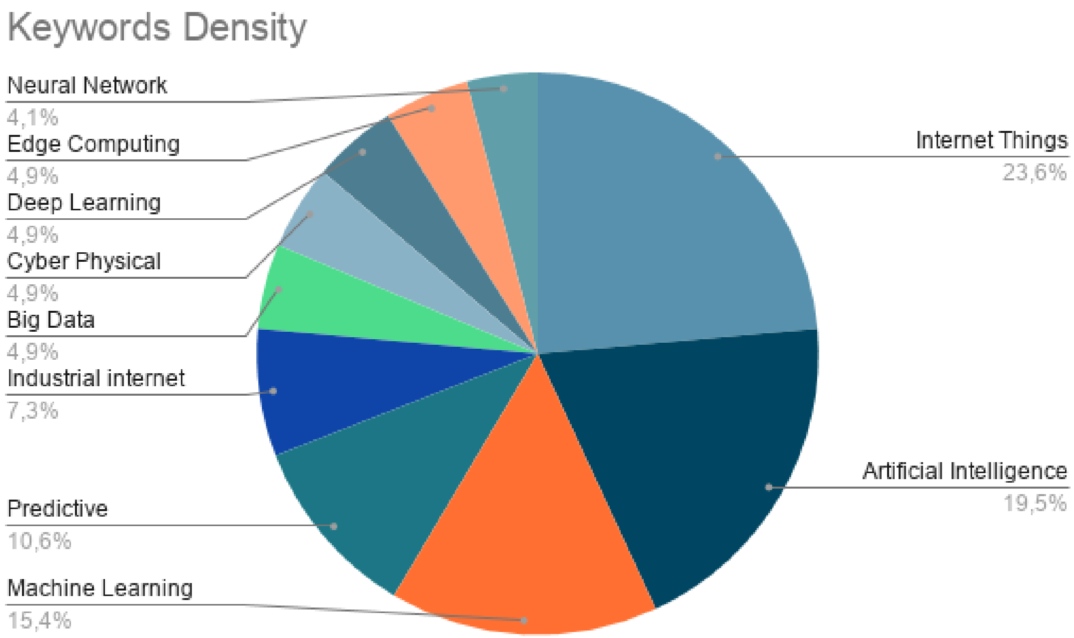

Figure 1: Keywords Density [1]

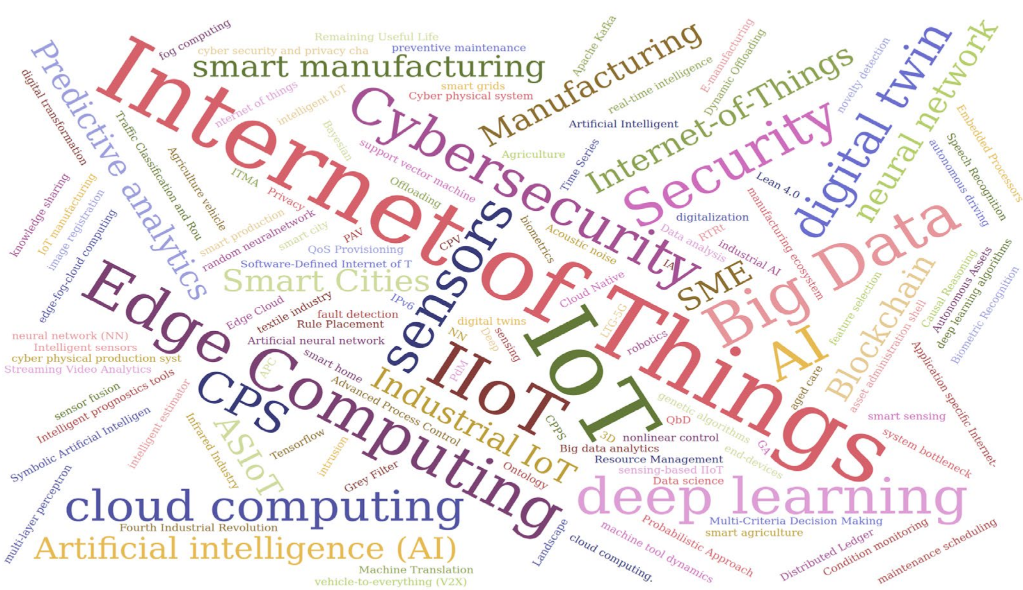

Figure 2: Keywords Presence[2]

[1] Figure generated from https://wordcounter.net/
[2] Figure generated from https://www.jasondavies.com/wordcloud/

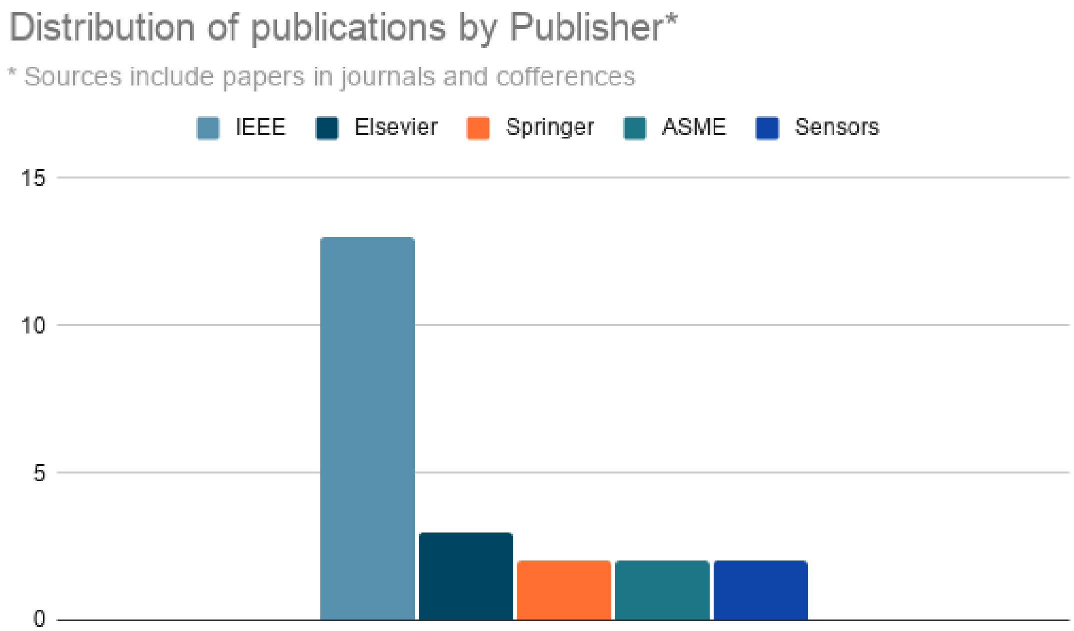

Figure 3 – Distribution of publications by Publisher

4. Results and Discussion

This section presents how AI enables IoT applications in Industry 4.0 discussing the progress from three perspectives. Section 4.1 is dedicated to the improvements in AI towards IoT in Industry 4.0, Section 4.2 is dedicated to PdM and finally Section 4.3 discusses how AI, IIoT and PdM are correlated.

4.1 AI and IoT/IIoT in Industry 4.0

AI has developed rapidly in the past few years. It combines naturally with IoT on several forms and drives the development of applications based on Machine Learning algorithms, Deep Learning, and Neural Networks to extract knowledge from Big Data. This development is mainly focused on AI Technologies and on Computing Architectures to support the execution of such applications. Table 3 classifies the set of papers related to AI and IoT/IIoT in Industry 4.0 according to the main topic of discussion.

Table 3: Selected Papers for Section 4.1

Paper	Focus of Paper
Ghahramani et al., 2020	AI Technologies; Case Study
Trakadas et al., 2020	Architecture Reference for Industry 4.0
Ma et al., 2019	AI Technologies; Case Study
Wu, 2020	Computing Architecture
Kharchenko et al., 2020	AI Technologies
Perico & Mattioli, 2020	AI Technologies
Zhang & Tao, 2020	AI Technologies
Magaia et al., 2020	AI Technologies
Khan & Al-Badi, 2020	AI Technologies
Burkhardt et al., 2019	AI Technologies

4.1.1 Architecture Perspective

The recent developments in several fields of computer science on the fabrication process can grant intelligence for the industrial process (Ghahramani et al., 2020; Magaia et al., 2020; Perico & Mattioli, 2020; Stracener et al., 2019; Zhang & Tao, 2020). According to Ghahramani et al., (2020) and Trakadas et al., (2020), Industry 4.0 in the manufacturing department has adopted IIoT and Machine Learning (ML) for a data driven approach that utilizes IoT devices and multiple monitoring sensors. These modern technologies based on IoT and Cloud Computing in manufacturing provides access to valuable data on different levels of the manufacturing industry (Stracener et al., 2019). However, several authors present obstacles and concerns while analyzing the adoption and integration of AI and IoT solutions in industrial manufacturing (Ghahramani et al., 2020; Trakadas et al., 2020; Zhang & Tao, 2020)

Essentially, masses of data need to be transmitted to a computing infrastructure for storage, processing and extraction of knowledge. The data provided by IoT devices can create a significant increase in traffic on the network (especially wireless networks) and demand a higher capability of computing capacity in the industry installation.

In this context, the software architecture is divided into three layers (Cloud / Fog / Border). Border Computing can operate as the perception layer supporting the management and control of sensors and actuators, thus, enabling IoT systems to perceive and behave on the environment. The Fog Computing layer is incorporated within the network hubs, routers, and gateways and can support several services such as data storage and processing. The devices on both Border and Fog layers are decentralized and are scattered inside the installation of the factory, in comparison to the Cloud layer that is centralized in a Processing Data Center.

Cloud computing is an option to meet several computing requirements on an IoT solution. According to Wu, (2020), cloud computing gained popularity as a provider of computing and storage resources for many applications, including the IoT-based ones. Companies like Microsoft, Google, IBM and Amazon host several IoT services on their cloud computing platforms (respectively, Microsoft Azure IoT Suite, Google Cloud IoT, AWS IoT Platform, and IBM Watson IoT Platform). Khan & Al-Badi, (2020) mention that despite the size, industry feels the need to use machine learning techniques in its processes and investigate open-source frameworks developed for the industrial domain.

However, Cloud Computing is usually located far away from the IoT devices installed inside the factory and the long-distance data transmissions may incur in latency that may not be tolerated by the IoT applications on the factory level. Additionally, studies show that the use of Cloud Computing may result in a significant increase in band-width usage on the communication network between the IoT devices and the cloud (Burkhardt et al, 2019; Kharchenko et al., 2020; Perico & Mattioli, 2020; Wu, 2020; Zhang & Tao, 2020) and a concern about privacy and data security while IoT transfers the data to the Cloud (Magaia et al., 2020; Stracener et al., 2019).

Fog and Border computing approximate the cloud to IoT devices (Wu, 2020; Zhang & Tao, 2020) solving the intrinsic issues mentioned above. Wu, (2020) call Border Computing as "border servers" (both Border and Fog are used by the author as synonyms). Fog and Border computing can be installed near any IoT device, for example inside a house or in the top of a building, by a highway and with a base station. As a general characteristic, border servers will have less computing and storage capabilities when compared to cloud servers and may not be able to completely satisfy the requirements of some IoT devices. Wu, (2020) emphasizes on the combination between border and cloud servers in certain IoT scenarios to meet both latency requirements as well as storage and processing requirements.

4.1.2 AI Technologies Perspectives

The use of AI together with IoT raises the era of artificial intelligence known as AIoT (Zhang & Tao, 2020). Zhang & Tao (2020) use the term smart industry splitting the analysis in three scenarios related to intelligent systems in IoT in Industry 4.0: fabrications, defect detection, and machine failure diagnostics (PdM). Zhang & Tao (2020) explicit that AI, especially Deep Learning, is a proven success in many areas including computational vision, voice recognition and natural language processing.

While Zhang & Tao (2020) approach AI solutions based on Deep Learning, Ma et al. (2019) present a wide range of Machine Learning algorithms adopted to deal with the challenges of IoT data in the context of Industry 4.0. The cases studied by the authors include technologies based on Neural Networks, classifications methods (such as K-Nearest Neighbors - KNN), clustering and regression methods.

The solutions presented by Ma et al. (2019) are implemented in disperse and isolated components within the manufacture technological systems and are used to optimize specific processes. Trakadas et al. (2020) debate the use of AI in disperse and isolated components; according to the authors, to perceive the full potential of AIoT in Industry 4.0, it must be considered on a wide approach which encompasses the end-to-end manufacturing process. Trakadas et al. (2020) defends the implementation of modern technologies such as IoT together with cloud computing in the fabrication process to provide valuable data in different levels of the manufacturing process that will include also the machine in the industry.

On this direction Trakadas et al. (2020) extends the Reference Architecture Model for Industry 4.0 (RAMI). For the authors, the current reference architectures for Industry 4.0 do not properly integrate the necessary construction blocks, such as new implantation paradigms (machine learning in Border Computing to reduce the band-width usage in corporate networks), scalable data processing pipelines, and information models such as Digital Twin, which are enabled by AI and used to monitor and optimize the intelligence in the manufacturing process. The extension of the architecture for Industry 4.0 also considers the roles of human beings as irreplaceable, defining layers and procedures that creates man-machine interaction.

In a study case of the use of AIoT in the fabrication of Printed Circuit Boards (PCB), Ghahramani et al. (2020) propose an approach to promote intelligence in semiconductors fabrication by using a dynamic algorithm to obtain useful "insights" about the fabrication process. The authors use a genetic algorithm and neural networks to design an intelligent feature selection system and, as a result, they are able to reduce the risks in cost and production.

Ghahramani et al. (2020) also mention that the traditional approaches regarding the management of data in IoT are impractical in most industries due to the high dimension of data provided by the IoT devices in the manufacturing process. The authors point that an effective and efficient data management strategy is now crucial given the massive generation of data. To achieve this, Machine Learning can help to develop strategies to automatically identify patterns in Big Data.

4.2 PdM with IoT and PdM with AI

This section introduces the concept of PdM and how the papers selected for this systematic literature review are related to PdM with IoT and PdM with AI.

PdM is a necessary evolution of the industrial scenario in the 21st century to adapt to the recent economy, social and environmental changes. In this subject, industry leaned in cyber-physical systems, IoT, Internet of Service (IoS), and Big Data to achieve the goals of improving productivity and efficiency. (Martins et al., 2020; Ruiz-Sarmiento et al., 2020; Yu et al., 2020). The costs of maintenance represent between 15% and 60% of the productive costs and strategies to reduce these percentages have been a continuous search in industry. Previous work also indicates that one third of maintenance costs are wasted in wrong interventions and replacing parts that are still usable (Cavalieri & Salafia, 2020).

As described by Zheng et al. (2020) the concept of PdM exists prior to the evolutions of IoT and AI, dating back to the beginning of the 1980s. The new characteristics of the Industry 4.0 market showed new path and challenges, in which the innovations in PdM and IIoT becomes the next logical step (Martins et al., 2020). This scenario is also relevant for Small and Medium enterprises as seen in Rastogi et al. (2020). To Martins et al. (2020) Industry 4.0 in not only an industry development, but also an evolution in society, markets and services that reduces the work force by automatizing machines and operations making them more complex and sustainable.

The evolution from preventive maintenance, where parts are exchanged by failure history, to PdM that accounts for real time data in the industrial environment on a large scale was not possible previous to the amount of data provided by IoT sensors and by the analysis of AI (Zheng et al., 2020). PdM does not replace standard maintenance, but adds values to the general maintenance activity by using IIoT as a backbone to capture data for the PdM algorithms (Rastogi et al., 2020).

However, this amount of data presents new difficulties such as ubiquitous data processing capabilities, and the selection of which variables will be controlled and monitored -that still highly depends on expert human knowledge, according to Yu et al. (2020). Cavalieri & Salafia (2020) mention the difficulty in adapting the AI models to the natural changes in the process as well as the fact that "shelf" solutions do not allow for integration between systems. Other models, such as the Digital Twin, help current production lines, but do not generate advance studies on production lines in which personalization is a key component.

The papers related to the topics discussed in this section can be divided into three major groups as detailed in Table 4.

Table 4. Papers concerning PdM

Model Proposition	Case Studies	Literature Review
Cavalieri & Salafia (2020)	Burresi et al. (2019)	Zonta et al. (2020)
Martins et al. (2020)	Calabrese et al. (2019)	Lee et al. (2020)
Rastogi et al. (2020)	Ruiz-Sarmiento et al. (2020)	
Yu et al. (2020)		
Zheng et al. (2020)		

The real cases studies show the importance and concern with reducing maintenance costs and machine down time (Calabrese et al., 2019; Ruiz-Sarmiento et al., 2020). In all cases, Neural Networks and Machine Learning algorithms are used to tune the response of the models, nevertheless, the authors do not mention the importance of IIoT. Burresi et al. (2019) shows two different industrial applications and the difficulty in achieving high sensor output due to IIoT manipulation of data and the collection of information to be used to assert the actual machine condition of use.

The papers in the modeling group present computational models validation, however, they do not show real applications (Cavalieri & Salafia, 2020; Martins et al., 2020; Rastogi et al., 2020; Yu et al., 2020; Zheng et al., 2020). Rastogi et al. (2020) focus on the challenge in creating a model pertinent to small and medium enterprises due to the lack of extensive research in the area. This factor is also indirectly mentioned by Martins et al. (2020) when they show the need for high initial capital investment to implement such models (even if it gets compensated in the long run).

The Literature review group, Zonta et al. (2020) survey literature published prior to 2019, which is one of the main reasons why this paper focuses on 2019 and 2020 periods. Lee et al. (2020) provide a literature review focused on several aspects such as: Availability of Systems, Maintenance Operations, Technologies, Difficulties and Futures Directions. Even though the main goal of Rastogi et al. (2020) is not a literature review, the paper includes a comprehensive collection of references about objectives in PdM in Industry 4.0 and architectures and PdM types.

4.3 IA, IoT and PdM

This section discusses the papers that explore the combination of AI and IoT in problems related to PdM in several industry segments. Since the concepts have been described in Sections 4.1 and 4.2, the goal here is to present the current state-of-the-art of adopted practices.

Firstly, as shown in Figure 4, it is important to understand the relationship between Industry, IoT and AI. This paper does not aim to explore all possibilities of the intersection of these vast areas, but those correlated to work seen here so far. The subdomains seen in Figure 4 are:

- *Data*: the possibility of using IoT technologies to gather data from different machines the industry process;
- *Smart Systems*: the use of AI in industry allows ideas and knowledge to be generated from the analysis the data gathered in the productive process
- *Models*: Between AI and IoT, mathematical models can be elaborated allowing relevant information being generated from the massive volume of IoT generated data. This can be done in real time or in post-processing procedures as it depends on the available architecture and infrastructure.

- *Industry 4.0 [PA]*[3]: IoT and AI are only some of the tools that, jointly applied in an industrial environment leverage the Industry 4.0 concept. In the scope of this paper these tools allow the implementation of PdM.

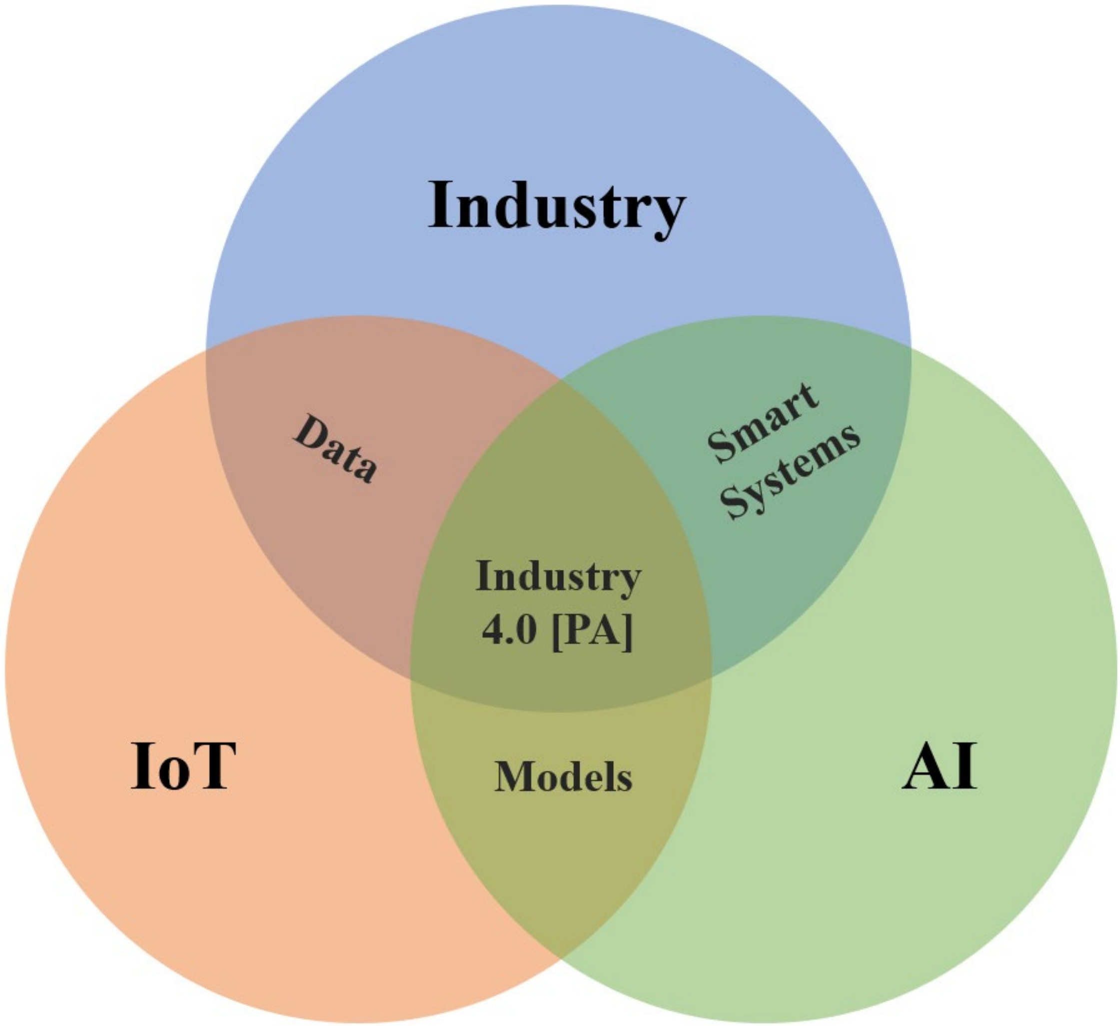

Figure 4. An example how AI and IoT and Industry are related

The combination between AI and IoT is defined by some authors with the term Digital Twin (Bellavista et al., 2020; Cerquitelli et al., 2019; Dalzochio et al., 2020; Hansen & Bøgh, 2020). For Radanliev et al. (2020), the scenario in which several computational resources are being allocated in the Internet´s border and IoT local networks brings a higher concern with security and data privacy and, as a solution, the authors propose the use of AI to automatize and detect anomalies in the network.

The infrastructure to provide the services of AI and IoT used in PdM analysis usually presents a combination between Border and Cloud Computing. Cerquitelli et al. (2019) present the SERENA project, a distributed computer system architecture in which a pre-processing is performed at the Border level using a computer model that is trained in the Cloud. This solution leads to low latency in obtaining results from processing and optimizes the resources of the network due to less information traffic. A similar approach is proposed by Bellavista et al. (2020), in which AI distributed local models in the Border have the ability to improve and develop the general model stored in the Cloud.

Some papers did not use a proprietary data base and in order to prove their hypothesis they relied on third party data. In Cardoso & Ferreira (2020), a Microsoft database with telemetry, faults, maintenance, and failures history from

[3] [PA] stands for predictive analysis.

machines was adopted. Naren & Subhashini (2020) used a NASA database with a set of 100 motors from a 2008 competition. An open source database from Scania with data collected from several trucks was used by Bellavista et al. (2020). Christou et al. (2020) used a database from the automotive industry.

The works of Cakir et al. (2020), Cerquitelli et al. (2019) and Liulys (2019) used proprietary databases. Cerquitelli et al. (2019) gathered the database from a robot and in Liulys (2019) used a database from Siemens DCS SIMATIC WinCC v6.1 by applying an open-source code called Node-RED. Cakir et al. (2020) creates a configuration to monitor the functionality of bearings and collects data from several IoT sensors, creating thus a local base to apply machine learning algorithms.

Among the selected papers, the application of AI and IoT is present in the PdM analysis of the bearings of and induction motor (Cakir et al., 2020), in current and belt tension in a robot motor (Cerquitelli et al., 2019), in monitoring tension, pressure, vibration and rotation of 100 machines (Cardoso & Ferreira, 2020), in motors (Naren & Subhashini, 2020), in cybernetic risks present in Border communication devices (Radanliev et al., 2020), in motor speed deviations (Liulys, 2019), in an air pressure system (Bellavista et al., 2020), and in the prediction of usable lifecycle of a drilling machine in the automotive industry (Christou et al., 2020).

Two papers made a systematic literature review searching for state-of-the-art work using machine learning (Dalzochio et al., 2020) and Deep Learning (Rieger et al., 2019) applied to PdM issues. It is worth mentioning that within the research area of this paper, there is a need for research on strategies to simplify the use and implementation of AI and IoT solutions in small and medium enterprises, as they rarely have the resources and knowledge that those areas demands (Hansen & Bøgh, 2020).

5. Conclusion

This work aimed to perform a systematic literature review to answer the research question: How AI technologies enhances and allows IIoT applications in Industry 4.0, especially for PdM? It is clear by the work reviewed literature that AI and IIoT are enhancing the applications of PdM with solutions to fill in the gaps in Industry 4.0. Nevertheless there are still some answers to be found in future research, for instance, the creation of a model that can adapt to the ever changing production lines and personalization needs of Industry 4.0, providing better applicability and being more flexible to the realities in this context.

PdM is seen as a challenge, but more importantly, as an opportunity in Industry 4.0. This paper discussed current approaches on PdM, covering architectures and AI technologies employed in this endeavor. The systematic literature review presented an overview of PdM using IoT applications with AI in Industry 4.0. For this end a total of 33 papers selected from 926 originally found about the subject creating a discussion about methods, architectures and technologies of AI aligned with applications used in Industry 4.0. With this work, the authors expect to contribute with the research community focusing on the advancement of PdM.

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Juliana Freitag Borin is assistant professor at the Institute of Computing, University of Campinas (Unicamp), Brazil. She holds a BSc in Informatics (2002) from University of West Parana, an MSc (2004) and a PhD (2010) in Computer Science from Unicamp. Her research is centered on the design and development of Internet of Things solutions for Smart Campus/Cities and Industry 4.0. Her main interests lie in facing the communication challenges posed by scenarios which require handling heterogeneous multimedia traffic. Juliana is also the head of the Technical Committee for Smart Campus at Unicamp