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Application of IoT with haptics interface in the smart manufacturing industry

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Abstract. The emerging technologies that make up Industry 4.0, include the Internet of Things and big data. The haptic interfaces have been used in different industries, but apparently, they are not integrated with the two technologies mentioned above. This work aims to know what the current use of IoT is, haptic interfaces and big data in the manufacturing industry. In turn, the fact of implementing an IoT platform leads to selecting an architecture that adapts to the needs of a specific organization. That is why this work also seeks to describe the IoT architectures available in the literature. Finally, we seek to know what the potential benefits for the manufacturing industry are combining IoT, haptic interfaces and big data in an intelligent environment enabled by machine learning. To have a better understanding, this work includes the description of the relevant concepts of the topic, including the description of supervised learning algorithms. In the end, this work allows us to open the door to other areas of research for future research.

Keywords: IoT, haptic interfaces, IoT architecture, machine learning, supervised algorithms, big data, manufacturing.

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1 Introduction

Industry 4.0, a concept proposed in Germany in 2011 and was proposed as a strategic initiative, which has had a great impact, not only in the manufacturing industry, but also in different industries [1]–[3] and has been adopted by the manufacturing industry in countries such as Mexico [4]. To increase its advantages, elements such as the Internet of Things (IoT) -evolution of cyber-physical systems- have been added and it is used in the new intelligent forms of manufacturing known as Smart Manufacturing. The IoT offers the advantage of generating a considerable volume of data, given the constant monitoring (telemetry). It should be noted that such data must be stored and analyzed. This process is done through big data by concentrating the information transmitted by each device in a specific data structure and then being exploited [5]. With so much data from each system, it is possible to identify patterns, which in turn allows predicting behavior and acting accordingly. These attributes are called analytical and are part of Industry 4.0 [6]. One of the useful tools of this are the haptic interfaces [7]. Haptic interfaces provide feedback to the user through the sense of touch. Haptic responses are related to virtual reality and tactile internet, given their applications in various areas such as health sciences, and video games for training. [8]–[10], but the relationship in the manufacturing industry with IoT is not heard. The purpose of this paper is to find an answer to: 1) What is the current use of IoT, haptic interfaces and big data in the manufacturing industry? 2) What architectures or platforms exist to implement IoT in the manufacturing industry? 3) What are the potential benefits for the manufacturing industry when combining IoT, haptic interfaces and big data in a smart environment?

To answer the previous questions, the review of the literature in a methodological way will allow us to know the relevant topics, between those that are Industry 4.0, cyber-physical systems, IoT, the architecture of the IoT platforms, haptic interfaces and machine learning. The article is organized as follows: 1) Definition of the literature search methodology; 2) Results of the methodological search; 3) Relevant concepts; 4) Current use of IoT, haptic interfaces and big data; 5) Current IoT architectures; 6) Potential benefits for the manufacturing industry when implementing IoT with haptic interfaces, using big data in an intelligent environment; and 7) Conclusions and future work.

2 Review of Literature

We used a combination of databases available at the Autonomous University of Ciudad Juárez (UACJ) and online academic search engines, such as Google Scholar, Microsoft Academic, and the same UACJ search engine. Relevant articles were searched in the databases ScienceDirect, IEEE Xplore, ACM, Emerald and EBSCOHOST, among the most outstanding. Google Scholar was the main source to know the metrics of available literature. For this review of literature were considered academic journals, conference reports and articles that make up a book chapter. The publication dates that were considered are within the range of 2015 to 2018, with a few considerations from previous literature to support concepts of the subjects investigated. Although the researchers speak several languages, the search was limited to articles in English. Most of the results in academic searches yielded articles in English. The review followed the systematic and independent literature review structure [11] shown in Figure 1, which has also been used by other authors [12], [13].

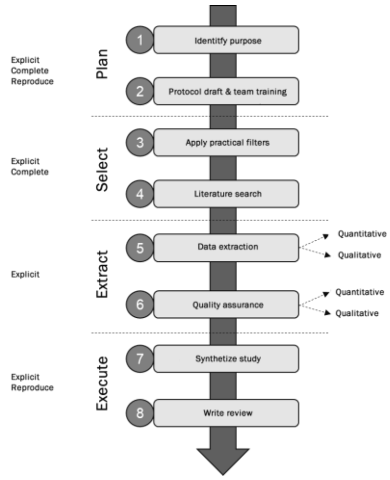

Figure 1. Systematic guide for the development of a literature review

3 Results of the Literature Review

The search was done in two parts. First quantify the amount of information on the general topics, which in this case was "Industry 4.0", "Cyber-physical Systems" and "Internet of Things". The second part of the search was the particularities of the topic that we are investigating or specific topics. The topics pursued were: IoT and machine learning; haptic interface; IoT in manufacturing; finally, IoT with a haptic interface in manufacturing. The summary of the findings is in Table 1. The findings of the general themes suggest a constant increase of publications where the central theme is IoT, with a considerable number of publications. On a smaller scale, the number of publications on Industry 4.0 is in second place, followed by the cyber-physical systems. When making an analysis of variations between years, contrary to the incremental trend in the number of publications, a downward trend is observed. When analyzing the two perspectives (number of publications and variations) it is suggested that there is a possible lack of interest in the topic of cyber-physical systems, and that space is filling the topic of IoT, which also has a low variation, but its volume of publications is the highest in the study.

In the second part of the search, the results indicate that there is little literature that talks about the topics sought as the main theme of the publication. The most successful topic was haptic interface, followed by IoT and manufacturing. The theme that combines IoT and machine learning was the last. However, when doing the search where the main theme was the combination of IoT, haptic interface and manufacturing, no results were obtained. For this reason, the search was expanded so that the topics appeared in the body of the document. This leads us to a separate and detailed analysis of the 45 articles found under this criterion, which we explain later. Figure 2 shows the trend of the number of publications. Also, as in the general topics, when doing the analysis of the annual variations of the results of specific topics, the subject IoT and machine learning shows a constant growth except in the last year, where it grows little more than half. IoT in manufacturing grows at a constant rate of 33% but in 2018 it decreases by 8%, while haptic interface is a subject that was in decline between 2015 and 2016, but that decrease is slowed down and in 2018 it grows by 20%. When reviewing the 45 articles in detail, we use a classification method, which qualifies the relevance that it has in our specific topic. Although the search reports these articles with our keywords, it is important to review them to know the contribution to the literature review. The rating scale was: (0) Not relevant, that is, it mentions the topic but in isolation or in the bibliography; (1) Mention as additional use, indicating that the topic may be added in a future work or as an improvement; (2) Specific use, when the topic is presented as a success case or a series of examples; (3) Related, when the topic is contributing to another of the two topics of interest; (4) Central Theme, is when the topic has the full relevance of this research.

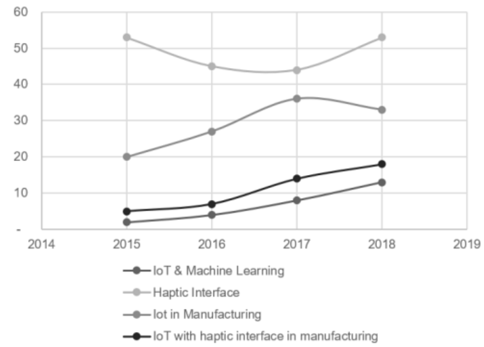

Figure 2. Number of publications per year of the topics of interest

Table 1. Results of the searched topics

Topic	2015	2016	2017	2018	Total
Industry 4.0	130	333	642	941	2,046
Cyber-physical systems	150	169	217	226	762
Internet of things (IoT)	1,880	2,630	3,180	3,740	11,430
IoT and Machine Learning	2	4	8	13	27
Haptic interface	53	45	44	53	195
IoT in Manufacturing	20	27	36	33	116
IoT with haptic interface in manufacturing*	5	7	14	19	45

* The search as the main topic did not yield results, so the topics were searched in the body of the article.

With this classification we allow filtering which are relevant articles for our literary review. The selected articles were included in the uses or benefits of IoT and haptics used in the manufacturing industry. Unfortunately, the findings indicate that there is not a single article covering all three subjects, which indicates that there is a research opportunity. Figure 3 shows the distribution of the results. The articles that can be used are those that obtained a classification of six or more, which represent almost 29% of the population.

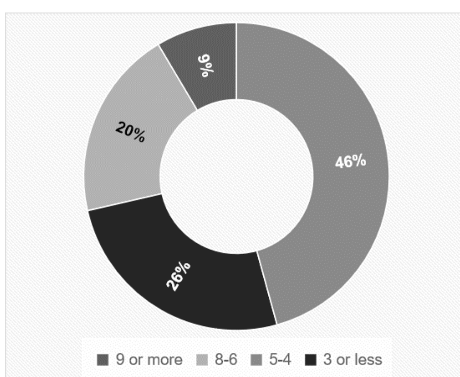

Figure 3. Distribution of qualified articles

4 Relevant Concepts

4.1 Industry 4.0

The industrial revolution was not an isolated event of the nineteenth century, but it has evolved. Historians agree that the first industrial revolution was characterized by mechanical manufacture. The second was for the introduction of the assembly line and serial production. The third revolution was to introduce flexible manufacturing, robotics and quality control and optimization by 1970. Each of these revolutions have named it by number: Industry X.0, where X is the ordinal number of the revolution [14]. During the fair in Hannover, Germany in 2011, the term Industrie 4.0 (original of the German language) was coined, which is the fourth industrial revolution [3], [15] and was later officially announced. in 2013 as a strategic initiative of Germany. Smart Manufacturing is a term coined in the United States of America by the Smart Manufacturing Leadership Coalition initiative in 2014, which coincides with the German term Industrie 4.0, which is the one used in Europe. In the literature both terms are found interchangeably, and are based on cyberphysical systems, the internet of things and cloud computing. Industry 4.0 (hereinafter referred to as I4.0 and including Smart Manufacturing) has key elements that have been accepted by the community dedicated to this topic. The Boston Consulting Group [6] has identified nine pillars of I4.0, which are (i) big data and Analytics, (ii) Autonomous Robots, (iii) Simulation, (iv) Vertical and Horizontal Integration of Systems, (v) Industrial Internet of Things (IoT), (vi) Cybersecurity, (vii) Cloud or Cloud, (viii) Additive Manufacturing including 3D printing, and (ix) Augmented Reality. These pillars can all be implemented in the factories or take some depending on the case.

Cyber-physical systems (CPS). Systems that match digital systems (cyber) with the physical world are commonly referred to as cyber-physical systems (CPS). The term was coined in the National Science Foundation (NSF) in the USA in 2006 [16], [17]. CPS are complex systems that be an extension of embedded systems, alerting their environment, with an effective computational combination with physical processes. CPS must operate in real time. A control in real time is traditionally implemented through different forms of control mechanisms, called open loop control, feed-forward control, and feed-back control. Open loop uses only the input signal to actuate the output according to the requirements of the control and lacks a feedback mechanism to adjust the output of the system, waiting then for the manual adjustment made by the operator. The feed-forward control considers the environmental effects measured from sensors on the physical system. Then, the control of the action is adjusted by the controller according to the anticipation of the relationship between the physical system and its environment. The feed-back control (also known as closed loop) automatically refines the output based on the difference between the feed-back signal of the output and the input signal [17]–[20].

The CPS must be in an open, flexible and independent model of any platform. The CPS also has a close relationship with the idea of asset management, presented in the Industry 4.0 initiative, which is a virtual representation of one or more assets and manages their data and status [21]. The CPS architecture partially breaks with the traditional automation pyramid by taking a more decentralized look and for that reason the 5C architecture is introduced to be able to build a product-oriented CPS (Cyber-physical product system or CPPS). The 5C architecture has 5 levels. These range from the physical to the cybernetic: 1) intelligent connection level, which acquires data for monitoring; 2) level of data conversion, which is where readings are recorded in logs; 3) Cyber level, here live the analytics that are based on similar cases or historical data; 4) level of knowledge, to make the decision based on the best alternatives; and 5) the level of configuration, which includes the application of predictive corrective decisions [22]. The concepts of IoT and CPS are intimately related, being complementary to each other. The CPS represents a physical machine or a process that censuses and acts in the physical environment. CPS makes extensive use of machine-to-machine communication (M2M). The term CPS often appears in the context of engineering problems and their consequent applications in real time. A CPS event is typically modeled with the following parameters: DeviceID, event ID, and time-date. Previously, PLC (programmable logic controller) and CNC (computer numeric control) were used to link legacy systems to an IT-based system [23]. Today, systems are linked with IoT, cloud, big data and analytics, and their events typically contain data on the identification of sensors, actuators, RFID tags, GPS and high definition cameras [23]. IoT offers concepts and infrastructure that links CPS to devices, systems and services in different domains, enabling access to control distributed manufacturing equipment [24]. This relationship of CPS / IoT takes us to what is known as industrial IoT (IIoT). The use of CPS aims to increase the implementation of large scale systems, improve the adaptability, autonomy, efficiency, functionality, reliability, security and usability of such systems [18]. These systems are being applied to different areas such as intelligent manufacturing, smart cities, intelligent energy systems and smart buildings, defense, energy, health care, manufacturing, society and transportation [18], [21], [22]. With these applications and scopes, CPS makes use of cloud and a new paradigm called Ciber-Physical Manufacturing Cloud (CPMC) is introduced [25]. This new paradigm in manufacturing requires sensors, actuators (IoT), data processing (big data), storage and computing power (Cloud), all elements of Industry 4.0.

4.2 Internet of Things (IoT) and its components

The Internet of Things (IoT) is a network of physical devices, vehicles, appliances, and other devices with embedded electronics, software, sensors, actuators, and connectivity that enable these objects to connect and exchange data. The applications of IoT were mainly observed in logistics and transport, health care, intelligent environments, and personal and social applications, proposing ubiquity as a concept that could materialize in advance [26], [27]. In Industry 4.0, the IoT is a fundamental component and its penetration in the market is growing. Companies dedicated to telecommunications such as Cisco Inc. expects that by 2020 there will be 50 billion (trillion in English) of connected devices [28] and Ericsson Inc. estimates 18 billion [29] and other firms such as Gartner, estimate that in 2020 there will be 20.4 billion [30]. These estimated amounts of connected devices will be due to the increase in technological development, development in telecommunications and adoption of digital devices, and this will invariably lead to the increase in the generation of data and digital transactions, which leads to the mandatory increase in regulations, for security, privacy and informed consent in the integration of these diverse entities that will be connected and interacting with each other and with the users. The increase of these aspects is presented as one of the factors for the increase of cyber-attacks to users [31]. IoT is also a complex environment due to the number of components and layers that make it up. These layers contain many sensors, actors and processing devices with heterogeneous software and different manufacturers [32], [33]. The growth requires and depends on connectivity, forming favorable environments for IoT. The main environment is the computational cloud, which IBM (2009) defines as "the delivery of computing resources on demand". However, small connectivity ecosystems that use the same Wi-Fi or Bluetooth techniques to connect and form two new levels of environments have been developed at the same time. The first is called Fog Computing and was introduced by Cisco in 2012 and is a layer model to enable ubiquitous access to shared and scalable computing resources, performing data analysis by applications running on the device instead of the cloud [34]–[36]. Fog Computing (the fog) is located between the intelligent devices and the centralized services offered by the cloud. The second environment is Mist Computing (in Spanish it can be called the dew) which is a rudimentary and lightweight form of Fog Computing [34]–[36]. Fog Computing (the fog) is located between the intelligent devices and the centralized services offered by the cloud. The second environment is Mist Computing (in Spanish it can be called the dew) which is a rudimentary and lightweight form of Fog Computing [34] and allows communication with smart devices to be distributed and faster, thanks to its power of computation with microprocessors and microcontrollers.

4.3 Supervised Machine Learning

In machine learning (Machine Learning (ML) is the most recognized term in the industry) there are at least four types of learning: supervised, reinforced, stochastic and unsupervised; ML can also be considered online learning when using a stream of data in real time, or it can be batch using previously classified historical instances [37], [38]. This review focuses on supervised learning, which will be used in IoT with haptics. ML allows you to learn without a code explicitly created for a given scenario. Supervised ML is a technique where each instance in any data set must be represented by the same number of characteristics (continuous, categorical or binary). When instances have a known label that indicates the correct result, it is called supervised learning. There are several algorithms among which we can select the most appropriate to our problem. The process for selecting an algorithm is shown in Figure 4. This process begins with the identification of the problem, knowing what is being sought and defining it. The next step is to identify the data required to then perform the preprocessing of the data, which can involve from data collection, transformation, to standardization and data cleansing, commonly supported by the knowledge discovery methodology from the data (KDD) as shown in Figure 5. Until this step is when the definition of the training data set is made. This data set should be divided into two subsets: the training and the testing. The data that goes into each subset must be selected randomly. Also, the recommended training / test ratio is 2/3 for training and 1/3 for tests; another technique is cross-validation, with data divided into the same number of instances and mutually exclusive; one more is the Leave-One-Out technique that is a special case of cross-validation (it requires a lot of computing power). The next step is to select the algorithm to train and perform the training, with the training data. Then, an evaluation is made with the test instances and if the results are adequate, then a supervised classifier is taken. If the results are not as expected, you can fine tune the parameters and re-train the algorithm [39].

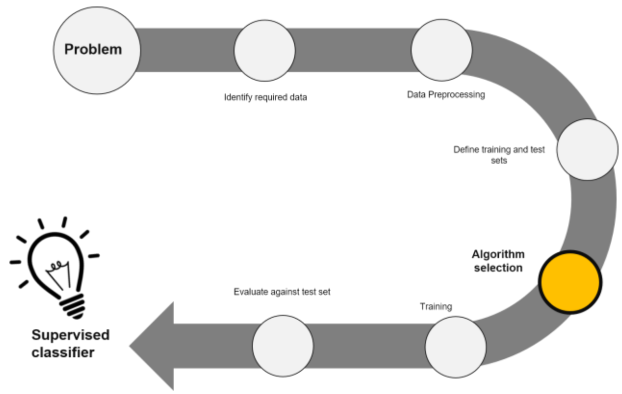

Figure 4. Supervised ML project generation process

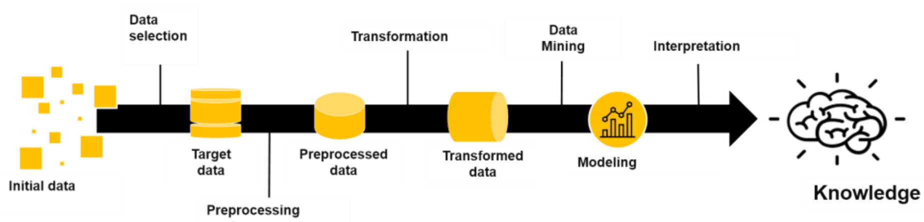

Figure 5. KDD process

Decision tree algorithms classify instances into nodes and leaves. Each node represents a characteristic to be classified, its branches the values that that characteristic can take, and the leaves the tag value sought (typically Yes or No). To select the feature that best divides the data and that will be the root node, there are several methods. Two of them, very useful are the information gain and the G_{ini} index, dating from 1966 and 1984 respectively. These have been the basis for other techniques and inspired other decision tree algorithms. One of the most used algorithms is the C4.5 that starts with the selection of an attribute to test it as a root node. This assumes that the training data fit into the computer's memory, and this same restriction is used in its favor by the Random Forest technique to develop trees that adapt to the available memory capacity [40]. Other well-known algorithms are based on the notion of perceptrons, which are defined as a vector of input characteristics and a vector of connections that represent the weight or prediction. A perceptron calculates the sum of the weights of the inputs and compares it against an exit threshold. If the output is greater than the threshold, the result is 1, otherwise it is 0. This notion is known as a perceptron layer. When ordered in multiple layers of perceptrons, a neural network system is created [41]. Neural networks have at least three layers: i) input layer, which is the one that receives the information to be processed; ii) the output layer where the result is found; and iii) the hidden layer, which may be one or more. The computation of a neural network can be by Feed-Forward that calculates the values of the hidden layers, and Back-Propagation, which is the most used to train a neural network [40], [42]. Unlike neural networks, there are algorithms with a statistical-probabilistic approach that provide the probability that an instance belongs to a class.

Bayesian networks are very simple networks that have a single parent node and multiple child nodes. Here, the assumption is made that the child nodes are independent of each other in the context of the parent node [43]. Within the category of statistical algorithms is the method based on instances, which are lazy algorithms that require less computing power. An algorithm of this type that is widely used in ML is the k-nearest neighbor (k-nn), which is based on the precept that instances in a data set will generally exist in proximity to other instances that have similar properties. Each instance evaluates the smallest distance to a set of possible centers, and that will be their class affiliation, and iteratively, the centers are recalculated to determine their best location, until the least possible error is achieved. The k-nn method is expensive in storage and its computation speed depends on the initial location of each center. An initial position close to the optimum will need fewer iterations than a center located far outside the optimal position. A final category of supervised ML algorithms is the vector-supported machine (SVM). SVM is the most recent technique proposed by Vapnik in 1995 in “The Nature of Statistical Learning Theory”. SVMs have the notion of a margin that separates a hyperplane from two classes. Maximizing this margin has the maximum possible distance between the hyperplanes and the instances that are located in the domains of each hyperplane will have the smallest generalized error, as shown in Figure 6.

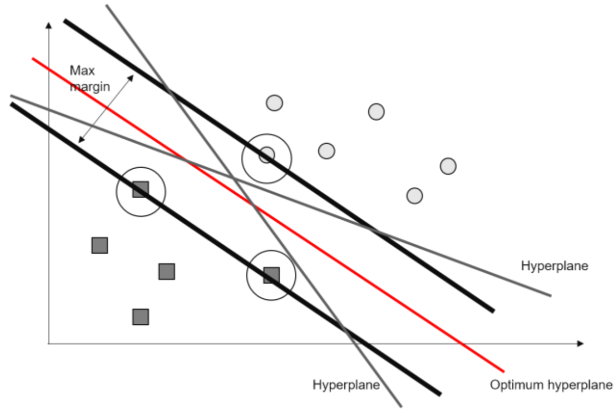

Figure 6. Maximum margin in SVMs with two classes

SVMs and neural networks tend to perform much better with multidimensional problems and continuous characteristics, requiring a very large sample set. Logic-based systems tend to work better with discrete or categorical characteristics and can work well with small data sets. The SVMs are the most accurate, while the Bayesian classifiers are the least accurate. Accuracy is measured by adding the true plus true negatives, divided by the total number of instances.

4.4 Haptics

The haptic term is related or based on the sense of touch; it can also be characterized by a predilection for the sense of touch, e.g. a haptic person (definition taken from the Merriam-Webster dictionary). The research firm Gartner defines haptic as the use of tactile interfaces to provide touch feedback or force as part of its user interface. Vafadar [44] also defines haptics as the "feedback generation of touch and strength information." This can be applied in the automotive industry to the user interface in automobiles to alert the driver of a pedestrian willing to cross the street by vibrating the seat. Haptic technology has the potential to add new forms of communication with the user, improve usability and user experience (UX, User Experience in English), and improve information applications. In technology, everything related to haptic receives the term "haptics" or "haptics" in English. Haptics can be studied in three major areas: (i) Human Haptics, which is relative to touch perceived by humans, (ii) Computational Haptics, which is the software for touching and feeling virtual objects, and (iii) Haptic Machines, which refers to the design and use of machinery that can increase or replace human touch. The haptic feedback channels can be tactile sensations, such as pressure, texture, temperature, etc., can be tactile vibro-stimulating Meissner's corpuscles that detect 5-50 Hz vibrations and Pacinian's corpuscles that detect vibrations of 40- 400 Hz, or kinetic perception, which detects the state of the body. Haptic devices can be classified according to their interaction: (i) Take or grasp, (ii) carry, and (iii) touch [45], [46]. The inclusion of IoT with haptic interfaces is a topic where few works have explored the principles of tangible interaction that can guide the design of interfaces for IoT located in the physical world [26]. On the other hand, the combination of VR and AR in three-dimensional scenarios with haptic feedback has also been carried out in other industries, such as the health industry, where virtual surgeries, rehabilitation systems, video games for training, etc. have been explored. including studying brain-computer interfaces that receive haptic information among other stimuli [8], [10]. The development by Choi [9] called CLAW, is a device that uses force feedback and index finger movement information to take a virtual object, press virtual surfaces and shoot an object. Finally, haptic interfaces can allow machinery to operate remotely, but the user experience should be like interacting directly with the machine. Other authors [47], [48] mention the challenge to transmit sensations through the network, called the "1 ms challenge of the Touch Internet" and the have an "ultra-reliable" and "ultra-responsive" network. Another of its great challenges is to make the device feel exactly like the original artifact [49].

5 Current Use of IoT, Haptical Interfaces and Big Data in Manufacturing

In the literature, the use of IoT and big data in manufacturing is frequently found, and it is very varied. Intelligent factories can be evaluated, proposing a model of maturity of the intelligent factory (verification, monitoring, control, optimization and autonomy), in which the integration of the use of IoT and its data is increasing [50]. Also, companies that use IoT in their processes do not directly interact with devices and applications. The applications fulfill three critical functions: they enable the human being to interact with the IoT system through a graphical interface; provide a mechanism for data analysis; and provides the necessary capabilities to visualize the data. For applications to fulfill these functions, they rely on IoT, its architecture and devices, the storage of data of the big data type, and the infrastructure to transport the data [51]. However, the analytics that can be evaluated in big data on the data collected from the company, can reach the order of 5,000 dimensions, updated by 200 million data per day, useful for the planning and control of manufacturing operations, by example. That is why smart manufacturing must adopt big data [23], [32], [52]. Thanks to this IoT relationship with big data it is possible to introduce artificial intelligence and machine learning, achieving learning, generating knowledge, predicting actions and making judgments [5], [53]. The literature also reports two types of consumption and data processing, in real time and batch processing. Kho (2018) [5] reports a very limited number of references on real-time processing, which is explained by the high demand for infrastructure to enable this type of processing. The characteristics of big data that allow to evaluate a large volume of data to discover patterns, their correlations and trends, are known as analytics, and sometimes involve the ML concept. Kho et al. [5] mentions that big data analytics are used successfully in manufacturing but does not report a large number of data analysis references in real time in IoT-enabled environments. It also highlights the importance of visualizing data coming in real time with tools such as TensorFlow. Organizations wishing to venture into analytics and ML have several challenges of understanding before them: the maturity of the company, the types of IoT, the role of ML and its predictive models [54]. For example, if you want to implement IoT with ML in a smart city, you can require sets of millions of data to process and more than one prediction algorithm. In an example of climate correlation and the use of intelligent bicycles in the United Kingdom, 4 more algorithms were used [55]. The IoT and ML combination can be seen beyond analytics in data obtained by sensors, such as access security using other emerging technologies [56]. As mentioned above, the challenge of understanding predictive algorithms is great. Simply, there are at least nine different algorithms to choose from, plus the deep learning algorithm [57], [58]. As you can see, the selection of algorithms is not trivial. The integration that is taking place between IoT and ML is allowing the development and research of new models and novel algorithms, such as genetic algorithms, which are already being proposed to integrate IoT with fog computing and cloud computing [59].

6 IoT Architectures

Internet of Things (IoT) continues to evolve from its conception. Several ideas have existed, adding complexity to solve the recently perceived challenges. In the IT industry, it is good practice to look at architectural references to avoid work and have a starting point to solve a problem based on the requirements. In IoT there are five main requirements in general [60]: 1) Enable communication and connectivity between devices and data processing; 2) Establish a mechanism to manage devices, including tasks such as adding or removing devices, updating software and settings; 3) Gather all the data produced by the devices and then analyze them to provide a meaningful perspective to the companies or users; 4) Facilitate scalability to handle the increased flow of "data pipes" (hereinafter referred to as data pipelines) and the flow of data, and handle an increasing number of devices; 5) Protect the data by adding the necessary functions to provide privacy and trust between the devices and the users. Several reference architectures with layers for IoT have been proposed: one of the main reference architectures is IoT-A [60]–[63]. A layer is a conceptual group of components to provide a specific functionality and an audience or objective perspective. Weyrich and Ebert (2016) suggest three perspectives of layers: 1) perspective oriented to observe physical devices and data link functions with low-level communication protocols; 2) Internet-oriented perspective, focuses on interconnectivity and protocol conversation such as HTTP or MQTT; and 3) semantic perspective with service protocols for use and data exchange. As mentioned above, IoT has evolved and is constantly evolving. Architectures with different layers have been proposed, starting in their simplest form with two layers. The OpenIoT architecture consists of two layers, one for sensor middleware and another for the semantic directory service [63], but in the end, it can be classified as a three-layer architecture, due to the need to have applications that consume data coming from the devices. Three-layer architectures are more popular and proposed by different authors and different applications. They consist of the device layer, the communication layer and the application layer [64], [65]. Krishnamurthy and Cecil (2018) proposed a layer dedicated to machines in the flooring plant, a second layer to handle the collection and transport of data, and the last layer as cloud computing processing. Ray, P. (2018) mentions a unified detection platform (USP) with distribution, the USP itself and applications. It also refers to a social IoT architecture, which consists of detection tasks, network functions and applications to consume that information. Tomas Girones proposed an architecture for smart meters, with a layer of device, a layer of management and processing and an application with artificial intelligence layer [66]. Four-layer architectures also appear in literature. No conclusive layer has been added, but each author added the missing functionality or created a layer for specialized functions extracted from an existing layer. The architecture "building the environment for things as a service" (BeTaaS for its acronym in English) has the physical layer with machine-to-machine (M2M) systems, an adaptation layer that handles all connections to physical devices, the third layer is the TaaS that provides access to devices throughout the network, and finally, the fourth layer whose responsibility is to manage the functionality and services of the applications [61], [63]. Another proposed four-layer architecture consists of the service layer, the control layer, the communication layer and the execution layer, where the devices are considered [67]. Ray (2018) makes a reference to the military IoT architecture, called IoTNetWar. It consists of a physical detection layer, a gateway communication layer, an administration layer called C4ISR and an application layer. An IoT architecture proposed for the application of sustainable tourism consists of: 1) real world layer, 2) virtualization layer, 3) service layer and 4) application layer [68]. An architecture more than four layers is found in the work of Firdous, as the International Union of Telecommunications -- Telecommunication Standardization Sector (ITU-T) consisting of the device layer, the network layer, the service and application support layer and the application layer [69]. Five-layer architectures are not so common. A good example is presented by Home Health Hub, Internet of Things [65] which includes: 1) layer for physiological detection (devices); 2) local communication layer; 3) information processing layer; 4) internet application layer; 5) user application layer. This architecture adds a layer of local processing, exploring the intermediate entity between the local scope and the scope of the cloud. This intermediate entity has been named as a fog count [34], [36], [70]. A greater number of layers are receiving tracking lately. Architectures of seven and eight layers have been proposed by different authors. One of them is the Internet of Vehicles (IoV) architecture with seven layers. The layers are: 1) Business layer, 2) Administration layer, 3) Communication layer, 4) Preprocessing layer, 5) Acquisition layer, 6) User interaction and 7) Security in all other layers [71]. This is one of the most representative architectures in IoT. The most interesting layers are the preprocessing layer and the business layer. First, it is proposed to have filtering and dissemination of data in perimeter computing, that is, within the device. The second interesting layer is the business whose purpose is to allow the analysis and interaction between vehicles and business services. Another seven-layer architecture is the ITU-T improvement proposed by Firdous et al. [69]. This proposal adds two layers to the original architecture. In the end, the seven layers are: 1) application layer, 2) new management layer and application support, 3) service layer, 4) new communication layer, 5) network layer, 6) hardware layer, equivalent to the device layer, and 7) New environment layer, with the responsibility of perceiving objects or places. Eight-layer architectures are not yet common in the literature, but a 5G IoT architecture was proposed. This consists of: 1) physical device layer; 2) communication layer, enabling device-to-device communication; 3) edge or fog calculation layer; 4) data storage layer that receives only relevant data from the previous layer; 5) management service layer to manage the network, the cloud and the analysis; 6) application layer; 7) the collaboration and process layer to allow different users to access the same application for different purposes; and 8) security layer [72].

6.1 Commercial Offers

Architecture is the plane to build something. In the IT industry, architecture must be independent of the product. This feature provides an extreme value to users because a separate architecture can be implemented with different products. Therefore, it is understandable that several companies offer IoT platforms that can be useful for our architectures. Commercial providers recognize that a solution cannot be adapted to all users, so flexible options are offered, and consumers are responsible for using each component in the best way they consider. The main commercial players identified are, in alphabetical order: Amazon Web Services, Bosch IoT Suite, Google Cloud Platform, IBM Blue Mix (now Watson IoT), Microsoft Azure IoT and Oracle Integrated Cloud [73]. Each of these suppliers has similar characteristics among them and they have differentiators within their offer. The architecture proposed by AWS has a layer of devices, which provides a free operating system for devices called Amazon FreeRTOS, the interconnection layer that can scale to billions of devices, management layer, security layer, application layer and analysis. This architecture is supported by the huge AWS catalog of services for storage and computing. AWS has regions around the world, providing a short distance location on almost every continent. Even the charge model is based on USD cents per million transactions, messages or rules executed, the charges could be exponential. AWS provides a sample of exercises with charge per 100,000 devices connected per month and can reach almost $ 2,000 per month. Since AWS provides a free layer, it has been used in comparisons and projects [74], [75]. Bosch IoT Suite is based on open standards and open source [14], and it has the capacity to execute independent local projects or it can be implemented as a hosted service in different clouds. Bosch IoT has a device layer, a device management layer to perform software and configuration updates, an integration layer, an application and analysis layer, a security layer, and an administration layer. A trial period is available with limited capabilities. To have a cost of ownership and operations, contact Bosch directly. Another important player in the IoT field is Google Cloud Platform. It even has a simplistic way of representing architectural layers, they can be interpreted in a more standard way. The Cloud IoT Core is a large block of the Google IoT architecture, but inside it there is a communication layer, a device management layer, an authentication layer, a monitoring layer and a data processing layer; all this is connected to the cloud publishing / sub functionality that transmits data to big data and analysis services (another layer). Google has a free trial option and a commercial offer that is based on the data exchanged, regardless of the number of devices deployed. This pricing option is flexible for devices that transmit small packages and only the configurations that are sent to them are large. In addition, the frequency of data exchange must be considered. As an example, having 50,000 devices that transmit 48 messages per day per month with 137GB will cost around $ 650 USD per month. IBM has evolved its IoT platform and merged it with its artificial intelligence platform (AI) called Watson. Its architecture is a three-layer approach consisting of a device layer that can interact with devices or a gateway, and the data is transported directly to the IBM Watson IoT platform layer. This layer can manage devices, communicate with devices and pass data to the next layer; The analytical layer that uses Watson Intelligence, and makes data available for applications. Security is provided as an additional feature; therefore, it cannot be considered a layer. Pricing options include a free level to handle up to 500 devices and 200 MB of data exchanged and analyzed. Moving the same 137GB of data with security included will cost around $ 660 USD per month. In addition to this cost, analysis packages are required, starting at $ 500 per month. Microsoft Azure IoT proposes a simple three-layer architecture: things, ideas and actions. However, it is more complex than it seems. Azure has an IoT hub that functions as a gateway to receive all incoming messages from the devices and is also used to communicate with the devices. It involves two layers in one: device layer and communication layer. The Insights layer has more built-in functionality: application layer with user interfaces, administration, data processing layer by Stream Processing Service plus storage. Finally, the actions layer is another type of application layer that is integrated with business processes. Azure requires experienced architects to choose the right services to configure an IoT architecture. For example, it is required to calculate the prices in different components, with different units. Making the best effort to move and process 137 GB of information, Azure requires around $ 1600 USD to process a similar amount. The difference in price is due to the analytical part and reporting. Oracle is another provider that offers the IoT platform. It has four layers. The first layer is dedicated to administration, and includes messaging, device management, and user interface functions to manage functions. The second layer consists of acquiring data, and routes messages, stores data and processes events. The third layer is dedicated to analytics. The fourth layer consists of acting on the data, exposing the interfaces to the applications. Its pricing model is based on CPU consumption per hour or an unregistered business edition, for $ 2,500 USD.

7 Potential Benefits for the Manufacturing Industry by Implementing IoT with Haptic Interfaces, Using Big Data in a Smart Atmosphere

In the literature, limited information was found on the combination of these issues in the manufacturing industry. The reported uses of haptic interfaces are specific and in industries other than manufacturing, such as in the health industry, the arts, and in education [76]–[79]. There are interesting topics from which you can obtain indications for applications in manufacturing, such as the time of uncertainty between the action of the human, the registration of this, and the action performed on the machine [80], or the way to send signals to the human being in front of events detected by IoT [81]. One more is the use of haptic interfaces in interactive museums [82], which could serve as inspiration for manufacturing processes. The haptic interfaces are already including garments, or wearables, which include smart lenses [83]. In the manufacturing processes, we are experimenting with collaborative interactions, where the components of IoT, RFID and haptic interfaces are integrated in a simulation environment. This simulation can have a direct impact on productivity and cost reduction [64]. They can also be applied in prototype designs, minimizing the cost of developing these as they are virtual products [84]. Another area with potential benefits for manufacturing is the integration of ergonomics with postural sensors in chairs. This integration of furniture technology can have benefits in other areas, including administrative ones, for example to reduce the cost of watch clocks when identifying the user [85]. In manufacturing, the use of IoT has brought benefits such as the resolution of complex assembly plans for aircraft engines, or also in the process of printing and assembly of packaging material [86]. The use of IoT and haptics opens the door to natural interaction with computers that have the potential to decrease the learning curve of using a system or tool compared to man-computer interfaces [87]. An example of this benefit is in the rehabilitation at home by means of an apparatus that helps the patient to perform the exercises dictated by their doctor, without having a screen or a keyboard [88]. This can be applied to a manufacturing process that is carried out remotely, minimizing the risk to the user or decreasing travel expenses of an expert [89]. Now, these processes where IoT intervenes are key in the data collection that is stored in big data, coming from the environment data, human beings and robots and artificial intelligence applications [90]. This large amount of data are candidates to be analyzed by ML, applying supervised or unsupervised prediction algorithms, or simulation. Albuhamood [86], in his doctoral thesis, makes mention of the use of genetic algorithms to schedule subtasks to optimize the system. Also, the combination of IoT with ML has created very high expectations that must be taken seriously by the number of billions of devices that will be connected [91]. The specific potential benefits of combining IoT and ML are reported or proposed in different industries as success stories. The uses are as varied as the detection of diseases in plants, crops and fruits [92]–[94], the prediction of air quality [95], or in the health sciences, to help with Parkinson's disease, Alzheimer's or other related issues [96]–[98]. In the field of manufacturing, the use of a conveyor belt with the ability to detect types of electronic slats was found thanks to ML [99]. The other aspect where there is a very narrow use between IoT and ML is in the security that must persist in IoT and how to detect intruders and attacks to the devices through intelligent predictions [100]–[102]. The study of cybersecurity in IoT is as important as its uses and applications for the business and deserves a separate investigation.

8 Conclusions and Future Research

The IoT has been predicted since 2015 that it will reach its plateau of productivity in the industries in the next five to ten years. When reviewing the forecasts published by Gartner in 2016 and 2017, IoT, its platform and the integration in the industry is still forecast in the same period. The architecture of an IoT platform is the only element that has been predicted since 2015 to be productive in the space of two to five years, and this is being fulfilled, as indicated in the literature reviewed. These indicators lead us to think that the adoption of IoT in factories, cities, and homes, still has a way to go, because in 2017 it is predicted that in five to ten years it will reach its productivity plateau. In Figure 7 we show a summary of how IoT has behaved in the hype cycle proposed and reported by Gartner. The lack of acceleration in the adoption of IoT can be explained by the lack of a fast, economic and reliable network, such as the next 5G cellular network. This point is a topic for future research about what the characteristics, benefits and requirements for IoT will be.

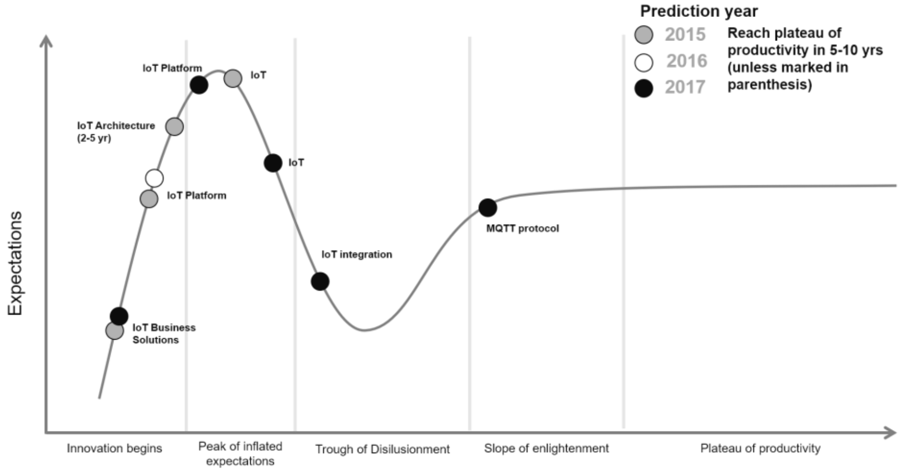

Figure 7. Hype cycle curve focused on IoT from 2015 to 2017

IoT platforms were estimated in 2015 that it would take 5 to 10 years to reach their productivity plateau. However, in only two years it is estimated that they will reach their productivity plateau of 2 to 5 years. This is because, also, one of the proposed communication protocols, the MQTT, is also less than 5 years from reaching its productivity plateau. In Figure 7, the portable devices by the human had in 2015 a forecast of more than 10 years to be in its productivity plateau. Within this type of devices are the haptic devices. Haptic devices have had an interesting development and applications, especially in the health, education, and interaction industries with end users in the entertainment industry. However, the use of haptics in manufacturing in combination with IoT is not reported, visualizing the data, either in dashboards or as inputs for a haptic device. In this topic, only one article was found that combines haptics and data visualization [7]. Albuhamood [86] presents a project very close to the research questions, where it combines IoT, with VR and artificial intelligence, within a proof of concept and simulation, but executes it in sequential stages, and not in an integral way from the beginning. The literature review accomplished resolves the questions posed at the beginning of this work. Regarding the current use of IoT, haptic interfaces and big data in the manufacturing industry, it was found that there are proposed ideas and suggested uses in other industries that can be implemented in the manufacturing industry. No specific cases were reported where the environment was the industry of our interest. It was also discovered that big data is the key piece to store and process the information that comes from the different IoT devices. So, a research and proposal opportunity may be to develop a haptic interface based on IoT to improve competitiveness in an industry 4.0 model for the manufacturing sector.

Regarding the architectures or platforms to implement IoT reported in the literature, these are very varied, contemplating a configuration from two to eight layers, which, far from helping to decide, introduces more confusion to the reader. This is a good opportunity for future work, in which the minimum viable IoT architecture can be proposed, and for organizations to have more clarity when selecting the architecture of their platform. The variety of providers of platforms for IoT also have different forms and methods of marketing their services, making the economic proposal cannot be directly comparable. For future work, we will explore the use of multivariate analysis to help select methodologically the provider that best suits the needs of each organization.

Finally, the potential benefits for the manufacturing industry when combining IoT, haptic interfaces and big data in an intelligent environment are promising, but there is still work to do. Three beneficial aspects have been identified during this literature review: (1) Potential Administrative Benefits, where processes such as entry and exit registration with haptic devices connected with IoT and intelligent face recognition can be optimized and automated; This would lead to cost reductions in hardware, optimization of the work force by knowing exactly where they are in the process and monitoring a contingency. (2) Benefits in the production process, such as minimizing risks when working with hazardous materials and thus including haptic interfaces for handling them; Optimizing resources by leveraging an expert resource that can remotely service multiple plants. (3) Technological benefits, such as the automation of processes and the predictive analysis offered by artificial intelligence; both aspects optimize costs and processes, in addition to providing a competitive advantage.

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