Master Thesis

A smart shop-floor monitoring system through Internet of Things and wireless sensor networks

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PATRAS 2016
To Sophia
Executive summary

The advent of modern technologies such as Cyber-Physical Systems, Internet of Things (IoT), and big data analytics open new horizons towards the industrial digitalisation by enabling automated procedures and communication by means that were not attainable in the past. This transformation of manufacturing has a big significance in the economy of Europe as manufacturing accounts for more than 28% of the gross domestic product.

The contemporary production systems can be regarded as ecosystems that are composed of interconnected entities that refer to the resources, the employees, the customers, the supply chain partners and other stakeholders of the value chain. Aiming to contribute to the digitisation of modern industry, this master thesis presents a monitoring framework and the development of a data acquisition device for machine-tools. The state-of-the-art analysis makes it evident that IoT requires interoperable solutions that can be integrated into systems from various vendors. Moreover, IoT can support the awareness on the actual condition of a production system and facilitate proper decision making.

The developed system consists of three layers, i.e. the data acquisition from sensors installed in machine-tools, the organisation of the data in the shop-floor level by a microcomputer gateway, and the transmission of reports to a Cloud server for administrative purposes. The data acquisition device (DAQ) is designed for installation into the electrical cabinet of the machine-tools following a plug-and-play philosophy, instead of interfacing the on-board controller to collect information. This approach enables the transition of legacy resources into the digital era. The data acquisition devices of a shop-floor are organised in a wireless sensor network using a star wireless sensor network topology. The final data transmission to Cloud is performed via internet protocols.

The collected data provide information about the status of the resources, along with a set of performance indicators to support decision making in the higher levels of the enterprise. Moreover, the electrical energy consumption and the corresponding electrical cost are calculated through the system. The solution is open for integration in all three layers by offering the capability for the addition of more types of sensors in the acquisition layer, connectivity with the OPC-UA and other industrial networks in the gateway layer, and integration with industrial software through web services in the Cloud layer.

During experiments performed using machine-tools in actual machining operations, the framework provided accurate results in the identification of their actual status and extracting reports related to the machining tasks. Moreover, a case-based reasoning
Executive summary

methodology is utilised to reuse the knowledge gained from the framework in new tasks.

The developed system is cost efficient for manufacturing enterprises and easy to install. Furthermore, the adoption of the Internet of Things enables the improvement of operations and the reduction of operating costs, along with the realisation of novel business models such as the equipment-as-a-service and the manufacturing-as-a-service.
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Abstract

With the advent of the fourth industrial revolution manufacturing systems are transformed into digital ecosystems. In this transformation, the Internet of Things (IoT) and other emerging technologies pose a major role. Small and medium enterprises (SMEs) in manufacturing, often employ outdated equipment which does not have connectivity capabilities. Therefore, smart sensor systems are required to connect these resources into the digital world. To address this issue, this master thesis presents a monitoring framework and the development of a data acquisition device for machine-tools. The system is designed for installation into the electrical cabinet of the machine-tools and transmits the data related to their operation to a Cloud server via a wireless sensor topology. The data transmission is performed in two levels i.e. locally in the shop-floor using a star wireless sensor network topology coordinated by a microcomputer gateway, and from the microcomputer to Cloud using Internet protocols. The collected data provide information about the status of the resources, along with a set of performance indicators to support decision making. The developed system follows the IoT paradigm in terms of connecting the physical with the cyber world and offering integration capabilities with existing industrial systems. The gateway level supports connectivity with industrial networks through the OPC-UA standard, while the higher level supports integration with industrial software tools via Web-Services. The operation of the system was evaluated in a 3-axis machine-tool under actual machining operations. Moreover, the capabilities for knowledge reuse were validated through the case-based reasoning methodology in the subject of the energy consumption estimation.

Patras, 07/07/2016
Organisation of the document

This Master thesis deals with the development of a monitoring framework for smart manufacturing shop-floors following the Internet of Things (IoT) paradigm. The objective of the framework is to identify the actual status of the resources and support decision making in higher levels of the enterprise. The Introduction section discusses the transformation of contemporary manufacturing towards digitalisation with the contribution of modern key enabling technologies. The second chapter performs a literature review on the IoT and its state of practice, along with a brief review on the other enabling technologies related to this thesis. The third chapter presents the proposed method that consists of three layers, i.e. the data acquisition on the shop-floor, the gateway for the central server, and the central server in Cloud. Chapters four and five present the hardware and software developments respectively. The sixth chapter demonstrates the experimental results on the status identification of machine-tools, and the knowledge reuse through case-based reasoning. The seventh chapter discusses the emerging business models for manufacturing with the adoption of IoT technologies. Finally, chapter eight concludes the thesis.

The organisation of this document
1. Introduction

Manufacturing enters a new era, where higher levels of flexibility are required to address the challenges of shorter product lifecycles, increasing number of new products and variants, uncertainties and fluctuations in the market demands [1], [2] especially for addressing the needs for mass customization and personalisation [3]. Nowadays production systems change from being located into a single area with centralised control into being distributed with decentralised control [4]. This transformation of traditional factories into smart factories can be very disruptive for the daily operations of manufacturing.

Manufacturing has a big significance in the economic growth. In Europe alone, manufacturing accounts for more than 28% of the gross domestic product (GDP), even in today’s economic recession [5]. Moreover, the presence of Small and Medium Enterprises (SMEs) is very strong in the European industry. Specifically, European SMEs are the backbone of manufacturing industry in Europe with micro, small and medium enterprises to constitute around 45% of the value added by manufacturing while they provide around 59% of manufacturing employment [6]. Therefore, the European SMEs need to be competitive in order to keep up with the fluctuating and the unexpected demands from the emerging market needs. Moreover, as companies make strides towards this new era, they will need to differentiate from the competition. To achieve this, manufacturing companies need to be innovative, create strong supply chain partnerships and being able to embrace modern technologies.

The pinnacle of computing technology in the 21st century, that has transformed the personal computers into smart devices, has been accompanied by a trend of providing information technology (IT) infrastructure and services. In conjunction with ever greater miniaturisation and the unprecedented progress of the Internet, this trend is to move towards a world where ubiquitous computing is becoming a reality. Advances in the semiconductor industry with powerful and cost-efficient processors, storage devices that can contain many terabytes of information, along with autonomous embedded systems that are being wirelessly networked with each other enable the convergence of the physical and the cyber worlds. The contemporary factories need to take advantage of the latest innovations in IT solutions, as well as refined best practices for shop floor operations. This procedure of digitalisation is not straight forward and depends highly on the nature of each manufacturing system. Nevertheless, the companies that are forward-thinking and confident into adopting innovative operational models will be able to endure the emerging market demands.
Chapter: 1

Introduction

The advent of modern technologies such as Cyber-Physical Systems (CPS), Internet of Things (IoT), and big data analytics open new horizons towards the industrial digitalisation by enabling automated procedures and communication by means that were not attainable in the past. Interconnected manufacturing systems and supply chains constitute and integrated whole that follows the System of Systems paradigm. In this context, the factory can be regarded as an ecosystem that is composed of interconnected entities that refer to the resources such as machine-tools and robots, the employees, the customers, the supply chain partners and other stakeholders of the value chain following the idea of Cyber-Physical Systems.

Moreover, the usage of processors with high processing capabilities to embed intelligence into manufacturing resources transforms passive systems into active entities with decision support capabilities. This transformation is described in the paradigm of IoT with the definition “In what’s called the Internet of Things, the physical world is becoming a type of information system—through sensors and actuators embedded in physical objects and linked through wired and wireless networks via the Internet Protocol” [7]. The term IoT characterises the radical evolution of the internet into a network of interconnected objects that create a smart environment. Despite the fact that various definitions for IoT have been proposed, a universal definition may not be the most important issue for the developers’ society. The most important issue is to have agreed-upon standards for connectivity and security to ensure a future of IoT technologies that can communicate and collaborate instead of existing in their own standalone ecosystems. Nevertheless, another definition of IoT is “The Internet of Things allows people and things to be connected Anytime, Anyplace, with Anything and Anyone, ideally using Any path/network and Any service” [8]. This definition encapsulates the broader vision of IoT. In industry the term Industrial IoT (IIoT) is introduced and refers to the application of IoT in industry and implies the use of sensors and actuators, control systems, machine-to-machine, data analytics, and security mechanisms.

However, the application of IoT, especially in industry, results into the creation of vast amounts of information that needs special manipulation and analysis in order to perform meaningful reasoning and extract the actual value. To meet this challenge, the big data analytics is a facilitator to overcome the bottlenecks that are created by the data generated by IoT.

For years, sensors and data capture capabilities have been designed, built and embedded into production lines. Nevertheless, very little has been done so far with this capability, falling short of what could be done with it. Machines and automation on production lines have been equipped with sensors and intelligence since the mid-70’s, but their
embedded intelligence was scarcely exploited in terms of autonomous operation and decision making. Hence, data collection was rarely leveraged to make strategic decisions due to closed, hard-wired manufacturing environments.

The Internet of Things (IoT) is a new paradigm that combines aspects and technologies coming from different approaches. Ubiquitous computing, pervasive computing, Internet Protocol, sensing technologies, communication technologies, and embedded devices are merged together in order to form a system where the real and digital worlds meet and are continuously in symbiotic interaction. By definition, IoT refers to an emerging paradigm consisting of a continuum of uniquely addressable things communicating one another to form a worldwide dynamic network. A thing can be any real/physical object (e.g. RFID, sensor, actuator, smart item) but also a virtual/digital entity, which moves in time and space and can be uniquely identified by assigned identification numbers, names and/or location addresses. Therefore, the thing becomes a smart object that is easily readable, recognisable, locatable, addressable, and/or controllable via Internet. One of the greatest benefits of the IoT has been its ability to standardise and commoditise technologies. Recent IoT reference models can be used and can be enhanced, acting like live systems, where features are gradually developed and integrated in or on top of the IoT network infrastructure, slowly transforming it into an infrastructure for providing global services for interacting with the physical world.

The main reasons for the recent appearance and the big publicity that comes with IoT, and as a result with industrial IoT (IIoT), can be found in the new technologies. First of all, the Internet and cellular networks are ubiquitous. The internet bandwidth has increased and IPV6 addresses can connect trillions of devices. Moreover, the 4G and 5G cellular networks enable internet access for mobile devices with low cost. Regarding the energy storage for IoT devices, the increase of the energy density and the decrease of the cost per kWh of lithium-ion batteries has enabled the development of devices that can operate autonomously for long periods without recharging (Figure 1). Furthermore, the semiconductor industry has created cheap high performance processors (Figure 2) and data storage. Finally, the networks are getting smarter through the development of new standards for communications.

In the field of manufacturing there are many opportunities from the industrial IoT. IoT will create 3.9-11.1 trillion $ of economic growth per year globally by 2025, from which approximately 1.2-3.7 trillion $ will be generated in production systems [11]. IoT makes monitoring possible where it was not possible before. It makes things simpler, less expensive, and more accurate The key is to know what are the problems that need to be solved. Knowledge of the application and the potential of IoT results into the definition of KPIs that could not be considered in the past. Sensor data can be used to
predict when equipment is wearing down or needs repair can reduce maintenance costs by as much as 40 percent and cut unplanned downtime in half.

Figure 1: Historical Prices and Specific Energy Trends for Li-Ion Batteries [9].

Inventory management could change radically (keeping stocks to minimum). Supply chain management and logistics can gain a real benefit from IoT. Harvesting data generated from the usage of products can support the companies to realise how do they get actually used. IoT can create new business models that would shift competitive
dynamics within industries. One example is using IoT data and connectivity to transform the sale of industrial machinery and other goods into a service. The Industrial IoT increases the speed of manufacturing and reduces labour costs by giving the ability to monitor high-value and high-impact assets. Thus, the smart object should be seen as the building block of the IoT vision. By putting intelligence into everyday objects, they are turned into smart objects, able not only to collect information from the environment and interact with the physical world, but also to be interconnected with each other through Internet and exchange data and information.

This research work aims to explore the potential of IIoT in manufacturing in terms of creating the digitalised factories of the future. Existing applications will be presented along with conceptual frameworks not yet present. Moreover, the issues related to IoT will be examined in terms of security, data storage, bandwidth limitations etc. To leverage the modern technologies towards the digitalisation of contemporary manufacturing systems this master thesis presents a Cloud-based monitoring framework for machine-tools following the IoT and CPS paradigms. The framework includes the collection of information from data acquisition devices (DAQs) on machine-tools. The DAQs employ sensors and are organized into a star wireless sensor topology with a microcomputer being the coordinator. Data processing is performed inside the DAQs and the microcomputer, in order to extract meaningful information and transmit them to a Cloud server for aggregation and visualization. The outputs of this monitoring system are referred to the actual status of the resources, the electrical energy consumption, and information related to the machining tasks that are performed.
2. State of the Art

2.1 IoT

The cyber instances in a CPS can be regarded as virtual objects with storage and processing power, that communicate with other cyber entities and humans, and can control the physical device on which they are attached. These virtual objects are following the paradigm of IoT. The dramatic reduction of the microelectronic prices during the previous years, along with the increase of the processors capability (following the Moore’s law) triggers research on novel monitoring and control systems. The feasibility for the adoption of autonomous and intelligent microcontroller systems in real-life applications is also based on the reduction of the battery prices and the increase of their energy density [12]. The use of sensors and the computational capabilities of modern microcontrollers are complemented by the communication capabilities that embedded systems provide. Moreover, the information networks that are based on the IoT can create new business models, improve business processes and reduce costs and risks [12]. Many significant applications of industrial IoT are emerging. Industrial IoT can strengthen modern industries with the three pillars i.e. the process optimisation, the optimised resource consumption, and the creation of complex autonomous systems [12].

The IoT is a multi-disciplinary field. In [13] the authors state that the IoT paradigm is a result of the convergence of the visions that are Internet-oriented, semantic-oriented, and embedded electronics-oriented (Figure 3). The identified challenges include the standardisation, issues related to network bottlenecks, the security of the communication and the intellectual property protection. The huge amount of data that are generated by IoT require huge processing capabilities. Therefore, the context-aware computing methodologies will facilitate the decision making on which data will be processed and in which layer [14]. Recently, many scientific publications have contributed into improving the technologies and the methods used in IoT. The role of the gateway in IoT is of crucial importance as it is responsible for the management of the local network of devices [15]. In addition, frameworks for specific applications of IoT using novel sensing devices have been proposed [16]. Moreover, middleware and Cloud platforms have been evaluated to integrate the IoT devices and host the generated data [17]. Nevertheless, the existence of numerous Web-services that can be used for IoT applications requires a methodology for predicting the quality of these services (QoS) and support the engineers selecting the appropriate [18]. The IoT is an emerging paradigm that penetrates a wide range of industry. Successful applications that enhance the value for the customer in the subjects of monitoring and control, business analytics, and information sharing and collaboration have already been evaluated in real-world case studies [19].
Despite the fact that, various topologies for the communication of monitoring devices can be employed. In manufacturing the wireless sensor network topologies are the most eligible candidates as they offer flexibility and scalability, especially in flexible environments such as the shop-floors [20]. A wireless sensor network (WSN) consists of a large number of wireless-capable sensor devices working collaboratively to achieve a common objective [21]. In the context of manufacturing systems, the sensors that are monitoring the production can compose a WSN with the objective to increase or reduce production KPIs. Many wireless standards have been created in the context of WSN and their selection lies in the requirements of each specific application [22]. For the local communications of WSNs, the ZigBee specification has gained much attention lately. A dedicated work on the coverage evaluation for ZigBee has been performed in [23], where the authors developed an intelligent self-adjusting node.

2.1.1 IoT on manufacturing resources

For the inventory management

The first aspect of the IoT in manufacturing is in the inventory management. The management of the inventory is of crucial importance, due to the fact that maintaining inventory levels low reduces the relevant cost. High levels of inventory often occur due to inaccurate stock numbers that increase sludge and result into unreliable demand planning necessitating safety stock, or overproduction.
IoT can contribute in the direction of reducing inventory levels by providing automated tagging and scanning solutions for the stocked goods. The tagging can be performed by using the labels of barcode and quick response code (QR code), or by using the most sophisticated radio-frequency identification (RFID) tags. Hence, the good can store information related to its manufacturer, and its production on no expiry dates. This information can be scanned and provided to an enterprise resource planning (ERP) software for complete awareness. If RFID tags are selected, the capability for multiple reads and writes on the same chip is offered. Thus, the product can contain information from more than one hub in the supply chain, due to the capability for multiple read and writes on the same tag. Moreover, the RFID scanner can read sequentially in very high speed up to hundreds of tags in one second [24].

Two significant case studies of IoT in the inventory management are the cases of the Macys and Proctor & Gamble. In the first, RFID tags were used to keep inventory levels low, while in the second inter-connected systems in supply chains collaborate to share information about delivery dates.

**For machine-tool monitoring and control**

In the context of monitoring the production resources, [25] have developed a data acquisition device (DAQ) to identify the actual status of machine-tools. This architecture has been also demonstrated in [26] supporting maintenance activities by providing the actual machining time of machine-tools, and in [27] combined with a knowledge retrieval methodology, the case-based reasoning, to provide knowledge on the energy consumption of the machining of a new product.

![Figure 4: The monitoring architecture proposed in [26].](image)

Summarising, the benefit of the aforementioned method can be found in the directions of increasing the utilization of the resources, providing adaptive scheduling capabilities, correctly planning maintenance activities, and measuring energy consumption related key performance indicators (KPIs).
The machine-tool manufacturer, Mori Seiki, followed the IoT paradigm to create a network of machine-tools in order to acquire the operating status, perform diagnostic and analysis remotely, and conduct necessary preventive maintenance. The developed system uses the MTconnect standard which facilitates the communication with the controller and is based on the XML standard [28].

*For robot communications and control*

In the case of the more intelligent robots, the IoT can contribute to the Machine-to-Machine (M2M) communications. In a pilot case by ABB, the robots where able to monitor their actual usage and report their performance. Specifically, M2M refers to the automated data transmission and measurement between mechanical or electronic devices. The key components of an M2M system are: Field-deployed wireless devices with embedded sensors or RFID-Wireless communication networks with complementary wireline access includes, but is not limited to cellular communication, Wi-Fi, ZigBee, WiMAX, wireless LAN (WLAN), generic DSL (xDSL) and fiber to the x (FTTx) [29].

As previously stated, machine-to-machine communication makes the Internet of Things possible. According to Forbes, M2M is among the fastest-growing types of connected device technologies in the market right now, largely because M2M technologies can connect millions of devices within a single network aiming to exchange information directly from one machine to another. The range of connected devices includes anything from vending machines to medical equipment to vehicles to buildings. Virtually anything that houses sensor or control technology can be connected to some sort of wireless network [30].

The modern trend of machine tending is a special case of M2M. Machine tending refers to overseeing a machine while it performs a job, as well as the process of feeding parts in and out. Robotic machine tending keeps workers safe from the tedious, injury-inducing jobs, raising safety levels in facilities. Using industrial robots for machine tending tasks is a great way to add automation to a production line while decreasing part cycle time, saving customers money while ramping up productivity. Machine tending robots are used to secure the product from a supply position, transport it to a machine, interact with the machine and then remove the finished part from the machine. Managing this process by robot minimizes incorrect product placement due to human error and increases speed and efficiency of production [31].

*For production line monitoring*

The aggregation of the data from the independent resources gives useful insights also in the production line level. This is easily achievable by the integration and
communication capabilities that are provided by IoT. In this interconnected potential lies the actual value of IoT through seamless communication among various and heterogeneous sources of information.

In this context, the work of [33] proposes an integration method for adaptive and holistic scheduling. The authors propose a scheduling module that considers the actual availability of resources. The latter is obtained through an IoT based monitoring system. The adoption of this solution can contribute to the creation of feasible production plans that consider the actual manufacturing situation.

![Diagram](image)

*Figure 5: The architecture proposed in [33].*

**For monitoring the life cycle of the product**

Through the monitoring of the product during its actual usage, the manufacturers can gain valuable knowledge related to the behaviour of the product and the efficiency of the design. This knowledge can contribute to the enhancement of the product specifications towards the direction of meeting the customer requirements. Until recently, product lifecycle management (PLM) technology only considered the lifecycle until the product rolled off the production line and was put into use. This meant that any failures or issues that occurred had to be manually reported by the customer. As not every failure or issue will necessarily be recorded, catalogued, and then analysed, it has proven to be very difficult to notice patterns and make necessary changes to ensure that future products do not experience the same problems [34].

Some significant case studies are the case of General Electric where sensors are used to monitor how jet engines are performing in the air, and to diagnose emerging
problems and the one of John Deere, the maker of agricultural equipment, helping farmers get the most out of their land by building machines that can receive data on weather and soil conditions, enabling better decisions on when and where to sow and plough [35].

To connect humans with the cyber world

The industrial IoT paradigm is not intended only for the manufacturing equipment, but also for the integration of the employees with the cyber world. This is facilitated with the use of personal mobile devices i.e. smart-phones, smart-watches, and augmented reality (AR) glasses.

A detailed review on the research and development of augmented reality (AR) applications in design and manufacturing has been performed in [36]. The identified hardware devices that are most commonly used are classified under the sections of display devices, user tracking devices, and systems for haptic and force feedback. AR can support manufacturing during the design phase by projecting virtual objects into the real world and thus being a major part of the prototyping process. Moreover, the authors reviewed several occasions where AR facilitated the support of the operators in ad-hoc tele-robotic tasks. The IoT paradigm combined with AR technologies can support the maintenance activities within a factory. Therefore, the training of the maintenance operators in new maintenance activities can be performed faster and with the appropriate guidance. The same applies also to the assembly phase of a new product where the operators can visualise the assembly process step by step.

In the machining industry, it is a fact that the operators of the machine-tools need to oversee the manufacturing process by standing next to the machine and make corrections if needed. This is accumulated into a non-productive and boring for the operator period, especially in large batch orders where the same process is repeated many times. The processing of the outputs of the sensors that are installed in machine-tools and the transmission of alerts relevant to the status of the equipment to the operators can reduce significantly the time that is required to oversee the process. This can be achieved with the use of the afore mentioned mobile devices by systems that provide real-time visualisation of measurements and KPIs [37].

The prevalence of the mobile devices in contemporary shop-floors can enable the usage of enterprise social media applications for collaboration among the employees that participate in the same of in different groups. Aiming to support this collaboration, [38] introduce a knowledge-enriched problem solving methodology that is based on the principles of root-cause analysis (RCA). The proposed system is validated through a real-life case study obtained from the die construction department of an automotive
industry and gives the capability of reporting problems met during production, obtain results from past similar cases, and collaborate on finding the solution.

*To maintain optimal environmental conditions*

IoT can also contribute towards maintaining the optimum environmental conditions inside a manufacturing plant. This is achievable through the usage of the appropriate sensors that sense humidity, temperature, and lightning. Hence, the heat, ventilation, and air-conditioning equipment can be controlled from intelligent devices to tune the humidity and the temperature, and the internal lightning conditions can be controlled through smart windows that can adjust appropriately their transparency. Therefore, the operating conditions of the equipment can be held to optimum levels and the working conditions of the employees can be improved to increase their productivity and satisfaction.

2.1.2 Gateway Topologies

After briefly presenting the aspects of manufacturing that can be improved through the usage of IoT, this study aims to present some technical methodologies for implementing a network of IoT. Due to the fact that the connection of each sensor-node independently to the Internet, might be a high-cost and complicated solution; the use of a gateway is often used. As defined in [39] “An IoT Device gateway is a device that glues or connects incompatible networks or protocols and provides a mean to connect devices to the internet”. Therefore, considering that the connection of each sensing device to the Internet can increase dramatically the costs of the hardware and require more programming efforts in the software, the use of a gateway is necessary to stand in the middle between the local area network that includes the sensing devices that perform the data acquisition, and the Internet.

There are various types of gateways referring to both hardware and software selections. For example, when referring to the hardware capabilities of the device, one selection can consider the gateway only as a proxy device for the internet and another can consider it also as a sensing node of the network. From the software perspective, one possible solution is to pre-install all the software components into a gateway before employing it in the field; or another could be to download the software from an independent management server. The latter solution has the benefit of providing stability in the case of software crashes inside the gateway, as the software resides in a central server [40].

The objective of the gateway is not limited to passing the information from the corresponding DAQs to the Internet server. As it has an overview of a large part of the local sensor network (in many occasions it has the control of the whole network) it can...
perform local data processing and data aggregation in a higher level. For this purpose, the gateway can have its own database for local storage of information. Finally, the data processing on the gateway has the benefit of reducing the amount of data that is transferred to the internet server.

Figure 6: A gateway topology with the gateway including also sensors embedded and the software pre-installed (adopted from [40]).

2.1.3 Local Communications

Wired communications

The first part of the communication actions is performed in the local sensor network level. In continuous manufacturing systems where the requirements for flexibility are low, the local communications can be wired. One significant industrial communication protocol is the Modbus which was specified by Schneider Electric in 1979. Modbus RTU is an open, serial (RS-232 or RS-485) protocol derived from the Master/Slave (nowadays Primary/Replica) architecture. It is a widely accepted protocol due to its ease of use and reliability. Modbus RTU is widely used within Building Management Systems (BMS) and Industrial Automation Systems (IAS) [41]. MODBUS is considered an application layer messaging protocol while on the OSI model, MODBUS is positioned at level 7.

Another wired industrial protocol is controller area network (CAN) bus which was specified by Bosch Gmbh in 1986. CAN bus is commonly used in automotive and low-cost industrial applications. The main benefits of CAN standard are the transmission in a single channel, the automatic error identification, the support for multi-master communications, and its high tolerance to electromagnetic interference. It is a flexible protocol that enables the connection and the removal of nodes without the redesigning of the network, and organizes the data transmission based on the message identifier [42].

The third industrial protocol that can facilitate the wired communications in the era of IoT is the Profibus, developed by the German department of education and research in 1989. Profibus is based on standards and modularity. User benefits are the ease of use and flexibility. The single communication protocol enables fully integrated solutions of
continuous as well as discrete and safety-related processes to run on the same bus. This eliminates the need for separate systems and allows hybrid automation. Profibus is optimized for distributed I/O applications. Up to 126 I/O devices can be connected to a PROFIBUS DP cable. Since each I/O device can handle hundreds of connection points, this provides a very large number of connection possibilities for a single controller [43].

**Wireless communications**

The wireless communications are preferred in the cases where flexibility in terms of restructuring the network is needed. This is usually the case in discrete manufacturing systems that changes in the topology of the equipment is often needed in order to meet the variety of demands for production.

An important protocol for the realization of the wireless communications in the IoT domain is IEEE 802.15.4. It specifies the physical layer and media access control for low-rate wireless personal area networks (LR-WPANs). It is maintained by the IEEE 802.15 working group, which defined it in 2003. It is the basis for standards such as the ZigBee, ISA100, and WirelessHART. Alternatively, it can be used with 6LoWPAN as Network Adaptation Layer and standard Internet protocols, defining the upper layers with proper granularity to build a wireless embedded Internet [44].

The topology of the wireless sensor network (WSN) can be selected according to the special needs of each application. Three are the most common topologies used within IoT, i.e. star, mesh, and cluster trees. All of them have coordinator devices, full function devices, and reduced function devices [45]. The star topology considers a coordinator which organizes the traffic within the network. Any packet exchange between end devices must go through the coordinator. The disadvantage of this topology is the operation of the network depends on the coordinator of the network, and because all packets between devices must go through coordinator, the coordinator may become bottlenecked. Also, there is no alternative path from the source to the destination. The advantage of star topology is that it is simple and packets go through at most two hops to reach their destination. In the tree topology the network consists of a central node (root tree), which is a coordinator, several routers, and end devices. The function of the router is to extend the network coverage. The end nodes that are connected to the coordinator or the routers are called children. Only routers and the coordinator can have children. Each end device is only able to communicate with its parent (router or coordinator). A cluster tree topology is a special case of tree topology in which a parent with its children is called a cluster. Each cluster is identified by a cluster ID. Mesh topology, also referred to as a peer-to-peer network, consists of one coordinator, several routers, and end devices. A major characteristic of a mesh topology is that is a multi-hop network where packets pass through multiple hops to reach their destination.
Hence, the range of a network can be increased by adding more nodes. The most important benefit of the mesh topology is that it is self-healing. If a path fails during transmission, the node will find an alternate path to the destination.

Figure 7: The major topologies of the WSN as presented in [45].

2.1.4 Communication with the Internet

This section of the text is composed based on the information found in [40] for the standards that facilitate the communications within IoT and subsequently their brief description from their specification documents. The communications of IoT with the Internet are based on the TCP/IP protocol which is specified as layer 4 of the Open Systems Interconnection model. TCP guarantees that the information will reach its destination with data integrity, while IP is responsible for the routing of the data. In the application layer of the communications the representational state transfer (REST) is commonly used and is the architectural style of the whole Web. It uses HTTP requests with all the parameters passed in the URL of the request. Another standard which is met during the communication of Web-services is Simple Object Access Protocol (SOAP) which is a protocol specification for exchanging structured information in the implementation of web services. Dedicated standards for the communication of the IoT with the Internet are the MQTT (Message Queue Telemetry Transport) which is a publish-subscribe based light weight messaging protocol; the AMQP (Advanced Message Queuing Protocol) which is an open standard application layer protocol for message-oriented middleware; the CoAP (Constrained Application Protocol) which is a software protocol intended to be used in very simple electronics devices that allows them to communicate interactively over the Internet.

As the facilitator of the communications in Industry 4.0 the OPC-UA (Open Platform Communications – Unified Architecture) has gained much publicity lately [46]. It is an industrial M2M communication protocol designed for interoperability among systems of various vendors and level in the manufacturing hierarchy. It enables data exchange between products from different manufacturers and across operating systems. OPC-U
combines the benefits of web services and integrated security with a consistent data model. It is a TCP-based binary protocol, and HTTP/HTTPS web service with XML-coded messages. The feature of OPC-UA that facilitates the interoperability among heterogeneous systems is that the servers carry their instance and type system, while the clients can navigate and obtain all the information they need, even for types that were unknown to them before.

![Figure 8: The OPC-UA in the software ecosystem for manufacturing [47].](image)

### 2.1.5 Issues in the IoT operation

This section deals with the main issue that can be found in the field of computer networks and therefore are inherent in the IoT systems. At first, the methodologies to maintain the integrity of the data are presented. Secondly, the issues of the lack of bandwidth and storage are discussed. The section will close with the issue of security in data transmission.

**Data integrity**

When data is transmitted in or computer network, it needs to be truthful, accurate, complete, retrievable, and verifiable. Therefore, data integrity checking mechanisms are employed in the lowest level of communication networks.

One of the first and easiest ways to check the integrity of the data is the parity checking. Parity checking uses parity bits to check that data has been transmitted accurately. The parity bit is added to every data unit (typically seven or eight bits) that are transmitted. The parity bit for each unit is set so that all bytes have either an odd number or an even number of set bits. Using the parity bit, the transmitter indicates the parity for the data that are sent. When the data are received, the recipient performs a parity checking to extract the parity bit and compares it with the one that the transmitter added in the data.
packet. If the two parity bits are the same, the data is considered valid. Else, an error flag is raised and corrective actions are initiated.

The drawback of the parity checking method is that if two bits are received wrongly, the parity bit in the two sides of the communication channel is the same and the receiver detects no error. For this reason, more sophisticated methods are used and parity checking is preferred when simplicity and reduced-sized data packets are required. A similar method that is applied in the data integrity checking of data packets is the checksum. In the checksum, all the information bytes included in a packet are arithmetically added in the two ends of the communication line to conclude into the checksum byte.

A more sophisticated method for the data integrity checking is the cyclic redundancy check (CRC). The transmitter performs a division with a 16- or 32-bit polynomial to a data packet that is to be transmitted and appends the resulting cyclic redundancy code (CRC) to the packet. The receiver applies the same polynomial to the data and compares its result with the result appended by the sender. If they agree, the data has been received successfully. If not, the sender can be notified to resend the block of data. The CRC method is able to identify a number of errors in the data packet that is less than the length of the CRC polynomial.

An improved method includes the addition of adequate information in the data packet to enable the server correct any potential errors that can be occurred during the communication. These methods are referred as error-correcting code (ECC) or forward error correction (FEC). These methods require extra information which makes the data packet bigger, but they are suitable for uni-directional (simplex) and high speed
communications. The first error correction code was invented by the mathematician Richard Hamming.

Summarizing this section, the error correction can be classified under the two categories of the error identification that are followed by a repeat request, and the error identification and automatic correction by the receiver.

**Bandwidth/Storage**

Considering the trillions of devices that will be connected to the internet following the IoT paradigm, the issues of network bandwidth and data storage are crucial. It is evident that if the storage of or the data that is generated by IoT is stored in internet servers, the available storage will not be sufficient. Accordingly, if all these data are transmitted to the internet servers, bandwidth problems will emerge.

A promising methodology to address the bandwidth and storage issues is the distributed data processing. Hence, the data can be processed and stored in many layers i.e. the IoT device, the gateway, middleware systems, and higher level servers. Thus, each layer will contain on sufficient volume of information, manageable by its processing resources and suitable for its operation. In the case study of the machine-tool monitoring, [27] propose a distributed processing method comprised of three layers i.e. the IoT device, the gateway, and the Cloud server.

**Security**

So far, IoT devices are mostly targeting the hobbyists and home automation applications. Even now, the issues related to the security of the IoT data are remarked. These issues become more crucial in the case of industrial IoT where deviations from the actual situation due to altered data may result into wrong strategic decisions.

The security measures are applied into both local networks and the internet. In the former occasion, the advanced encryption standard (AES) encryption is often used. In the latter occasion, the authentication token and hash algorithms are the most frequent choices. The authentication token is a user authentication method for Web-services and comprises the following steps [48]:

1. The client initializes and sends authentication request to the Secure Token Server (STS)
2. The STS validates the client's credentials
3. The STS issues a security token to the client
4. The client initializes and sends a request message to the service
5. The service validates the security token and processes the request
Two similar encryption methods that are commonly used in Web-services are the MD5 hash and the secure hash algorithm (SHA). The hash algorithms employ hash functions that can be used to map data of arbitrary size to data of fixed size. Therefore, the hash function is used on the parameters of the URL of a REST request, along with or unique key that is known only to the client and the server, in order to avoid interception by a man-in-the-middle attack.

2.2 Other enabling technologies

2.2.1 Cyber-Physical Systems (CPS)

CPS have been defined as “the systems in which natural and human made systems (physical space) are tightly integrated with computation, communication and control systems (cyber space)” [49]. CPS are open, linked-up systems that operate flexibly, cooperatively (system-system-cooperation), and interactively (human-system-cooperation). They link the physical world seamlessly with the virtual world of information technology and software [50], and by doing so, use various types of available data, digital communication facilities, and services [51]. CPS must be capable to integrate complex heterogeneous large-scale systems efficiently in order to deliver expected performance and operate reliably in uncertain environments. Towards the creation of Industry 4.0 factories, [49] introduce a stepwise approach for the design of manufacturing CPS. The method is called 5C and consists of five levels namely smart connection, data-to-information conversion, cyber, cognition, and configuration. In the same work, the authors use an adaptive clustering method for pattern recognition in order to determine the health status of the machine. The adoption of CPS in industry gives the opportunity for novel business models. A study aiming to collect information from industry in order to evaluate the effects of CPS in the service industry has been presented in [52]. The impact of CPS is recorded by performing structured interviews in enterprises belonging in the industry of equipment manufacturers, equipment operators, and service organisation. CPS are closely related to the service oriented architectures (SOA) where autonomous yet interoperable systems are built through loosely coupled web-services [53]. A scientific work that explores the efficiency of the Acquire-Recognise Cluster as a field level SOA has been performed in [53] where the systematic computation was separated by the functional control at the different CPS layers. The evolution of manufacturing science and technology, along with the recent advances in computer sciences and the information-communication technologies are the basic pillars for the adoption of CPS in industry, also known as Cyber-Physical Production Systems (CPPS) [54]. The modelling of the CPS for manufacturing systems can follow well-known system description frameworks, or extending existing such as the EAST-ADL modelling language [55]. The concept of CPPS applies also in the resources as a low-level CPS modelling. A detailed model of a machine tool following
the CPPS can be presented as a function of the work task that needs to be performed by a machine-tool and the required manufacturing resources [56]. Despite the connection with the tangible resources, the CPS can be extended with the social media usage in industry towards Social Manufacturing [57], [58].

2.2.2 Shop-floor monitoring
The monitoring and data collection during the manufacturing operations is the foundation for factory automation and decision making. Accurate and real-time data collected by monitoring devices can be assessed to provide a holistic view of the production and give information on the actual status and the condition of manufacturing resources. The CPS paradigm suggests the use of monitoring devices under the IoT philosophy that go beyond the traditional approaches for on-site data collection, processing, and visualisation. The necessity for the use of real-time monitoring in manufacturing has been stressed in the work of [59]. The authors identified that the main requirements for monitoring systems in production are the robustness, the capability for reconfiguration, the reliability, the intelligence, and the cost efficiency. In the context of monitoring machine-tools, there is a variety of sensors that can be employed (acoustic, vibration, force, current, etc.)[59]. Electrical current sensors are promising candidates for measuring energy related operating characteristics due to the fact that they are cost efficient and non-intrusive in nature [25]. In previous literature, monitoring systems have been proposed for the purposes of preventive maintenance [60], remaining useful life estimation [61], and cutting tool reconditioning [62] among others. The application of monitoring devices in the shop-floor to track the availability of machine tools, results in an adaptive holistic scheduling has been introduced in [37], [33]. The framework is introduced in five layers i.e. the machine monitoring, the data preparation and diagnostics engine, the prediction engine, the visualisation of results and actions, and the maintenance planning and adaptive scheduling of the system.

2.2.3 Cloud manufacturing
Manufacturing systems require intelligence in collaboration, and adaptability to dynamic changes. Towards this end, the philosophy of Cloud manufacturing can act as enabler for data exchange between IT tools and users [63]. Cloud manufacturing implies the use of Cloud technologies in manufacturing. This new paradigm offers ubiquitous access to information, integration platforms for industrial equipment and software, along with flexible licensing models in the provision of services. A recent study performed an extensive literature review in Cloud Manufacturing presenting the key benefits brought by the adoption of Cloud technology in manufacturing, such as scalability to business size and needs, and ubiquitous network access [64].
Considering the previous literature and the industrial practice in the aforementioned fields, this thesis proposes a framework for machine-tool monitoring to improve the awareness on the shop-floor condition and the utilization of resources. The decision to develop DAQs, instead of interfacing the controllers of the machine-tools, results into a plug-and-play approach that is suitable even for legacy resources to advance into the IoT era. This facilitates the transformation of contemporary shop-floors into CPS and their benefit from digitization technologies. The Cloud is selected in this work to host the central server, as it is an enabling technology for the “always online” operation of the software and the potential for flexible licensing models.
3. **The monitoring method**

3.1 **Overview of the method**

This study aims to present a monitoring method for smart shop-floors from the IoT perspective. The main objective of the proposed system is to improve the awareness on the actual status of the manufacturing resources and especially machine-tools. It is rather common in industry to create production schedules while taking into consideration resources that might not be available when required due to various reasons. Hence, the issue of the awareness is of crucial importance to avoid bottlenecks and increase productivity. This monitoring system consists of sensors that are installed in the machine tools, a data acquisition device for each machine-tool, and a microcomputer coordinator. The outputs of the system are intended to be transferred to a Cloud server for visualisation (Figure 10).

The proposed system is designed as an add-on for the commercial machine tools, rather than communicating with the machine controller. This decision is mainly driven by the fact that the lifespan of the industrial equipment can reach the 50 years (averaging 26-34 years) [65], and hence old machinery often do not have the required capabilities for connectivity. Therefore, special effort should be made in order to transform each legacy controller into an IoT device.

Another pillar for the proposed architecture is the distributed data processing. Each sensor may produce a large amount of data which can result into some gigabytes per day. It is evident that the unprocessed data streams do not contain meaningful information. Hence, in order to extract meaningful information from the raw data that will result into knowledge on the monitored entity, the appropriate processing needs to take place. In this work, the processing and the reduction of the data is performed on the source of its generation, i.e. the sensor. This is achieved through the microcontrollers of the data acquisition devices that are installed in the machine tools.

In addition, the connection of each individual IoT device directly to the internet may result into communication bottleneck due to the lack of sufficient bandwidth. For this reason, each IoT device (i.e. the DAQ) connects to a gateway via a local wireless sensor network. The gateway is the coordinator of the network and its objective is to transmit the meaningful information of each machining task to a central repository.

Each layer of the proposed architecture follows the idea behind IoT and provides integration aspects for the realisation of interoperable systems. The DAQ architecture allows for more sensors; the gateway provides interfaces with industrial networks, in this study OPC-UA is considered and an information model is provided; and in the
higher level of the central server integration with industrial software such as ERP and MES can be achieved.

![Figure 10: The proposed IoT-based monitoring method](image)

### 3.2 Sensors and data capturing

The sensors for the status identification of the machine-tools measure the overall electrical power consumption of the system and the individual current consumption of each one of the main motor drives. Specifically, the individual motor drive measurements include current sensors on the spindle and on each one of the moving axes. The sensors for the axes drives are split-core current transformers. The current transformer is an electrical device which is used for current measurement purposes. The current transformer employs a coil (secondary winding) where current is induced proportionally to the current that flows in a conductor (primary winding) whose current needs to be measured (Figure 11).

Especially for the case of the spindle a close-loop hall effect current sensor is selected in order to capture the overall harmonic content of the spindle current. This type of sensor employs a Hall element to identify the presence of a magnetic field due to the current (DC or AC) that flows inside the conductor whose current needs to be measured. For current measurements, this magnetic field is concentrated into a magnetic core (usually ferrite). The benefit of the closed-loop Hall sensor, compared to the open-loop ones, is that a secondary coil is used to balance the magnetic field inside the ferrite core.
(Figure 12). Hence, core saturation is avoided in high currents and better linearity and frequency response are achieved.

Figure 11: The operating principle of the current transformer [66].

Figure 12: The operating principle of the closed-loop Hall effect sensor [67].

The overall electric power consumption of the machine tool is measured through a current sensor installed in one of the three mains lines. The measurement of one line is preferred instead of measuring all three lines, due to the fact that the machine-tools act as balanced loads. Therefore, Eq. 1 applies without errors.

In order to make the output of the current sensors suitable for the microcontroller of the DAQ, the AC current of the output of the sensor needs to be transformed into a DC voltage. This is achieved using a resistor to transform the current into voltage, followed by a shift of the waveform to positive voltage values (Figure 13).

Moreover, the voltage of the mains is measured through an insulating transformer for safety reasons. In order to identify correctly the status of the machine, a proximity switch is installed in the door of the machine-tool which is open when it is in the setup mode.
\[ P = \sqrt{3} \cdot V_l \cdot I_l \cdot \cos\phi \]  \hspace{1cm} \text{Eq. 1}

Where, \( P \) is the active power in W, \( V_l \) is the line voltage in V, \( I_l \) is the line current in A, \( \cos\phi \) is the power factor of the three phase load.

The outputs of the current transformers are sampled by a frequency of 1kHz which corresponds to 20 samples per period (in the case of 50Hz). For these current measurements, only the root mean square (RMS) values are calculated through Eq. 2.

\[ I_{RMS} = \sqrt{\frac{1}{n} \sum_{i=1}^{n} i_i^2} \]  \hspace{1cm} \text{Eq. 2}

Where \( i_i \) are the sensor measurements and \( n \) is the total number of measurements.

For the close-loop hall effect current sensor the bandwidth is 200kHz, therefore the maximum sampling rate was set to 1MHz. Except for the RMS value which is also calculated following Eq.2, the fast Fourier transform (FFT) is also calculated for the hall effect sensor. Hence, the harmonic content of the current is extracted. When digital sampling is applied to analog signals, the discrete Fourier transform (DFT) is used to extract the spectrum of the signal (Eq. 3) [68]. The FFT is a very efficient algorithm for computing DFT coefficients.

\[ X(k) = \sum_{n=0}^{N-1} x(n)e^{-j\frac{2\pi kn}{N}} = \sum_{n=0}^{N-1} x(n)W_N^{kn}, \quad k = 0, 1, ..., N - 1 \]  \hspace{1cm} \text{Eq. 3}
Where X(k) are the DFT coefficients, x(n) is the periodic digital signal after the sampling of its analog counterpart and N are the acquired data samples. \( W_N \) is defined as:

\[
W_N = e^{-j\frac{2\pi}{N}} = \cos\left(\frac{2\pi}{N}\right) - j\sin\left(\frac{2\pi}{N}\right)
\]

This functionality was considered while designing this monitoring system, driven by the fact that, in every electric motor, the mechanic torque is closely related to the motor current [69], [70]. Thus, observing the harmonic content of the motor current, useful insights that are related to maintenance aspects can be deduced. The full implementation of this functionality paired with the necessary pattern recognition method to identify deviations in the spindle current spectrum that are related to mechanical faults, will be demonstrated after the long-term installation of the system in machining industry. This will provide the amount of data required to conclude into accurate results. In the context of this thesis, the hardware infrastructure and the firmware for the signal analysis is developed.

### 3.3 WSN design

The DAQs of a shop-floor are organised in a wireless sensor network (WSN) following the star topology. The selection of the WSN was driven by the requirements for flexibility and reduced infrastructure. The data transmission is coordinated by a central gateway which is responsible to collect the data from the DAQs and organise them into packets before transmitting them to a Cloud server for further processing and visualisation.

The WSN is facilitated with the use of DIGI XBee ZigBee radio frequency (RF) module. The selection of ZigBee over other wireless standards and specifications is performed due to its support to various network topologies and encryption algorithms, and its robust operation with functionalities such as collision avoidance, retries, and acknowledgements performed in the hardware. Moreover, ZigBee modules can communicate in ranges more than 100m [71]. A DIGI XBee ZigBee RF module is also installed on the microcomputer that is responsible for the coordination of the data transmission in the WSN.

The data within the WSN are transmitted as ZigBee frames that have unique recipients. In order to automate the addition and the removal of the nodes in the WSN the following procedure is developed (Figure 14).
In the first step, each DAQ node transmits a beacon message once every 5s. If a DAQ is in range with a coordinator, the coordinator receives the message and verifies the DAQ address with a list of registered DAQs. If the DAQ address is registered in the coordinator, the coordinator transmits an “initiate communication” frame. Then the DAQ abandons the beacon mode and waits for the coordinator to request a measurements packet. Subsequently, the coordinator requests the measurements of each DAQ once every 0.25s and the operation of the network continues following this manner.

In order to avoid network malfunctions due to problematic devices or absent nodes, supervisory mechanisms are implemented into both DAQ and coordinator devices (Figure 15). The coordinator sets a specific flag when a request for packet is sent to each DAQ. If the DAQ fails to reply before the beginning of the next cycle of requests by the coordinator, the latter adds the value ‘1’ to the counter of a scorecard for the corresponding DAQ. In the opposite occasion of the successful reply by the DAQ the coordinator subtracts the value ‘1’ of the counter of the scorecard. If the counter of each DAQ reaches the value of 20 the coordinator perceives this node as offline and stops requesting the corresponding measurements. On the other side, the DAQ which is not in the status of beacon and communicates with a microcontroller monitors the presence of the coordinator following a similar algorithm. The DAQ has a scorecard for the coordinator and adds into the sum the value ‘1’ if the coordinator does not send a request for measurement in the expected timeframe of 0.28. For a successful receive of a request for measurements the DAQ subtracts the value ‘1’ of the scorecard. After the counter reaches the value of twenty, the DAQ considers the coordinator absent and re-enters the beacon mode.
3.4 Outcome and Selected Performance Indicators

The proposed monitoring system provides information about the operation of the machine related to the machining tasks. This is achieved by synchronising the physical with the digital world through the IoT based DAQs. The main outcome of the system that it increases the awareness on the resources for their actual status determination. The sensors identify whether the machine is ‘Processing’, ‘Non-Processing’, or in ‘Setup’. This information is useful in production scheduling activities where the knowledge on the actual availability of the resources is crucial to the design of feasible production schedules. Furthermore, the detailed information on the time periods that are required to perform specific tasks, along with the required setup times can make the future production schedules more accurate.

Moreover, the use of current and voltage sensors can provide accurate information on the electrical power consumption of the machine-tool and its independent drives. This knowledge can contribute towards the estimation of the electrical cost per product and

Figure 15: Supervisory mechanisms to detect malfunctions in the network. In black is the flowchart of the DAQ and in red is the flowchart of the Gateway.
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The monitoring method

the reduction of the environmental footprint of the production systems. As aforementioned, the output of the hall sensor can give insights on failures prior to their occurrence. Furthermore, the calculation of the actual machining time of the machine-tool subsystems enables a more efficient preventive maintenance planning, instead of making maintenance tasks into fixed time intervals without considering the usage of the machinery.

Based on these outputs of the monitoring system, a relevant set of performance indicators (PI) is selected. These performance indicators can be found in the following table (Table 1).

<table>
<thead>
<tr>
<th>PI Name</th>
<th>Description</th>
<th>Formula</th>
<th>Units</th>
<th>Refers to</th>
</tr>
</thead>
<tbody>
<tr>
<td>Processing Time</td>
<td>The total time that a machine is producing parts.</td>
<td></td>
<td>Hours</td>
<td>Machine/Task</td>
</tr>
<tr>
<td>Idle Time</td>
<td>The total time that a machine is powered up and in the ‘Non-processing’ status.</td>
<td></td>
<td>Hours</td>
<td>Machine</td>
</tr>
<tr>
<td>Up Time</td>
<td>The total time that a machine is powered up and able of producing parts.</td>
<td>ProcessingTime + IdleTime</td>
<td>Hours</td>
<td>Machine</td>
</tr>
<tr>
<td>Setup Time</td>
<td>The total time that the machine is in setup mode</td>
<td></td>
<td>Hours</td>
<td>Machine/Task</td>
</tr>
<tr>
<td>Remaining processing Time</td>
<td>The remaining processing time until the next maintenance task that is defined by the MTBF</td>
<td>MTBF - ProcessingTime</td>
<td>Hours</td>
<td>Machine</td>
</tr>
<tr>
<td>Utilisation</td>
<td>The percentage of the ProcessingTime over the UpTime</td>
<td>ProcessingTime / UpTime</td>
<td>%</td>
<td>Machine</td>
</tr>
<tr>
<td>Availability</td>
<td>The percentage of the IdleTime over the UpTime</td>
<td>IdleTime / UpTime</td>
<td>%</td>
<td>Machine</td>
</tr>
<tr>
<td>Instantaneous electrical power consumption</td>
<td>The instantaneous three-phase active power consumption as a product of the line voltage, line current, and the power factor of the load</td>
<td>( P = \sqrt{3} \cdot V_l \cdot I_l \cdot \cos \varphi )</td>
<td>W</td>
<td>Machine</td>
</tr>
<tr>
<td>Average electrical power Consumption</td>
<td>The average value of the instantaneous electrical power consumption</td>
<td>AVERAGE(P)</td>
<td>W</td>
<td>Machine/Task</td>
</tr>
<tr>
<td>Electrical energy consumption</td>
<td>The electrical energy consumption per machining task as a product of the average power consumption and the task duration</td>
<td>Average power consumption per task x total task duration</td>
<td>kWh</td>
<td>Task</td>
</tr>
<tr>
<td>Electrical cost per task</td>
<td>The cost for the electrical energy required by the machine-tools.</td>
<td>ElectricalEnergyConsumption x ElectricityCostPerKWh</td>
<td>€</td>
<td>Task</td>
</tr>
</tbody>
</table>

Table 1: The list of selected performance indicators (PIs) and their definition.

Except for these PIs that can be directly obtained, this IoT based monitoring system can give low level information as an input to PIs that are referring in the higher levels of the production hierarchy. Such PIs can be aggregations of the PIs presented in Table 1 and refer to the production line, such as the PI ‘production line availability’. Moreover,
composite PIs can be defined that require the measurement of more than one simple PIs and metrics. 

The final step in the data transmission is the Cloud server. The communication with the Cloud server is performed for two different purposes, the first is the live streaming of the measurements and the second is the task related information for future reference. The live streaming of the measurements is rather useful for the operators as they will be relieved from the obligation to stand next to the machine-tool for the whole duration of the tasks, and they will be able to supervise many machines simultaneously. Furthermore, both data streaming and the task reports are useful information for administrative purposes in the higher levels of the enterprise. In the Cloud level, integration with other industrial software modules, such as ERP and manufacturing execution systems (MES), can be performed. This facilitates the interoperability among various systems and the multi-directional information flow.
4. Design and developments of the DAQ

4.1 DAQ Version 1 (Proof of concept)

In the first step of the hardware developments, a DAQ with reduced operation was developed to validate the proof-of-concept of the method. For this purpose of the rapid prototyping, a microcontroller supported by a large community (Arduino) was selected. This microcontroller is the ATmega 2560 and the community provides an API for the IEEE 802.15.4/ZigBee communications and special functions for the electrical energy monitoring. In this version, only the split-core current transformers for the spindle, the moving axes, and the 3-phases of the mains were considered, and the corresponding sensor board was designed in the open-source PCB designing suite KiCAD (Figure 16). This board supported measurements for all 3-phases of the mains and experiments that were performed indicated that the machine-tools are balanced electric loads. Therefore, the next version of the DAQ included only one measurement for the mains current. Furthermore, this version supports communications only via ZigBee.

Figure 16: The first version of the sensor board supporting nine split-core current transformers.
4.2 DAQ Version 2 Specifications
The selected split-core current transformers have a transformer ratio of 1:2000 and are rated to 100A RMS nominal primary current. The closed-loop hall-effect sensor for the measurement of the spindle current is selected in comparison to an open-loop due to its immunity to temperature changes and the non-saturation of its core, therefore excellent linearity is achieved.

Following the monitoring method that was described in the previous section, the developed DAQ needs to comply with the appropriate specifications for supporting the selected sensors, communication capabilities, and computational requirements. Therefore, the STM32F429 microcontroller from ST Microelectronics was selected [72]. The microcontroller has the ARM Cortex-M4 microprocessor at its core and special processing units for digital signal processing (DSP) and floating point arithmetic. The operating frequency of 180 MHz along with the special processing units give the capability for real-time signal processing on the DAQ which is essential considering the sampling frequencies for the machine motor electrical operating characteristics.

For the measurements of the currents of the machine five axes drives and the mains, five analog inputs for the split-core current transformers are considered. Moreover, one analog input is specified for the mains line voltage measurement. The main benefits of the transformers as sensing devices are that they do not require auxiliary power supply for their operation and they can be acquired with low cost. Thus, they are ideal for cost-
efficient applications where high accuracy is not required. Due to the fact that the split-core sensors have a low frequency response of 60 Hz, an external analog to digital converter (ADC) is used instead of using the high-speed embedded ADC of the microcontroller. This ADC has 8 analog channels and operates in 6ksps that corresponds to a sampling frequency of 1 kHz for each split-core sensor. This corresponds to 20 samples per one period of 50 Hz. The communication with the microcontroller of the DAQ is performed via the SPI protocol.

For the closed-loop hall-effect current sensor a power supply of ±15 V is provided by a power supply board developed for this reason. The sensor has a frequency response of 200 kHz, for this reason the sampling is performed by the embedded ADC of the microcontroller at a variable sampling rate up to 1 Msps. The harmonic content of the current of the spindle is calculated by the fast Fourier transform (FFT) functions that are provided by ARM for the Cortex M microcontrollers.

### 4.3 Connectivity

The connectivity requirements for the DAQ are separated in two layers. The first layer considers the communication of the DAQ with external systems. Hence, for the communication with the microcomputer coordinator of the WSN a XBEE ZigBee module is installed. Moreover, to support the on-site and high speed data transmission for high resolution on the measurements, a USB serial interface is considered. In addition, to communicate with wireless sensors in small ranges or with mobile devices, a Bluetooth interface is also implemented. Finally, to provide openness in the hardware, a general purpose connector is added to support UART, SPI, and I2C communications.

The second layer includes the communication of the microcontroller with the other hardware peripherals inside the DAQ. This includes the communication with the ADC converter via 1.4 MHz SPI, and the communication with the XBEE via UART in 115200 bps. UART in the same baud-rate is implemented also for the Bluetooth and the USB communication. Taking advantage of the openness of the designed DAQ, other types of sensors are supported such as an accelerometer or a microphone.

The IoT philosophy considers interoperable systems with capabilities to support updates in an automatic manner. In this context, the digital input/output pins of the XBEE module are used to perform over-the-air updates on the microcontroller of the DAQ. This maintains the reconfiguration of the DAQ and the addition of features that will emerge as new requirements from industry as manufacturing evolves.

A block diagram representing the architecture and the components of the proposed DAQ is presented in Figure 18. The DAQ board was designed in KiCAD and a 3-dimensional model is presented in Figure 19.
Figure 18: The block diagram of the developed DAQ.

Figure 19: The 3-dimensional model of the developed DAQ.
4.4 ZigBee communications specification

The ZigBee specification is based on the IEEE 802.15.4 standard and operates on 2.5GHz. Digi provides modules for both IEEE 802.15.4 and ZigBee, which are the XBEE and XBEE Pro for the former case, and the XBEE2, XBEEPRO2, and PRO S2B for the latter. The modules for both communications have the pins for the UART communications in the same places, hence they can be used by the same infrastructure.

According to the datasheet for the ZigBee modules [71], the communications stack can be shown in Figure 20, and the corresponding description in Table 2.

![Figure 20: The layers of the communication stack of ZigBee [71].](image)

<table>
<thead>
<tr>
<th>ZigBee layer</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>PHY</td>
<td>Defines the physical operation of the ZigBee device including receive sensitivity, channel rejection, output power, number of channels, chip modulation, and transmission rate specifications. Most ZigBee applications operate on the 2.4 GHz ISM band at a 250kb/s data rate (details in IEEE 802.15.4 specification).</td>
</tr>
<tr>
<td>MAC</td>
<td>Manages RF data transactions between neighbouring devices (point to point). The MAC includes services such as transmission retry and acknowledgment management, and collision avoidance techniques (CSMACA).</td>
</tr>
<tr>
<td>Network</td>
<td>Adds routing capabilities that allows RF data packets to traverse multiple devices (multiple “hops”) to route data from source to destination (peer to peer).</td>
</tr>
<tr>
<td>APS (AF)</td>
<td>Application layer that defines various addressing objects including profiles, clusters, and endpoints.</td>
</tr>
<tr>
<td>ZDO</td>
<td>Application layer that provides device and service discovery features and advanced network management capabilities.</td>
</tr>
</tbody>
</table>

Table 2: The description of the layers in ZigBee communications stack as presented in [71].

In the context of this thesis the ZigBee firmware for the DAQ is developed supporting operation under API 2 with escaped characters. The data integrity within the transmitted
frames is checked through the checksum method and is calculated and verified on non-escaped data. Based on the directions of the Digi ZigBee manual [71] the receiver calculates the checksum and compares it with the one that is received to verify the data integrity. The ZigBee API frame has the structure that is depicted in Figure 21.

![The structure of the ZigBee frame](image)

**Figure 21:** The structure of the ZigBee frame [71].

### 4.6 Power supply board

The power requirements for the components of the DAQ are fulfilled by an auxiliary board that is developed for this purpose (Figure 22). The power supply is decided to be developed into a separate board to provide flexibility on the selection of the power supply components and reduce the total size of the DAQ. The required power is provided through DC-DC switching converters that operate approximately under the switching frequency of 20kHz.

![The 3-dimensional model of the power supply board](image)

**Figure 22:** The 3-dimensional model of the power supply board.

The switching voltage converters are developed using the modules of a control circuit developed by ST Microcontrollers. Hence, the board gains the power from a 24 V DC power supply and creates 15 V DC through a step-down (buck) converter, -15 V DC
through an inverting step-down (buck-boost) converter, 5.5 V DC through a step-down (buck) converter, and 3.3 V DC through a linear regulator with input the 5.5 V. The ±15 V are used for the power supply of the closed-loop Hall sensor. The 5.5 V is used for the power supply of the microcontroller, and thee 3.3 V for the power supply of the ADC, the XBEE, and the other electronic circuits of the system. The selection of the power supply from the linear regulator is driven by the requirements for reduced ripple in the power supply of the ADC and the Operational Amplifiers of the board.

4.5 Main design challenges

The development of the system met various design challenges. The first was the need for flexibility. This challenge was addressed by the selection of a microcontroller with adequate processing capabilities and a great number of available pins that can be used for various purposes. Moreover, the specification for over-the-air updates through the embedded bootloader that is provided for the microcontroller and the digital input/output pins of the XBEE, offers capabilities for remote updates of the system without huge efforts. Another aspect of the flexibility of the hardware lies with the potential for the addition of other sensors, such as an accelerometer or an acoustic sensor, along with the connectors of general purpose SPI, I2C, and UART communications, and the connectivity with Bluetooth and USB.

A second challenge is the requirements for operation in the electrical cabinet of the machine-tool which is an environment harsh in electromagnetic noise due to the presence of high switching currents created by the operation of the motor drives. To reduce the effects of the electromagnetic noise, especially in the analog measurements of the current sensors, co-axial shielded cables were used. Moreover, both split-core current transformers and the closed-loop Hall sensor have as outputs currents, which are less sensitive to noise than the voltage signals. Therefore, the measurement signal is transferred as a current signal through the coaxial cable, from the sensor to the DAQ board and the transformation to voltage is performed on the DAQ. Hence, less distortion of the signal occurs. The developed boards are presented in Figure 23.
Figure 23: The developed power supply board (left) and the developed DAQ hosting the microcontroller board (right).
5. Design and development of the gateway

5.1 Software development

The WSN is coordinated by a microcomputer which is responsible to collect all the data from the nodes of the network. These data are locally stored in the gateway and reports are created at the end of each task. These reports are then transmitted to the central server for administrative purposes. The selected microcomputer for this purpose is a Raspberry Pi 2 with a Linux operating system. The communication with the DAQs of the shop-floor is performed through an XBEE module on a USB-to-serial converter.

The measurements for each task are stored into a structured query language (SQL) database which has an entity relationship diagram (ERD) presented in Figure 24. The factory is modelled in a four-layer architecture that consists the factory, the job-shops, the workcenters, and the resources (in our case the resources are the machine-tools) [1]. Each machine belongs necessarily to a workcenter and therefore their relationship is an ‘identifying’ one. An ‘identifying’ relationship is selected also for each machining task, as it is necessarily assigned to a machine-tool. On the other hand, the measurements that refer to a machine-tool may belong to a task or correspond to the idle status. Hence the relationship between measurement and task is ‘non-identifying’.

As soon as the DAQs are connected with the microcomputer, the transmission of the data is initiated. The measurements that are transmitted every 0.25s from the DAQs are captured by the microcomputer and are stored in the database. The microcomputer adds a timestamp on each measurement, along with the machine status flag. The status is determined by comparing the measurements with calibration values that correspond to each individual machine. Therefore, the calibration levels must represent the threshold of the idle current for each one of the monitored electric motor drives. If the measurement exceeds this level the status is set to ‘Processing’, else the status is set to ‘Non-processing’. Moreover, if the proximity sensor that is attached on the door of the machine is triggered, the status is set to ‘Setup’.

At the end of the machining task, the microcomputer automatically performs a query to the database in order to retrieve the measurements related to this machining task. Subsequently, the necessary calculations are performed in order to create a task report that will be sent to the main server. The task report includes the timestamp of the start
and the end of the task, the total energy consumption, the total setup time, the total processing time, and the total non-processing time. The task report is transmitted via Hyper Text Transfer Protocol (HTTP) requests to the main server which is deployed on Cloud. The selection of a Cloud server provides ubiquitous access to information and flexible licensing schemes for the delivery of this monitoring system as a service [63]. Furthermore, the microcomputer can stream the measurements directly to the Cloud server for real-time visualisation of the monitoring results. This functionality, is of great importance in the case of distributed manufacturing environments, where the production control may be on a different location than the actual production.

5.2 OPC-UA compatibility

This IoT-based monitoring system is designed to support integration with existing industrial equipment. The Open Platform Communications – Unified Architecture (OPC-UA) standard has the potential to support integration of equipment of different vendors and architecture towards realising the Industry 4.0 vision [46]. The OPC-UA is a standard that allows servers to provide real-time process data, environment metadata and even non-process data to clients, in a unique and platform-independent way [73]. The OPC-UA can provide communications in all levels of manufacturing enterprises, from the resource to the factory level, via a service oriented architecture [74].

Figure 25: The information model for the OPC-UA integration.

OPC UA provides all data in its unified address space. It can represent anything starting from a simple variable to a complete machine. The OPC-UA provides an extensible data model which provides the data schema. Hence, even systems that are not familiar with the data model can retrieve information from other systems. The client can browse
through the server to gather the required information and understand its content through metadata and semantic representation. In the proposed system the microcomputer acts as an OPC-UA server with binary encoding. The information model follows the specification [75] and is designed to correspond to the data stored into the SQL database. In Figure 25 a reduced version of the model, which does not include the job-shop and workcenter objects, along with the low level variables and variable types is presented for simplicity. The main objects of the information model are the shop-floor, machine, task, spindle, axis, and measurement. The relationships among them are defined through the references “HasComponent”.
6. Experiments

6.1 Status identification and task report generation

In order to ensure the appropriate operation of the developed DAQ, the outputs of the sensors were calibrated using the MAVOWATT 20 [76], which is a commercial energy measurement system. After performing this calibration and extracting the appropriate coefficients, the developed system was installed in a 3-axis machine-tool to evaluate its performance. All functionalities were tested in real manufacturing environments except for the Hall effect sensor of the spindle which will be evaluated in future work along with a pattern recognition method. Nevertheless, the relevant signal processing firmware for the microcontroller was evaluated using test signals with results depicted in Figure 26.

![Figure 26: Test signal \(x(t) = \sin(2\pi \cdot 1000 \cdot t) + 0.5\sin(2\pi \cdot 2 \cdot 1000t)\)](image)

The evaluation of the developed system was performed on an XYZ SMX SLV 3-axis machine-tool with specifications presented in Table 3. The developed DAQ was installed in the electrical cabinet of the machine and measurements were captured for machining tasks of short and long duration respectively. The measurements were stored in the database in a rate of two measurements per second.

<table>
<thead>
<tr>
<th>XYZ SMX SLV Turret Mill</th>
</tr>
</thead>
<tbody>
<tr>
<td>Spindle drive motor</td>
</tr>
<tr>
<td>Spindle max velocity</td>
</tr>
<tr>
<td>Longitudinal travel - X axis</td>
</tr>
<tr>
<td>Cross travel - Y axis</td>
</tr>
<tr>
<td>Knee vertical travel - Z axis</td>
</tr>
<tr>
<td>Overall power consumption</td>
</tr>
</tbody>
</table>

*Table 3: Specifications of the XYZ SMX SLV case study.*

The results from the short duration machining task are presented in Figure 27. The duration of this task was approximately 3.5 minutes and included a small milling
operation. In Figure 27, the discrete events that are associated with the variations in the level of the power consumption are identified and marked. The first event that corresponds to a very high peak in the apparent power is the acceleration of the spindle. This high peak is justified by the fact that an induction motor consumes approximately 7 times higher values of current when accelerated from zero rpm. Following the spindle peak, the power consumption rises a little when the positioning of the Z-axis is performed. During the material removal process, a rise in the overall power consumption can be observed. Finally, a peak, but significantly lower than the spindle’s, can be observed when positioning of the axes is performed in rapid feed. From the graph, it can be concluded that even though in the selected machine tool the peripherals account for a little portion of the overall power consumption, the portion that is related to the actual machining process is very small. The largest portion of the energy consumption in this machine tool is related to the spindle movement.

Subsequently, the DAQ was collecting measurements from the machine-tool for a whole milling operation in order to correlate the measurements with the actual status of the resource. The operation lasted approximately 130 minutes and the measurements that correspond to the apparent power consumption and the current of the spindle motor are presented in Figure 28. Moreover, the discrete events of the operation are identified and marked in Figure 28.
The task report that is generated from the IoT-based monitoring system and refers to 
the long-term milling task that is depicted in Figure 28 are presented in Table 4.

<table>
<thead>
<tr>
<th>Database field</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Task id</td>
<td>10005</td>
</tr>
<tr>
<td>Task Name</td>
<td>MILL5</td>
</tr>
<tr>
<td>Start DATETIME</td>
<td>2016-04-12T11:44:03.314025</td>
</tr>
<tr>
<td>End DATETIME</td>
<td>2016-04-12T13:55:05.156367</td>
</tr>
<tr>
<td>Processing Time</td>
<td>6,135 s</td>
</tr>
<tr>
<td>Non-processing time</td>
<td>179 s</td>
</tr>
<tr>
<td>Setup Time</td>
<td>1,187 s</td>
</tr>
</tbody>
</table>
| Average Power 
Consumption | 1,303 VA                       |
| Electrical Energy 
Consumption       | 0.896 kWh                      |

Table 4: The task report that is generated for the long-term milling task.

Considering the fact that the advent of thousands of IoT devices may result into storage 
bottlenecks, the data that is generated and stored in each level of the proposed 
monitoring system, referring to the operation of one machine, are depicted in Table 5.

The electrical current consumption of the developed DAQ was measured of an RMS 
value of 90 mA which corresponds to 2.16 Watts of power consumption using a power 
supply providing 24 V DC. The low power consumption is resulted due to the low 
power consumption of the ST Microcontroller and the selected peripheral devices.
Moreover, the power supply electronic circuits that have been developed are switching DC-to-DC converters, instead of linear voltage regulators that are characterised by their low energy efficiency.

<table>
<thead>
<tr>
<th>Sensor</th>
<th>Sampling rate</th>
<th>Megabytes per hour</th>
</tr>
</thead>
<tbody>
<tr>
<td>Spindle Closed-loop Hall sensor</td>
<td>1 MHz</td>
<td>13.733</td>
</tr>
<tr>
<td>Axis X split-core CT</td>
<td>1 kHz</td>
<td>13.733</td>
</tr>
<tr>
<td>Axis Y split-core CT</td>
<td>1 kHz</td>
<td>13.733</td>
</tr>
<tr>
<td>Axis Z split-core CT</td>
<td>1 kHz</td>
<td>13.733</td>
</tr>
<tr>
<td>Mains current split-core CT</td>
<td>1 kHz</td>
<td>13.733</td>
</tr>
<tr>
<td>Mains voltage insulation</td>
<td>1 kHz</td>
<td>13.733</td>
</tr>
<tr>
<td>transformer</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Proximity sensor (For setup mode)</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>SUM</td>
<td>-</td>
<td>13,802</td>
</tr>
</tbody>
</table>

Transmitted to the next level (i.e. gateway)

<table>
<thead>
<tr>
<th>Value</th>
<th>Size in bytes</th>
<th>Kilobytes per hour</th>
</tr>
</thead>
<tbody>
<tr>
<td>Spindle current RMS</td>
<td>4</td>
<td>56.25</td>
</tr>
<tr>
<td>Axis X current RMS</td>
<td>4</td>
<td>56.25</td>
</tr>
<tr>
<td>Axis Y current RMS</td>
<td>4</td>
<td>56.25</td>
</tr>
<tr>
<td>Axis Z current RMS</td>
<td>4</td>
<td>56.25</td>
</tr>
<tr>
<td>Mains current RMS</td>
<td>4</td>
<td>56.25</td>
</tr>
<tr>
<td>Mains power consumption</td>
<td>4</td>
<td>56.25</td>
</tr>
<tr>
<td>Machine-tool power factor</td>
<td>4</td>
<td>56.25</td>
</tr>
<tr>
<td>Setup (ON/OFF)</td>
<td>1</td>
<td>14.06</td>
</tr>
<tr>
<td>SUM</td>
<td>29</td>
<td>407.81</td>
</tr>
</tbody>
</table>

Gateway Level

<table>
<thead>
<tr>
<th>MySQL database table</th>
<th>Bytes per table</th>
<th>Kilobytes per hour</th>
</tr>
</thead>
<tbody>
<tr>
<td>Factory</td>
<td>52</td>
<td>-</td>
</tr>
<tr>
<td>Job-shop</td>
<td>56</td>
<td>-</td>
</tr>
<tr>
<td>Workcenter</td>
<td>60</td>
<td>-</td>
</tr>
<tr>
<td>Machine</td>
<td>144</td>
<td>-</td>
</tr>
<tr>
<td>Task</td>
<td>72</td>
<td>-</td>
</tr>
<tr>
<td>Measurement</td>
<td>100</td>
<td>1,406</td>
</tr>
<tr>
<td>Fixture</td>
<td>52</td>
<td>-</td>
</tr>
<tr>
<td>SUM</td>
<td>528</td>
<td>1,406</td>
</tr>
</tbody>
</table>

Transmitted to the next level (i.e. Cloud server)

<table>
<thead>
<tr>
<th>Task Report</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>72 bytes per task</td>
<td></td>
</tr>
</tbody>
</table>

Table 5: The data bytes generated and transmitted to each level.
6.2 Case based reasoning for energy consumption estimation [27]

The establishment of the IoT paradigm in manufacturing results into the generation of production related information that can provide knowledge that can be exploited in order to improve manufacturing operations. In this context, knowledge reuse mechanisms should be employed to communicate the knowledge of the previous tasks to the planning of the new ones.

The Case-Based Reasoning (CBR) process is a problem solving technique that relies on the reuse of past experience. The main benefit of CBR is that it can be used as a similarity measurement among different cases [77]. The CBR method is utilised in this research work due to its suitability for complex and difficult to model systems, such as machine tools, and because case generalization is required. This technique has been successfully applied in various domains such as design, decision making, planning, diagnosis, medical applications, law, e-learning, knowledge management, image processing or recommender systems, etc. [78].

To enhance the information that refers to a machining part with the requirements of energy consumption, a method for the energy consumption estimation in machining operations is utilised in this scientific work. Leveraging the information and knowledge that lies in historical data. This method exploits the knowledge on the machining tasks that is sent to the Cloud server by the aforementioned monitoring framework. This knowledge retrieval is performed through the CBR methodology, along with a similarity mechanism.

In this paragraph, a brief state-of-the-art review has been performed on the subject of energy consumption estimation. Dahmus [79] performs a high level recording of the energy consumption in machining processes to identify the contribution of the machine tool subsystems. The rest of the scientific work on this subject can be classified in the categories of theoretical modelling, the generalisation of experimental data, and the use of real-time monitoring. Avram and Xirouchakis propose in [80] an analytical model for the estimation of the variable mechanical energy requirements of a machine tool system with experimental verification. This approach takes into account both steady-state and transient conditions. The exploitation of experimental results to conclude on a model for the estimation of energy consumption based on the material removal rate (MRR) has been performed in [81]. In a higher level, a framework was proposed by [82], based on multi criteria decision making methods to incorporate energy consumption and environmental impact considerations. Therefore, the assignment scheme results to the reduction of the energy consumption of the manufacturing plant.

The effect of the cutting parameters modification on the power consumption of machine tools is also investigated by [83]. Furthermore, the authors leveraged their capability to
modify the control method of the spindle and the axes to reduce the energy consumption by synchronizing the spindle acceleration with the feed system.

The method that is followed in this scientific work combines the real-time monitoring framework with the CBR to estimate the energy consumption in a machining task. The choice of using a cased-based approach to estimate the power consumption is mainly driven by the fact that the machine tool capabilities are scarcely exploited in real life machining operations [84] supported by the fact that the machining power consumption accounts for less than 60% of the overall under full load [79]. These two facts allow the estimation of the power consumption in a more abstract level without constructing a detailed mathematical model that is bounded with specific machine tools. This procedure is facilitated by the CBR methodology and the similarity mechanism. Case Based Reasoning (CBR) focuses on solving problems by adapting acceptable solutions and comparing differences and similarities, between previous as well as current products (Figure 29).

The CBR takes as inputs information from the process plan that is related to a new part and include the raw material, the cutting parameters, and the use of lubrication, along with the machine tool and cutting tool parameters. The detailed algorithm for the similarity mechanism that is employed in this work is presented in Figure 30 [78]. The similarity mechanism distinguishes the features in two categories, i.e. the numerical and the alphanumerical. The similarity for the numerical features is calculated through the normalised ratio of the new feature over the old feature. For the alphanumerical features a similarity equal to 1 is assigned if the features are the same and the similarity equal to 0 is assigned if the features are not the same. The similarities for the individual
features are then multiplied by the corresponding weights and then the results are combined to conclude to the overall similarity of the two cases.

Figure 30: A detailed presentation of the similarity mechanism used in the presented CBR methodology.

The weight assignment has been according to the reflection of each feature on the overall power consumption as it was indicated in experiments in various situations. A
detailed presentation of the selected features and the corresponding weights can be found in Table 6.

<table>
<thead>
<tr>
<th>Feature</th>
<th>Type</th>
<th>Weight</th>
</tr>
</thead>
<tbody>
<tr>
<td>Machine specifications</td>
<td></td>
<td>40%</td>
</tr>
<tr>
<td>Spindle power</td>
<td>Num</td>
<td>20%</td>
</tr>
<tr>
<td>Overall power</td>
<td>Num</td>
<td>20%</td>
</tr>
<tr>
<td>Process plan parameters</td>
<td></td>
<td>55%</td>
</tr>
<tr>
<td>Depth of cut (mm)</td>
<td>Num</td>
<td>5%</td>
</tr>
<tr>
<td>Spindle rpm utilisation</td>
<td>Num</td>
<td>20%</td>
</tr>
<tr>
<td>Feedrate (mm/min)</td>
<td>Num</td>
<td>10%</td>
</tr>
<tr>
<td>Material (mm)</td>
<td>Alpha</td>
<td>10%</td>
</tr>
<tr>
<td>Use of lubricant</td>
<td>Alpha</td>
<td>10%</td>
</tr>
<tr>
<td>Tool parameters</td>
<td></td>
<td>5%</td>
</tr>
<tr>
<td>Teeth number</td>
<td>Num</td>
<td>1%</td>
</tr>
<tr>
<td>Width of cut</td>
<td>Num</td>
<td>1%</td>
</tr>
<tr>
<td>Tool material</td>
<td>Alpha</td>
<td>3%</td>
</tr>
<tr>
<td>Sum of weights</td>
<td></td>
<td>100%</td>
</tr>
</tbody>
</table>

Table 6: The features and the corresponding weights that are used in the CBR

After performing pairwise comparisons with the historical data of past cases, a similarity mechanism returns the most similar cases. Hence, the process planning engineer is aware on the energy consumption of the new part and the machining strategy that was followed in the past. The output of this mechanism is the process plan information and the average power consumption of the most similar cases. Therefore, the engineer can reuse information from past process plans and also estimate the energy consumption of the new part using the past case average power consumption and the machining time that is calculated in the CAM tool.

An important benefit of the CBR is that knowledge can be retrieved for different goals by selecting different features that are stored in a database and the appropriate weights. For example, the process plan engineer can use the CBR with other features to get results on similarity according to geometrical features.

The outcome of the similarity mechanism is that the new case is most similar with case two by a percentage of 96.67%. The final phase of the CBR is the adoption of the similarity degree to further estimate the power consumption of the new case. The 96.67% indicates a power consumption of 1555 VA for the new case. This value can be verified by the results of the experiments and also by the Figure 4 which demonstrates the power consumption profile of the new case.
### Table 7: The set of experiments and the results.

<table>
<thead>
<tr>
<th>Feature</th>
<th>Case1</th>
<th>Case2</th>
<th>Case3</th>
<th>Case4</th>
<th>New case</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Machine specifications</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Spindle power (kW)</td>
<td>3.75</td>
<td>3.75</td>
<td>3.75</td>
<td>3.75</td>
<td>3.75</td>
</tr>
<tr>
<td>Overall power (kW)</td>
<td>10</td>
<td>10</td>
<td>10</td>
<td>10</td>
<td>10</td>
</tr>
<tr>
<td><strong>Process plan parameters</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Depth of cut (mm)</td>
<td>2</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>Spindle rpm utilisation (mm/min)</td>
<td>0.439</td>
<td>0.447</td>
<td>0.414</td>
<td>0.447</td>
<td></td>
</tr>
<tr>
<td>Feedrate (mm/min)</td>
<td>100</td>
<td>200</td>
<td>100</td>
<td>300</td>
<td></td>
</tr>
<tr>
<td>Material</td>
<td>Alum.</td>
<td>Alum.</td>
<td>Steel</td>
<td>Alum.</td>
<td></td>
</tr>
<tr>
<td>Use of lubricant</td>
<td>No</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td></td>
</tr>
<tr>
<td><strong>Tool parameters</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Teeth number</td>
<td>2</td>
<td>4</td>
<td>2</td>
<td>4</td>
<td></td>
</tr>
<tr>
<td>Width of cut</td>
<td>10</td>
<td>10</td>
<td>10</td>
<td>10</td>
<td></td>
</tr>
<tr>
<td>Tool material</td>
<td>S.Carb.</td>
<td>HSS</td>
<td>S.Carb.</td>
<td>HSS</td>
<td></td>
</tr>
<tr>
<td>Similarity with new order (%)</td>
<td>85.73</td>
<td>96.67</td>
<td>86.56</td>
<td>-</td>
<td></td>
</tr>
<tr>
<td>Estimated average power consumption</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>1555</td>
<td></td>
</tr>
<tr>
<td>Actual average power consumption</td>
<td>1395</td>
<td>1502</td>
<td>1465</td>
<td>1562</td>
<td></td>
</tr>
</tbody>
</table>
7. Emerging business models

The adoption of IoT, in the process of the digitalisation in manufacturing, results into opportunities for novel business models and improvements in the manufacturing operations. Firstly, this section deals with the identified benefits of the digitalisation of manufacturing and specifies them as the impact of the IoT paradigm. Subsequently, the opportunities for the equipment-as-a-service and the manufacturing-as-a-service business models are briefly presented.

7.1 Benefits for manufacturing

As identified the by McKinsey in [85], the benefits of the digitisation of manufacturing lie in the increasing of the resources utilisation, reducing the total machine downtime, increasing the productivity by automating the knowledge work, reduce inventory costs, reduce quality costs, increase forecasting accuracy, reduce the time to market, and reduce the maintenance costs. Towards these ends, the IoT can contribute to the increase of the resources utilisation by identifying their actual status, reduce the machine downtime through condition-based preventive maintenance [26] and predictive maintenance by processing of the data gathered from the sensors, and knowledge reuse through machine-to-machine communications and information retrieval from the Cloud server [27]. These aspects were implemented and discussed in the context of this thesis and their quantification has been documented in the referred report by McKinsey (Table 8).

<table>
<thead>
<tr>
<th>Value drivers</th>
<th>Quantification of value drivers</th>
</tr>
</thead>
<tbody>
<tr>
<td>Resource/process</td>
<td>Productivity increase by 3-5%</td>
</tr>
<tr>
<td>Asset utilisation</td>
<td>Reduction of total machine downtime 30-50%</td>
</tr>
<tr>
<td>Labour</td>
<td>Increase of productivity in technical professions through automation of knowledge work by 45-55%</td>
</tr>
<tr>
<td>Inventories</td>
<td>Costs for inventory holding decrease by 20-50%</td>
</tr>
<tr>
<td>Quality</td>
<td>Costs for quality reduced by 10-20%</td>
</tr>
<tr>
<td>Supply/demand match</td>
<td>Forecasting accuracy increased to 85+%</td>
</tr>
<tr>
<td>Time to market</td>
<td>Reduction in time to market by 20-50%</td>
</tr>
</tbody>
</table>

*Table 8: The quantification of the value drivers for the digitization in manufacturing [85]*

7.2 Equipment-as-a-Service

The IoT paradigm can enable the data capturing from manufacturing resources with the purpose of creating novel business models such as the Equipment-as-a-Service (EaaS) provision of equipment. Therefore, instead of having high fixed costs/capex, the cost of machinery can be translated into variable costs/opex. This can be a win-win situation for both equipment providers and product manufacturers. Hence, the equipment providers gain continuous benefit of the equipment through services that they provide. The real-life data can lead to the improvement of the equipment. On the other hand, the
manufacturers gain access to equipment that may not be affordable before. Moreover, the manufacturing systems are constantly up-to-date with the new technological advances in their equipment. For this provider-customer relationship, the collected data from the manufacturing systems need to respect the IPR of the customer, the manufacturer.

A recent successful example of the equipment as-a-service business model is the Philips Light-as-a-Service which supports also the transition to a circular economy. This has been applied in the Amsterdam Schipol Aerport, where the airport pays for the amount of light that it uses, while Philips and the collaborating companies remain the owners of the infrastructure and maintain its proper operation [86]. This business model can be found under the Industrial Machines-as-a-Service (IMaaS) [87] or Machines-as-a-Service (MaaS) terminology [88].

Moreover, with the use of the framework developed in this thesis, the EaaS business model can also been extended in the machine-tool market that has gained a significant economic growth the last years. The machine-tool manufacturing industry is important for the EU economy as it accounts for the 40% of the global machine-tool production share[89] (Figure 31).

![Figure 31: The machine-tool production rates in EU for the last years [89].](image)

### 7.3 Manufacturing-as-a-service

The IoT and the philosophy of Cloud Manufacturing can transform also the relationships of the manufacturer and the customer. Through the novel business model of manufacturing-as-a-service, and a novel platform that integrates the manufacturers into a digital ecosystem; flexible manufacturing services can be provided to the customers.

This vision considers a Cloud platform which gives the capability to the customer to enter the design of a new product, and automatically identify the features that need to
be machined (pockets, slots, holes, etc.). In the next step, the required bill of material (BOM) and a generic process plan is extracted automatically, based on the machining features. Subsequently, the platform communicates with the manufacturers that are registered in the collaboration network to identify their availability. This part is where the IoT contribute. The IoT monitoring devices are installed in the shop-floors of the manufacturers and collect information about the production schedule and the utilisation of the resources in order to determine their availability for the new job. The manufacturers are notified for the new job and verify their availability and the corresponding price. Then, this information related to the available manufacturers and the lead times that they can offer, along with the corresponding price for the job is provided to the customer through the platform. After the selection of the manufacturer by the customer, the platform generates the process plan for the specific resources that will be used for the job.

This vision can support the regionalisation of manufacturing by providing services near the customer. Moreover, the registered SMEs in the network can benefit from this collaboration and provide cost-efficient manufacturing services with short lead times.
8. Conclusions and future work

This scientific work presented a machine-tool monitoring framework based on the IoT paradigm. The framework consists of three layers i.e. the DAQs in the machine-tools, the microcomputer gateway with the local database, and the central Cloud gateway. The developed method provides automatically reports on the tasks performed in a shop-floor, which is a task that up until now included a lot of manual work. This provides new capabilities for manufacturing companies to advance into the digital era and harvest the benefits that arise. Moreover, the developed system enables the control of distributed manufacturing environments through the Internet and Cloud technologies.

The DAQs are installed in the electrical cabinets of the machine-tools and employ sensors to capture measurements related to their operation. All the DAQs of the shop-floor are connected with a microcomputer in a WSN. The use of the ZigBee specification allows flexibility into the addition of new nodes in the network and robust operation. The results of the machine-tool monitoring are stored locally on the microcomputer, where task reports are created and sent to a Cloud server for administrative and knowledge reuse purposes. A CBR methodology for the knowledge reuse is utilised in order to estimate the energy consumption of new parts in machining industry. The similarity mechanism of the CBR resulted into a good estimation of the average electrical power consumption for machining operations and can be extended to provide more information such as the cutting parameters used in past cases.

The main outcome of the system is the increase of the awareness on the actual status of the manufacturing resources and the support to the integration with existing industrial systems via the OPC-UA communication standard and Internet Web-services. This aspect of integration and interoperability is of crucial importance in a digitised ecosystem.

Other benefits of the system are the easy installation in the electrical cabinet of the machine-tools and its non-intrusive nature as it does not require modifications in the electrical wiring of the machine. Moreover, the selected sensors and electronics are cost efficient that enables the purchase of the DAQ and the gateway with low investment. The low cost, along with flexible licensing models that are facilitated by the Cloud technologies make the system ideal for SME manufacturers.

In the future work, the integration with the Cloud server and its corresponding software that visualises the data captured by the sensors and communicates with the scheduling module of a planning system and the operators of the machine-tools will be fully exploited. All this information from the heterogeneous sources will be fused through an information fusion technique to enhance the captured results. In this context, detailed
information on the machining tasks will be provided by the integration with the industrial software and process related information such as cutting parameters will be provided from the operator. Moreover, in the future work, the OPC-UA model for machine-tools will be presented in detail along with the corresponding software developments. Finally, the installation of the system in the shop-floor of a machining SME will provide the required dataset for the identification of the status of various machine-tools and its correlation with the harmonic content of the spindle current.
9. Acknowledgments

The work presented in this thesis is partially supported by the EU funded research project “Collaborative and Adaptive Process Planning for Sustainable Manufacturing Environments – CAPP4SMEs” (314024), and the EU funded research project “Advancing Legacy Machine Tools into the Digital Manufacturing Century – LegInt” from the “CPS Engineering Labs - expediting and accelerating the realization of cyber-physical systems” (644400).

I would like to express my gratitude to my supervisor Prof. Dimitris Mourtzis and Prof. George Chryssolouris for introducing me to the topic as well for the support on the way. Furthermore, I would like to thank my colleague Katerina Vlachou, PhD candidate, for the useful comments, remarks and engagement through the learning process and the developments of this master thesis. Also, I would like to thank all the members of the Laboratory for Manufacturing Systems and Automation (LMS) for the excellent collaboration these two years.
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