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A cloud-based cyber-physical system for adaptive shop-floor scheduling and condition-based maintenance

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ABSTRACT

Manufacturing, through the Industry 4.0 concept, is moving to the next phase; that of digitalization. Industry 4.0 enables the transition of traditional manufacturing systems to modern digitalized ones, generating significant economic opportunities by reshaping of industry. This procedure requires high-performance processes and flexible production systems. The adoption of the Internet of Things (IoT) in manufacturing will enable effective and adaptive planning and control of production systems. Towards that end, the proposed work presents a cloud-based cyber-physical system for adaptive shop-floor scheduling and condition-based maintenance. The proposed system demonstrated that it is possible to deploy a cost-effective and reliable real-time data collection, processing, and analysis from the shop floor. It also demonstrates that such collected data can be used in an adaptive decision making system, which includes a multi-criteria decision-making algorithm and a condition-based maintenance strategy aiming to improve factory performances when compared to traditional approaches. The proposed system consists of different modules (monitoring, adaptive scheduling, condition-based maintenance) interconnected through the cloud-based platform, enabled by communication protocols under the Industry 4.0 and IoT paradigms. The proposed system is applied and validated in a real-case study from a high-precision mold-making industry.

1. Introduction

Traditional manufacturing, through the fourth industrial revolution, is transformed into a digital ecosystem [1]. In this transformation, the Internet of Things (IoT) and the Cyber-Physical Systems (CPS) hold a major role. The advent of modern technologies such as cyber-physical systems, IoT, and the cloud technology 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 an integrated whole that follows the System of Systems (SoS) paradigm [2]. 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 CPS [3].

Moreover, the integration of smart sensory systems, wireless sensor networks, as well as industrial communication protocols will support industries in adopting new ICT-based tools or to transform existing ICT-based production systems into adaptive ones. The interfacing of ICT-based systems with monitoring systems can provide the desired awareness of shop-floor condition, which is necessary for the realization of adaptive shop-floor planning and control. In parallel, the enabling technology of smart sensor networks can support in bridging the current gap in information distribution [4,5]. Web technologies, and especially cloud technology, can be used to establish integration interfaces in between disparate IT tools and enable a common data flow. Existing cloud-based applications in manufacturing have pointed out that the use of cloud technology enables the ubiquitous access to information and minimizes investment costs, among other key benefits that it offers [6].

To leverage the modern technologies towards the digitalisation of contemporary manufacturing systems, this paper presents a cloud-based cyber-physical system for shop-floor scheduling and control following the IoT and Industry 4.0 paradigms. The proposed system includes a monitoring system supported by a wireless sensor network. The monitoring system collects information from different sources (sensors, mobile devices, other IT systems) and analyses it through an information fusion technique [7] in order to derive meaningful information. Industrial communication protocols as well as security mechanisms are implemented. The storage of the gathered information is performed in a cloud server, along with the visualisation of the results

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to the end-user. The derived data are utilized as input in a scheduling algorithm in order to perform adaptive scheduling. In addition to that, the data is utilized as main input in a condition-based maintenance approach [8] which is developed within the proposed work. Exploiting cloud-based remote connectivity capabilities, the proposed system is delivered under the Software-as-a-Service (SaaS) model that can be applied in parallel in more than one manufacturers.

Modern manufacturing systems have to serve the increasing need for heavily customized products and deal with turbulences on their shop-floors which lead to increased complexity and difficulties during decision-making [9]. One of the main current challenges in production scheduling is the generation of efficient schedules under uncertainty factors [10]. Towards that, the proposed architecture aims to support adaptive scheduling taking into consideration not only monitoring data from shop-floor but also data related to maintenance.

The structure of the paper is organised as follows. Section 2 deals with the literature review on the technologies and the previous approaches related to the proposed cloud-based cyber-physical system. Section 3 describes the proposed method followed in this paper. Section 4 presents the hardware and the software developments. In Section 5, the case study where the cloud-based cyber physical system was evaluated is analysed. The results and the relevant discussion are presented in Section 6. Finally, Section 7 concludes the paper.

2. State of the art

CPSs 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)"[11]. CPSs link the physical with the virtual world through flexible, cooperative, and interactive operation [12]. In the context of CPS, complex and heterogeneous large-scale systems are integrated through the service-oriented architecture (SOA), to deliver high performance and reliable operation [13]. In the digitalised era, the quality of services plays a crucially important role in meeting the emerging demands of customization and personalization. The adoption of CPS in industry is defined with the term Cyber-Physical Production Systems (CPPS) [3]. Towards the creation of Industry 4.0 factories, a stepwise approach is introduced for the design of CPS in manufacturing systems [14]. Moreover, the modelling of CPPS can be performed by following commonly accepted description frameworks such as the EAST-ADL modelling language. Apart from the connection with the tangible resources, the CPS can be extended with in-industry social media usage towards Social Manufacturing [15].

The physical entities enter the cyber world through microelectronic devices and internet communication protocols following the IoT paradigm [16]. Applications of Industrial IoT (IIoT) can empower the three pillars of the modern industry, i.e. the process optimization, the optimized resource consumption, and the creation of complex autonomous systems [17]. The robustness of the existing industrial networks makes them eligible candidates for several IIoT applications. Existing applications of IIoT have already demonstrated their potential in real-life case studies [18]. A key enabling technology for the digitalization of the modern industry is cloud manufacturing [19], as it enhances the integration of various industrial IT tools, and provides ubiquitous access to information and flexible licensing models [6]. Two major challenges that can decelerate the adoption of cloud manufacturing are the quality of services and the intellectual property protection [20]. Security is one of the main issues as different security protocols and standards should be developed and used, increasing data security and enabling companies to share their data.

The CPS paradigm suggests the use of monitoring devices under the IoT philosophy that goes beyond the traditional approaches for on-site data collection, processing, and visualisation. The main requirements for monitoring systems are to be robust, reconfigurable, reliable, intelligent and cost-efficient [4]. Various technologies of sensors can be employed for monitoring purposes. In the case of measuring energy-related operation characteristics, electrical current sensors are the most appropriate as they are cost-efficient and non-intrusive in nature [21]. A relatively new approach for monitoring, relevant to the resource awareness in the concept of CPS, is the machine-tool availability monitoring [22]. Despite the fact that various topologies for the communication of monitoring devices can be employed, in discrete manufacturing systems, the wireless sensor network topologies are the most eligible candidates as they offer flexibility and scalability, especially in environments such as the shop-floors [23][6]. A wireless sensor network consists of a large number of wireless-capable sensor devices, working collaboratively to achieve a common objective to increase or reduce production KPIs [24].

The use of various and heterogeneous types of sensors in monitoring systems requires specific manipulation of their output in order to extract meaningful information. This information extraction from various sources is realised through information fusion methodologies [7]. In 1988, concerning the topic of tool wear estimation in machining, [25] mentioned that the synthesis of system information can provide a number of benefits in process monitoring, such as maximum amount of information for making control decisions or reliable information during the process. The information fusion architectures are referred to as sensor level fusion, feature level fusion and decision level fusion [7]. In the decision level fusion, the Dempster-Shafer (DS) theory of evidence is mostly used, as in the work of [26], which aimed to identify the condition of a diesel engine. The Analytical Hierarchy Process (AHP) is coupled with the Dempster-Shafer theory in order to extract the corresponding weight for each source of information [21,27]. Several literature reviews have been performed regarding data fusion techniques. One of them is performed by Castenado in [28], explaining the different classification schemes for data fusion and reviewing the most common algorithms. The last years, most of the data fusion techniques were enhanced and enriched in order to deal with big data analysis. Zheng in [29] presented a review of data fusion methodologies, classifying them into different categories aiming to support the communities to find a solution for data fusion in big data projects. Another interesting review of Big Data analytics algorithms is presented by Ahmed et al., in [30], emphasizing on their role in Internet of Things and presenting several open challenges as future research directions.

Once the data are retrieved from the shop-floor, they are analyzed and meaningful information can be provided to the IT production systems, transforming them from isolated to adaptive. Several approaches have been reported in literature related to dynamic scheduling. Chryssolouris et al. in, [31] proposed a dynamic scheduling approach for manufacturing job shops using genetic algorithms and multiple criteria evaluation of alternative schedules. Michalos et al. [32] present a novel web-based tool for dynamic job rotation scheduling based on a multi-criteria intelligent search algorithm. The development of a multilevel adaptive control and scheduling solution for reconfigurable manufacturing environments from a real-time system automation perspective is proposed in [33]. Solution approaches for real-time control of manufacturing systems are also proposed by Monostori et al. in [34], where a scheduling system integrated with production monitoring subsystems is introduced to deal with common daily production disturbances. Furthermore, another dynamic scheduling approach is presented by Kumara et al. [35] by modelling dynamic scheduling systems as a virtual economy, where the "resource timeslots" are traded as goods.

During the last years, a number of research works have also introduced real-time scheduling. Subramanian et al. analyzed real-time scheduling algorithms for coordinated aggregation of deferrable loads and storage. In this study the authors compared three different scheduling policies and investigated their performance through simulations [36]. Buyurgan and Saygin proposed a multi-criteria decision-making algorithm for real-time scheduling and part routing solutions by implementing pairwise comparison of possible future states of a manufacturing system [37]. Yan and Wang proposed a two-layer dynamic scheduling approach for a reentrant production line, considering that all the parts have the same processing routes and need to be processed on every machine [38]. Wang et al. in [39], presented a real-time scheduling method based on timed Discrete Event Simulation (DES) running on uni-processors. Although the proposed real-time scheduling algorithm is interesting the shift towards digitalization and Industry 4.0 paradigm, and the collection and analysis of real-time measurements from IoT-based application for adaptive decision-making remain main challenges for further research. Another approach of real-time scheduling is presented by Zhang et al. in [40]. In this work, the authors proposed a game theory based real-time shop-floor scheduling strategy considering also cloud manufacturing. The paper implements a dynamic optimization model considering data from one source, the RFID sensors, however the parts regarding the data analysis and the application in real-industrial environments are filed of further investigation. Although the last years there have been research work related to dynamic and real-time scheduling, it is hard to achieve effective real-time scheduling due to the inefficient feedback of real-time information in the shop-floor as well as the gap between planning and control [41]. The idea behind adaptive and real-time scheduling is for the scheduling algorithm to become aware of the different information coming from shop-floor, regarding suitability and availability of the resources when performing assignments of resources to tasks, regarding machine tools status, regarding human operator input, among others. A mean to achieve that, is the effective integration between monitoring and planning systems.

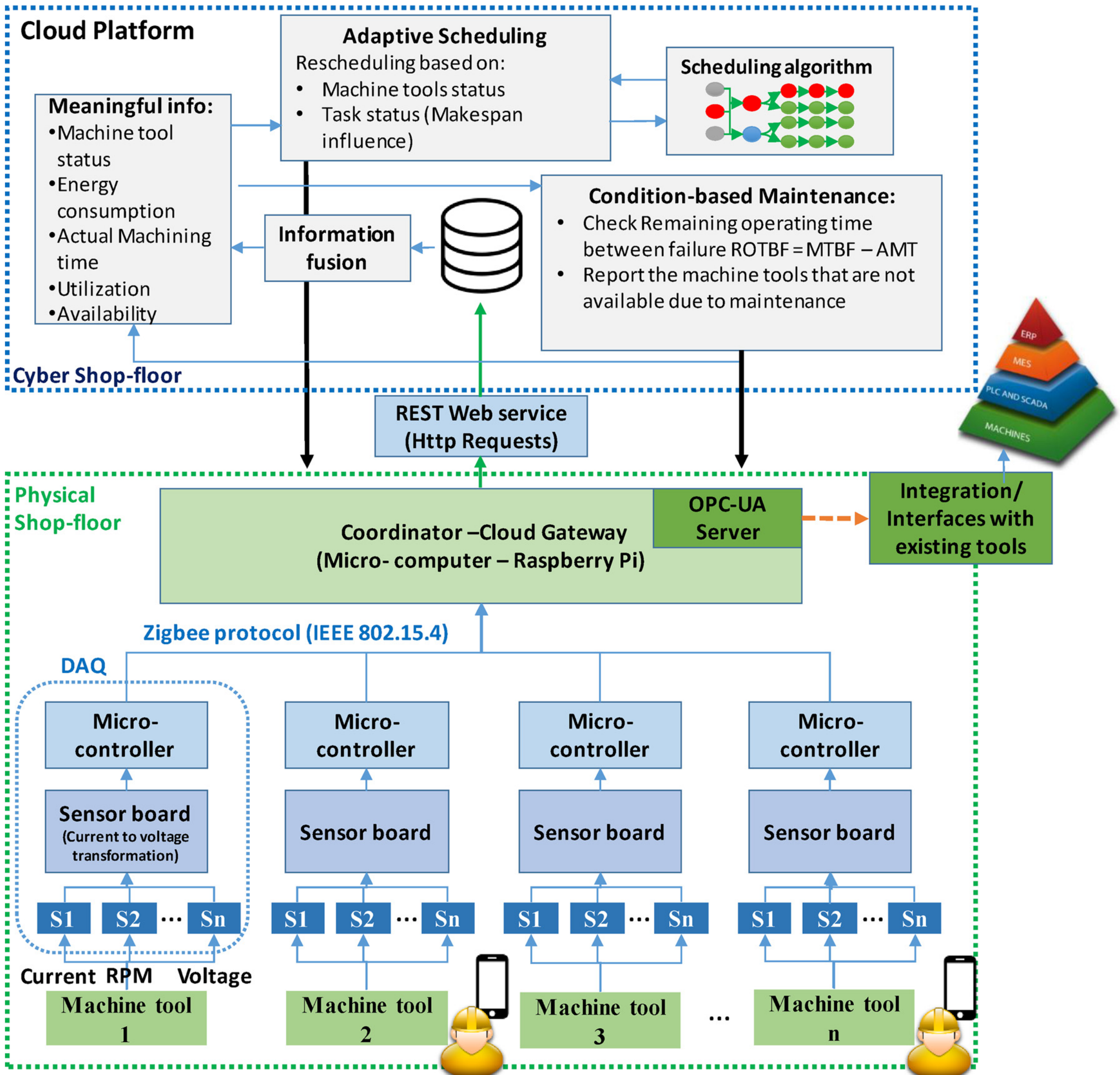
Moreover, the data captured by the monitoring systems can be further used for condition-based maintenance of machine tools [42]. Among the main benefits of condition-based maintenance is the increased uptime and as a result the reduced down time of the machine tools. Moreover, the maintenance failures and as a result also the maintenance costs can be reduced improving the overall equipment performance [43]. Last but not least, condition-based maintenance supports the increased efficiency of the maintenance management by performing more accurate planning of maintenance activities. Predictive maintenance is one step forward, as it analyzes the data and utilizes prediction algorithms to predict possible failures of machines tool. Predictive maintenance gives the ability to ensure product quality, perform just-in-time maintenance, minimize equipment downtime, and avoid machine-tool failure [8,44]. A condition-based preventive maintenance approach is proposed by Mourtzis et al. [45]. In addition to that, a predictive maintenance platform is proposed by Efthymiou et al. [46] for production systems maintenance, taking into consideration data acquisition systems, knowledge management and a maintenance dashboard.

Several approaches have been proposed in literature related to cyber-physical systems and control of manufacturing systems. However, there are still fields of further research and investigation, including real-time integration of different data from various sources, real-time analysis and feedback from shop-floor, effective integration of planning and control systems by incorporating communication standards and protocols that will allow interoperability, as well as advanced scheduling algorithms that will be capable of tackling different production changes of large variety and small batch size productions, and also considers real-time information from maintenance system [11,41,47]. Moreover, robust, reconfigurable, reliable, intelligent and inexpensive monitoring systems need further investigation in order to meet the demands of advanced manufacturing technology [4]. In addition to the above, although the last years, dynamic and real-time scheduling algorithms have been introduced, most of them are concentrated in simulation scenarios and solutions and there are limited approaches that consider the enabling technologies of Industrial IoT and Industry 4.0 paradigms. The effective industrial application of existing approaches and their integration with various and different industrial systems is also a field of further investigation. Towards that end, the proposed work presents a cloud-based cyber-physical system for adaptive shop-floor scheduling and condition-based maintenance. The present work aims to address real-time data acquisition and monitoring from various sources, multi-source data analysis, integration of planning and control as well as effective, accurate, and adaptive scheduling capable of dealing with real-time information from shop-floor. To achieve that, the proposed system consists of different layers and modules aiming to present not only an effective approach for adaptive scheduling and condition-based maintenance but also a real implemented system which considers the enabling technologies of IoT and Industry 4.0 and is applied in a real industrial case. The proposed system consists of a reconfigurable, reliable, as well as inexpensive monitoring system that provides meaningful information to a short-term scheduling algorithm, enabling adaptive scheduling. Moreover, a condition-based maintenance approach for machine tools is proposed based on the monitoring results and provided information. The monitoring system consists of a wireless sensor network and is integrated with industrial communication protocols and standards. The proposed system captures the shop-floor condition (machine tools status, tasks status) taking into account also the information from the condition-based maintenance approach aiming to perform adaptive scheduling. Finally, the proposed system is designed and developed in a cloud environment, as Software-as-a-Service, enabling collaboration, interoperability, as well as increased scalability by providing the resources on demand, avoiding high investment costs. More specifically, the module of the proposed system can be delivered as services through the cloud environment upon user-request. The cloud environment includes an infrastructure as a service (IaaS), virtual Linux machine, an Apache Hyper Text Transfer Protocol Secure (HTTPS) server, a Ruby on Rails framework (RoR), as well as a MongoDB database capable to handle and analyse high volume of data. The main contribution of the present work can be summarized below:

- An inexpensive and reliable monitoring system which integrates data from different sources implementing also industrial communication protocols and standards following the Industrial IoT and Industry 4.0 paradigms
- Data analysis algorithms that can easily identify the status of the shop-floor and calculate important key performance indicators in real-time
- An adaptive scheduling algorithm which consists of a multi-criteria algorithm capable of taking into consideration in real-time various data from shop-floor (machines, human operators, etc.) as well as, input from condition-based maintenance performing accurate and effective production scheduling and re-scheduling in real-time
- Implementation of the different modules of the proposed cyber-physical system in a cloud environment, implementing also technologies for data storage and handling, and finally providing the different modules (monitoring, scheduling, maintenance) as services upon end-user request.

3. The proposed architecture

The paper proposes a cloud-based cyber-physical system for adaptive shop-floor scheduling and condition-based maintenance. The developed cloud-based cyber-physical system is designed and developed under the IoT and Industry 4.0 concepts, in order to enable the digitalization of manufacturing companies in a cost-efficient, reliable and robust way. Real-time sensing, interoperability as well as adaptiveness were the main requirements during the system design and implementation. Currently, most of the existing scheduling methods yield non-feasible production schedules, since they are not aware of the actual shop-floor condition. Moreover, in many conventional manufacturing systems, the scheduling of jobs is done empirically using rules of thumb. Such an approach nevertheless, leads to inferior utilization of resources even in cases that the system is considered underutilized. In



Legend

OPC-UA	Open Platform Communication – Unified Architecture
DAQ	Data Acquisition Device
S1..Sn	Multiple Sensors
ROTBF	Remaining Operating Time Between Failure
AMT	Actual Machining Time
MTBF	Mean Time Between Failure
REST	Representational State Transfer
HTTP	Hyper Text Transfer Protocol

Fig. 1. The cloud-based cyber-physical system.

addition, it is also common practice for scheduling methods and tools to assume a time-bucketed environment, with constant and inflated, and thus unrealistic processing times [48]. As a result, awareness and adaptiveness are main requirements to perform feasible schedule.

In this research work, the proposed cloud-based cyber-physical system is designed and developed in order for it to contribute to the overall adaptiveness of the system, as it is capable of monitoring the production shop-floor, analyzing the monitoring data and utilizing them as input in a scheduling algorithm as well as in a condition-based maintenance approach (Fig. 1). Through the proposed system, an initial schedule is dispatched in the shop-floor. The developed monitoring system monitors the machine tools status as well as the progress of the planned tasks. Once disturbances are detected, including machine breakdowns, planned maintenance of machines tools based on the condition-based maintenance approach, as well as extension of processing time planned for the task, the monitoring system informs the scheduling system on the shop-floor condition and the scheduling system generates a new schedule which is then dispatched to the production after its approval by the production engineer.

The developed cloud-based cyber-physical system consists of different components. More specifically, the proposed system consists of a monitoring system that includes a wireless sensor network, and an information fusion technique and supports an industrial communication standard Open Platform Communication-Unified Architecture (OPC-UA). The monitoring system includes the sensors, the microcontroller, the ZigBee protocol and the cloud gate way as hardware (inside the physical shop-floor rectangular of Fig. 1) and also the database, the information fusion technique, and the visualization of the meaningful information (parts of the cyber-shop-floor rectangular of Fig. 1). More specifically, t1he monitoring system has two main input data sources:(i) a wireless sensor network, (ii) the human operator of a machine. The acquired data are analyzed through an information fusion technique that consists of the Analytical Hierarchy Process and the Dempster-Shafer theory of evidence [26]. Once the data are analyzed, meaningful information including machine tool status, machine tool energy consumption, utilization, availability, as well as actual machining time and task status are provided to a scheduling algorithm in order to perform adaptive scheduling. In addition to that, the analyzed data are used for condition-based maintenance of machine tools. The proposed cloud-based cyber-physical system is capable of monitoring the machine tools as well as the planned tasks, and triggering the re-scheduling procedure if any disturbance is detected in the shop-floor. Moreover, the status of the machine tools and their availability are highly influenced by the maintenance procedure, for that reason, a condition-based maintenance approach is used in order to support the machine tool status identification and reduce the machine tools breakdowns by measuring their remaining operating time between failures.

Each one of the components of the proposed cloud-based cyber-physical system is described in more details in the following subsections.

3.1. Cloud-based monitoring system

The main objective of the proposed system is to improve the awareness on the shop-floor status. Most of the existing IT tools are working in isolation without considering the status of the production [4]. As a result, increased awareness of the production condition is of high importance in order to avoid breakdowns and increase productivity.

To achieve the aforementioned objectives, the system employs sensors in order to measure the electrical energy related operating characteristics of the machine-tools. The outputs of the sensors are connected to a data acquisition device (DAQ) for each machine-tool. The DAQs of a shop-floor are organised in a wireless sensor network coordinated by a microcomputer gateway to cloud. In the last step of the data transmission, a cloud-server is implemented for further data processing and visualisation.

3.1.1. Data acquisition device

The design and development of the proposed DAQ are performed in order to achieve an inexpensive, reliable as well as reconfigurable solution for the industrial companies. In addition to the DAQ, a main aspect of the proposed monitoring system is the connectivity (communication protocols and standards). Different communication protocols are applied to the proposed monitoring system in order to support its connectivity and ensure the quick and accurate data transmission.

The DAQ of the proposed monitoring system, consists of sensors that are installed in the machine tools. Current sensors are utilized to measure the current of the main motors of the machine tools and the overall energy consumption. In addition to that, the voltage of the main network of electicity is measured through an insulation transformer. Finally, an angular velocity sensor is considered, especially in the case of the spindle, in order to identify its status. The currents sensors are split-core transformers. The outputs of the current transformers are sampled with a frequency of 1 kHz, which corresponds to 20 samples per period (in the case of 50 Hz).

The developed DAQ needs to comply with the appropriate specifications for supporting the selected sensors, communication capabilities, and computational requirements. Therefore, the STM32 F429 microcontroller from ST Microelectronics was selected [49]. The microcontroller has the ARM Cortex-M4 microprocessor at its core, and special processing units for 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 of the machine motor electrical operating characteristics.

For the measurements of the currents of the machine, five axes drives and the mains, six analog inputs for the split-core current adapters are considered. Moreover, one analog input is specified for the mains line voltage measurement and one digital input is specified for the angular velocity sensor. The main benefits of the current transformers as sensing devices are that they do not require auxiliary power supply for their operation and they can be acquired with low cost. 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 embedded high speed ADC of the microcontroller. This ADC has 8 analog channels and operates at 6 ksps that correspond 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 Serial Peripheral Interface (SPI) protocol.

3.1.2. Wireless sensor network (WSN)

The data acquisition devices, described in the previous section, are organized in a wireless sensor network. The WSN follows the star topology, and is facilitated with the use of DIGI XBee ZigBee RF module [50]. The ZigBee module is a specification of the IEEE 802.15.4 standard, which operates at 2.4 GHz. ZigBee was selected over other wireless standards, due to its support to various network topologies and encryption algorithms, and its robust and reliable operation with functionalities such as collision avoidance, retries, and acknowledgements performed in the hardware. Moreover, ZigBee modules can communicate in ranges of more than 100 m [51], enabling its application in larger industrial cases.

In the WSN, the data transmission is organized by a central gateway which is responsible for collecting all the data from the DAQs and organize them in packets in order to transmit them to the cloud server. The DIGI XBee ZigBee is installed on the microcomputer-coordinator as well as in all the DAQs. The data within the WSN are transmitted as Zigbee packets, with a transmission frequency of four packets (each packet has the required data for identifying the status of the machines and calculating the performance indicators) per second that have unique recipients (micro-computer-gateway). The developed WSN is designed in a way that can also support a higher transmission frequency following the needs of different industrial cases including automotive, machining, and aerospace industry.

The main functionality of the proposed wireless sensor network, is the automated addition and removal of data acquisition nodes to and from the network. To support the adding and removing of nodes in the WSN, a task sequence is developed. This automated procedure increases the system's re-configurability. To support that, a procedure is designed and developed with four main steps (Fig. 2):

Step 1: Each DAQ node transmits a beacon message once every 5 seconds

Step 2: If a DAQ is in transmission range of a coordinator, the coordinator receives the beacon 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.

Step 3: Then the DAQ abandons the beacon mode and waits for the coordinator to request a measurements packet.

Step 4: Finally, the coordinator requests the measurements of each DAQ once every 0.25 s and the operation of the network continues as described.

In order to further increase the robustness and the reliability of the proposed system, by avoiding network malfunctions due to problematic devices or absent nodes, a mechanism is implemented into both the DAQs and the coordinator devices (Fig. 2). Firstly, a scorecard is defined, through which the system can monitor and control the network malfunctions. 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

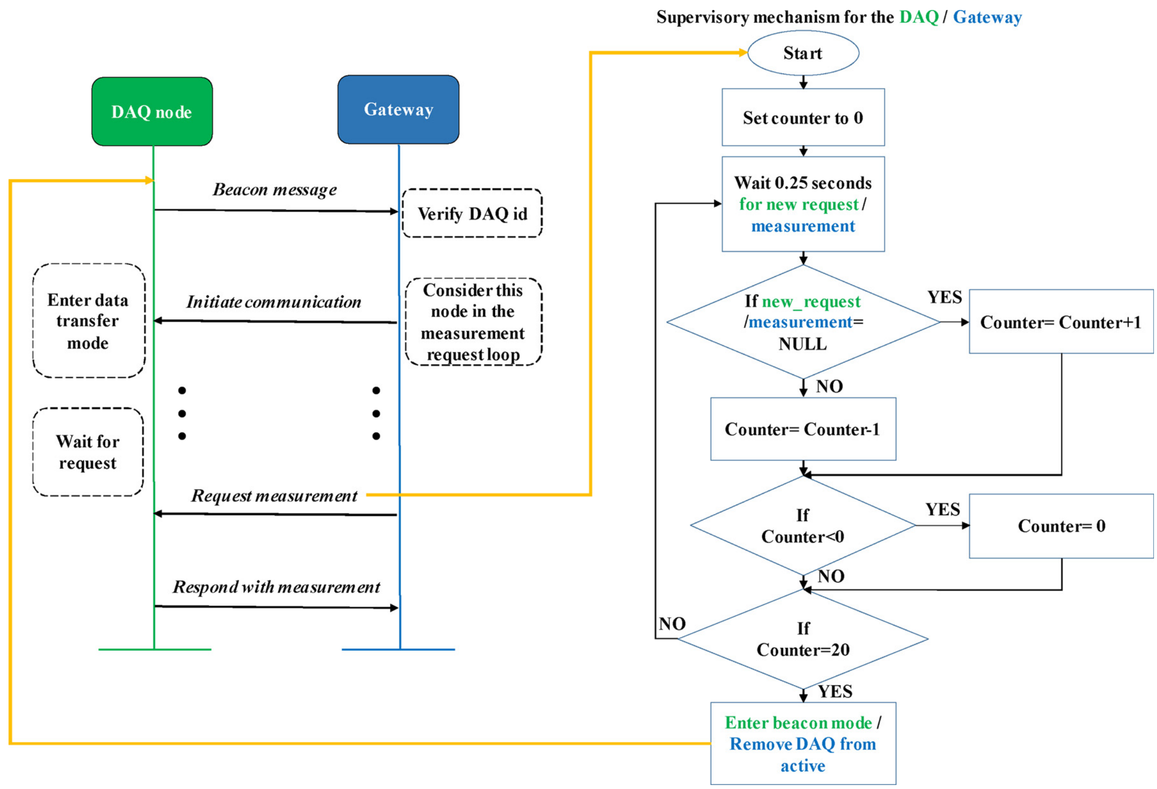


Fig. 2. The developed communication protocol between one DAQ and the Gateway together with the Supervisory mechanisms to detect malfunctions in the network.

value '1' to a scorecard of the corresponding DAQ. In the case of a successful reply by the DAQ, the coordinator subtracts the value '1' from the sum in the scorecard. If the score 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 of the network, 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 the value of '1' to the sum if the coordinator does not send a request for measurement in the expected timeframe of 0.25 s. In the case of successfully receiving a request for measurements, the DAQ subtracts the value '1' from the scorecard. When reaching the score of twenty, the DAQ considers the coordinator absent and re-enters to beacon mode.

The presented monitoring system is designed and developed in order to be cost-effective and affordable for SMEs. In this direction, the overall cost of the data acquisition device and the wireless sensor network is about 70 Euros per machine tool. Considering also a microcomputer gateway for every 8 machine tools which cost is about 100 Euros, we can estimate a cost of about 660 Euros for 8 machine tools which is much lower than existing commercial solutions.

3.1.3. OPC-UA connectivity

The adoption of the OPC-UA standard in the monitoring module is selected as a mean for interoperability with other IT tools in the production. The OPC-UA standard has been identified as a key enabler for the realisation of the Industry 4.0 factories of the future [52]. In brief, the OPC-UA represents a safe, reliable platform-independent industrial communication standard. Following the CPS paradigm, OPC-UA provides an object-oriented concept to model the physical objects and their interrelations. Therefore, the information flow within complex industrial IT systems is improved towards the realisation of adaptive ICT. The OPC-UA network stack is implemented on top of the TCP/IP transport layer of the OSI model. By implementing the application layer in a platform-independent way, integration of heterogeneous data from various sources can be implemented without the need for specific software adapters. Two transport protocols are currently supported; the UA TCP with UA Binary encoding to satisfy the need for high speed communication; the HTTP communication Soap Web-Service with XML encoding for Web-based applications. In this work, the OPC-UA with binary encoding is selected to support high data throughput.

The OPC-UA standard was considered in this work in order to support machine-to-machine communications (M2M), where machines communicate with machines, workpieces and components to create an adaptive and decentralised production system. This can be achieved by enabling the machine to contain all the information related to its settings or operation. Hence, this information can be shared directly with the automation level, reducing the complexity of integrating software from different vendors (Fig. 3). The OPC-UA communication takes place in parallel to the real-time communication that occurs between the developed DAQ and the sensors on the machine. OPC-UA is implemented in the microcomputer gateway and all data are provided to the shop-floor layer. The standard is complementary to the developed cloud server, which acts as the shop-floor database.

Based on the design of the system, the developed namespace is presented in (Fig. 3). The root node is the shop-floor which is the parent node for the machines. The components of the machine are depicted as nodes and the hierarchy is declared with the OPC-UA reference "HasComponent". The "HasComponent" reference is applied also in the case of the variable nodes. The components of the machine that are considered in the namespace are those that are important to the workflow within the proposed platform. These are the spindle and the linear axes, which have sensors attached, the specifications, and the tool magazine.

In the proposed architecture, the measurements from the DAQs are updated every 0.25 s. Therefore, it depends on the Clients requirements to select a polling rate. During the development phase of the system, the OPC-UA client that is used performed polling every 0.25 s to match the data rate of the DAQs.

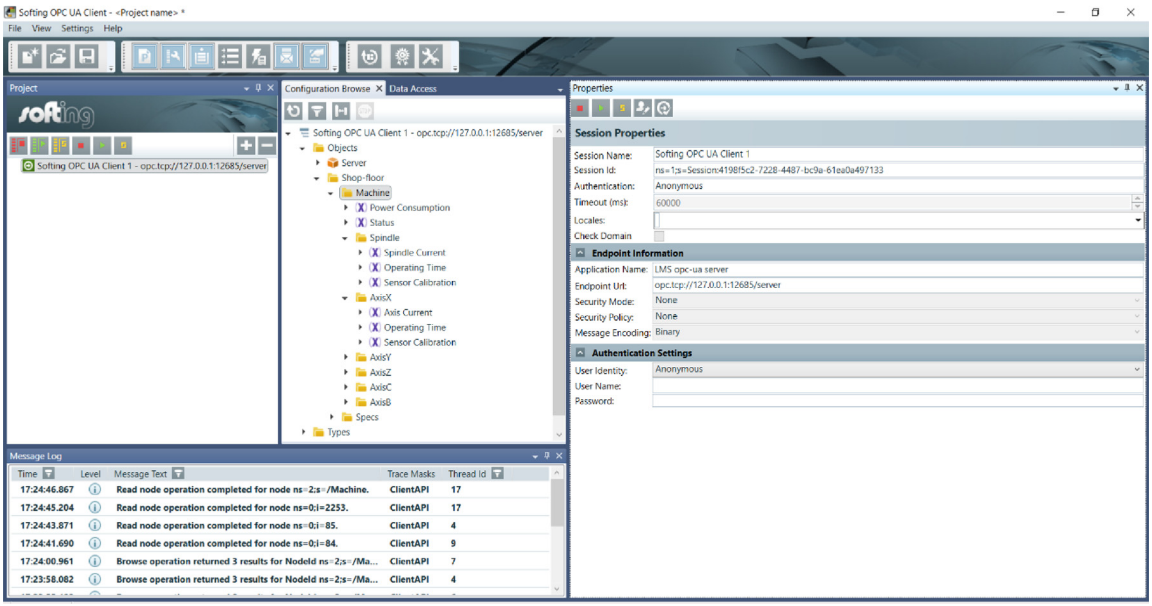


Fig. 3. The developed information model of the implemented OPC-UA communication standard.

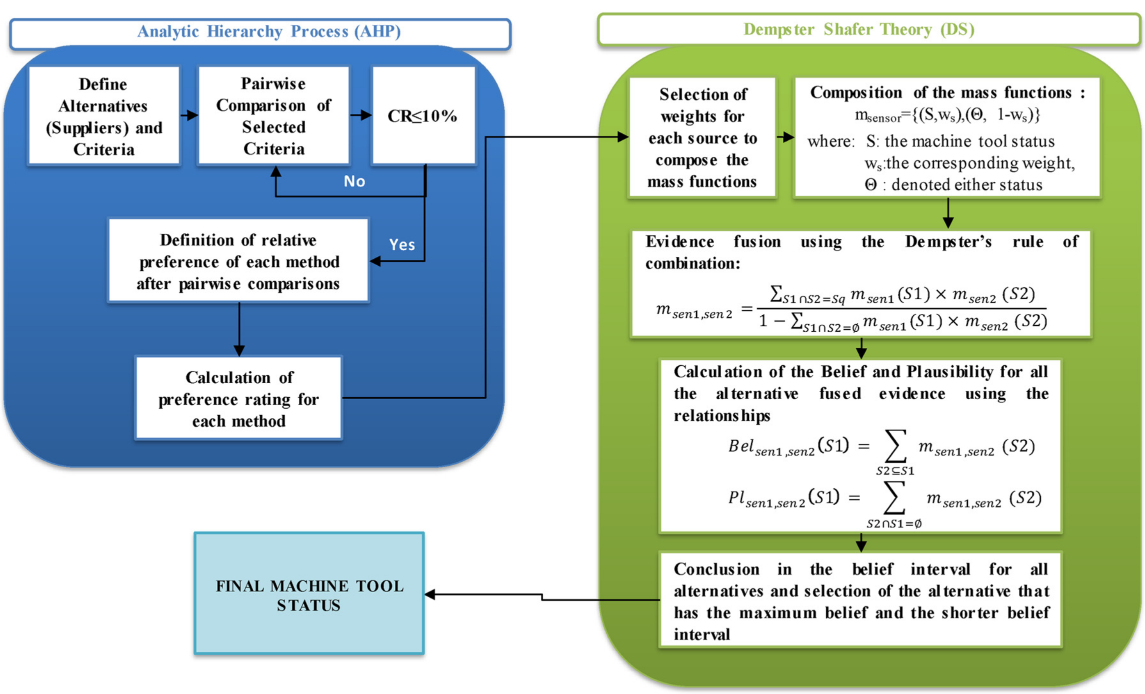


Fig. 4. The information fusion technique.

3.1.4. *Information fusion*

The proposed cyber-physical system retrieves data from two different sources; the wireless sensor network and the machine-tool operators. The human operator provides the status of the machine tool, the currently running task and the fixture and tool availability, through mobile devices on the shop-floor. Specifically, the operator is able to report the following machine statuses: (i) down, and (ii) setup. Furthermore, they report all occurring failures, thus providing the system with the reason for a defined down mode. According to the severity of the damage or failure, they can resume or reset the running task on the machine tool.

Once the data are captured from the aforementioned sources, they are processed through an information fusion technique, consisting of the AHP and the DS theory [7]. The information fusion is implemented in two different levels; the low and the high level. In the low level, the status of the spindle and the axes are identified based on the sensor measurements (current measurements). In the high level, the actual machine-tool status is comprised having taken into account the status indicated by both the sensors and the human operator inputs. In the low level the statuses of the axes and the spindle are identified by analysing the sensor measurements. Following signals from the sensors and specifically the current measurements, it can be identified if the spindle or the axes are working. Once the statuses of the axes and the spindle is identified (if they are working or not), the information is sent to the high level fusion, where the status of the machine is identified. In this stage, an input regarding the status of the machine is provided by the analysed sensor data (if the axes and the spindle are working or not) of the low level and the input by the human operator. Based on the data analysis methods and the defined weights for each source, the final status of the machine tool is identified.

In each level of the information fusion technique, two different steps are followed. The first step includes the AHP method. In this step, a logical framework to determine the benefits of each alternative (data sources) is considered. Criteria including accuracy, flexibility, error probability, and real-time response are defined in order to compare the alternative ranking and calculate the reliability of each source. As a second step, once the reliability of each source is calculated, the DS theory of evidence is used to derive a degree of belief about the machine-tool operating status, combining the evidence from the different sources. The Dempster-Shafer theory indicates belief in a hypothesis given a piece of evidence for each machine status. In the DS theory the weights are assigned to indicate the credibility of each source of information towards identifying the status of the machine tool. The impact of each distinct piece of evidence is represented by a mass function (Fig. 4).

Weights are assigned to all mass functions in both levels of fusion and for each source. The selection of these weights is based on measurements that were performed for each sensor separately considering different operating environments. In the low-level fusion, the weights that are applied in axes fusions are 0.3 for available mode and 0.8 for processing mode. Moreover, for the spindle status fusion the weights are 0.3 for the available mode, 0.8 for the processing mode of the spindle current, and 0.9 for the processing mode of the angular velocity sensor. In the high-level fusion, the weights that are applied for the two different sources namely the sensory system and the operator input are 0.9 for processing and 0.8 for available and finally 0.7 for processing and 0.4 for available respectively. By the defined weights the credibility of each source of information towards identifying the status of the machine, is calculated. For example, the output of the sensor can identify the processing mode (machine is busy) with high probability. However, the sensor input cannot identify the non-processing status (machine is idle) with high probability as it can only identify that the motor that the sensor is attached on is not operating, but it does not have the information regarding the other motors.

In general, by available mode we consider that the inputs that we receive from the sensors and the human operator reveals that the machine is idle. However, by processing mode we consider that the inputs from the sensors and the human operator reveal that the machine status is busy.

In the present work the weights of the information fusion technique are defined after a number of tests and experiments with the system. The weights are defined once the system is installed in the machines tools and they are adjusted in case that the sources of the low and high levels will be changed or the inputs of the sources will be changed. Once the sources will be changed, for example another sensor will be added or information will be retrieved also by another system, the weights of the information fusion technique are re-adjusted following a number of runs based on the new inputs.

The main data provided by the monitoring system includes the machine-tool status, the machine-tool energy consumption, the machine-tool utilization, the actual machining time of the machine tool as well as the task status. The monitoring system monitors the execution of the running tasks and retrieves data related to their statuses. These results are generated per machine-tool. Nevertheless, they can be accumulated in the higher levels of the production line and the factory in order to provide a holistic view of the manufacturing system. With this knowledge transferred to the higher levels, accurate decisions can be made by taking into account the status of the shop-floor and reduce the bottlenecks that can occur due to non-feasibilities.

3.1.5. Integration aspects

Integration and interoperability are key aspects of Industry 4.0 paradigm. Integration of systems as well as of data is of high importance, as it provides the capability of interfacing different systems and increase the communication as well as the interoperability [53].

The proposed cyber-physical system, taking into account the main aspects of integration and interoperability, offers a high level of interconnection with other legacy and commercial systems. The cloud database is implemented in order to store the facility data considering machine-tool specifications, cutting tool specifications, as well as the monitoring data, and to update these data through integration with other systems.

The developed solution was integrated with the tool database of a well-known cutting tool manufacturer in order to get the cutting tools specifications and update the cloud repository accordingly. In addition to that, it was also integrated with a legacy planning system from a European company in order to demonstrate and validate the integration capability of the proposed system.

3.2. Adaptive shop-floor scheduling and condition-based maintenance

Short-term scheduling belongs to the typical decision-making problems in manufacturing. The increasing product variety generates further uncertainties and turbulence in modern shop-floors, making scheduling a challenging everyday problem. The integration between scheduling and monitoring systems will provide adaptive decision making, thus increasing the shop-floor awareness and improving the common information flow. In this work, the data from the monitoring system are utilized in order to identify possible machine-tool breakdowns and generate feasible and adaptive schedules. The monitoring data can be utilized in two different ways. In the first way, the scheduling tool and algorithm can utilize the monitoring data from the monitoring system upon its request, e.g. every 8-hours [54]. The second way, and the one followed in this work, is that the monitoring system informs the scheduling tool and algorithm on turbulences in the shop-floor.

The monitoring system checks the execution of the running tasks and retrieves data related to their status. More specifically, the status of each scheduled task can be either completed, on-going, or pending. The aforementioned data are utilized as input to the scheduling algorithm in order to produce feasible and accurate schedules.

In this work, adaptive scheduling is considered as the capability to re-generate alternative and feasible schedules based on the real-time shop-floor condition. The re-scheduling is performed whenever a change is required, driven by the feedback from the monitoring system. Following the captured data from the monitoring system, re-scheduling can be performed in two different occasions:

- Once the status of the machine tool is detected to be down as well as when a machine tool returns from down or set up mode.
- Once the monitored processing time of a task is higher than the scheduled time and the makespan is highly influenced. In this case and if there is no idle time between this task and the next task in this machine or between its post condition in another machine, the influenced tasks are shifted forward based on the additional time. This additional time is added in the initial makespan and in this way the monitored makespan is calculated. The makespan is considered highly influenced and a re-scheduling is required based on Eq. (1) below:

$$MS_m - MS_{sch} \geq m \tag{1}$$

Where: MS_m is the monitored makespan, MS_{sch} is the scheduled makespan and m is a parameter that expresses time and can be adjusted based on the nature of the company and on its main needs and goals. The parameter m is user defined and is affected by the mean task time, as well as by the generated makespan.

More specifically, and based on Fig. 5, firstly the status of the machine tools is examined. If the status of the machine tools is not detected to be down or the machine tools do not return from down or setup mode, then the running tasks are monitored. The status of each task is

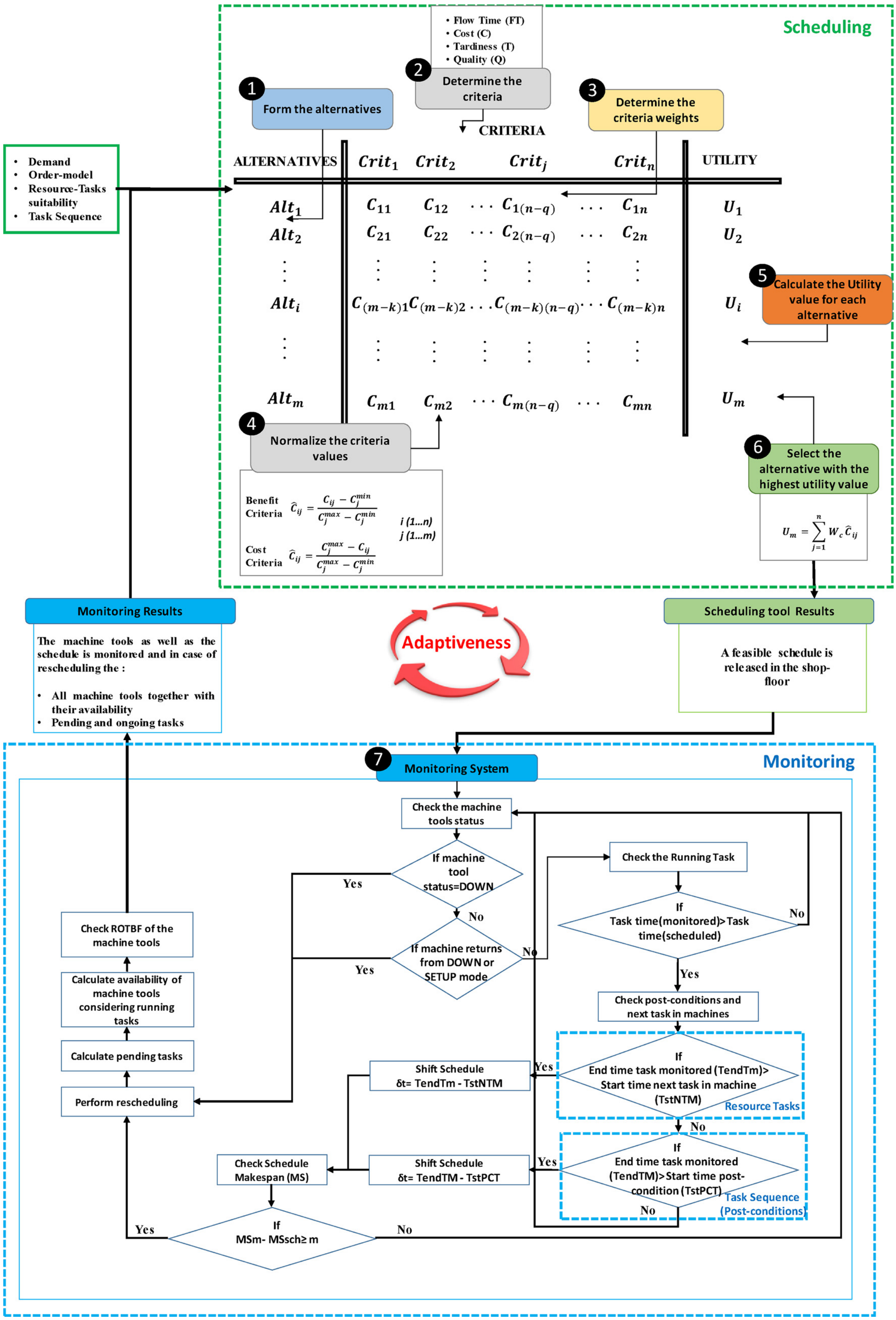


Fig. 5. The workflow of the developed adaptive scheduling.

monitored, and specifically the task duration. As task duration is considered the time that is required to fulfil a task based on the generated schedule. If the task duration of a monitored task is higher than the scheduled task duration provided by the scheduling tool, then the system examines two different conditions based on the Eqs. (2) and (4) below:

$$\textbf{Condition 1}: t_{endTM} > t_{stNTM} \tag{2}$$

Where: t_{endTM} is the end time of each monitored task and t_{stNTM} is the start time of the next task in the machine tool.

Based on Eq. (2), the system checks the next task in the machine tool. If the end time of the monitored task is higher than the start time of the next task in the machine tool, then, the overall schedule is shifted foreword by:

$$\delta t = t_{endTM} - t_{stNTM} \tag{3}$$

$$\textbf{Condition 2}: t_{endTM} > t_{stPCT} \tag{4}$$

Where: t_{endTM} is the end time of each monitored task and t_{stPCT} is the start time of the post-condition task.

Based on Eq. (4), the system checks also the post-condition of each task. If the end time of a task is higher than the start time of the post-condition task, then the overall schedule is shifted foreword by:

$$\delta t = t_{endTM} - t_{stPCT} \tag{5}$$

Once the aforementioned situations are examined, the makespan of the schedule is checked based on Eq. (1). If the makespan is highly influenced, then re-scheduling is required in order to product a new schedule.

In all the aforementioned occasions, when re-scheduling is required, the monitoring system calculates the pending tasks as well as the availability of each machine tool. As available, are considered not only the idle machine tools but also the busy machine tools based on remaining time needed for finishing a running task. Finally, the remaining operating time between failure for each machine tool is calculated and is considered in the machine tools availability calculation.

As a result, once re-scheduling is required the monitoring system provides to the scheduling algorithm the machine tools together with their availability as well as the pending and ongoing tasks.

The scheduling algorithm, which consists of a multi-criteria decision-making algorithm, is utilized to generate feasible scheduling alternatives. Each alternative is considered as a set of resources (machine tools or human operators) to tasks assignments that can carry out the workload. The number of generated alternatives is guided by three adjustable control parameters, namely the maximum number of alternatives (MNA), the decision-horizon (DH) and the sampling rate (SR). MNA controls the breadth of the search, DH controls the depth, and SR directs the search towards branches of high-quality solutions. Through the three adjustable parameters, the algorithm can identify a good solution by reducing the solution space, and consequently reduce the computational time. The selection of the preferable values of the three parameters is performed through a statistical design of experiments [55] in order to reach the results of the highest possible quality [56].

The workflow of the proposed adaptive scheduling is presented below (Fig. 5).

As show in Fig. 5, the procedure has a first step the determination of the alternatives. The second step is to determine the attributes, which are the criteria used to evaluate the alternatives. Once the criteria are defined, the consequences need to be defined. The consequences are the values of the attributes at the time the decisions are perfomed in order to evaluate the alternatives. The main criteria that are considered by the proposed algorithm are the flowtime (6), the tardiness (7), the cost (8) as well as the quality (9):

$$FT(alt_q) = \frac{\sum_{i=1}^{\ell} (T_i^{comp}(alt_q) - T_i^{arr})}{N} \tag{6}$$

$$TD(alt_q) = \frac{1}{N} \sum_{i=1}^{\ell} \max[0, \quad T_i^{comp}(alt_q) - T_i^{dd}] \tag{7}$$

$$CT(alt_q) = \frac{\sum_{i=1}^{\ell} T_i^{est}(alt_q)^{*}R_i^{cost}}{N} \tag{8}$$

$$QT(alt_q) = \frac{\sum_{i=1}^{\ell} Q_i}{N} \tag{9}$$

where

$R_i$ith resource (i = 1,…,ℓ)

alt_q qth alternative formed at the decision point

Nnumber of completed tasks in the work center/jobshop at a decision point

$T_i^{comp}(alt_q)$ completion time of the ith pending task if alt_q is implemented

T_i^{arr} time at which the ith pending task arrived at the work center

$T_i^{est}(alt_q)$ estimated time required to process ith pending task if alt_q is implemented

R_i^{cost} cost of resource i to process the pending task if alt_q is implemented

$Q_i$quality index of the resource R_i to perform a ith pending task if alt_q is implemented

T_i^{dd} due date of the ith pending task

The weights of the criteria are user-defined based on manufacturing experts, and represent the main goals and needs of each industry.

The proposed scheduling algorithm is selected compared to other approaches, as it has the ability to adapt to new orders and perform quick rescheduling with high-quality solutions [56]. Once the monitoring system detects a turbulence in the shop-floor, all the available monitoring data including machine tools status and availability, as well as the status of the tasks are sent to the smart search algorithm in order to generate new feasible schedules. More specifically, the on-going tasks remain in their position and the pending tasks are re-allocated to the available machine tools. The availability of the machine tools is highly influenced by their maintenance plan [57]. In this work, the machine tools status is derived also by taking into consideration the outputs of a condition-based maintenance approach. In this approach which will be described in more details in the following section, the remaining operating time between failures (ROTBF) [45] is calculated based on the actual machine time and the define mean time between failures (MTBF) of the machine tool.

The scheduling algorithm is also developed in a software that hosts a graphical user interface and a database where all the data required for the scheduling or are produced by the scheduling are stored and can be exchanged with the monitoring tool. More specifically, the defined orders, the jobs, the task- resources suitability, the task sequence (post-conditions), as well as the set up times for different combination of task-resource are defined in the graphical user interface of the scheduling tool. As a result, when rescheduling should be performed, the scheduling algorithm gets all the necessary information from the monitoring tool as well as from its database based on the user data entry.

3.2.1. Condition-based maintenance

Maintenance and its cost continue, over the years, to draw the attention of production management, since the unplanned failures increase the reliability of the system and decrease the return of investments. Maintenance is a core activity of the production lifecycle since it accounts for as much as 60–70% of its total costs [57]. Towards that end, this work proposes a condition-based maintenance approach based on monitoring data. Condition-Based Maintenance (CBM) is defined as the maintenance strategy where the decisions are made based on the machine condition indicators obtained in most cases through measurement systems [8]. This definition is the one that is followed also in this work. The cloud-based monitoring system described in the previous sections is employed in order to monitor and calculate the status of the machine tools as well as its actual machining time. In addition to that, the proposed monitoring system includes a database, where shop-floor data regarding machine-tool and cutting-tool specifications are stored.

Once the status and the machining time of the machine tool are calculated, the MTBF is retrieved from the database of the monitoring system in order to calculate the ROBTF. The ROTBF is calculated based on the actual machining time of the machine tool (AMT) and the defined MTBF of the machine tool, following Eq. (10) below:

$$\mathrm{ROTBF} = \mathrm{MTBF} - \mathrm{AMT} \tag{10}$$

Where:

ROTBF Remaining Operating Time Between Failure of each machine tool

MTBF Mean Time Between Failure of each machine tool

AMT Actual Machining Time of the machine tool

Once the machine tool status as well as the ROTBF are calculated, the monitoring system investigates two different scenarios. The first is whether the machine tool status is down. If the status of the machine tool is down, the operator as well as the maintenance department are informed. The operator reports through the mobile device possible failures that occur in order to inform the maintenance department and perform accurate and quick maintenance. The second scenario under investigation is whether the deviation between the MTBF and the ROTBF is lower than a parameter/threshold *"k"* In this case, if the AMT has reached a high percentage of the MTBF, the machine tool operator as well as the maintenance department are informed to perform condition-based maintenance. The parameter *"k"* expresses time (hours) and can be changed based on the different types of machine tools or the different types of production. The aforementioned parameter is user-defined based on the experience of the maintenance experts and on the needs of the company. The second scenario can be presented below also as pseudo code:

maintenance and also providing meaningful information to the scheduling system regarding the availability of the machine tools based on the real shop-floor condition. Subsequently, the maintenance department is capable of performing quick and efficient maintenance of the machine tools. In addition to that, the proposed cloud-based cyber-physical system is informed on the status of the machine tools and can perform adaptive scheduling as well as condition-based maintenance increasing the system's reliability and the company's productivity. Among the main benefits of condition-based maintenance is the increased uptime and as a result the reduced down time of the machine tools. Moreover, Through the proposed condition-based maintenance, the maintenance failure and as a result also the maintenance cost can be reduced improving the overall equipment performance. Last but not least the increased efficiency of the maintenance management and the real-time feedback also to the production scheduling will increase production systems' efficiency and performance.

With the proposed approach adaptive control can be performed and companies can raise their competitiveness by delivering new and existing products quickly, efficiently as well as in low cost and high quality.

4. Software implementation

Cloud technology and specifically cloud-based services support collaboration and enable ubiquitous data access by multiple users and IT tools. Cloud-based services address the challenges of collaboration, re-configurability, as well as adaptability of manufacturing system in dynamic changes. Thus, a cloud- based cyber-physical platform is developed in order to enable ubiquitous information sharing. The developed platform is provided as a software-as-a-service (SaaS) and supports several communication and security mechanisms and protocols. The cloud platform includes an infrastructure as a service (IaaS), virtual Linux machine, an Apache Hyper Text Transfer Protocol Secure (HTTPS) server, as well as a Ruby on Rails framework (RoR) (Fig. 6).

```
Pseudo code for condition-based maintenance
// check Remaining operation time between failure for each machine tool
// q denotes the number of machines tools
// k is a threshold
FOR i ← 1 to q DO
        ROTBF[i] = MTBF[i] – AMT[i]
IF MTBF – ROTBF < k THEN
Machine i needs maintenance
END IF
END FOR
```

The monitoring tool is developed in a cloud-based platform in order to enable ubiquitous data [3] information sharing of the services among users and IT tools alike.

As a result, the proposed maintenance approach is capable of identifying the potential failures of the machine tools. Informed of the remaining operating time between failure of the machine tools and the frequency of the failures, the maintenance department is aware of the shop-floor condition. In addition to the above, the proposed system is capable of identifying possible failures also through the analysis of the current measurements of the main motors of the machine tool. This part is not presented in this work, however the proposed system through the real-time captured data can identify deviations from the current measurement which can be correlated with the status of the motor and identify possible failures before they will occur [58]. Moreover, through the proposed system, although the MTBF is a technical characteristic, it can be adjusted based on the analysis of the monitoring data, supporting the maintenance department to perform more accurate

To enhance the proposed architecture in terms of compatibility with various sources, both OPC-UA and RESTful interfaces are implemented to provide integration capabilities with industrial software and increase system's interoperability.

The database selected for the developed platform is a MongoDB (No SQL) database, in order to support sensorial data storage and processing. Due to the ever-increasing requirements, flexibility in the database schemas is required. Therefore, for these purposes, non-relational (NoSQL) databases are more convenient compared to the relational (SQL) databases that are not flexible when changes in the schema are required. In the developed database, the data is stored as documents instead of tables with columns and rows, and as a result it is capable of quickly retrieving data over a large number of nodes, in our case sensor nodes [59]. The NoSQL database as distributed database is built for

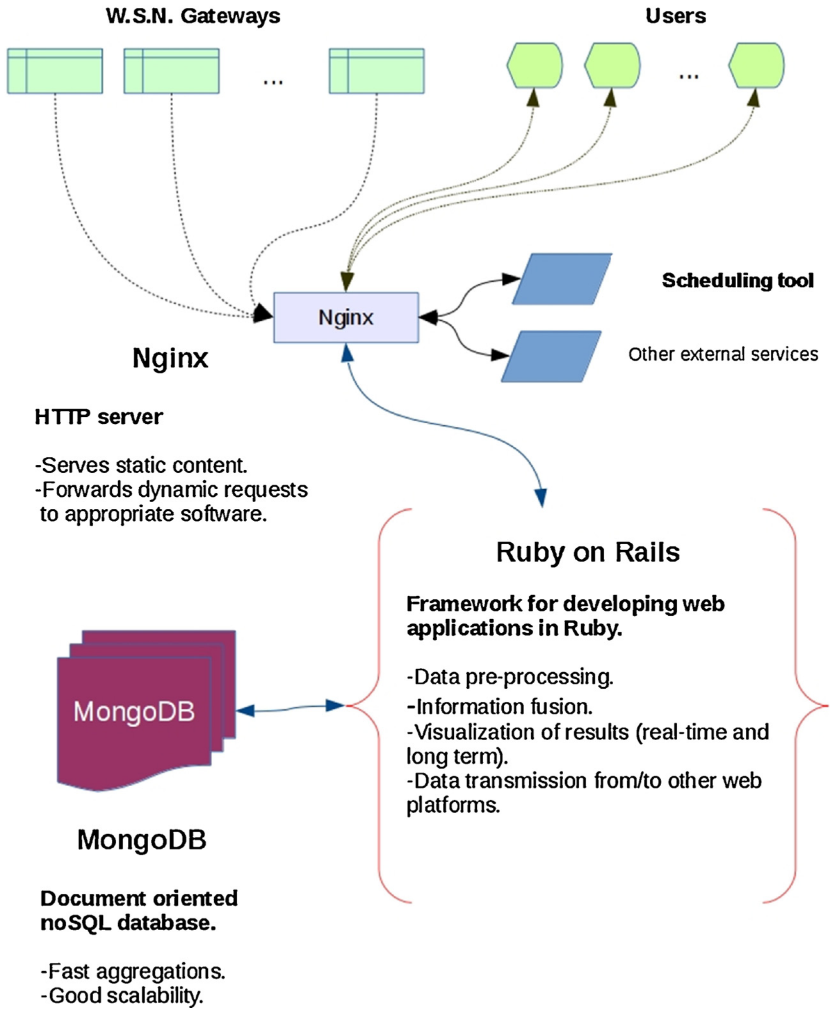


Fig. 6. The Cloud software platform.

increased performance and scalability. As a result, in case of large amount of documents due to sensor data, the MongoDB can support storage on more than one server by dividing server into mongos –a set of routing server, and achieving parallel access and efficient operation. The relationship diagram of the database can be shown in Fig. 7.

Security was applied in three layers, namely the shop-floor layer, the web application layer, and the cloud service-operating layer. In these layers, there is a variety of countermeasures against different threats, such as encryption during data transfer in the shop-floor level using AES 128-bit encryption algorithm, identification of clients through Secure Sockets Layer (SSL) and Transport Layer Security (TLS) protocols, used along with a secure database authentication system and the Virtual Private Network (VPN) technology.

5. Case study – mould-making SME

The presence of Small and Medium Enterprises (SMEs) is very strong in the industrial sector. Industry 4.0 and IoT paradigms aim to enable SMEs to shift from their traditional way of manufacturing to a new digitalized one. In order to address today's challenges of adaptability to changes and high-quality products, SMEs should begin to adopt new technologies and reap their benefits. One main concern regarding the adoption of new technologies and IT tools, is that most of the provided solutions cannot be financially affordable by SMEs [60]. Moreover, SMEs can benefit from new reconfigurable and easy-to-install solutions.

Towards that, the proposed cloud-based cyber-physical system has been validated in a high-precision mould-making industry. The mould-making industry is highly specialized and knowledge-dependent. Once a new production order is released, a scheduling of its tasks must follow. Work is delegated among engineers based on their expertise, who are usually in charge of a project from start to end. Unofficial verbal meetings take place in order to schedule resources, and, if the situation demands it, the management department is involved in the decision making and work prioritization, most of the times without considering the actual shop-floor condition. The company considers two different dispatch rules during the decision-making and the work prioritization, the First in First out (FIFO) and the Earlier Due Date (EDD). No scheduling or monitoring software tools are used to support shop-floor control. In addition to that, maintenance scheduling is performed based on unforeseen machine-tool breakdowns (corrective maintenance) or following the defined MTBF of the machine tools (preventive maintenance). Therefore, through the proposed cloud-based cyber-physical system, not only will the shop-floor and the maintenance schedule be more accurate, flexible and adaptive to handle uncertainties and unpredictable events; but also the communication among the different employees and managers in the company will be improved through reduced iterations. In addition to that, via the mobile devices, anyone from the machine-tool operator to the company manager, will be informed on the status of the company and its performance.

The shop-floor of the mold-making industry, consists of 8 job-shops, which are defined as groups of work-centers (including design, milling, EDM, measuring, etc.) and 14 work-centers, which are defined as group of machines, (for example job-shop milling which includes the work-

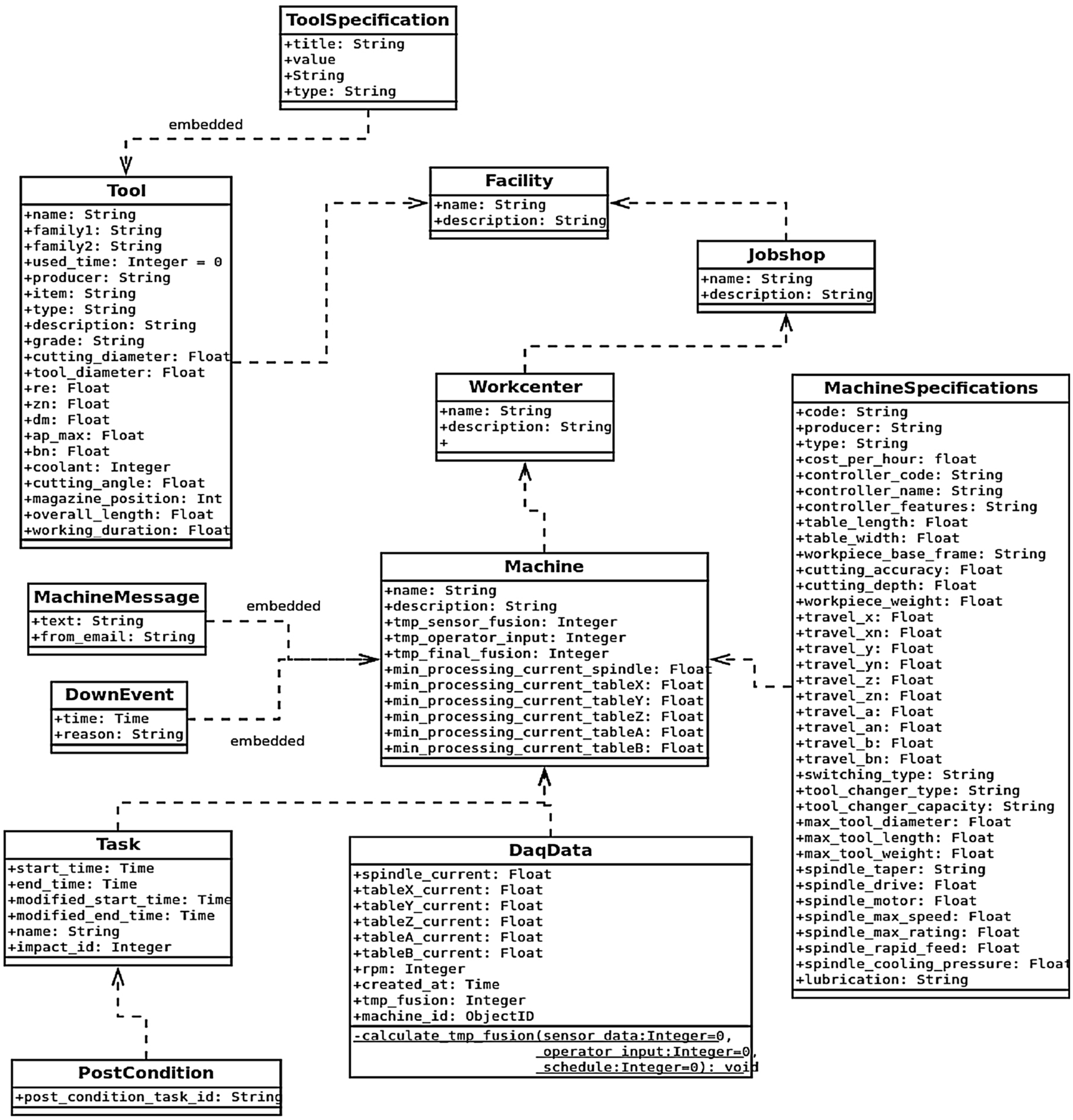


Fig. 7. Database schema of the software of the monitoring system.

centers roughing, finishing, drilling, among others) and include 40 individual resources in total (Fig. 8).

Among the 40 resources are the CNC machine tools that are capable of performing milling, drilling, turning, grinding, as well as hardening, and human operators that perform manual operations such as design, assembly, measuring etc. The mold-making industry produces a high number of molds every year that are utilized, among others, by consumer-goods companies and plastic manufacturers.

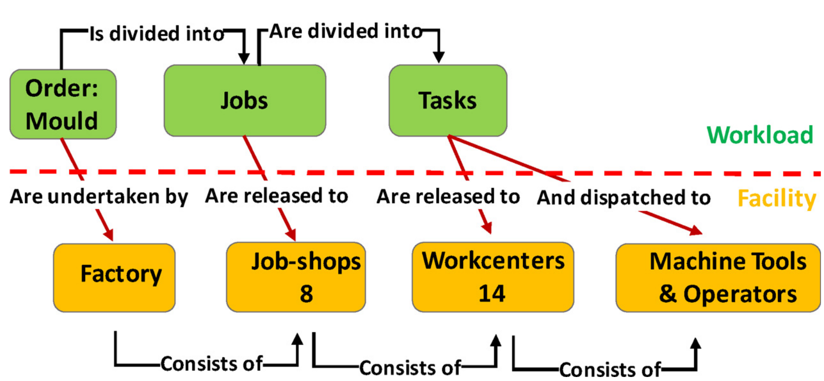


Fig. 8. The four-level hierarchical workload and facility model.

Fig. 9. The monitoring system installed in different machines and the mobile device provided to human operator.

The proposed cyber-physical system was installed in the company, both the hardware monitoring system as well as the software for adaptive scheduling and condition-based maintenance. The hardware of the monitoring system was installed in the machine tools, and mobile devices were provided to the machine tool operators (Fig. 9). This was performed in order to identify and measure the time required to monitor and track the changes in the production with and without the proposed solution. The total set up was carried out in less than 10 min per machine tool. Once the DAQs were installed, the wireless sensor network was set up and the internet bandwidth of the shop-floor was tested. The captured data were transmitted into the developed cloud server of the proposed system. The monitoring data were analyzed through the information fusion technique and finally, the status of the machine tools, their energy consumption, availability, utilization, as well as their actual machining time were calculated and provided. In addition to that, the overall progress of the generated schedule was calculated, reporting the completed, on-going, and pending tasks. Al the above information was provided through the developed software to the machine tool operator as well as to the production manager. In this way, the machine tools operators were capable of providing easily and in near real-time the necessary data and also the production and company managers were capable of visualizing the shop-floor condition in real-time through the calculated performance indicators (energy consumption, machine status, utilization, actual machining time).

As far as the shop-floor scheduling, the developed adaptive decision-making algorithm was used and a comparison was performed with three different dispatch rules taking into consideration the two that are already used by the mould-making company during the manual scheduling. The three dispatching rules that were used are FIFO, EDD, as well as SPT (Shortest Processing Time). The comparison was performed taking into account 5 different moulds as orders. The required tasks for producing the 5 moulds together with their main information (task time, post-conditions, due date), were added in the developed software and several runs were performed aiming to compare the generated schedules with the ones generated by the aforementioned dispatch rules. The performance of the proposed approach compared to other existing was examined based on the mean values of the performance indicators of utilisation, flowtime, and tardiness, which are given by the following formulas (11)–(13).

$$Tardiness\ MT\,(t_n) = \frac{1}{N^{comp}} \sum_{i=1}^{N^{comp}} \max(0, t_i^{comp} - t_i^{dd}) \tag{11}$$

$$Flowtime\ MF\,(t_n) = \frac{1}{N^{comp}} \sum_{i=1}^{N^{comp}} (t_i^{comp} - t_i^{arr}) \tag{12}$$

$$Utilisation\ MU\,(t_n) = \frac{1}{N^{comp}} \sum_{i=1}^{N^{comp}} \left(\frac{t_i^{comp} - t_i^{start}}{t^{tot}}\right) \tag{13}$$

where:

N^{comp} the number of completed jobs up to time t_n
t_i^{comp} the completion time of job i
t_i^{dd} the due date of job i
t_i^{arr} the arrival time of job i
t_i^{start} the start time of job i
t^{tot} the total operating time of the facility
t_n the time point at which all performance measures are calculated

The utilisation of the facility (multiple machines) is calculated as the percentage of the time required for executing each job compared to the total operating time of the facility. Following the fact that multiple jobs can be executed in parallel, the calculated percentages for each job are summed and then divided by the total number of jobs, that are executed in the facility, to calculate the mean utilization of the facility. Each job is consisted by several tasks that are executed in several machines.

For the proposed adaptive scheduling algorithm, the three adjustable factors were defined using statistical design of experiments, in order to generate the shop-floor schedule: the MNA, the DH, and the SR. The statistical design of experiments reduced the required number of experiments for determining the impact of tunable parameters on the cardinal preference of the decision-making process. The number of experiments was 25, and each factor had five levels. The analysis of means (ANOM) diagrams were created, which depict the impact of the values of the factors on the utility value. According to ANOM diagrams, the preferable values to be used in the particular scheduling experiment are MNA = 100, DH = 15, and SR = 20. Based on these values, the adaptive scheduling algorithm was used and its generated schedules were compared with the ones from the dispatch rules.

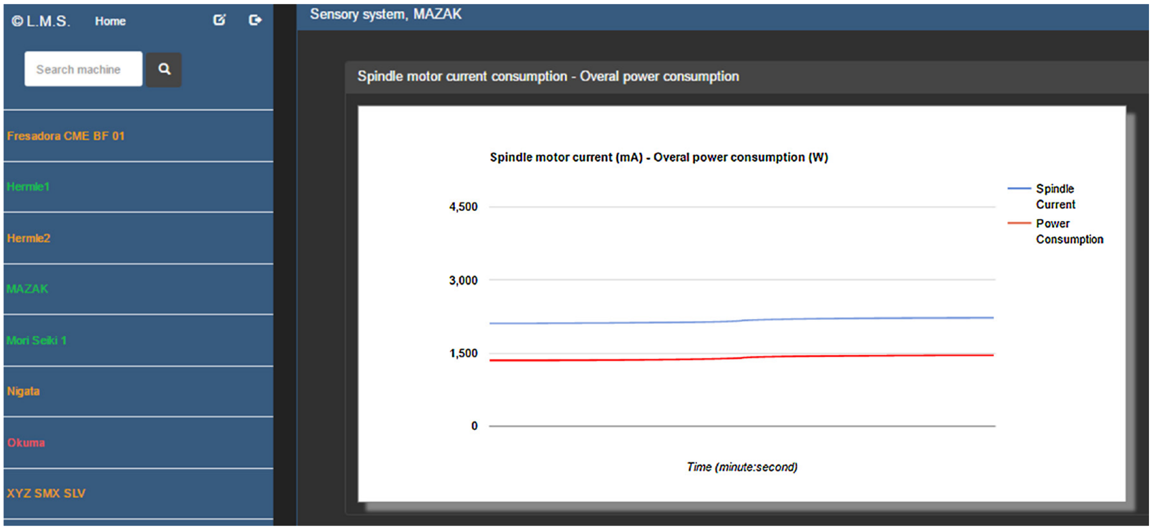


Fig. 10. Screenshot from the developed monitoring system presenting machine tool real-time monitoring.

6. Results and discussion

The proposed system monitored the machine tools and calculated their status as well as their energy consumption, as shown in Fig. 10 below. Based on Fig. 10, the status of the machine tools can be identified, considering set up mode, busy mode, idle mode, as well as down mode. In addition to that, User-friendly traffic lights (red, yellow, green, blue) that represent the status of each machine are employed (Fig. 10).

Moreover, detailed monitoring data for each machine are provided to the end-user (Fig. 10), who has the capability to visualize performance indicators including machine's energy consumption, be informed on machine's utilization, and inspect the monitored data in real-time (data strips obtained from sensors).

In addition to the above, in a case that any machine tool of the shop-floor was down as well as once the monitoring processing time of a task has exceeded the scheduled one, and the makespan was highly influenced, the proposed platform started the re-scheduling procedure using as main input the captured data from the monitoring system and the maintenance approach. The data included the machine tools together with their availability, as well as the pending and ongoing tasks, in order to generate the feasible alternative schedules and select the optimum one, the most appropriate to be executed (Fig. 11). Different scenarios were examined including machine tools to go down, exceed of original tasks duration as well as makespan influence as shown in Fig. 11. As shown also in Fig. 11, the status of the machine tool as well as the ROTBF of each machine tool is calculated. In addition to that, a real-time tracking on the produced schedule is performed, examining the different conditions for which re-scheduling should be performed. In this way, the proposed solution provided adaptability and awareness to the company, leading to increased productivity, machine tools utilization and reduced breakdowns.

The evaluation of the proposed approach has been performed in two different directions. Firstly, the proposed adaptive scheduling algorithm (ASA) was compared with existing dispatch rules (FIFO, SPT, EDD) in order to examine its performance compared to other approaches that were followed in the manual scheduling by the mould-making industry (Fig. 12).

More specifically, a data set was used, which was provided by the company after workshops and discussions with the production manager. The data set was consisted of 40 resources and five orders (moulds) that can run simultaneously in the production. The five orders consisted of 255 tasks in total. Based on this data set, four different scenarios were executed with three different dispatch rules (FIFO, SPT, EDD) and with the multi-criteria scheduling algorithm. Three performance indicators were measured to compare their performance including mean flowtime, mean utilization, and mean tardiness. The results of these scenarios are depicted in Fig. 12.

The diagrams of Fig. 12 reveal the superiority of the ASA in terms of the calculated performance indicator values. Still, in cases when a specific production target must be achieved, dispatch rules yielded high quality results. For instance, EDD identified schedules with lowest flowtime compared to the other dispatch rules and ASA.

Secondly, the proposed cloud-based cyber-physical systems for adaptive scheduling was examined in comparison to the traditional manner of scheduling and monitoring the machining tasks as discussed with the engineers of the company. This way of scheduling includes a lot of manual input and oral meetings within the company. Specifically, the weekly schedule is generated manually by the production engineers during a meeting that last for an average of 90 min every Monday morning. In addition to that, to compensate the unpredicted events that occur during production, manual rescheduling actions are performed which require approximately a total time of 60 min per week. In each unpredicted event, the production engineers perform short oral meetings, discussing on the condition of the production and deciding on how the production schedule will be changed. The total time required for manual rescheduling actions (weekly) includes the oral meeting as well as the time required to change the schedule and provide it again to the production through papers. The equivalent procedure after the adoption of the proposed monitoring/scheduling system requires an average time of 15 min in the beginning of the week to generate the initial schedule and approximately 30 min per week to make rescheduling actions using the aforementioned algorithm (Table 1). In both manual and automated procedures, the time needed to perform the data entry (orders, jobs, tasks, etc.) is identical and is not considered during the calculation of the required time durations. This procedure involves many actors such as the order department, the product designers, the CAM engineers, and the shop-floor engineer. Therefore, the total time that is required for scheduling and rescheduling during the time period of one week is reduced by 70% (Fig. 13). The aforementioned values of the time required after the adoption of the proposed system were measured during several experiments that were performed once the monitoring system were installed in the machine tools and the mobile devices were provided to the human operators. In addition to that, the values of the time required for the traditional scheduling were measured together with the production engineers considering several unpredicted events during the production.

The formula for calculating the time required for generating

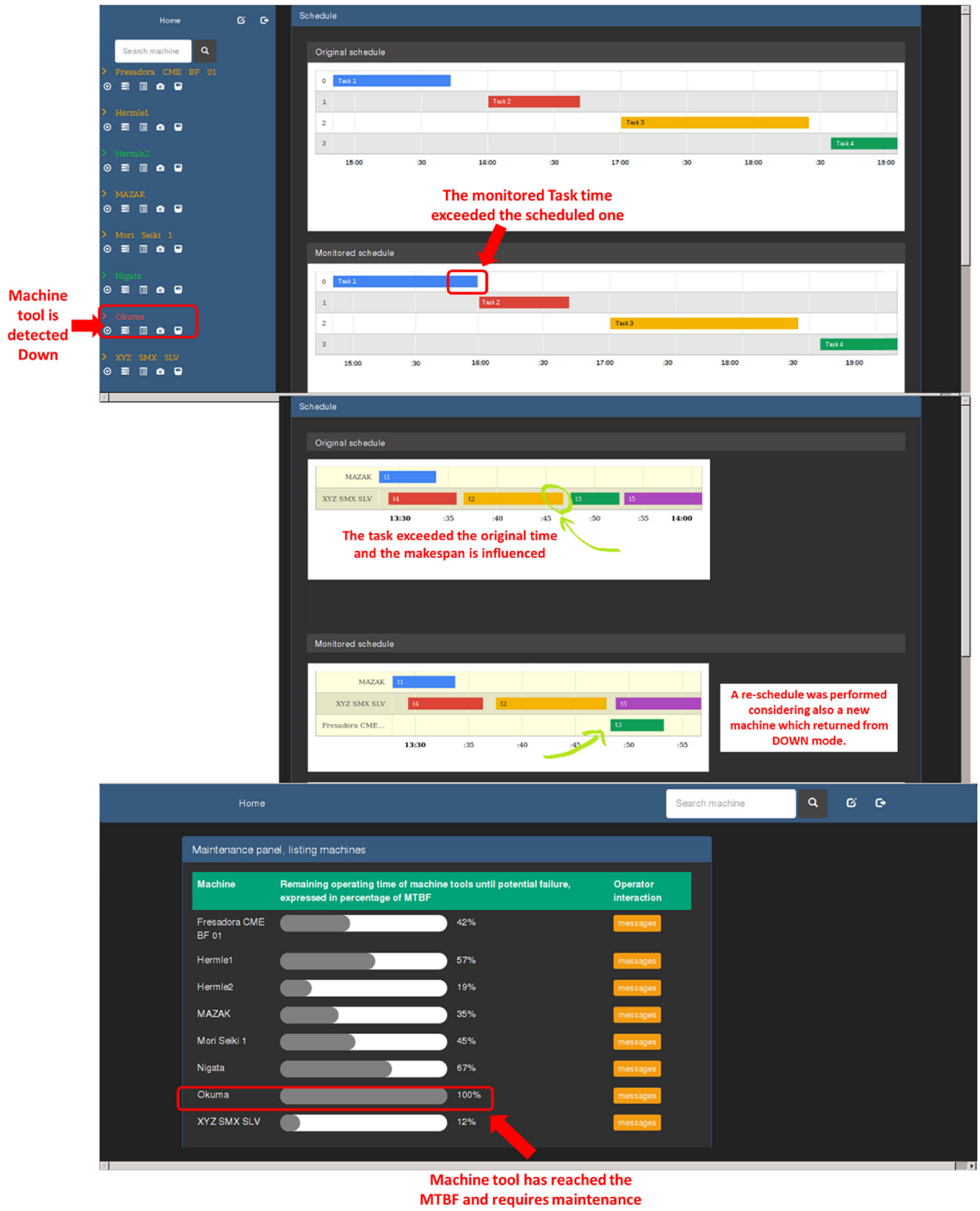


Fig. 11. Screenshot from the developed monitoring system showing the results, (i) the identification of the machine tools status, (ii) the monitoring of the proposed schedule, and (iii) the ROTBF based on the condition-based maintenance approach.

schedules within a week is presented below (14):

$$TS = TSin + l * TSre \ (min/Week) \tag{14}$$

Where:

TS is the total time required for generating schedules within a week

TSin is the total time required for generating the initial schedule in the beginning of the week

TSre is the total time required for performing rescheduling

l is the number of times that rescheduling is needed

The above results demonstrate that the adaptive scheduling algorithm together with its software provide to the company the capability of easily scheduling their production as the proposed algorithm can provide a good solution in a couple of minutes compared to the traditional way. Moreover, it enables company to perform re-scheduling in half of the initial time taking also into consideration the real shop-floor data. Compared to the traditional way where the identification of the down status of the machine tool and the deviation in the expected due date were time-consuming, the proposed system reduces this time as well as the time needed to re-generate again a schedule. Moving towards digitalisation, the proposed adaptive scheduling algorithm not only provides a digitalized way of scheduling enriched with a multi-criteria decision-making algorithm but also is capable of being

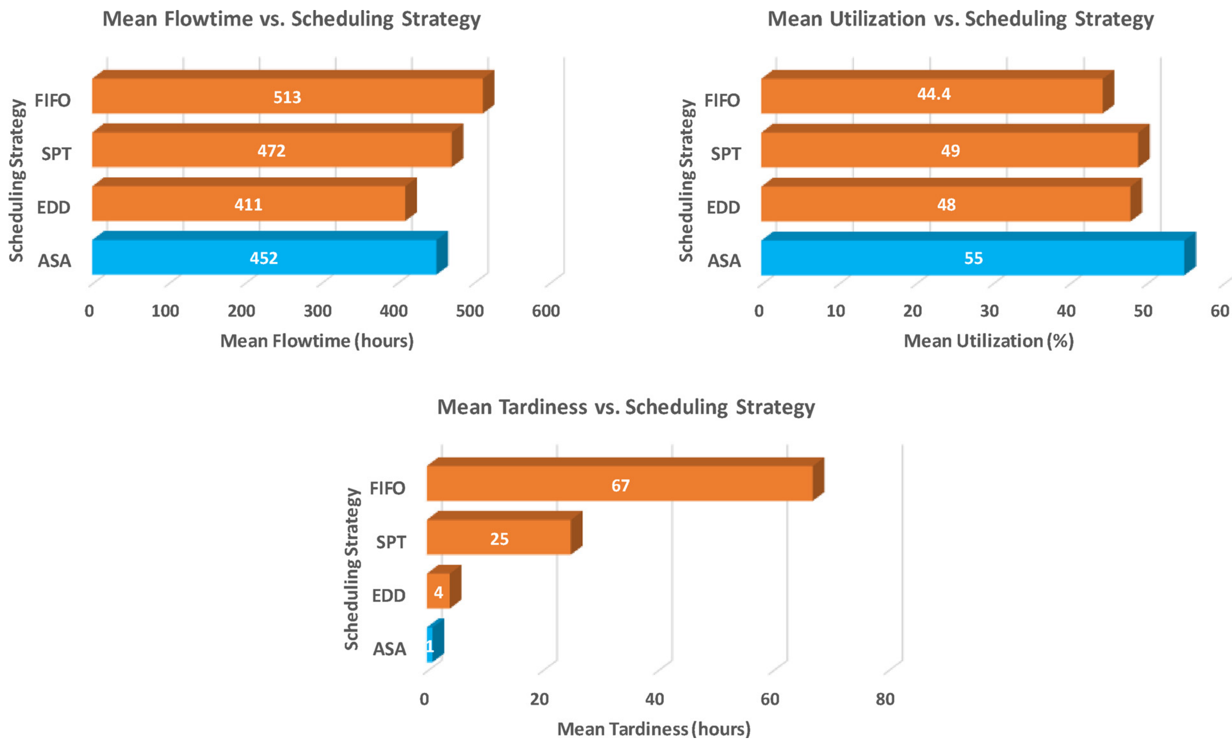


Fig. 12. Performance indicators (Mean Flowtime, Mean Utilization, Mean Tardiness) vs Scheduling Strategy.

Table 1
Time required for scheduling within a week based on the adaptive scheduling and the traditional approach.

Time Required for scheduling/week	Adaptive Scheduling	Traditional approach
Initial schedule	15 min	90 min
Rescheduling	30 min	60 min
Total	45 min	150min

integrated with different production systems (maintenance, monitoring), retrieving their data in real-time analysing them, and generating accurate and effective schedules.

The same comparison between the manual operation and the automated one was performed also for the monitoring component. The time to monitor one task is estimated based on tests with a stop watch to be 45 s (0.75 min) and based on discussions with the operators and the experience of the engineers, another 20 min per machine, on a weekly basis, are spent in order for the operators to make sure that the proper information for each task is documented correctly. The average number of machining tasks per week is 25 and the number of working machines is 20. Therefore, a total 418.75 min per week is required for manual monitoring purposes. The engineer responsible to report these time sheets in the online Excel file also spends 45 s per task (0.75 min), and an additional 1.5 h/week, to correct errors, retrieve missing information when necessary and mostly check the data for consistency. This results into 108.75 min per week for reporting. The system is error prone, the operators might use different code names among them, forget to put in the completion times, and unreadable handwriting are reasons for delays and mistakes. The total required time for tracking is 527.5 min per week.

Considering the proposed system, the tracking of the task will be performed through the monitoring system supported by the input from the human operator through the provided mobile device This process has been timed to be 15 s (0.25 min) per task, which is 6.25 min per week. This is a 66% reduction in time per task and also eliminates the 20-minute flat time per week that was calculated for retrieving missing information. In order to check the reported tasks for potential errors, a total time of 50 min per week is estimated. Therefore, the whole tracking procedure requires 56.25 min on a weekly basis (Table 2). It is evident that the automation of this procedure eliminates dramatically the amount of manual work (Fig. 13).

The formula for calculating the time required in task tracking per week is presented below (15):

$$TT = TR + TM\ (min/Week) \tag{15}$$

where:

TT is the total time required for tracking the tasks within a week

TR is the total time required for reporting the monitored tasks within a week

TM is the total time required for monitoring the duration of the tasks within a week

Fig. 13 presents the results of the proposed approach compared to the traditional one. Technically, the industrial company has moved towards digitalization by incorporating IoT-based monitoring system for machine tools, mobile devices for human operators and industrial communication protocols to enable data integration from different sources. Through the implementation of the wireless sensor network and the communication protocols, the data can be captured, pre-processed and transmitted in real-time. The implemented information fusion technique is capable is calculating important performance indicators that can be utilized not only by the scheduling algorithm but also by the condition-based approach, providing accurate information to the adaptive scheduling algorithm. Last but not least, the software implementation and the cloud platform enable the effective data storage and the efficient data processing, enabling also ubiquitous data access. As a result, the proposed cyber-physical system supports the effective production scheduling by reducing the required time, the efficient production monitoring by increasing the awareness on the shop-floor condition, the effective and accurate maintenance management through the condition-based maintenance approach, as well as the moving towards digitalisation and Industry 4.0 paradigms empowering the company and making it more competitive.

The digitalization of the mould-making industry was performed in

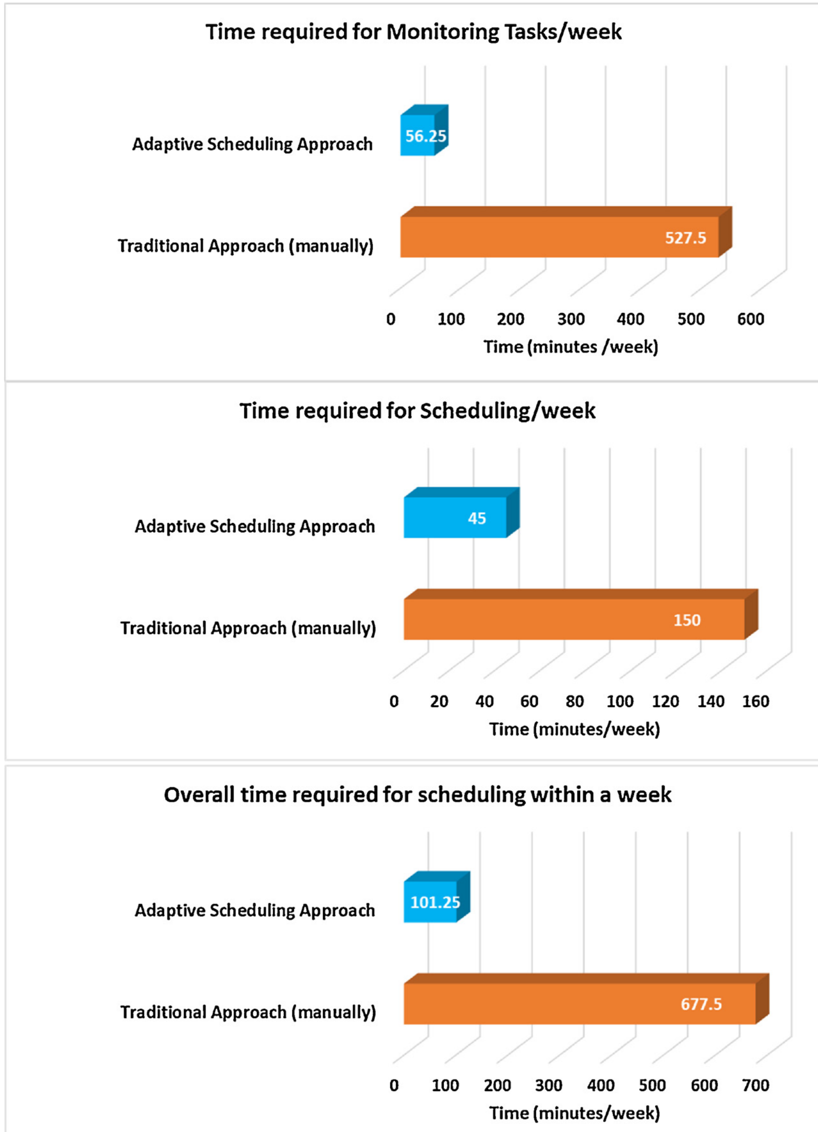


Fig. 13. The results comparing the traditional approach with the proposed cloud-based cyber-physical system for adaptive scheduling.

Table 2
Time required for task monitoring within a week based on the adaptive scheduling and the traditional approach.

Time Required for task monitoring/week	Proposed cyber-physical system	Traditional approach
Manual monitoring of tasks	6.25 min	418.75 min
Manual Reporting of tasks	50 min	108.75 min
Total	56.25 min	527.5 min

the different levels of the enterprise. Firstly, the machine tools were connected to the wireless sensor network, and were transformed into cyber-machine tools. Moreover, the monitoring system retrieved and analysed the shop-floor data, providing meaningful information to the scheduling algorithm as well as to the condition-based maintenance approach. The decision-making tools and practises, which were previously used in isolation without considering any feedback, are now connected under the umbrella of the cloud platform. The different levels of communication were improved through the digitalization and the use of mobile devices, reducing the iteration between the different roles in the company and raising their awareness.

A reliable, reconfigurable and cost-efficient system was applied addressing some of the main challenges of the IoT and Industry 4. 0 paradigms in manufacturing and specifically in SMEs: A cloud-based cyber-physical system capable of performing adaptive scheduling and control of modern shop-floors. The proposed system increases the system's productivity and reliability, by increasing the awareness on the actual condition of the shop-floor and quickly react and control the turbulences in modern shop-floors.

Finally, the main points/benefits of the proposed system compared with commercial real-time shop-floor production planning software, is that the proposed system in inexpensive, reliable, and affordable for SMEs. It also supports different communication protocols and standards like OPC-UA enabling the efficient integration of MES, ERP, and other systems. Moreover, the proposed system can also consider data not only from the shop-floor but also from the maintenance planning, enabling the integration of information and the generation of accurate schedules. Last but not least, the proposed approach is enhanced with a scheduling system that includes a multi-criteria decision making algorithm capable of retrieving real-time data and re-generating accurate and effective schedules and which can be customized by incorporating different criteria based on the main goals and needs of industrial companies.

7. Conclusions

This paper proposes a cloud-based cyber-physical system for adaptive shop-floor scheduling and condition-based maintenance. Current approaches related to shop-floor scheduling and control are working in isolation without considering the actual status of the production. This paper proposes a cloud-based system capable of performing adaptive shop-floor scheduling and condition-based maintenance. The main contribution of the proposed system can be summarised below:

- A cost-effective monitoring system which is capable of retrieving data from various sources and transmitting these data through a developed wireless sensor network and communication protocols
- A multi-criteria decision-making algorithm for adaptive scheduling capable of taking us input in real-time data from different sources from shop-floor (not only sensor data but also data from human operators, data from maintenance systems, etc.), and performing accurate and effective production scheduling
- A real cyber-physical system which consists of different modules which can communicate all together enabling interoperability (monitoring, adaptive scheduling, condition-based maintenance), and which are developed in a cloud environment supported by different technologies aiming to move towards Industry 4.0, digitalization and IoT.
- An overall system which can be easily applied in different kind of companies and which has been applied in a mould making industry in this case, presenting highly satisfied results compared to traditional ways.

Among the main advantages of the proposed platform and its application are:

- Increased awareness on both machine and shop-floor level condition.
- Effective and accurate maintenance of machine tools.
- Accurate decisions though condition-based maintenance and adaptive scheduling.
- Increased interoperability and communication among the different systems in the company.
- Increased automation which will support companies to shift towards Industry 4.0 environment.

To conclude, the present work contributes to the digitalization of manufacturing companies, providing a reliable, reconfigurable as well as cost-efficient approach that will support companies in changing their way of manufacturing, increasing their productivity, raising their awareness and reducing unforeseen failures. The feasibility of the proposed approach has been validated in a mould-making SME that is part of a larger supply chain, in which its position will be strengthened. In the case study, the SME was benefit from reduced schedule and monitoring time and from adaptive scheduling efforts.

In future work, the captured data from the monitoring system will be further analysed and used for energy consumption prediction as well as for predictive maintenance planning considering the available time windows of the machine tools.

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References

[1] Deloitte, Challenges and solutions for the digital transformation and use of exponential technologies, Report, http://www2.deloitte.com/content/dam/Deloitte/ch/Documents/manufacturing/ch-en-manufacturing-industry-4-0-24102014.pdf; 2014.
[2] Nativi S, Mazzetti P, Santoro M, Papeschi F, Craglia M, Ochiai O. Big data challenges in building the global earth observation system of systems. Environ Modell Softw 2015;68:1–26.
[3] Mourtzis D, Vlachou E. Cloud-based cyber-physical systems and quality of services. TQM Emer J 2016;28(6):29.
[4] Teti R, Jemielniak K, O'Donnell G, Dornfeld D. Advanced monitoring of machining operations. CIRP Annals – Manuf Technol 2010(59/2):717–39.
[5] Mourtzis D, Vlachou E, Xanthopoulos N, Givehchi M, Wang L. Cloud based- adaptive process planning considering availability and capabilities of machine tools. J Manuf Syst 2016;39:1–8. http://dx.doi.org/10.1016/j.jmsy.2016.01.003.
[6] Xu X. From cloud computing to cloud manufacturing. Robot Comp-Integr Manuf 2012;28(1):75–86.
[7] Hall DL, Llinas J, editors. Handbook of multisensor data fusion. USA: CRC Press; 2001.
[8] Schmidt B, Wang L. Cloud-enhanced predictive maintenance. Int J Adv Manuf Technol 2016:1–9. http://dx.doi.org/10.1007/s00170-016-8983-8.
[9] Chryssolouris G. Manufacturing systems: theory and practice. 2nd ed. New York: Springer-Verlag; 2006.
[10] Herroelen W, Leus R. Project scheduling under uncertainty: survey and research potentials. Eur J Operat Res 2005;165:289–306.
[11] Monostori L, Kádár B, Bauernhansl T, Kondoh S, Kumara S, Reinhart G, Sauer O, Schuh G, Sihn W, Ueda K. Cyber-physical systems in manufacturing. CIRP Ann - Manuf Techn 2016;65:621–41. http://dx.doi.org/10.1016/j.cirp.2016.06.005.
[12] Wang L, Törngren M, Onori M. Current status and advancement of cyber-physical systems in manufacturing. J Manuf Syst 2015;37(2):517–27.
[13] Morgan J, O'Donnell GE. The cyber physical implementation of Cloud manufacturing monitoring systems. Proc CIRP 2015;33:29–34. http://dx.doi.org/10.1016/j.procir.2015.06.007.
[14] Bagheri B, Yang S, Kao HA, Lee J. Cyber-physical systems architecture for self-aware machines in industry 4.0 environment. IFAC-Papers On Line 2015;48(3):1622–7.
[15] Mourtzis D, Doukas M, Milas N. A knowledge-based social networking app for collaborative problem-solving in manufacturing. Manuf Lett 2016;10:1–5. http://dx.doi.org/10.1016/j.mfglet.2016.08.001.
[16] Siemieniuch CE, Sinclair MA, Henshaw MJC. Global drivers, sustainable manufacturing and systems ergonomics. Appl Ergon 2015;51:104–19. http://dx.doi.org/10.1016/j.apergo.2015.04.018.
[17] McKinsey Quarterly, The Internet of Things, http://www.mckinsey.com/industries/high-tech/our-insights/the-internet-of-things ;2010[ACESSED 25.05.2016].
[18] Lee I, Lee K. The internet of things (IoT): applications, investments, and challenges for enterprises. Bus Horiz 2015;58(4):431–40.
[19] Wu D, John Greer M, Rosen DW, Schaefer D. Cloud manufacturing: strategic vision and state-of-the-art. J Manuf Syst 2013;32(4):564–79.
[20] Mourtzis D, Schoinochoritis B, Vlachou E. A New era of web collaboration: Cloud computing and its applications in manufacturing. TQM; 2015. ISBN: 978-86-7083-858-1.
[21] Tapoglou N, Mehnen J, Vlachou A, Doukas M, Milas N, Mourtzis D. Cloud based platform for optimal machining parameter selection based on function blocks and real time monitoring. ASME J Manuf Sci Eng 2018. http://dx.doi.org/10.1115/1.4029806.
[22] Mourtzis D, Doukas M, Vlachou A, Xanthopoulos N. Machine availability monitoring for adaptive holistic scheduling: a conceptual framework for mass customisation. Proc CIRP DET 2014;25:406–13.
[23] Wright P. Cyber-physical product manufacturing. Manuf Lett 2014;2(2):49–53.
[24] Li Y, Thai MT, Wu W. Wireless sensor networks and applications. Springer; 2008.
[25] Chryssolouris G, Domroese M. Sensor integration for tool wear estimation in machining. Sensors and controls for manufacturing- 1988, The Winter Annual Meeting of the American Society of Mechanical Engineers. 1988.
[26] Parikh C, Pont M, Jones N. Application of dempster-Shafer theory in condition monitoring applications: a case study. Pattern Recognit Lett 2010;22:777–85.
[27] Awasthi A, Chauhan S. Using AHP and dempster-Shafer theory for evaluating sustainable transport solutions. Environ Modell Softw 2011;26:787–96.
[28] Castanedo F. A review of data fusion techniques. Sci World J 2013;19.
[29] Zheng Y. Methodologies for cross-domain data fusion: an overview. IEEE Trans Big Data 2015;1(1):14–34.
[30] Ahmed E, Yaqoob I, Abaker I, Hashem T, Khan I, Ahmed A, Imran M, Vasilakos A. The role of big data analytics in internet of things. Comput Netw 2017;129(2):459–71.
[31] Chryssolouris G, Subramaniam V. Dynamic scheduling of manufacturing job shops using extreme value theory. J Prod PlannControl 2000;11:122–32.
[32] Michalos G, Makris S, Mourtzis D. A web based tool for dynamic job rotation scheduling using multiple criteria". CIRP Ann-Manuf Technol 2011;60:453–6.
[33] Valente A, Carpanzano E. Development of multi-level adaptive control and scheduling solutions for shopfloor automation in reconfigurable manufacturing systems. CIRP Ann 2011;60:449–52.
[34] Monostori L, Kádár B, Pfeiffer A, Karnok D. Solution approaches to real-time control of customized mass production. CIRP Ann-Manuf Technol 2007;56:431–4.
[35] Kumara SRT, Lee YH, Chatterjee K. Distributed multi-project Resource control: a

market-based approach. CIRP Ann-Manuf Technol 2010;51:367–70.
[36] Subramanian A, Garcia MJ, Callaway DS, Poolla K, Varaiya P. Real-time scheduling of distributed resources. IEEE Trans Smart Grid 2013;4(4):2122–30.
[37] Buyurgan N, Saygin C. Application of the analytical hierarchy process for real-time scheduling and part routing in advanced manufacturing systems. J Manuf Syst 2008;27(3):101–10.
[38] Yan Y, Wang Z. A two-layer dynamic scheduling method for minimising the earliness and tardiness of a re-entrant production line. Int J Prod Res 2012;50(2):499–515.
[39] Wang X, Li Z, Wonham WM. Dynamic multiple-Period reconfiguration of real-time scheduling based on timed DES supervisory control. IEEE Trans Indus Inf 2016;12(1):101–11.
[40] Zhang Y, Wang J, Liu S, Qian C. Game theory based real-time shop floor scheduling strategy and method for Cloud manufacturing. Int J Intell Syst 2017;32:437–63.
[41] Zhang Y, Tao F. Real-Time information-driven production scheduling system Chapter 8 - in optimization of manufacturing systems using the internet of things. Academic Press; 2017. p. 147–63. ISBN 9780128099100.
[42] Mori M, Fujishima M, Komatsu M, Zhao B, Liu. CIRP Ann-Manuf Technol 2008;57:433–6.
[43] Prajapati A, Bechtel J, Ganesan S. Condition based maintenance: a survey. J Qual Maint Eng 2012;18(4):384–400.
[44] Gao R, Wang L, Teti R, Dornfeld D, Kumara S, Mori M, Helu M. Cloud-enabled prognosis for manufacturing. CIRP Ann Manuf Technol 2015;64:749–72. http://dx.doi.org/10.1016/j.cirp.2015.05.011.
[45] Mourtzis D, Vlachou E, Milas N, Xanthopoulos N. A cloud-based approach for maintenance of machine tools and equipment based on shop-floor monitoring. Proc CIRP 2015;41:655–60.
[46] Efthymiou K, Papakostas N, Mourtzis D, Chryssolouris G. On a predictive maintenance platform for production systems. Proc CIRP 2012:250–7.
[47] Huang GQ, Wright PK, Newman ST. Wireless manufacturing: a literature review, recent developments, and case studies. Int J Comput Integr Manuf 2009;22:579–94.
[48] Chryssolouris G, Pierce J, Dicke K. An approach for allocating manufacturing resources to production tasks. J Manuf Syst 1991;10:368–82.
[49] STM32F429/39, ST Microelectronics, Website, http://www.st.com/content/st_com/en/products/microcontrollers/stm32-32-bit-arm-cortex-mcus/stm32f4-series/stm32f429-439.html?querycriteria=productId=LN1806.
[50] Zigbee, http://www.zigbee.org/ [ACESSED 20-12-2016].
[51] Digi International. XBee / -PRO ZB RF Modules. Product Manual, http://ftp1.digi.com/support/documentation/90000976.pdf ;[accessed 10.05.2016].
[52] Seilonen I, Tuovinen T, Elovaara J, Tuomi I, Oksanen T. Aggregating OPC UA servers for monitoring manufacturing systems and mobile work machines. IEEE 21st International Conference on Emerging Technologies and Factory Automation (ETFA). 2016. p. 1–4.
[53] McKinsey & Company report. Industry 4.0 after the initial hype. 2016, https://www.mckinsey.de/files/mckinsey_industry_40_2016.pdf.
[54] Mourtzis D, Vlachou E, Doukas M, Kanakis N, Xanthopoulos N, Koutoupes A. Cloud-Based adaptive shop-floor scheduling considering machine tool availability. Texas: ASME 2015 Houston; 2015.
[55] Phadke MS. Quality engineering using robust design. 1st ed. New Jersey, USA: Englewood Cliffs, Prentice Hall; 1989.
[56] Mourtzis D, Doukas M, Psarommatis F. Design and operation of manufacturing networks for mass customisation. CIRP Ann - Manuf Technol 2013;62:467–70. http://dx.doi.org/10.1016/j.cirp.2013.03.126.
[57] Dhilon BS, Maintenability. Maintenance, and reliability for engineers. Taylor and Francis; 2006.
[58] Gyftakis KN, Spyropoulos DV, Kappatou JC, Mitronikas ED. Taking advantage of the induction motor inherent eccentricity aiming to discriminate the broken bar fault from load oscillations. Int Conf on Electr Mach (ICEM). 2014. p. 1933–9.
[59] Sangat P, Indrawan-Santiago M, Taniar D. Sensor data management in the cloud: data storage, data ingestion, and data retrieval. Concurrency Computat: Pract Exper 2018;30.
[60] Cruz-Cunha M, Varajao J. E-business issues, challenges and opportunities for SMEs: driving competitiveness. USA: Premier Reference Source; 2010.