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ARTICLE

Cloud-based manufacturing process monitoring for smart diagnosis services

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ABSTRACT

A cloud-based manufacturing process monitoring framework for online smart diagnosis services has been developed with the aim of performing tool condition monitoring during machining of difficult-to-machine materials. The proposed architecture allows to share process monitoring tasks between different resources, which can be geographically dislocated and managed by actors with different competences and functions. Distributed resources with enhanced computation and data storage capability allow to improve the efficiency of tool condition diagnosis and enable more robust decision-making, exploiting large information and knowledge sharing. Diagnosis on tool conditions is offered as a cloud service, using an architecture where the computing resources in the cloud are connected to the physical manufacturing system realising a complex cyber-physical system using sensor and network communication. Based on sensorial data acquired at the factory level, smart online diagnosis on consumed tool life and tool breakage occurrence is carried out through knowledge-based algorithms and cognitive pattern recognition paradigms. On the basis of the cloud diagnosis, the local server activates the proper corrective action to be taken, such as tool replacement, process halting or parameters change, sending the right command to the machine tool control.

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Cloud manufacturing; machining; tool condition monitoring; sensors; cyber-physical system; Industry 4.0

1. Introduction

The evolution of modern advanced manufacturing systems is going towards the increasing integration of information and communication technologies (ICTs) in the production environment, realising the so-called 'Smart factories' where physical objects are seamlessly integrated into the information network (Smit et al. 2016).

The combination of the newest developments of ICT, such as cyber-physical systems (CPS) based on the use of sensors, processors and communication technologies, and the newest developments of manufacturing science and technology, is producing new manufacturing paradigms such as cyber-physical production systems (CPPS) and is considered the driver of the Fourth Industrial Revolution, also known as Industry 4.0. (Monostori 2014; Monostori et al. 2016; Wang, Törngren, and Onori 2015).

A key role in the realisation of these new manufacturing paradigms is played by cloud computing. The extension of the cloud computing paradigm to the manufacturing sector has generated the concept of cloud manufacturing, recognised as one of the most innovative Key Enabling Technologies for modern manufacturing industry, which is claiming increasing attention in manufacturing research (Horizon 2020; Zhang et al. 2012; Xu 2012; Tao et al. 2011; Li et al. 2010).

Cloud technologies provide an environment to connect and share distributed manufacturing resources including knowledge, computing and software tools, as well as physical resources via the Internet networking infrastructure, and can be employed for a wide range of manufacturing applications such as process planning, machine tool monitoring, process monitoring and control (Zhang et al. 2012; Xu 2012; Tao et al. 2011; Li et al. 2010).

In this paper, a new cloud manufacturing framework is developed to realise online process monitoring through cloud-based smart diagnosis services. The framework is configured with particular reference to tool condition monitoring (TCM) in the machining of difficult-to-machine materials, which is a critical issue due to the rapid development of tool wear and the unpredictable occurrence of catastrophic tool failure (CTF) (Teti et al. 2010; Teti 2015; Segreto, Caggiano, and Teti 2015).

2. State of the art on cloud manufacturing

Cloud manufacturing may be defined as 'an integrated CPS that can provide on-demand manufacturing services, digitally and physically, at the best utilisation of manufacturing resources' (Wang, Törngren, and Onori 2015).

Compared with cloud computing, the services that are managed include not only computational and software resources, but also various digital and physical manufacturing resources, including manufacturing software, manufacturing facilities and manufacturing capabilities (Wang, Törngren, and Onori 2015).

This manufacturing paradigm may significantly change the way manufacturing services are provided and accessed, giving to the user ubiquitous access via cloud to CPPS, including smart machines and large amounts of data generated through sensor systems and intelligent computation (Wu et al. 2015).

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At present, the main research gaps of the cloud manufacturing paradigm can be summarised as follows: cloud-based control platforms; real-time capability of production cloud platforms; interfaces between cloud and production system; and service-based provision of automation functionalities.

In order to tackle the above research gaps, diverse authors in the very recent literature have proposed innovative cloud manufacturing applications for several manufacturing purposes at different levels.

In Wu et al. (2013a), a review of research initiatives and applications of cloud technologies in collaborative design, distributed manufacturing, data mining, semantic web technology and virtualisation is reported. The concept of cloud-based design and manufacturing (CBDM) is proposed, expanding the cloud computing paradigm to the field of computer-aided design and manufacturing. CBDM represents a service-oriented networked product development model in which service consumers are able to configure, select and utilise customised resources and services for product realisation ranging from computer-aided engineering software to reconfigurable manufacturing systems (Wu et al. 2015).

One of the most common aspects in the cloud manufacturing frameworks presented in the literature is the use of sensors to gather information from the physical manufacturing system and intelligent algorithms for data processing to provide services supporting different manufacturing tasks.

Mourtzis et al. (2016a) developed a cloud approach to realise condition-based preventive maintenance of machine tools and equipment based on the use of advanced monitoring techniques. In this approach, the cloud-based software service collects and processes in near-real-time data on the status of the machine tools and their actual operating time and estimates the remaining useful life of components.

Tapoglou et al. (2015) presented a cloud-based approach for dispatching jobs to the available computer numerical control (CNC) machines and creating the optimum machining code based on relevant information acquired on the shop floor. The approach is based on the use of a sensor network, information fusion technique and data communication through the Internet to a cloud-based platform.

In Mourtzis et al. (2016b), an approach for cloud-based adaptive process planning taking into account availability and capabilities of machine tools is proposed. A service-oriented cloud-based software framework gathers data from shop-floor machine tools through sensors, input from operators and machine schedules and through information fusion technique provided to the process planning service processed data on the status, specifications and availability time windows of machine tools.

Wang (2013) developed a web-based service-oriented system for distributed machining process planning in a decentralised and dynamic manufacturing environment. Real-time monitoring of machine availability and web-based user interface allow adaptive decision-making capability even in the case of unpredictable shop-floor changes and network-wide accessibility to manufacturing services.

Wang et al. (2016) proposed a cloud-based framework for prognosis of machine degradation and failure propagation to support preventative maintenance scheduling.

In Wu et al. (2016a), an approach for predictive maintenance through the parallel implementation of machine learning algorithms on the cloud is developed, while in Wu et al. (2016b), a fog-enabled architecture consisting of smart sensor networks, communication protocols, parallel machine learning and private and public clouds for automatic failure detection and preventative maintenance scheduling is proposed.

Gao et al. (2015) presented the concept of cloud-enabled prognosis as an innovative service-oriented technology supporting prognostic services for manufacturing over the Internet. In this framework, machine condition monitoring is realised by collecting data remotely and dynamically on the shop floor via sensors and data acquisition systems; based on these acquired records, remote data analysis and degradation root-cause diagnosis and prognosis are performed. The result of the prognostic service is used as the basis for preventive maintenance planning.

Beyond the specific target of machine condition monitoring, the wider field of manufacturing process monitoring could benefit from the implementation of cloud manufacturing for further scopes including monitoring of tool conditions, chip form, process parameters, surface integrity, chatter detection, etc.

However, as regards TCM, which is a major issue in manufacturing process monitoring, a significant lack of cloud-based applications/frameworks proposed in the literature is verified. The work reported in the present paper contributes to filling the current cloud manufacturing research gap related to the development of a new cloud-based control platform aimed at service-oriented provision of online smart diagnosis and automation functionalities for TCM in machining.

Cloud-enabled diagnosis in online TCM can provide several benefits compared to traditional TCM methodologies. Data are remotely and dynamically gathered on the shop floor via sensors and data acquisition systems while data analysis can be performed in remote, where expert know-how can be made available and shared in the cloud, realising the knowledge base referenced on-demand by users through the Internet. Improved accessibility and robustness are achieved by offering modular and configurable diagnostic services that can be selected from the cloud when necessary or applicable in the form of pay-as-you-go services. Improved computational efficiency and data storage are allowed by the higher speed characterising cloud-enabled computation via parallel computing. Collaboration and distribution are enhanced as diagnosis is offered as a remote service instead of a local, centralised function. Information sharing and fusion realised by crowdsourcing allow to improve data interpretation and robustness (Gao et al. 2015).

3. Advantages of cloud-based smart TCM in manufacturing processes

The aim of this research work is to develop a cloud manufacturing framework to provide smart TCM services, realised through the combination of real-time cloud-enabled diagnosis based on sensor monitoring and cognitive decision-making procedures.

The development of smart monitoring procedures in manufacturing can significantly increase productivity and reduce production costs, enhance the performance of manufacturing processes in the perspective of zero defect manufacturing and support the reliable automation of manufacturing systems via smart system adaptation (Teti 2015; Wang and Gao 2006).

Monitoring of manufacturing processes has several scopes. This work is developed with particular reference to TCM, which is a critical issue, especially when machining difficult-to-cut materials such as those employed in aeronautical and aerospace applications, due to the rapid development of tool wear and the unpredictable occurrence of CTF (Jemielniak et al. 2012; Teti et al. 2010).

The availability of real-time diagnosis on tool conditions may allow to optimise tool life by implementing smart strategies such as condition-based tool replacement (i.e. by replacing cutting tools only when they are close to the end of life) instead of conservative time-based tool replacement (in which the cutting tool is replaced after a predetermined time independently of its real wear conditions). In this way, it is possible to decrease the tooling costs and reduce the risk of damages to the machine and workpiece, e.g. by allowing fast reaction when a tool breakage occurs.

TCM has been extensively studied by many researchers since the late 1980s (Teti et al. 2010). The majority of TCM research to date has been focused on widespread machining processes such as turning, drilling, milling and grinding, but also less frequent machining processes such as broaching were investigated (Boud and Gindy, 2008).

The typical TCM system operates according to the following procedure: selected process variables (e.g. cutting forces, vibration and acoustic emission) are measured by the application of appropriate physical sensors; the detected signals are subjected to analogue and digital signal conditioning and processing with the aim to generate functional signal features relevant to the tool condition. The TCM is based on these features (Teti et al. 2010; Teti 2015; Jemielniak and Arrazola 2008; Jemielniak et al. 2012; Boud and Gindy 2008; Wang et al. 2014). In a smart monitoring system, the sensor signal features are then fed to and evaluated by cognitive decision-making support systems based on pattern recognition techniques for the final diagnosis that can be used to suggest or execute appropriate adaptive/corrective actions (Teti et al. 2010; Teti 2015; Kunpeng, San, and Soon 2009).

Many of the TCM approaches presented in the literature employ multiple sensors and advanced signal processing techniques that require the local availability of high-level computational resources, storage capability, interoperability and user skills (Teti et al. 2010; Teti 2015; Jemielniak and Arrazola 2008; Jemielniak et al. 2012; Boud and Gindy 2008; Wang et al. 2014). Such requirements may represent barriers to the online implementation of such approaches in industry.

Hence, the possibility to realise the remote and timely acquisition, distribution and utilisation of data from manufacturing processes is extremely interesting for the realisation of innovative monitoring procedures (Monostori et al. 2016).

In this direction, the new paradigms such as Industry 4.0, Internet of Things and cloud manufacturing represent key enablers to overcome the traditional barriers of TCM applications and achieve objectives such as increased use of sensors, interoperability, cloud-hosted analysis and wider technology acceptance by operators (Byrne et al. 2016).

The implementation of a cloud manufacturing framework proposed in the present paper represents a remarkable advancement for smart process monitoring, allowing to exploit the cloud capabilities in order to offer real-time diagnosis on tool conditions according to a service-oriented approach. Introducing sensors and networked communication into the factory strongly supports smart in-process diagnosis as well as the timely activation of adaptive actions based on actual process conditions (Gao et al. 2015). These actions include human interventions and proper commands directly fed to the machine tool numerical control, improving the robustness and adaptability of processes and systems.

According to the proposed cloud manufacturing-based monitoring framework, the computing and service resources in the cloud are connected to the physical production devices (i.e. machine tools and sensor systems) realising a complex CPS (Wang et al. 2014; Monostori 2014; Wang, Törngren, and Onori 2015).

The cloud server receives the preprocessed sensorial data acquired by a multiple sensor system mounted on the machine tool and provides services consisting in the diagnosis on tool conditions related to the detection of tool failure events through a knowledge-based approach as well as to the estimation of tool life through a neural network (NN)-based cognitive paradigm using features extracted from the acquired sensorial data (Teti 2015).

The diagnosis on tool conditions benefits from the cloud infrastructure in terms of enhanced computational capability, which improves the execution efficiency of the diagnosis and enables more robust decision-making due to large information and knowledge sharing available in the cloud (Gao et al. 2015).

Based on the diagnosis on tool conditions provided by the cloud service, it is possible to locally select and automatically activate proper actions at factory level, such as emergency process halting, tool replacement or parameters' change.

4. Architecture of the cloud-based framework for manufacturing process monitoring

The cloud-based manufacturing process monitoring framework developed to realise online smart diagnosis is based on the architecture shown in Figure 1. The computing and service resources in the cloud are connected to the physical resources (machine tool and sensor system) realising a complex CPS, which can be defined as a 'physical and engineered system whose operations are monitored, coordinated, controlled and integrated by a computing and communication core' (Rajkumar et al. 2010).

The cloud manufacturing architecture is structured in three layers corresponding to:

- Physical resources
- Local server
- Cloud server

This structure allows to share the computational effort between different resources, which can be geographically distributed and managed by diverse actors with different

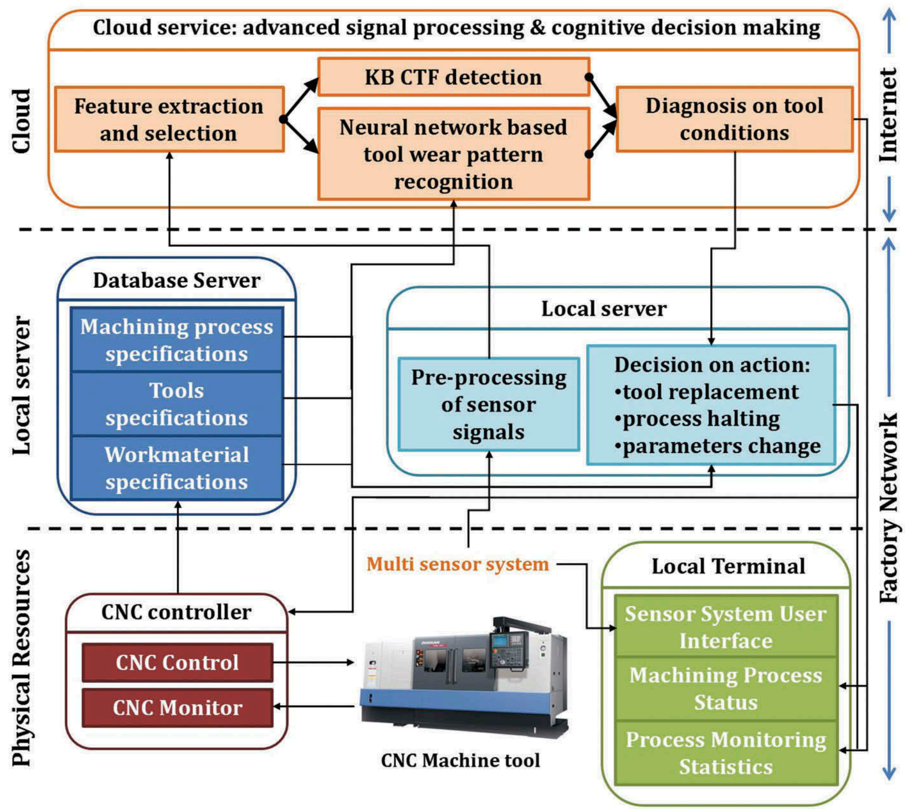

Figure 1. Architecture of the cloud-based cyber-physical system for smart monitoring of machining processes.

competences and acting at different levels. In this way, while exploiting the different skills of each actor involved, network communication allows to overcome the traditional distance between office floor and shop floor and to share their results and information.

The physical resources and the local server are both included in the Factory Network, representing the hardware and software resources available within the production system. On the other hand, the cloud service is Internet based and can be potentially connected inside the boundary of the manufacturing company (private cloud) or outside that boundary (public cloud, requiring higher protection of data). Different methods can be adopted to connect machines, local server and provider cloud, and they must be selected based on stability, speed, distance coverage and security. Within the factory environment, local area network (LAN) is preferable to Wi-Fi and Bluetooth. Moreover, communication beyond the boundary of the manufacturing company often implies great distances to be covered and requires the availability of connections of LANs with high security and time performance. Tactile Internet, characterised by very low latency (<1 ms) in combination with high availability, reliability and security, represents a key target to fulfil the communication requirements of cloud manufacturing (Neugebauer 2016).

By examining the three-layer structure of the proposed cloud manufacturing architecture, at the physical layer, the CNC machine tool employed to perform the machining process must be equipped with a multi-sensor system to collect in real time various sensor signals containing valuable information on process conditions. Reliable sensor monitoring of machining processes requires the employment of a multiple sensor system to overcome the limitations of a single sensor and to realise the sensor fusion technology to integrate information from several sensors of different nature in order to improve the quality and robustness of the process characterisation (Teti et al. 2010; Teti 2015).

The system is employed to collect in real time during machining multiple sensor signals that contain relevant information to use as input for the diagnosis on tool conditions.

The computing tasks related to sensor signal preprocessing are assigned to the local server. To support high computing power, the local machine works as data buffer and preprocesses the data into stand-alone data packages (sensor signal segments) which are sent to the cloud over the network (Gao et al. 2015).

The cloud computing capability is employed to rapidly perform online diagnostic tasks, and the potentially huge cloud database is used to maintain and share relevant information and knowledge that can support further cloud services.

The cloud server receives the preprocessed sensor signal segments, carries out the extraction of relevant signal features and performs the required diagnosis on tool conditions, detecting faults such as CTF through a knowledge-based approach, as well as estimating consumed tool life through cognitive pattern recognition paradigms. After the computing task is completed, the cloud sends back the diagnostic output to the local server, which utilises the diagnosis result as input and reference for decision-making on corrective actions. Based on the cloud diagnosis on tool conditions, the local server may select actions such as tool replacement, process halting or parameters change and send the necessary commands directly to the CNC machine tool control. Any corrective action is displayed on the local terminal for visualisation by the operator, and proper warning is displayed in case human intervention is required.

5. Development of the cloud-based framework in turning of difficult-to-machine materials

The presented cloud-based manufacturing process monitoring framework for smart diagnosis may be virtually employed for any machining process, by properly adapting the multi-sensor system, the signal processing procedures and the cognitive algorithms for the diagnosis on process conditions based on the specific process involved.

In this paper, the proposed framework for cloud-based manufacturing process monitoring has been developed with particular reference to the application in turning of difficult-to-machine materials, where a prompt diagnosis on tool conditions may determine a significant process improvement.

The cloud server proposed in the cloud-based framework for smart diagnosis provides for knowledge-based algorithms and cognitive paradigms able to make a diagnosis on tool conditions based on the acquired sensorial data.

The development of the methodologies for the smart diagnosis on tool conditions requires the creation of a comprehensive training set: therefore, experimental data have been collected through a preliminary experimental campaign of turning of difficult-to-machine materials such as titanium alloys.

When turning these materials, rapid tool wear occurs since most of the heat generated during machining is conducted into the tool, and unpredictable CTF may occur during the process due to the extremely low machinability. The degradation and failure of the cutting tool have adverse effects on accuracy and surface finish of machined parts and significantly contribute to scrap generation.

Therefore, the development of smart diagnosis procedures supported by cloud technologies could lead to significant improvements in terms of scrap reduction, rework and inspection costs, tooling costs, machine and workpiece safety and process robustness and would reduce down time related to maintenance and tool replacement operations.

5.1. Physical resources: multi-sensor monitoring system

By examining the three-layer structure of the proposed cloud manufacturing architecture (Figure 1), at the physical level, a multi-sensor system is mounted on the CNC machine tool.

The selection of the most adequate sensors depends on the specific machining process and the monitoring scope: the most commonly utilised sensors for online measurement during machining include force, torque, power, acoustic emission, vibration and temperature sensors. In the specific case of turning of difficult-to-machine materials, the smart diagnosis is based on the employment of a multiple sensor system comprising a triaxial force sensor, an acoustic emission sensor and a vibration sensor mounted in the proximity of the tool, with the aim to capture useful information for TCM. In Figure 2, the lathe-mounted multiple sensor system for turning process monitoring is shown.

Figure 2. Multiple sensor monitoring system for smart monitoring of turning processes.

6. Local server

The local server in the middle layer is installed and configured to carry out the preprocessing of signals coming from the multiple sensor system and send the preprocessed sensor signal segments to the cloud service.

Preprocessing of signals coming from the multiple sensor system for TCM involves signal filtering, amplification, A/D conversion and segmentation. The analogue sensor signals are amplified and then digitised through an acquisition board at a sampling rate of 10 kS/s. Only the relevant part of the signals acquired during machining is taken into further consideration, removing air cut or transient conditions (Teti et al. 2010; Teti 2015).

The preprocessed and segmented signals are buffered by the local server and delivered via Internet protocols to the on-demand web-based cloud service system according to the needs of the cloud sensor monitoring procedure. The data buffer length may be different depending on the requirements of the specific algorithm to which the signal segments are inputted. For a fixed-signal sampling rate, the shorter the data buffer, the highest the frequency of the diagnosis loop will be, with consequent faster manufacturing system reaction time. On the other hand, when choosing the data buffer length, concerns regarding the algorithm processing time and the amount of relevant information included in the data buffer for the monitoring scope should be taken into account, and a sufficiently long buffer length should be selected.

When the cloud server completes the diagnosis on tool conditions and forwards it to the local server, the latter selects the proper corrective action to be taken based on the cloud server diagnosis output as well as on the specifications about processes, tools and work materials stored in the local database.

Corrective actions may include process halting, tool replacement or parameters' change: the proper command, such as process halting or parameters' change, is directly sent from the local server to the CNC control. Moreover, the selected action can be visualised on the local terminal to make the user aware of the control actions taken automatically by the local server. In the case of tool replacement, the local terminal displays a warning to the operator with the instruction to replace the tool.

6.1. Communication between local server and cloud server

The cloud-based diagnosis function is offered as a web service application hosted on a web server accessed through the network. As regards the communication between client and cloud server, the Hyper Text Transfer Protocol (HTTP), which is a widespread protocol for web-based applications, has been selected for data transmission.

In this way, the web service can be invoked with any HTTP-capable web client, application-to-application data exchange can be easily carried out and remote monitoring and control can be performed.

To secure the network data exchange, Transport Layer Security cryptographic protocol, upgrade of Secure Sockets Layer, is adopted to provide privacy and data integrity between communicating parties. In this way, the connection is private (or secure), the identity of the communicating parties can be authenticated and connection integrity is ensured using a message authentication code to prevent undetected loss or alteration of the data during transmission. These security-related features are particularly critical in the cloud manufacturing framework to protect the exchanged data against misuse and unauthorised access, ensure transmitted data integrity and prevent data losses that would cause serious production damages.

HTTP as communication protocol has been adopted in various cloud manufacturing frameworks, including those presented by Mourtzis et al. (2016a) and (2016b), Tapoglou et al. (2015) and Wang et al. (2011).

In the literature, there are current efforts to develop server-oriented architectures using different web services standards providing greater interoperability and security for CPS (Morgan and O'Donnel 2015). Moreover, innovative open standards and communication protocols, in particular for what concerns machine-to-machine communication and interoperability, have been recently proposed and are still under development (MTConnect Institute, n.d.; Wu et al. 2013b). In the future, new communication protocols could allow for faster and easier communication of manufacturing facilities and applications through the Internet.

7. Cloud server

The cloud server provides for knowledge-based algorithms and cognitive paradigms able to make a diagnosis on tool conditions based on the acquired sensorial data. This is offered as a web service application hosted on a web server accessed through the network via HTTP protocol.

The developed cloud manufacturing framework takes advantage of the cloud capabilities by outsourcing the activities for advanced signal processing and cognitive decision-making. The cloud service consists of four parts. The first part carries out advanced signal processing on the preprocessed sensor signal segments in order to extract and select relevant sensorial features for TCM. The latter are utilised in two different modules: the first module is employed to detect the occurrence of a CTF through a knowledge-based algorithm, whereas the second module is utilised to estimate consumed tool life through an NN-based pattern recognition approach.

In this way, the cloud is able to provide online diagnostic services. The output diagnosis on tool conditions is sent back to the local server which can determine the proper actions to be taken such as tool replacement, process parameters' variation or emergency halting.

7.1. Feature extraction and selection procedure

The extraction of relevant features related to the tool and/or process conditions from the acquired sensor signals is a key issue in machining monitoring systems (Teti et al. 2010). Several methodologies for sensor signal feature extraction are available, based on signal representations both in the time domain and in the frequency domain (Teti 2015).

In this cloud manufacturing framework, sensor signal features maintaining the relevant information about the process will be extracted in the time domain and in the time–frequency domain from the preprocessed sensorial data coming from the local server.

The methodology for the diagnosis on CTF is based on the extraction of statistical features from the sensor signals in the time domain, whereas the methodology for the diagnosis of consumed tool life is based on sensor signal features extracted in the time–frequency domain through Wavelet Packet Transform (WPT) (Teti et al. 2010; Teti 2015).

Feature selection is then carried out to select only the relevant features that can be correlated to the tool conditions. As a matter of fact, although a sensor signal may be characterised by many diverse representative features, not all of them are useful for the specific monitoring purpose (Teti et al. 2010; Teti 2015).

Moreover, direct fusion paradigms (i.e. fusion of sensor data from heterogeneous sensors) and/or indirect fusion paradigms (i.e. using other information sources such as machine process specifications) are applied (Teti et al. 2010; Teti 2015; Segreto, Simeone, and Teti 2013).

7.2. Knowledge-based CTF detection methodology

The first module for the diagnosis of tool conditions is focused on identifying the occurrence of CTF through a knowledge-based detection algorithm.

A CTF is an unpredictable fracture of the cutting edge, e.g. through brittle failure, and might cause substantial damages to the workpiece and/or the machine tool. Therefore, the ability for online detection of a CTF event during machining and the prompt halting of the process are essential to reduce workpiece scraps and machine downtime with positive effects on product quality and cost.

In the literature, some methodologies to detect the occurrence of CTF have been proposed with particular reference to turning processes (Kim and Choi 1996; Jemielniak et al. 1998a; Jemielniak et al. 1998b; Balsamo et al. 2016). The procedure employed in this cloud manufacturing framework is based on sensor signal acquisition of the three components of the cutting force (Fx, Fy and Fz) during machining, following previous results reported in Balsamo et al. (2016). The methodology is based on the extraction of relevant signal features from signal segments corresponding to 10 ms of machining, consisting of 100 samplings at sampling frequency of 10 kS/s: below this time window, the CTF procedure proved not to be sufficiently reliable. With the aim to speed up the CTF diagnosis, instead of considering consecutive signal segments of 100 samplings each, a moving window with a total length of 100 samplings and a step of 20 samplings is considered. Signal segments of 100 samplings are constructed by shifting forward of 20 samplings at a time: at each run, 20 new samplings are collected and added to the signal segment, and the oldest 20 samplings are removed from the signal segment.

Therefore, at each step, very small signal segments, corresponding to 2 ms of machining, are sequentially processed and collected into larger signal segments corresponding to 10 ms of machining to extract selected signal features (e.g. signal mean, variance and max–min range) useful for CTF event identification: these features are input to a knowledge-based algorithm that compares the feature values with previously specified thresholds for CTF detection.

The logic scheme of the knowledge-based CTF detection procedure is shown in Figure 3. The CTF detection algorithm receives in input the sensor signal segments as well as the specifications concerning the machining process, the tool and the work material. These data allow to identify the proper procedure for CTF detection and the values of the thresholds for the specific process conditions.

The sensor signal arrays containing 20 samplings of each signal are sequentially buffered and delivered in input to the CTF detection algorithm; for a sampling frequency of 10 kS/s, the 20 signal samplings correspond to 2 ms of cutting time. Therefore, the frequency of the CTF diagnosis loop is equal to 500 times/s, which means that the CTF detection algorithm must take a time ≤2 ms.

The output of the knowledge-based CTF detection algorithm is a Boolean variable, where true means that a CTF event is detected. In the 'true' case, the CTF signal is fed to the local server that sends an emergency process halting command to the machine tool control.

Therefore, the time between the CTF event and the actual feed stop of the process, t_{tot}, is given by the sum of the time for signal processing, t_{sp}, the time for processed signal delivery to the cloud server, t_{cs}, the time for the CTF detection diagnosis, t_{dd}, the time to transmit the CTF alert signal from the cloud server to the local server, t_{ls}, the time to deliver an

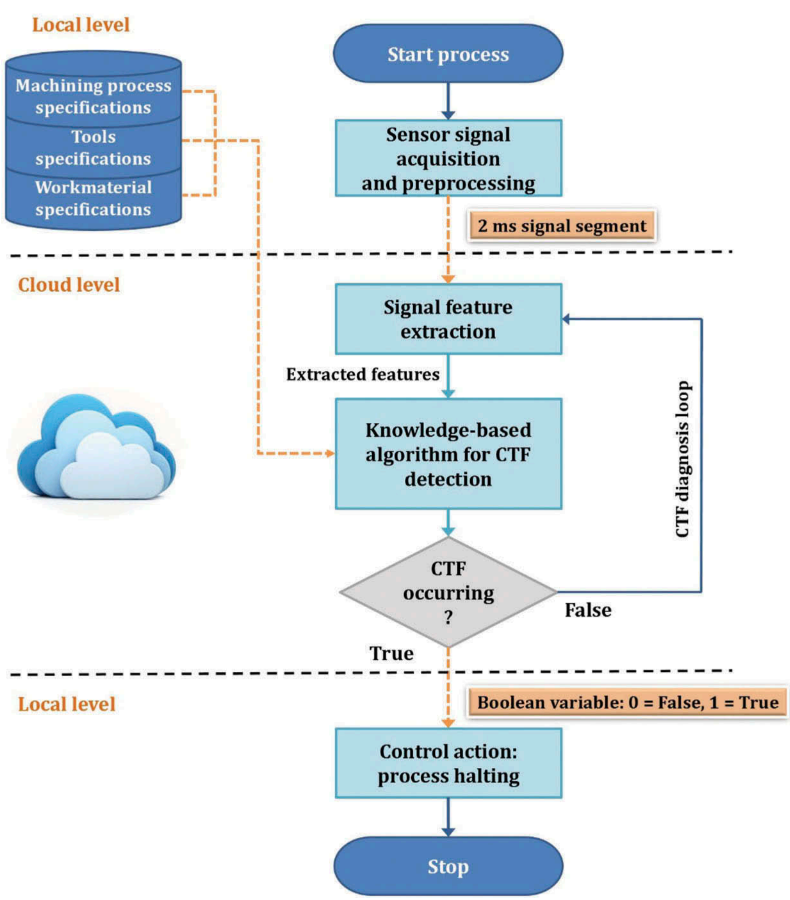

Figure 3. Workflow for online knowledge-based CTF detection procedure.

emergency stop command to the machine tool control, t_{es}, and the time required to stop the feed drive, t_{fd}, which depends on the machine tool hardware and software.

$$t_{tot} = t_{sp} + t_{cs} + t_{dd} + t_{ls} + t_{es} + t_{fd}$$

where:

t_{sp}: equal to 2 ms

t_{dd}: maximum duration 2 ms

t_{es}: local communication <1 ms

t_{fd}: can be assumed approximately equal to 50 ms, depending on the machine tool reaction time

t_{cs} and t_{ls}: given by the Internet signal data transmission delay, i.e. the latency time which is variable in the range 1–100 ms, depending on the device and the protocol used for connection as well as the distance to be travelled (Neugebauer 2016; Morgan and O'Donnell 2015).

The Internet bandwidth available in contemporary shop floors does not yet allow for latency times as low as 1 ms. However, significant efforts are made today to achieve high-speed communication with extremely low latency times (lower than 1 ms) attaining the so-called 'tactile Internet' (Neugebauer 2016). Under these conditions, t_{tot} can be reduced to as low as 60 ms or lower (Morgan and O'Donnell 2015).

The described methodology allows to realise a prompt identification of CTF occurrence during machining and, if the factory infrastructure is sufficiently fast, a quick reaction of the system that immediately stops the machining process.

7.3. NN-based tool wear pattern recognition procedure

The second cloud service module is dedicated to the diagnosis on consumed tool life through an artificial NN-based pattern recognition procedure.

The knowledge-based NN paradigm requires the creation of a comprehensive training set through a preliminary experimental campaign. The training set for NN machine learning consists of couples of input feature vectors and corresponding output quality parameter values. The elements of each input feature vector are given by the features extracted from the sensor signals in the time–frequency domain, and the output quality parameter value is the corresponding tool flank wear level. By setting a maximum acceptable flank wear level (e.g. VB = 0.3 mm) as the criterion for end of tool life, the tool flank wear level can be expressed as percentage of consumed tool life (100% corresponds to end of tool life).

The proposed feed-forward backpropagation NN architecture is characterised by three layers: the input layer with a number of input nodes equal to the number of selected sensor features, the hidden layer with a number of hidden nodes related to the number of input nodes and the output layer containing only one node providing the percentage of consumed tool life.

The Levenberg–Marquardt trained and tested NN is employed by the cloud manufacturing server to provide a diagnosis output in terms of estimated percentage of consumed tool life based on the input characteristic features extracted from the acquired sensor monitoring signals.

Figure 4 describes the NN-based consumed tool life diagnosis procedure.

The latter is based on sensor signal acquisition of the three components of the cutting force (F_x, F_y and F_z), the acoustic emission RMS (AE_{RMS}) and the vibration during machining. The minimum time interval of sensor signal acquisition for relevant feature extraction in this case is equal to 1 s; therefore, the data buffer length is higher than in the CTF detection algorithm. Accordingly, sensor signal segments, corresponding to 1 s of machining time, are sequentially buffered at the local level and delivered to the cloud for the extraction of relevant signal features. Feature extraction and selection is performed by the cloud server in the time–frequency domain via the WPT method (Teti et al. 2010; Teti 2015).

The WPT provides level by level transformation of a signal from the time domain into the frequency domain. Starting from the first level, the original signal *S* is split into two frequency band packets called approximation, *A*, and detail, *D*. The process is repeated in the next levels generating other decomposition packets. The top level of the tree is the time representation of the signal, while the subsequent levels are characterised by an increase in the trade-off between time and frequency resolution. The bottom level of a fully decomposed tree is the frequency representation of the signal.

In the tool life diagnosis module, WPT using Daubechies db02 mother wavelet and three-level decomposition is applied. For every packet, several statistical features, i.e. mean, variance, skewness, kurtosis and energy, are calculated, and only the signal features that during training result more correlated to the consumed tool life are selected for NN input.

The extracted and selected features are fed as input to the NN paradigm for tool life pattern recognition, together with the specifications on machining process, tool and workpiece material coming from the local server.

These specifications, provided via Internet by the local server, allow to identify the correct NN trained with the appropriate set of sensorial features and related output quality values. When machining starts, the relevant NN is identified and the tool life diagnosis algorithm is started.

The frequency of the tool life diagnosis loop is equal to 1 time/s, which means that the NN tool life pattern recognition paradigm must take a time ≤1 s.

The output of the NN tool life diagnosis paradigm is a percentage value representing the estimated portion of consumed tool life. If this value is <100%, the subsequent 1 s signal segment is processed and the NN loop is repeated. For each 1 s of machining, the extracted sensorial features are coupled with the estimated consumed tool life obtained by the NN, and these data are stored sequentially in a buffer.

This process is repeated till the estimated consumed tool life reaches 100%, i.e. when the maximum acceptable tool wear level is reached and the tool must be replaced. When this condition is attained, the diagnosis output is fed to the local server, which sends an emergency halting command to the CNC control in order to interrupt the machining process. Moreover, the local server sends an alarm to the local terminal, where the operator can visualise a warning with the indication that the threshold of 100% consumed tool life has been reached and the advice to replace the tool.

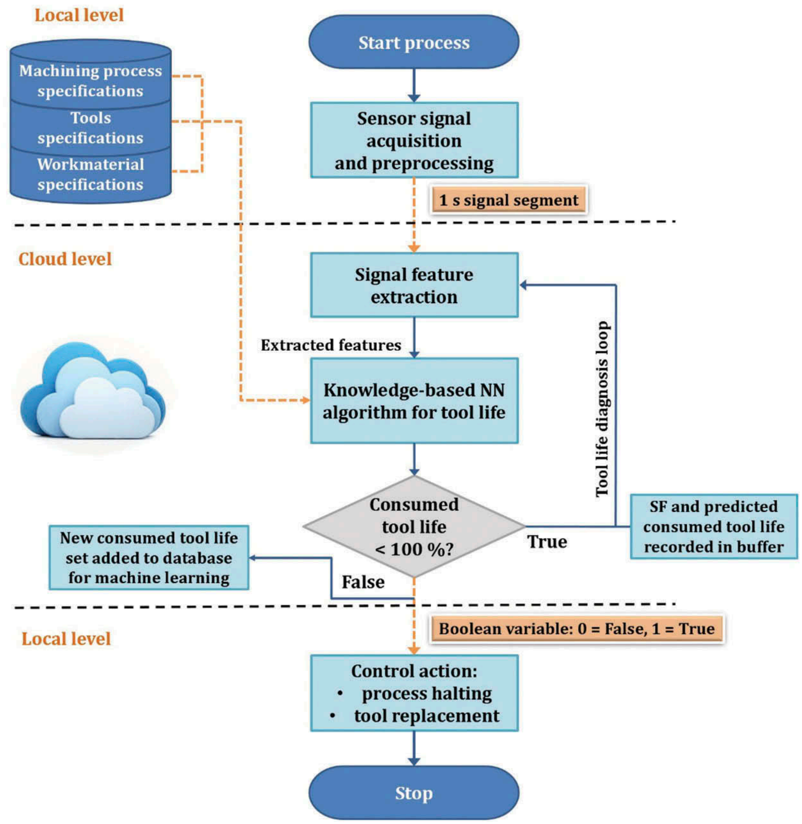

Figure 4. Workflow of the NN-based consumed tool life diagnosis procedure.

Meanwhile, the initial data set used for training the initial NN is modified. The new tool life set is added to the data set for NN retraining using the expanded training set. However, the new tool life set addition is conditioned by the metrological verification that the final flank wear value of the tool is in actual agreement with the predicted value within an acceptable tolerance range.

The time between the attainment of the 100% consumed tool life and the actual feed stop in the process, t_{tot}, is longer than in the CTF detection case and can be estimated around 2 s because the tool life diagnosis loop works on signal segments of 1 s duration. However, this higher value of t_{tot} is still amply acceptable to stop the process for tool replacement, without actual risk for the workpiece quality and integrity.

8. Cloud framework users and local terminal

Three types of user groups, with different roles and knowledge degrees, and therefore different access levels to relevant information, have been identified in the cloud-based framework for smart diagnosis: administrator, supervisor and operator.

The administrator is responsible for the configuration of the sensor monitoring system, in terms of both hardware and software, and for the database management, and should have access to all the functionalities of the cloud-based process monitoring system. The supervisor, on the other hand, is responsible for process design and tool selection and should observe the process monitoring statistics and diagnosis results to verify the need to modify products and tools or to retrain the cognitive knowledge-based paradigms for tool condition diagnosis. At a lower level, with more limited access to information, the operator is the one directly acting on the physical machine tool, in charge of performing machine start/stop and tool replacement; he should check if tool replacement is required based on the cloud diagnosis results and observe the system performance to point out maintenance needs.

The local terminal should provide the proper interface to each of the different users defined above following their specific access authentication. As an example, the administrator should get into all the functionalities related to the sensor system configuration and testing, the cognitive knowledge-based paradigms for diagnosis, etc. The supervisor, on the other hand, should be able to get access to the functionalities related to process design and tool selection and should be able to observe the status of the machining process and the cloud diagnosis results to monitor the process and verify the well functioning of the cloud-based smart diagnosis system.

At the operator level, the local interface should allow to monitor the machining process status, to visualise a warning concerning the need to change the tool or the occurrence of a CTF and to input information related to manually performed actions such as tool replacement, product change, etc.

Through separate remote terminals connected to the cloud, diverse users dislocated in distinct sites and with different skills may access the same information on the TCM diagnosis and the process performance statistics carried out by the cloud server.

Moreover, by extending the monitoring system to multiple machines and processes, the same user could access data related to different machines and processes at the same time and on the same terminal. As an example, a single operator may supervise multiple processes all together and have a unique portable terminal where the status of several machines can be accessed.

The local terminal interface provided to the local users such as the operators to monitor the machining process status is described in more details the following section.

8.1. *Local terminal interface for machining process status monitoring*

The local terminal provides an interface to the local users to monitor the machining process status, displaying the cloud diagnosis results, the control actions activated by the local server and the proper alert when human intervention is needed, such as in the case of tool replacement.

The local interface shows the following information:

- Machine tool – ID of the machine tool on which the sensor system is installed
- Workpiece – ID of the workpiece under machining
- Machining parameters – cutting speed, feed rate and depth of cut
- Tool – ID of the tool used for machining
- Status – graph illustrating changes in process state (on/off of working feed, detected cutting process and CTF alarms)
- Signal – ID of the selected sensor signal (e.g. 1 = x-axis force component, 2 = y-axis force component, etc.)
- Diagnostic signal – graph visualising the selected signal
- TCM results – operation number, tool ID and estimated consumed tool life in percent
- Selected control action – process halting, tool replacement requisite and parameters change

The TCM results are displayed in two ways: CTF detection is illustrated in the status diagram (red line), whereas the subsequent indications of estimated consumed tool life (in %) are shown in the TCM results array together with operation numbers and tool numbers (Figure 5).

9. Conclusions

A cloud manufacturing framework to provide smart diagnosis services for online manufacturing process monitoring was developed with the aim to perform TCM. The major advantage of the cloud-based approach is the enhanced computation and data storage capabilities, available from distributed resources, which, compared to traditional TCM approaches, can greatly improve tool condition diagnosis efficiency and enable more robust decision-making by exploiting large information accessibility and knowledge sharing.

Diagnosis on consumed tool life and tool breakage occurrence is offered as cloud services, using an architecture where the computing and service resources in the cloud are connected to the machine tool, realising a complex CPS.

The cloud manufacturing server offers a prompt online diagnosis on tool conditions, based on sensorial data acquired at factory level, through knowledge-based algorithms and cognitive pattern recognition paradigms. Grounded on cloud diagnosis, the local server activates the proper corrective action, such as tool replacement, process halting or parameters' change, sending the right command to the machine tool control.

The CTF diagnosis loop is performed every 2 ms and the consumed tool life diagnosis loop every 1 s, allowing a quick system reaction to immediately halt the machining or modify the process parameters to increase tool life.

With a suitable Internet infrastructure in the production environment, the time between the CTF event and the actual feed stop was estimated as low as 60 ms, whereas the time between achievement of 100% consumed tool life and actual feed stop was around 2 s. These times can be further reduced through superior infrastructure availability and new data communication methods, which are open challenges today. As a matter of fact, one limitation to the real-time application of the cloud-based monitoring of machining processes is related

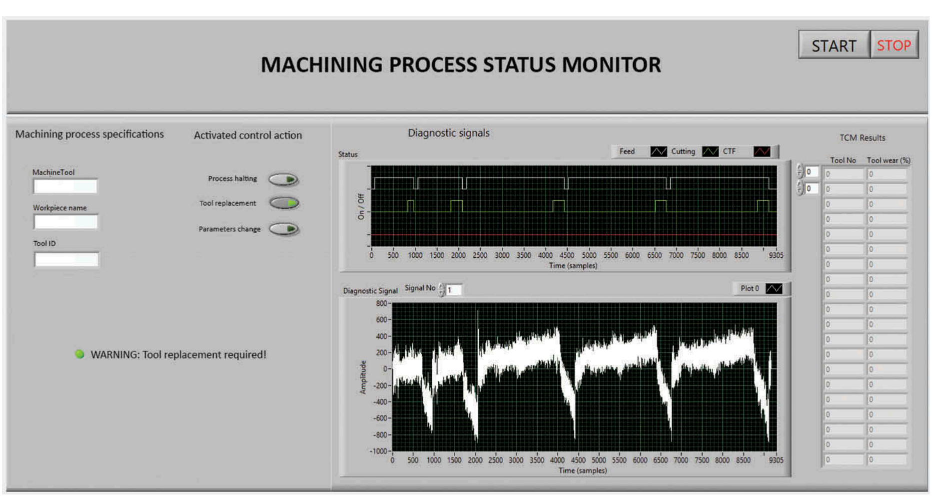

Figure 5. Machining process status monitor on the local terminal.

to the time delay between an event and the actual feed stop, which critically depends on several time factors, such as latency of Internet communication as well as reaction time of machine tools. Enhanced control systems allowing for very high-speed reaction times to control commands, together with tactile Internet, characterised by low latency in combination with high availability, reliability and security, represent key targets to fulfil the time requirements of cloud manufacturing.

As regards near to medium-term future developments, the cloud monitoring service could be extended to several machines and machining processes, allowing to represent the status of the entire manufacturing system where CPS monitor physical processes and communicate and cooperate with each other. In this way, a single operator may supervise multiple processes simultaneously and have a unique portable terminal where the status of several machines can be accessed.

As concerns a more long-term outlook, information from data collected by the monitoring system, such as statistics of sensor signals, consumed tool life, tool failures and emergency stops, could be collectively made available in the cloud in order to create a knowledge base on tool conditions that could reinforce tool maintenance and tool management activities in supply networks: e.g. the correct estimation of the expected number of tools required for the planned processes could allow for procurement procedures to be triggered precisely when needed in the supply chain.

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