A Fog Computing-based Framework for Process Monitoring and Prognosis in Cyber-Manufacturing

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Technical Paper

A fog computing-based framework for process monitoring and prognosis in cyber-manufacturing

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ABSTRACT

Small- and medium-sized manufacturers, as well as large original equipment manufacturers (OEMs), have faced an increasing need for the development of intelligent manufacturing machines with affordable sensing technologies and data-driven intelligence. Existing monitoring systems and prognostics approaches are not capable of collecting the large volumes of real-time data or building large-scale predictive models that are essential to achieving significant advances in cyber-manufacturing. The objective of this paper is to introduce a new computational framework that enables remote real-time sensing, monitoring, and scalable high performance computing for diagnosis and prognosis. This framework utilizes wireless sensor networks, cloud computing, and machine learning. A proof-of-concept prototype is developed to demonstrate how the framework can enable manufacturers to monitor machine health conditions and generate predictive analytics. Experimental results are provided to demonstrate capabilities and utility of the framework such as how vibrations and energy consumption of pumps in a power plant and CNC machines in a factory floor can be monitored using a wireless sensor network. In addition, a machine learning algorithm, implemented on a public cloud, is used to predict tool wear in milling operations.

1. Introduction

Owing to globalization, modern manufacturing activities are performed in an increasingly geographically distributed environment in which small- and medium-sized enterprises (SMEs) as well as large-scale enterprises have formed complex and decentralized manufacturing networks [1–8]. To perform digital and intelligent manufacturing in a distributed and collaborative environment, SMEs and large-scale enterprises have been faced with an increasing need for (1) hardware and software systems that efficiently collect and analyze large volumes of data generated from machines and manufacturing processes and (2) algorithms that effectively diagnose the root cause of identified defects, predict their progression, and forecast maintenance activities proactively to minimize unexpected machine down times [9–15]. Cyber-manufacturing refers to the use of high performance computing, optimization, simulation, sensing technology, and data analytics to create innovative products [16,17]. In recent years, advancing cyber-manufacturing has received much attention and funding. For example, according to the National Science Foundation (NSF), over $300 million dollars will be invested on cyber-enabled intelligent manufacturing systems [18,19] over the next five years. In 2015, 25 Early-Concept Grants for Exploratory Research (EAGER) projects were granted to 28 universities to support collaborative research between manufacturing and computer and information science and engineering researchers. The Digital Manufacturing and Design Innovation Institute (DMDII) has released several project calls for real-time machine and process monitoring, diagnostics, and prognosis for both legacy equipment and modern machine tools equipped with CNC controllers and sensors. In addition, the European Union (EU) has released several project solicitations for smart cyber-physical systems and high performance cloud computing infrastructures in manufacturing under the Horizon 2020 program. For example, one of the open project calls, ICT-01-2016, focuses on the development of time- and safety-critical embedded and cyber-physical systems

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for smart manufacturing. The particular challenge that this project call is addressing is to design and implement highly distributed and connected manufacturing devices through the Industrial Internet of Things (IIoT) [20]. Another project call, FOF-11-2016, focuses on exploiting the digital models of processes and products as well as synchronizing the digital and physical world through IIoT, machine-to-machine communication, cloud computing, artificial intelligence, and data analytics [21].

From a hardware perspective, there exists a continued lack of affordable sensing technologies that can be readily integrated into both legacy and modern manufacturing systems. For example, most legacy machines are not equipped with sensors and/or CNC controllers that can monitor equipment conditions for fault detection and diagnosis. Although modern manufacturing machines are equipped with various sensors and are connected to networks through standard fieldbuses, a continued challenge in effective and efficient data exchange remains due to 1) the variety in communication protocols, ranging from RS232, RS485, Modbus, OPC Unified Architecture (OPC UA), process field net (PROFINET), the newly adopted MTConnect, etc., and 2) the interoperability between hardware and sensing systems. Consequently, custom-designed sensing systems are often required to monitor manufacturing machines as well as connect them to networked manufacturing resources. From a software perspective, information and communication technology (ICT) infrastructures and parallel algorithms with sufficient computational capacity and bandwidth are required for analyzing multi-physics data streams with high speed, high volume, and high variety, in real-time. Although on-premise high performance computing (HPC) infrastructure can be deployed on factory floors, it is very expensive to build HPC clusters and scale up the computing capacity of on-premise HPC infrastructure for training highly iterative data-driven machine learning models and algorithms. For example, the initial cost of building a large-scale HPC cluster with the peak performance of several petaFLOPS is several million dollars [22], and the cost for operating and maintaining such a cluster can be more than one million dollars per year.

To address the aforementioned limitations, fog computing-based cyber-manufacturing is proposed in this paper. The objective of fog-based cyber-manufacturing systems is to provide the foundation to next-generation smart manufacturing networks in which manufacturers will have access to on-demand computing infrastructures, mobile applications for cyber-manufacturing, and parallel machine learning tools. As an extension of cloud-based manufacturing, the specific benefits of fog computing-based online machine and process monitoring, diagnosis, and prognosis include:

1) Connectivity between physical devices and network infrastructure. Edge or gateway devices (i.e., networking hardware) in fog computing provide a communication link between factory floors and the cloud. For example, an edge device interconnects networks with different network protocols.
2) Low network latency. Fog computing reduces network latency by moving computing infrastructure geographically closer to the servers at the network edge where manufacturing data is collected and stored. Manufacturers can collect and analyze large volumes of data at a local edge cloud without transferring all raw data from one server to another or from one place to another. The significant reduction in data transmission can solve bandwidth bottleneck issues.
3) Ubiquitous and instant remote access to near real-time data without spatial constraints. This enables users to access and process streaming data flows from hundreds of thousands of data sources such as sensor networks using a desktop computer or a mobile device regardless of their locations [23–25].
4) Secure and high volume data storage. Fog computing provides manufacturers with reliable, secure, scalable, and economical storage of massive static and dynamic data. Manufacturers can store sensitive proprietary data in a local edge cloud without sharing them in a remote public cloud.
5) Scalable, high performance computing (HPC). Compared to the traditional manufacturing paradigms, fog-based manufacturing can significantly increase computing capacity by providing multiple- and many-core processors to complement high-volume storage and high-speed I/O interconnects. This allows manufacturers to scale up computing capacity rapidly and cost-effectively when computing needs arise, and then scale down as demands decrease.
6) Real-time big data analytics. Enabled by parallel computing frameworks such as MapReduce, data mining and machine learning algorithms can be parallelized to process and manage massive data streams on a cloud-based computing platform [26–28].

Although both academia and industry are motivated to explore advanced technologies for cyber-manufacturing, little work has been reported on integrating fog computing, cloud computing, smart sensors, and data analytics into online machine and process monitoring, diagnosis, and prognosis. Addressing this gap, this paper answers the following question: *What architecture is required to implement online process monitoring and prognosis for data-driven cyber-manufacturing?*

The main contributions of this paper include:

- A fog computing-based framework for data-driven machine health and process monitoring in cyber-manufacturing is introduced. The framework consists of four integral elements, including a workflow, wireless sensor networks, communication protocols, and predictive analytics.
- An online process monitoring system that is capable of collecting real-time machine condition data and monitoring the vibrations and energy consumption of pumps is demonstrated through a case study.
- A machine learning algorithm (i.e., random forests) is implemented on the Amazon Elastic Compute Cloud (EC2) to create predictive models on scalable high performance computing resources. The cloud-based machine learning algorithm is demonstrated using a tool wear prediction example in milling operations.

The remainder of the paper is organized as follows: Section 2 presents a brief overview of process monitoring, diagnosis and prognosis, grid computing, cloud computing, and fog computing. Section 3 presents a fog computing-based system architecture for online process monitoring and prognosis in the context of cyber-manufacturing. Section 4 presents a proof-of-concept prototype and two case studies. Section 5 concludes the paper with a summary of the contributions made and future work.

2. Related work

2.1. Process monitoring

Smart sensors are an integral element in manufacturing process monitoring. To collect real-time data from factory floors and monitor the health conditions of manufacturing equipment and processes, sensors or sensor networks that can detect events and measure signals are required. Wright et al. [29] developed a condition-based monitoring system for predicting cutting tool wear and surface finish using accelerometer-based wireless sensor networks. The wireless sensor platform based on the IEEE 802.15.4 standard was used to measure the vibrations of a high-speed steel end milling tool. The wireless sensing system was demonstrated to be able to measure cutting conditions such as tool wear of the milling machine. Rangwala and Dornfeld [30] proposed a computational framework for intelligent tool condition monitoring using neural networks and multiple sensors. An acoustic emission transducer was mounted on the tool shank to measure vibrations. A force dynamometer was used to measure cutting forces. Experimental results have shown that the monitoring system based on the framework was able to perform sensor fusion and detect process abnormalities. Li and Li [31] developed a bearing condition monitoring system for detecting the onset of fatigue cracks using acoustic emission sensors. To observe rapid release of localized stress energy, AE transducers were mounted on the bearing housing. Lu et al. [32] developed an online and remote energy monitoring and fault diagnostic system for industrial motor systems using wireless sensor networks. An in-line torque transducer was used to measure the shaft toque of the motor. An optical encoder was used to measure the speed of the motor. The monitoring system was demonstrated in a real industrial environment. Hou and Bergmann [33] presented an industrial wireless sensor network for machine condition monitoring and fault diagnosis. Standard wireless communication protocols (e.g., IEEE 802.15.4, IEEE 802.11, and IEEE 802.15.1), ZigBee, and WirelessHART were integrated into the machine condition monitoring system. The proposed system was demonstrated by a set of experiments on a single phase induction motor.

2.2. Diagnosis and prognosis

The objective of process monitoring is to assess the health conditions of machine components (e.g., bearings and spindles), manufacturing processes (e.g., machining and joining), and manufacturing systems [34–37]. Diagnosis is focused on fault detection, isolation, and identification. Prognosis is focused on predicting the remaining time before a machine component or a manufacturing system will no longer perform its intended function due to fault propagation and progression. The predicted time is referred to in the literature as remaining useful life (RUL). Over the past two decades, many data-driven methods for diagnosis and prognosis in manufacturing have been developed. Specifically, data-driven methods for diagnosis can be classified into signal processing techniques [38,39], artificial intelligence [40], pattern recognition analysis, and statistical learning [41]. The classical data-driven methods for prognosis include autoregressive (AR) model, bilinear model, multivariate adaptive regression, neural networks, fuzzy set theory, and machine learning. Unlike physics-based methods, data-driven diagnosis and prognosis do not require deep understanding of the physics underlying machining processes and complete knowledge of the system behaviors. As opposed to model-based methods, data-driven diagnosis and prognosis do not require assumed probabilistic distributions such as Gaussian-Markov processes. In comparison with statistical methods, AI-based methods such as machine learning do not assume certain stochastic or random processes such as Wiener processes and Gamma processes, although machine learning requires large volumes of training data sets and high performance computing platforms such as cloud computing.

2.3. Grid, cloud and fog computing

Existing process monitoring systems and prognostic methods have limited capability of collecting and storing large volumes of data in distributed settings and limited computational capacity for analyzing these data in real-time. Foster and Carl Kesselman proposed the concept of grid computing in 1999 [42]. A computational grid refers to a hardware and software infrastructure that provides dependable, consistent, pervasive, and inexpensive access to high-end computational capabilities [43]. The concept of cloud computing is based on grid computing. According to NIST, cloud computing is "a model for enabling ubiquitous, convenient, on-demand network access to a shared pool of configurable computing resources (e.g., networks, servers, storage, applications, and services) that can be rapidly provisioned and released with minimal management effort or service provider interaction." The term "Cloud" is often used as a metaphor for the Internet, and refers to both hardware and software that deliver applications as services over the Internet.

To extend cloud computing and bring high performance computing capability to the edge of an enterprise's network, fog computing was introduced by Cisco [44]. Fog computing, also known as edge computing or fogging, is a computing model that provides high performance computing resources, data storage, and networking services between edge devices (e.g., wireless router and wide area network access device) and cloud computing data centers [45–47]. In cloud computing, the massive amounts of data have to be transmitted to data centers on the cloud, yielding significant performance overhead. As opposed to cloud computing, computationally intensive workloads such as training large datasets and visualizing data analytics are conducted in fog computing at locations where large volumes of data are collected and stored instead of centralized cloud storage. One of the key benefits of fog computing is that it enables users to avoid transferring numerous data between edge devices and cloud computing data centers by moving computing nodes closer to local physical objects or devices and executing applications directly on big data. Because fog computing is in close proximity to the source of raw data, fog computing is able to considerably reduce latency. This is particularly important for latency-sensitive applications. Cisco applied fog computing into smart grids in which energy load balancing applications are executed on edge devices such as smart meters, enabling real-time applications and location-sensitive services [48]. Another key feature of fog computing is that it is an effective approach for securing cloud-based manufacturing systems [49].

In summary, the related work presented in this section builds on previous research to explore how the health conditions of machines can be monitored using sensors as well as how predictive models can be developed for prognosis. However, existing monitoring systems and prognostics approaches are not capable of collecting the large volumes of real-time data or building large-scale predictive models due to the lack of ubiquitous sensor networks, manufacturing industry standards, and scalable high performance computing systems. In this paper, wireless sensors, cloud computing, and machine learning are integrated to address the gap.

3. System architecture

This section presents a high-level system architecture based on fog computing and IIoT. This generic system architecture enables manufacturers to collect large volumes of real-time streaming data and monitor machine health conditions and processes. Several specific aspects of the fog computing-based system architecture, including its workflow, IIoT infrastructure, communications protocols, and predictive analytics, are presented in the following sections.

3.1. Workflow

Fig. 1 illustrates a workflow for fog-based online machine and process monitoring and prognosis. The workflow consists of four steps. Each step is described in detail below:

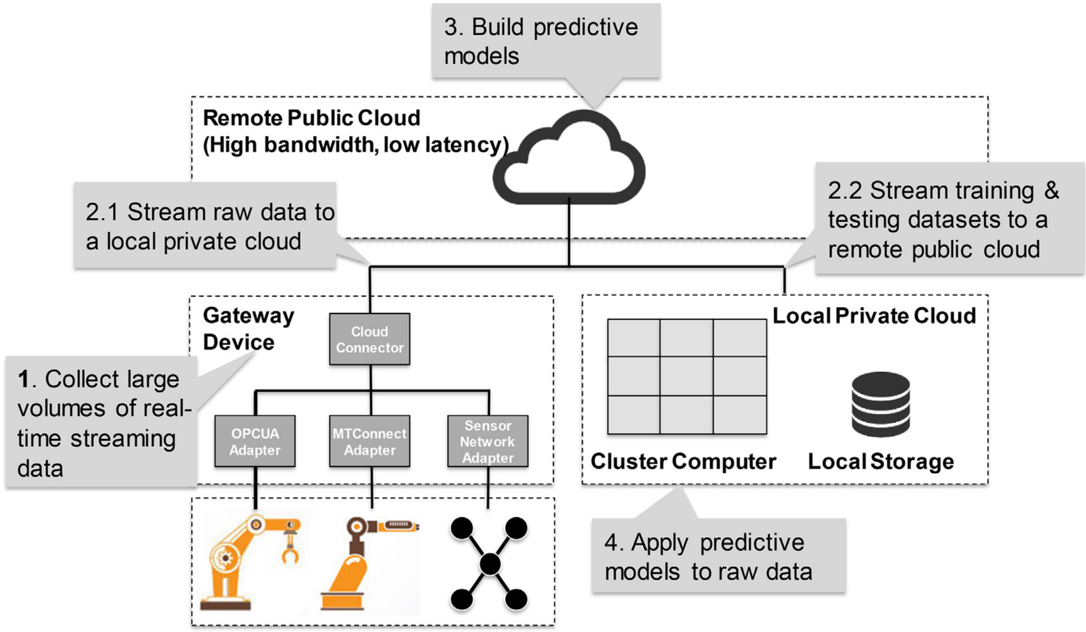


Fig. 1. A Computational Framework for Fog-Based Cyber-Manufacturing Systems.

Step 1: Collect machine data by gateway devices. An interoperable data acquisition gateway device collects real-time streaming data from factory floors through sensor networks, communication adapters, sensor adapters, and I/O adapters. These adapters are developed based on communications protocols such as Simple Object Access Protocol (SOAP), MTConnect, and Open Platform Communications Unified Architecture (OPC UA).

Step 2: Stream all the raw datasets and sample datasets to a local private edge cloud and a remote public HPC cloud, respectively. Through the data acquisition gateway devices, all the real-time datasets are collected and streamed into a local private edge cloud. Meanwhile, sample datasets (i.e., training datasets) are streamed into a remote public cloud. These sample datasets are used to train predictive models using machine learning algorithms.

Step 3: Build diagnostic and prognostic models using parallel machine learning algorithms and streaming datasets. Based on the training datasets, diagnostic and prognostic models are developed using cloud-based distributed/parallel machine learning algorithms. The key advantage of cloud-based machine learning algorithms against conventional machine learning techniques is the enabling of large-scale machine learning through parallel implementation on the cloud. While Hadoop MapReduce is an effective approach for processing massive amounts of data, it might incur a significant runtime cost for computational-intensive workloads such as highly-iterative machine learning algorithms. Apache Spark runs programs significantly faster than Hadoop MapReduce both in memory and on disk because Spark supports cyclic data flow and in-memory computing.

Step 4: Apply the diagnostic and prognostic models to the raw datasets stored in the local private edge cloud for online diagnosis and prognosis. The diagnostic and prognostic models developed on the remote public cloud using the training datasets are applied to real-time raw streaming datasets (i.e., test datasets) stored on the local private edge cloud.

3.2. Industrial internet of things infrastructure

Fig. 2 illustrates an infrastructure architecture for fog-based cyber-manufacturing systems. In the architecture, data acquisition gateway devices monitor and capture machine conditions in digital forms using various sensors (e.g., force, rotational speed, temperature, vibration, acoustic emission, and torque sensors). An edge device provides an entry point into Internet or Intranet networks. Through the edge devices, manufacturing machines are connected to a hybrid cloud system consisting of on-premise private edge clouds and public HPC clouds. This generic infrastructure architecture allows manufacturers to collect, screen, and clean raw data acquired from machines in the private cloud so that manufacturers can monitor machine utilization and equipment conditions remotely. Meanwhile, the public cloud performs computationally-intensive workloads such as generating big data analytics and data visualization for online condition monitoring, fault diagnosis, forecasting, and proactive maintenance. The key benefit of this architecture is that it employs the existing on-premise private cloud and combines it with a public cloud so that the hybrid cloud enables manufacturers to gain control over their proprietary data and mitigate security risks while acquiring access to scalable public clouds for compute-intensive workloads. In the fog-based architecture, manufacturers store sensitive data on the edge clouds while utilizing intelligence and analytics applications provided by HPC public clouds. The HPC public clouds provide a large set of supervised and unsupervised machining learning algorithms for managing machine learning processes and performing machine learning.

In addition, online machine and process monitoring, diagnosis, and prognosis typically require low-latency and high throughput communication systems. Latency refers to the time delay between a stimulation operation and its response. Low latency provides real time characteristics. Throughput refers to the number of messages that can be delivered per unit time. High-bandwidth communication systems provide high throughputs. Various wireless communication technologies (e.g., Wi-Fi, Bluetooth, IEEE 802.15.4, and 4G LTE) enable network connectivity. Among these wireless technologies, Wi-Fi has been widely adopted to provide wireless internet access because it provides high data rates. However, because Wi-Fi provides no bandwidth and latency guarantees, Wi-Fi might not be able to provide sufficiently low latency for online machine monitoring. While 4G wireless networks have higher data transfer rate than Wi-Fi, the cost of employing 4G LTE-based IIoT devices is too high for many applications such as

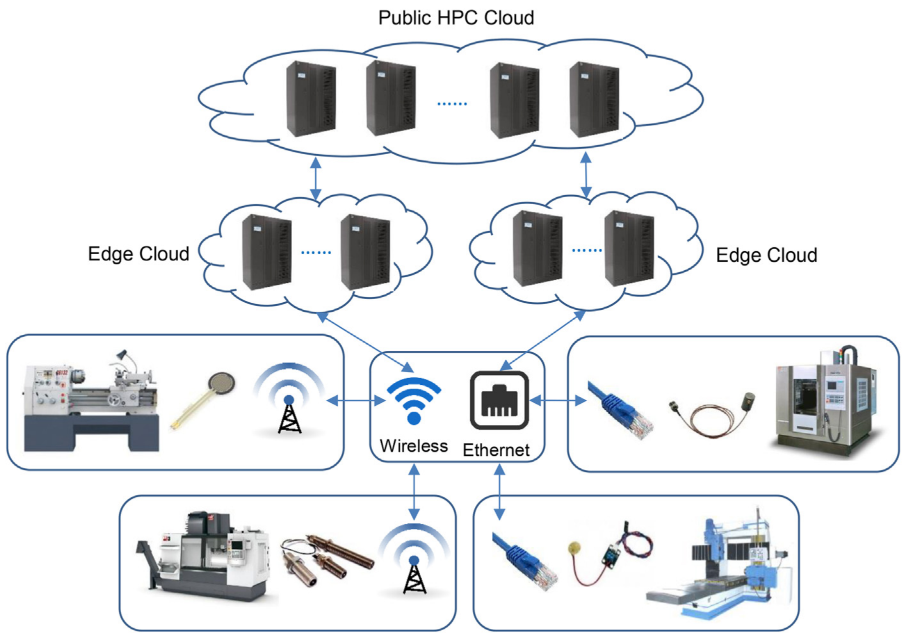


Fig. 2. An Infrastructure Architecture for Fog-Based Cyber-Manufacturing Systems.

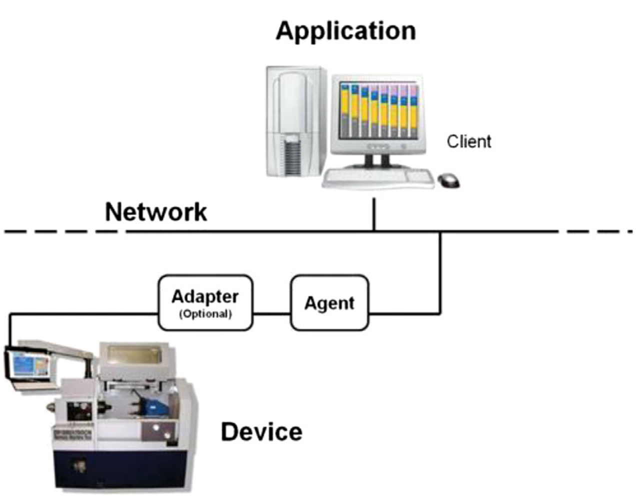


Fig. 3. Key Components of MTConnect [51].

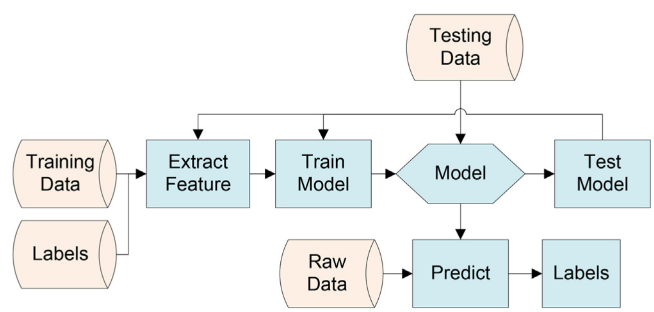


Fig. 4. Supervised Machine Learning.

large-scale machine-to-machine communications in a factory floor. In addition, power consumption in 4G wireless networks is much higher than Wi-Fi. Because IEEE 802.15.4 is a low-cost, low-power, wireless mesh network standard, it is used to develop the wireless sensor networks that can reliably transmit data with low latency.

3.3. Communications protocol

To improve interoperability between physical devices and software applications in a data-driven cyber-manufacturing environment, it is critical to have standardized communications protocols. MTConnect [50] is an open set of standards based on standard Internet technologies such as HTTP and XML. As shown in Fig. 3, MTConnect consists of five fundamental components, including device, adapter, agent, network, and client. MTConnect provides manufacturers with a simple yet powerful way to access data collected by MTConnect compatible machines. For example, manufacturers can monitor real-time machining and process-related data, including spindle speed, angular acceleration and velocity, axis feed rate, displacement, load, temperature, emergency stop, and power status. Because MTConnect is implemented as a web service, it is easily accessible to any device that is connected to the machine network. However, due to the protocol's reliance on the machine controller for the data, the number of available data are limited. For example, additional sensors such as accelerometers are required to monitor vibrations because most CNC machine tools do not include accelerometers in their spindles.

3.4. Predictive analytics

After collecting large volumes of raw data through IIoT infrastructures and communications protocol, the next step is to conduct on-line diagnosis and prognosis of manufacturing machines and processes using cloud-based machine learning. Machine learning techniques are typically classified into three broad categories, including supervised learning (e.g., classification and regression), unsupervised learning (e.g., clustering), and collaborative filtering that uses both supervised and unsupervised learning.

Fig. 4 illustrates a typical process of supervised machine learning. Machine learning algorithms require two types of data: training and testing data. A set of features or attributes are extracted as input to a learning algorithm based on the training data sets and labeled data. Training data sets are also used to train a learning algorithm. Testing data sets are used to evaluate the learning algorithm. Once a machine learning model is evaluated, it can be used to predict the potential outcome of an event. In the context of manufacturing,

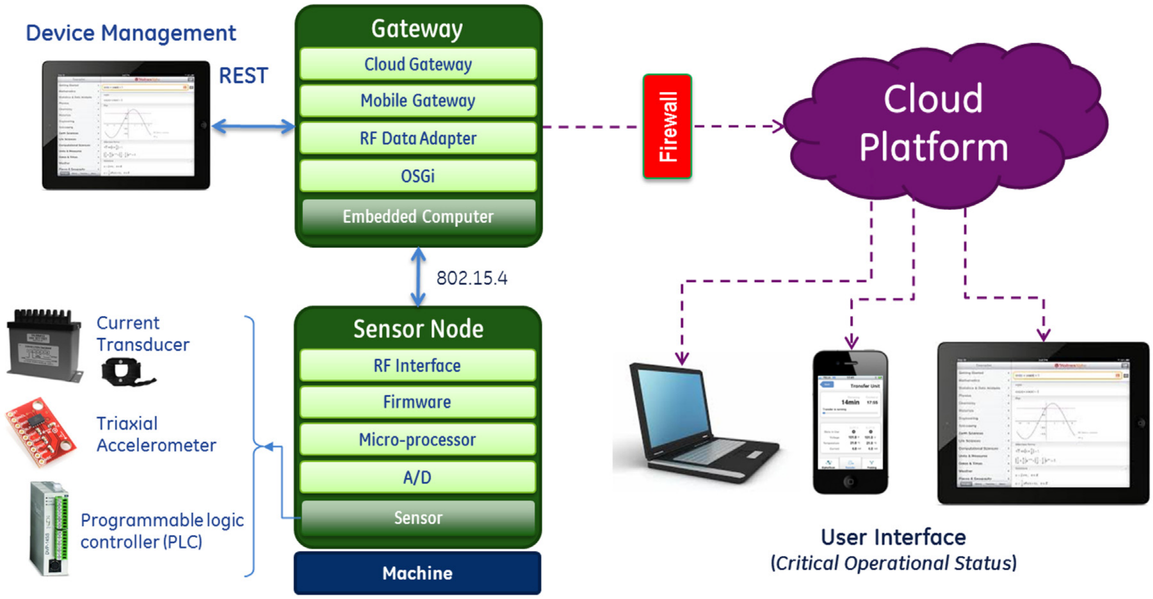


Fig. 5. Industrial Internet-Based Architecture of the Prototype.

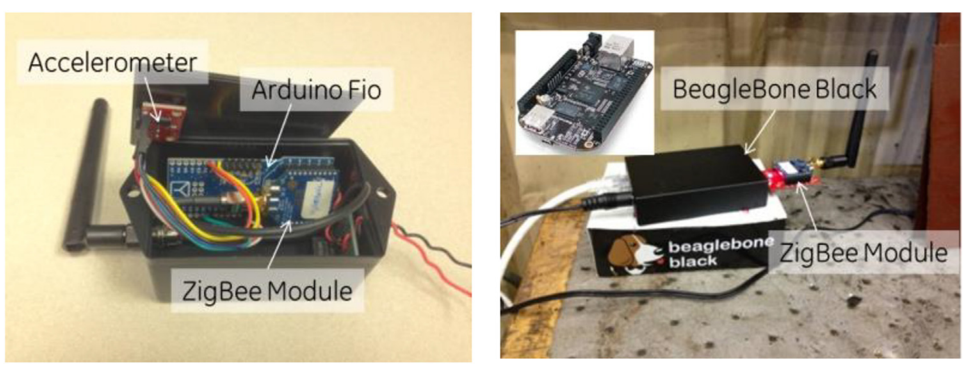


Fig. 6. Sensing Hardware: (a) Sensor Node; (b) Gateway.

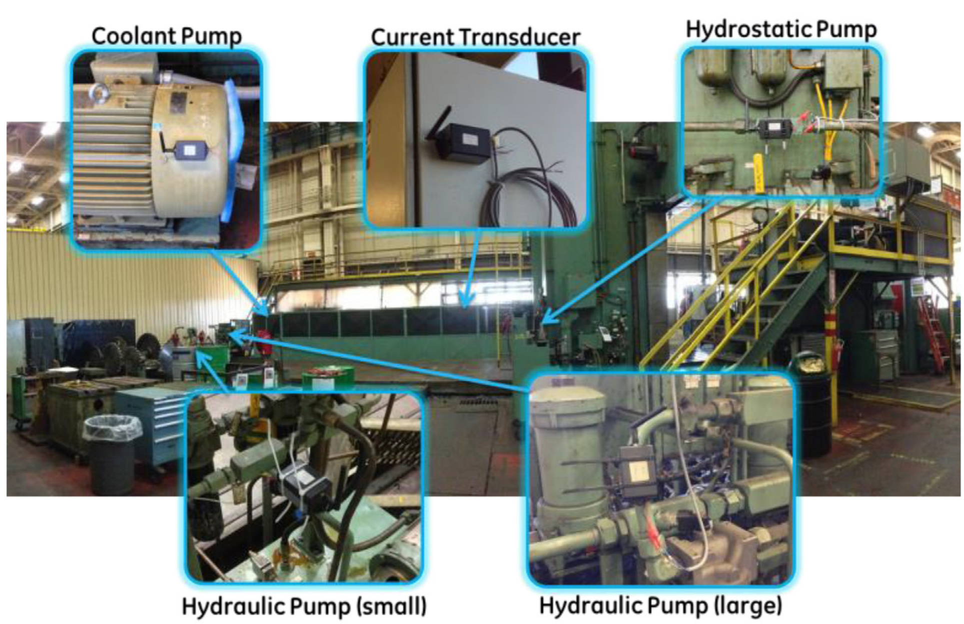
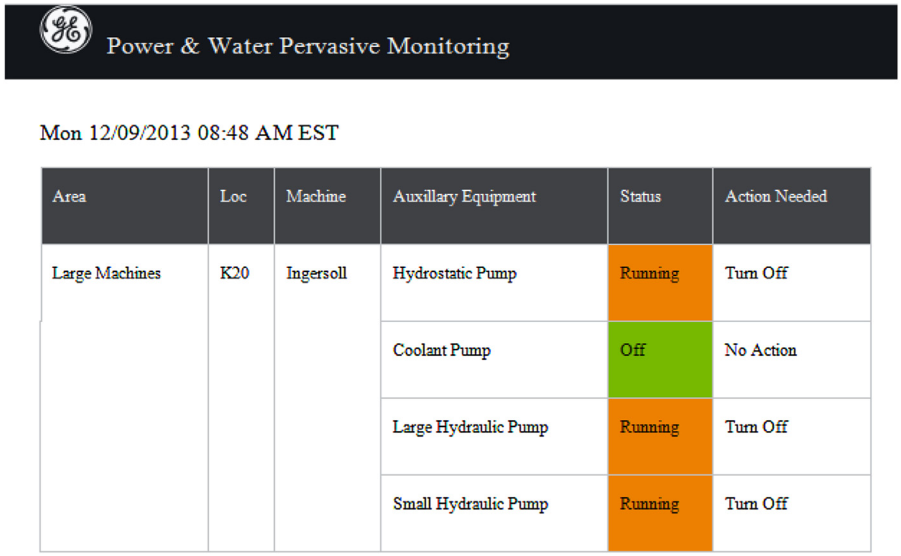


Fig. 7. Sensor Placement for a Legacy Manufacturing Machine.



Power & Water Pervasive Monitoring

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Area	Loc	Machine	Auxillary Equipment	Status	Action Needed
Large Machines	K20	Ingersoll	Hydrostatic Pump	Running	Turn Off
			Coolant Pump	Off	No Action
			Large Hydraulic Pump	Running	Turn Off
			Small Hydraulic Pump	Running	Turn Off

Fig. 8. Monitoring the Operating Conditions of Pumps in a Power Plant.

machine learning can be used to predict tool wear as well as determine when maintenance should be performed. Because machine learning on very large volumes of training data can require significant amounts of memory and CPU cores, implementing machine learning algorithms on the cloud helps accelerate predictive modeling. Several commercial tools have been developed for performing distributed machine learning on the cloud. For example, Amazon Elastic Compute Cloud (EC2) provides users with scalable high performance computing services to build predictive models on the cloud.

4. Case study

Based on the generic architecture presented in the previous section, a prototype has been developed to support real-time, scalable, and plug-and-play data collection for both legacy and modern manufacturing machines. This system consists of "drop-in" sensor nodes for legacy machines that are not equipped with sensors and lightweight gateway devices for data aggregation, edge computing and cloud communication. Leveraging open source hardware, the wireless sensor nodes were designed using a modular approach. To provide a wide range of sensing capabilities, a variety of sensors can be easily swapped without modifying microcontrollers and wireless radio interfaces.

The prototype was built based on the Predix™ Machine, an Industrial Internet software developed by General Electric. Predix™ Machine is a device-independent software application container and service platform, providing developers with an environment and a set of tools to develop plug-and-play solutions to connect manufacturing machines to the Industrial Internet cloud. These solutions enable online remote manufacturing process monitoring, diagnosis, and prognosis, as well as proactive maintenance scheduling. Selected features of Predix™ Machine include [52]:

- High Speed Network Infrastructure: Predix provides high-speed fiber optic lines to support IIoT. The high-speed network can transfer data at 100 gigabits per second to support low-latency machine-to-machine communications.
- Machine-to-Machine Communication: Predix provides machine-to-machine and IIoT connectivity services, software agents, and toolkits that enable manufacturers to establish connectivity between physical components of manufacturing systems and the Predix Platform.
- Data Analytics: Predix enables manufacturers to monitor machinery health using predictive analytics, pattern recognition and machine learning techniques. For example, Predix enables manufacturers to predict the time when a physical component or a manufacturing system will no longer perform its intended function using cloud-based parallel machine learning algorithms.
- Mobile Apps Development: Predix provides software developers to build, test, deploy, and scale cloud-based applications for mobile devices such as smart phones and tablets using standard application programming interfaces (APIs).

4.1. Process monitoring

As illustrated in Fig. 5, the proof-of-concept prototype is currently being tested and validated in a power plant and a factory floor [53]. More than 50 physical sensors have been installed on 16 selected pumps and CNC machines to collect real-time data related to vibration and energy consumption. Fig. 6(a) shows an example of the sensing hardware, including sensor nodes and the gateway. Specifically, three types of sensor nodes, including accelerometer, current transducer, and programmable logic controller (PLC) sensor nodes, were developed and deployed. Accelerometers are used to detect and monitor vibration in rotating machinery. Current transducers are used to measure electric current, which is proportional to the output torque and affected by the workload and condition of the machines being monitored. Each sensor node consists of a microprocessor with analog-to-digital converter, and a radio frequency (RF) interface, and one of three types of sensors. For example, a RF interface such as a ZigBee wireless module transmits and/or receives radio signals between two devices wirelessly. The accelerometer sensor node consists of a low power, low profile capacitive micro-machined accelerometer produced by Freescale Semiconductor Inc. The accelerometer measures the vibration of individual auxiliary pumps of the machines. The microcontroller board, Arduino Fio made by Arduino, digitizes the signals generated by the accelerometer, and transmits digital signals to the gateway through the ZigBee module (XBee, Digi International Inc.) wirelessly. The current transducer-based sensor node consists of a split-core current transducer, CTRS 501 $\times$ 5 produced by Flex-Core, a microcontroller, and a ZigBee module. The current transducer measures the current consumption of the machines and provides the benchmark for the accelerometer measurement. The current consumption data is also used for measuring energy consumption.

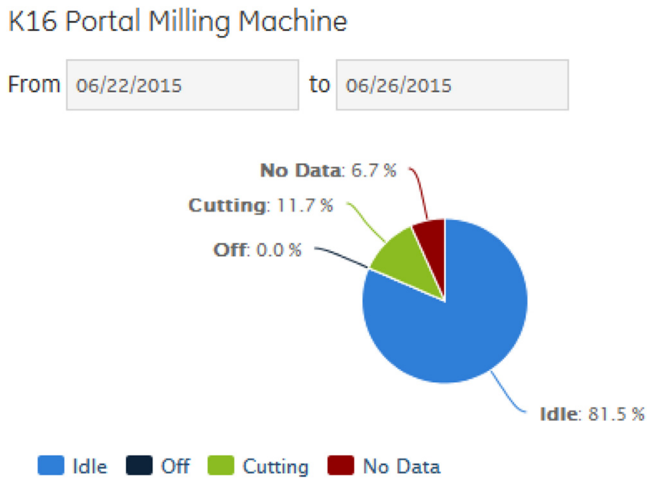

Fig. 9. Monitoring the Operating Conditions of a Milling Machine.

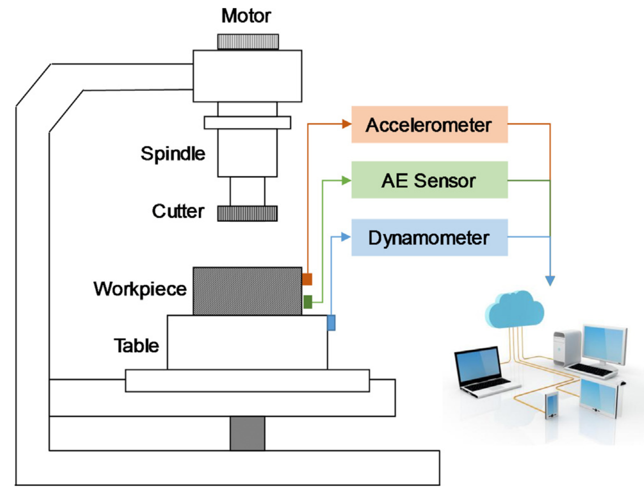

Fig. 10. Experimental Setup.

The gateway device consists of an ARM-processor-based single board computer, BeagleBone Black produced by Texas Instruments, and a ZigBee module, XBee produced by Digi International, as shown in Fig. 6(b). The single board computer monitors vibration signals for the pumps through the ZigBee module. The software running on the gateway is built upon the Predix™ Machine software platform using open source OSGi [45]. The OSGi specifications provide a modular service platform for the Java programming language. The gateway software transmits sensor data to the private cloud on the Predix platform.

Fig. 7 illustrates the placement and deployment of the sensor nodes and the gateway unit for one of the legacy machines in the power plant. The current transducer-based sensor node is installed near the controller box. The accelerometer-based sensor nodes are installed on four auxiliary pumps, including a hydrostatic pump, a coolant pump, and two hydraulic pumps.

Figs. 8 and 9 show the interfaces that monitor the operating conditions of the pumps and a milling machine in a factory floor, respectively. For example, the vibration and energy consumption of the pumps and milling machine are monitored in real time. Users can access to these real-time data through an email notification and/or a web portal.

4.2. Prognosis

This section presents another case study to demonstrate cloud-based machine learning for data-driven prognosis. The dataset used in this case study was obtained from *Li*, et al. [54]. The experiment was conducted on a three-axis high speed CNC milling machine (Röders Tech RFM 760). The experimental setup is shown in Fig. 10. The detailed description of the operating conditions in the milling operation can be found in Table 1.

As shown in Table 2, seven signal channels, including cutting force, vibration, and acoustic emission data, were monitored. A stationary dynamometer, mounted on the table of the CNC machine, was used to measure cutting forces in three, mutually perpendicular axes (x, y, and z dimensions). Three piezo accelerometers, mounted on the workpiece, were used to measure vibration in three, mutually perpendicular axes (x, y, and z dimensions). An acoustic emission (AE) sensor, mounted on the workpiece, was used to monitor a high frequency oscillation that occurs spontaneously within metals due to crack formation or plastic deformation. Acoustic emission is caused by the release of strain energy as the micro structure of the material is rearranged. The datasets contain 315 individual data acquisition files in the csv format. The size of each dataset is about 2.89 GB.

A predictive model was developed using one of the most accurate machine learning algorithms, random forests. An in-depth discussion of the mathematical formulation of random forests can

Table 1
Operating conditions.

Parameter	Value
Spindle Speed	10400 RPM
Feed Rate	1555 mm/min
Y Depth of Cut	0.125 mm
Z Depth of Cut	0.2 mm
Sampling Rate	50 KHz/channel
Material	Stainless steel

Table 2
Signal Channel and Data Description.

Signal Channel	Data Description
Channel 1	Force (N) in X dimension
Channel 2	Force (N) in Y dimension
Channel 3	Force (N) in Z dimension
Channel 4	Vibration (g) in X dimension
Channel 5	Vibration (g) in Y dimension
Channel 6	Vibration (g) in Z dimension
Channel 7	Acoustic Emission (V)

Table 3
Accuracy and Training Time.

	Random Forests		
Training size (%)	MSE	R^2	Training time (Second)
50	14.170	0.986	1.079
60	11.053	0.989	1.386
70	10.156	0.990	1.700
80	8.633	0.991	2.003
90	7.674	0.992	2.325

Table 4
Performance Improvement Metrics.

Metric	Present State	Future State
Data-driven methods	Fuzzy theory, neural network, wiener process, and gamma process	Parallel machine learning and data mining approaches
Software portability	Lack of portability due to incompatibility between applications and computing systems	Improved portability enabled by container technology
Computing scalability	Limited scalability by adding or removing computing resources	High scalability enabled by cloud computing
Data accessibility	Limited access to data due to the lack of data synchronization	Ubiquitous access to data enabled by centralized cloud storage
Data volume	Limited data storage	Potentially unlimited and scalable data storage
Infrastructure flexibility	In-house ICT infrastructure and/or private cloud	Integration of both private and public cloud in flexible hybrid cloud model
Security and cost-effectiveness	Private clouds are the most secure but also most expensive; Public clouds are the least secure but least expensive.	Hybrid clouds offer a reasonable level of security while providing the most powerful and least expensive computing resources.

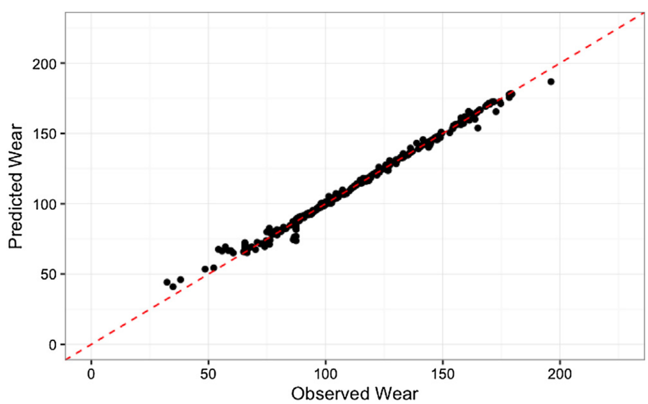

Fig. 11. Comparison of Observed and Predicted Tool Wear.

be found in [55]. The random forest algorithm was implemented on an Amazon C3.8 instance server. The process of launching an Amazon instance is as follows:

1. Choosing an Amazon Machine Image (AMI). An AMI defines the base operating system such as Linux or Windows system, an application server, and applications that will be automatically installed on an Amazon instance.
2. Choosing an instance type. An instance type specifies the hardware configuration and the size of an instance. The hardware configuration includes the type of virtual machines, memory, the number of CPU cores, storage, and network performance.

Fig. 11 shows the predicted against observed tool wear values using the experimental dataset.

The performance of the random forest algorithm is evaluated using accuracy and training time. The accuracy of the random forest algorithm is measured using the R^2 statistic, also referred to as the coefficient of determination, and mean squared error (*MSE*). In statistics, the coefficient of determination is defined as $R^2 = 1 - \frac{SSE}{SST}$ where *SSE* is the sum of the squares of residuals, *SST* is the total sum of squares. The coefficient of determination is a measure that indicates the percentage of the response variable variation that is explained by a regression model. The higher the R-squared is, the more variability is explained by the regression model. For example, an R^2 of 100% indicates that the regression model explains all the variability of the response data around its mean. In general, the higher the R-squared, the better the regression model fits the data. The MSE of an estimator measures the average of the squares of the errors. The *MSE* is defined as $MSE = \frac{1}{n}\sum_{i=1}^{n}\left(Y_{\hat{i}} - Y_i\right)^2$ where $Y_{\hat{i}}$ is a predicted value, Y_i is an observed value, and n is the sample size. The random forest algorithm uses between 50% and 90% of the input data for model development (training) and uses the remainder for model validation (testing). As shown in Table 3, the predictive model is very accurate based on the MSE and R-squared. The training time is also very short.

5. Conclusions and future work

In this paper, a fog computing-based framework for data-driven machine health and process monitoring in cyber-manufacturing has been presented. The workflow, wireless sensor networks, communication protocols, and cloud computing infrastructure of a prototype have been demonstrated using an experiment conducted on a factory floor. More than 50 wireless sensors such as current transducers and accelerometers were installed on a number of pumps and CNC machines to collect real-time condition data. Accelerometers and current transducers were used to monitor the vibrations and energy consumption of these machines. A microprocessor with analog-to-digital converter and a ZigBee wireless module were integrated into each sensor node to transmit radio signals from the sensors to the private cloud on the Predix platform. Sample datasets were uploaded to the Azure public cloud for data analysis.

In the future, it will be worthwhile to build predictive models using machine learning algorithms and integrate these models into the online process monitoring system for diagnosis and prognosis. Table 4 summarizes present and future states of data-driven cyber-manufacturing for online machine and process monitoring, diagnosis, and prognosis. As shown, significant advancements in the areas of predictive analytics, software portability, computing scalability, infrastructure flexibility, and cyber security are needed. Specifically, our future work will focus on analyzing the vibration and electric current data using cloud-based parallel machine learning algorithms to predict when maintenance should be performed.

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