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Predictive Maintenance and Condition Monitoring in Machine Tools: An IoT Approach

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***Abstract*—To maximize efficiency, quality of products, and profits, it is important to maintain machine tools to reduce downtime and maximize output. Predictive maintenance is the most efficient method of condition monitoring and maintenance. An Internet of Things approach can help implement an autonomous predictive CM system in manufacturing facilities. The critical parameters of sensor selection, communication, and data analysis have been examined. The components that make up an effective IoT CM system have been discussed and analyzed. An IoT approach has been shown to eliminate the disadvantages of traditional manual CM approaches.**

***Index Terms*—Feed drives, Machine tools, Condition monitoring, IoT, Internet of Things, Industry 4.0.**

I. Introduction

The manufacturing world has entered the fourth industrial revolution, often referred to as *Industry 4.0*. The fourth industrial revolution builds upon the automation and digitization of the third industrial revolution. It includes the implementation of the Internet of things (IoT), machine to machine communication, and improved communication and condition monitoring (CM).

The manufacturing sector is one of the most competitive sectors in developed nations. They must compete not only with other firms in developed nations but also with developing nations, which have the advantage of lower wages and less strict labour and environmental laws. To remain competitive, firms must embrace industry 4.0. Embracing Industry 4.0 can help to reduce costs, reduce errors, increase efficiency, and improve throughput. These advantages can help firms propel themselves above the local competition and compete with the prices of firms in developing nations. Advanced manufacturing is very capital dependent. Expensive machine tools such as CNC lathes, mills, laser cutters, and grinders are staples of modern manufacturing facilities. It is of utmost importance to maximize the output of these machines. Substantial costs are accrued if machines are not working at high levels of output. It is in the best interest of these manufacturing facilities to maintain these machines adequately. Machines are maintained through maintenance and CM.

Maintenance and machine condition has several associated costs: Expected downtime, unexpected downtime, quality, and replacement parts. The cost of expected downtime is the lost production due to the machine being down for scheduled maintenance. Unexpected downtime is the cost of lost production and damage due to sudden failures and crashes. The cost of quality is the cost of defects that arise due to poor machine conditions, such as not meeting dimensional tolerance. Replacement part cost is the cost associated with replacing a part before it has reached the end of its useful life.

Predictive and prognostic maintenance is the latest evolution of maintenance paradigms. The first level of maintenance paradigms is reactive maintenance. Reactive maintenance is simply fixing machines as they break. This is the least effective form of maintenance. Reactive maintenance increases unexpected downtime as unexpected failures arising from neglect force the machines down. The next level of maintenance is planned maintenance, where maintenance occurs at set intervals. This is a better method compared to reactive maintenance but is still not ideal. Doing maintenance at set intervals increases the cost of expected downtimes and can mean replacing parts that are still far away from the end of their life. Predictive maintenance involves analyzing data from the machine and predicting when it requires maintenance. This paradigm can reduce expected, and unexpected downtime costs as machines are serviced only when necessary and before critical failures occur. Cost of quality and replacement part costs can be reduced as well as parts are used for the majority of their useful life and not past the point where the cost of quality begins to rise. A summary of the relative costs of each paradigm is seen in Table I below.

Predictive maintenance requires a great deal of data to

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TABLE I
COSTS OF MAINTENANCE

Paradigm	Associated cost			
	Expected downtime	Unexpected downtime	Quality	Replacement parts.
Reactive	Low	High	High	Moderate
Scheduled	High	Low	Low	High
Predictive	Moderate	Low	Low	Low

analyze. Traditional CM is labour intensive and prone to human error. It often requires a worker to inspect and test machines over time individually. This approach is too expensive to inspect at a high enough frequency, and inspection is done too infrequently, therein faults and wear are detected too late. IoT can facilitate autonomous CM. Sensors can be installed on machines to collect a large stream of data in real-time. Data collected from the machines can be analyzed to determine the machine's condition. This information can be used to take corrective action if required. Autonomous CM will maximize machine performance and up-time, which will, in turn, maximize manufacturing efficiency.

Machine tools have several components whose condition is worth monitoring. The primary investigation of this paper will be on machine tools with ball screw feed drives. Machine tools feed drives and spindles are typically run by AC servo motors. Ball screw feed drives are the most common feed drive for machine tools. The main components of a ball screw system can be seen below in Fig.1. Ball screws are normally supported on either end by fixed and free ball bearings. A table is connected to the ball nut, and this table is a set of linear guides that support it to slide back and forth with minimal friction.

This paper will cover the following: Section II will cover the current literature on the subject of CM. Section III will cover the sensors used in the machine tool CM system. Section IV will cover the communication within the system. Section V will cover the data analysis used for CM. Finally Section VI will cover the conclusion and future work.

II. STATE OF CONDITION MONITORING IN THE LITERATURE

Condition monitoring has been a field that has been studied extensively in the literature. A paper by Martin [2] covered machine tool CM and fault detection technology. Numerous CM analysis methods for bearings and other moving parts exist in the literature. A survey by Zhou, Habetler, and Harley [3] outlines many common methods for CM. Many of these methods will be outlined in section V. A journal by Tandon, Yadava, and Ramakrishna [4] compared four methods for CM to determine which was most effective at detecting a fault in a bearing. They examined velocity vibration, motor stator current, acoustic emission and shock pulse method. They found that acoustic emission and shock pulse methods were the most effective method in detecting a bearing fault. In another study by Tandon [5] several vibration analysis techniques were compared to determine which was the most effective at detecting a bearing failure. It was found that peak vibration and vibration power were good predictors of wear. Temperature is another method for CM. A study by Touret et al. [6] reviews sensors and methods involving temperature for detecting faults. An IoT system for CM of CNC machine was proposed in a paper by Al-Naggar et al. [7].

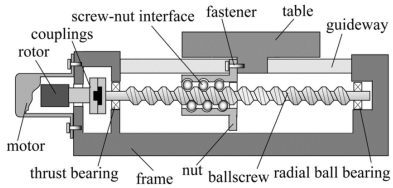

Fig. 1. Ball Screw System [1]

There are several studies to detect wear in machine tools. In a study by Pichler, Klinglmayr, and Pichler-Scheder [8] they examined methods such as vibration, temperature and current to detect wear in a ball screw system. In one study by Verl et al. [9] they used information from the CNC controller to measure positioning error, repeatability and reversal error to determine if the system had encountered a fault. In a study by Huang, Tan, and Lee [10] they used Kalman filtering to detect mechanical and sensor failure in a ball screw system. Methods for detecting preload loss and determining levels of preload in a ball screw have been covered by several studies. In a study by Frey, Walther, and Verl [11] they inserted a force sensor between nuts in a system preloaded with a double nut setup. By doing this, they were able to determine the force of preload and measure changes over time and over the stroke of the screw. Studies by Feng and Pan [12] [13], Chang et al. [14], Tsai, Cheng, and Hwang [15], and Nguyen, Ro, and Park [16] used ball pass frequency, temperature, motor current and vibration analysis to detect preload loss.

IoT approaches to CM exist in the literature. Machine learning has become a popular data analysis method over the past decade. In a study by Ayvaz and Alpay [17] they implemented an IoT system and used machine learning to predict the time until failure for machine equipment. In another study by Kanawaday and Sane [18] they could predict a bad production cycle with a high degree of accuracy using machine learning. Both edge computing [19] and cloud computing [20] approaches to IoT CM have been proposed in two studies.

III. SENSORS AND DATA COLLECTION

Sensors on a machine tool can broadly be categorized into *integrated sensors* and *external sensors*. Integrated sensors are sensors that are built into the CNC controller or are required for normal operation. External sensors are sensors not normally included with the CNC controller or required for normal operation. External sensors can collect information from many different components such as the bearings, spindle, motor, and linear guides.

A. Integrated Sensors

Integrated sensors are the sensors and information that are required for the normal operation of the machine tool. These typically include both linear and rotary encoders for measuring the position of the worktable in each axis, as well as the torque signal which is sent to the motor from the CNC controller.

1) Encoders: Position measurements are performed using linear and rotary encoders. Encoders can either be incremental or absolute encoders. Absolute encoders do not require a reference position, while incremental encoders do. As a result, incremental encoders need to have zero points established after being powered down. Glass scale encoders are the most common type of linear encoder used, as seen in Fig. 2.

Most servo motors are equipped with optical rotary encoders to measure the rotational position of the output shaft. The derivation of readings from encoders can be used to determine velocity and acceleration. Disagreement between the two encoders can be used to detect faults. If there is disagreement during changing of directions, it could mean there is substantial backlash in the system. Constant disagreement between the two encoders could represent miscalibration or misalignment of the system.

2) Measuring Torque and Current: The torque input signal of the system and motor current information can be retrieved from the CNC controller. These can be used to determine the torque applied to the system. If torque is greater or less than expected, it could represent a fault [16]. Analyzing the torque signal behaviour [22] or motor current behaviour [23] can also provide useful analysis.

B. Temperature Sensors

Temperature can be a useful characteristic to measure. Heat is normally generated as a result of friction. Excess heat can result in increased wear in both mechanical and electronic components. It can indicate faults in components such as bearings and motors. When selecting a sensor, it is important to consider what temperature range will be examined, the sensitivity, response time, and linearity of measurement. Temperature sensors are either contact or non-contact. A summary of popular temperature sensors can be seen below in Table II.

A comparison of the performance of popular contact temperature sensors can be seen below in Table III. Contact temperature measurement sensors are ideal if it is possible to make a solid physical connection without interfering with the operation of the machine.

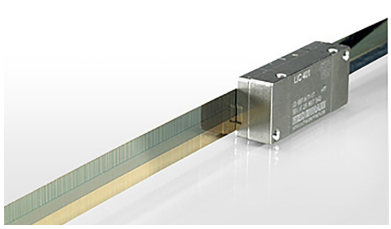

Fig. 2. Glass scale linear encoder [21]

TABLE II
COMMON TEMPERATURE SENSORS

Contact	Non-Contact
Thermistor	Radiation thermometer
Resistance temperature detectors	Optical pyrometer
Thermocouple	Fiber optic sensors
Semiconductor thermometer	

TABLE III
COMMON CONTACT TEMPERATURE SENSORS

Sensor type	Thermistor	RTD	Thermocouples
Range (C°)	-55 to 125	-200 to 850	-600 to 2000
Sensitivity	High	Low	Medium
Response time	Fast	Slow	Fast to Slow
Linearity	Exponential	Fairly linear	Fairly linear

Thermocouples are one of the most common contact temperature sensors. They can sense a large range of temperatures, have linear sensing of temperatures, and can have fast response times. They do not require an external power supply. Contact sensors may be useful to measure non-moving objects such as the bearings and motors. The expected temperatures for these in normal operating conditions are around 50° to 80° Celsius. IoT specific thermocouple exist and have built-in communication capabilities.

Non-contact sensors may be more useful in situations where contact with the object is not feasible or easy, the object is moving, or there are multiple objects to be measured at once. The most common of these sensors are radiation thermometers. These sensors measure the infrared radiation emitted from objects. They are often used for measuring the temperature of electronic components, and bearings [24].

C. Vibration Sensors

Vibration sensors are sensors that measure the mechanical vibrations of components. Papers by Goyal and Pabla [25], and Xu et al. [26] provide an overview of sensors used to detect vibrations. Vibration sensors can mostly be categorized into displacement, velocity, and acceleration sensors. An overview of these sensors can be seen below in Table IV. These sensors can also be categorized as contact and non-contact.

Certain characteristics must be considered when selecting a vibration sensor [27]. Some of these characteristics include Level of vibration, the frequency range of interest, environmental conditions, size constraints, contact type, and linearity of measurement.

Anticipating the expected sensitivity and frequency range of the vibrations is important. With high vibration amplitudes, low sensitivity sensors are preferable. The expected frequency of vibrations must reside within the range of the sensor. Different frequencies can represent different faults, as discussed in section V-A. Environmental conditions such as humidity, extreme

TABLE IV
COMMON VIBRATION SENSORS

Type of sensor	Common sensors	Frequency range
Displacement	Eddy current Inductive proximity	Low frequency
Velocity	Coil and magnet	Low to mid
Acceleration	Piezoelectric accelerometer Capacitive MEMS	All frequencies

temperatures, hazardous chemicals, and corrosion must be considered. Machine tools can expect a great deal of exposure to metal chips and lubrication fluid. Shielding the sensor from these is important to ensure accurate measurement. Sensors must fit into the machine tool without interfering with moving parts. For non-moving components such as bearings or motors, wired contact sensors are adequate. For moving components such as the cutting tool spindle or ball nut, it may be necessary to use a wireless and/or non-contact sensor. Otherwise, special considerations may be needed for cable management so that interference does not occur. Linearity of sensor measurements makes vibration analysis easier.

The piezoelectric sensor and the capacitive micro-electromechanical system (MEMS) are two very common sensors used for vibration sensing. They are useful for a wide range of frequencies and have low noise characteristics. They also boast high linearity over a large range. MEMS sensors are usually incredibly small. A study compared the performance of each of these two sensors and found that they had similar performance in metrics such as maximum load before failure, peak amplitude and linearity. [28]. A 3 axis IoT vibration sensor can be seen in Fig. 3.

D. Other Useful Sensors

Other than vibration and temperature sensors, there are a few other external sensors which can provide useful data. Oil quality sensors are useful devices for analyzing the quality of lubricants. Sensors are available which can provide information about the oil such as pH, temperature, capacitance [30].

Sound pressure sensors can be used to measure the sound energy emitted from moving parts. Components such as bearings will emit more noise as they wear or in the cases of misalignment. One study used sound to detect faults in machine tool carbide inserts during facing operations [31]. They are not often used for CM because there is a great deal of background noise during the use of the machine.

Force sensors are useful for measuring process forces such as cutting or drilling as well as component forces such as the preload of the ball screw [11]. Common force sensors include load cells, strain gauges, and force-sensing resistors.

Cameras are useful for collecting visual data such as wear on the components like the ball screw. Many low cost cameras for IoT exsit, such as the camera module available for the Raspberry Pi as seen in Fig.4.

IV. COMMUNICATION AND NETWORKING

Two key levels of communication exist in a CM system: the machine sensing level and the decision making factory level. A system overview which shows the interaction between the nodes can be seen in Fig. 5 below. The machine-level consists of individual machine tools with CNC controllers and external sensors. The factory level consists of all the machines, a central data analysis node, data storage, and nodes for each department. This is a similar framework as proposed in papers by Yaseen, Swathi, and Kumar [33], and Takemura et al. [34].

Four communication technologies are considered for IoT CM: Wired, Bluetooth, Wi-Fi, and Zigbee. An overview is seen below in Table. V. Zigbee is a popular communication technology used in literature. In one study by Lee at al. [35] they prototyped a smart factory to simulate measuring plastic extrusions. They used Zigbee with star topology for their communication. In another study, Zigbee was used for CM of motors [36]. Bluetooth technology was used in a study for the CM of welding stations [37] and a study on an IoT monitored factory [38]. In one study, the performance of Wi-Fi 2.4 GHz was examined for use in an IoT factory [39].

A. The Machine Level Communication

The machine level is the interaction between the sensors, CNC controller and machine computing and communication unit. This level represents a single machine. Table VI outlines

Fig. 3. Wireless 3 axis vibration sensor [29]

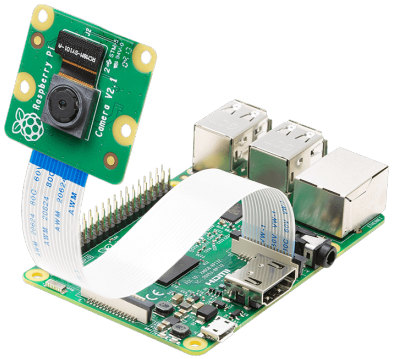

Fig. 4. Raspberry Pi camera [32]

the key considerations when selecting communication technology. The subsections below cover communication technology recommendations based on each design factor. Some computation occurs on this level for applications requiring low latency or immediate corrective action.

1) Range: Machine tools are typically never larger than a few meters. Sensors in the system can either be wired or wireless, depending on the sensor and application. If a sensor can be cannot be wired, Bluetooth or Zigbee wireless connection makes the most sense.

2) Latency: Certain analysis and control methods such as Kalman filtering may require low latency. Sensors for methods requiring very low latency should use a wired connection. For analysis methods with more lenient latency requirements such as temperature analysis, Bluetooth or Zigbee would be adequate.

3) Throughput: Certain types of sensors, such as cameras, will require a large throughput; these sensors should be wired if possible. Sensors with lower throughput, such as temperature sensors which may only pass on a single value every few seconds, can use either Zigbee or Bluetooth.

4) Scalability: Sensors may need to be added or removed. If a large number of sensors are required, issues may arise with the number of physical connections for wired sensors. Bluetooth has a maximum of 7 devices connected to a local network at once. There is not expected to be an excessive amount of wireless sensors, so Bluetooth is as adequate as Zigbee.

5) Topology: The topology of this level is a star. Communication occurs between the sensors and the central computing and communication node and between the CNC controller and the central computing and communication node. Communication between sensors or communication of external sensors with the CNC controller is unnecessary. Bluetooth or Zigbee could be used here.

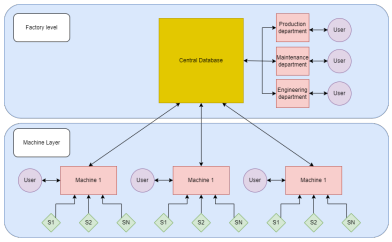

Fig. 5. Overview of the levels of comunication

TABLE V
COMMUNICATION TECHNOLOGY COMPARISON

	Wired	Bluetooth	Wi-Fi	Zigbee
Typical range	5 m	10 m	100 m	50 m
Latency	Lowest	Moderate	Low	Moderate
Throughput	High	Low	Moderate	Low
Scalability	Difficult	Easy	Easy	Easy
Power	-	Moderate	High	low
Topology	Star	Star	Star	Mesh or Star

TABLE VI
COMMUNICATION CONSIDERATIONS AT MACHINE LEVEL

Range	A few meters maximum
Latency	Low latency required for some application
Throughput	Low throughput for most sensors
Scalability	Ability to add additional sensors
Topology	Star topology

6) Optimal Communication Technology: When possible, a wired connection is preferred. Wired connections have the lowest latency, do not require a battery, have the highest throughput, and have adequate scalability for up to a dozen or so sensors. For sensors that must be wireless, Bluetooth technology is the ideal choice. Bluetooth's short range is fine for the expected range of communication, has low enough latency, moderate throughput and good scalability up to about seven devices.

B. The Factory Layer

The factory level is the interaction between the individual machine tools, a central computation and data storage server, and several relevant departments. Table VII outlines the key considerations when selecting communication technology. The subsections below cover communication technology recommendations based on each design factor. Most serious computation, data analysis, and data storage occur at this level.

1) Range: Communication on this level would be over the entire factory. Typically factories would be about 100 m to 1000 m across. Nodes at this level are all stationary, so wired communication is an adequate solution. If wireless is preferred, 2.4 GHz Wi-Fi would be adequate for these ranges if there are receivers throughout the factory, or Zigbee could be used, and communication could be routed between machines.

2) Latency: Most communication on this level does not require low latency. If wireless is preferred, Wi-Fi 2.4 GHz or Zigbee would be more than adequate.

3) Throughput: Most communication at this level has high throughput, typically on the scale of KB or MB. For this consideration, a wired or Wi-Fi wireless approach is favourable

4) Scalability: It may be necessary to add additional machines to the network. These machines will need power infrastructure so connecting them via a wired connection is not very

TABLE VII
COMMUNICATION CONSIDERATIONS AT FACTORY LEVEL

Range	Up to a few hundred meters
Latency	Low latency not required for most applications
Throughput	High thoughput for some applications
Scalability	Ability to add additional machines
Topology	Star topology

cumbersome. Adding machines via Wi-Fi or Zigbee is very easy, and a large number of devices can be easily connected this way.

5) Topology: The topology of this level is a star. Communication occurs between the machines and a central data processing server and the server and relevant departments. This communication resembles a star topology. The larger range of communication could mean that a cluster topology (Fig. 6.) may be preferable in some situations.

6) Optimal Communication Technology: In many situations, wired connections would be adequate given the static position of each node in this level of communication. If a wireless approach is preferred, Wi-Fi is the prefered technology. The high levels of throughput necessitate communication technology that can transfer large quantities of data; thus, Zigbee is not as viable.

C. Human Interaction in Each Level

There must be a method of interaction between humans and the IoT CM system. At both levels, there will be human interaction, at the individual machine level and at the factory level.

1) Interaction with the Machine Level: Operators and maintenance staff need access to information about each machine. The machine interface could provide information to operators, such as if all the sensors are functional, if wireless sensors need to be recharged, and if the machine is still in operating condition. For individuals who are performing maintenance, the machine could tell them the specific issues that are occurring as well as components to inspect or replace. A dashboard similar to the one seen below in Fig. 7 would be available to workers to gather information about the condition of the machine quickly.

2) Interaction with the Factory level: Many different users from different departments can interact with the IoT system at the factory level. The maintenance department can access information about the health of each machine and get alerts when there are issues, faults, or crashes. Production can use information about what machines are available as well as information about the expected availability of each machine to make production decisions. Engineering can examine data from the machines to make decisions about future machine purchasing and program creation. A dashboard should be available for each department which provides them with relevant information for decision making, such as in Fig. 8.

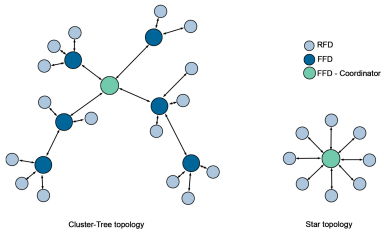

Fig. 6. Cluster topology [40]

Fig. 7. Machine monitoring dashboard [41]

V. Analysis Methods

Data collected from sensors must be analyzed. This data analysis can be used to determine the condition of the machine tool. Many different types of analysis can be used to determine the condition of the machine. The following methods will be discussed: Vibration analysis, temperature analysis, Kalman filtering, lubrication analysis, machine learning, and statistical process control.

One thing that must be considered when doing analysis is where the analysis will be computed. Some methods require low latency and immediate action. These methods are best done at the machine level. Methods requiring a great deal of data or high levels of complexity should be done on the server level of the factory.

A. Vibration Analysis

Vibration analysis is one of the most common methods of CM available. Vibration measurements are used to detect many faults such as misalignment, imbalance, wear, and looseness [43]. Several factors of vibration can be considered, such as Vibration peak amplitude, velocity, and acceleration. Analyzing the different frequencies of vibration can be useful. Using the Fast-Fourier transform, you can transform a vibration from the time domain to the frequency domain. In the frequency domain, different frequency components of vibration can be analyzed. Different faults manifest at different frequencies. Lower frequency vibration analysis includes imbalance, misalignment and looseness. Higher frequency vibration analysis includes bearing faults and gear faults, among others.

Vibration analysis would primarily be done at the factory level of computing, where trends of vibration could be analyzed. Other vibration analysis methods could be done at the machine level, such as alerting the user if vibrations exceed a certain amplitude.

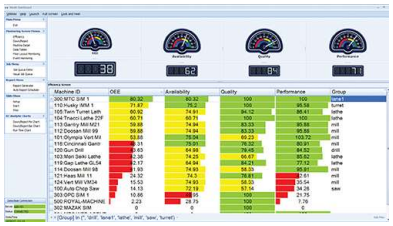

Fig. 8. Factory level monitoring dashboard [42]

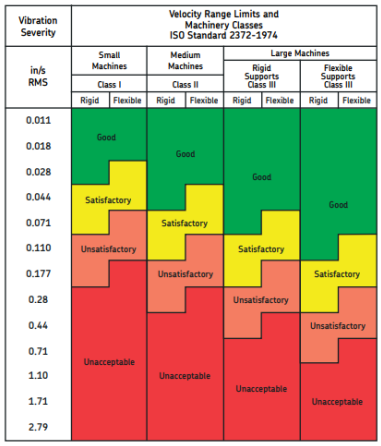

Fig. 9. ISO 2372-1974 Standard for machine vibration [44]

B. Temperature Analysis

The temperature in moving components such as bearings is directly correlated to certain variables such as speed, applied load, and lubrication [45]. Increases in rotational speed applied load, and lubrication velocity will increase temperature. Faults and wear will also increase temperature. The temperature will increase over the course of the run time of machinery. Fig. 10 shows a typical temperature increase of a bearing over its run time. Knowing a system's speed, applied load, and lubrication, you can build a model for the expected temperatures of a component. Substantial variation from this model can indicate substantial wear or faults. Readings will need to be taken over a long period and compared to models and previous data. Most temperature analysis will occur at the factory level of computation as it involves looking at trends of data.

C. Kalman Filtering

Kalman filtering is an estimation method which uses the systems dynamic model, system inputs, and measurements to estimate the variables of the system. It is often used to improve target tracking and the control of moving objects. Kalman filtering has many derived methods, such as the extended Kalman filter and unscented Kalman filter, which are better estimators for non-linear systems. [46]. Most systems have multiple models to describe their behaviour. Interacting multiple models (IMM) is a method to use multiple filters to improve estimation. IMM has often been used for fault detection [47]–[50] in actuators. Kalman filtering methods require a steady stream of low latency data. Kalman filtering is best to be performed at the machine level.

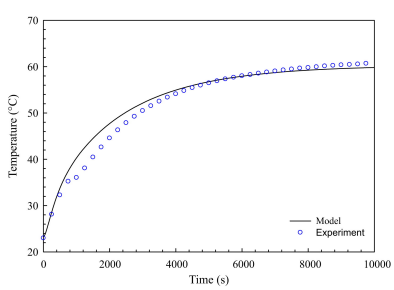

Fig. 10. Temperature change under running conditions [45]

D. lubrication Analysis

Lubrication analysis involves analyzing the oil used to lubricate moving parts. This analysis is often only performed on large machines ($>$ 50 horsepower) that use circulating oil systems. Qualities such as oil pH, capacitance, and temperature can be used to determine the condition of lubrication. The presence of chips and debris could also be detected to predict pitting or spalling on a bearing. An overview of lubrication oil CM is covered in a paper by Zhu et al . [30]. Data about the oil condition over time can be analyzed at the factory level. Simple analysis such as alerting the user if oil temperature has gone above a certain level can be computed at the machine level.

E. Machine Learning and Machine Vision

Machine learning is algorithms which can improve automatically through experience and collection of large quantities of Data. Machine learning algorithms are *black box* systems, that is that we only understand the inputs and outputs but not the calculations and variables used to determine outputs. Machine learning is an excellent method for estimating parameters given a large number of inputs making it an ideal choice for CM.

Machine vision is extracting data from images. Visual data collected from cameras could be processed for useful information. Machine vision has been used to detect faults in machine equipment [51] and detect wear in machine cutting tools [52]. Machine vision can be combined with temperature analysis in the form of thermography. Temperatures of each component can be taken without contact using a single infrared camera. Temperatures of the entire system can be analyzed this way.

These methods of analysis require high levels of data storage and computation, so they are best done at the factory level of computation.

F. Statistical process control and trend analysis

Data collected from the IoT CM system can be used for statistical process control (SPC) and trend analysis. Data collected can be used for SPC methods such as control charts Fig. 11 and histograms which can be useful for CM and fault detection applications. These methods would be computed at the factory level as they require data sets over long periods of time. [53]–[55].

VI. Conclusion and Future Work

After examining available IoT technology and current techniques for CM, it is apparent that IoT technology is advantageous for the application of CM. The primary disadvantage of CM is the requirement to manually collect a great deal of data at a high frequency and the possibility of human error. These

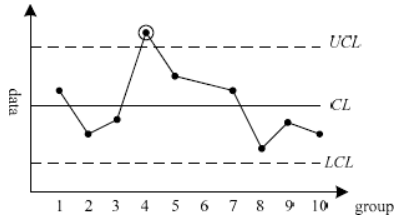

Fig. 11. Control chart [56]

disadvantages are eliminated if data can be collected and analyzed autonomously using an IoT system. An IoT autonomous CM system can help increase production throughput, reduce costs associated with maintenance, and help with decision making. When designing an IoT system for CM, the following design considerations have been examined: Types of available analysis, communication technology, and what sensors are available to collect the needed data. After considering these design criteria, and IoT CM system can be created.

To future augment the literature in the field, additional real-life applications of IoT CM systems should be studied. With more real-life examples, their benefits can be further examined and studied.

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