Mine Automation and Data Analytics

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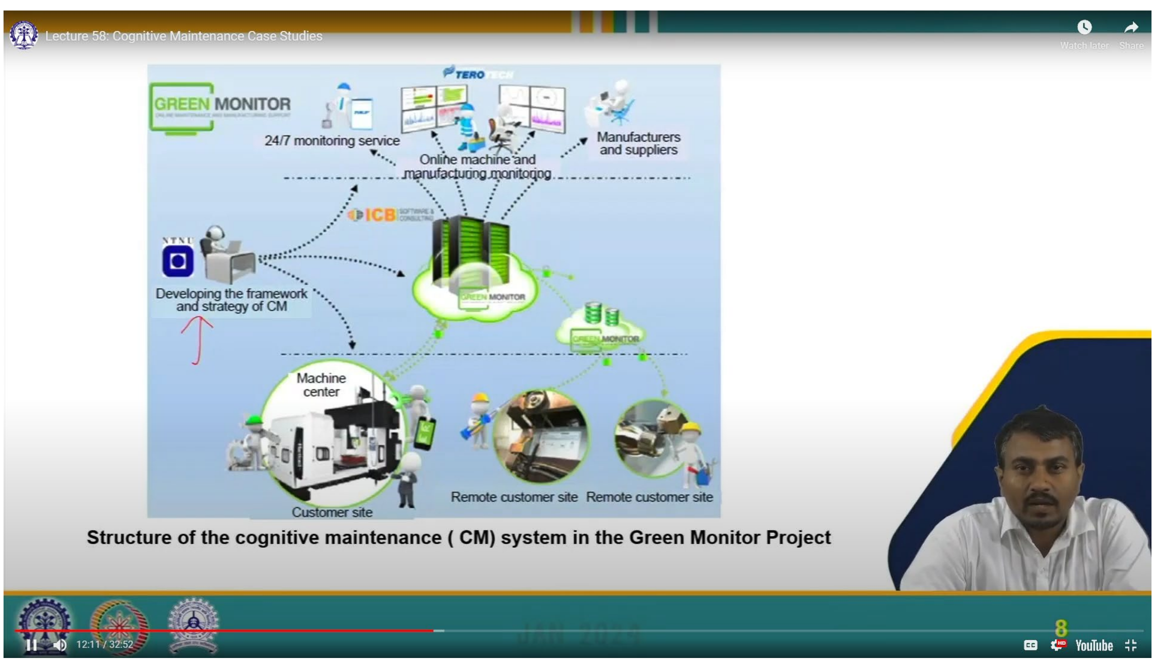
Week-12

Lecture-58

Cognitive Maintenance Case Studies

Hello, welcome back to my course, Mine Automation, and Data Analytics. Today we will discuss some case studies on cognitive maintenance. In the last lesson, we discussed the framework of cognitive maintenance, and during that, we expressed and tried to percolate that this cognitive maintenance plan is the most updated maintenance plan till date, and it is working to fulfill the goal of Industry 4.0 in mining engineering. Particularly in mining engineering, with the automation strategy implemented, large machines are deployed, and it is a huge capital investment. safety and the optimum level of operation of these machines are of utmost importance for mining companies. To supported appropriately by the manufacturing companies, this cognitive maintenance plan or the cognitive maintenance strategy comes as a very powerful tool, and they aid the mining organizations to really help and really change the paradigm of the maintenance of conventional mine machines. In today's lesson, we will discuss two case studies briefly. One is basically conducted by some scientists at the University of Norway, and the other is a mosaic company. today we will discuss the first case study, and this case study will elaborate on how the CPS are implemented, how the IoT and cloud computing systems are integrated, how the data mining system is used for prediction, and how iOS and optimization systems work to deliver maximum efficiency. finally, using this, we want to predict the backlash error using the sensor data beforehand with the actual error that will come in the next week. This is a very good advancement made in the progress of research to implement cognitive maintenance, and finally, we will close this lecture with the second case study of the mosaic.

let me discuss again that the machining center is closely connected with the mine site-level equipment to monitor the present status of the machine, its performance, and its behavior under the particular geomining conditions. This machining center basically supports and basically keeps connections with these big machines that operate at different mine sites. The shutdown of this machining center will lead to significant losses for an enterprise, it is a big loss. So, it is necessary to keep maintaining this machining center? Here, the development of online cognitive maintenance is a crucial element to ensure that these machines operate sustainably and seamlessly without any kind of hiccup, any kind of fault, or any kind of shutdown. This online cognitive maintenance strategy also helps the mining company be competitive in the market because many other companies are also there to take the market and to take a share of it, the better the supply, the better the health, and the and the better the service to the mining company, the more the more they remain competitive in the market. This is a very good strategy by the companies, and they are utilizing it to be relevant in the market. In equipment health monitoring, the CM, which is a cognitive maintenance system, gathers operation status data through the different sensors. the CM basically integrates the large data analysis, the data collected by the different sensors, and transfers the data to the cloud. A computational process goes on, and based on the advanced intelligence technology, it diagonalizes, predicts defaults in advance, and that is basically the strategy of these companies to rely on the online cognitive maintenance strategy. The project is focused on implementing a cognitive maintenance system in numerical control machine equipment. This research study was conducted by the Norwegian University of Science and Technology (NTNU) of Norway, and they led the research with a green monitor project supported by the Norwegian Research Council. This particular project and this particular R&D, they basically collaborate with two companies. One company provided the entire software, which is ICB, which is in Bulgaria, and another company that basically provides support for the maintenance is Kongsberg Terotech, which is abbreviated KTT. This research is aimed at monitoring the condition of the machining center online. The theoretical aspect of cognitive maintenance strategy is targeted at the field level, and that is basically the target: to monitor the conditions of the machining center online in real time. An intelligent data mining algorithm was utilized to predict machine degradation and assist in maintenance decision-making. if we are able to predict that after a certain amount of time, or maybe two, three, or four weeks, the machine is going to degrade because that pattern has been shown in the data. if that pattern is already captured and analyzed and we reach this conclusion, we have a few weeks in our hands. we can basically take some corrective action that we can avoid a machine shut down, a machine accident, a fault, or a machine being stopped in an emergency condition. we can avoid this kind of situation because we have prior information and a prior diagnosis about what is going to happen in the future. In this framework, using the intelligent data mining algorithm, we are utilizing this sort of thing to give a better service to the machines and to the mining company that mining can run and machines can run seamlessly smoothly without any disturbances. The NTNU utilizes its research advantages to propose a framework for the project implementation based on industry 4.0 with the focus on cognitive maintenance. Here at ICB, the company basically provides the software, and they are basically the service company, and they provide throughout the entire project the software support to integrate the platform with the Internet of Things and the clouds, they are basically responsible for that, and the KTT is contributing by providing maintenance services for the machining center, ensuring their continuous and healthy operations where the site-level KTT is at the service level and the interface-level software-level ICB is under full control by the NTNU research team.

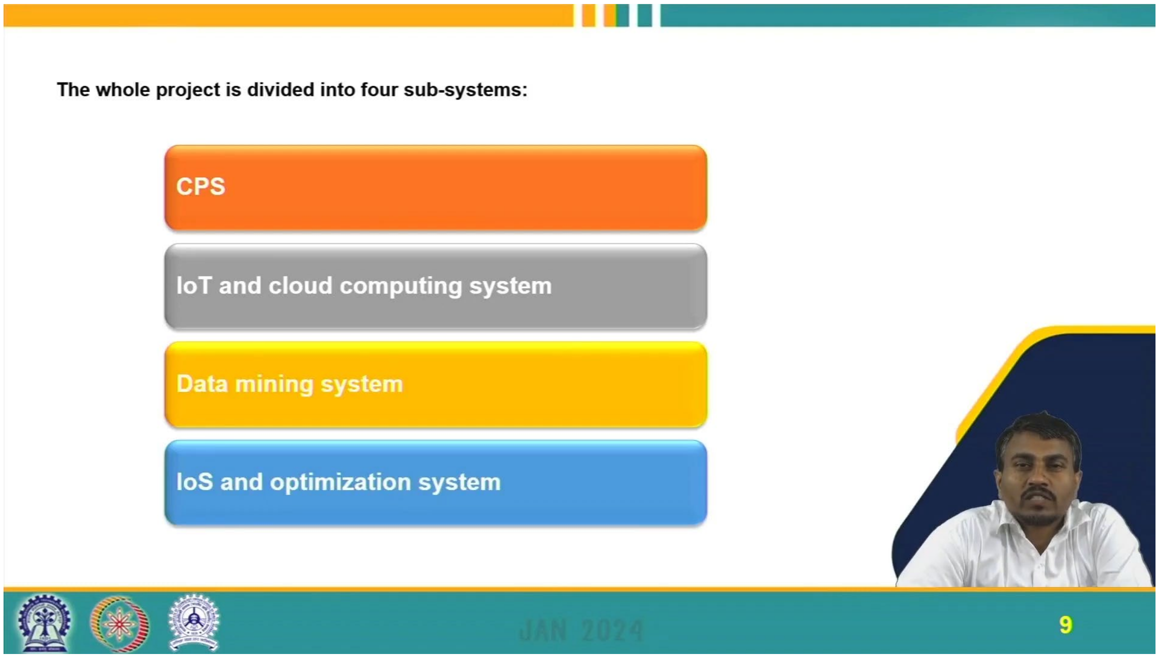


The machining center was selected as the testing platform due to its significance as the core of machinery manufacturing enterprises and the ease of obtaining state data. This data could be directly collected from the control system or indirectly through relevant sensors installed on the equipment during the production process. The project's significance lies in analyzing remote monitoring data in the production process using intelligent, in-depth learning of the data analysis model. The aim is to generate an appropriate online maintenance strategy to minimize cost losses caused by downtime and failure. This is the strategy of the cognitive maintenance plan by the NTNU. here you can see that this is the master control point; they are developing the framework and strategy of the cognitive maintenance plan by the NTNU. At the machine center level, this is basically the customer side. This is the service provided by the KTT, and they have basically installed different kinds of sensors, different mechanics are also there, and different kinds of applications are there to collect the status of the machines. and these are connected to the network and the monitor through the cloud, okay, and here they are monitoring 24/7; they are monitoring the machine status and machine health; and these are the dashboards, which are basically the KPI key performance indicators. Different kinds of plots and different kinds of representations are there to understand the different status of different machines and different works. here they are closely integrating the service with the manufacturers and the suppliers.

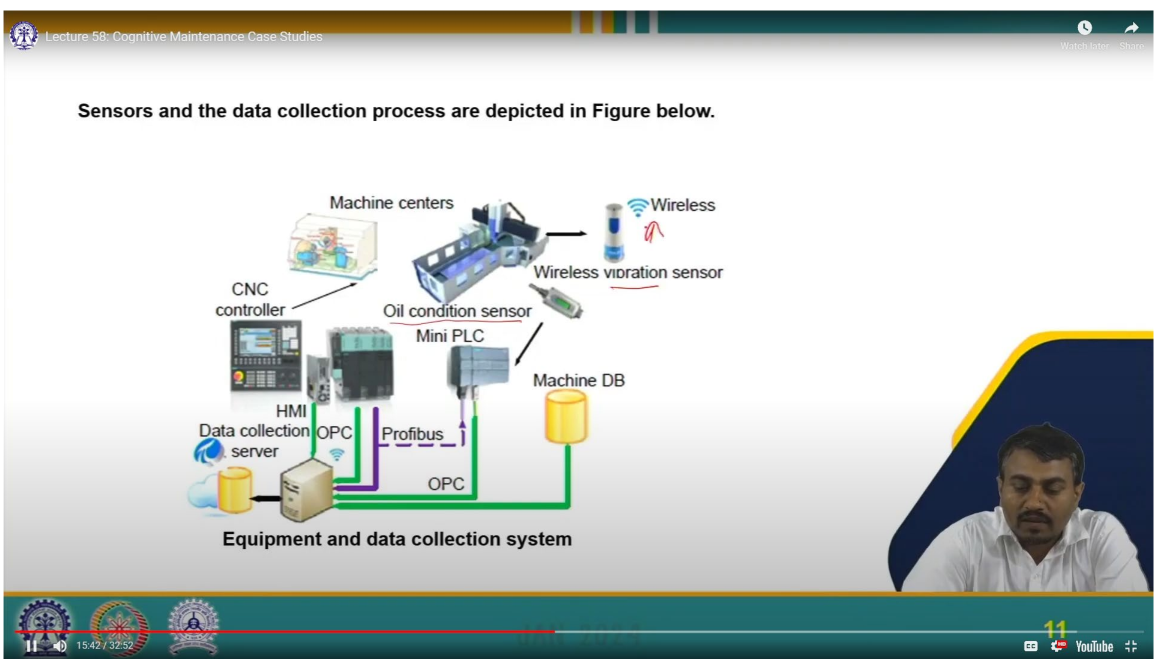
Here there are three components: one at the machining center level, another at the control level, and another at the representation level and analysis level and using this analysis, they are also coming back with the decision of what to do at the maintenance level.

The whole project is divided into four subsystems. the first one is the cyber-physical systems (CPS); the second is the Internet of Things and cloud computing system; the third is the data mining system; and the fourth is the Internet of Services and optimization system.

The CPS is for monitoring the condition of equipment. here, the integration of the physical manufacturing equipment with the information system is very essential for enabling self-perception, environmental monitoring, and information sharing. The green monitor project selected the specific same sensors and controller to create a data

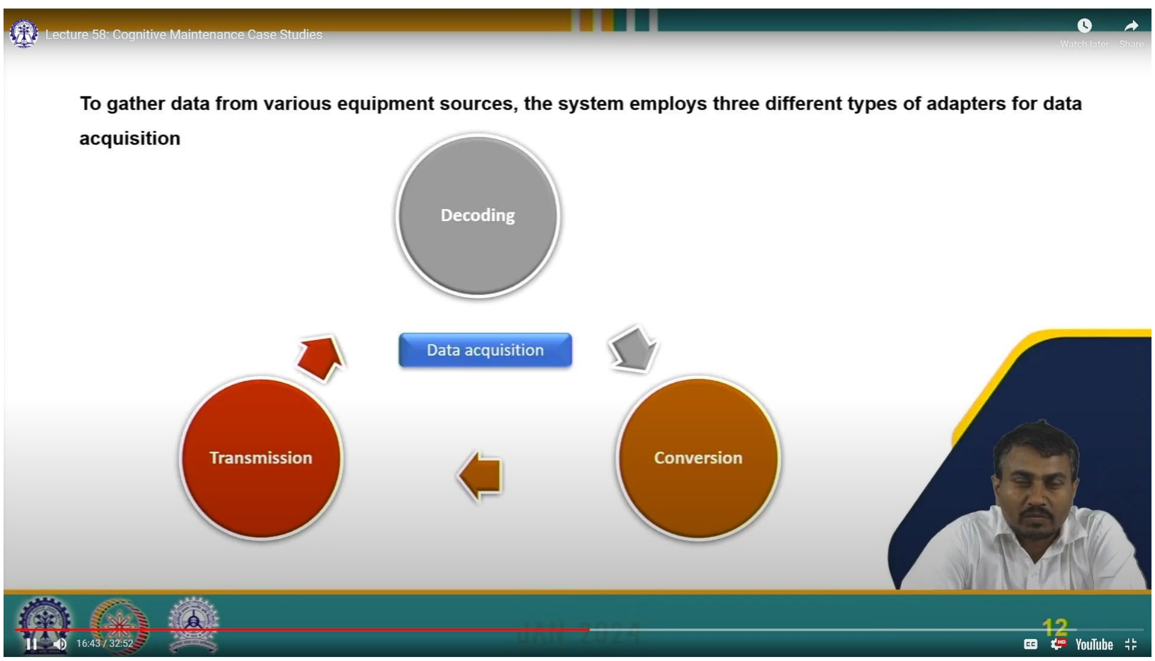


acquisition system. These data acquisition systems are the most vital, and at the IoT level, you are basically selecting which kind of sensor is most appropriate to be installed at those particular positions and those particular geomining conditions. The system interconnects all hardware devices through a wireless network, integrating them into the cyber-physical systems (CPS).

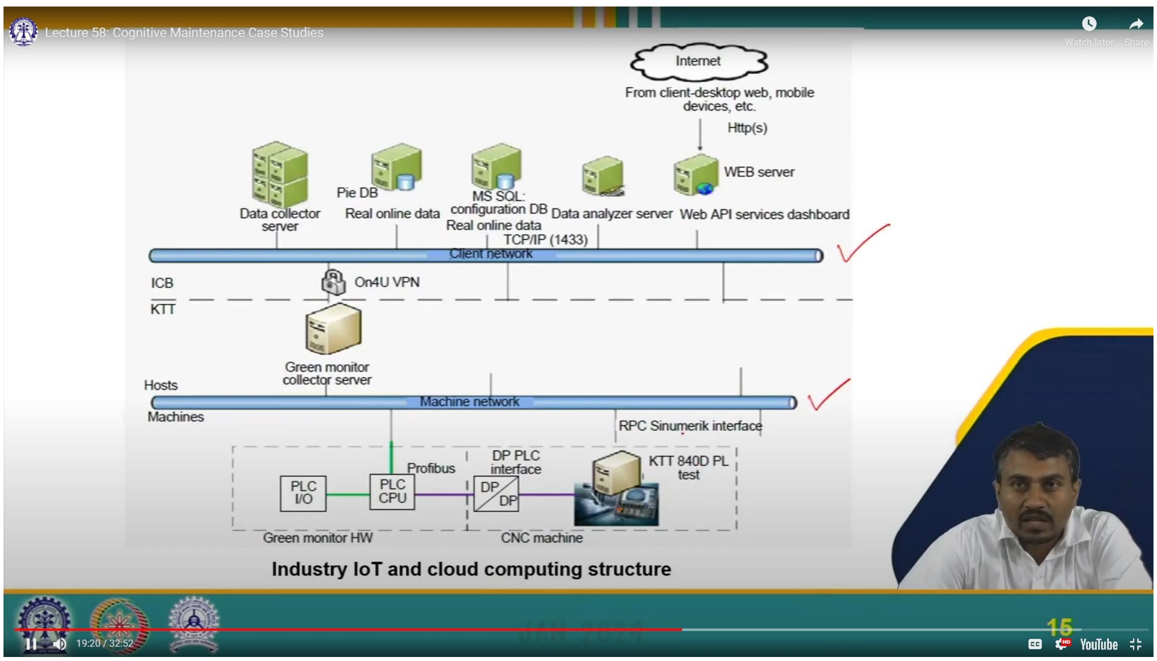


The sensor and data collection process-this is the flowchart for the process of how the data collection goes on continuously, these are the controllers machining centers, and here we are monitoring the oil condition of the machines. We are monitoring the vibration of the machine, and we are also monitoring different parts of the machine, and these data are wirelessly transferred. here we have the human machine interface, the data collection server, the Profibus and the mini-PLC at the machine level, and the machine DB. These are basically the data collection processes that are continuously going on and up on the server in the cloud, and based on that cloud data, we are basically plotting the different kinds of behavior of the machines, and based on that, we are going to suggest what needs to be done in those particular conditions.

To gather data from various equipment sources, the system employs three different types of adapters for data acquisition.



The decoding, conversion, and transmission go on. Why it is required is to make this system robust and secure from third parties or any kind of unwanted situations. decoding is required, these data are basically coded and encrypted, decoding, conversion, and transmission. During the data acquisition process, if the equipment data alone does not fulfill the requirements of the upper system, additional sensors are required to gather supplementary data. The specific sensor needs to be employed in the green monitor project to collect energy consumption data, the oil status of the machine, and the temperature. The data acquisition system consists of a programmable logic controller and sensors. This PLC manages the collection of sensor data and subsequently transmits this data to the data acquisition server through the adapters. Then the IOT and cloud computing of the Internet of Things empower all ordinary objects within an enterprise to execute independent functions, facilitating interconnection and interoperability. The primary function of the IOT module is data transmission, the IOT system comprises two network levels: the machine network and the client network, the data gathered by sensors installed on the device is transmitted via IOT to a local database in our cloud data center for subsequent system utilization.



This is the industry IOT and the cloud computing structure, where one is the machine network and the other is the client network. here input output PLC, CPU and DP this is the interface; this is connected through the Profibus; this is the KTT 840 DPL test; and this is the RPC interface; this is connected with the machine network, this is the host and machine, and this is the green monitor collector server. Now, through VPN, it is with the client network, this is the data collection collector server, then the real online data, then this is the MSQL database, then the data analyzer server, web API service dashboard, web server, and HTTP, and from the client desktop, web, mobile devices, and the internet, through that basically providing real support to the customer level as well, using the data processing, analyzing this data, and using the data mining process and the deep learning process to determine the patterns in the data, in the data, and subsequently suggesting the action plan that needs to be taken.

The data mining system in this module uses deep learning to analyze the backlash error. In this particular case study, we are basically predicting the backlash error in advance. the internet of service and optimization system uses the industry internet to connect the equipment with the maintenance company KTT, which is providing the service to make maintenance decisions, for example, the selection of a maintenance strategy and maintenance schedule optimization.

Backlash error prediction-The backlash error can significantly impact the positioning accuracy of machining centers. The project utilizes the deep-belief network method for backlash error prediction in the machining center. during the experiment, a prediction model was established in the 31st week to forecast future backlash errors. The data collected after this week was not utilized for training up to the 31st week, they have used the data to forecast the 33rd week backlash error, and they try to match. while some machining centers may operate without failure for extended periods, potential serious failure can incur economic costs, post-safety hazards, and require an accurate prediction model. The DBN model, comprising four restricted Boltzmann machines, was constructed to predict backlash errors by superimposing them. The maximum permissible error MPE is set at 15.8 by comparing the predicted backlash error value with the MPE, it becomes possible to assess the likelihood of equipment failure. In this scenario, equipment failure is forecasted two weeks in advance, enabling the prediction of failure occurrence in the 33rd week. consequently, maintenance measures can be implemented in the 32nd week to ensure that the backlash error in the 33rd week does not exceed the MPE. this is basically a blue line indicating the actual backlash error and a red line indicating the predicted backlash error. The advantage is that we are getting an beforehand estimation of what could be the backlash error, and there is a permissible limit, based on the time available with us, we can take some precautionary actions that will help to improve the performance of the machine.

Now let us discuss the second case study the predictive maintenance model predicts equipment failure before it happens to minimize downtime and optimize the maintenance schedule. machine degradation over time is a natural aspect of the equipment life cycle resulting from wear and tear during normal use and leading to decreased efficiency. regular maintenance practices help minimize degradation severity and keep machines operating at maximum efficiency. A good maintenance plan and a good maintenance strategy always keep the machine at its optimum level of operation. There could be some kind of planned maintenance strategy, and there could be some unplanned maintenance strategy, and we all know the unplanned maintenance strategy is going to cost a huge amount to the mining company or any company because it is associated with many things, such as the idleness of the asset, and a large amount of investment required to overcome those kinds of situations, whether complete productions are down or partial productions are down. That helps in a big way to the company. it is always desirable that the planned maintenance strategy be maintained in such a way that there is less unplanned maintenance. you want to avoid basically unplanned maintenance. This unplanned maintenance causes the equipment to be permanently shut down for some amount of time. that basically affects the whole production process. So, in view of these kinds of situations, there is a need to build some kind of database on the machine performance based on installing some kind of sensor on the machines at different parts of the machines to understand the machine behavior, as we already saw in Case Study 1, and based on that, we are going to predict the performance, the pattern, and the behavior of the machines. in that way, using the advent of artificial intelligence and the different modules of the machine learning tools, we are going to take advantage of that and forecast the future performance or future behavior of the machine. that we have some time in our hands and the corrective action that may be required to incorporate on the machines can be taken well in advance that we can avoid as much as possible the unplanned maintenance. this is basically the target of this particular project, and Mosaic is the company that basically developed this framework. In manufacturing companies, machine uptime is very crucial. The higher the uptime, the better the machine performs, the issue is that we always want to go through a regular maintenance strategy rather than face unplanned maintenance. The unplanned maintenance basically disrupts the factory-level work at different levels. There are some kinds of assets that will be idle for some point. the frequency of the planned maintenance should be such that we can avoid unplanned maintenance, and the performance of the machines in the machines in the factory should go smoothly without any hindrance or obstructions. But however, the machine may fail anytime, unexpectedly, despite the regular maintenance schedule. here is the need to install a suitable sensor to understand the machine behavior in greater detail compared to the conventional one, that will help and give more insight into the performance and behavior of the machines, the IOT technology enables constant monitoring of machinery performance through the sensor, facilitating the implementation of predictive maintenance. predictive maintenance utilizes AI tools to predict machinery failure, thereby minimizing downtime and improving efficiency and productivity. here, deep learning is particularly effective for predicting maintenance due to its ability to identify complex patterns in large data sets containing multiple types of data. here, implementing deep learning in predictive maintenance can enhance the machine or service degradation management. here, based on the data, we have tried to understand how the machine performance is degraded and what it could be with some time. we have some time, in the meantime, we can take some kind of corrective action that will streamline the process and avoid the downtime. the methodology is that the goal is to predict engine failure in large mining equipment by means of analyzing the measurement of engine pressure and temperature at various points in the engine and exhaust system. the custom deep learning models were designed and developed by MOSAIC to test this concept. once it is deployed, these models continuously monitor engine behavior to ensure smooth operations and predict engine failure well in advance, thereby preventing unexpected disruptions. when constructing these and training predictive maintenance using the deep learning model, MOSAIC incorporated pressure and temperature differentials between specific components of the engine. if these differentials are much higher, there is some kind of potential that the machine is going to fail. These differentials serve as indicators of potential engine failure, whether they could be catastrophic or slow in sedulously. In order to assess the severity of the impending failure and determine the necessary maintenance actions, the data science team trained a model, and this model was designed to utilize the signal from pressure and temperature differential to differentiate between the various failure modes, including different types of leaks and part failures. The primary conclusion drawn from the analysis was that predictive maintenance is indeed feasible, but it necessitates new meticulous-level data to achieve production-ready outcomes. This project effectively showcased one of the fundamental challenges of machine learning and AI: obtaining precise and consistent training levels. The quality of the model heavily relies on the quality of the data used for learning and generalization. when a model fails to improve, it is crucial to reassess whether the implementation information provided by the learning is truly representative. as a result of this project, the customer gained insight into the steps required to develop an accurate predictive maintenance model for their fleet of industrial machines.

These are the references, let me summarize in a few sentences what we covered. we have explored the cognitive maintenance and cyber-physical systems (CPS)s for predictive maintenance in an industrial setting. We have discussed the IoT integration with cloud computing for efficient equipment and data analysis and maintenance. We have explored data mining for insight from equipment sensor data and introduced the industrial internet of services for optimization. We have investigated predictive analysis and machine learning for identifying machinery failures to minimize downtime and optimize maintenance schedules. Thank you.