

Proposal of Real Time Predictive Maintenance Platform with 3D Printer for Business Vehicles

Yoji Yamato, Yoshifumi Fukumoto, and Hiroki Kumazaki

Abstract—This paper proposes a maintenance platform for business vehicles which detects failure sign using IoT data on the move, orders to create repair parts by 3D printers and to deliver them to the destination. Recently, IoT and 3D printer technologies have been progressed and application cases to manufacturing and maintenance have been increased. Especially in air flight industry, various sensing data are collected during flight by IoT technologies and parts are created by 3D printers. And IoT platforms which improve development/operation of IoT applications also have been appeared. However, existing IoT platforms mainly targets to visualize "things" statuses by batch processing of collected sensing data, and 3 factors of real-time, automatic orders of repair parts and parts stock cost are insufficient to accelerate businesses. This paper targets maintenance of business vehicles such as airplane or high-speed bus. We propose a maintenance platform with real-time analysis, automatic orders of repair parts and minimum stock cost of parts. The proposed platform collects data via closed VPN, analyzes stream data and predicts failures in real-time by online machine learning framework Jubatus, coordinates ERP or SCM via in memory DB to order repair parts and also distributes repair parts data to 3D printers to create repair parts near the destination.

Index Terms—3D printer, predictive maintenance, local production, industry 4.0, cloud computing, Jubatus, vehicle maintenance.

I. INTRODUCTION

Recently, IoT (Internet of Things) technologies have been progressed and many IoT applications have been increased. IoT is the technology to attach communication functions to physical things, connect things to networks, and analyze things data to enable automatic control. IoT application areas are wide such as health care, traffic, smart city, agriculture, sports, manufacturing and maintenance. Especially, manufacturing and maintenance are regarded as the most likely application areas which Industry 4.0 [1] also targets. We can visualize statuses of factories, facilities, parts and products by collecting and analyzing sensor data, and we can also monitor production effectiveness, reflect production plan, control logistics, monitor production usage, change defective products, optimize supply chain and maintain timely.

On the other side, 3D printers also have been progressed and those are spread for manufacturing and designing. 3D printer is an industrial robot which creates 3 dimensional

objects [2] based on 3D CAD (Computer Aided Design) or 3D CG (Computer Graphics) data. Especially in air flight industry, because an airplane is a machine made from huge number of parts and maintenance vendors need to provide various maintenance parts for long time, there increases cases to create maintenance parts by 3D printers while only keeping parts design data (E.g. BAE systems and GE (General Electric) [3]).

Based on these backgrounds, new applications which analyze statuses of facilities or distribution in real-time and creates products or parts by 3D printers near the area where products or parts are necessary based on statuses of demand or failure parts will appear in the future. And for business vehicles such as airplane or high-speed bus, cases of analyzing sensing data and detects parts failure sign on the move and creating repair parts by 3D printers near the destination and delivering them to the destination will be increased in the future.

To utilize IoT data, IoT platforms also appeared to develop and operate IoT applications effectively. For example, Amazon Kinesis [4] is a platform to collect and deliver IoT data by MQTT (MQ Telemetry Transport) [5] to analyze IoT big data in Amazon cloud. However, existing IoT platforms mainly target to visualize things statuses of a certain period by batch processing of sensing data. Thus we think factors of real-time, automatic control by backend coordination and stock parts cost is insufficient to accelerate supply-chain or maintenance in existing IoT platforms.

This paper targets maintenance of business vehicles such as airplane or high-speed bus. We propose and design a maintenance platform with real-time analysis, automatic orders of repair parts and minimum stock cost of parts for business vehicle maintenance. The proposed platform collects data securely, analyzes collected data and predicts failures in real-time, takes optimum actions such as repair parts order based on the predicted failure impact, creates repair parts by 3D printers near the destination and enables fast maintenance after arrival. To achieve them, the proposed platform provides sensing data collection via closed VPN such as Universal One [6], stream data analysis by online machine learning framework Jubatus [7], backend system integration via in-memory DB such as VoltDB [8] and distributing repair parts data to 3D printers.

The rest of this paper is organized as follows. In Section II, we review existing IoT technologies. In Section III, we explain typical applications and clarify current problems. In Section IV, we propose the maintenance platform to solve existing problems. We summarize the paper in Section V.

II. OVERVIEW OF IOT PLATFORM TECHNOLOGIES

Because IoT technologies include a lot of topics such as

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Yoji Yamato and Hiroki Kumazaki are with the Software Innovation Center, NTT Corporation, Tokyo, Japan (e-mail: yamato.yoji@lab.ntt.co.jp, kumazaki.hiroki@lab.ntt.co.jp).

Yoshifumi Fukumoto was with the Software Innovation Center, NTT Corporation, Tokyo, Japan (e-mail: fukumoto.yoshifumi@lab.ntt.co.jp).

sensor, actuator, big data, platform, communication protocol and so on, this section only introduces existing platform technologies to enhance IoT application.

Regarding to platform technology for sensors, MICA [9] is major. MICA and TinyOS [10] which is for sensor network OS are designed to standardize development environment of sensor network. After these technologies, sensing experiments have become active and many fundamental technologies have been established.

To utilize IoT data collected by sensing technologies such as MICA, Amazon Kinesis [4] and Machine Learning [11] can be used as platforms. Amazon Kinesis is a PaaS (Platform as a Service) to deliver IoT data to Amazon cloud by MQTT (MQ Telemetry Transport) protocol. To analyze IoT big data delivered by Amazon Kinesis, Amazon Machine Learning provides machine learning functions such as regression or classification.

NTT DOCOMO and GE release an IoT solution which provides GE's industrial wireless router Orbit (MDS-Orbit platform) with NTT DOCOMO's communication module in 2015 [12]. Companies can collect operation statuses of

facilities such as bridge, electric and gas by setting Orbit. Moreover, companies can develop IoT applications on Toami which is an IoT cloud platform provided by NTT DOCOMO and enables visualization of collected data easily.

For manufacturing, Industrial Internet [13] and German Industry 4.0 [1] are major. Both scopes are not only improvement within factory such as visualizing IoT sensing data but also supply chain optimization of logistics, production planning and so on. These discussions are very active including standardization. One of platform to achieve these concepts, SAP and Siemens release approaches of HANA Cloud Platform for IoT [14] with Siemens's factory technologies and SAP's analyzing and managing software technologies in 2015.

In Japan, VEC (Virtual Engineering Community) [15] is an organization to promote manufacturing solutions and VEC discusses to apply IoT technologies to factories actively. VEC aims to detect failures of facilities automatically from sensing data based on predefined rules and thresholds. VEC expects IoT monitoring to improve restoration support and working effectiveness in factories.

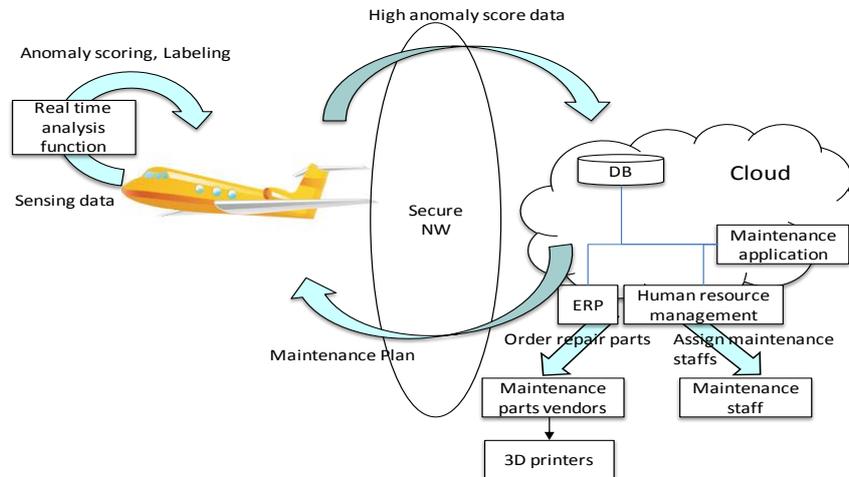


Fig. 1. Example of real time vehicle maintenance application with backend coordination.

III. TYPICAL APPLICATION AND PROBLEMS OF EXISTING TECHNOLOGIES

In this section, we explain a typical application and clarify problems of existing technologies.

An airplane is one of the huge and precision machinery. To guarantee safety during flights, various data such as engine operation statuses are sensed and checked, thus total sensing data reaches more than TB for each one flight. However, almost all of sensing data is thrown away except for serious failure event data. Even used, it is analyzed by batch processing after some troubles are occurred. Then, failures are discovered during maintenance after an air plane arrival and these are the cause of about 0.2-0.3% flights are missing flights or very delayed flights. Missing or delayed flights increase costs to arrange substitute air planes and frustrate passengers.

Then, we explain our supposed real-time air plane maintenance application with backend coordination (See, Fig. 1). Stream sensing data during flight is analyzed in real-time by a computer in an airplane and anomaly is detected by machine learning or other methods. For example, sensing

data difference from normal flight data is large or sensing data exceeds a certain threshold. Data related to detected anomaly is sent to a cloud server by wireless secure network. In the cloud server, sent data is deeply analyzed, suspicious parts are specified, and repair parts/maintenance staffs are arranged by the flight company's ERP (Enterprise Resource Planning). Because arrangements of repair parts and staffs can be done during flight, the flight company can do appropriate maintenance as soon as the air plane arrives. Thus, the company can reduce missing flights or delayed flights. And because many parts companies of air plane such as GE create air plane parts by 3D printers, our application also orders to create repair parts by 3D printers near the arrival airport and to deliver created parts to the airport during the flight.

When we suppose examples like above airplane case, there are some problems in existing platforms or technologies.

Amazon Kinesis [4] basically collects IoT data via the Internet, secure data communication like flight sensing data is not suitable. And network cost is also high to send huge sensor data to a cloud server. Though Amazon Machine

Learning [11] analyzes collected data deeply, applications which take real-time actions such as repair parts order based on analyzed data are not considered.

The IoT solution of NTT DOCOMO and GE [12] enables secure data collecting by GE's robust Orbit. However, IoT applications developed on Toami are mainly visualize applications of collected data by batch processing. Therefore, applications which take real-time actions based on analyzed data are not considered.

VEC [15] discussions have difficulties to define rules and thresholds. And even if the rules and thresholds are defined, strict rules and thresholds are difficult to deal with each factory different environment. Therefore, VEC cannot detect facility failures sufficiently in real-time.

Generally, existing IoT platforms and technologies target a certain period Check in PDCA (Plan, Do, Check and Action) cycle and are insufficient for optimum Action based on real-time situation.

IV. PROPOSAL OF REAL TIME PREDICTIVE MAINTENANCE PLATFORM FOR BUSINESS VEHICLES

In this section, we propose real-time maintenance platform with backend coordination to accelerate vehicles operator' businesses based on IoT data. IV.A explains ideas to solve existing problems. IV.B explains proposed maintenance platform architecture and processing steps. IV.C explains Jubatus processing step for real-time analysis.

A. Ideas to Solve Existing Problems

Firstly, we explain ideas to solve real-time analysis, backend coordination and stock cost.

Most of big data analysis technologies use batch processing such as Hadoop HDFS [16] and MapReduce and lack real-time processing. We adopt online machine learning framework Jubatus [7] to process stream sensor data and take immediate actions. Jubatus judges or learns each one event in stream data and is suitable for stream data processing such as twitter postings. We deploy Jubatus on edge side and cloud side both. Edge Jubatus analyzes sensing data, extracts suspicious anomaly data and adds labels compared to previous problems, cloud Jubatus updates/distributes learning model to edge Jubatus.

Regarding to backend coordination, an analysis application such as IoT data visualization is called information system and its DB is different from backend system DB which is for accounting or ordering. And data transfer between backend system DB and information system DB is usually done by batch processing because of DB performance bottleneck. To take immediate backend system actions such as ordering based on IoT data analysis results, we adopt an in-memory DB such as VoltDB which integrates information system DB and backend system DB. Using in-memory DB, we can propagate IoT data analysis results to ERP which processes repair parts ordering immediately.

To reduce parts stock cost, we distribute ERP ordering data to 3D printers and create repair parts by 3D printers near the destination of the vehicles. To create parts and to deliver the destination on the move, we can reduce stock cost of parts. Especially in air flight industry, because an airplane is made of many parts, we can reduce stock cost

much.

Regarding to security, business data communication via the Internet has many threats. Thus, we adopt closed VPN networks such as UNO mobile M2M [6] to communicate IoT data between a cloud data center and customer sites.

B. Proposed Platform Architecture and Processing Steps

Based on above ideas, Fig. 2 shows proposed platform architecture and processing steps. Fig. 2 architecture has following functions.

In vehicle site such as airplane, sensors and gateways to send sensing data are deployed. Raspberry Pi [17] installed Jubatus is one of example of gateway. Sensing data is sent via closed VPN network by MQTT protocol.

In cloud data center, Jubatus server is deployed and analyzes sent data deeply. Cloud applications on Cloud Foundry/OpenStack control analyzed data. Here, OpenStack [18] is open source IaaS software and Cloud Foundry [19] is open source PaaS software, we can use them for cloud application development and operation. We previously contributed to develop OpenStack and many cloud providers such as NTT Communications adopt OpenStack and Cloud Foundry for their cloud services [20].

In cloud data center, an in-memory DB is also deployed as a baremetal server for backend system coordination. In-memory DB is referred from information system and backend system both. Statistical analysis function refers in-memory DB and evaluates failure impact. ERP also refers in-memory DB and orders parts to vendors. Human resource management function also refers in-memory DB and assigns maintenance staffs.

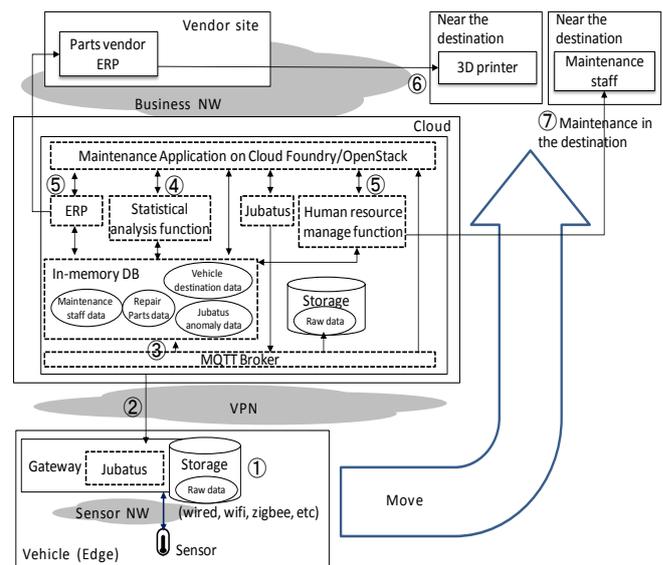


Fig. 2. Proposed platform architecture and processing steps.

Using Fig. 2, we explain processing steps.

1. Vehicles to be monitored attaches plural sensors and sensing data are collected periodically. A gateway such as Raspberry Pi with Jubatus is deployed on each vehicle (Edge side) and analyzes plural sensors' stream data by anomaly detection algorithm of Local Outlier Factor. Anomaly detection algorithm scores high anomaly value when a multidimensional data point from plural sensors is differed much from normal data points. This algorithm can detect anomaly without predefined rules or thresholds.

When edge Jubatus detects suspicious data which anomaly score is higher than a certain threshold, the gateway sends related data to a cloud data center.

When the gateway sends suspicious data to a cloud, edge Jubatus also adds labels of failure by using Classifier algorithm such as Support Vector Regression comparing to previous failure data, and the gateway sends anomaly scores, labels and sensing data. Jubatus Classifier may not add labels when there is no previous similar case.

2. For data sending to a cloud data center, a VPN solution such as UNO mobile M2M [6] is used. Using UNO mobile M2M, a communication module with specified SIM card sends data to a data center via closed VPN Arcstar Universal One. MQTT is a light weight publish-subscribe message queue protocol for sensors. Because data is transferred via queues, edge servers and cloud servers can behave independently.

3. Suspicious anomaly data is analyzed by cloud Jubatus and cloud applications to specify anomaly parts and the anomaly data is inserted to in-memory DB. Because cloud Jubatus can gather anomaly data of multiple vehicles, cloud Jubatus updates learning model using them and distributes models to edge Jubatus (We also explain this in Section IV.C).

4. Referring inserted anomaly data, a cloud application evaluates failure impacts such as how much failure probability is within a certain period and how much damage is based on anomaly scores and added labels. To evaluate failure impact, a cloud application uses statistical analysis function such as PSPP. If there is no label of similar previous failure and a cloud application cannot judge failure cause, a cloud application may notify operators to analyze in manual.

5. Depending on predicted failure impact, ordering data of ERP is inserted to arrange automatic maintenance. Maintenance needs repair parts arrangement and maintenance staff reservation for the destination location such as airports. ERP requests vendors for repair parts. And human resource management functions also assigns maintenance staffs based on cloud application requests.

6. A maintenance parts vendor receives orders via its ERP. ERP checks stock of repair parts near the destination. When there is no stock, ERP distributes repair parts 3D CAD data to 3D printers near the destination and the 3D printer creates parts. ERP also arranges a delivery of stock parts or created parts to the destination of vehicles. These are processed during the vehicle move.

7. A vehicle operator conducts maintenance after the vehicle arrives the destination using delivered repair parts and assigned maintenance staffs.

C. Real Time Analysis and Machine Learning Model Update by Jubatus

By separating Jubatus analysis to edge side and cloud side, both sides have merits. In edge side, light computers such as Raspberry Pi are sufficient because Jubatus only processes simple anomaly detection and classification algorithm, and network cost can be reduced because only suspicious anomaly data is sent to a cloud server. In cloud side, Jubatus analyzes suspicious data deeply and detects anomaly with high accuracy, and Jubatus updates a learning model by

aggregating multiple sites data and distributes it.

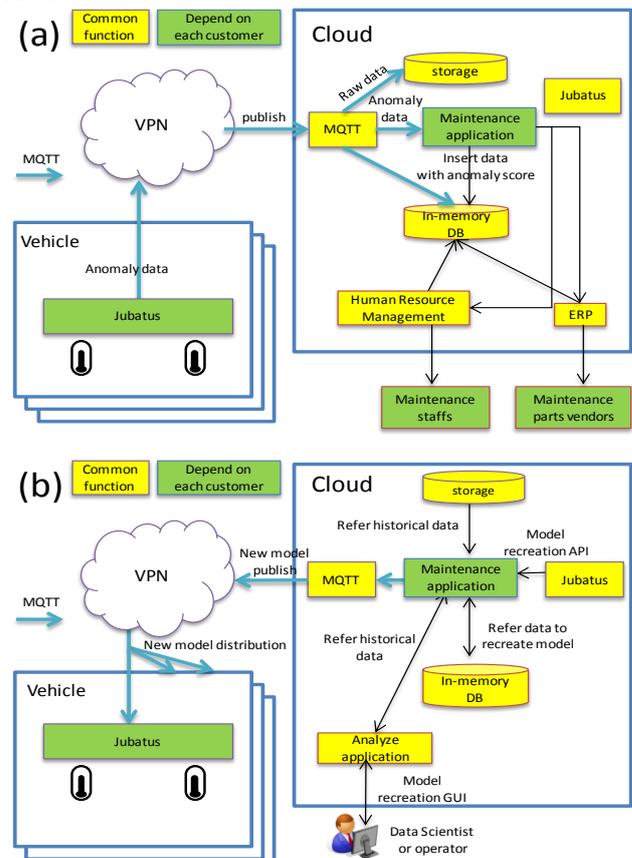


Fig. 3. Jubatus processing flow. (a) Real-time analysis. (b) Machine learning model update.

Fig. 3(a) shows a behavior of Jubatus detection and (b) shows a behavior of Jubatus learning model update.

From Fig. 3(a), customer sites' sensing data are sent to a cloud server via VPN by MQTT protocol when edge Jubatus detects anomaly. Cloud Jubatus analyzes data deeply and inserts sensing data with anomaly score to in-memory DB. In this timing, raw data is also stored in storage. Inserted data is referred by Cloud applications and ERP to use for visualization, prediction and maintenance arrangement.

From Fig. 3(b), cloud Jubatus updates a learning model by validating Jubatus historical judge records using in-memory DB data and raw data in storage. There are two options to update a learning model. One is a platform operator updates it and the other is a customer updates it by him/herself. The policy can be determined based on platform use fee and customers' machine learning knowledge. Updated learning model is distributed to edge Jubatus by MQTT.

V. CONCLUSION

In this paper, we proposed a real-time maintenance platform for business vehicles to detect failure signs during transportation, create repair parts by 3D printers and deliver them to the destination. The platform provides real-time analysis, backend coordination and stock cost reduction for failure prediction and automatic control of vehicles.

The proposed platform collects sensing data via closed VPN such as Universal One, analyzes stream sensing data and detects anomaly in real-time by edge/cloud Jubatus, and

coordinates backend system processing such as repair parts order and maintenance staff assign by real time processing with in memory DB and ERP. Repair parts data are distributed to 3D printers near the destination of vehicles, so that repair parts creation and delivery during transportation can be done.

In the future, we will study failure patterns of each machine. And we also will expand application areas of our platform not only vehicle maintenances but also vehicle control to reduce traffic congestion which need real time IoT data analysis and we will support vehicle operations.

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and IEICE.

Yoji Yamato received his B. S., M. S. degrees in physics and Ph.D. degree in general systems studies from University of Tokyo, Japan in 2000, 2002 and 2009, respectively. He joined NTT Corporation, Japan in 2002. There, he has been engaged in developmental research of cloud computing platform, Peer-to-Peer computing, service delivery platform. Currently, he is a senior research engineer of NTT Software Innovation Center. Dr. Yamato is a member of IEEE