Journal of Information Systems Applied Research

Volume 16, No. 2
July 2023
ISSN: 1946-1836

In this issue:

iscap
Information Systems & Computing Academic Professionals

The **Journal of Information Systems Applied Research** (JISAR) is a double-blind peer reviewed academic journal published by ISCAP, Information Systems and Computing Academic Professionals. Publishing frequency is three to four issues a year. The first date of publication was December 1, 2008.

JISAR is published online (https://jisar.org) in connection with CONISAR, the Conference on Information Systems Applied Research, which is also double-blind peer reviewed. Our sister publication, the Proceedings of CONISAR, features all papers, panels, workshops, and presentations from the conference. (https://conisar.org)

The journal acceptance review process involves a minimum of three double-blind peer reviews, where both the reviewer is not aware of the identities of the authors and the authors are not aware of the identities of the reviewers. The initial reviews happen before the conference. At that point papers are divided into award papers (top 15%), other journal papers (top 30%), unsettled papers, and non-journal papers. The unsettled papers are subjected to a second round of blind peer review to establish whether they will be accepted to the journal or not. Those papers that are deemed of sufficient quality are accepted for publication in the JISAR journal. Currently the acceptance rate for the journal is approximately 35%.

Questions should be addressed to the editor at editor@jisar.org or the publisher at publisher@jisar.org. Special thanks to members of ISCAP who perform the editorial and review processes for JISAR.

Journal of Information Systems Applied Research

A Predictive Unmanned Aerial Vehicle Maintenance Method: Using Low-Code and Cloud-Based Data Visualization

Taejin Kim
kimtaejin@cityuniversity.edu

Ahreum Ju
juahreum@cityu.edu

Brian Maeng
maengjooyol@cityu.edu

Sam Chung
chungsam@cityu.edu

School of Technology and Computing (STC)
City University of Seattle (CityU

Abstract

Demand for Unmanned Aerial Vehicle (UAV) usage in various industries rapidly increases from one year to another. The Federal Aviation Administration (FAA) anticipates that the number of commercial drones will increase to 1.44 million by 2025. But at the same time, there is a growing concern about UAVs' electrical, mechanical, and system reliability. The problem is that those reliability issues can interfere with safe operations and may lead to accidents due to malfunctions during flight. One of the effective ways to solve the reliability issues is to improve the UAV maintenance method. For this purpose, we first review existing UAV maintenance methods and investigate technologies utilized for the current maintenance in the aviation industry. Second, we propose a Cloud-based and Low-Code Predictive Maintenance Method (CLPMM) that uses a low code development platform and Azure Cloud Services. Third, we compare each technology of the existing maintenance methods with the CLPMM to verify the benefits. Lastly, we discuss the strengths and weaknesses of the CLPMM.

Keywords: Low-Code Development Platform, Cloud Computing, Cloud-based Predictive UAV Maintenance Method

1. INTRODUCTION

Unmanned Aerial Vehicles (UAV) have been widely used for monitoring, delivery, and field management tasks because they bring significant benefits in decreasing workload and fixed costs and increasing work efficiency and productivity. For that reason, logistics, agriculture, and other industries are taking advantage of UAVs, which is accelerating the UAV industry's growth (FAA Aerospace Forecasts, 2020).

From a report by the Federal Aviation Administration (FAA), 351,244 of 868,838 commercial UAVs are registered in the United States and the number is growing (FAA, 2021).

https://jisar.org/; https://iscap.info

And another FAA report notes that the number of commercial drones will increase to 1.44 million by 2025 (FAA Aerospace Forecasts, 2020). Although the number of companies operating UAVs is rising in various industries, the existing maintenance method that is one of the key factors that directly influence UAV reliability remains without improvement (Mrusek, Kiernan, & Clark, 2018).

Studies on UAV reliability and risk analysis highlight that mechanical and system failures are still risk factors (Lum & Tsukada, 2010), and improvement of system reliability and standardization is necessary for safe UAV operation (Belzer, 2017). But issues of UAV reliability still have not been solved, and the question of reliability in UAV has been continuously raised.

For ensuring that all components are operating the required functions as designed for safe UAV operation, we challenge a question in this paper – How can we improve UAV maintenance reliability even while a UAV is being operated? For this purpose, first, we review existing UAV preventive or predictive maintenance methods and investigate technologies utilized for the current maintenance in the UAV industry. Second, we propose and describe a cloud-based low-code predictive maintenance method for UAVs (CLPMM) that uses a low-code development platform, Microsoft Power Platforms, and cloud computing, Azure Cloud Services. Third, we compare current preventive and predictive maintenance methods with the CLPMM to verify the benefits. Lastly, we discuss how CLPMM improves UAV maintenance reliability even while a UAV is being operated.

2. BACKGROUND

UAV Maintenance Methods

There are two types of maintenance - preventive and predictive maintenance. Preventive maintenance is to repair parts at a scheduled interval. On the other hand, predictive maintenance is to repair parts before they fail (Barlow, 2015).

Cloud Computing for IoT

Internet of Things (IoT) is the network of connecting smart devices and allows to exchange data in real-time with other devices using sensors on the devices over the internet. The Azure IoT Central platform of Microsoft is a Software as a Service (SaaS) and plug & play IoT application platform. It provides various built-in functions that include templates, data analytics, data management, auto-scaling, recovery, and protocol. This platform also offers a built-in GUI dashboard that allows users to manage, customize, and visualize data for monitoring (Microsoft, 2021, March 29).

Low-Code Development Platform

The Microsoft Power Platform consists of Power Apps, Power Automate, Power BI, and Power Virtual Agents and offers solutions with low-code and no-code development platform for building and developing the application.

- Power Apps provides a friendly development environment that allows developers to easily build custom mobile and web applications that run on any device and connect and interact with existing data.
- Power Automate is used to create an automated workflow to reduce the workload on repetitive processes such as communication, data collections, and task assignments. Also, it provides an auto-notification function that sends notifications via email when the event occurs.
- Power BI, which is a data analysis software and Software as a Service (SaaS), allows users to easily connect to a broad set of data sources and process and visualize data to discover valuable information in the cloud, hybrid cloud, or on-premises environment.

3. RELATED WORK

Table 1 shows three related work - Su and Yon's (2018), Berbente et al. (2020), and Massaro, Selicato, and Galiano's (2020).

Su and Yon's (2018) study presented a Predictive

Criteria	Su & Yon, 2018	Berbente et al., 2020	Massaro, Selicato, & Galiano, 2020
Maintenance Method	Predictive	Preventive /Predictive	Predictive
Data Collection Location	Cloud Computing/On Premise	N/A	Cloud Computing
Data Storage	On Premise	On Premise	On Premise
Dev.	High code dev.	Low and High code dev.	Low and High code dev.
Capital Cost	High	High	High
Difficulty for Dev.	High	Intermediate	High
Data Visualization	Low (text only)	High	High
Auto & Timely Notification	Warning message	No	No

Table 1: Summary of Previous Work

Analytics Framework (PAF-HD) system to detect a sign of Hard Disk Drive (HDD) failure in the data center using a Machine Learning (ML) and Hadoop with Apache Spark. This architecture used a Random Forest algorithm and Hadoop with Apache Spark to distribute and process data and predict HDD failures. Also, this system includes a warning system to report HDD failures to a user, and raw data is manually uploaded to the system or is received from cloud storage.

Su and Yon (2018) utilize a Smartmontools software to provide the status of HDD health information for monitoring. The data is displayed in text only, and a user can only access data through a computer that is installed with this software.

Su and Yon (2018) build a system with complementary software to reduce development costs. But the system develops with high-code, and data is stored in an on-premise database. Furthermore, the paper provides two approaches for data connection with the system. One approach is to manually upload HDD historical health data to the system, which leads to high development and capital cost.

Bernente et al. (2020) highlighted that monitoring tooling, maintenance procedures, and analyzing components' data are crucial to detect equipment failures proactively. For that reason, the paper suggested an advanced Engine Health Management that is added a pro-active system and Business Intelligence from existing Engine Health Management. The pro-active system with predictive algorithms compares current patterns with historical data to predict component failures. Business Intelligence in engine condition monitoring detects impending failures by monitoring key parameters, such as temperature, engine thrust, oil temperature, and others.

Bernente et al. (2020) use business intelligence that offers a user-friendly environment for creating a data pipeline with an on-premise database and generating new valuable information from existing data. Furthermore, the business intelligence provides enriched templates and features to visualize the engine’s key parameters based on user selection and allow users to share and access a dashboard and report with others for monitoring.

Massaro, Selicato, and Galiano's (2020) study proposed a new maintenance method that anticipates the timing of maintenance for a bus fleet through classifying the driver behavior and bus engine status using a hybrid cloud. This method is used for the Internet of Things (IoT), multilayer perceptron artificial neural network, and data visualization to collect, transfer, analyze, and display data. The data from internal sensors and OBD-II transfers to Raspberry Pi and is streamed to a company’s on-premise database using the IoT cloud. Artificial intelligence algorithms process collected data to indicate engine stress and key performance indicators of driver behaviors. This information links to a cloud platform with a graphical dashboard for monitoring.

The system suggested includes a cloud platform with dashboards to visualize vehicle health status, fuel consumption, and key performance indicators of driver behaviors using various templates and visual aids for monitoring. This system uses a hybrid cloud. Data is transferred using the IoT cloud platform. But, data is sent to an on premise database, so capital cost is expensive.

4. DESIGN & IMPLEMENTATION

The concept of CLPMM can be classified into three main sections: data collection, data processing, and data visualization, and the steps of CLPMM are as follows (Figure 1):

1) Massive telemetry data from sensors on the device of drone parts is received in real-time via Azure IoT Central (Microsoft, 2021, May 3).
2) Azure Steam Analytics structures the telemetry data and stores it in Azure Storage (Microsoft, 2021, November 12).
3) The data is transferred to Power BI for real-time monitoring of the status of the drone's parts to detect the imminent part failure and is also utilized to predict the part life and part failure for predictive maintenance using Azure machine learning.
4) Power BI visualizes key parameters of drone parts in real-time.
5) Power Apps allows mechanics to access Power BI dashboard on mobile and upload maintenance records to Azure Storage.
6) Azure Automate automatically sends an email to assigned mechanics when the data shows that the part function is lower than standard.

In order to demonstrate the concept of CLPMM, a Tello drone and artificial flight data are used to show data processing and data visualization. Telemetry data from the Tello drone is transferred to IoT central in real-time using IoT and DJI Tello SDK in Figure 2.

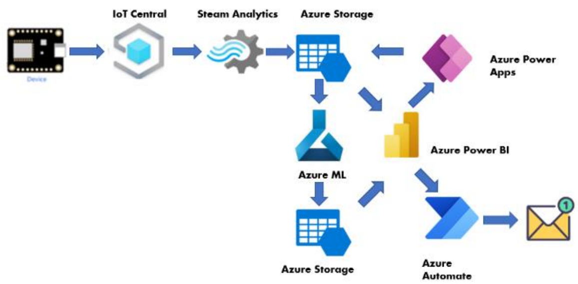

Figure 1: Architecture of CLPMM

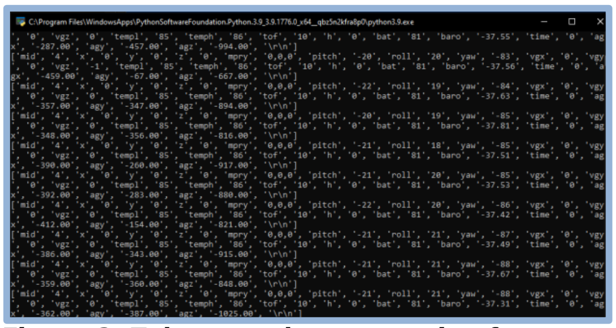

Figure 2: Telemetry data streaming from Tello Drone

Using IoT central service, telemetry data processes and displays on a dashboard in IoT central in Figure 3. The data is stored in Azure table storage.

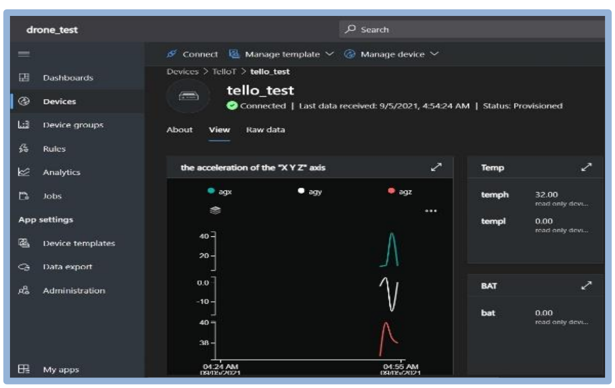

Figure 3: Telemetry data received through Azure IoT

Power BI connects with the storage and visualizes key data to detect impending failures of drone components in Figure 4.

From Figure 5, UAV just took off on Walnut St in Everett, WA at 12:17 PM to return home, and data showed that motor #one's rpm suddenly dropped on a line chart. Mechanics could easily recognize the abnormal condition of motor #one during monitoring the UAV's key indicators and quickly determine that it needs to replace. Furthermore, assigned mechanics would receive an email notification through the CLPMM.

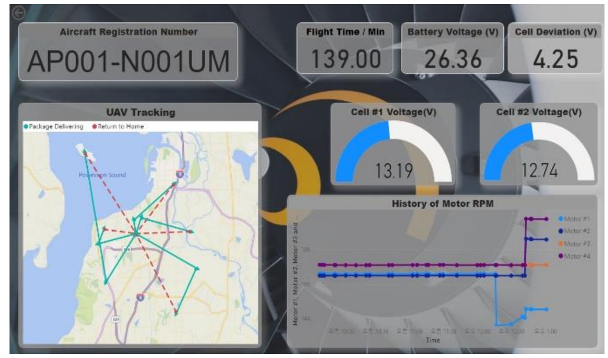

Figure 4: Key indicators of drone components

Figure 5. Monitoring abnormal behavior

Time series data in Azure storage are pulled from the storage and down into Azure notebooks. And then, it needs to set Azure subscription id and IoT hub name, storage account name, key, container, and others, and data is loaded using pandas. Lastly, a regression model is trained with Azure Auto ML. Azure Power Apps that connects with the storage and Power BI allows mechanics to access the dashboard in Power BI via mobile devices, so the mechanics can access it at any time for monitoring. Also, mechanics can easily upload the maintenance data to the storage. Using Azure Automate, supervisors or assigned mechanics automatically receive notification of impending component failure.

5. FINDINGS

From architecture and technology, cost, and data visualization and monitoring perspectives, the features of each architecture and the CLPMM will be analyzed and compared. Furthermore, the following requirements are considered to compare with each architecture.

- Allow mechanics to access the report and dashboard at any time for increasing collaboration and maintenance efficiency.
- Enable to flexibly expand IT resources depending on the workload in a short time to respond to massive data from UAVs.
- Need to consider operating costs.
- Require enriched features and templates to visualize data for providing insights to UAV mechanics.
- Provide strong security and recovery system to satisfy FAA maintenance records regulations.

CLPMM uses a PaaS and SaaS cloud architecture. Telemetry data is received from drones through Azure IoT, and Azure Stream Analytics processes and routes data to a dataset in Power BI. The Power BI performs to visualize data using templates and tools. Azure ML is used to predict drone component lifetime for predictive maintenance, and Azure Power Apps provides enhancement of mobile experience for access Power BI dashboard and uploading maintenance record to cloud storage. So, this environment satisfies FAA FAR part 91 which is maintenance record storage requirement. Lastly, Azure Automate automatically send notification to assigned mechanics or supervisors when the part function is lower than normal standard. These features of CLPMM bring several advantages over other existing architectures for UAV maintenance, as given below.

Architecture
- Low downtime
- High availability and scalability
- Easy to backup data
- Disaster recovery available

Cost
- No initial large investment
- Various pricing models available, such as Pay as you go, Monthly, and 1- 3 year reserved upfront plan

Data Visualization and Monitoring
- Easy to share and access reports and dashboard with others
- Enriched features and templates
- Intuitive dashboard and high accessibility

However, the concept of CLPMM is not free from the inherent limitations of the cloud and other drawbacks.
- Possibility of cloud outage
- Level of control
- Long-term costs (Increasing the total cost of ownership)
- requirement of reliable connection
- Risk of IoT security

Overall, architectures that are used on-premise and hybrid cloud have strengths. However, in the light of the above requirements for improvement of predictive UAV maintenance, the CLPMM has more benefits and satisfy more requirements than other architectures. In other words, those technological advantages from CLPMM help mechanics efficiently monitor critical indicators of UAV components to maintain the airworthiness condition and contribute to improving UAV reliability. Furthermore, existing UAV companies or start-up companies just jumping into the UAV industry can quickly launch their UAV maintenance program and flexibly manage and store flight data depending on the amounts of data using CLPMM. On the other hand, reliable connection and the risk of IoT security might be hurdles to adopting and operating CLPMM because the meaning of a lost connection is unable to receive flight data from a drone. Therefore, a reliable connection should guarantee. Also, vulnerabilities of IoT security should remove to avoid hacking or data breaches.

6. CONCLUSIONS

The Cloud-Based and Low-Code Predictive Maintenance Method (CLPMM) that uses cloud services is designed to receive data from UAV in real-time and process and visualize the data for providing valuable information for predictive UAV maintenance. Azure IoT Hub receives data in real-time from UAV, and the Azure Steam Analytics processes and routes the data to a dataset in Power BI, Azure Table storage, and Azure ML.

This architecture has the ability to handle resources depending on demands without impacting performance and availability, so it can flexibly respond to growing UAV data during flight. Furthermore, a large initial investment in IT equipment is not necessary as a cloud provider services software, storages, operating systems, and other resources. Moreover, the cloud provider offers various types of pricing models, so there is an opportunity to optimize the operating cost.

The Power BI in the CLPMM architecture furnishes an intuitive visualization dashboard that consists of significant data to UAV technicians using Power BI enriched features and templates, and the UAV mechanics are able to access the latest updated dashboard at any time for monitoring the status of UAV components and detecting impending component failures. Azure ML is used to predict part lifetime and timing of maintenance, and Power Apps offers a good mobile experience to mechanics to access Power BI dashboard and upload maintenance record to the cloud storage.

Furthermore, Azure Automate provides automatic notification that send email to assigned mechanics when the component's performance is below the normal standard. These features show that the CLPMM is improved and reduces maintenance efforts more than other architectures, and it is suitable for improving predictive UAV maintenance and reliability.

7. FUTURE WORK

First, this paper could only test the CLPMM using a single drone due to the limited resources. Accordingly, an examination to check that this concept flexibly deals with unexpected network overload, processing power, and a sudden increase of telemetry data for smooth and stable data transfer when connected to multiple drones is needed.

Second, the main required future work will be researching IoT technologies because the CLPMM has utilized IoT technology to receive telemetry data from a drone. In other words, the data connectivity between UAV and IoT is essential to get the data stably. Therefore, it is necessary to research types of IoT networking technologies to find what technology is suitable, such as wireless mesh network systems or Long-Range Radio (LoRa).

Last, IoT security cannot be neglected. IoT vulnerabilities lead to allowing unauthorized access and may cause a hijacking. Additionally, an unauthorized person who obtains data during the streaming can get information about the shipping destination based on data and steal packages. The data is from sensors of UAV components, so it is unable to detect UAV structure problems using CLPMM. For that reason, the future work may involve in investigating a method to get structural data from the drone in real-time. In addition, the data collected from the failed components may be used to influence the current or future policy on preventive and predictive maintenance. This work does not focus on this topic but finding the improved window for maintenance intervals can be an area for future addition.

10. REFERENCES

Barlow, M. (2015). Predictive Maintenance (1st edition). O'Reilly Media, Inc.

Belzer, J. A. (2017). Unmanned aircraft systems in the national airspace system: Establishing equivalency in safety and training through a fault tree analysis approach (Doctoral dissertation, Ohio University).

Berbente, S., Andrei, I. C., Stroe, G., & Costea, M. L. (2020). Topical Issues in Aircraft Health Management with Applications to Jet Engines. INCAS Bulletin, 12(1), 13-26.

Federal Aviation Administration. (2020). FAA Aerospace Forecast Fiscal Years 2021–2041. Federal Aviation Administration. Retrieved from https://www.faa.gov/data_research/aviation/aerospace_forecasts/media/FY2021-41_FAA_Aerospace_Forecast.pdf

Federal Aviation Administration. (2021, July 21). UAS by Numbers. Federal Aviation Administration. Retrieved from https://www.faa.gov/uas/resources/by_the_numbers/

Lum, C. W., & Tsukada, D. A. (2010). UAS reliability and risk analysis. *Encyclopedia of Aerospace Engineering*, 1-12.

Massaro, A., Selicato, S., & Galiano, A. (2020). Predictive Maintenance of Bus Fleet by Intelligent Smart Electronic Board Implementing Artificial Intelligence. *IoT*, *1*(2), 180-197.

Microsoft. (2021, March 29). What is power BI. Microsoft. Retrieved from https://docs.microsoft.com/en-us/power-bi/fundamentals/power-bi-overview

Microsoft. (2021, May 3). What is Azure IoT Hub. Microsoft. Retrieved from https://docs.microsoft.com/en-us/azure/iot-hub/about-iot-hub

Microsoft. (2021, November 12). Welcome to azure stream analytics. Microsoft. Retrieved from https://docs.microsoft.com/en-us/azure/stream-analytics/stream-analytics-introduction

Mrusek, B. M., Kiernan, K. W., & Clark, P. J. (2018). UAS maintenance: a critical component in maintaining airworthiness. International Journal of Aviation, Aeronautics, and Aerospace, 5(5), 2.

Su, C. J., & Yon, J. A. Q. (2018). Big Data Preventive Maintenance for Hard Disk Failure

Detection. *International Journal of Information and Education Technology*, *8*(7).

Editor's Note:

This paper was selected for inclusion in the journal as an CONISAR 2022 Meritorious Paper. The acceptance rate is typically 15% for this category of paper based on blind reviews from six or more peers including three or more former best papers authors who did not submit a paper in 2022.