Improving Inspection Processes with Wireless Technology, Cloud Computing, and Machine Learning

Introduction

In August of 2018, TechKnowServ approached Workpad LLC to investigate possible solutions for an automated pipe wall thickness data collection and analysis system. TechKnowServ has a number of customers who utilize a diverse selection of piping components in the field, including elbows, tees, and connectors used to pump drilling fluid at elevated pressures. These components have a limited working life, and are inspected both when new and at regular intervals for wall thickness, corrosion, and defects.

The current method of using ultrasonic thickness gauges in the field resulted in many inefficiencies and inaccuracies in the data generated by the field inspectors. Transferring data manually with memory cards to a stand-alone computer was slow, and offered no ability to securely store data and analyze at scale.

Difficulties in reading and writing long serial numbers which were often obscured with scale and rust or inaccessible made accurate logging of asset identity a tedious and time-consuming process. Similarly, logging inspection results and post-inspection analysis were manual processes which could be rendered only slightly more efficient with the use of spreadsheets and simple databases.

TechKnowServ endeavored to build an integrated inspection, data collection, and analysis system which could improve the efficiency of this process and create a repository of useful data which could provide not only a history of individual parts, but also predict expected service life of components. The goal was to enable customers to predict the service life of parts and assemblies segmented by manufacturer, part geometry, operating environment, and other factors.

Requirements

RFID tagging for part identification was identified as a key aspect of the project. In addition, the remote locations and harsh conditions of the work sites necessitated the use of sparsely connected data storage devices, i.e. inspection data would need to be stored until wireless connections to the Internet were available, and then the device would have to synchronize the data to the cloud.

TechKnowServ requested a proposal for a system which would automate the following processes:

1. Facilitate data entry for RFID tagged assets into a cloud database
2. Allow field technicians to quickly scan RFID tagged assets in the field
3. Utilize a connected ultrasonic thickness gauge to wirelessly transmit inspection data
4. Store and forward asset and thickness data to the cloud platform
5. Display and report on asset data and thickness measurements from a web application
6. Analyze data for actual and expected lifetimes with respect to various parameters.

Usability requirements for the projected included:

1. No or minimal keypad data entry in the field
2. Sparsely connected devices capable of store-and-forward of asset and inspection data
3. Flexible framework for future analytics needs
4. RFID readers and wireless communication devices capable of operation in harsh environments
5. Centralized, secure web-accessible data storage capable of sharing inspection data.

TechKnowServ specified a delivery date of no more than 13 weeks from contract to delivery of a production system, with a budget which would allow them to resell the system to their customers.

Solution

TechKnowServ contracted with Workpad to specify the wireless RFID and ultrasonic thickness devices, program the software to integrate the RFID scanner with an ultrasonic thickness gauge and the Workpad® cloud data platform, and implement a machine learning analysis system for the data. Workpad provided a complete solution in 12 weeks at a price point which allows TechKnowServ to resell the system to their customers.

A Danatronics ECHO-series bluetooth-enabled ultrasonic thickness gauge was selected for its ability to wirelessly connect to other devices, operate in harsh environments, and meet the price target for TechKnowServ. With a sunlight-readable screen and IP67 water resistance, the device was well suited to the shale oil job sites where it would see duty.

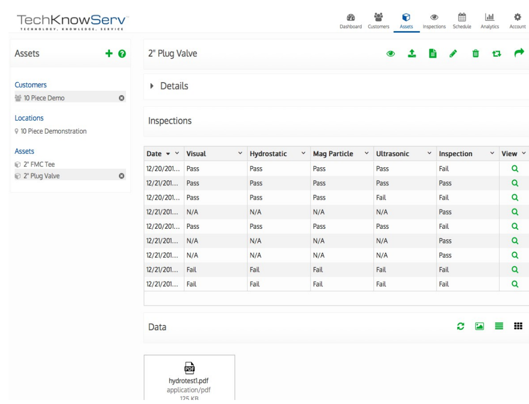
The two-way bluetooth communication of the device allowed not only the download of data to an Internet-connected intermediary device, but also the ability for the intermediary device to poll the thickness gauge to automatically download thickness data without pressing any buttons on the device.

The RFID reader used to connect the thickness gauge and communicate with the cloud data platform is a pistol-grip RFID reader with a trigger which runs the Android mobile operating system and includes both bluetooth and Wi-Fi communications to connect to the internet. An Android mobile application was programmed to run on the device. The mobile application handles the communication with the Danatronics thickness gauge and the Workpad platform application programming interface (API). The RFID reader communicates with the thickness gauge via a wireless bluetooth connection, eliminating the need for cumbersome and fragile wires between the devices.

The RFID reader's pistol-grip trigger allows scanning, inspecting, and saving data without the need for keyboard entry of any sort. With a single trigger press, the device scans the RFID tag of the part. Subsequent trigger pulls sample thickness data points from the thickness gauge, allowing the operator to keep one hand on the transducer as it is moved from place to place, and each trigger pull stores an additional data point for the selected part.

As a store-and-forward device, the Android-based RFID reader allows information to be stored until a viable wireless connection to the Internet is available, typically at the end of the work day when the operators have returned to an office. Once turned on and a Wi-Fi Internet connection is found, the RFID reader automatically synchronizes all stored data with the Workpad platform.

The Workpad platform was configured to TechKnowServ's specifications to allow each of their customers to securely collect and store data, with asset and inspection data display customized to this specific use case.



With the ability to compartmentalize data for security, yet also combine data for broad analysis with machine learning, the Workpad cloud platform bridged the gap left by existing desktop computer and server-based data storage systems.

In order to perform comprehensive analysis and lifetime predictions, Workpad tightly integrates industry-standard machine learning tools which allow the implementation of algorithms which predict lifetime, identify defects and anomalies, and identify preferred vendor and asset classes for maximum service life.

What is machine learning? Machine learning, sometime referred to as artificial intelligence, is defined as the scientific study of algorithms and statistical models that computer systems use to progressively improve their performance on a specific task. Historically, data was stored in structured databases upon which a query would be generated to return a specific snapshot of the data, for instance a minimum value or a statistical calculation of a series of values. Machine learning allows us to go beyond a simple query by creating a model, and training that model to look for patterns and trends in the data to generate a result or prediction. For instance, we can train a machine learning model to recognize the identify of a person from a picture of their face, or the expected lifetime of a part from historical data compared to data from other parts which have failed.

Machine learning *models* are programmed using a programming *language*, and run within a machine learning *framework*, or a set of tools designed to do the heavy lifting of mining the data to find a desired result. Many machine learning frameworks exist, each optimized for a particular task such as numerical analysis, image recognition, or motion and control. Sets of *training data* are then generated and fed into the model, allowing the model to classify trends and outcomes which it will eventually use to predict outcomes based on data it is given.

The machine learning model is far more powerful than a simple query because it does not require prior knowledge of the the specific data in question in order to make an assessment or return a result, it only needs to recognize a pattern which it has seen in other data from similar inspections. As such, a machine learning model has the ability to continually improve its accuracy in detecting interesting results with every new piece of data added to its training data sets.

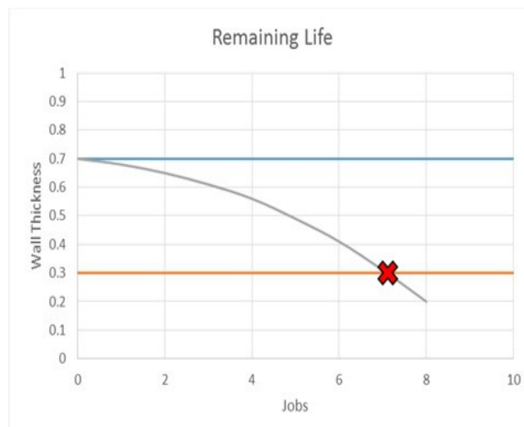
Workpad integrates industry-standard machine learning tools and frameworks, including:

1. Amazon Machine Learning service, a managed service for building ML models which includes a graphical interface to a proprietary machine learning framework. Amazon machine learning

is a simple solution which does not require an extensive background in machine learning algorithms and techniques, and does not require programming by the operator. While limited in what types of data it can analyze and what results it can generate, this service allows simple machine learning models to be quickly generated and tested.

2. Jupyter Notebooks, the open-source solution for programming and running machine learning models in a variety of languages (Python, Node, R, etc.) using any commonly used machine learning framework including TensorFlow, Pytorch, Gluon, Caffe, and many others. Jupyter Notebooks are a standard tool of business intelligence analysts to create, manage, and run machine learning models. Capable of text and image recognition, most any machine learning model can be created and run within the Jupyter Notebook system.
3. Rekognition, another Amazon managed service for image recognition and classification. While limited to a more narrow range of scope than can be achieved by programming open-source image analysis frameworks, Rekognition is already configured for quick and easy facial recognition, scenes, activities, and much more.

For this project the goal of predicting component lifetime was completed with the integration of the Amazon Machine Learning service. Workpad automatically pushes relevant data to the Amazon Machine Learning service, where pre-defined models are trained with live data and predict the lifetime of in-service components, regardless of their manufacturer, configuration, or operating conditions.



Future capabilities of Workpad's integrated machine learning platforms will include automated image recognition of defects from visual inspection images and video, and analysis of c-scan ultrasonic data, eddy-current inspection data, and x-ray image data.

Conclusions

Workpad benefits its users from the integration of wireless technologies, cloud data storage, and machine learning analysis, which results in a state-of-the-art system capable of transforming tedious and time-intensive inspection jobs into efficient processes with greater accuracy, precision, and quality of data. Data which previously could only be subjectively analyzed is now useful not only for evaluating asset condition and status with pinpoint accuracy, but also to objectively predict the service life of consumable assets.

For the end-user, simple expected lifetime results allow optimized inspection schedules and minimized cost of inspection, ensuring minimized likelihood of in-service failures. For the designers and programmers of machine learning analysis models, the ease of model training and development is greatly enhanced with an integrated data collection, storage and analysis system. Finally, for employers, greater efficiencies for the workforce and increased service life of components from accurate service life predictions result in greater returns on investment for inspection programs.

Visit Workpad.com to learn more about data collection, cloud computing, and machine learning for inspection and nondestructive testing.