Data Processing for IoT in Oil and Gas Refineries

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***Abstract*— This paper summarizes and gives examples of the using of IoT in Industry 4.0, especially in Oil and Gas Refineries. Industry 4.0 and Industrial Internet of Things (IIoT) technologies are driving digitalization driven by software and data solutions in many areas, particularly in industrial automation and manufacturing systems. Global refineries are currently all heavily instrumented, and process regulated in real-time to the millisecond. To meet the ever-increasing needs of operational demands, SCADA, Distributed Control Systems and Programmable Logic Controllers (DCS & PLCs) have grown significantly. On the other hand, certain assets and operations in a refinery are still not being monitored or evaluated in real-time. If an error occurs that causes production to be hampered, the company must bear large losses even though production stops in just a matter of minutes. This is one of the reasons why the oil and gas sector is starting to implement the Internet of Things (IoT). The overall aim of this paper is to give and summarize several papers to provide solutions for a simple process monitoring system that would enable process operators to identify any sources of abnormality quickly and easily in the process. A system is being made so that it can be accessed and transmit data remotely via a computer network and will display conditions in real-time without being limited by distance, space, and time. This will allow all previously disconnected assets and processes to be linked and monitored in real-time in a simpler, cost-effective, and easy-to-implement manner.**

***Keywords*— IoT, Oil and Gas, Refining, Instrumentation, Data Processing, Predictive Analytics**

I. INTRODUCTION

The oil and gas refining industry is very capital-intensive, with massive inventories of physical assets and equipment, ranging from pumps to pipelines connected to units, streams, and fluid systems. Despite the fact that these facilities are at the forefront of technology, they are typically sluggish to embrace digital ways to monitor operations due to worries about disturbing safety protocols. The oil and gas (O&G) industry is a highly regulated and capital-intensive industry that plays a central role in meeting global energy demand. Despite global initiatives to introduce green energy sources, global demand for crude oil is expected to remain high in the coming decades. [15]

In the industrial sectors, there are various processes used to produce a finished or semi-finished product that is suitable for sale. To produce these products, a process control system is needed in order to make it easier for humans to work and can minimize human errors [1]. The control system is a system that is used to control the magnitude of the process so that it can be within certain area limits or at the desired value. In the control system, there are important elements such as sensors that are used to detect process quantities, transmitters that are used to send the value of process quantities in the form of standard signals, controllers that are used to compare with setpoints to produce a command signal and final control elements used to perform actions that can change the magnitude of the process being controlled [2].

Industry 4.0 and Industrial Internet of Things (IIoT) technologies are driving digitization driven by software and data solutions in many areas, especially in industrial automation and manufacturing systems. ML and cloud computing software tools, for example in the design of advanced data analysis platforms. Although this is an area of increased interest, information on how to implement data analytics in the context of Industry 4.0, particularly in oil and gas refining industries, is scarcely available in the scientific literature.

In the current age of connection and mobility, which has increased user-oriented patterns in every facet of life, there is an urgent need to apply this idea to sectors, particularly traditional industries such as oil and gas. This point of view is a catalyst for the path that will allow the disconnected components of refining to be connected using the powerful Internet of Things (IoT) platform.

Global refineries are currently all heavily instrumented, and process regulated in real-time to the millisecond. To meet the ever-increasing needs of operational demands, SCADA, Distributed Control Systems and Programmable Logic Controllers (DCS & PLCs) have grown significantly. Certain assets and operations in a refinery, on the other hand, are still not being monitored or evaluated in real-time. Because these assets and processes are not extremely important in terms of refinery process control, safety, or operational bottlenecks, they are not required to be monitored by SCADAs/DCS/PLCs.

In the oil and gas industry, productivity is a very valuable asset. If an error occurs that causes production to be hampered, the company must bear large losses even though production stops in just a matter of minutes. This is one of the reasons why the oil and gas sector is starting to implement the Internet of Things (IoT).

Along with the development of the industry, which continues to grow, it gives birth to an increasingly complex industrial plant control system. A distributed control system that has monitoring, controlling, and data acquisition facilities in real-time and can be carried out without distance limitations is a solution for the ever-increasing complexity of the system and a solution for the guidance of increasing the effectiveness and efficiency of industrial control systems.

The reason for this might be that routing through SCADA/DCS/PLC is not economically viable. They are generally checked on a regular basis and occasionally only by human intervention. It is not feasible to analyze past performance or anticipate failure. Steam traps, pressure relief valves, corrosion monitoring, catalyst life, liquid carryover in compressors, dosing chemicals, primary supply & distribution, and so on are examples of these types of assets and activities.

The interface between information technology (IT) and operational technology (OT) distinguishes between IIoT and IoT. The network of operational processes and industrial control systems (ICS) is called OT. OTs include Human Machine Interface (HMI), Monitoring Control and Data Acquisition Systems (SCADA), Distributed Control Systems (DCS), and Programmable Logic Controllers (PLC). OT focuses primarily on industrial equipment and worker safety, as the greatest operational risk in the industrial environment is the loss of human life and property. [14]

Nowadays a monitoring system is needed as a tool for human resources to monitor the state of an object, but the efficiency of energy and time to view data from the system is sometimes still neglected. However, if a more cost-effective technique of monitoring them in real-time can be found, they may make a significant contribution to increasing productivity, efficiency, asset life, and process safety, which this study is going to be reviewed. So, a system is made that can be accessed and transmit data remotely via a computer network and will display conditions in real-time without being limited by distance, space, and time. In this paper, we contribute by summarizing and giving examples of the use of IoT in Industry 4.0, especially in Oil and Gas Refineries.

II. LITERATURE REVIEW

A. *Process Control System*

A process control system (PCS) consists of several series of field instruments to determine field conditions. This system is equipped with sensors that are connected to a number of controller devices. From here, users can find out data about fluid flow, pressure, and temperature in the pipe.

Then, the process control system can also be used for things that include utilities. In the production of oil and gas, there are several types of power plants used, ranging from electricity, water, to air.

In studying process control, it is necessary to understand how the equipment works so that it can explain how to process and process the signals that occur. The process that occurs comes from processing signals of physical quantities to electrical quantities which have been standardized by international regulations so that the controller can read and process these signals according to the equipment used to process the interlocking signal.

Industrial monitoring and control systems usually consist of a central host or master (commonly referred to as a master station, master terminal unit or MTU), one or more field data collection and control units (commonly called remote stations, remote terminal units or RTUs). and a set of standard and customized software used to monitor and control data elements in the field. Most SCADA systems have many characteristics of open-loop control and use a lot of remote communication, although some elements are closed-loop and/or use short-range communication.

B. *Supervisory Control and Data Acquisition*

SCADA (Supervisory Control and Data Acquisition) is a system that refers to a combination of telemetry and data acquisition. It consists of gathering information, transferring it back to the control centre, performing the necessary analysis and control, and then displaying this data on a number of operator displays. SCADA is used to monitor and control plants or equipment. Control may be automatic or may be initiated by SCADA systems that have evolved primarily from monolithic to distributed and networked. The networked SCADA design allows the system to be geographically distributed over one or more LAN networks. As the IoT revolution grows, SCADA systems will move to the next generation, leveraging cloud technology to operate more and more in real-time. [13]

SCADA systems [17] are not scalable due to their low temporal and spatial density, are expensive in terms of equipment and maintenance, are not interoperable in terms of hardware and software, and are protocol changes and inflexible if software needs to be updated. Provides data and results with long delays. Various architectures based on the Internet of Things (IoT) have been proposed in the literature in various domains, including Social Internet of Things (SIoT) [18], Resilient IoT architecture for smart cities [19], and future internet [20]. However, there is still no IoT-based architecture for the oil and gas industry. Given the critical environment of oil fields, it is necessary to develop IoT architectures according to the industrial environment of oil and gas [21].

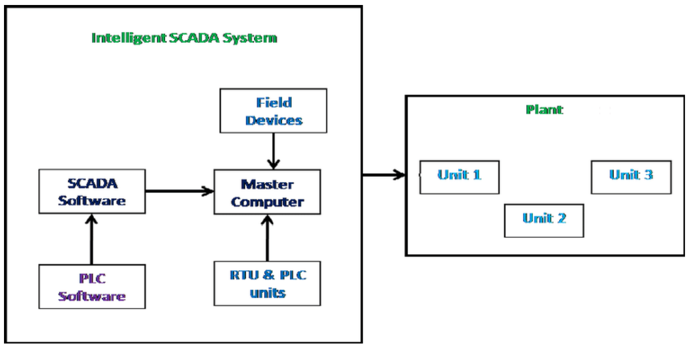

Figure 1 SCADA Schematic Diagram [3]

Figure 1 shows the SCADA Schematic Diagram, one of these examples is telemetry. Telemetry is often associated with SCADA systems. It is a technique used in transmitting and receiving information or data over a medium. Information can be in the form of measurements, such as voltage, velocity or flow. The data is sent to other locations through media such as cable, telephone or radio. Information can come from a variety of locations. A way of dealing with different places that are incorporated into the system.

Data acquisition refers to the methods used to access and control information or data from controlled and monitored equipment. The data is then accessed forwarded to a telemetry system ready for transfer to a different place. It can be analog and digital information collected by sensors, such as flowmeters, ammeters, etc. It can also be data to control equipment such as actuators, relays, valves, motors, etc.

C. *Distributed Control System*

We can also find systems similar to the SCADA system in some process plants, maintenance, and others. This system is called DCS (Distributed Control Systems). DCS has a similar function to SCADA, but the data collection and control units are usually located in a limited number of areas. Communication can use a local network (LAN), reliable and high-speed.

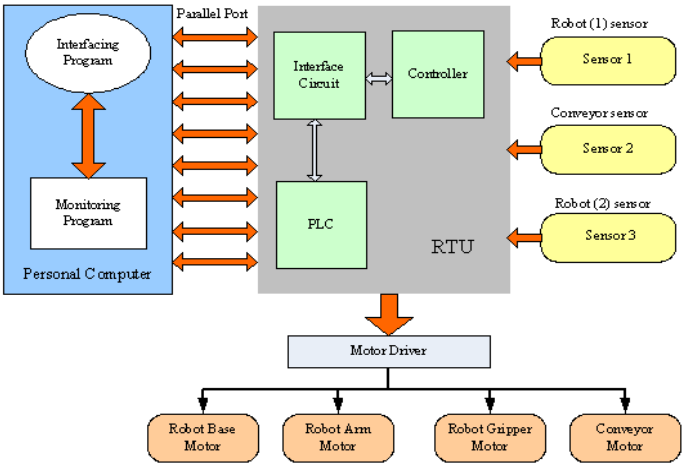

Figure 2 DCS Schematic Diagram [4]

Figure 2 shows DCS is a collection of several parts or components that interact with each other to achieve the same goal and is a control system that functions to control or regulate the course of processes in a system/plan by distributing control. There are also those who say DCS is a distributed control system where the components or parts of the DCS are distributed to various places.

D. *Programmable Logic Controller*

A programmable Logic Controller (PLC) is basically a computer specifically designed to control a process or machine. This controlled process can be in the form of continuous variable regulation such as in servo systems or only involves two-state control (ON/OFF) (Figure 3) but is carried out repeatedly as we commonly encounter in drilling machines, conveyor systems, and so on.

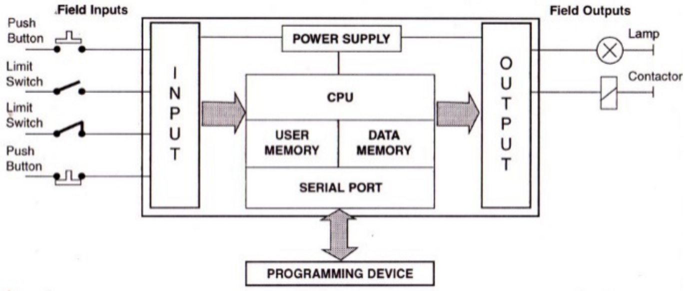

Figure 3 PLC Block Diagram [5]

The National Electrical Manufacturers Association (NEMA) standard ICS3-1978 defines a PLC as a "digitally operating electronic apparatus which uses a programmable memory for the internal storage of instructions by implementing specific functions, such as logic, sequencing, timing, counting, and arithmetic to control through digital or analog I/O modules various types of machines or processes."

III. RESULTS AND DISCUSSION

A. *Case Study Real-Time Monitoring and Analytics of Plant Data*

Technology advancements like the Internet of Things (IoT) are generating new and imaginative approaches to improve operational efficiency. It has enabled more accessible and cost-effective monitoring channels to emerge. This will allow all previously disconnected assets and processes to be linked and monitored in real-time in a simpler, cost-effective, and easy-to-implement manner.

Real-time performance monitoring and early detection of degraded process performance and equipment failures are becoming critical to maintaining both production capacity and plant profitability [6]. One approach to avoiding or better managing such situations is to make more use of the data that is routinely collected from the process plant. The advent of modern process measurement, automation, and information systems has resulted in a significant increase in the amount of process data available to plant operators and engineers.

Recent developments related to Industrial Internet of Things (IIoT) technologies, machine learning algorithms and the availability of Big Data provide platforms for performing sophisticated process data analysis. Several cloud computing platforms are available for use in the industrial internet of things and big data analytics. Key players include cloud service providers (like Microsoft Azure, Amazon Web Services, IBM, Intel, etc.), enterprise solution providers (particularly PTC and Oracle), network companies (like Cisco and AT&T), and industrial engineering companies (namely General Electric, Siemens and Bosch). Some of these platforms are available under proprietary licenses and some others are accessible as open-source projects. In predictive data analysis in the process industry, soft sensors are invaluable tools for gaining insight into the status of operations where directly measuring key process variables is extremely difficult, or even almost impossible.

The fundamental architecture for a connected solution involves:

1. Site area: Retrofitting equipment with suitable IIoT sensors, connecting scattered equipment, and sending data out through a communication gateway to the data historian or IoT platform
2. Security: Ensuring data security between the sensor and the reception platform
3. Receiving system: The data from the sensor can go straight to the data historian or IIoT platform. To allow real-time corrective action, the historian will retain data, do analysis, offer KPI dashboards, visualization, and mobile messaging/access.

B. Case Study Implementation: Pressure Relief Valve

Consider the typical Pressure Relief Valve as an illustration of how IoT enables connecting the disconnected (PRV). Figure 4 shows the conventional Spring-Loaded Pressure Relieve Valve. Beyond a certain pressure, the PRV is meant to expel surplus gas from containers and pipelines. Over time, the PRVs' springs get fatigued, their set-points shift, and the PRVs begin to leak gas at a lower pressure into the environment. This results in product loss as well as an environmental and safety danger. The manual examination is difficult since PRVs are not instrumented and are installed in inaccessible locations.

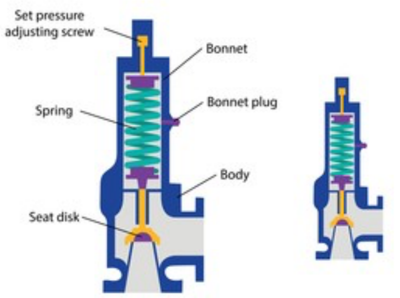

Figure 4 Conventional Spring-Loaded Pressure Relieve Valve [7]

As a result, they are only evaluated during turnarounds/shutdowns. However, due to current strict safety rules, electronic monitoring of PRVs is now required. The answer is to install an IoT differential pressure sensor across the PRV, which will continuously check its health.

This will communicate real-time information, allowing any defective PRVs to be spotted in real-time and addressed without having to wait months for the next shutdown. Consider what would happen if this happened to all of a refinery's thousands of PRVs. According to studies, real-time monitoring of all PRVs in a refinery can possibly save an additional 20% in operational expenses.

C. Case Study Implementation: Steam Traps

The steam traps are another example. Steam traps are now checked on a monthly basis. As a result, any steam trap failure will be replaced after roughly 20 to 30 days. Condensate stuck in steam lines or steam flowing through the condensate header has an influence; both circumstances result in inefficient heat transfer and process functioning.

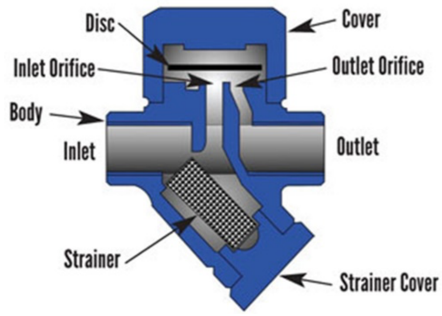

Figure 5 Thermodynamic Steam Trap [8]

On the steam trap, an IoT-enabled acoustic sensor can be placed. When a steam trap fails, it produces a sound that is louder than the required decibel level. Instead of waiting for the next inspection after 30 days, the IoT sensor may send data straight to the data historian for real-time monitoring and analysis, allowing immediate action and replacement of the steam trap as soon as it fails.

D. Cast Study Plant Predictive Maintenance

Advanced analytics, artificial intelligence, edge computing, and the industrial Internet of Things are enabling predictive maintenance. According to a case study published by Deloitte, the effort began with a review of the refinery's existing maintenance processes, which included a combination of reactive maintenance, which involved responding to an immediate asset outage; planned maintenance, which involved performing updates on a regular schedule; and proactive maintenance, which involved tending to specific pumps based on historical utilization patterns [9].

Data-driven soft sensors are also widely used in various process industries [10]. Recently, the remarkable performance of machine learning (ML) methods, especially deep learning-based algorithms in areas such as pattern recognition, computer vision, and robotics, offer other options for realizing soft-based sensors in more sophisticated databases. Such soft sensors are able to leverage industrial big data, resulting in improved variable prediction.

There are several machine learning software tools available, both commercial and open-source software. Popular commercial machine learning software is provided as Machine Learning as a Service (MLaaS). Major proprietary MLaaS include Amazon Machine Learning (Amazon ML), Microsoft

Azure Machine Learning, Google Machine Learning, and IBM Watson Machine Learning. Machine learning tools can often be accessed through their respective cloud platforms or through third-party cloud application services. They offer highly scalable environments and a variety of machine learning algorithms for data preprocessing, dimensionality reduction, and predictive data analysis. and many more functionalities.

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In addition, most of the commercial machine learning frameworks also provide deep learning libraries and big data computing software tools like Apache Spark, Hadoop, etc. In addition, there are several machine learning software tools, libraries, and frameworks that are open-sourced under Licenses that are freely accessible. In addition, these can be provided via the cloud environment or on-premises. Examples of open-source machine learning software tools are Apache Spark MLlib, Scikitlearn, TensorFlow, H2O.ai, BigML, Accord.NET, Apache SystemML, Apache Mahout, Oryx 2 to name a few. Some of these libraries can be accessed through proprietary machine learning platforms. For example, both Apache Spark MLlib and H2O.ai are available on Microsoft Azure HDInsight, a cloud service platform for big data analytics.

Most industrial automation cloud platforms, such as Predix and MindSphere, provide application services for data analysis. For example, MindSphere now offers built-in application programming interfaces (APIs) for anomaly and outlier detection. In addition to the built-in APIs, in many cases, customers have the option to deploy their own applications on the cloud platform. Therefore, more efficient machine learning algorithms can be implemented in data analysis. In addition, general cloud service providers such as Microsoft Azure and Amazon Web Services offer machine learning and deep learning services, as well as big data software tools such as Apache Spark, Hadoop, Apache Storm, etc. [11]

The transition to predictive maintenance took place in three stages [12] :

1. Create a digital foundation by employing edge-to-core connections and wireless sensors to enable location-based services.
2. Integrate an IoT platform (here, HPE's Edgeline Converged IoT platform) for high-speed data collecting and analytics.
3. Work with the ecosystem to provide a turnkey IoT solution that includes predictive maintenance and asset tracking.

Predictive maintenance based on personas was crucial to these efforts. "These data-driven personas represented the everyday duties of different job kinds," the case study continues, "providing a framework to allow quick reductions in workers' existing manual chores." Employees have the chance to learn new abilities as they progressed through the process.

The program has enhanced the mean time between failures and can now more rapidly identify underlying causes thanks to predictive maintenance. The refinery estimates a 50% decrease in budgeted maintenance expenses, with the potential to save 1,000 hours per year on walk-downs and vibration analysis to identify faults. Predictive maintenance aids the organization in predicting and avoiding asset breakdowns before they occur.

E. Case Study Plant IIoT Data Architecture

The platforms presented in this work follow the general database-based process monitoring procedures, including data acquisition, data pre-processing, model design, and model maintenance. The data acquisition layer allows measurements to be collected from various local devices in the process for purposes that may include inspection or data visualization, analysis, and storage. [11]

The platform is using edge-based operational technology (OT). Compute nodes and storage nodes (servers) are installed outside a typical data center, the so-called edge center (microdata center inside a box). The server is specialized for OT environments and uses System on a Chip (SOC) technology. This enables data center-class computing power and storage to be delivered in a small footprint that does not need to be operated by data centers or IT staff.

The various software components of this solution work together to turn your data into insights. The new IoT data will be paired with existing process data to identify the root cause of the detected problem. For example, vibration data (impeller vibration, new IoT data) may indicate the existence of a problem. Pressure data (low inlet pressure process data) may indicate that cavitation may be the cause of the problem. [12]

Figure 6 below describes the key components of the proposed data-driven soft sensor development environment, leveraging state-of-the-art machine learning algorithms, big data tools, and industrial cloud computing platforms. Details of the key components of the platform, such as data collection, industrial IoT platforms, and machine learning software tools, among others, are discussed below.

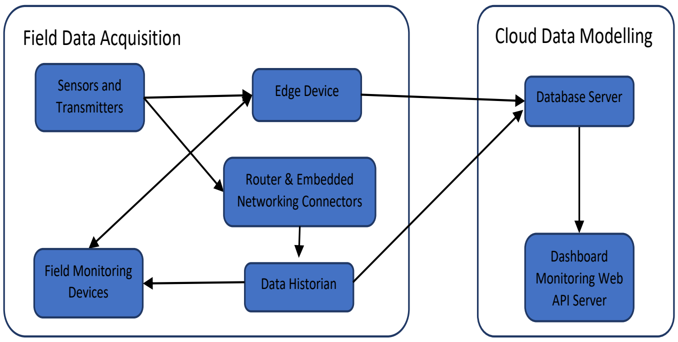

Figure 6 Plant Data Architecture [12]

The description of the architecture is as follows [12] :

1) Data Historian is a type of time-series database designed to efficiently collect and store process data from a SCADA or automation system.
2) Field Monitoring Devices are smart devices like computers or smartphones directly connected to Data Historian or Edge Devices under Field's Local Area Network, either Wired or Wireless.
3) Monitoring Dashboard is hosted on a cloud server, fetching data from the database server which will be updated on every change and request from Data Historian and Edge Device. Realtime monitoring and analytics are provided via Web API from the server which can be accessed remotely using internet access, both on PC or Mobile.

F. *Case Study Oil Production Process*

The advent of the Internet is revolutionizing the industry in steam engines, production lines, and industrial automation, in a way to achieve the so-called Fourth Industrial Revolution after the previous revolution. [16]

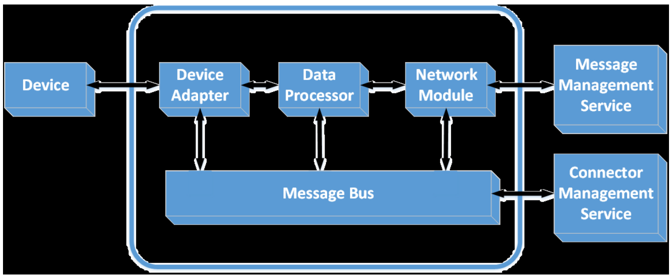

Figure 7 Required IIoT Device [16]

The improvement of the OPC (Open Platform Communications) server innovation permitted the association of the different gadgets delivered by diverse companies and utilized diverse communication conventions with each other utilizing the one-window guideline for the purposes of observing, control and mechanization. This window is SCADA, LabVIEW, MATLAB ... etc. Server back IoT Conventions such as MQTT are utilized to put through distinctive PLCs and IIoT gadgets to Citect SCADA Program for checking and control reason Too interface to LabVIEW to apply complex control calculations such as Fluffy, Neural or NeuroFuzzy Control systems. [16]

IV. CONCLUSION

In this paper, hardware and software platforms applicable in developing and implementing process data analytics in modern process automation systems were reviewed, and a concept of a process monitoring platform was developed. The platform highlights the use of state-of-the-art machine learning methods coupled with big-data processing tools and cloud computing technologies in-process data analytics. With such an environment, different data-driven models for increased plant productivity can be realized. The application of the platform was demonstrated by developing data-driven soft sensors, which can be employed to monitor an oil and gas refining plant.

The study also showed that the system could result in improved variable prediction for the plant operators, which included a combination of reactive maintenance, which involved responding to an immediate asset outage; planned maintenance, which involved performing updates on a regular schedule; and proactive maintenance, which involved tending to specific pumps based on historical utilization patterns.

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