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Data Analysis on Automation of Purging with IoT in FRAMO Cargo Pump

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Abstract

Oil and chemical tankers use the FRAMO system to transport cargo from ship to shore. FRAMO cargo pumps, which are installed inside cargo tanks, are an essential component of the system. The results of the purging operation are used to determine whether or not these cargo pumps are operationally ready. The purging procedures confirm the integrity of the sealing arrangements on both the cargo and hydraulic systems. The cofferdam that separates the cargo from the hydraulic fluid collects any leakage from the FRAMO cargo pump's seals. The AUDRINO control board and electronic control of various solenoid-signaled hydraulic actuated valves are recommended for this automated purging procedure. Control signals from the shore control center or the inbuilt timer circuit can be delivered via IoT. This control board also oversees the purging sequence. The leak-off liquid is lifted from the cofferdam space to the sample container by automated purging.

The identification of the liquid is essential for obtaining the purging result. The method proposed in this paper employs three distinct sensors to identify the liquid in the cofferdam space in the autonomous ship environment. The three parameters are density meter, pH meter, and a color sensor. These three characteristics distinguish the cargo liquid from the hydraulic oil used in the system. This test result is useful for cargo operation planning. The content received in the cofferdam is revealed by comparing the measured data set to the preloaded database. The major goal of this research

is to use physicochemical data to predict oil content. Two distinct data sets were obtained in this investigation. These data sets include three major cargo and hydraulic oil physicochemical properties. Using the random forests algorithm, the instances were effectively identified as cargo oil or hydraulic oil with an accuracy of 98.6229%. The detection of both cargo oil and hydraulic oil was then classified using three distinct data mining techniques: k-nearest-neighbor, support vector machines, and random forests. The random forests algorithm provided the best accurate classification.

2.1 Introduction

The energy requirements of today's industrial activity are critical in any part of the world. A variety of products derived from crude oil meet this energy demand. Product tankers are the preferred mode of transportation for these various oils. Product tankers transport a wide range of liquid cargoes, including various chemicals used by different industries. The time it takes to transport cargo from ship to shore is used to determine these tankers' operational efficiency. Because product tankers transport a wide range of commodities, the FRAMO [1] method is widely used for cargo operations. The readiness of the FRAMO cargo pump is critical for optimizing cargo discharge time. A purging test, which analyses the amount of leaked liquid and the type of liquid in the cofferdam, certifies the cargo pump's readiness. This article describes the automatic purging operational test in the context of autonomous shipping [2–6].

2.2 FRAMO Cargo Pump

The FRAMO cargo pump (Figure 2.1) is housed within the cargo tank. The impeller of this centrifugal pump is located at the bottom of the tank. The hydraulic motor, which is connected to this impeller, is also located at the bottom of the tank. Pressurized hydraulic oil required to power this pump is delivered to the motor via pipe stock. This pipe stock takes up nearly the entire height of the tank. The hydraulic system's required pressure is generated at Powerpack, which is located in the remote Engine Room.

2.2.1 Cofferdam

These pumps were built with a cofferdam [7] area between the cargo and hydraulic seals. The hydraulic motor is installed inside the tank, and hydraulic oil is allowed to flow into the tank to power it. The seal is installed between

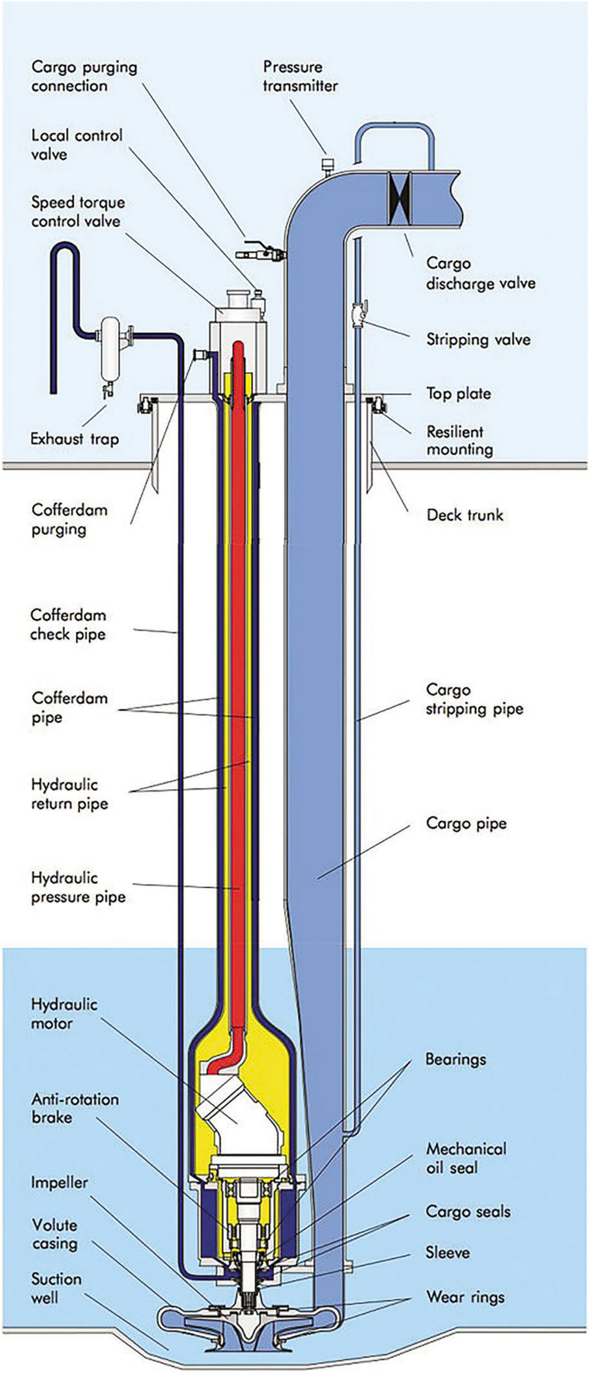

Figure 2.1 FRAMO pump.

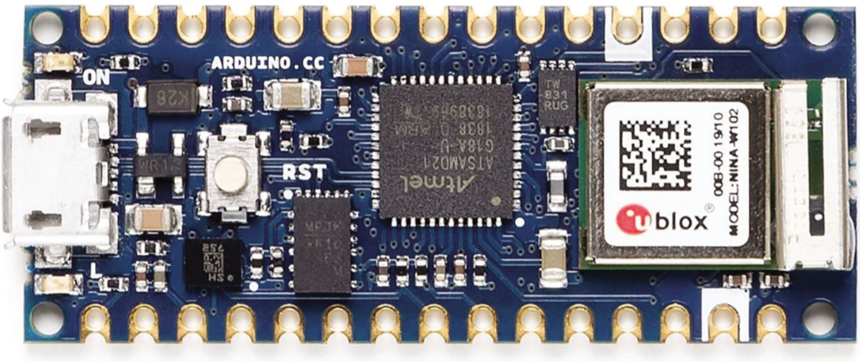

Figure 2.2 Arduino board.

the shaft and casing to prevent hydraulic oil leakage through the driving shaft. While cargo oil is being lifted through the pump impeller, a cargo seal is located between the shaft and the pump casing to prevent cargo leakage around the shaft. A cofferdam space exists between these two seals to catch any leaks from either side.

2.2.2 Cargo pump purging operation

The condition of the cargo pump is critical for an efficient cargo transfer operation [8]. If any deficiencies in the cargo pump conditions are discovered, operators implement corrective plans for alternative transfer methods such as the use of a spare pump. To avoid the vessel turnaround delay, this planning should have been completed prior to the vessel berthing in the terminal.

A purging test certifies the cargo pump's readiness. The setup is available at the tank's top to allow purging air/nitrogen to pass through the cofferdam space. When the cofferdam is pressurized, the leakage content collected in this space is lifted to the tank's top. The leakage liquid is collected by an exhaust trap installed in the outlet pipeline. Identifying the leakage content aids in determining which seal is damaged, and measuring the volume of the liquid reveals the extent of seal damage.

2.3 ARDUINO Board

Arduino [9] is a hardware and software which is customizable electronic platform, as in Figure 2.2. It can read various sensor inputs and respond to any IoT signals or inbuilt activation signals. In addition, the output signal from this board can perform the physical activities as programmed in this control board.

Arduino board is used in various smart applications such as simple home automation to intelligent cargo management systems. Cloud enabled feature of this board very much useful on data handling on any application.

2.3.1 Fork-type density meter

Density is one of the important characteristics useful to identify the liquid. This project chooses a liquid density measurement sensor that uses a tuning fork [10]. Tuning fork sensor works based on the resonance principle to measure the density of liquids. Being a quasi-digital sensor, it can directly monitor liquid density. Even though the measuring sensor of lightweight and simple in structure, its precision and reliability levels are high.

The tuning fork liquid density measurement sensor inserts the vibrating element in the measuring chamber filled with liquid, that is operated in a piezoelectric manner. The actuator allows the tuning fork to vibrate at its natural frequency. The frequency of vibration is inversely proportional to the density of the surrounding liquid. The extra mass of the tuning fork varies when it comes into contact with the liquid being measured, resulting in changes in vibration frequency (vibration cycle). The detector detects the vibration frequency by picking up the vibration signal.

The temperature sensor is also added to the part of this density meter as the density of liquids varies depending upon the temperature. The density of the liquid being examined can be calculated by measuring changes in the natural frequency or vibration cycle and its temperature value.

2.3.2 pH Meter

pH value is a measure of hydrogen ions [11, 12] (acidic or alkalinity) in a solution. This is measured electronically in a pH meter. A pH meter is made up of a voltmeter that is connected to two electrodes, one is a pH-responsive electrode, and another is the reference (unvarying) electrode. The two electrodes work similarly to a battery when immersed in a solution.

The glass membrane and the requisite reference electrodes are usually included in the same electrode body, which is the most typical design for pH electrodes. The inner fill solution touching the glass membrane in this configuration has a fixed H+ activity, as shown in Figure 2.3. This inner solution typically has an Ag/AgCl reference electrode in contact with it, and the solution includes 0.1 M HCl saturated with AgCl. A second Ag/AgCl reference

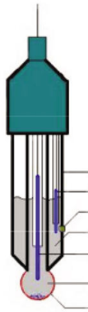

Figure 2.3 Glass electrode pH meter.

electrode is positioned in the next compartment encircling the inner solution. Through a porous frit on the side of the electrode barrel, the measuring solution comes into touch with an external solution with unknown H+ activity.

As the internal fill solution pH is fixed, the variation in the potential between the two electrodes is due to the pH of the solution in contact with the second compartment. This digital device which can read out the difference in potential in terms of pH.

2.3.3 Color sensor

Liquid color can be used as one attribute to identify the leakage content. To find the color, the light is passed through the sample to the color sensor [13, 14]. The color sensor is a configurable silicon photodiode that converts current to frequency. This module has three color filters. The basic theory is various colors are a mixer of three basic colors in different proportions. When one color filter is selected, it allows only one color and blocks the other two; for example, if the red color filter is selected, it allows red but blocks blue and green. Basis of the intensity of the red color its equivalent pulses of certain frequency delivered in output. Similarly, two other color intensities can also be obtained. In the end, three different frequency values obtained. The color can be identified by analyzing these three frequency values.

2.3.4 Level sensor

The liquid level in the sample container is measured to calculate the leakage content volume. The capacitance type level measurement is a good choice to perform this task. When two electrodes [15] with known distance are inserted in the liquid column. The measured capacitance value changes depending upon the die-electric constant of the material between the two electrodes.

As air is a nonconductor, capacitance measured in this circuit is the basis on the liquid level between the two electrodes. Vessel trim and list influence the level measurement, so the necessary correction value is to be added. With the known area of the sample container volume of the liquid can be calculated.

2.3.5 Internet of Things (IoT)

Internet of Things is a network connection of various physical objects [16, 17] through internet that have been embedded with programmable actions such as sensing [18], data collection, data processing [19], and data/signal transmission [18]. It is the connection point between the physical and digital worlds. Much development has taken place on IoT maritime applications [20–22], particularly related to cargo carriage. As autonomous ships evolve, more such applications are in the developing stage of monitoring vessel machinery [23] and operations.

2.4 Proposed Method

The proposed method of automating the purging operation can be explained with three suboperations, as in Figure 2.4.

1. Purging Automation
2. Data Acquisition and Analysis
3. Communication

2.4.1 Purging automation

An air/nitrogen supply valve at the top of the tank can be used to manually execute the purging. When automating the process, this valve must be changed to signal control. The Arduino control board can be programmed with the activation signal. The FRAMO hydraulic system [1] itself can provide the external power required to operate these valves. This operation is carried out using hydraulically powered and signal-controlled valves.

The presence of moisture in the air used affects the test findings. The service air must be drained to ensure dryness for accurate data collection. Place the auto-drain valve in the service air system and turn it on before opening the air supply valve removes the moisture. The timer feature on the Arduino board [9] can be used to program the entire operation. Even though some air is lost during each purging function, this procedure ensures that

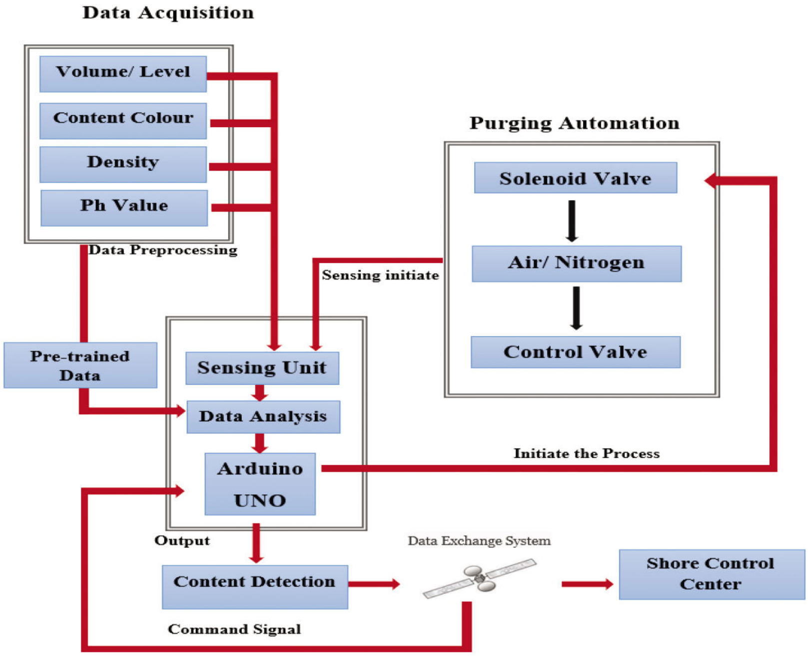

Figure 2.4 Proposed methodology on automation of purging.

good-quality air is utilized. The collected leakage liquid in the exhaust trap should be emptied into the sample beaker at the completion of purging the cofferdam. Another auto-operated drain valve should be installed below the exhaust trap for this purpose.

The cleanliness of the sample beaker has an impact on the test findings; to get the right result, each purging procedure requires a fresh sample beaker. Therefore, at the start of the voyage, several samplers must be stored upside down, and at the end of each purging cycle, these sample beakers are positioned upright below the drain valve. This motion is carried out by a robotized arm that is controlled by an Arduino system.

2.4.2 Data acquisition and analysis

The following sensors are used to capture the physical parameters of the leaked liquid. Color sensor [13, 14], density meter [10], and pH meter [11, 12]. The level of the leaking liquid is detected using a level sensor. The sample beaker must travel to different testing stations using the planned conveyor system, and these sensors must be set in the correct order. After all, testing has been completed, and the sample beaker and leakage liquid should be placed into the garbage can. The same Arduino board transfers the sample to different test points and waits for the sensors to collect its sensing value.

The level sensor and data analysis of these physical attributes allow us to confirm the leaked liquid and the severity of the seal damage.

2.4.3 Communication

This proposal's communication is split into two parts: internal and external. Different automatic valves, various sensors, conveyor movement, and the central control module are all connected via internal communication. Optical fiber cables are used to transmit signals between various components. The Arduino board's supervisory role is efficiently delivered through efficient data transmission throughout the ship. The satellite facility is used for external communication. The VHF data exchange system (VDES) [24] allows for efficient data transmission between the ship and the shore control center.

2.5 Experimental Data Analysis

The development of new sensory materials is critical to modern IoT sensing and intelligent system. These novel materials aid in developing modern sensing technologies [25]. The study of chemometrics, a branch of chemistry that employs analytical data to develop appropriate measuring methods for providing relevant chemical information. The algorithm is being developed in this direction in order to reach a conclusion in this investigation. The following are a few of the factors that played a role in selecting sensors and developing the algorithm.

(i) Without compromising data that would somehow or another be important for future arrangement, the entire arrangement of qualities that describe a dataset of detecting examinations can be utilized as a contribution to multidimensional projection calculations.

(ii) Other multidimensional perception strategies, like equal directions, empower the recognizable proof of the viewpoints that most altogether add to the sensor's separating limit.

(iii) Nonlinear models, for example, have been found to be beneficial for managing bio-sensing data in particular situations.

There are 500 instances in the dataset, each with 15 attributes for hydraulic oil and cargo products. Objective tests (such as pH values, density, and color) are used as inputs, and the aquation is based on sensory data.

Table 2.1 The physicochemical properties of hydraulic oil.

Hydraulic oil	pH value	Color (appearance)	Density
Castrol hyspinAWH32	9.00	Golden	870

The data set's purpose is to use various physicochemical parameters [25] to determine the content sample of the leakage from the cofferdam. Only physicochemical and sensory variables are used due to privacy and logistical concerns. The k-fold cross-validation mode [26] and the percentage split test modes are employed for evaluation.

This investigation randomly divides the database into two unique datasets for percentage split mode. The training set is the main data from which the data mining system attempts to extract knowledge. The extracted data can be compared to the second set, referred to as the testing set.

Different k values are examined for each technique in k-fold cross-validation mode. When the k value is set to 10, the best classification results of each technique are achieved. Using the 10-fold cross-validation approach, the training data contains 80% of the dataset at random, whereas the second set contains 20% of the testing data. The main three physicochemical properties of hydraulic oil and few cargo product sets are presented in Tables 2.1 and 2.2, respectively.

Datasets were developed in the original form of these datasets, combining hydraulic and cargo products. The objective is to sort container samples into two categories: hydraulic oil and cargo product. **Our research** used three different data mining methods [25,26]. Support vector machines (SVM), K-nearest neighbor (k-NN), and random forests (RF) were the categorization techniques used on the data set.

1. Classifiers for k-Nearest Neighbor: The fundamental presumption behind the KNN classifier is that assuming most of a question test's K most-comparable examples have a place with a particular classification, then, at that point, the inquiry test does also. KNN does not require any earlier information.

2. Random Forests: RF produces another preparation set by arbitrarily choosing tests with situations from the first preparing set, then, at that point, rehashes the previously mentioned techniques to prepare various choice trees to develop an arbitrary timberland. Every choice tree is

Table 2.2 The physicochemical properties of cargo oil.

Cargo products	pH value	Color (appearance)	Density
Alkanes (C6-C9)	7.00	Silver	700
Alkyl (C3-C4) benzenes	2.25	Brown	863
Alkylbenzene sulfonic acid, sodium salt solution	8.00	Colorless	1070
Ammonium polyphosphate solution	6.00	White	1900
Ammonium sulfate solution	5.50	White	1770
n-Amyl alcohol	7.00	Colorless	814
Calcium hydroxide slurry	11.27	Colorless	2211
Calcium lignosulfonate solutions	3.00	Yellow	1081
Camelina oil	7.50	Bright yellow	840
Cashew nutshell oil (untreated)	4.50	Dark reddish-brown	1009
Castor oil	6.34	Pale yellow	959
Choline chloride solutions	6.50	White	1100
Citric acid (70% or less)	4.50	White	1660
Coal tar	5.30	Black	960
Cocoa butter	5.60	Pale yellow	920
Coconut oil	5.00	White	910
Coconut oil fatty acid	6.00	Colorless	925
Corn oil	7.00	Dark yellow	910
Cotton seed oil	3.50	Light golden	917
Cycloheptane	7.20	Colorless	751

given a question test and is utilized to settle on a choice prior to casting a ballot to figure out which class it has a place with [27].

3. Support vector machines (SVMs): To arrange information in high-dimensional space, SVM searches for hyperplanes. SVM's motivation is to augment the edge among hyperplanes and support vectors, which can be refined by changing over the undertaking into a raised quadratic programming issue [28].

Moreover, some standard presentation estimations, for example, precision, Recall, *F* measure, and ROC, are determined to assess the calculations' exhibition. For both test modes, the random forests algorithm delivered the best order results for water powered oil and freight item tests. With this strategy, cross-approval and rate split mode precision is 98.622% and 98.461%, individually. Table 2.3 obviously shows that the random forests calculation outperforms the other two calculations in both assessment modes.

Table 2.3 The random forests algorithm.

Evaluation modes	Classifier	Precision	Recall	*F* measure	ROC
Cross-validation	SVM	98.2	98.2	98.2	97.6
	k-NN	98.3	98.3	98.3	98.0
	RF	98.6	98.6	98.6	98.8
Percentage split	SVM	98.3	98.3	98.3	97.6
	k-NN	98.3	98.3	98.3	97.7
	RF	98.6	98.6	98.6	98.9

2.6 Limitations

Current investigation considered the following limitations

(a) Vessel carrying a single cargo – In practice, tanker vessels can transport multiple cargoes in different tanks. In this regard, the presented algorithm is only useful if the cargo loaded in the tank is specified. Multi-cargo information will be added as a new data set, and the algorithm will need to be fine-tuned using multi-layer classifications.

(b) Only one seal is leaking – The algorithm is now applied with the assumption that only one seal is leaking and that only a specific liquid, either cargo or hydraulic oil, is collected in the cofferdam. If both seals fail simultaneously, the sensory values of density and pH cannot determine the leakage liquid. In the case of out-of-range property values, a new algorithm must be developed to determine whether the out-of-range value is the result of multiple leaks or a lack of sensor accuracy.

2.7 Conclusion

In the present installed rehearses, the total cleansing method is performed physically. The compressed air supply through the cofferdam powerfully eliminates the substance in that space, and it helps the team part to recognize any disappointment of seals and the degree to which the disappointment is. This paper examined robotizing the cleansing system under automated climate and imparting the analysis results to the control community for the decision utilizing the specific pump [29].

Classifier analysis on hydraulic oil and shipping product data sets is covered in this study. The results are provided as a proportion of correctly identified instances, recall, precision, *F* measure, and ROC after cross-validation or percentage split mode.

Various classifiers, such as k-nearest neighbor, support vector machines, and random forests, are tested on datasets. The random forests (RF) classifier surpasses the support vector machine and the k-nearest neighbor algorithm in classification tasks, according to the results of the trials.

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