NAVSEA Using Supervised and Unsupervised Machine Learning Techniques for Condition Based Maintenance

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1 Abstract

To ensure the ease of condition-based maintenance aboard Navy ships amid active service, the United States navy began an active process of retrofitting existing equipment with condition sensors starting in the late 1990s[1]. The modernization of these maintenance heavy components include everything from asynchronous induction motors to navigational positioning instruments to weapon guidance systems. In recent years, there emerged a growing desire among top Navy officials to capitalize on the burgeoning amounts of data collected among Navy ships to streamline tasks such as performance optimization or need-based maintenance[2]. This has spiked demand for more intelligent remote processing, assessment, automated technologies. In this report, we take another look at the York HFC R134a/R407c Marine AC Plants over the past four years. The 200-ton R134a/R407c Marine AC possesses unique compatibility with newer systems and are widely installed aboard current vessels. These plants utilize hydrofluorocarbons (HFCs) for refrigerants as they boast high latent heat of vaporization compared to other refrigerants and are more environmentally friendly for the ozone layer[3]. Our study looks at the potential for supervised and unsupervised machine learning algorithms to assist in advanced real-time maintenance among marine AC plants. We learn that unsupervised learning techniques can accurately identify deviations among fleet performance, creating a short list of potential candidates to inspect. Supervised learning can supplement our faulty plant identification process with another verification check while also predicting missing/inaccessible sensor readings. Lastly, existing physics modules can be utilized to explain deviations or further supplement missing data for internal sensor readings.

2 Introduction

To further assist the United States Navy (USN) in their maintenance efforts about increasing smart warships, we developed several predictive data-driven models to forecast potential errors within current Marine AC plant systems. Growing interest in Condition-Based Maintenance (CBM) aboard U.S. ships has already led to the installment of existing monitoring software aboard ships[4]. CBM is predicated on the ability to monitor active equipment performance parameters and immediately alert crews to failing/abnormal equipment behavior.

Currently, a new generation of CBM software is being developed for the USN named the Condition Based Maintenance Plus Enterprise System (CBMPES). CBMPES will comprise of multiple systems integrated together to provide real-time analysis of ship equipment[5]. A shipboard enterprise Remote Monitoring (eRM) system includes embedded sensors, data terminals, log sheets, and notification alerts for information collection and ship crew communication. A Consolidated Machinery Assessment System (CMAS) component is an on-shore cloud-based data repository performing data analysis, equipment condition reports, and maintenance schedules[6]. These two systems would complete a data loop with each other via satellite communication for remote condition assessments.

This project focuses on the 200-ton HFC R134a and R407c AC plants installed among DDG 51, DDG 81, and LPD 17 class ships. Much of hull, electrical, and mechanical equipment aboard sophisticated warships such as these require liquid cooling[7], which is pumped using air conditioning units. Each warship holds 4-7 of these plants to sufficiently cool all their equipment. These ships operate globally across a wide diversity of ocean environments. The harsh variety of conditions these plants are exposed to requires extensive monitoring as varying ocean environments accelerates the gradual degradation of these marine plants.

Figure 1: Image of active LPD 17 class ship[8]

Given the limited resources and time of maintenance crews among ships, being able to identify high risk AC plants significantly cuts down on inspection time. The active monitoring of these plants also provide a preventative measure, enabling precautions to be executed ahead of time to mitigate equipment failures during critical moments. Patterns among dysfunctional plants can be analyzed to accurately determine the time frame and priority of where maintenance should be delegated.

Our data models are based off historical fleet data collected within the past few years aboard Rleigh Burke-class ships. Historically, data-driven monitoring software utilizes a mix between physics and data-driven methodologies[9]. This project builds off existing studies through introducing supervised and unsupervised techniques combined with existing physics modules for a more accurate and precise machine learning model.

3 Inside the Plant

To understand our training decisions later, we will go over the basic operation and engineering of the marine AC plants. The ideal temperature output from the AC plant should be around 44 degrees Fahrenheit[10]. There are three main systems within the marine AC plant: the condenser, the evaporator, and the compressor drive line.

The compressor is the prime mover to move the refrigerant around. In the York marine model, the compressor utilizes a single stage centrifugal design with pre-rotational vanes and a variable geometry diffuser. There is an electrical drive motor attached to the compressor to power the piston or scroll compression. The compressor turns the low-temperature low-pressure refrigerant into high-temperature high-pressure gas before passing it into the condenser. By compressing the gas, the temperature of the refrigerant significantly increases.

The condenser's main purpose is to cool down the refrigerant. Aboard marine ships, the condenser utilizes sea water to cool down the refrigerant. The hot gaseous refrigerant is passed through a series of pipes surrounded by flowing sea water. The sea water is constantly being pulled from and ejected into the ocean. As the refrigerant is passed through the pipes, the heat is transferred to the seawater. Thus, the seawater discharge is always a few degrees higher than its intake. The cooled refrigerant, now in its liquid state, is now sent through the expansion valve.

At this point, the refrigerant is roughly around seawater temperature, but it needs to be much cooler to chill our cooling water. The expansion valve is necessary to chill the refrigerant before it reaches the evaporator. The condensed refrigerant is funnelled through variable orifices, which are controlled from the oil pressure and solenoid valves. This expands the volume and lowers the pressure on the refrigerant, further lowering the temperature of the refrigerant past seawater. Finally, the cold refrigerant enters the evaporator.

The cooling water, not to be confused with the refrigerant, is the water that is circulated throughout the ship, cooling all machinery. The cooling water enters the AC plant warm after heating the equipment and needs to leave at around 44 degrees Fahrenheit. To achieve this, the warm cooling water enters the evaporator and flows around coils of flowing chilled refrigerant. The heat from the cooling water is transferred to the refrigerant, turning it back into gas. The now low-pressure gas refrigerant gets sent back to the compressor and the cycle repeats. The now cold cooling water is pumped throughout the ship to cool down its critical systems[11]

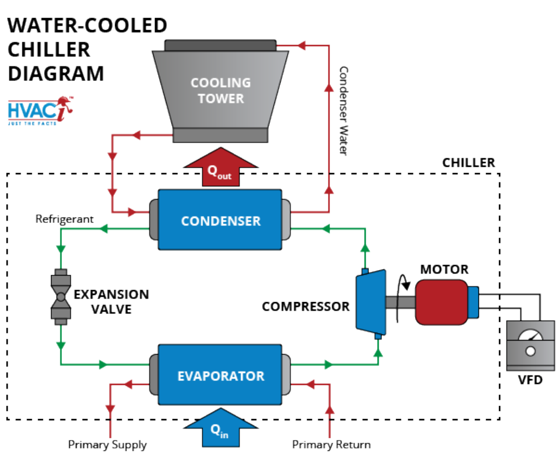


Figure 2: Diagram of a basic marine chiller[12]

There are various electronic sensors placed throughout the AC plant to actively monitor plant behavior. These sensors help adjust the AC plant to maintain constant temperature of the cooling water leaving the AC plant. Information from these sensors are sent to the AC Plant microprocessor and then to the machinery control system for navy crews to interpret. This also feeds into the Condition-Based Maintenance Plus Enterprise System mentioned above. Below are the conditions commonly monitored aboard ships. Our data-driven model will be trained based off the following condition information collected.

COND LIQUID TEMP The temperature of the liquid refrigerant leaving the condenser in the AC plant

CW CAPACITY The capacity for the cooling water flow rate within the system.

CW FLOW The actual flow rate of the cooling water.

CW INLET PRES The cooling water pressure at the inlet before the cooling process

CW INLET TEMP The temperature of the cooling water at the inlet

CW OUTLET PRES The cooling water pressure at the outlet after leaving the machine

CW OUTLET TEMP The temperature of the cooling water at the outlet after leaving the machine

DISCHARGE PRES The pressure at the discharge of the compressor

DISCHARGE TEMP The temperature at the discharge of the compressor

EVAP LIQUID TEMP The temperature of the liquid refrigerant entering the evaporator in the refrigeration system

HOT BYPASS VLV POS The position describing the opening of a valve used for hot gas bypass after the compressor

LO TO BRGS TEMP Temperature of the lube oil compressor bearing

LUBE OIL FILTER DP The pressure drop across the filter used for the system's lubricating oil

LUBE OIL SUMP TEMP The temperature of the lubricating oil sump or reservoir

MOTOR CURRENT The current drawn by the motor in the system.

REFRIGERANT LEVEL The level of refrigerant flowing through the pipes

SUCTION PRES The pressure at the suction side of a compressor

SUCTION TEMP The temperature at the suction side of a compressor

HRM Inlet Pressure The pressure at the inlet of the heat rejection medium (HRM) within the condenser

HRM Inlet Temperature The temperature at the inlet of the heat rejection medium which is sea water in this case

HRM Outlet Temperature The temperature at the outlet of the heat rejection medium which is sea water in this case

HRS Differential Pressure The pressure difference across a heat rejection strainer (HRS) in the heat rejection system

MECHANICAL CONTRL1 - Control constants for CW circulation

MECHANICAL CONTRL2 - Control constants for heat rejection system

MECHANICAL CONTRL3 - Control constants for equipment identification

AC NUMBER A unique identifier or code related for each air conditioning unit

Identifier A general manufacturing identifier for tracing the machine origin

4 Diagnostics Physics Modules

Because these plants are required to operate in a wide variety of seawater temperatures, the testing procedures performed in ideal temperatures produce results not actively reflected in most active AC plants. To supplement the performance predictions in the real world, previous physics-based software models were developed to simulate the AC plants. Software like the Advanced Diagnostics Module (ADM) were created to determine AC plant performances based off thermodynamic concepts and physical characteristics of the AC plant components. The sensor information acquired by ICAS are utilized as the inputs to the ADM and can actively predict various thermodynamic properties surrounding the cooling process[12]. These physics-based models, although not utilized in this project, add another layer of verification while also being able to explain certain levels of anomalies within the data we observe.

5 Data Wrangling

We start off with the sensor readings of the AC plants for the past 4 years provided by the Naval Sea Systems Command. After scraping and formatting the data, we arrive at 3.55 million lines of data, with each line containing sensor readings of one singular machine at one point in time.

5.1 Feature Selection and Dimensional Reduction

We start by deleting all lines with missing sensor information crucial for our data model training. Of the column inputs that we deemed as "crucial," we divided them into five broad categories as listed below. Any row with missing information in one of these following columns would be removed from our training set.

cooling_water_columns = ['CW CAPACITY', 'CW FLOW', 'CW INLET PRES', 'CW INLET TEMP', 'CW OUTLET PRES', 'CW OUTLET TEMP']

refrigerant_properties_columns = [COND LIQUID TEMP', 'EVAP LIQUID TEMP', 'HOT BYPASS VLV POS', 'LO TO BRGS TEMP']

oil_characteristics_columns = ['LUBE OIL FILTER DP', 'LUBE OIL SUMP TEMP', 'OIL PRES']

outflow_columns = ['DISCHARGE PRES', 'DISCHARGE TEMP']

mech2_columns = ['REFRIGERANT LEVEL', 'SUCTION PRES', 'SUCTION TEMP']

Of the remaining lines, we removed columns that were irrelevant to the model's purpose of identifying potential equipment failures. 'Mechanical Control1' and 'Mechanical Control2' were removed because the control constants assigned by the manufacturers had no bearing on the performance of the plants. The 'AC Number' and 'Identifier' were removed because they were purely for identification purposes. 'Heat influx' and 'Mechanical Control3' were too scarce to require, otherwise our training set would become too small. Lastly, 'HOT BYPASS VLV POS' was removed due to its insignificant variance of 4.3.

5.2 Encoding

There was one categorical variable present within our data set which was the refrigerant type used. Since models require numerical training sets and this study focuses on the HFC 134a type, we simply removed the few amount of rows that listed different refrigerants.

5.3 Scaling/Normalization

Even though decision trees are not sensible to the absolute scale of our data inputs, our other models we tested for this project required data scaling. To support faster and stable algorithmic training, we created a copy of our data set where all our data was normalized to have a mean at 0 and a unit variance of one. The data set we used to train our model was dependent on the model's sensitivity to not scaled data.

5.4 Noise Control

Unfortunately, the data does not differentiate between healthy and unhealthy models so some erroneous sensor readings are present. Initially, we left these erroneous sensor readings within our data set because the aggregation and voting of trees within our random forest model possesses an inherent resistance to a few erroneous readings. However, we later decided to further clean our data before constructing our neural networks. We further mitigated the distortion from faulty readings through examining the physical limits for these sensors. Anything below or above the physical limits are subsequently removed. The limits for these sensor readings are provided below. Additionally, any sensor readings more than 2.5 standard deviations above or below their counterparts were also removed and assumed to be erroneous.

Entry	**Lower Limit**	**Upper Limit**	**Units**
CW FLOW	250	1200	GPM
CW OUTLET TEMP	40	50	$^\circ$ F
CW INLET TEMP	35	102	$^\circ$ F
CW OUTLET PRES	20	130	PSIG
CW INLET PRES	20	130	PSIG
Heat Reject Medium Inlet Temperature	55	120	$^\circ$ F
Heat Reject Medium Outlet Temperature	55	120	$^\circ$ F
MOTOR CURRENT	25	125	FLA
DISCHARGE TEMP	75	180	$^\circ$ F
COND LIQUID TEMP	32	115	$^\circ$ F
EVAP LIQUID TEMP	32	115	$^\circ$ F
SUCTION TEMP	32	125	$^\circ$ F
SUCTION PRES	20	180	PSIG
LO TO BRGS TEMP	100	580	$^\circ$ F

5.5 Cross Validation

At last, we arrive at 915,608 lines of remaining lines, which is roughly 26% of the original data source. We plan on using a 5-fold cross validation technique to evaluate our models. This would ensure that our models are able to be more generalized.

6 Supervised Learning Approach

Supervised machine learning algorithms require some numerical target or output. In this case, we have a portion of the AC plant parameters/measurements as the targets. Engineering a supervised learning algorithm possesses two uses: (1) It augments our existing predictions with another layer. (2) It fills in missing sensor readings. Given the large amount of operational conditions/readings and abundance of data, regression would be the optimal data model to train. We trained a variety a models with varying success. Our linear regression ultimately proved to be inaccurate due to the nonlinear relationships between the variables. Our artificial neural nets and gradient boosting algorithms were too sensitive to the noise within our data set and suffered from extensive over-fitting. Our support vector algorithms were too computationally expensive. We finally settled on a Random Forest Regression model, which was less affected by the errors and noise in our training sets[13].

A decision tree is a hierarchical binary structure where each internal node represents an attribute and each branch represents a decision. The tree attempts to learn a sequence of decisions based off the input features that lead to a correct regression prediction. The random forest model consists of creating multiple decision trees trained on random subsets of the training data and averaging their predictions for the final output. Decision trees are inherently vulnerable to over-fitting especially as they grow in depth and complexity. Fortunately, the combination of multiple randomly generated decision trees in random forest creates a buffer for extremities.

$$\hat{Y} = \frac{1}{N} \sum_{i=1}^{N} T_i(X)$$

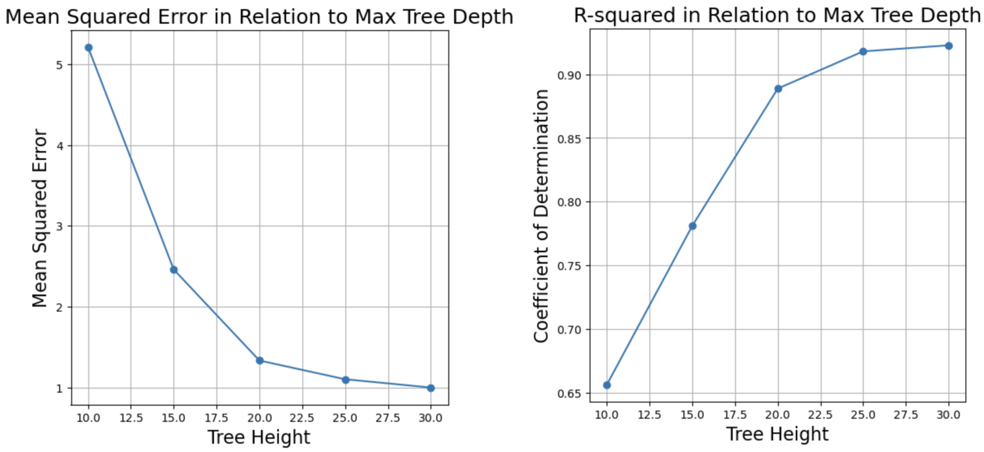
$\hat{Y}$ represents the predicted target variable, N is the total number of decision trees produced by our model, and $T_i(X)$ is the prediction made by the i-th decision tree in the ensemble.

Before we started training our random forest, we first cleaned the data further by deleting all rows where the CW outflow temperature was greater than the CW inflow temperature. This would suggest the marine plant was not cooling the water correctly. The resulting data set was still too large for our model so we randomly selected half of the training set. The resulting training set left us with around 480k lines.

Now we selected our feature and target parameters. We split the data into these two categories based off two things: accessibility and sensor robustness. The sensors that were more likely to constantly give accurate information and were the most commonly installed on marine ships were chosen as our features. This was done because one purpose of our supervised model was to fill in remaining/missing sensor data.

features = ['CW CAPACITY', 'CW FLOW', 'CW OUTLET TEMP', 'CW INLET TEMP', 'CW OUTLET PRES', 'CW INLET PRES', 'Heat Reject Medium Inlet Pressure', 'Heat Reject Medium Inlet Temperature', 'Heat Reject Medium Outlet Temperature', 'MOTOR CURRENT', 'DISCHARGE PRES', 'DISCHARGE TEMP']
target_values = ['COND LIQUID TEMP', 'EVAP LIQUID TEMP', 'REFRIGERANT LEVEL', 'Heat Reject Stariner Differential Pressure', 'SUCTION TEMP', 'SUCTION PRES', 'LO TO BRGS TEMP', 'LUBE OIL FILTER DP', 'LUBE OIL SUMP TEMP', 'OIL PRES']

Our training and evaluation data sets were randomly split on a 80 to 20 ratio. The training set contains roughly 390k lines of code and the evaluation around 90k lines. There ended up being 12 features and 10 target variables. We trained 35 decision trees with a maximum depth of 30 for our final model. The trials and errors of experimenting with the depth and tree count is shown below. We utilize both the mean squared error and the R-squared (Coefficient of Determination) to assess the accuracy of the models. The mean squared error is simply the average of the squared distance between predicted values and actual values contained in the evaluation data set (Figure 3a). R-squared coefficient measures the variance in the dependent variables that can be attributed to the variance in the independent variables (Figure 3b).



(a) Mean Squared

(b) R-squared

Figure 3: Model Performance

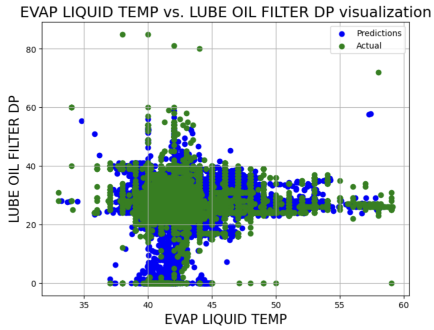
$$\mathrm{MSE} = \frac{1}{n}\sum_{i=1}^{n} \|\mathbf{y}_i - \hat{\mathbf{y}}_i\|^2 \tag{1}$$

Equation (1) explains how the mean squared error is calculated. The squared distance between every prediction y_i and the mean $\hat{y}_i$ is added together and averaged where y_i is a vector consisting of all target variables

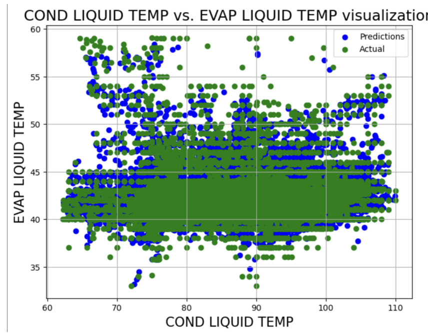
$$R^2 = 1 - \frac{\sum(x_i - \bar{x})^2}{\sum(x_i - \hat{y}_i)^2} \tag{2}$$

Equation (2) explains how the R-squared coefficient is calculated. x_i is the actual or observed data from our evaluation set and $\hat{x}$ is simply the mean. y_i is the corresponding prediction from our data model.

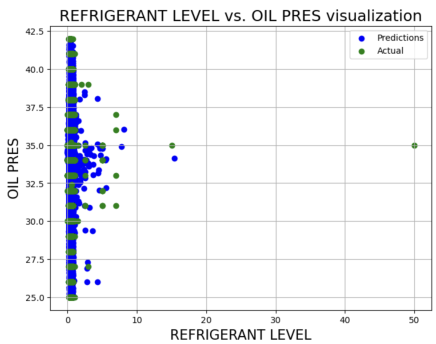
Our final mean squared error was 0.998367480548 59 after our cross validations, which is impressive considering the quantity of target variables and the fact we did not use the scaled/normalized data set for this model. Our final coefficient of determination was 0.9226945516003383 after setting a max tree height of 30. If we continue increasing the tree height, we would start to significantly suffer from diminishing returns. We could now graph exactly how our predictions lined up with our evaluation data set. We select two target variables as our two axis, blue dots represent our predictions while green dots are the actual corresponding value (Figure 4).



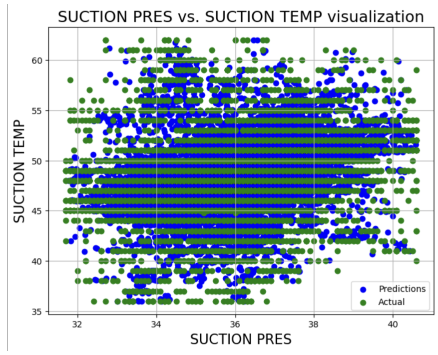
(a) Visual 1



(b) Visual 2



(c) Visual 3



(d) Visual 4

Figure 4: Model 1 Evaluation

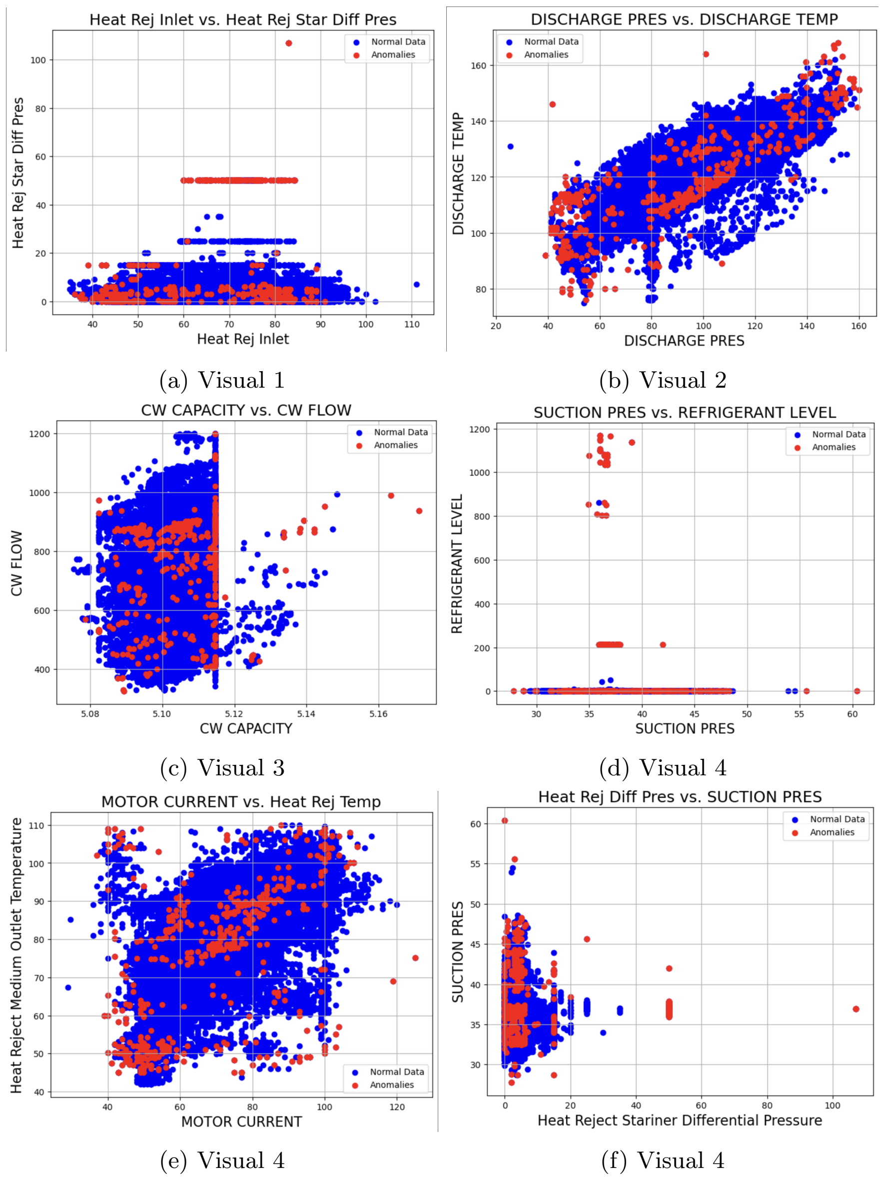
We can be fairly certain the green dots that deviate from the predictions are cause for concern that indicate abnormal machine behavior. For the final product, we deploy the model where any complete input row containing all necessary column values would be fed through the algorithm. If the squared distance between the prediction and the sensor readings within our target variables exceed more than 1.6 times the mean squared average, we flag the AC plant. This provides a sizeable buffer to avoid false positives in identifying faults. If only the feature variables are provided, the model outputs predicted values for the target variables. This enables naval crews to better understand the machine internal conditions whenever the internal sensors are difficult to install/not available. The predicted values can serve to facilitate further human-made calculations on the AC plant's performance.

7 Unsupervised Learning Approach

The unsupervised model required all sensor readings to be the input. Because there's not labeling or target we are trying to predict, our unsupervised model's sole purpose is to identify patterns within our data set and highlight points that deviate from the pattern. Once again, we explored a variety of models for our data and eliminated ineffectual models. Our k-means clustering algorithm assumed our clusters are uniformly spherical with similar size and density. Our actual data does not observe this behavior. Our Density-Based Spatial Clustering of Applications with Noise (DBSCAN) algorithm faced difficult hyper-parameter tuning considering the irregular shapes of our data clustering. Our autoencoders likely suffered from the noise in our data set. Although our model captured the complex non-linear relationships very well, the algorithm occasionally learns to reproduce the noise itself, resulting in over-fitting. The isolation forest was able to isolate subsets of abnormal data points well, but the intense clustering and high dimensional nature of our data made it computationally exhausting. Eventually, we decided on an ensemble between the isolation forest and auto-encoder models.

7.1 Isolation Forest

We start our models by splitting our data into training and testing sets. Our 95 to 5 split resulted in roughly 870k lines of code for training and 50k lines for testing. Our isolation forest model creates 424 isolation trees and flags exactly one percent of the AC plants every time. Each isolation tree randomly selects a feature and creates a random split value for that feature. This continues until either the max tree depth is reached or very few data-points are left in a node. The path length is the number of edges required to reach the leaf node with the data point. There are two parameters to tune in this model: the number of trees and the sample size for each individual isolation tree. Given the size of our data set, we used 424 trees on subset sizes of 128 condition inputs. The shorter the path length, the more isolated a point is. Our algorithm chooses exactly one percent of the points every time that seem to deviate from their peers. This significantly reduces the active maintenance inspection crews have to perform by selecting a small inspection set. Below are the anomalies our model highlights among our evaluation set (Figure 5). Unfortunately, because our data set is unlabeled, we can only visualize what data-points our model flagged for evaluation purposes.



(a) Visual 1 (b) Visual 2

(c) Visual 3 (d) Visual 4

(e) Visual 4 (f) Visual 4

Figure 5: Model 2 Evaluation

Examining the graphs in figure 5, we see the model is correctly able to ascertain what points should be considered as anomalies. The red points the model flagged are usually scattered around the fringes of the clusters. This would indicate the model is working correctly as points separated from large clusters are more easily separated and thus, displayed as red. In our final deployment, the percentage of sensor conditions to flag is set at five percent of plants but can be changed depending on the circumstances.

7.2 Neural Networks

We now supplement our anomaly detection model using a neural network autoencoder. Our autoencoder consists of two parts: an encoder and decoder. The encoder compresses our data into a latent space. The decoder reconstructs our data based off the encoder's representation. During the reconstruction process, if there are any data points that doesn't align with reconstructed patterns, we deem them as anomalies. We have three dense layers with several activation functions and the model is compiled with the adam optimizer plus mean squared error as the loss function. Given our high dimensional parameter space, an adam optimizer converges faster and more accurately by adaptive adjusting learning rates for each parameter based on the history of gradients. We set the batch size as 64 with 20 epochs over the course of gradient descent. Batch size is the number of lines/samples before our model is updated while epochs is the total amount of times our algorithm runs through our data set. Our feed forward neural network sequence composes of just three layers given our high volume of training inputs. The layering sequence is given in the following.

$$\begin{gathered}\text{32-node dense layer}\\ \downarrow\\ \text{Rectified Linear Unit (ReLu)}\\ \downarrow\\ \text{16-node dense layer}\\ \downarrow\\ \text{Rectified Linear Unit (ReLu)}\\ \downarrow\\ \text{32-node dense layer}\\ \downarrow\\ \text{Rectified Linear Unit (ReLu)}\end{gathered}$$

We use the mean squared error as the loss function for the model. The MSE calculates the difference between the predicted values and the actual evaluation values. The goal of the training is to minimize the mean squared error after every epoch or iteration through the data set. Our training loss over each epoch is depicted below with our validation loss.

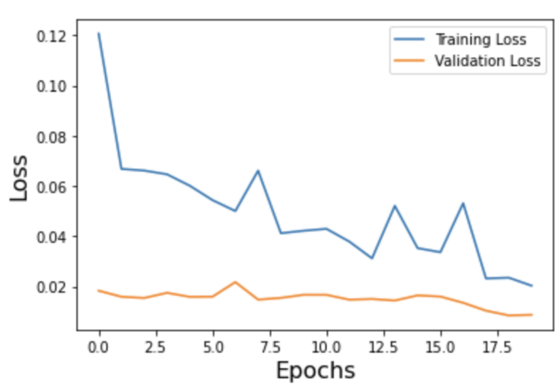
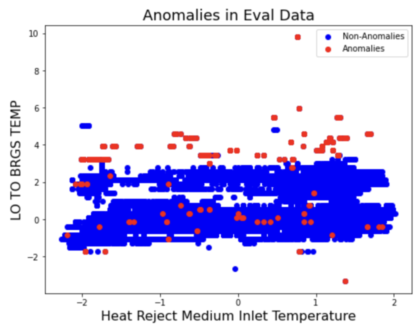
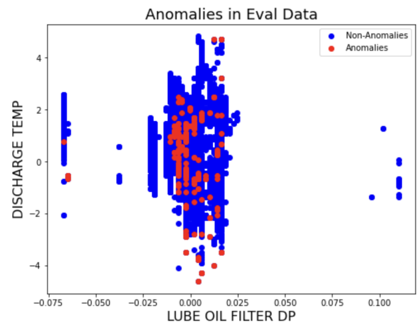


Figure 6: Training and Validation Loss Every Epoch

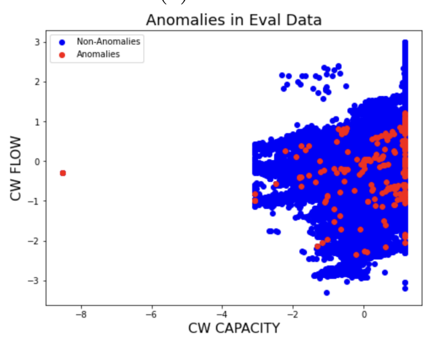
The threshold we set for a point to be discerned as an anomaly, measured by MSE, is set at 0.14. Any data point with a squared error greater than 0.14 is marked by our model. The average MSE in our data set is 0.012670696013010595 indicating most data points don't deviate far from predictions. Once again, because this is an unsupervised and unlabeled data set, the only real method for verification comes from plotting our flagged data points with not flagged ones using two input parameters. The relative positioning of our points gives us some sense of our model's accuracy



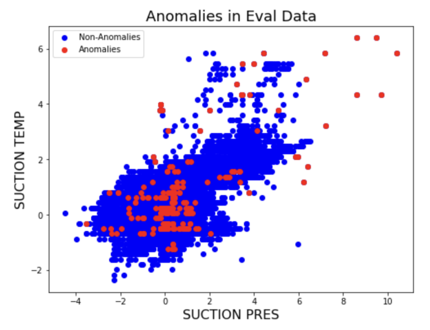
(a) Visual 1



(b) Visual 2



(c) Visual 3



(d) Visual 4

Figure 7: Model 3 Evaluation

For our final deployment, we created an ensemble between our two unsupervised models. Data points flagged/marked by both models as anomalies are recommended as severe risk while data points marked by just one are shown as moderate risk. The threshold/quantity of the anomalies identified by our ensemble can also be changed to give a full picture of the urgency level for each plant's maintenance.

8 Conclusions

As condition based maintenance becomes more widespread, the demand for data-driven models increases. The models we trained in this project pertain solely to the York marine chillers, but can easily be repurposed for other equipment provided there is enough data to train such models. We used a combination of supervised and unsupervised techniques for a robust analysis of high risk chiller marine plants. These two approaches offer unique benefits when assisting maritime crews with ship maintenance. The supervised model is able to predict missing sensor output for a complete picture of the equipment's performance parameters while also detecting abnormal behavior with just a few sensor readings available. On the other hand, our unsupervised model works perfectly with our unlabeled condition inputs to reveal underlying patterns and detect anomalies. A combination of these two approaches provides a multifaceted data-driven approach for condition based monitoring across the U.S. Navy.

9 References

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