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Prediction of Control Valve Cavitation Using Machine Learning Technique

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Abstract:
The deleterious phenomenon, cavitation, has long existed for several decades and commonly observed in various space of interest such as shipping, energy, oil and gas, water treatment industries etc. The presence of cavitation in industrial control valves dedicated to different service conditions and applications has raised massive concern among industries, manufacturers and researchers as they seek to determine the possible causes of cavitation and how to detect it early enough to avoid severe damage. Many valve manufacturers have special factors numerically calculated which does not have a generalized application across all valves. This study introduces the deployment of Linear Regression as a Machine Learning technique for prediction of cavitation based on observational data collected from sensing instruments monitoring the process condition and the control valve under study. Parameters were evaluated for degree of correlation with the ISA recommended cavitation index to determine the best dataset suitable to train the adopted ML model which provides accurate and reliable cavitation prediction results.

Keywords: *cavitation,correlation, model, Machine Learning*

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I. Introduction

When liquid process flow through pipelines and suddenly encounters a constriction in their travel path, passing through the constriction, the fluid pressure drops and its travel velocity spontaneously increases with its kinetic energy[1], [2]. Typical constrictions resulting to a reduced cross-sectional area in process pipelines are commonly caused by installed orifice plates, control valves and sometimes reducers. In a control valve, process fluids passing through it will always take arbitrary fluid pressure distribution in three regions: upstream, vena contracta and downstream. The constriction in a control valve is that area where the valve plug throttles or regulates the process flow through the valve[3], [4]. Achieving process flow modulation differs across many valve designs. In the case of a gate valve, the plug either moves towards or away from the valve seat.

However, in control valves, cavitation occurs when the process fluid's localized pressure at the vena contracta suddenly drops below its vapour pressure[5]–[8]. At that point, the fluid molecules begins to evaporate as vapour, leading to bubble formation. These bubbles interrupt continuity of flow and they force themselves through the valve's orifice throat at very high velocity[9]. As the fluid approaches downstream, its low pressure suddenly recovers, while the formed bubble implodes, returns back to the liquid phase (for liquid fluids) and with high kinetic energy impact the internal walls and plug of the valve, creating pitting which over time causes the valve to pass fluid even at tight-shut-off, vibrate, and may eventually impact the overall valve packing[10].

While no standard exists to predict cavitation damage in control valves, several methods can help manufacturers and industries to identify when this deleterious phenomena is present in a control valve. This study aims to achieve prediction of cavitation through Machine Learning techniques using collected dataset as raw materials to achieve reliable results. This study is relevant in planning and scheduling preventive maintenance for process plant to avoid incessant trips traceable to dangerous failures of control valves due to the effect of cavitation damage over time.

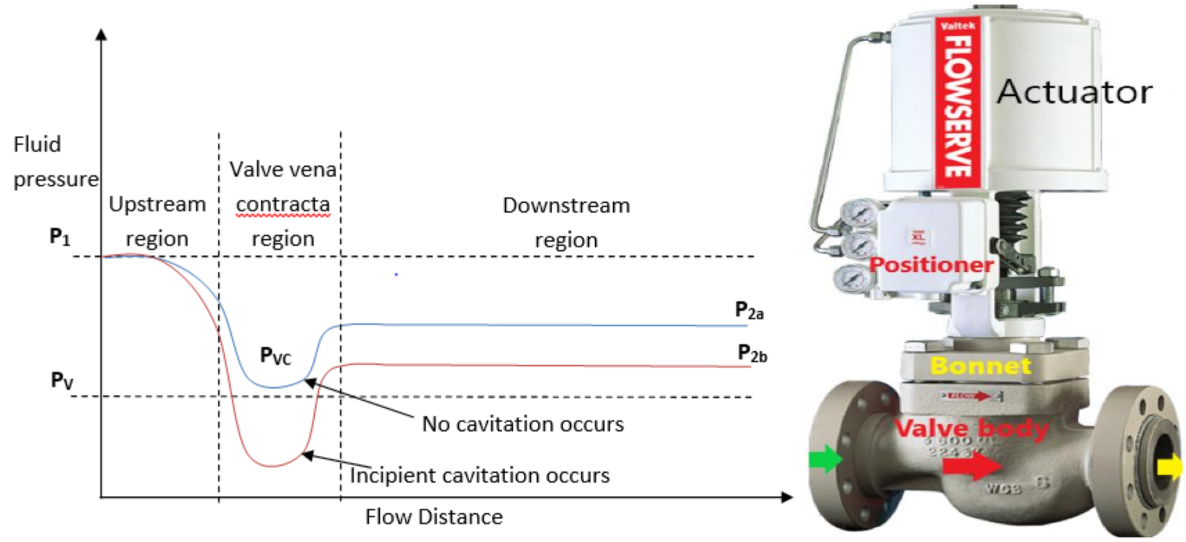

Figure 1: Pressure distribution across a control valve and cavitation points (the arrows on the valve indicate the flow direction of a typical valve)

II. Parameters Of Cavitation And Numerical Calculations

Cavitation is influenced by several factors which becomes the pointers and key indicators that must be considered when predicting cavitation in control valves or any equipment with rotating part which allows the passage of fluid through it. In this study, observational data were collected for Upstream Pressure [UP], Downstream Pressure [DP], Upstream Flow [UF], Downstream Flow [DF], and Temperature [T]. As it were, Differential Pressure [DP] was derived from the fundamental variables under the setup shown in figure 1.

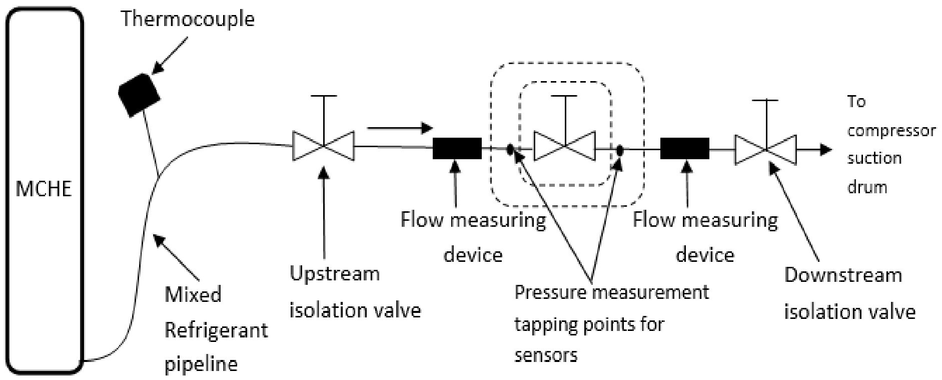

Figure 2: Typical field setup in schematic

$$DF = \Delta P = UP - DP \qquad (1)$$

Ideally, for liquid process, the upstream pressure is expected to be greater than the localized pressure at the vena contracta region[11]–[13]. Also, the downstream pressure is expected to be higher than the vena contracta pressure, but lower than the upstream pressure. Therefore,$\Delta P$is referred to as pressure drop across the control valve.

Although, there are other measurable parameters or factors which could serve as pointers for cavitation in a control valve like noise, vibration etc. These factors could be considered essentially when measurement devices are available to determine their magnitude as in the case of the installation setup shown in Figure 2. The International Society of Automation (ISA) recommended the use of sigma [σ], otherwise known as the cavitation index for generalized application in predicting cavitation in control valves. It is given as:

$$\sigma = \frac{(P_U - P_V)}{(P_U - P_D)} \qquad (2)$$

Where P_U,P_D andP_V represent upstream pressure, downstream pressure and vapour pressure of the process fluid respectively. Every control valve has a cavitation index value when computed. This values provides a clue of the level of cavitation present in such valve. This does not provide information on the extent of damaged caused.

Table 1: Cavitation index values and effects[14]

Cavitation index (σ)	Outcome and possible solution
$\sigma \geq 2.0$	No cavitation
$1.7 < \sigma < 2.0$	Incipient cavitation, hardened trim required.
$1.5 < \sigma < 1.7$	Intermediate cavitation, single stage pressure drop trim required.
$1.0 < \sigma < 1.5$	Severe cavitation, multi-stage pressure drop trim required.
$\sigma < 1.0$	Flashing

This study attempts to predict cavitation in an 18 inches ANSI class #600 RF, Reduced bore ball valve, 1092mm Metso Automation control valve used for cryogenic service on a Mixed Refrigerant line. The cavitation index data has been computed in accordance to the International Society of Automation standard (ISA-RP75.23-1995). Data sample were collected for the following process parameters:

- Upstream and downstream pressure
- Upstream and downstream flow
- Temperature

Other data generated by numerical computation are;

- Vapour pressure
- Pressure drop across the valve

To calculate for the vapour pressure of a process fluid especially for a mixture, at a given temperature, it is important to consider the partial vapour pressure of the components of the mixture.

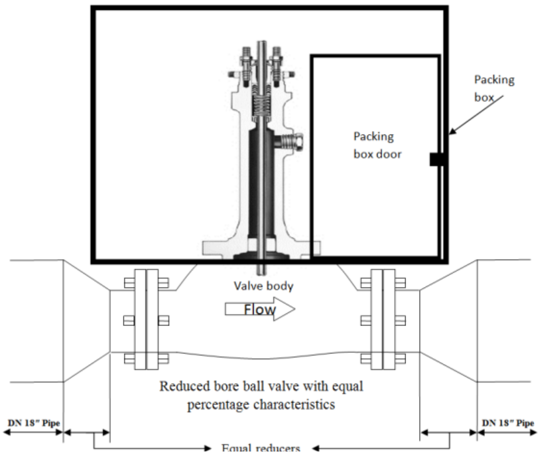

Figure 3: Cryogenic service valve under study covered in a hood due to negative process temperature.

According to Raoult's law for ideal mixture of liquids, the partial vapour pressure of a component in a mixture at a given temperature is equal to the vapour pressure of the pure component at that temperature multiplied by its mole fraction in the mixture. In a mixture of two liquids *A* and *B*, equations 3 and 4 applies.

$$P_A = X_A P_A^O \qquad (3)$$

$$P_B = X_B P_B^O \qquad (4)$$

Where and are the partial pressures of the any two components of a mixture and are the vapour pressures of A and B respectively as individual pure liquids. andare the mole fractions of A and B respectively. Mole fraction can be calculated using equation 5:

$$X_A = \frac{moles\ of\ A}{total\ number\ of\ moles} \qquad (5)$$

Therefore, the total vapour pressure of a mixture, is the sum of the individual partial pressures.

$$P_{total} = \sum_{k=1}^{n} \mathrm{p}_i \tag{6}$$

The control valve under study is designed for a cryogenic service and installed on a Mixed Refrigerant (MR) circuit. A Gas Chromatograph analyzer is required for continuous monitoring and analysis of MR sample composition.

Table 2: Mixed Refrigerant composition and molar fractions

MR composition	Vapour Phase Mole fraction (	Partial pressure Pa (at -127 145.928)	
N-butane	0.3	4.76094	0.0143
Methane	43.171	862445	372326.131
Ethane	41.899	7016.99	2940.0486
Nitrogen	3.524	>3400770 (at 126.26)	119843.135
Propane	11.107	234.088 (at 148.342)	26.0002

The total vapour pressure of the Mixed Refrigerant according to the mole fraction of its composition as collected from the Gas Chromatograph system (KROHNE software), which analyses the mixture sample, can be calculated using the partial pressure of individual pure components of the mixture collected from DWSIM. Applying equation 6, we have;

$$P_{total} = P_{N-butane} + P_{Methane} + P_{Ethane} + P_{Nitrogen} + P_{Propane} \tag{7}$$

$$P_{total} = 0.0143 + 372326.131 + 2940.0486 + 119843.135 + 26.0002$$

$$P_{total} = 495135.329\text{Pa}$$

$$P_{total} = 495.135\text{KPa} \approx 4.95\text{Barg}$$

Therefore, the calculated vapour pressure of MR is approximately 4.95barg.

III. The Linear Regression Model

Machine Learning models are categorized under Supervised, Unsupervised and Reinforcement Learning. For the purpose of this study, Linear Regression (LR) model – a subset of Supervised ML model has been adopted for this applicationas collected data samples can easily be analyzed using LR algorithms.

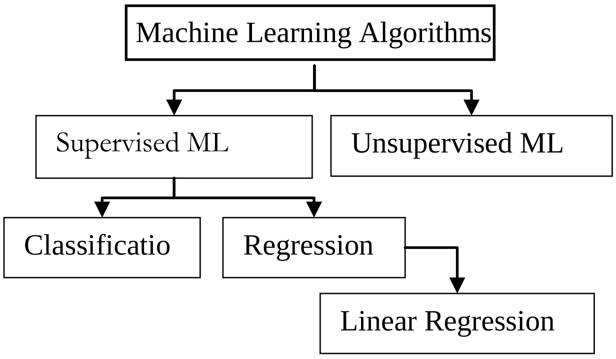

Figure 4: Machine Learning Models

The data for a Linear Regression model is usually a set in the form of:

$$\{x_i, y_i\}_{i=1}^{n} \tag{8}$$

Where x_i denotes inputs and y_i denotes outputs. Multivariate regression technique shall be adopted for more than one input variable; hence, to learn the relationship between the inputs x_i and the corresponding output(s) y_i. Typically, a Supervised Machine learning algorithm requires labelled data, i.e. both the inputs and the corresponding output. The process of labelling is often challenging and somewhat difficult or even impossible as it requires human to interpret the input and provide a corresponding output [15]. A simple Linear Regression model can be generally expressed as:

$$y_i = h(x) + \varepsilon_0 \tag{9}$$

Where *h(x)* is given as:

$$h(x) = \beta_0 + \beta_i X_i \tag{10}$$

Then substituting equation (10) into (9) gives equation 11.

$$y_i = \beta_0 + \beta_i X_i + \varepsilon_0 \tag{11}$$

In equation (5), y_i is a dependent variable (target), β_0 is the intercept term, β_1 is the population slope coefficient, X_i is the independent variable (features for multivariate Linear Regression) and ε_0 is the Random error or noise term which describes everything that cannot be captured in the model and accounts for the non-systematic errors between the data and the model. Statistically, ε_0 is considered as a random variable independent of x with a mean value of zero.[15].

	Unnamed: 0	DATE	UF_DCS	DP	UP_DCS	DF_DCS	UP	DP_DCS	T	fvp	Diff_P	Diff_P_DCS	sigma
0	9.0	DCS	17673.0	33.25	33.25	16732.0	33.59	33.59	-122.0	4.9514	0.34	-0.34	84.231176
1	10.0	DCS	17608.0	33.36	33.36	16582.0	33.59	33.59	-122.0	4.9514	0.23	-0.23	124.515652
2	11.0	DCS	17581.0	33.46	33.46	16553.0	33.79	33.79	-121.0	4.9514	0.33	-0.33	87.389697
3	12.0	DCS	17535.0	33.56	33.56	16469.0	33.87	33.87	-121.0	4.9514	0.31	-0.31	93.285806
4	13.0	DCS	17505.0	33.56	33.56	16300.0	33.90	33.90	-121.0	4.9514	0.34	-0.34	85.142941

Figure 5: Dataset head in Pandas Dataframe

The dataset collected for the ML task was imported into a Jupiter Notebook, wrangled to filter out unwanted data – irrelevant to the model learning process. Therefore, the data was first cleaned and properly arranged in the correct sequence it should be for easy identification, analysis and use. The observational data collected from sensor feedback to the DCS were recorded first on a spreadsheet over a period of time. Some values were missing, others were not correctly recorded, and redundant columns were created while converting the Excel file to CSV.

IV. Feature Selection

Not all possible features make good target prediction. Some feature combinations make better target prediction than others. Therefore, there is a strong need to quantify and summarize the relationships between variables to determine which feature(s) have good correlation with the target. It is that feature/s with good correlation that best suit the prediction; hence, this procedure helps to determine a suitable dataset for the model. This is achieved using a correlation matrix – usually a square matrix, but a rescaled version of a covariance matrix computed from standardized features like the Pearson's *'r'* correlation coefficient.

$$r_{x,y} = \frac{\sum_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i - \bar{x})}\sqrt{\sum_{i=1}^{n}(y_i - \bar{y})}} \qquad (12)$$

Given that:

$$\bar{x} = \frac{1}{n}\sum_{i=1}^{n}(x_i) \qquad (13)$$

When the correlation between two variables and is the same as that between and, it is said that the correlation coefficient between those two variables is symmetric.

Table 3: Pearson's r correlation

Pearson's correlation coefficient	**Possible values (strengths)**	**Statistical interpretation**
'r' value	1	Total positive linear correlation
	0	No linear correlation
	-1	Total negative linear correlation

If the value is near ± 1, it is said to be a perfect correlation, which implies that as one variable increases, the other variable tends to increase (if positive) or decrease (if negative) also. If the coefficient value lies between ± 0.50 and ± 1, it is said to be a strong correlation. If $r_{x,y}$ value lies between ± 0.30 and ± 0.49, it is said to be a medium correlation. However, when the value lies below ± 0.29, then it is said to be a small correlation. There is absolutely no correlation when the $r_{x,y}$ value is zero.

In [109]:
```
#The Pearson's correlation coefficient 'r' is a metric to determine correlation between variables
corrmat = data.corr()
corrmat
```

Out[109]:

	UF_DCS	DP	UP_DCS	DF_DCS	UP	DP_DCS	T	Diff_P	Diff_P_DCS	sigma
UF_DCS	1.000000	-0.055225	-0.055225	-0.980870	-0.017656	-0.017656	-0.289393	0.010175	-0.010175	0.032400
DP	-0.055225	1.000000	1.000000	-0.001687	0.077585	0.077585	0.225038	-0.406175	0.406175	-0.022743
UP_DCS	-0.055225	1.000000	1.000000	-0.001687	0.077585	0.077585	0.225038	-0.406175	0.406175	-0.022743
DF_DCS	-0.980870	-0.001687	-0.001687	1.000000	-0.012232	-0.012232	0.319330	-0.010406	0.010406	-0.041825
UP	-0.017656	0.077585	0.077585	-0.012232	1.000000	1.000000	0.004117	0.879528	-0.879528	0.415148
DP_DCS	-0.017656	0.077585	0.077585	-0.012232	1.000000	1.000000	0.004117	0.879528	-0.879528	0.415148
T	-0.289393	0.225038	0.225038	0.319330	0.004117	0.004117	1.000000	-0.103634	0.103634	0.120291
Diff_P	0.010175	-0.406175	-0.406175	-0.010406	0.879528	0.879528	-0.103634	1.000000	-1.000000	0.391363
Diff_P_DCS	-0.010175	0.406175	0.406175	0.010406	-0.879528	-0.879528	0.103634	-1.000000	1.000000	-0.391363
sigma	0.032400	-0.022743	-0.022743	-0.041825	0.415148	0.415148	0.120291	0.391363	-0.391363	1.000000

Figure 6: Correlation investigation using the Pearson's *r* correlation coefficient

The sigma row in Figure 6 reveals the correlation between the features and the cavitation index (sigma). However, only features with $r_{x,y} \geq 0.30$ will be considered as relevant dataset to train adopted Linear Regression model.

Table 4: Extract from sigma row.

Features	Sigma
UF_DCS	0.032400
DP	-0.022743
UP_DCS	-0.022743
DF_DCS	-0.041825
UP	0.415148
DP_DCS	0.415148
T	0.120291
Diff_P	0.391363
Diff_P_DCS	0.391363

As clearly shown in Table 4, no feature seems to have up to 50% correlation with the cavitation index, except for the Upstream Pressure, and Differential Pressure (computed from DCS values) which had a correlation of about 42% (medium correlation), although less than 50 percent. This may affect the overall prediction accuracy.

In [34]:
```
sns.heatmap(correlated_data.corr(), annot=True, annot_kws={'size':12})
```

Out[34]: `<matplotlib.axes._subplots.AxesSubplot at 0xd76cd10>`

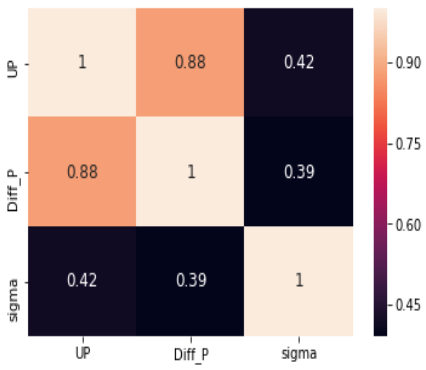

Figure 7: Heat map of correlated features at threshold = 0.30

V. Model Performance Evaluation

In this research work, the coefficient of determination R^2 quantifies the performance of adopted model as it describes the best fit line for the dataset provided. The values of R^2 range from 0 to 1, it captures the percentage of squared correlation between the predicted and actual values of the target variable.

Table 5: Coefficient of determination R^2

Coefficient of determination	**Possible values**	**Statistical interpretation**
	1	Perfectly predicts target variable
	0	Fails to predict target variable
	-1	Model provides wrong prediction

Other regression evaluation metrics considered in this Machine Learning task other than the loss functions that should be kept as minimal as possible to achieve a better prediction result include;

- **Mean Absolute Error (MAE):** refers to the mean of the absolute value of the errors. It is given as:
$$MAE = \frac{1}{n}\sum_{k=1}^{n}|y_i - \hat{y}| \quad (14)$$

- **Mean Squared Error (MSE):** Refers to the mean of the squared errors. This metric is mathematically expressed as:
$$MSE = \frac{1}{n}\sum_{k=1}^{n}(y_i - \hat{y})^2 \quad (15)$$

- **Root Mean Squared Error (RMSE):** This is the square root of MSE, typically expressed as:
$$\sqrt{RMSE = \frac{1}{n}\sum_{k=1}^{n}(y_i - \hat{y})^2} \quad (16)$$

```
In [65]: performance_metrics(correlated_data.columns.values, threshold, y_test, y_predict)
Out[65]:
```

	features name	feature	corr_value	r2_score	MAE	MSE
0	['UP' 'Diff_P' 'sigma']	2	0.3	0.270185	33.5848	2028.53
1	['UP' 'sigma']	1	0.4	0.322019	34.0247	1884.45
2	['UF_DCS' 'DF_DCS' 'UP' 'T' 'sigma']	4	0.03	0.352298	31.7846	1800.29
3	['UF_DCS' 'sigma']	1	0.03	-0.0148279	37.8703	2820.72
4	['UF_DCS' 'DF_DCS' 'sigma']	2	0.03	-0.0218545	37.9289	2840.25
5	['UP' 'Diff_P' 'T' 'sigma']	3	0.03	-0.0218545	37.9289	2840.25

Figure 8: Performance metrics for different feature combination

Considering the metrics shown in figure 8 with r2_score, MAE and MSE values, among the possible feature combination, any combination that increases the r2_score towards a perfect score of 1, while reducing the errors (MSE and MAE) becomes the feature combination to produce the best prediction. The objective remains to keep the errors as minimal as possible while improving the accuracy of result. Setting a correlation benchmark was an approach to filter out features which had very low correlation with the cavitation index. Figure 8 validates the outcome – the best fit line is located at the boundary where the correlation value and r2_score is highest while MAE and MSE are very minimal for the given dataset (corr_value = 0.4, r2_score = 0.32, MAE = 34.025, MSE = 1884.45). The Linear Regression model was trained with the UP and sigma dataset only to minimize model complexity and improve accuracy of prediction. Training and validation went along model testing (usually with the split data reserved for final evaluation to verify model reliability).

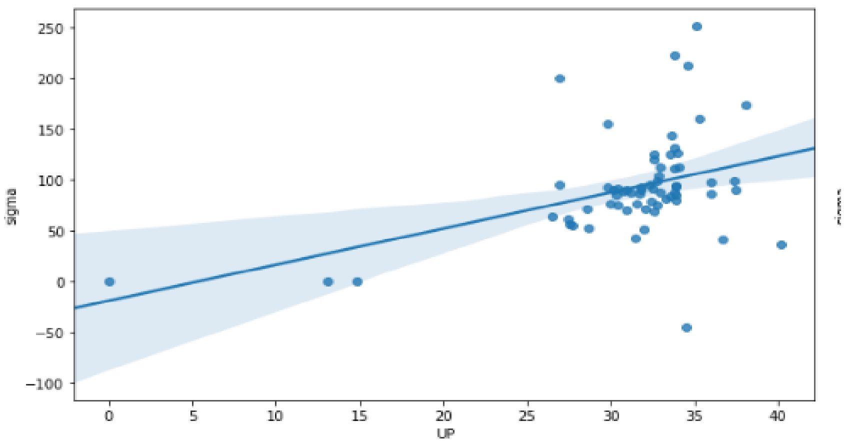

Figure 9: Best fit regression line (upstream pressure versus cavitation index

```
In [35]: X = correlated_data.drop(labels=['sigma'], axis=1)
         y = correlated_data['sigma']
         X.head(3)
Out[35]:
```

	UP	Diff_P
0	33.59	0.34
1	33.59	0.23
2	33.79	0.33

```
In [37]: #Spliting the dataset into training and testing dataset
         X_train, X_test, y_train, y_test = train_test_split(X,y, test_size=0.2, random_state

In [38]: X_train.shape, X_test.shape
Out[38]: ((52, 2), (13, 2))
```

Training the model

```
In [39]: model=LinearRegression()
         model.fit(X_train, y_train)
Out[39]: LinearRegression(copy_X=True, fit_intercept=True, n_jobs=None,
                  normalize=False)

In [40]: y_predict=model.predict(X_test)
         y_predict, y_test
Out[40]: (array([ 96.96833011,  97.30617031,  96.65016788,  95.80535952,
                 100.79517758, 100.59647085,  29.96833918,  95.79534637,
                  89.8213168 ,  95.08980069,  90.93471043,  96.8390918 ,
                  94.62245814]), 45     80.301667
          29    212.061429
          43    131.220909
          62     69.146500
          34    174.203158
          33     90.440556
          31     -0.414053
          40    103.365185
          26     95.559130
          63     42.029524
          22     55.460000
          2      87.389697
          11     75.910286
          Name: sigma, dtype: float64)
```

Figure 10: Model training and testing

VI. Conclusion

This paper has shown that it is possible to make predictions on the possible values of the ISA recommended cavitation index based on the quality of selected features, i.e. how correlated they are with the target variable (the cavitation index). This predication helps to determine the cavitation status of the control valve under study, with less time, high accuracy and reliability.

The results shown in Fig 9 and 10 above reveals that the control valve under study is not under cavitation as the sigma (cavitation index) values are above 2 (i.e.).

The predicted values of the control valve cavitation index show that the control valve under study (UZ 302) is not under cavitation. The field reports on recent Preventive Maintenance Routine (PMR) visual inspection carried out confirms the predicted outcome to be absolutely correct! In the report, UZ 302 is not subjected to any significant vibration due to process flow, there are no significant noise due to bubble nucleation from the valve's orifice throat and no leaks were detected from the actuator and other accessories including the air impulse lines.

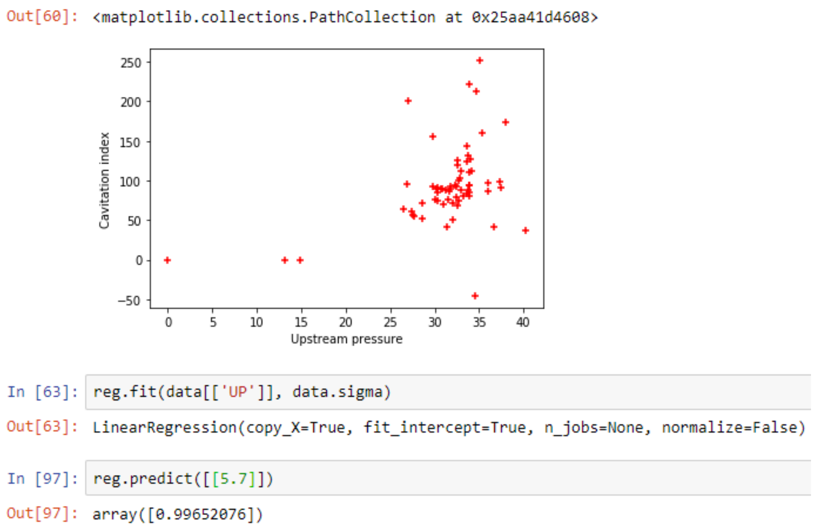

Figure 11: Cavitation prediction results

To further determine the upstream pressure that would produce significant cavitation in the control valve, possible values were entered as model input, the output were as follows:

Table 6: Upstream pressure and predicted sigma

Upstream pressure (bar)	Cavitation index (σ)
6	2.06
5	-1.49
5.5	0.29

By implication, at 5.5 bar, the control valve will experience flashing according to table (1). The control valve as observed from the model results, may possibly experience cavitation when upstream pressure values are within the range: 5.8≥Upstream pressure≤6. Other upstream pressure values above or below the values noted above will not subject the control valve under any form of cavitation.

The predicted values of the cavitation index may vary from the calculated values obtained using equation (2). This may be attributed to the quality of dataset used for model training. The correlation matrix was deployed to determine the parameter(s) most suitable for control valve cavitation prediction with high level of accuracy.

It is absolutely true that cavitation can be predicted in a control valve but there is no known formula for predicting the extent of damage caused by cavitation in control valves. Therefore, a larger dataset is highly recommended for training, validation and testing of learning model to have a better prediction. Also, more measurable features (parameters) data should be considered for inclusion in the model. Parameters like noise level, vibration, fluid viscosity, and factors related to valve geometry may together produce a stronger correlation to yield more accurate predictions. As much measureable parameters that can influence cavitation in control valves should be considered and their data collected for the prediction process.

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