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Predictive Analysis of Fluid-Hammer Effect on LNG Regasification System Pipeline Network

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SUMMARY & CONCLUSIONS

This paper proposes a comparison of various machine learning models used for fluid hammer pressure surge vulnerability assessment in seawater pipeline in the LNG regasification plant. One of the most critical components of natural gas production system is the Liquefied Natural Gas (LNG) regasification system which converts the LNG back from liquid phase to gaseous phase (Natural Gas) using a complex pipeline network carrying seawater to extract cold energy from the LNG which is susceptible to fluid hammer formation. In this paper, machine learning based methodology is presented to predict fluid hammer effect in the fluid flow in the complex pipeline network of LNG regasification system. The methodology consists of two parts: first, this study includes a simulation-based model developed in Aspen HYSYS to find the design parameters affecting the water hammer effect in the LNG regasification system pipeline based on the Design of Experiments principles and second, various machine learning algorithms are proposed to predict the vulnerability of the pipeline due to water hammer effect in the pipeline. The Support Vector Machine algorithm with radial kernel was found to be the best model to predict the vulnerability of the pipeline.

1 INTRODUCTION

Natural Gas, being a clean and affordable source of energy, is one of the most popular choice amongst the fossil fuels. This popularity has led to extensive research in the fields of natural gas extraction, transportation, and application. When transporting natural gas over long distances, this natural gas is converted to liquid state by freezing it to cryogenic temperatures of below -162°C and is then stored and transported via specifically designed ships called LNG carriers [1]. This phase transformation allows for volume shrinkage from gas to liquid by up to 625 times [2] which optimizes the transport of natural gas. On reaching the destination, this Liquefied Natural Gas (LNG) is converted back to its original gaseous form in a regasification plant [1]. These regasification plants are either situated offshore or onshore, however onshore LNG regasification facilities are more common and technologically developed [1].

The regasification plants use heat exchanger to convert the LNG from -162°C to natural gas at room temperature (e.g., 25°C). The common heat source for removing cold energy from LNG used in these heat exchangers is sea water, either in its naturally available form or processed form (e.g., Seawater + Ammonia), due to their affinity to sea and abundant availability of seawater [3]. The main focus of this research is the analysis of the pipeline network deployed in the heat exchangers

Majority of research conducted on the failure & risk analysis of pipeline networks of Oil & Gas industry is focused on the transport pipelines which carry oil or gas over long distances including causes of failures and risk analysis models based on these risks [4]–[8]. The research on oil & gas pipeline reliability is mainly focused on the long-distance pipelines, which are prone to failures due to human intervention or natural hazards like earthquakes and floods. But fluid hammer can also cause failure of pipeline. Fluid hammer is formation of pressure wave as a result of sudden change in fluid velocity in a pipe/column [9]. Sudden change in fluid velocity can be attributed to fluid flow starting or stopping quickly, or if there is a rapid change in fluid flow direction [10]. The sudden stopping of fluid flow can be caused by closing the valve rapidly, while sudden start of fluid flow can be caused by starting of a pump. The fluid hammer phenomenon can lead to pipe rupture due to high water pressure leading to pipe bursts, vacuum flattening of pipes, cavitation damaging pipelines as well as the impact force of pressure wave propagating through the fluid loosening the pipe joints [11].

Research that focuses on fluid hammer effect and pipeline reliability has been concentrated mainly on the water distribution networks [9], [11]–[13]. However, to the author's best knowledge, there is limited research that studies fluid hammer effect in LNG regasification terminals. Most of the literature relevant to LNG regasification terminals is focused on the energy recovery aspect of LNG regasification process and

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risk analysis of LNG regasification processes. This study provides a machine learning model to predict the fluid hammer effect and pipeline vulnerability in the seawater transfer pipeline used in LNG regasification system. Machine Learning has been playing an important role in variety of industrial applications which previously required extensive computing, expensive physical infrastructure, use of specialized software or a combination of all of these [14]. Moreover, using machine learning based statistical models does not require expertise in the related field of application, and the modelling process can be automated using a computer. Several machine learning algorithms have been proposed in previous work related to vulnerability & risk assessment of pipeline networks. Such models include the Artificial Neural Networks [15], [16], Decision Trees [17], Random Forest [18], Support Vector Machine [19] & Discriminant Analysis [20]. This paper constitutes the comparison of 5 main classification machine learning algorithms in case of prediction of the pipeline vulnerability. In this research, the vulnerability state of pipeline is predicted based on the output generated using Aspen HYSYS, a simulation software used in the oil & gas industry. The machine learning models were developed based on the data generated through simulation of an LNG regasification system in Aspen HYSYS V11 with application of concepts of Design of Experiments to understand the effect of the variables on the performance of the system. The machine learning techniques studied in this paper for vulnerability assessment are popular classification algorithms viz., Linear Discriminant Analysis (LDA), Decision Trees, Random Forest, and Support Vector Machine(SVM) [21].

The rest of the paper is organized as follows, with Section 2 consisting of the research methodology followed, Section 3 comprising of the results of the simulation and comparison between the machine learning models developed and the conclusions of the research and future research prospects of the project are presented in Section 4.

2 METHODOLOGY

The methodology is divided into design of the experiment, model development and simulation, simulation results and calculations, vulnerability predictive analysis calculations and performance evaluation of machine learning algorithms criteria. Figure 2 depicts the graphical representation of the methodology followed in this study.

2.1 *Design of the Experiment*

The design matrix for the research was developed based on the principle of Design of Experiments (DOE), with the design consisting of 3 factors, 2 of which had 3 levels and 1 with 2 levels. The experiment was designed at full factorial level [22], i.e., consisting of all possible combinations of all 3 factors all possible levels. This allowed for an 18-run experimental setup for the Aspen HYSYS simulation model development. Table 1 gives an overview of the 3 factors and their respective levels. For each flowrate setting [23], 300 random values were generated following a normal distribution [14] to eliminate the variability and the effect of unknown variables that may impact the response[22], thus providing 300 runs for each factor-level combination.

2.2 *Simulation Model*

The LNG Regasification system is modelled in Aspen HYSYS V11 based on a simple layout with LNG storage tank, pumps, pipes for transport of LNG and seawater and a shell and tube heat exchanger for converting LNG to natural gas. The heat exchanger has two material flow streams, the cold stream consisting of LNG flowing at cryogenic temperature and the hot stream consisting of seawater flowing at room temperature [3]. The pipeline carrying the fluids in the system (LNG and seawater) is complex and the joints cause rapid change in the direction of flow velocity and are thus prone to fluid hammer effect [10]. The chemical composition of both the fluids and the pressure and temperature are coded in the model along with the desired output temperature of the cold fluid (LNG). Figure 1 shows the layout modelled in the Aspen HYSYS software. Various scenarios are generated for the flowrate of the fluid, pipe material and pipe dimensions in the LNG regasification system. These various scenarios are used as the input in the model to generate the outputs of the simulation.

2.3 *Simulation Results and Calculations*

The outputs of each scenario are recorded which include initial fluid flow velocity and density of the fluid for the pipeline. Based on the above outputs, the final fluid flow velocity and the pressure rise in the pipe due to fluid hammer effect are calculated.

Table 1 – Factor levels and settings

Factor	Levels		
Flowrate	~2500 m^3/h	~5000 m^3/h	~7500 m^3/h
Pipe Diameter	16 inches	18 inches	20 inches
Pipe Material	Stainless Steel	-	Carbon Steel

The pressure surge in the pipe due to fluid hammer effect is calculated using the Joukowsky's equation, which is [9]:

$$\Delta P = \rho a \Delta V \tag{1}$$

Where, ΔP is the rise in the pressure caused by fluid hammer effect, ρ is the fluid density, a is the velocity of sound wave in the fluid i.e., the pressure wave speed, and ΔV is the change in the fluid flow velocity. Where, a is calculated using (2) [9]:

$$a = \sqrt{\frac{1}{\left(\frac{\rho}{k}\right)+\left(\frac{DC_1}{Ee}\right)}} \tag{2}$$

where, k is the elasticity modulus of the liquid, D is the diameter of the pipe, E is the elasticity modulus of the pipe material, e is the thickness of the pipe walls and C_1 is a constant that can be assumed to be one [9]. From equation(1), the pressure surge due to fluid hammer effect is dependent on the change in fluid flow velocity. However, as HYSYS is not a

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dynamic software, it cannot give change in the velocity over time as an output, thus, it is assumed that the change in velocity is the same as the initial fluid flow velocity, i.e., the fluid flow completely stops. The pressure rise in the pipe can lead to pipe rupture, which is calculated using equation (3) [11].

$$P_b = \frac{2(\sigma W e)}{D+e} \tag{3}$$

Where, P_b is the rupture design safety pressure of the pipe, σ is the maximum allowable pressure at the design temperature, which is pre-defined by ASME, W is the coefficient of welded joint, which is normally assumed to be 0.8 & 2 is the design safety factor [11].

2.4 *Vulnerability Predictive Analysis Calculations*

In this research, the objective is to use ML algorithms to predict the vulnerability of the pipeline due to fluid hammer effect based on the flow parameters of the pipeline. As the response variable (vulnerability of pipeline) is a categorical variable, standard regression analysis cannot be used[21] and thus, classification ML models are developed. The vulnerability of pipeline is based on the probability of failure of the pipeline due to pressure rise caused by fluid hammer effect, which is determined by using a physical probabilistic approach based on the rupture design pressure (P_b) and (P_{ASME}) which is pre-defined by ASME for given pipe dimensions and pipe material. The probability of failure is calculated using equation (4) [14]:

$$Prob_{failure} = \left(\frac{\left(rounddown\left(\frac{\Delta P}{P_b}\right) + rounddown\left(\frac{\Delta P}{P_{ASME}}\right) \right)}{N_{max}} \right) \tag{4}$$

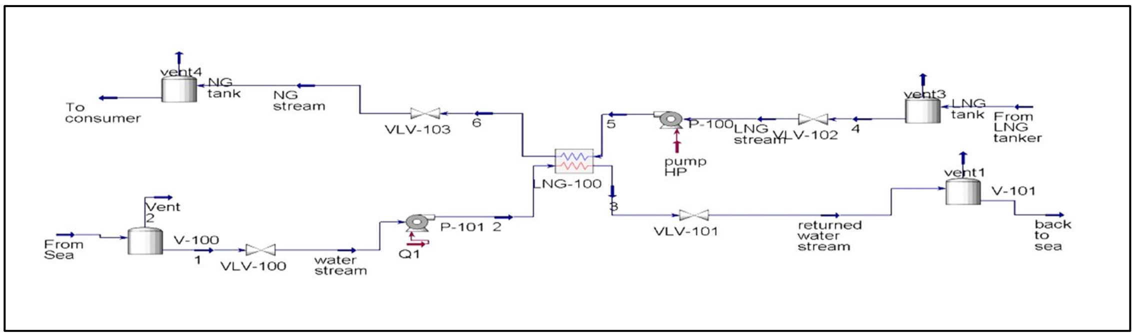

Figure 1 – LNG Regasification Simulation Model in Aspen HYSYS

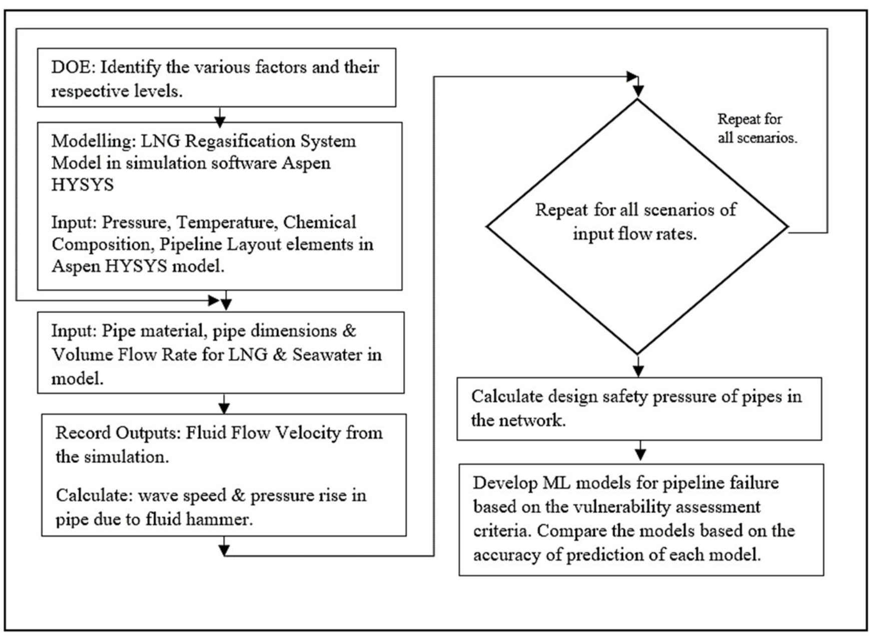

Figure 2 – Graphical Representation of Research Methodology

ΔP is the pressure surge due to fluid hammer effect, and N_{max} is given by equation (5) give below, where, $rounddown()$ is a function that returns the rounded down value of a given number as an integer, and max () is function that returns the maximum value out of all the given values. Based on the predicted failure probability calculated, each pipeline is classified into 4 classes, given in Table 2 [14].

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$$N_{max} = \max\left(rounddown\left(\left(\frac{\Delta P}{P_R}\right)\right)\right) + \max\left(rounddown\left(\left(\frac{\Delta P}{P_{ASME}}\right)\right)\right) \quad (5)$$

2.5 Performance Evaluation of ML Algorithms

Based on the prediction of the test dataset using the ML models for classification, a confusion matrix is developed, which is tabulated in Table 3 [14], [21].The accuracy of a model is calculated using equation (6) [21]:

$$accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (6)$$

Table 2 – Vulnerability classes

Sr.	Probability Criterion	Class Name
1	0 to 0.25	LOW
2	0.25 to 0.5	MODERATE
3	0.5 to 0.75	HIGH
4	0.75 to 1	SEVERE

Table 3 – Confusion Matrix

Confusion Matrix	Actual Class	
Predicted Class	True Positive (TP)	False Positive (FP)
	False Negative (FN)	True Negative (TN)

3 RESULTS & DISCUSSION

The LNG regasification process was modelled in Aspen HYSYS V11 software and simulation was performed on this model.

Based on the Design of Experiment principle, a total of 5400 different scenarios involving the 3 factors (flowrate, diameter & pipe material) were developed based on which simulations were conducted in Aspen HYSYS and the pressure surge and consequently the pipeline vulnerability class was determined for each of the scenario. The design matrix for the simulation is given in Table 6. This dataset was first analyzed to find out the correlation between the various predictors. Table 4 gives the correlation matrix for our dataset. As can be seen in the highlighted cells, the fluid flowrate and fluid flow velocity as well as the pipe diameter and pipe wall thickness are highly correlated. Correlation between 2 or more predictors can mask the importance of a predictor in a machine learning model, and hence it is always a good idea to develop a ML model by eliminating one of the two highly correlated predictors.

Also, as the Design of Experiment approach was used, the ANOVA(analysis of variance) was conducted on the simulated data to analyze the significance of factors & eliminate insignificant factors. The factors Flowrate, Diameter & Material were found to be significant. Based on the results of the ANOVA as well as the correlation matrix, various Machine Learning models were developed using the respective combination of predictors given in Table 5. Based on these combinations of the variables, the ML models of Linear Discriminant Analysis(LDA), Decision Trees, Random Forest, Polynomial Support Vector Machine(SVM(polynomial)) and Radial Support Vector Machine(SVM(radial)) were developed.

Table 4 – Correlation Matrix

Correlation Matrix					
Variable	Flowrate	Flow Velocity	Pipe Diameter	Pipe Wall Thickness	Pipe Material
Flowrate	x	0.9036847	-0.00705799	-0.006218471	-4.19E-22
Flow Velocity	0.903685	x	-0.3985393	-0.3978269	0.00E+00
Pipe Diameter	-0.00706	-0.3985393	x	0.9839808	7.30E-22
Pipe Wall Thickness	-0.00622	-0.3978269	0.9839808	x	-6.22E-21
Pipe Material	-4.19E-22	0.00E+00	7.30E-22	-6.22E-21	x

Table 7 provides the comparison between the accuracy of all the ML models developed. As can be seen, most of the models among LDA, Random Forest and the SVM models have more than 90% accuracy. The best model was observed to be the SVM with radial kernel for all the various combinations of variables selected with an accuracy of 99.9%.

4 CONCLUSIONS

Vulnerability assessment of pipelines in the LNG regasification terminal is critical to ensure a smooth and consistent supply of natural gas at all times. The application of experimental approach of vulnerability assessment requires huge computational cost, while using specialized simulation softwares requires prior field expertise and is computationally extensive. The research conducted was to investigate the effectiveness of machine learning techniques in vulnerability assessment and the performance of the ML algorithms was promising.

A set of 5400 datapoints was generated using the Aspen HYSYS simulation software and 5 ML algorithms were applied and their performance was evaluated by using confusion matrix. The prediction accuracy was used to compare the performance and SVM algorithm with radial kernel was the best model with 99.9% accuracy. Machine learning models can thus be a viable alternative to the computationally extensive analytical methods.

The current research can be further extended to predict the vulnerability assessment for multi-phase fluid flow (i.e., consisting of gas & liquid phase simultaneously), as fluid hammer effect in multi-phase fluid flow can be equally devastating leading to oscillating effect due to fluid hammer effect caused by liquid column formation. Another approach for research extension can be to investigate the interaction between multiple failure modes like fluid hammer effect, internal or external corrosion, etc. and reliability assessment of a pipeline

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network based on this can be beneficial.

Table 5 – Variable Selection Matrix

No. of Variables Used	Variable Selection Matrix				
5 -	Flowrate	Fluid Velocity	Pipe Diameter	Pipe Thickness	Pipe Material
4 -	Flowrate	Fluid Velocity	Pipe Diameter	Pipe Material	-
3 -	Flowrate	Pipe Diameter	Pipe Material	-	-
2 -	Flowrate	Pipe Diameter	-	-	-

Table 6 - Results of Simulation

Sr.	Flowrate (m^3/h)	Velocity (m/s)	Diameter (m)	Pipe Thickness (mm)	Elasticity Mod of Pipe (GPa)	WH Rise (in bar)	Rupture Design PR(bar)	ASME Safety PR(bar)	Safety_Status
1	7494	11.5	0.5	0.01509	22.5	170.9	155.78	100.32	Moderate
2	4981	7.66	0.5	0.01509	22.5	113.89	155.78	100.32	Moderate
3	2473	3.8	0.5	0.01509	22.5	56.52	155.78	100.32	Low
4	7537	14.4	0.45	0.01427	22.5	214.15	181.77	105.49	Moderate
5	5014	9.57	0.45	0.01427	22.5	142.33	181.77	105.49	Moderate
6	2507	4.8	0.45	0.01427	22.5	71.32	181.77	105.49	Low
7	7537	18.23	0.4	0.0127	22.5	271.09	204.62	105.56	High
8	5014	12.13	0.4	0.0127	22.5	180.34	204.62	105.56	Moderate
9	2507	6.05	0.4	0.0127	22.5	89.96	204.62	105.56	Low
10	7494	11.5	0.5	0.01509	19.3	170.89	87.04	56.05	Moderate
11	4981	7.66	0.5	0.01509	19.3	113.89	87.04	56.05	Moderate
12	2473	3.8	0.5	0.01509	19.3	56.52	87.04	56.05	Low
13	7537	14.4	0.45	0.01427	19.3	214.15	102.29	59.36	Severe
14	5014	9.57	0.45	0.01427	19.3	142.33	102.29	59.36	High
15	2507	4.8	0.45	0.01427	19.3	71.32	102.29	59.36	Moderate
16	7537	18.23	0.4	0.0127	19.3	271.09	115.21	59.43	Severe
17	5014	12.13	0.4	0.0127	19.3	180.34	115.21	59.43	High
18	2507	6.05	0.4	0.0127	19.3	89.96	115.21	59.43	Moderate

Table 7 – Comparison between performance of Machine Learning Models

Accuracy Matrix	Machine Learning Models				
Variables Used	LDA	Decision Trees	RandomForest	SVM(Polynomial)	SVM(Radial)
5	0.923	0.359	0.998	0.993	0.999
4	0.920	0.359	0.998	0.992	0.999
3	0.920	0.359	0.996	0.992	0.999
2	0.642	0.402	0.514	0.993	0.660

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