iJRASET
International Journal For Research in Applied Science and Engineering Technology

INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 11 **Issue:** V **Month of publication:** May 2023

DOI: https://doi.org/10.22214/ijraset.2023.50028

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International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 11 Issue V May 2023- Available at www.ijraset.com

Study of Machine Learning Methods to Predict and Prevent Gas Hydrate Formation

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Abstract: ***Formation of gas hydrates are a serious concern in oil and gas production systems. The formation and possible deposition of hydrates usually occur in suitable conditions, specifically as the gas-phases of reservoir fluid interact with water molecules. Hydrate formation represents a significant risk to process safety as it can result in the plugging of both pipes and instruments. Hydrates typically form in process where light hydrocarbons, water vapor and low temperatures or high pressures are present. We have studied the conditions under which hydrates form, how formation may be prevented and what can be done once hydrates have formed.***

Keywords: Gas Hydrates, Machine Learning, Prediction of Hydrate Formation, Neural Network, Linear Regression.

I. INTRODUCTION

Gas hydrates are crystalline solids composed of water molecules, known as host molecules, and hydrate-forming molecules, known as guest molecules. Guest molecules, including light hydrocarbons such as methane, ethane, and propane, as well as non-hydrocarbons like carbon dioxide, hydrogen sulphide, nitrogen, and hydrogen, become trapped inside the holes created by the hydrogen bonding of water molecules, forming hydrates. The size of the guest molecules, their interaction with water molecules, and the presence of inhibitors, mainly salt, in the aqueous phase, all play a role in hydrate stability.

Gas hydrates have attracted a lot of attention due to their numerous potential applications. They can store gas at a rate of about 170 times its volume, making them useful for carbon sequestration, gas storage, and transportation. Since only free water is involved in hydrate structure development, dissolved salt is eliminated during hydrate formation, making them suitable for desalination. Hydrates can also be used for gas separation by utilizing the selective partitioning of different gases in the hydrate and gas phases. Additionally, hydrate slurries have been suggested as an effective cooling agent in refrigeration applications.

However, gas hydrate formation can lead to pipeline blockage, resulting in economic losses and safety concerns in oil and gas pipelines. Drilling fluid used in deep-sea drilling contains both gas and water, which can produce gas hydrates under conditions of high pressure and low temperature, leading to blocking issues. Hydrate suppression is necessary to prevent these issues, which can be achieved by incorporating anti-freezing substances like salts or glycols into the drilling fluid. Natural gas hydrates, which are potential energy sources, have been discovered in sediments under the ocean's surface, in Arctic permafrost, and in Antarctic ice. Accurate gas hydrate formation and dissociation conditions are crucial for both theoretical and practical research of hydrates. It is essential to understand the hydrate stable conditions in salt solutions, particularly since recent oil and gas exploration has moved to deeper waters, and hydrate equilibrium investigations under these conditions are necessary due to the hostile high-pressure and salinity conditions. The exploration and development of unconventional natural gas resources, such as shale gas and natural gas hydrate, are crucial for global energy security. One cubic meter of natural gas hydrate can hold up to 164-180 cubic meters of natural gas STP, making it an efficient energy storage medium. The submarine has explored 97% of the hydrate resources, with the remaining 3% buried under permafrost. Natural gas hydrates are metastable, and their stability is affected by pressure, temperature, and guest gases and their mixtures, making it challenging to predict their formation and composition accurately. One of the fastest-growing areas of computer science is machine learning, a subfield of AI that aims to replicate human intelligence by learning from its surroundings. Machine learning automates the creation of analytical models for data analysis without significant human input. There are various types of machine learning, such as supervised learning/semi-supervised learning, unsupervised learning, and reinforcement learning. Supervised learning and semi-supervised learning infer the underlying link between observed data that has been labelled, and they can resolve classification and regression issues. Unsupervised learning uncovers the underlying structure of unlabelled data, primarily for clustering and outlier detection problems. Reinforcement learning involves an intelligent agent exploring a set of adaptive actions or behaviours in a particular environment, and its main application is in decision-making problems to maximize the cumulative reward given data, such as a computer playing chess.

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A. How Machine Learning is different from Neural Network data Feeding

A Neural Network arranges algorithms in such a way that it can make reliable decisions on its own, whereas a ML Model makes decisions based on what it has learnt from the data. As a result, while Machine Learning models may learn from data, they may need some human interaction in the early stages.

Classification algorithms can handle a discrete label in supervised learning. In a different scenario, regression algorithms should be used to handle the data with continuous labelling. Regression is used for prediction and ranking, whereas classification is primarily utilized for prediction, pattern identification, and outlier detection. Figure 2 illustrates the selection process for machine learning techniques. The volume of data is a crucial performance component in pattern regression. The algorithm's level of convergence is heavily influenced by the data and computational resources available.

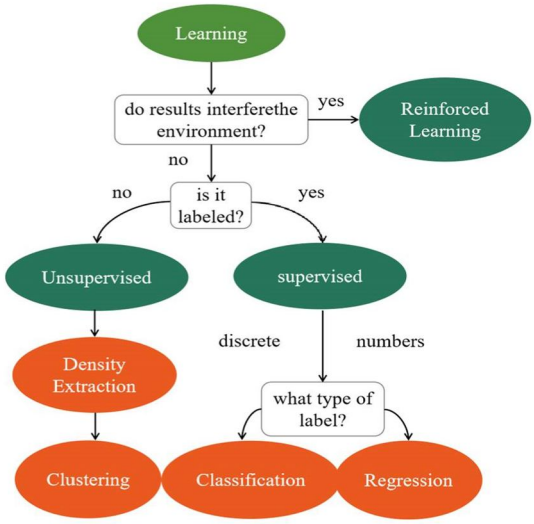

Figure 2 (ML Method Categorization)

II. TOOLS

We have used following tools and methods for this project:

A. Wolfram Mathematica

Wolfram Machine learning, statistics, symbolic computation, data manipulation, network analysis, time series analysis, natural language processing (NLP), optimization, plotting functions and different types of data, implementing algorithms, creating user interfaces, and integrating with programmed written in other programming languages are all possible with Mathematica, a software system with built-in libraries for several technical computing areas. Stephen Wolfram came up with the idea, and Wolfram Research in Champaign, Illinois, is working on developing it. Mathematica's programming language is called the Wolfram Language. On June 23, 1988, Champaign, Illinois, and Santa Clara, California, respectively, launched Mathematica 1.0.

We have feed the data in Mathematica program and done the Neural Network and Linear Regression methods of Machine Learning for a graph which predicts the hydrate formation.

B. Symbolic Manipulator

Symbol manipulation is a field of computer science that deals with the manipulation of complex and often unpredictable data structures. Different programming languages for symbol manipulation vary in their ability to operate on lists with varying degrees of generality.

III. METHODOLOGY

We utilized the predict command in Mathematica for our machine learning analysis. We employed two methods, namely Neural Network and Linear Regression, which are already built-in features of the Wolfram Mathematica software. These methods are commonly used for predictive modeling in machine learning, specifically in predicting and preventing gas hydrate formation given a certain temperature and pressure, for a relative gas uptake rate, which is represented by the percent Hydrate Saturation.

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The resulting predictions are visualized through a graph, which shows the relationship between the relative gas uptake rate and the corresponding Hydrate Saturation percentage. We limited our analysis to five cases of given data with five cycles each, containing the following information: temperature, pressure, percentage of relative gas uptake, and Hydrate Saturation percentage. We also noted that there is a constant percentage of CO2 present in C3H8 (propane) for each case. Further details on how we acquired the data and how we generated the graphs will be discussed in the Results and Discussion section.

IV. RESULTS AND DISCUSSIONS

CO2 hydrate formation in salt solution in the presence of C3H8 were experimentally investigated. The nine cases (54 cycles) were initially conducted at 1.0e6.0 MPa with propane mass fractions ranging from 0 to 13%.
Data was collected from research paper and feed in wolfram Mathematica for the prediction of gas hydrates, and the graph shows the comparison of training set data and predicted output.

For paper, we have just taken the first case of feed and that's output is also be there.

```
In[1]:= trainingset1 = {{3.0, 97.0, 281.39, 3.62, 11.89} → 27.74,
          {3.0, 97.0, 281.54, 3.13, 9.54} → 22.24, {3.0, 97.0, 281.10, 2.67, 6.64} → 15.48,
          {3.0, 97.0, 279.20, 2.12, 3.85} → 8.98, {3.0, 97.0, 277.11, 1.66, 3.0} → 6.99};

In[2]:= Length[trainingset1]

Out[2]= 5
```

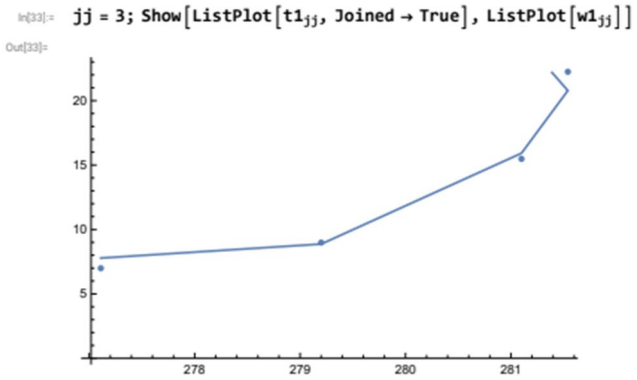
In this part, feed is embedded in the system and case 1 is named as trainingset1. Including %CO2 presesnt in C3H8, temperature (kelvin), pressure, relative gas uptake% and Hydrate Saturation%. And the lenght of traningset1 is 5. There are 5 data cycles.

In this part, p11 representing the Neural Network for traningset1 and p12 is representing Linear Regression for the same. And the values of p11 and p12 are same because they are representing to the same trainingset. The output value we get is from the inbuild code of mathematica for neural network and linear regression respectively predicted by them.

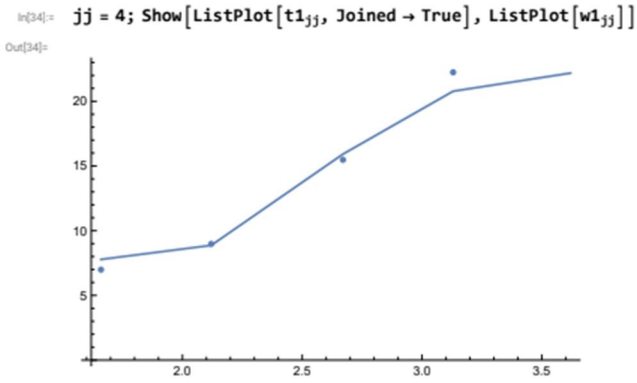
```
In[11]:= p11 = Predict[trainingset1, Method → "NeuralNetwork"];
         p12 = Predict[trainingset1, Method → "LinearRegression"];
         p11[{3.0, 97.0, 281.39, 3.62, 11.89}]
         p12[{3.0, 97.0, 281.39, 3.62, 11.89}]

Out[13]=
         22.1797

Out[14]=
         21.7625
```

This part is known as Command List Plot. w1jj is the points given in the data sets. This data is shown as points in the graph. And t1jj is the prediction for traningset1. Which is shown as the line joining the points.

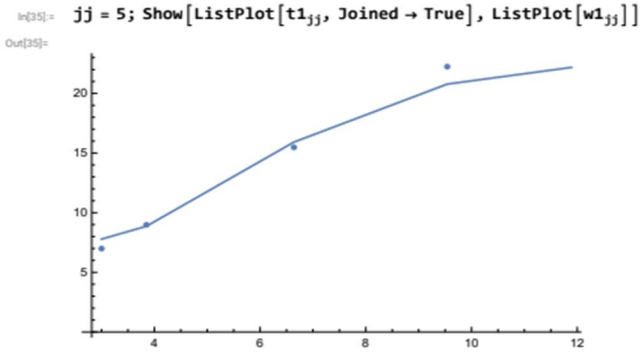
```
In[31]:= Clear[w1, jj];
         w1jj_ := Table[{Part[Part[Part[trainingset1, ii], 1], jj], Part[Part[trainingset1, ii], 2]},
           {ii, 1, Length[trainingset1]}]
         Clear[t1, jj];
         t1jj_ := Table[{Part[Part[Part[trainingset1, ii], 1], jj],
           p11[Part[Part[trainingset1, ii], 1]]}, {ii, 1, Length[trainingset1]}]
```



Graph is between hydrate saturation% and temperature(k).



Graph is between hydrate saturation% and pressure.



Graph is between hydrate saturation% and relative gas uptake.

A. Predicting the gas hydrate formation with the help of graph.

The graph shows how good the feed is. And accordingly, it predicts the possibility of formation of gas hydrates in the composition. If the graph goes upward the prediction is positive. Means there's a possibility to form a hydrate. And vise-versa if the graph goes downward.

To prevent the formation of gas hydrate, several remedial measures can be taken, including:

1) Maintaining the system temperature above the hydrate formation temperature by using a heater and/or insulation. This prevents the gas from reaching the temperature at which hydrate formation can occur.

2) Dehydrating the gas to prevent the condensation of a free water phase. Removing water from the gas phase ensures that there is no water available for hydrate formation.

3) Injecting thermodynamic inhibitors to suppress the hydrate formation temperature in the free water phase. These inhibitors alter the thermodynamics of the system, reducing the temperature at which hydrate formation can occur.

V. FUTURE SCOPE

We can setup proper code for prediction and classification of gas hydrates, in which we just have to input the properties of gas and it directly shows the output. Which helps for prediction of hydrate and we can prevent it also.

VI. CONCLUSION

Neural network and linear regression which is already on wolfram Mathematica help to predict the gas hydrate formation despite factor affection such as temperature and pressure. The provided models demonstrate how mathematics can be used to increase the accuracy of predictions regarding the development of gas hydrates. These predictions are based on experimental data gathered from papers published between 1951 and 2000. The prediction is done with the help of Mathematica. Through the graphs Prediction of hydrate saturation is done with the help of data take from literature survey.

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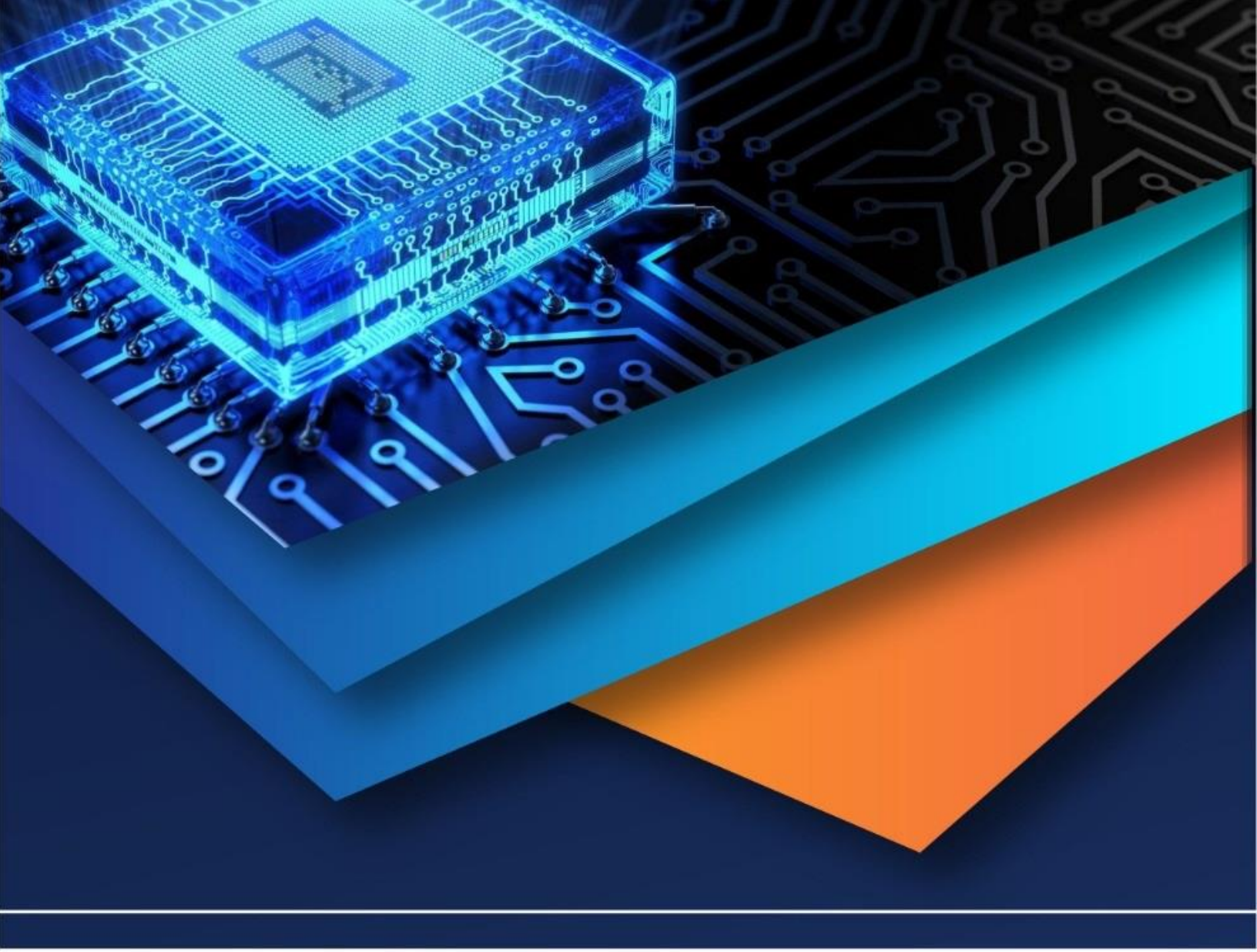

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