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# Optimizing Predictive Models for LNG Production and Temperature Forecasting

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**A B S T R A C T**

Predicting LNG (Liquefied Natural Gas) production and associated rundown temperatures is crucial for efficient operations in the LNG industry. Accurate predictions enable better resource allocation, cost management, and maintenance planning. In this study, we compared the performance of various machine learning algorithms for their ability to forecast LNG production and rundown temperatures. We evaluated the predictions using error metrics, specifically the R2score and Root Mean Square Error (RMSE). The study revealed that the K-neighbors algorithm outperformed other models, exhibiting the highest R2 score and the lowest RMSE, making it the optimal choice for accurate predictions. Additionally, the feature selection process played a critical role in model accuracy, with certain features proving to be more suitable for training the models. Detailed error analysis and data visualization further demonstrated the effectiveness of the chosen algorithm. This study highlights the significance of selecting the right predictive model and features for LNG production and temperature forecasting, providing valuable insights for optimizing operations in the LNG industry.

Keywords: LNG Production Forecasting, Rundown Temperature Prediction, Machine Learning Algorithms, R2 Score Analysis, Root Mean Square Error (RMSE) Evaluation and KNeighbour

## 1. INTRODUCTION

The world is moving to natural gas from fossil fuels. Natural gas has supplanted coal as the world's cleanest and most ecologically friendly energy source due to its lower carbon emissions and affordability (Mofid & Fetanat, 2019; Salehi, 2018; Wang, 2017). Natural gas use is expected to rise 40% between 2014 and 2040. (BP, 2017). Jackson, Eiksund, and Brodal found that natural gas-powered plants provided 37% of fossil energy in 2030, up from 30% in 2013. (2017).

LNG is rapidly replacing fossil fuels as a key energy source worldwide because to its reduced greenhouse gas emissions and cleaner burning. These LNG benefits have attracted attention recently due to the energy crisis (Sang et al 2020). Natural gas is mostly transported via liquefaction and pipelines. Energy companies have routinely employed liquefying natural gas to transport it across long distances instead of pipes. The pipeline pressure difference limits pipeline gas supply, the transit route is rigid, and long-term contracts are needed (Lee et al 2020).

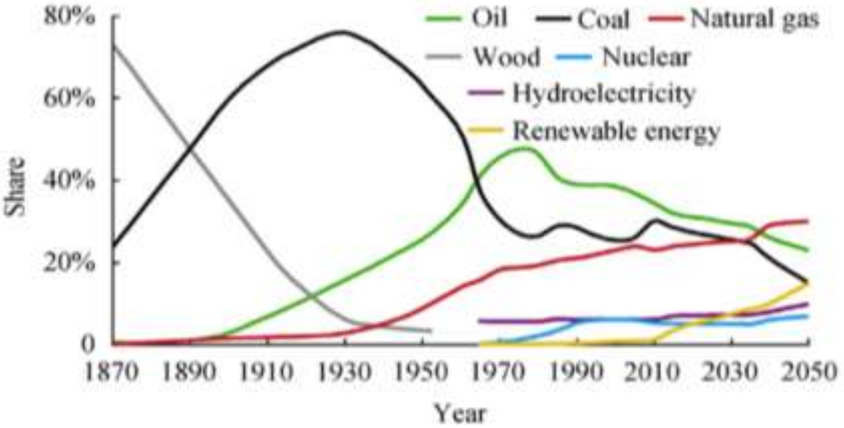


Figure 1. Global trend in energy consumption (U.S. Energy Information Administration, 2022)

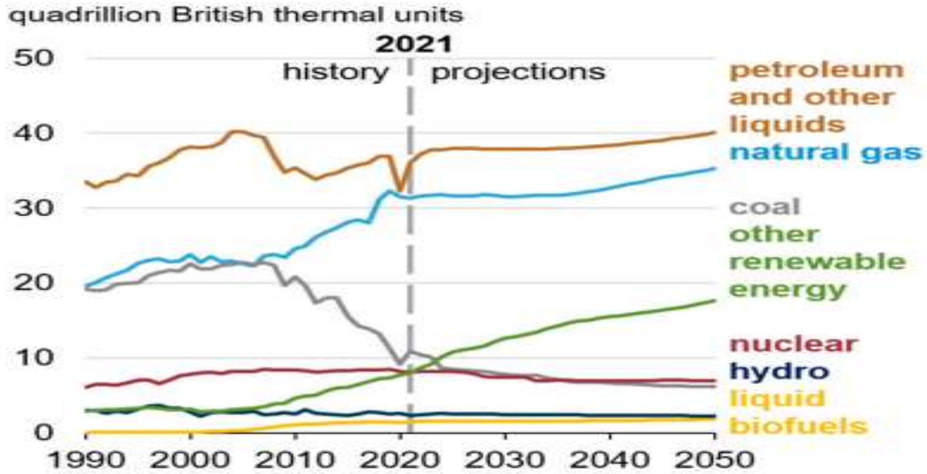


Figure 2. History and Projection of U.S. Energy Consumption (U.S. Energy Information Administration, 2022)

Liquefaction is the process by which gases are transformed into liquids. Liquefied natural gas (LNG) is natural gas that has been cooled to -162 degrees Celsius while maintaining an atmospheric pressure. Natural gas is more convenient to transport in this state since only one-six hundredth as much is utilized as when it is in its gaseous state (Khalilpour & Karima, 2009).

When temperatures drop below the critical temperature of natural gas, the gas changes phase and becomes a liquid. Refrigerants must be employed to reach such low temperatures, and the heating curves of these refrigerants must be as similar to the cooling curve of natural gas as is practically possible. A refrigerant is the fluid used to transport heat in air conditioning and refrigeration systems. Maintaining a cold temperature for the LNG product in LNG facilities is crucial for its storage and transport.

As a consequence, production will suffer if this section is inefficient. There is a need for environmentally friendly, fast-acting refrigerants that also save energy. Over the years, a number of distinct LNG production methods and refrigerant types have arisen, each with its own unique process configuration. Some examples are the turbo-expander process, the cascade process, and single/dual mixed refrigerant (SMR/DMR) technology. The primary distinctions between these methods are capital and operational costs. A company's capital expenditures (CAPEX) and operating expenditures (OPEX) are affected by a number of factors, including its production capacity, the quantity of equipment, and the cost of labor. However, the use of mixed-refrigerant (MR) processes greatly increases the complexity of process design and operation due to the increased number of thermodynamic interactions, making process management and optimization exceptionally challenging (Shukri, 2004). Factors like as desired temperature range, ease of access, cost, and past experience all factor into the decision of which refrigerant to use. Ethane and propane, for instance, may be on hand in a natural gas processing facility, whereas ethylene and propylene are on hand in an olefins factory. There is a substantial danger of contamination if propane or propylene were used in an ammonia facility, but ammonia might serve the same function. Due to their inability to catch fire, halocarbons have seen widespread use. The Propane Precooled Mixed Refrigerant (C3MR) system is one of the most popular refrigeration methods utilized today. Before entering the mixed refrigeration system consisting of methane, ethane, propane, and nitrogen, the liquefied natural gas is precooled to -35Oc in a propane refrigeration system (Bahadori et al., 2014).

### *2.1 Methodology*

#### *2.1.1 Material*

The material used in this research include: An artificial intelligent (Python programming language) software, PI Process book software 2015 version 3.6.2.271, PI datalink, Visual studio (VS) code editor and the Microsoft Excel 365. Python is an interpreted, high-level programming language that may be used for a wide variety of projects. The principle behind its design prioritizes the readability of the code by heavily indenting it. The PI process book and PI datalink add-in were basically used for data collection from the plant site. While the VS code editor is mainly an Integrated Development Environment (IDE) source code editor used to debug, highlight syntax and for coding of the GUI script. It is a user-friendly coding environment.

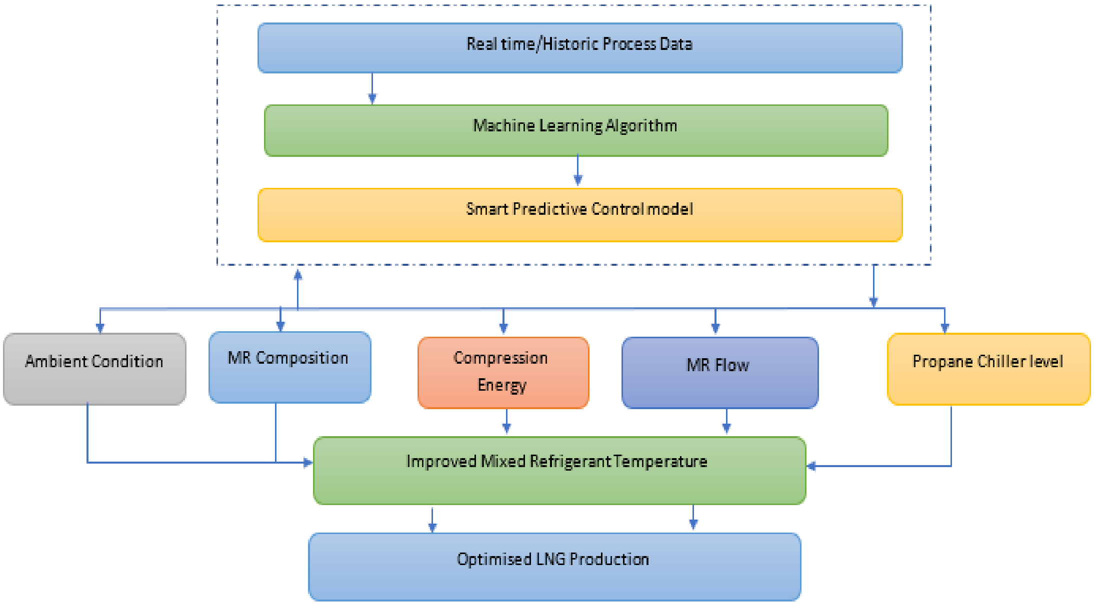


Figure 3. Research design framework for the optimization of LNG production using AI.

### *2.1.3 Process Optimization Description*

Figure 4 shows the sequential order or steps used to achieve the aim and objectives of this research. It depicts the schematic breakdown of the optimization process using the artificial intelligence data driven approach.

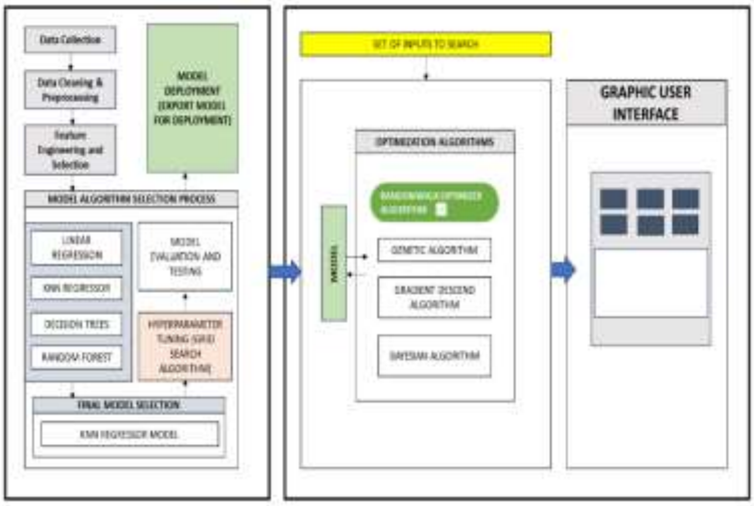


Figure 4. Process description of Artificial Intelligence optimisation

### *2.1.4 Data Collection*

The data collection for this work was done using PI Processbook 2015 software version 3.6.2.271 R2 and PI datalink. PI processbook is an OSIsoft vendor software that enable users to retrieve real-time data from the PI system which is linked to a live process plant. The software application can create dynamical graphical display, trends from historical and real time data. To retrieve the data used for the work, the PI datalink was connected to the PI server and then to the liquefaction plant via several process control schemes as shown in figure 3.3. The PI datalink is a Microsoft Excel add-in feature linked to the PI software. The PI datalink's sample data multiple value function was used to retrieve about 10 years liquefaction unit data set at an hourly interval.

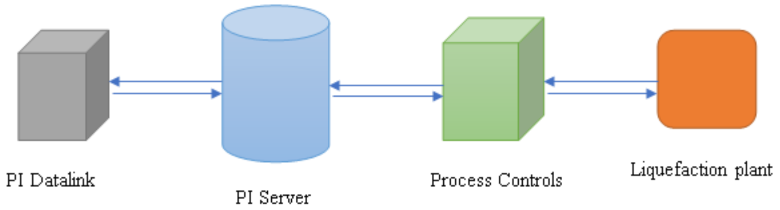


Figure 5. PI System data Collection scheme

### *2.1.5 Data Pre-processing and Cleaning*

In this phase, three important steps were followed which are the data importation, cleaning of data, and exporting of data for next stage.

- **Importation of library and loading of data**

The data used for this project contains about 70,000 rows and 43 columns of about 10 years sample data. Microsoft excel was used to get a preview of how the data looks. The images below show the preview of the data in MS excel. The data seen above, as expected, contains quite a lot of invalid data and errors. Jupyter notebook version 6.4.5 environment was used, which comes as part of a software called Anaconda. Anaconda comes with a lot of libraries that will be so useful for me in this project. The first library that I used is the Pandas. Pandas with the help of python programming language was used to load the data into the Jupyter notebook environment. Below is the image that shows the data already imported into Jupyter notebook using Panda's python library. Figure 3.2 consist of data collected from the industry. Figure 3.3 displays the data loaded for the optimization process (first five rows of the data).

- **Cleaning the data.**

3. As mentioned earlier, the data loaded above contains many invalid inputs from the data collection source. Neglecting these errors will lead to making an inaccurate model. Hence, there is need for me to handle and get rid of them. These involve creating the data in a floating type. Data cleansing involved the following processes.

i. Eliminated erratic values in LNG flow column.

ii. Found out the error values in "MCHE cold bundle dp" column.

iii. Found out the errors in "volumetric MR flow to MR component discharge" column.

iv. Found out errors in "percentage Nitrogen in MR" column.

v. Removed unnamed columns.

vi. Eliminated all the null values.

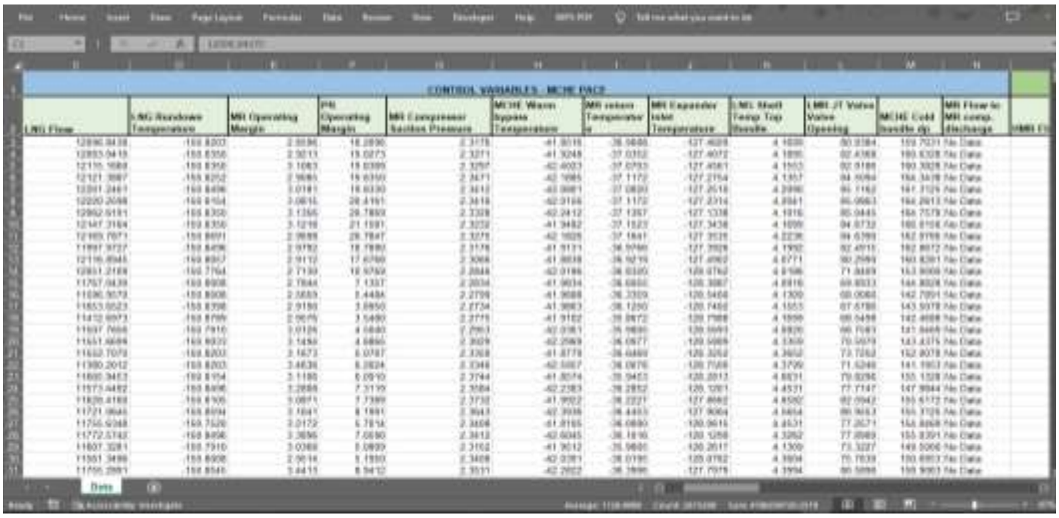

Figure 5. Data library from Microsoft Excel

```
[1]: # import libraries
import pandas as pd
import numpy as np
```

LOAD DATA

```
[2]: filepath = "./LNGDATA_%.xlsx"
df = pd.read_excel(filepath, skiprows=1)
df.head()
```

[2]:

| | Unnamed: 0 | Unnamed: 1 | LNG Flow | LNG Rundown Temperature | MR Operating Margin | PR Operating Margin | MR Compressor Suction Pressure | MCHE Warm bypass Temperature | MR return Temperature | MR Expander inlet Temperature | ... | Unnamed: 33 | Low Pressure Propane kettle level | Medium Pressure Propane/Natural Gas kettle level |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 0 | NaN | NaN | 12096.84375 | -150.820312 | 2.859555 | 18.209555 | 2.317578 | -41.851562 | -36.96875 | -127.460938 | ... | No Data | 57.330078 | 64.28125 |
| 1 | NaN | NaN | 12093.041016 | -150.834961 | 2.921342 | 19.027306 | 2.327148 | -41.924805 | -37.035156 | -127.407227 | ... | No Data | 56.773438 | 64.289062 |
| 2 | NaN | NaN | 12115.166016 | -150.834961 | 3.108348 | 19.838821 | 2.329688 | -42.402344 | -37.070312 | -127.458055 | ... | No Data | 57.082031 | 64.048828 |
| 3 | NaN | NaN | 12121.388672 | -150.825195 | 2.908482 | 19.634664 | 2.34707 | -42.188477 | -37.117188 | -127.275391 | ... | No Data | 57.013672 | 64.261719 |
| 4 | NaN | NaN | 12201.246094 | -150.849609 | 3.01808 | 19.833008 | 2.341211 | -42.080078 | -37.082031 | -127.250977 | ... | No Data | 56.988281 | 64.34375 |

5 rows × 43 columns

Figure 6 Previewed data for optimization process.

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 70129 entries, 0 to 70128
Data columns (total 43 columns):
 #   Column                                Non-Null Count  Dtype
---  ------                                --------------  -----
 0   Unnamed: 0                            0 non-null      float64
 1   Unnamed: 1                            0 non-null      float64
 2   LNG Flow                              70129 non-null  object
 3   LNG Rundown Temperature               70129 non-null  object
 4   MR Operating Margin                   70129 non-null  object
 5   PR Operating Margin                   70129 non-null  object
 6   MR Compressor Suction Pressure        70129 non-null  object
 7   MCHE Warm bypass Temperature          70129 non-null  object
 8   MR return Temperature                 70129 non-null  object
 9   MR Expander inlet Temperature         70129 non-null  object
 10  LNG Shell Temp Top Bundle             70129 non-null  object
 11  LMR JT Valve Valve Opening            70129 non-null  object
 12  MCHE Cold bundle dp                   70129 non-null  object
 13  Volumetric MR Flow to MR comp. discharge  70129 non-null  object
 14  HMR Flow                              70129 non-null  object
 15  HMR/MR Ratio                          70129 non-null  object
 16  LNG Flow Ex MCHE                      70129 non-null  object
 17  MCHE Warm Bypass Temperature          70129 non-null  object
 18  MR IGV Position                       70129 non-null  object
 19  MR Vessel Level                       70129 non-null  object
 20  MR Vessel Pressure                    70129 non-null  object
 21  Percentage Nitrogen in MR             70129 non-null  object
 22  Percentage Methane in MR              70129 non-null  object
 23  Percentage Ethane in MR               70129 non-null  object
 24  Percentage Propane in MR              70129 non-null  object
 25  Percentage Butane in MR               70129 non-null  object
 26  Nitrogen Make-up flow                 70129 non-null  object
 27  Methane Make-up flow                  70129 non-null  object
 28  Ethane Make-up flow                   70129 non-null  object
```

Figure 7. LNG data before cleaning

```
---  ------                                            --------------  -----
 0   LNG Flow                                          32024 non-null  float64
 1   LNG Rundown Temperature                           32024 non-null  float64
 2   MR Operating Margin                               32024 non-null  float64
 3   PR Operating Margin                               32024 non-null  float64
 4   MR Compressor Suction Pressure                    32024 non-null  float64
 5   MCHE Warm bypass Temperature                      32024 non-null  float64
 6   MR return Temperature                             32024 non-null  float64
 7   MR Expander inlet Temperature                     32024 non-null  float64
 8   LNG Shell Temp Top Bundle                         32024 non-null  float64
 9   LMR JT Valve Valve Opening                        32024 non-null  float64
 10  MCHE Cold bundle dp                               32024 non-null  float64
 11  Volumetric MR Flow to MR comp. discharge          32024 non-null  float64
 12  HMR Flow                                          32024 non-null  float64
 13  HMR/MR Ratio                                      32024 non-null  float64
 14  LNG Flow Ex MCHE                                  32024 non-null  float64
 15  MCHE Warm Bypass Temperature                      32024 non-null  float64
 16  MR IGV Position                                   32024 non-null  float64
 17  MR Vessel Level                                   32024 non-null  float64
 18  MR Vessel Pressure                                32024 non-null  float64
 19  Percentage Nitrogen in MR                         32024 non-null  float64
 20  Percentage Methane in MR                          32024 non-null  float64
 21  Percentage Ethane in MR                           32024 non-null  float64
 22  Percentage Propane in MR                          32024 non-null  float64
 23  Percentage Butane in MR                           32024 non-null  float64
 24  Nitrogen Make-up flow                             32024 non-null  float64
 25  Methane Make-up flow                              32024 non-null  float64
 26  Ethane Make-up flow                               32024 non-null  float64
 27  Propane Make-up flow                              32024 non-null  float64
 28  Ambient Condition                                 32024 non-null  float64
 29  Scrub Column inlet Temperature                    32024 non-null  float64
 30  Natural Gas temp at MCHE warm bundle              32024 non-null  float64
 31  Low Pressure Propane kettle level                 32024 non-null  float64
 32  Medium Pressure Propane/Natural Gas kettle level  32024 non-null  float64

0  1  Python 3 (ipykernel) | Idle
```

Figure 8 LNG data after cleansing showing floating columns.

### *2.1.6 Model Selection Process*

Several algorithms were tested on the two data set generated to determine the best LNG production and LNG temperature. In this process, LNG production (Uni-output) and LNG production and LNG rundown temperature (multi-output) were predicted. The data set up were loaded alongside the pandas, numpy and sklearn libraries. List of libraries and function loaded are listed below viz:

- Functions for calculating absolute, mean and standard deviation from the Numpy library
- Algorithm program from the sklearn library
- Programs chaining the algorithm available from the sklearn library
- Programs to process the data to make them suitable for the algorithm to work with
- Programs for metric calculations

Model selection

Since this is a regression problem. We will be using and testing the following regression algorithm

- LinearRegression
- KNeighborsRegressor
- DecisionTreeRegressor
- RandomForestRegressor

Setup

```
from numpy import absolute, mean, std

# import estimators
from sklearn.linear_model import LinearRegression
from sklearn.neighbors import KNeighborsRegressor
from sklearn.tree import DecisionTreeRegressor
from sklearn.ensemble import RandomForestRegressor


from sklearn.model_selection import cross_val_score
from sklearn.model_selection import RepeatedKFold
from sklearn.multioutput import RegressorChain

# pipeline for preprocessing
from sklearn.pipeline import Pipeline
from sklearn.preprocessing import StandardScaler

# metrics
from sklearn.metrics import mean_squared_error, r2_score
```

Figure 91 Library importation for algorithmic process

The following algorithms were imported:

- Linear Regression
- KNeighbors Regressor
- Decision Tree Regressor
- Random Forest Regressor

These are algorithms are considered fit for the nature of task to be solve. This task is a numerical input, continuous target problem. It is numerical input because all our input features are of numeric datatype, and it is continuous (or numerical) target because the variables that I intend to predict are also numeric in nature.

- **Linear Regression**

The multiple linear regression model was used in the process due to several independent variables. The underlying equation for the multiple linear regression.

$$\beta_o + \beta_1 x_1 + \beta_2 x_2 + \ldots\ldots{+}\, \beta_p x_p + \epsilon \qquad \text{Equation 1}$$

- $y_i$ is the dependent or predicted variable
- $\beta_0$ is the y-intercept.
- $\beta_1$ are the regression coefficients representing the change in y relative to a one-unit change in $xi_1$, $xi_2$,… xip respectively.
- $\beta_p$ is the slope coefficient for each independent variable
- ϵ is the model's random error (residual) term.

The cost function provides the best possible values for β0 , β1, β3… βp to make the best fit line for the data points. The algorithm converts this problem into a minimization problem to get the best values for β. The error is minimized in this problem between the actual value and the predicted value.

$$minimize\ \frac{1}{n}\sum_{i=1}^{n}(pred_i - y_i)^2 \qquad \text{Equation 2}$$

$$J = \frac{1}{n}\sum_{i=1}^{n}(pred_i - y_i)^2 \qquad \text{Equation 3}$$

- **KNeighbors Regressor**

The straightforward algorithm K nearest neighbors predicts the numerical target based on a similarity metric while storing all of the available cases (e.g., distance functions).

**Distance function**

**Euclidean** $\sqrt{\sum_{i=1}^{k}(\boldsymbol{x_i} - \boldsymbol{y_i})^2}$ Equation 4

Manhattan $\sum_{i=1}^{k}|\boldsymbol{x_i} - \boldsymbol{y_i}|$ Equation 5

Minkowski $\left(\sum_{i=0}^{n}(|x_i - y_i|)^q\right)^{\frac{1}{q}}$ Equation 6

***2.1.6 Model Development***

The algorithm with more acceptable metrics from the model evaluation was selected.

This works best for the prediction to be performed. The following steps were used to prepare the machine learning model and load library dataset and the useful libraries model.

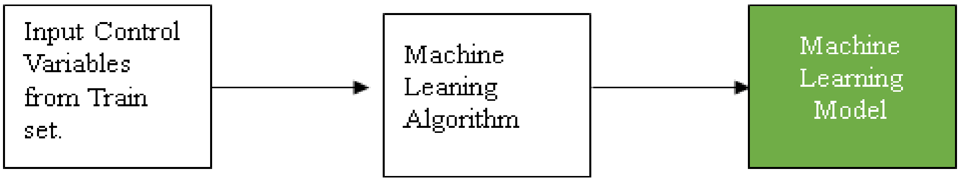


Figure 10. Flow chart for Model Development

The KNN algorithm was used to train the model.

**Model Testing and Input Optimisation Using Optimisation Algorithms**

The model was combined with several optimization algorithm on new set of inputs from another LNG plant data. The optimisation algorithm uses the model to find the best control variables or set points that will give an optimised LNG flow is shown below. Then compared with the new result.

The diagram below shows the model testing algorithm.

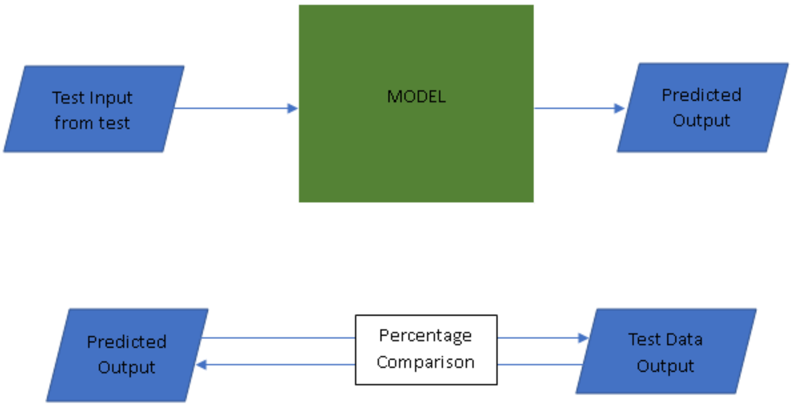


Figure 11. Model testing algorithm flow chart

## 3.0 Result and Discussion

### *3.1 Model performance (Kneighbor Regressor)*

Table 4. 1 Error analysis of algorithms

| S/No | Algorithm | R2 - Score | RMSE |
|---|---|---|---|
| **1.** | Linear Regressor | 0.9411 | 628.9384 |
| **2.** | K-neighbors | 0.9853 | 313.8738 |
| **3.** | Decision Tree | 0.9748 | 411.4508 |
| **4.** | Random Forest | 0.8981 | 826.8076 |

Table 2. Error Analysis on the Algorithm performance for the actual LNG flow and actual LNG Rundown temperature

| Data Row No | Actual LNG Flow | Actual LNG Rundown Temperature |
|---|---|---|
| **18778** | 13575.379883 | -145.473633 |
| **10519** | 11672.666016 | -145.039062 |
| **31757** | 13300.155273 | -145.786133 |
| **6400** | 12687.996094 | -145.610352 |
| **17354** | 11994.082031 | -145.502930 |

Table 3 Error Analysis on Algorithm performance for the Predicted LNG flow and predicted LNG Rundown temperature

| Data Row No | Predicted LNG Flow | Predicted LNG Rundown Temperature |
|---|---|---|
| **0** | 13363.826953 | -146.179688 |
| **1** | 12060.130078 | -145.521484 |
| **2** | 13391.834180 | -145.701172 |
| **3** | 12811.619531 | -145.620117 |
| **4** | 11980.771289 | -145.903320 |

Table 4 Comparison of predicted and actual LNG flow using the K-Neighbor regressor Model.

| Actual LNG Flow | Predicted LNG Flow | Error |
|---|---|---|
| **13575.3799** | 13363.8269 | 211.553 |
| **11672.66** | 12060.1301 | 387.4641 |
| **13388.1553** | 13391.8341 | 3.6788 |
| **12687.9961** | 12811.6195 | 123.6234 |
| **11994.082** | 11980.7713 | 13.3107 |
| **Actual Rundown Temperature (ºC)** | **Predicted Rundown Temperature (ºC)** | **Error** |
| **-145.4736** | -146.1797 | 0.7061 |
| **-145.0391** | -145.5215 | 0.4824 |
| **-145.7861** | -1455.7012 | 0.0849 |
| **-145.6104** | -145.6201 | 0.0097 |
| **-145.5029** | -145.9033 | 0.4004 |

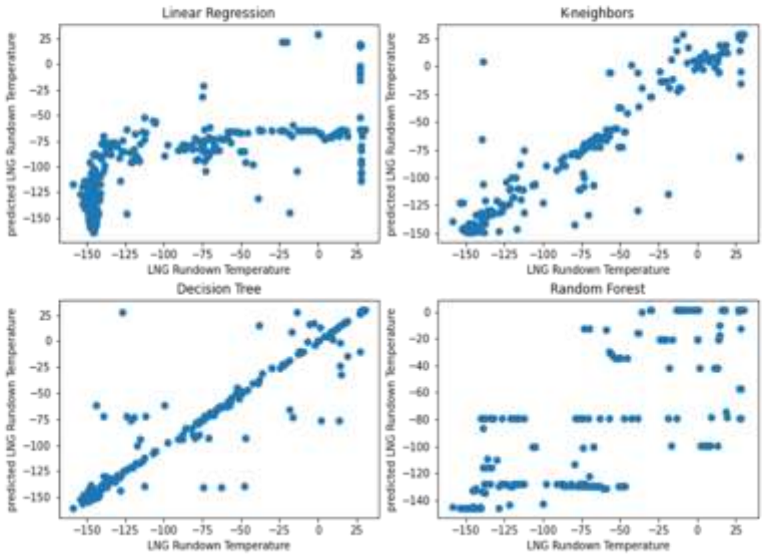


Figure 12. LNG Rundown Temperature Prediction

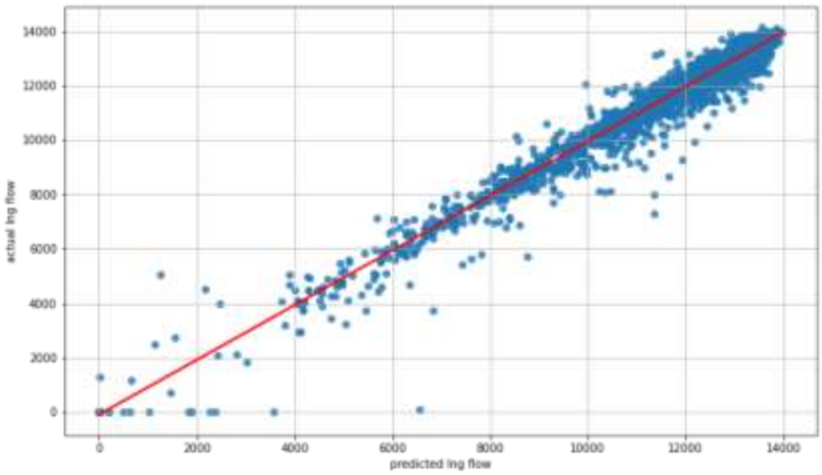


Figure 13. Final Visualization of Algorithm performance (actual LNG flow)

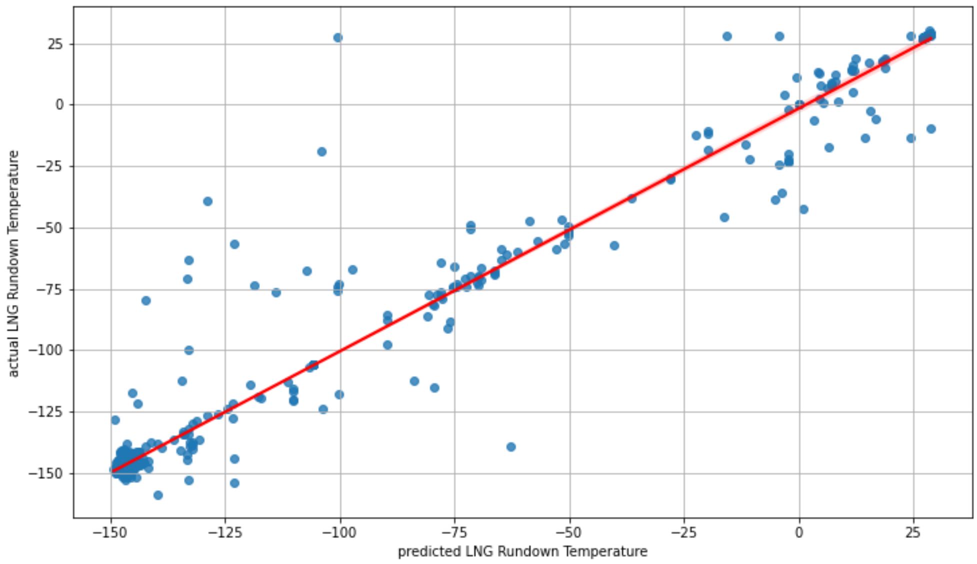


Figure 14. Final Visualization of Algorithm performance (LNG rundown temperature)

Table 5.. Improved prediction after hyper parameter tuning.

| **Data Row No** | **Predicted LNG Flow** | **Predicted LNG Rundown Temperature** |
|---|---|---|
| **0** | 13509.923222 | -145.550721 |
| **1** | 12170.430456 | -145.727184 |
| **2** | 13404.951410 | -145.707795 |
| **3** | 12735.611069 | -145.785677 |
| **4** | 11952.358026 | -146.056697 |

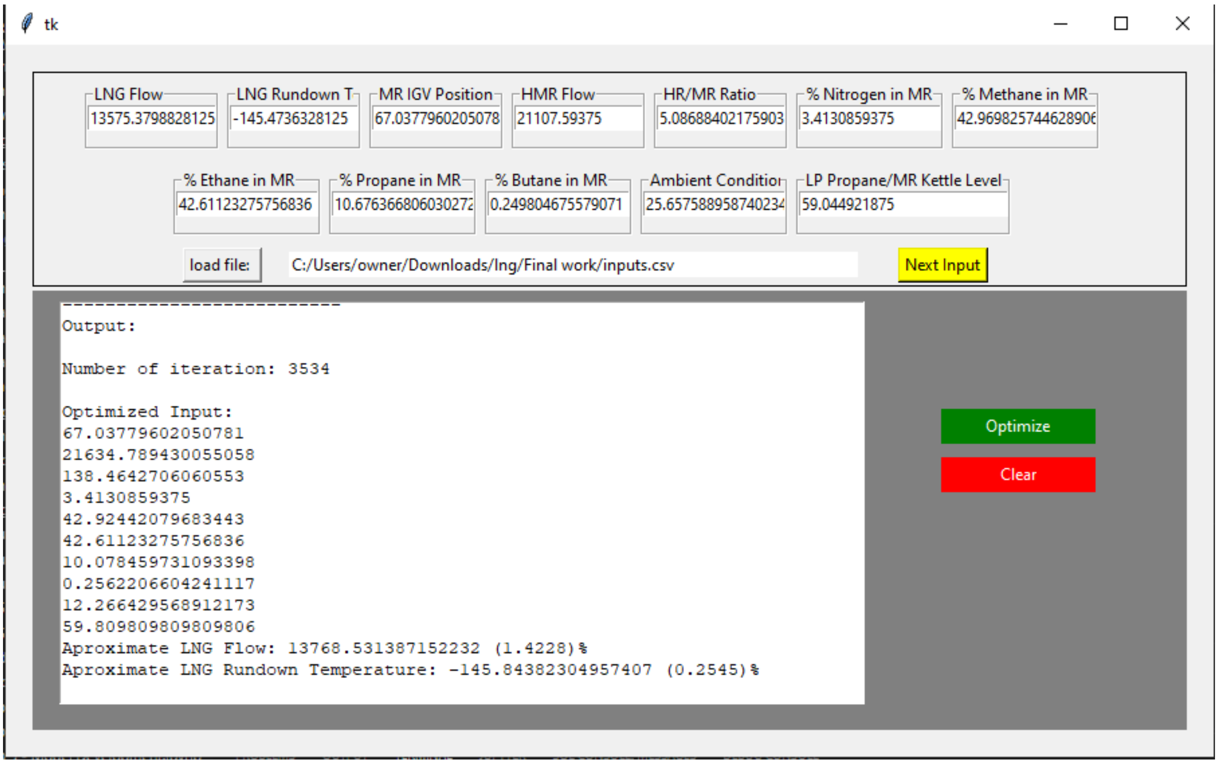


Figure 15. GUI run test 1

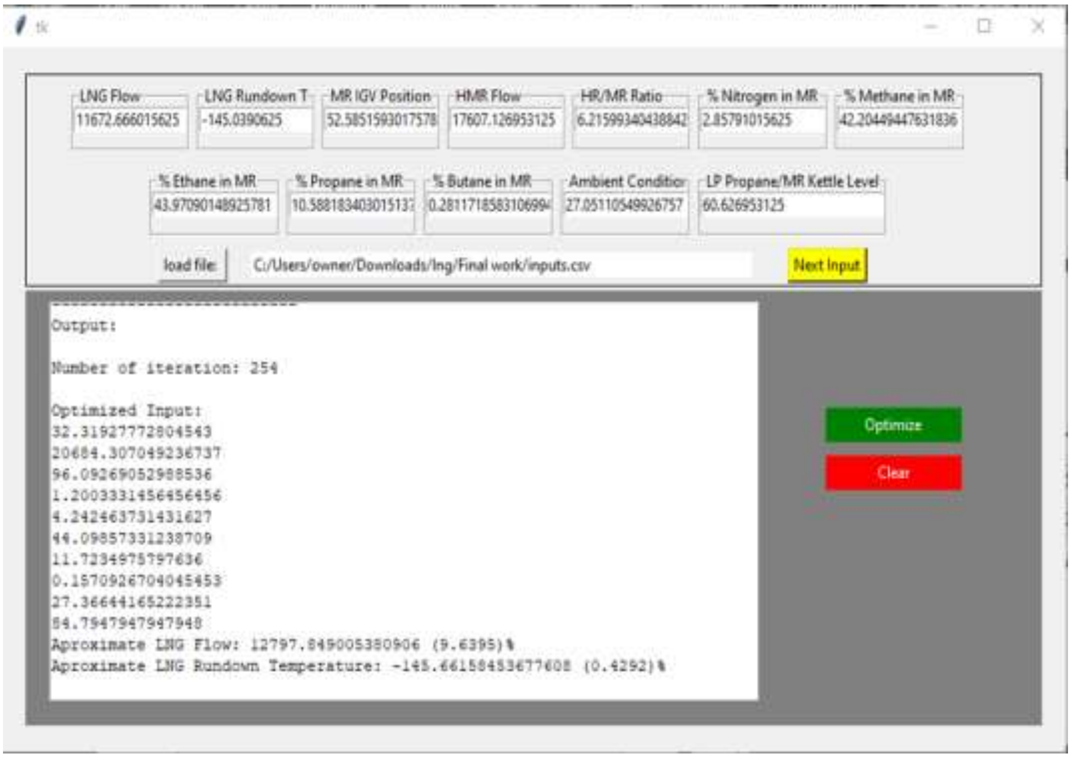


Figure 16. GUI run test 2

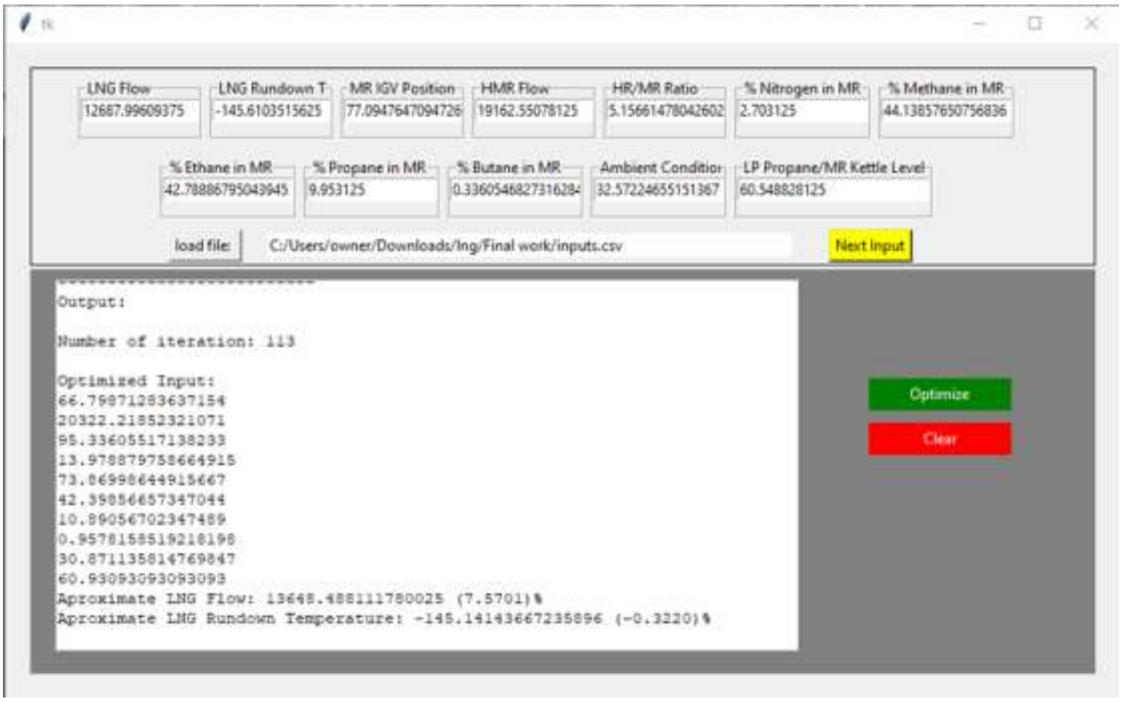


Figure 17. GUI run test 3


Figure 18. relationship between predicted and actual LNG flow

**Table 6. Improved prediction for hyperparameter tuning**.

| Actual LNG Flow | Predicted LNG Flow | Error |
|---|---|---|
| **13575.3799** | 13509.9223 | 65.458 |
| **11672.66** | 12170.4305 | 497.7645 |
| **13388.1553** | 13404.9514 | 16.7961 |
| **12687.9961** | 12735.6111 | 47.615 |
| **11994.082** | 11952.358 | 41.724 |
| **Actual Rundown Temperature (ºC)** | **Predicted Rundown Temperature (ºC)** | **Error** |
| **-145.4736** | -145.5507 | 0.07061 |
| **-145.0391** | -145.7272 | 0.6881 |
| **-145.7861** | -145.7077 | 0.0784 |
| **-145.6104** | -145.7856 | 0.1752 |
| **-145.5029** | -146.0567 | 0.5538 |

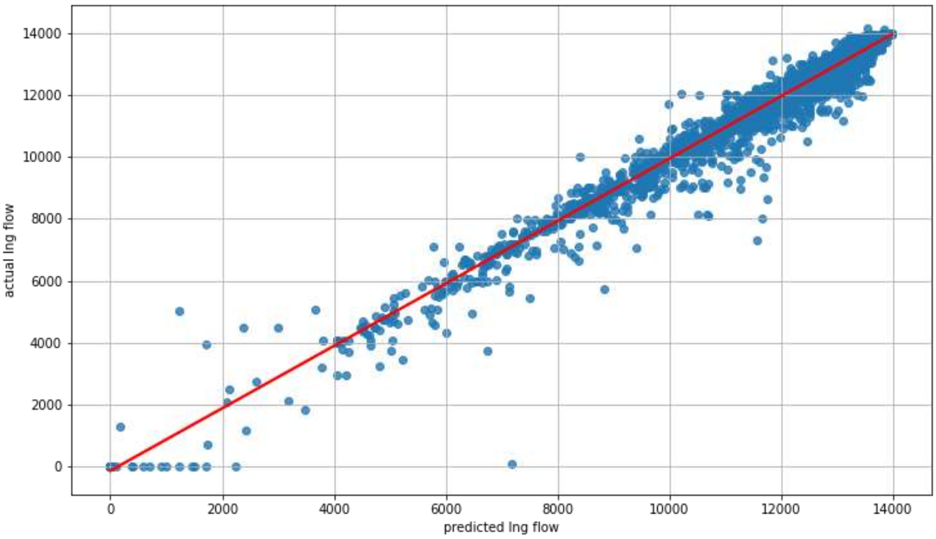


Figure 18. Visualization of Algorithm performance (based on LNG flow)

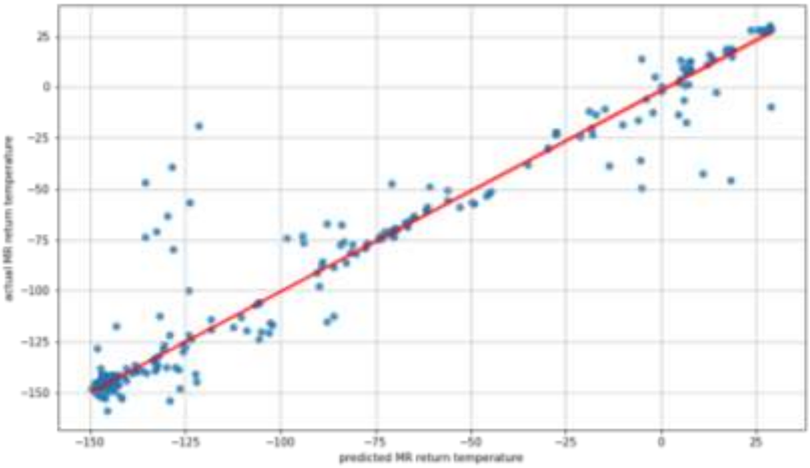

Figure 15. Visualization of Algorithm performance (based MR return and predicted temperature)

### *3.2 Discussion*

To interpret the algorithm results, we compare the errors (R2 error and Root Mean Square Error (RMSE)). A good prediction should have a high R2_score (range between 0 to 1) and a low RMSE. The RMSE has to be as low as possible. The lower the RMSE, the more accurate the prediction. The goal here is to determine which of the algorithms will give the best R2_score and RMSE. The algorithms were trained with the train dataset command that was selected by intuition to learn how to predict LNG production (uni-output regressor). It was deduced that all the different algorithms' predictions had very good R2 scores. The K-neighbours algorithm gave the best regressor, with an R2 score of 0.9853, followed by the decision tree, whose R2 score was 0.9748, and the linear regressor, whose score was 0.9411. Although still a very good score, Random Forest had the lowest R2 score of 0.8981 amongst the other algorithms. Observing the RMSE metrics, it can also be seen that the K-neighbours had the lowest error in their prediction compared to the others. The RMSE of K-neighbours was 313.8738, and the Decision Tree came closest with an error of 414.4508.

Comparing Figure 12 and Figure 14, we see that the features chosen by intuition serve as the best to train and build the model for predicting LNG production and LNG rundown temperature. From the figures, we chose K-neighbours because it gave the best R2-score and the lowest RMSE. Figure 15 shows the actual part of the output in the test dataset, while Figure 16 shows the predicted output in the test dataset from the K-neighbour regressor model.

Using K-Neighbours, the actual LNG flow and rundown temperatures were compared to what was predicted, and the errors were also calculated. The lowest error (3.6788) was computed when the flow of the LNG was 13388.1553 and the predicted flow was 13391.8341; next to the actual flow of 11994.082 and a predicted flow of 11980.7713; the error computed by the K-neighbours was 13.3107. The corresponding temperatures are (-145.7861 and -145.7012; -145.5029 and -145.9033) while the errors are 0.0849 and 0.4004 See Table 1 above. Figure 17 and Figure 18 show the scatter plot representing the relationship between the actual output and the predicted output of LNG production and LNG rundown temperatures, respectively. We observe a sharper, high-positive correlation in Figure 18, which explains that the difference between the actual LNG production and predicted LNG production is close and within an acceptable range.

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### References

Mofid, N. & Fetanat, A. (2019). Liquefied Natural Gas (LNG) as a Promising Fuel for Road Transportation in Iran. Energy Sources, Part B: Economics, Planning, and Policy, 14(5), 331-337.

Salehi, A. (2018). Liquefied natural gas: A review on development and environmental impacts. Renewable and Sustainable Energy Reviews, 81, 2088-2109.

Wang, X. (2017). The prospects for natural gas as a transport fuel in China. Energy Policy, 107, 640-647.

BP. (2017). BP Energy Outlook 2017. Retrieved from https://www.bp.com/content/dam/bp/en/corporate/pdf/energy-economics/energy-outlook/bp-energy-outlook-2017.pdf

Jackson, E., Eiksund, G., & Brodal, H. (2017). Liquefied natural gas in Norway: A study of the potential for developing a new export industry. International Journal of Energy Economics and Policy, 7(6), 117-127.

Sang, Y., Jia, Y., Ma, X., Zhang, X., Cai, Z., & Li, Y. (2020). Optimization of a liquefied natural gas supply chain with carbon capture and storage using mixed-integer linear programming. Journal of Cleaner Production, 252, 119855.

Lee, J., Kim, Y., Lee, J., & Lee, C. (2020). A study on the economic feasibility of small-scale liquefied natural gas plants in Korea. Energy Policy, 138, 111234.

Khalilpour, R., & Karima, B. (2009). Natural gas liquefaction technologies: A brief review. Journal of Natural Gas Chemistry, 18(4), 443-452.

Shukri, M. N. (2004). The use of mixed-refrigerant processes for natural gas liquefaction: A review. Applied Thermal Engineering, 24(18), 2757-2775.

Bahadori, A., Vuthaluru, H., & Ghalami, M. (2014). LNG production using propane pre-cooled mixed refrigerant process. Journal of Natural Gas Science and Engineering, 21, 1130-1143.