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Optimisation of liquefied natural gas production: genetic algorithm and custom-developed method

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Abstract

This study comprehensively analyses various optimisation techniques applied to Liquefied Natural Gas (LNG) production. Two datasets were used to assess the performance of these techniques, with a focus on improving LNG output. The results revealed that the genetic algorithm exhibited the highest average percentage improvement in the first dataset, achieving a 12% optimisation, followed closely by a custom-developed optimisation method at 11%. Bayesian optimisation showed an average of 4%, while gradient descent demonstrated the lowest optimisation with -2%. Notably, the second dataset displayed even more significant improvements, with the custom optimisation algorithm leading at an average of 32%, surpassing the genetic optimization method's 30%. This study underscores the efficacy of the custom algorithm and its potential for enhancing LNG production, positioning it as a promising alternative to traditional optimisation approaches.

Keywords: LNG Production; Optimisation Techniques; Custom Algorithm; Genetic Algorithm and Bayesian Optimisation

1. Introduction

The world is already making the switch to natural gas as a cheaper and cleaner energy source. It is mostly replacing coal as the most eco-friendly choice because it produces fewer carbon emissions (Mofid & Fetanat, 2019; Salehi, 2018; Wang, 2017). The amount of natural gas used is expected to rise by a large 40% between 2014 and 2040. (BP, 2017). Jackson, Eiksund, and Brodal's study from 2017 found that natural gas-powered plants made up 37% of fossil fuel energy in 2030, up from 30% in 2013.

Because it burns cleaner and releases fewer greenhouse gases, liquefied natural gas (LNG) is quickly becoming the world's main energy source. This trend has sped up since the recent energy crisis (Sang et al., 2020). Pipelines or liquefaction are the main ways that natural gas is moved. Energy companies often use liquefying natural gas for long-distance transport because pipeline restrictions, fixed transit routes, and long-term contracts make it hard to get pipeline gas (Lee et al., 2020).

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Gases are liquefied, which turns them into liquids. LNG is made by cooling natural gas to -162 degrees Celsius at room temperature and pressure. Natural gas is much easier to transport when it is liquefied because it takes up only one-six hundredth as much space as when it is gaseous (Khalilpour & Karima, 2009).

To get these very low temperatures, you need refrigerants, and the way they heat up and cool down must be very similar to natural gas. Refrigerants, which are often found in air conditioning and refrigeration systems, are very important for keeping LNG at the low temperatures it needs to be stored and transported.

Because of this, how well this refrigeration process works is very important, since a bad system can cause less production. The industry needs refrigerants that are good for the environment and use little energy. As time has gone on, different types and methods of refrigerants have been used to make LNG. These include the turbo-expander process, the cascade process, and single/dual mixed refrigerant (SMR/DMR) technology. The main differences between these methods are their start-up and running costs, which depend on things like how much they can produce, how much equipment they need, and how much labour costs.

Mixed-refrigerant (MR) processes, on the other hand, make design and operation more difficult because there are more thermodynamic interactions. This makes it harder to manage and improve the process (Shukri, 2004). Which refrigerant to use depends on things like the temperature range you want, how easy it is to get, how much it costs, and what you know from past experience. For example, an olefins factory might have ethylene and propylene on hand, while a natural gas processing plant might have ethane and propane on hand. To keep things clean, it's important to use the right refrigerant. Halocarbons are often preferred because they don't catch fire.

The Propane Precooled Mixed Refrigerant (C3MR) system is a common way to cool things down these days. This method uses a propane refrigeration system to cool LNG to -35°C before it goes into a mixed refrigeration system that has methane, ethane, propane, and nitrogen (Bahadori et al., 2014).

2. Material and methods

To optimise the liquefied natural gas production of an industry, an artificial intelligence (AI) program was used. Specifically, the python programming language was the optimum and readily available software to be used.

This study collected data comprising the LNG production, refrigerants, temperature, and pressure of the refrigeration processes. These data were processed in the software using four regression analysis models.

2.1. Material

The material used in this research include: An artificial intelligent (Python programming language) software, PI Processbook software 2015 version 3.6.2.271, PI datalinks, Visual studio (VS) code editor and Microsoft Excel 365. Python is an interpreted, high-level programming language that may be used for various projects. The principle behind its design prioritizes the readability of the code by heavily indenting it. The PI processbook 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.

2.2. Process Optimisation Description

Figure 1 shows the sequential order or steps used to achieve the aim and objectives of this research. It depicts the schematic breakdown of the optimisation process using the artificial intelligence data driven approach.

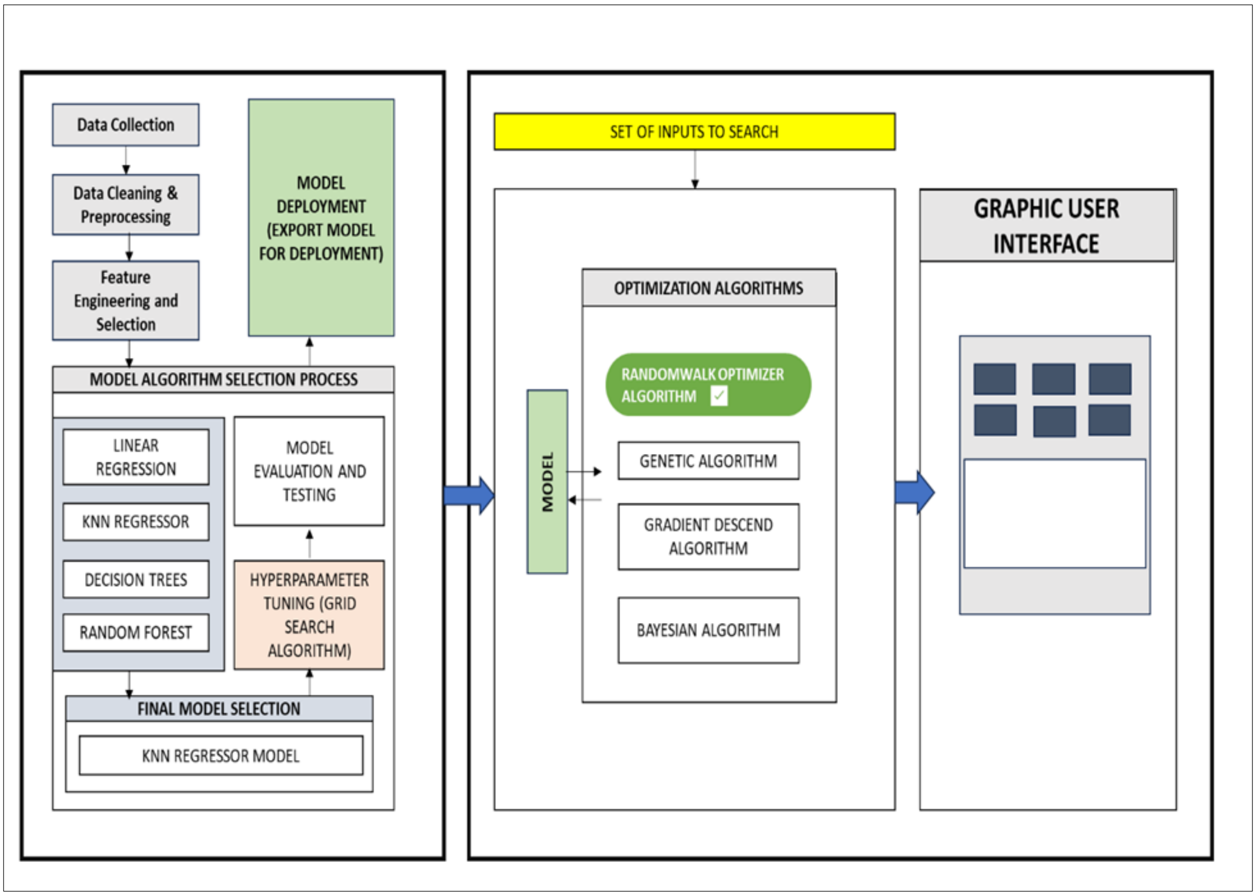

Figure 1 Process description of Artificial Intelligence optimisation

2.3. 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 has the capability to 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 2. The PI datalink is a Microsoft Excel add-in feature linked to the PI software. The sample data multiple value function of the PI datalink was used to retrieve about 10 years liquefaction unit data set at an hourly interval.

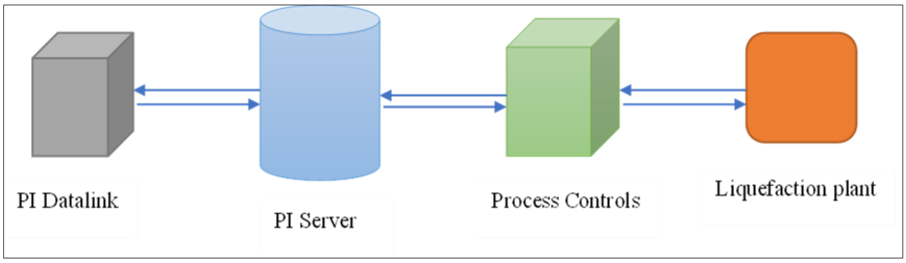

Figure 2 PI System data Collection scheme

2.4. Optimisation Algorithms Tested

Three optimisation algorithms were used in the process and these are'

- Bayesian Optimisation
- Genetic optimisation
- Gradient Descent Optimisation

3. Result

3.1. First Dataset

Table 1 Average Percentage Increase on First 20 observations in the First Sample set

No	Initial	Custom	Gradient	Bayesian	Genetic
1	13575.38	13690.92672	12408.69984	13286.58859	13640.8994
2	11672.666	13878.96094	11414.97127	12046.54229	13595.3128
3	13388.155	13570.98471	12327.32382	13126.86519	13621.9232
4	12687.996	13326.51261	12258.71911	12031.73332	13593.8581
5	11994.082	13291.19481	12795.36119	13483.87126	13492.2626
6	12854.625	13578.56662	12418.47643	13092.26836	13636.4246
7	13238.532	13708.82436	13029.82239	12112.42656	13482.9398
8	9791.7119	12724.55071	10764.20079	12132.75837	13580.4337
9	13011.92	13560.2891	12695.11191	11937.67382	13582.5959
10	12745.037	13689.32319	11510.46207	12127.82168	13631.7646
11	10310.596	13260.75199	10816.96873	13063.15677	13609.6981
12	12422.842	13733.09121	11013.41439	13298.60512	13366.8523
13	8127.2803	12672.0695	8298.333296	13503.3147	13630.3422
14	12024.938	12514.84944	11989.99156	13515.43054	13608.465
15	12265.893	13618.32549	12089.75725	12058.69319	13595.4567
16	12296.931	13508.91553	13108.9153	13402.33799	13595.3373
17	12576.334	13348.72273	11665.48343	12129.38427	13595.3116
18	12305.014	13529.32789	12516.85648	11999.2301	13565.2765
19	12714.961	13361.63746	12431.58694	11931.28539	13372.6477
Average Percentage Increase		**11%**	**-2%**	**4%**	**12%**

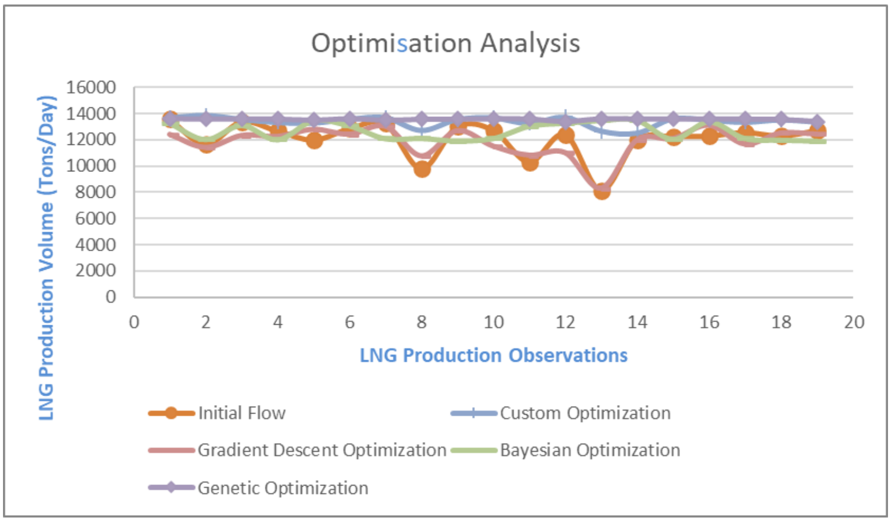

Figure 3 Overall Optimisation Result on First Dataset

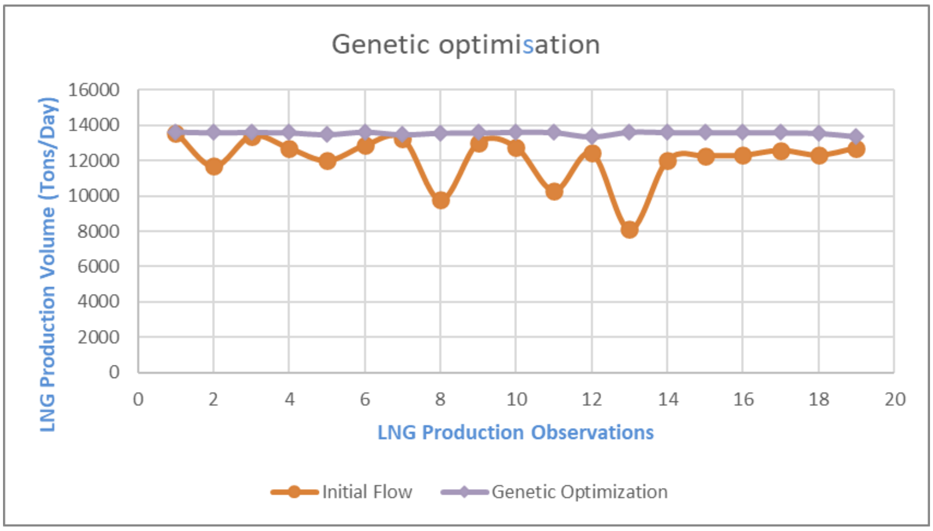

Figure 4 Genetic Optimisation result on First Dataset

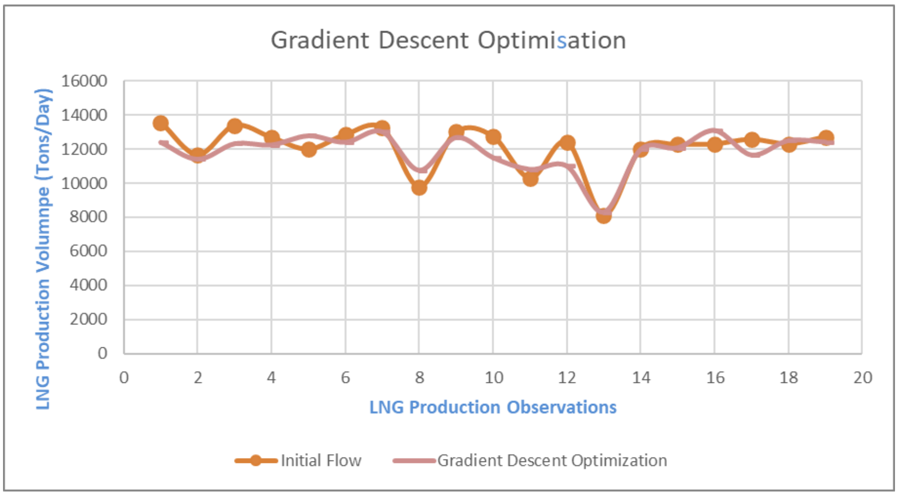

Figure 5 Gradient Descent Optimisation result on First dataset

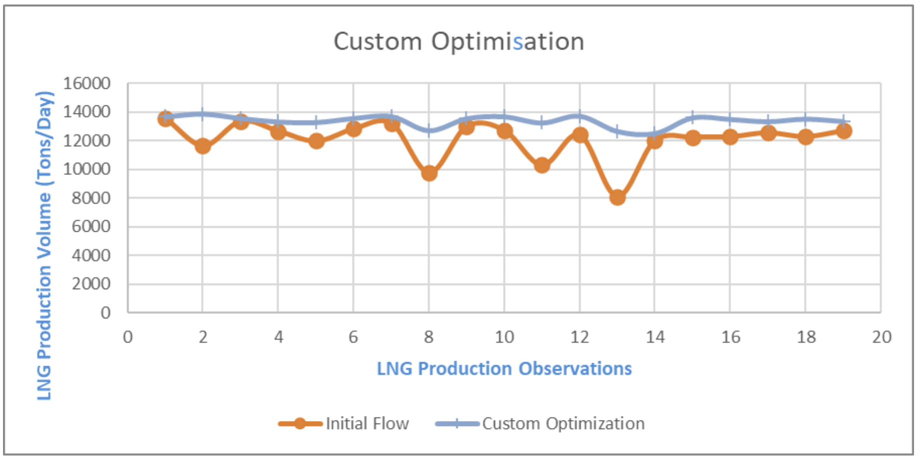

Figure 6 Custom Optimisation result on First dataset

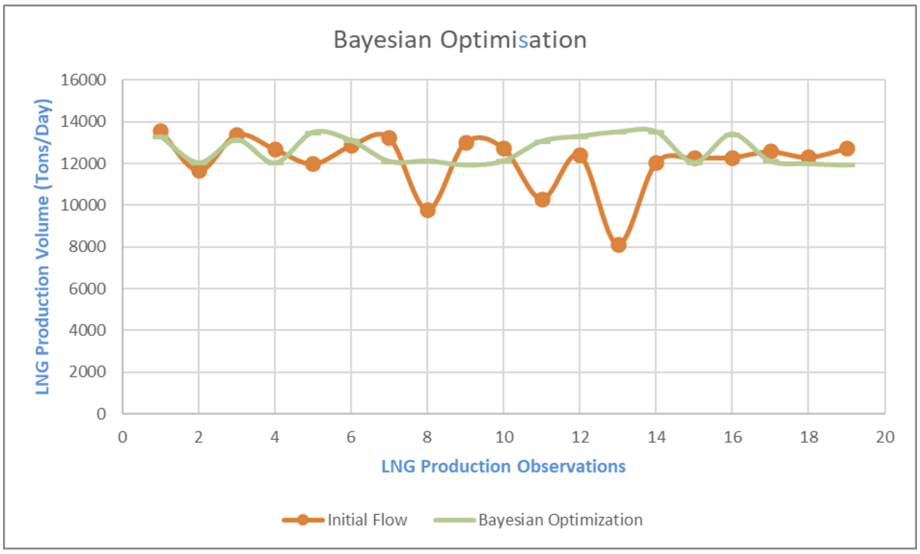

Figure 7 Bayesian Optimisation result on First dataset

3.2. Second Dataset

Table 2 The Average Percentage Increase on the First 20 observations in the second Sample set

No	Initial	Custom	Gradient	Bayesian	Genetic
1	9469.942	12500.27655	9605.8074	11903.22683	11909.47272
2	9507.516	12767.79539	7.738E-05	11929.14465	12578.28478
3	9519.393	12575.07081	9791.5131	12049.67537	11778.76945
4	9497.821	12681.60965	9839.8082	11928.7085	12293.87974
5	9516.682	12459.98689	8688.4875	11362.76731	12358.01606
6	9522.152	12650.87519	8781.4379	11956.23706	13190.72628
7	9525.817	12288.37789	9839.0206	11928.46048	12645.4177
8	9526.972	12252.29457	8781.6409	11573.72382	13010.37597
9	9493.407	12553.85172	10040.611	11957.85412	12208.0415
10	9448.166	11899.0564	5020.9062	11939.44838	11568.7573
11	9450.67	12907.64916	9797.7888	11929.24294	12172.05655
12	9362.8	12390.50338	10241.193	11860.93731	11754.67057
13	9332.197	11706.353	10583.188	11928.70445	12465.95528
14	9320.287	12316.978	9877.7832	11826.7475	12076.78333
15	9300.343	12799.35098	7626.7525	11366.09037	11358.94368
16	9303.986	12758.33018	11176.033	11957.7574	12233.65892
17	9312.156	11910.23625	4325.2674	12049.44558	11584.85472
18	9332.209	12465.95529	11992.965	11928.55336	12463.47605
19	9346.166	12490.48372	9472.0143	11368.1586	12208.13999
20	9389.598	12472.47473	9472.1984	11928.96994	12463.37431
Average Percentage Increase		**32%**	**-7%**	**26%**	**30%**

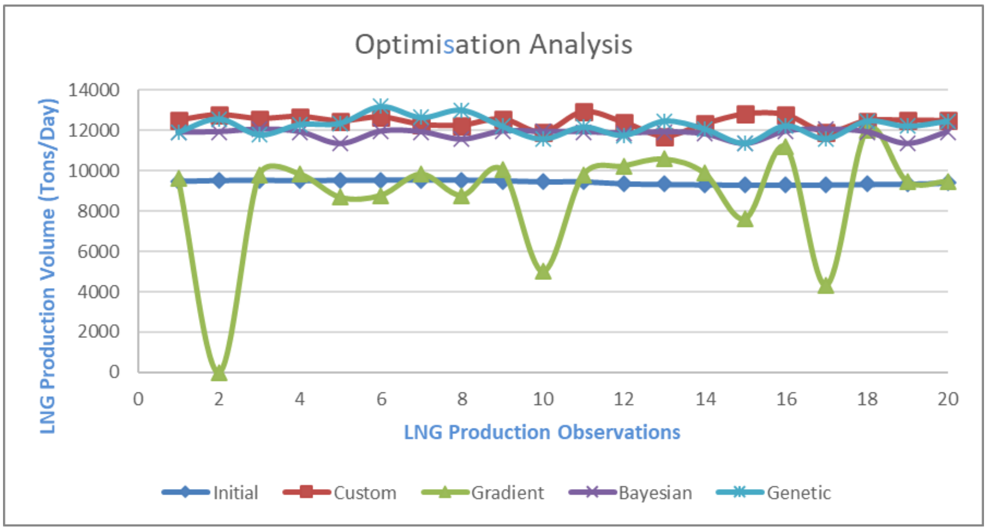

Figure 8 Overall Optimisation result on Second dataset

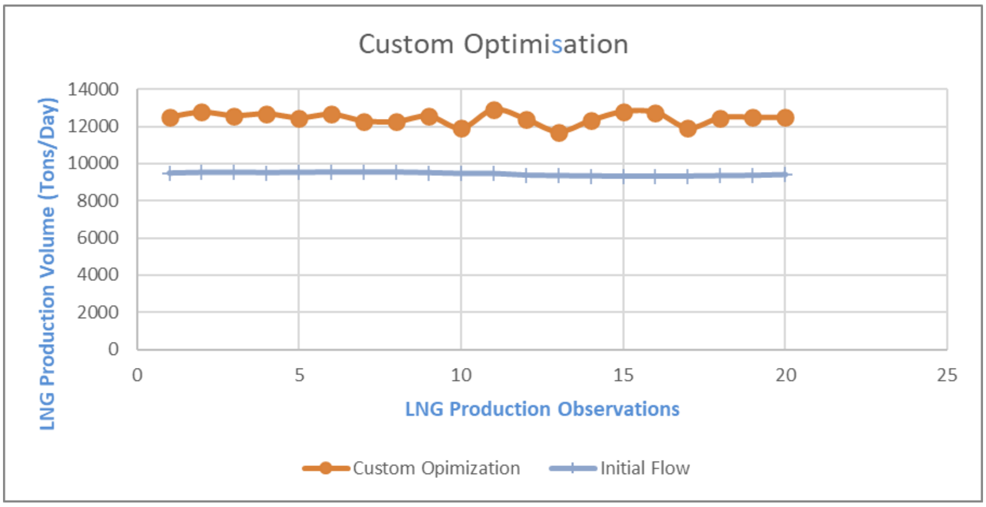

Figure 9 Custom Optimisation result on Second dataset

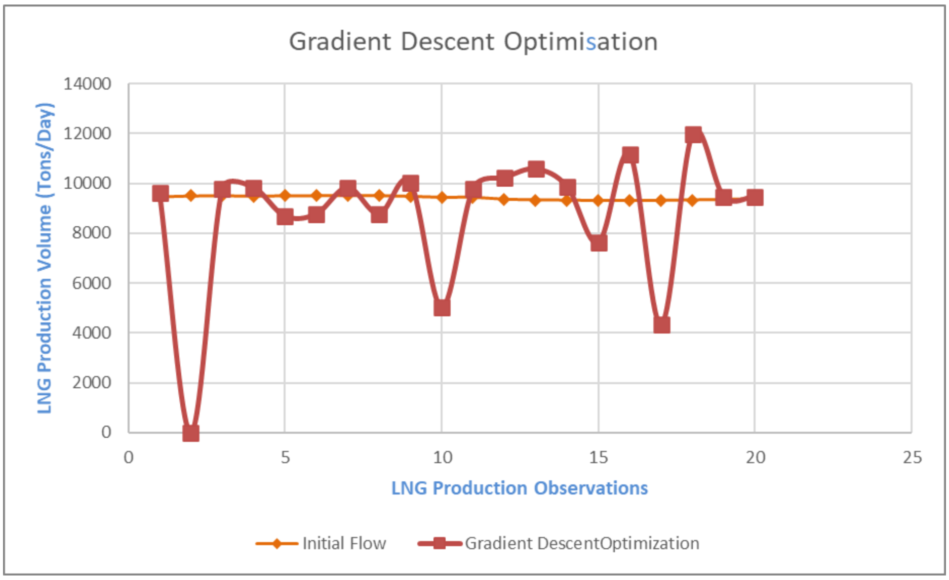

Figure 10 Gradient Descent Optimisation result on Second dataset

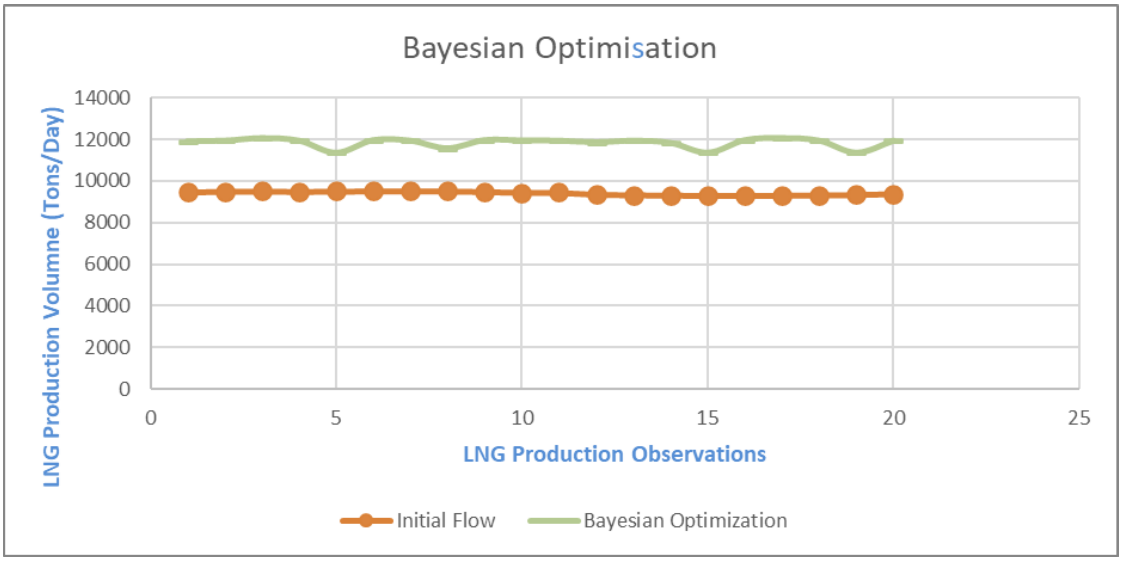

Figure 11 Bayesian Optimisation result on Second dataset

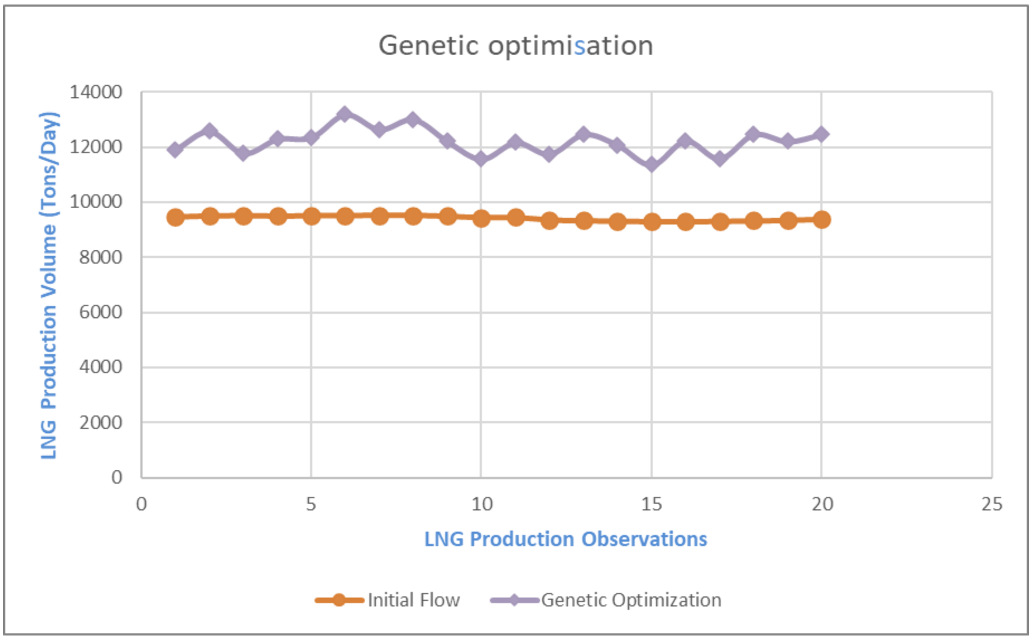

Figure 12 Genetic Optimisation result on Second dataset

4. Discussion of Results

Tables 1 and 2 demonstrate, respectively, the average percentage improvement in the flow of 20 observations from the first and second datasets that each of the various optimisation techniques were able to accomplish. In Table 1, it can be observed that the genetic algorithm had the greatest optimisation, which resulted in a 12 % gain on average, followed by the custom optimisation method (11 %). The Bayesian method produced an average of 4%, while the gradient descent method produced the lowest percentage, which was -2 %. Figures 3 to 12 provide a visual representation of the optimisation findings, respectively. According to Table 2, the average optimisation result achieved by the custom optimisation algorithm was 32 %, which was higher than the average optimisation result achieved by the genetic optimisation method, which was 30 %. Figure 3 to Figure 12 provide a graphical representation of the performance of each optimisation technique, respectively.

5. Conclusion

The Genetic algorithm achieved the best results, with an average improvement of 12 % in optimisation, followed by the custom-developed optimisation method that we produced, which achieved 11 %. The Bayesian method produced an average of 4 %, while the gradient descent method produced the lowest percentage, which was -2 %. We found that our built bespoke optimisation method had the greatest average optimisation result of 32 % for the second validation LNG data set. This was followed by genetic optimisation, which had a result of 30 % for average optimization.

Compliance with ethical standards

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Disclosure of conflict of interest

No conflict of interest to be disclosed.

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