A Straightforward Optimization Approach for a Baseload Propane-Mixed Refrigerant Process

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Abstract
As the energy markets adjust to the increasing demand on liquefied natural gas (LNG) and growing global warming concerns, a compelling need arises to operate existing LNG plants as efficiently as possible. Cryogenic systems, such as those used for natural gas (NG) liquefaction, are very complex. This makes optimizing their performance a frustrating task. In this paper, we propose a simple and systematic optimization approach for cryogenic processes characterized by large numbers of independent variables and sophisticated heat integration schemes. The method is composed of successive optimization levels that rely on shortcut thermodynamic techniques and sequential quadratic programming (SQP). In this paper, we are reporting the results of the proposed approach for optimizing an actual baseload propane mixed refrigerant (C3MR) process. Results showed a 6 % compression power reduction compared to the plant’s current consumed power. The method is currently being tested for a more sophisticated LNG system employing C3MR cycles integrated with natural gas liquids (NGL) recovery, helium extraction, and nitrogen rejection processes.

Keywords: Natural gas liquefaction, C3MR LNG plant, Optimization, Aspen Plus™, Simulation

1. Introduction
Liquefied natural gas (LNG) plants are associated with large energy penalties, mainly compression power, that are costly and result in significant amounts of greenhouse gas emissions (Almeida-Trasvina and Smith, 2019). However, compared to other fossil fuels, LNG has gained popularity due to its abundance and high energy content per mole carbon (Bittante et al., 2015). As of November 2019, global nominal and proposed liquefaction capacity reached 393 and 843 million tonnes per year (tpy), respectively (IGU, 2019). A significant portion of the forecasted capacity is expected to be from Qatar’s North Field Expansion (Energy Insights by McKinsey, 2019). Qatar’s plans of increasing its production by 64 % in the 2020s solidifies its position as the global leader in terms of capacity and exports (John, 2019). Increased LNG demand and stringent environmental regulations place utmost importance on energy efficiency optimization. In addition to potentially higher production volumes and profit, LNG process optimization can reduce CO₂ emissions, thereby assisting with the global dual challenge of producing more energy with less carbon (BP, 2019).

Figure 1 illustrates the block flow diagram of a typical LNG plant. After the removal of condensate, carbon dioxide, and sulfur-containing compounds (H₂S, mercaptans, etc.), the NG is routed to the dehydration unit prior to entering the cold section. First, heavier hydrocarbons (NGLs) are removed from the NG, after which the gas gets liquefied and sent to the helium extraction and nitrogen removal units to produce in-spec LNG ready
to be stored and shipped to the consumers. Within the LNG processing plant, our LNG supply chain model showed that over 55% of CO$_2$ emissions originate from the cold section (Katebah et al., 20XX). Furthermore, our chain exergy analysis indicated that within the cold section ~91% of the losses occur in the propane pre-cooled mixed refrigerant (C3MR) liquefaction cycles and natural gas liquids (NGL) recovery unit (Bouabidi et al., 20XX). Therefore, this paper focuses on the energy efficiency optimization of an actual C3MR process in Qatar, the world’s largest LNG capacity holder and exporter. While there are numerous studies in the literature on the optimization of LNG liquefaction cycles, most of them require linking standard simulators to sophisticated solvers and/or time intensive coding, resulting in complex and time-consuming calculations and convergence challenges (Austbø et al., 2014). For example, the work of Wang et al. focused on minimizing energy consumption of a C3MR plant by using LINDO Global solver in GAMS to solve the optimization problem. (Wang et al., 2012). Sun et al. utilized GA for the optimization of an AP-X process by reducing the process’s power consumption (Sun et al., 2016). Aspelund et al. used a gradient free optimization-simulation method for a LNG process modeled using Aspen HYSYS®. Their approach was based on a Tabu Search and Nelder-Mead Downhill Simplex method (Aspelund et al., 2010). Almeida-Trasvina and Smith optimized a novel cascade refrigeration cycle and other commercial cycles by applying a stochastic search optimization (GA) routine and the best solution was used as an initial point for deterministic optimization (SQP) (Almeida-Trasvina and Smith, 2018). In this work, we are proposing a simpler optimization approach that relies on system decomposition and thermodynamic considerations to simplify such optimization problems without compromising solution quality. In addition to reducing computational times and easing convergence, the simplicity of this approach caters to both experienced and inexperienced standard simulators users such as process engineers and students. Moreover, the methodology can result in meaningful process insights that are otherwise unseen in conventional approaches.

2. Methodology

Instead of optimizing the entire linked model at once, we suggest dividing the system into subcomponents for subsequent optimization in a step-wise approach, while using simplified black-box exergy models to predict the performance of the surrounding units. We also recommend shortlisting adjustable operating variables by conducting a degree of freedom (DOF) analysis. Furthermore, process constraints (such as design limits, products specification, etc.) need to be identified based on insights and discussions with plant operators. Variables and constraints that should be maintained at their limits (referred in this article as active variables and constraints, respectively) for enhanced performance should also be identified. In addition to prediction using exergy techniques, the method capitalizes on pairing designated variables with constraints that should be maintained active, thereby reducing the number of optimization variables and search space, and easing flowsheet convergence. We are currently validating methods, such as parametric analysis, that can be integrated with the proposed approach for validation and/or enhancing solution quality.
3. Process Description and Simulation

Figure 2 depicts a process flow diagram of the process at hand. We utilized actual plant data and AspenPlus™ software to build and validate a base-case model for the liquefaction section of a LNG plant with a 3.65 million tpy capacity. Sweet, dry, pre-treated NG enters the cold section of the LNG plant, where it gets pre-cooled by the C3 cycle from 21 to -27 °C. NG is then throttled to 54.9 bar before entering the NGL recovery unit. GERG-2008 equation of state was used to model the NGL recovery as it was best suited to match model results with plant data. The process is essentially a distillation column (C-1) that uses part of the main cryogenic heat exchanger (MCHE, E-1) as the condenser. The liquid portion leaving the condenser at -54ºC, re-enters the column as reflux, whereas the gas is routed to the MCHE for liquefaction and subcooling. This unit also produced approximately 9.9 KSbbl/day (at 15.6 °C and 1.01 bar) of extracted NGLs to be sent to the fractionation unit for further processing. The C3MR process comprises of two refrigeration cycles: a mixed refrigerant (MR) and C3 cycle. Peng-Robinson equation of state was used to simulate the cycles. C3 cycle pre-cools the NG and MR to about -31 °C with four C3 evaporation pressures: high high pressure (HHP) at 7.8 bar, high pressure (HP) at 5.1 bar, medium pressure (MP) at 2.9 bar, and low pressure (LP) at 1.6 bar. Other streams cooled in the cycle include streams in the fractionation unit such as de-ethanizer overhead and liquefied petroleum gas (LPG). The evaporated C3’s enter a 3-stage compressor (K-1) and gets compressed to 16.7 bar for subsequent condensation using sea water available at 33°C. At base-case conditions, the C3 cycle required ~ 44.3 MW of compression power. MR comprising of 2.1 % nitrogen (N₂), 43.8 % methane (C1), 40 % ethane (C2), and 13.8 % C3 passes through another 3-stage compressor (K-2), sea water intercooler, and pre-cooling exchangers in sequence. After reducing its temperature and pressure to -154 °C and 3.1 bar, respectively, the MR, in addition to a cold fuel gas stream from the helium extraction and nitrogen removal units, provide the cooling duty of the MCHE. LNG leaving the MCHE was subcooled to -144 °C. The MR cycle required ~78.6 MW of compression energy. In total, the entire cycle necessitated 123 MW of compression power. When comparing simulation results with plant data, minimal discrepancy was observed.
4. C3MR Optimization

For the C3MR process shown in Figure 1, the optimization approach consisted of two successive steps: first the MR cycle was rigorously optimized while predicting C3 cycle compression power. Next, the C3 cycle power was rigorously optimized at optimum MR cycle variables. DOF analysis showed that the process under consideration has 57 adjustable variables. After fixing active variables and devoting certain operating variables to maintain product specifications and active constraints (via for loop routines), variables available for optimization were reduced to 20. After further simplification, the adjustable variables decreased to 8.

4.1. MR Cycle

Optimization of the MR cycle was performed while modeling the C3 cycle as a black-box. The C3 cycle’s power was predicted using exergy balances and C3 cycle base case efficiency, see Eq. (1) and Eq. (2). At base case conditions, the C3 cycle’s efficiency was calculated to be 22%. The cycle’s main constraints are the MCHE minimum temperature approach (MTA), NGL recovery/purities, and final LNG temperature. Pairing them with appropriate variables reduced the optimization variables from 57 to 13. Literature shows that the MR composition is one of the primary parameters in the cycle’s optimization (Abdullah Alabdulkarema, Amir Mortazavi, 2011). Therefore, to simplify the problem, the effect of varying the composition (flowrates) was investigated while maintaining remaining adjustable variables at base values. Relative to the base-case, optimum MR composition was found to be 1.4, 39, 36.9 and 22.6 mol% N₂, C1, C2, and C3, respectively at a total MR and predicted C3 power of 105.5 MW (MR and C3 power of 87 and 18.5 MW, respectively). The system favored increasing the cooling load on the
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MR, while decreasing the C3 load relative to the base case. This can be explained by the cycles’ efficiencies, as the MR cycle (base-case efficiency of 37%) is almost twice as efficient as the C3 one. Since this method aims towards obtaining predictive independent variables values rather than actual power values, a final step of optimizing the C3 cycle at optimum MR was necessary to obtain actual powers that are operationally feasible.

\[ W_{\text{C3,min}} = E_{\text{NG,in}} + E_{\text{MR,in}} - E_{\text{NG,out}} - E_{\text{MR,out}} \]  

(1)

\[ W_{\text{C3,predicted}} = \frac{W_{\text{C3,min}}}{\mu_{\text{C3}}} \]  

(2)

Where:

- \( W_{\text{C3,min}} \) and \( W_{\text{C3,predicted}} \) are the C3 cycle’s minimum and predicted power, respectively.
- \( E_{\text{NG,in}} \) and \( E_{\text{NG,out}} \) are the exergy rates of the NG streams entering and leaving the C3 cycle, respectively.
- \( E_{\text{MR,in}} \) and \( E_{\text{MR,out}} \) are the exergy rates of the MR streams entering and leaving the C3 cycle, respectively.
- \( \mu_{\text{C3}} \) is the C3 cycle efficiency at base-case conditions (22%).

4.2. C3 Cycle

In this final step, rigorous C3 cycle optimization was performed at optimum MR variables. C3 flowrates/ split fractions to evaporators and HHP/LP evaporation pressures were devoted towards maintaining base-case MTAs for all the chillers, in addition to propane degrees of superheat at the chillers’ outlets. C3 was allowed to be slightly superheated to prevent the formation of liquid at the compressor suction. After variable pairing, the system was left with 2 adjustable variables available for optimization: HP and MP C3 evaporation pressures. Results showed that a C3 power of 28.5 MW was achievable at optimum operating variables. This gave a total actual C3MR power of 115.5 MW.

5. Conclusion

A simple and systematic method is proposed and tested for optimizing an actual C3MR liquefaction process. A base-case model was simulated using Aspen Plus™ software, and results were validated with plant data with minimal discrepancy. Detailed DOF analyses pinpointed the variables available and effective for optimization. Each unit was rigorously optimized while predicting the performance of its interlinked sections via an exergy model. Results showed that near 7 MW reduction of compression power can be achieved, which amounted to 6 % of current requirements. Advantages of this method compared to other approaches include its simplicity, lower computational time, and ability to produce trends/insights. This approach is viable and can be extended to other highly integrated chemical processes. Currently we are testing the method for the rigorous optimization of a fully integrated system comprising of NGL recovery and helium/nitrogen extraction. Techniques to improve the quality of the solution are also under investigation and we expect to publish them soon.
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