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Development of a robust refrigerant mixture for liquefaction of highly uncertain natural gas compositions

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ABSTRACT

To export natural gas to overseas, it has to be liquefied and transported by the LNG tankers. Some LNG plants will receive their natural gas from different shale gas reservoirs so that one of the key challenges in developing a refrigerant mixture is the variation the of natural gas compositions. Previous attempts to create refrigerant mixtures for LNG plants were focused on implementing deterministic optimization methods. However, we demonstrate in this paper that these optimized refrigerants are so sensitive to natural gas composition that a slight variation in natural gas composition makes them unsuitable for the liquefaction process. To demonstrate the Gradient Assisted Robust Optimization technique capabilities, we developed a refrigerant mixture for propane precooled mixed refrigerant natural gas liquefaction cycles with an exaggerated variation in feed gas composition. This refrigerant is relatively unaffected by the variation of the natural gas compositions. We compared the performance of the new refrigerant to five other refrigerants found in literature and found the newly developed refrigerant is the only one satisfying the design constraints for all of the tested natural gas mixture compositions. This technique can be used for developing refrigerant for any LNG cycle that has a variation in feed composition.

1. Introduction

Natural gas (NG) is primarily transported either through pipelines in a gaseous phase, or liquefied and shipped in Liquefied Natural Gas (LNG) tankers. With the expansion in American shale gas production, the price of natural gas has declined significantly in the US. This situation has created an opportunity to export US natural gas to Asia and Europe. In order to ship the natural gas to the Asian and European markets, it must be liquefied and shipped by LNG tankers, as it is not cost-effective to transport natural gas for long distances via pipeline (Foss [1]).

LNG plants are ideally located near coast to minimize the distance between the liquefaction plant and LNG tanker ship loading terminals. The natural gas from the shale gas reservoirs can be transported to the LNG plants via pipelines. Ambient temperature variation affects the demand of natural gas in a specific region, which may also influence the amount of gas transported from each shale gas reservoir to the LNG plants. Due to the fact that the composition of the gas may vary among shale gas reservoirs, variation of the shell gas reservoirs output to an LNG plant may vary the feed gas formation of that plant.

There are several uncertainties involved in the design of an LNG plant that receives its natural gas feed from multiple shale gas basins. For convenience, in this paper we will refer to this type of LNG plant as a "multi-source LNG plant". One of the main uncertainties is the natural gas composition, because each field has a specific natural gas compositions. Therefore it needs a precise refrigerant composition that matches the liquefaction cooling curve (i.e., matches the boiling temperature and liquefaction load). In fact, the refrigerant mixtures used in the LNG plants are fed from a single reservoir that is optimized for a given natural gas compositions. Otherwise, a multi-source LNG plant is supposed to handle several natural gas compositions. For this reason a multi-source LNG plant should be unaffected by the natural gas composition of the gas field.

Another case where the natural gas composition varies is when Enhanced Gas Recovery (EGR) is applied. The natural gas composition may vary with recovery and injection. Therefore, one of the primary challenges is the development of a refrigerant mixture that is both insensitive to the natural gas compositions and leads to a minimum amount of energy consumed per unit mass of LNG produced. One method to develop this refrigerant mixture is by implementing optimization techniques. However, conventional

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Nomenclature

Acronyms

APCI	Air Products and Chemicals Inc.
C	Constraint
COP	Coefficient of performance
Det	Deterministic
GA	Genetic algorithm
GARO	Gradient Assisted Robust Optimization
LNG	Liquefied natural gas
MCR	Multi-component refrigerant
NG	Natural Gas
P	Parameter
S.t.	Subject to
U	Uncertainty
V	Number of variables

English symbols

dv	Vector of design variables
$\mathbf{g}(\mathbf{z})$	Vector of constraint functions $\mathbf{g} = [g_1(\mathbf{z}), g_2(\mathbf{z}), g_3(\mathbf{z}), \ldots]$
h	Specific Enthalpy (kj/kg)
I	Number of constraints
k	Iteration counter
$\dot{m}$	Mass flow rate (kg/s)
n	Dimension of the $\mathbf{z}$ vector
N_i	Number of moles of component i
NU	Number of uncertain variables and parameters
$\mathbf{p}$	Vector of design parameters $\mathbf{p} = [p_1, p_2, p_3, \ldots]$
$\mathbf{P}$	Pressure (kPa)
P_{comp}	Compressor power consumption (MW)
$Pw_{Liquefaction}$	Liquefaction cycle power demand (MW)
Q	Heat exchanger heat duty (MW)
$\mathbf{x}$	Vector of design variables $\mathbf{x} = [x_1, x_2, x_3, \ldots]$
$\mathbf{z}$	Vector of design variables and parameters, $\mathbf{z} = (\mathbf{x},\mathbf{p})$

Greek symbols

$\Delta\tilde{\mathbf{P}}$	Vector of design parameters' uncertainty range
ΔT_p	Pinch temperature (°C)
$\Delta\tilde{\mathbf{X}}$	Vector of design variables' uncertainty range
$\Delta\tilde{\mathbf{Z}}$	Vector of design variables and parameters uncertainty range
η_{comp}	Compressor isentropic efficiency
ω	Mass fraction

(deterministic) optimization techniques cannot handle problems which involve uncertainty in their design variables or parameters. Robust optimization techniques would be a suitable choice based on the design goal, which is the ability of a multi-source LNG plant to process varying natural gas compositions. The results of robust optimization techniques are both optimal and insensitive to the variation of uncertain design parameters and variables.

The literature is rich with optimization studies that were conducted on a fixed natural gas composition. For example, Alabdulkarem et al. [2] optimized APCI cycle using Matlab Genetic Algorithm (GA) coupled with HYSYS software. The authors also investigated the effect of the cryogenic heat exchanger pinch temperature on the power consumption. Xu et al. [3] optimized a Prico cycle, the simplest LNG mixed-refrigerant liquefaction cycle, with different ambient temperatures using GA and ASPEN Plus software. Their results show that when ambient temperature increases, the concentrations of methane, ethylene and propane decreases (whereas i-pentane should increase).

Lee et al. [4] conducted an optimization study on a Prico cycle using non-linear programming (NLP). Their approach optimized the refrigerant mixture composition of methane, ethane, propane, butane and nitrogen at given pressures and mass flow rates. If there is no temperature cross within the heat exchanger, they propose using a new refrigerant mass flow rate and pressure levels based upon heuristics, judgment, or optimization. Lee et al. [4] also compared three forms of objective function: minimization of the crossover, minimization of the sum of the crossovers, and minimization of the compressor power. Aspelund et al. [5] modeled the Prico cycle using HYSYS and optimized it using a Tabu Search (TS) method combined with the Nelder-Mead Downhill Simplex (NMDS) methods [6]. The reason for combining the global TS with the NMDS local search according to Aspelund et al. is that the local search, i.e. NMDS, usually converges to the best solution in the TS-detected area more rapidly than the TS would on its own.

Taleshbahrami et al. [7] modeled a propane precooled mixed refrigerant (C3-MR) cycle using Matlab software and validated their model against HYSYS software. They applied GA to optimize the refrigerant compositions. Their optimization resulted in closely matched cooling curves with as low as 3 °C pinch temperature. A similar optimization approached was applied on a Single Mixed Refrigerant (SMR) cycle by Shirazi et al. [8]. Wang et al. [9] applied mixed-integer nonlinear programming (MINLP) in GAMS software to minimize the APCI cycle power consumption. Vaidyaraman et al. [10] also used NLP to minimize the power consumption of a cascade MR cycle. Their optimization variables were refrigerant composition (methane, ethane, propane and n-butane), vaporization fraction in flash tanks and compressor pressure ratios. Their modeling formulation, however, only considered temperature cross at the ends of heat exchangers, and so did not guarantee that the Second Law of thermodynamics was not violated by having a temperature cross in the middle of heat exchangers.

Nogal et al. [11] developed a thermodynamic model for a mixed refrigerant cycle and optimized it using GA. Their refrigerant mixture composition was methane, ethane, propane, butane and nitrogen. Jensen et al. [12] modeled and optimized Mixed Fluid Cascade (MFC) process using gPROMS software [13].

Paradowski et al. [14] carried out a parametric study on a APCI cycle. They varied the MCR refrigerant composition, propane cycle pressures, pre-cooling temperature and propane cycle compressor speed. Their aim was to demonstrate that the APCI cycle could be adapted to even larger plants than those already built, thus maintaining its position as the first choice liquefaction cycle.

Venkatarathnam [15] performed an optimization study on a APCI cycle using the Sequential Quadratic Programming (SQP) method [16], available in the ASPEN Plus optimization tool. He varied refrigerant composition and compressor pressure ratios to maximize the cycle exergy efficiency. Cao et al. [17] employed GA and ASPEN Plus to optimize refrigerant mixture for SMR cycles. They also performed exergy analysis to verify the robustness of their results.

Although many researchers tried to develop and optimize the refrigerant composition for natural gas liquefaction plants, none of the previous studies considered the uncertainty in the feed gas compositions in the development and optimization of refrigerant mixtures. In this paper we used the Gradient Assisted Robust