Computers and Chemical Engineering 99 (2017) 13–20

Contents lists available at ScienceDirect

Computers and Chemical Engineering

journal homepage: www.elsevier.com/locate/compchemeng

Practical optimization for cost reduction of a liquefier in an industrial air separation plant

Yanan Cao[a], Jesus Flores-Cerrillo[b], Christopher L.E. Swartz[a,*]

[a] Department of Chemical Engineering, McMaster University, 1280 Main St W, Hamilton, ON L8S 4L7, Canada
[b] Advanced Control and Operations Research, Praxair Technology Center, Tonawanda, NY 14150, USA

ARTICLE INFO

Article history:
Received 29 October 2015
Received in revised form
19 December 2016
Accepted 21 December 2016
Available online 24 December 2016

Keywords:
Nitrogen liquefier
Particle swarm optimization
Operation under disturbances
Simulation-based optimization
Industrial application

ABSTRACT

Commercial and in-house simulation software used by industrial practitioners are often of a "black box" type from which derivatives cannot be directly obtained. This paper demonstrates a linkage between available industrial tools and cost reduction opportunity creation through the application of a derivative-free optimization technique. An operational liquefier in an air separation unit is used in our study due to the increasing importance of liquid production in the plant's overall operation strategy, and limited evaluation on the operation of such systems under disturbances. Particle swarm optimization is implemented, and optimization results show that when the plant is forced to operate away from its nominal operating/design conditions, it is possible to reduce the unit power consumption by adjusting different operation set-points. A reference map is generated to guide the operation under selected realizations of cooling water temperature, production load and feed conditions.

1. Introduction and background

Simulation has been widely implemented as a descriptive tool in the modeling and analysis of complex systems in academic and industrial research over decades. With progress in computing technology, simulation can nowadays also be utilized as a prescriptive tool in the decision support process (Tekin and Sabuncuoglu, 2004). Efficient optimization frequently relies on obtaining the gradient information of the cost function and/or constraints with respect to the decision variables, and although in some cases, it is possible to extract such information from simulation, the associated procedures are typically time-consuming and non-trivial (Kramer et al., 2011). In circumstances when commercial simulation software is used, the source code, e.g. the form of the underlying mathematical equations, is simply inaccessible; hence, derivative information of some part of the simulation may not be available for optimization studies (Kramer et al., 2011). These are situations that industrial researchers commonly face. Developing a tailored simulator for a particular process is a high investment project in terms of time, financial and human resources. It would be beneficial if existing tools can be leveraged to create additional value with minimal modification. Derivative-free optimization meets these requirements. Methods within this class are typically easy to implement and have been successfully applied in a number of areas, from finance to production management and engineering (Kramer et al., 2011; Boussaï et al., 2013).

Large-scale production and distribution of liquid cryogen, such as liquid nitrogen, oxygen, argon and helium, from air separation plants emerged in the 1940s. It has been well recognized that despite the operation cost, transportation and storage costs of liquid products are lower for the equivalent quantity of the gaseous products (Kerry, 2007). More recently, in addition to much broader direct applications, e.g. cryosurgery, stored liquids can also be vaporized and used for peak load-saving or during emergency/planned shutdowns of the main air separation units (Kerry, 2007). The practice of liquefaction, storage and evaporation of liquids is of particular importance in planning and scheduling, as the operation of air separation units (ASUs) is now subject to dynamic market conditions due to electricity price deregulation. Therefore, like many other chemical plants, operations of the liquid cryogen production process should be optimized for maintaining the plant's competitive position. However, optimal operation of liquefaction processes, especially operation policy changes due to disturbances, has received relatively little attention (Jacobsen and Skogestad, 2013).

Optimization studies on liquefaction systems reported in the literature often focus on liquid natural gas production, such as Mokarizadeh Haghighi Shirazi and Mowla (2010), Moein et al. (2015), Khan and Lee (2013) and Aspelund et al. (2010). In these studies, several derivative-free optimization paradigms have been

* Corresponding author.
E-mail address: swartzc@mcmaster.ca (C.L.E. Swartz).

http://dx.doi.org/10.1016/j.compchemeng.2016.12.011

Nomenclature

Symbol	description
ADM	turbine admission rate (engineer defined variable)
ASU	air separation unit
C1	compressor 1
C2	compressor 2
CB	cold booster
CT	cold turbine
FP	flash pot
GA	genetic algorithm
IP	intermediate pressure
LHX	liquefier heat exchanger
LN_2	liquid nitrogen
LT	liquid turbine
MP	medium pressure
MR	mixed refrigerant
NG	natural gas
PSO	particle swarm optimization
TS	Tabu Search
WB	warm booster
WT	warm turbine

Variables

$F_{\mathrm{MP\,GN_2}}$	medium pressure GN_2 feed flow rate
F_{turbine}	turbine flow rate
JP	unit power (i.e. power consumption per unit of net LN_2 produced)
L_j	lower bound of decision variable j
$n_{\max}$	maximum number of iterations in the efficiency update calculation
N_{const}, N_{DV}, N_{equip}	the total number of constraints, decision variables and equipment units
P_{suction}	pressure at the turbine inlet
T_{suction}	temperature at the turbine inlet
U_j	upper bound of decision variable j
$v_{i,j,k}$	velocity of decision variable j of particle i at iteration k
$\mathbf{v}_{i,k}$	velocity vector of particle i at iteration k
$x_{i,j,k}$	value of decision variable j of particle i at iteration k
$\mathbf{x}_{i,k}$	position vector of particle i at iteration k
$\mathbf{x}_k^{GB}$	corresponding position vector of population's best until k
$\mathbf{x}_{i,k}^{PB}$	corresponding position vector of particle i's personal best up to iteration k
α	initial velocity factor
β	neighborhood factor for adjusting the decision variable bound
γ	relaxation factor for adjusting the decision variable bound
δ_i	violation/scaled violation of constraint i
$\varepsilon_{\max}$	max. bound on efficiency change in efficiency update calculation
η_i	efficiency of equipment i
$\eta_{i,n}$	efficiency of equipment i at iteration n
θ	penalty factor for constraint violation
ϕ	objective function (unit power + constraint violation penalty)
χ	constriction factor
ω_1, ω_2	acceleration coefficients for $\mathbf{x}_{i,k}^{PB}$ and $\mathbf{x}_k^{GB}$

implemented with ASPEN Engineering Suite and Honeywell UniSim Design as the typical simulation or validation platform. A genetic algorithm (GA) was implemented in Moein et al. (2015) to optimize the operation of a natural gas (NG) liquefaction cycle, including component flow rates of the mixed refrigerant (MR) and outlet pressure of the compressor and valve, to minimize the total power consumption under different realizations of ambient temperature and feed pressure with Aspen HYSYS as the process simulator. Apart from GAs, researchers also applied particle swarm optimization (PSO) and Tabu Search (TS) paradigms while studying NG liquefaction systems. In the study of Khan and Lee (2013), PSO is used with the process model in UniSim to determine the optimal refrigerant flow mix, condenser pressure and the temperature of the MR after expansion, with other system conditions at the design specifications to reduce the compressor energy requirement. In Aspelund et al. (2010), a TS was combined with the Nelder–Mead Downhill Simplex method to determine the total refrigerant flow rate and composition, and the refrigerant suction and condenser pressures, that minimize energy requirements of the liquified NG process. Two conditions in the NG feed composition were considered and the process simulator was Aspen HYSYS. Only a few of these studies address disturbances or different realizations of selected process variables, while others optimize process conditions to meet design specifications. None of the studies focused on an industrial N_2 liquefaction process.

This paper intends to demonstrate the potential of adding value by harnessing existing tools in industrial research through conducting optimization studies using particle swarm optimization and a simulator for an operational nitrogen liquefier. While one could in principle derive equation oriented models and use a derivative based optimization approach, the cost and complexity of adopting this approach within an industrial setting pose significant obstacles due to the time and effort required for such model development. Additionally, although the process selected may not appear to be as complex as other chemical plants, operation of this liquefier involves supercritical fluids, small approach temperatures and phase changes in a multi-stream heat exchanger. Hence, converting an already existing simulator to an accurate equation based model is a challenging task. The overall objective is to determine a reference map of turbine flow splits for energy efficient operation of the liquefier under selected disturbances. Since the actual constraints used in the existing control infrastructure are enforced in the study, the optimization results can then be readily implemented through the existing plant control system using a simple independent supervisory control structure, or directly into the primary control system as a look-up table. This paper is structured as follows. Section 2 gives a brief description of the nitrogen liquefaction process and the operation problem that will be addressed. Section 3 documents details of the proposed problem formulation and solution approach, including objective function and constraints. Key results for model validation and optimization studies are highlighted in Section 4.

2. Process description

An industrial turbine-booster N_2 liquefier is used in this study with the configuration shown in Fig. 1. This N_2 liquefier contains a parallel turbine-booster system and utilizes closed recycle loops. The recycle streams (i.e. turbine exhaust and flash stream) act as cold streams/heat sinks in the multi-stream heat exchanger. Energy input (i.e. electricity) is required only by compressors 1 and 2. The warm and cold boosters are compressors in a power relation with the warm and cold turbine, respectively (i.e. parallel turbine-booster system). The booster is connected with the turbine through a shaft and powered by expansion of the compressed gas on the