Real Time Optimisation of Industrial Gas Supply Networks

Richard Adamson* Martin Hobbs Andy Silcock** Gary Montague*****

**School of Chemical Engineering and Advanced Materials, Newcastle University, NE1 7RU, UK (e-mail: richard.adamson1@newcastle.ac.uk).*
*** BOC Gases Ltd, Bawtry Road, Brinsworth, Rotherham, S60 5NT, UK*
**** School of Science and Engineering, Teesside University, Middlesbrough, TS1 3BA, UK (e-mail: g.montague@tees.ac.uk)*

Abstract: A supply network consisting of multiple air separation units and compressors supplies oxygen gas at two pressures to a major steelmaker in South Wales. Each machine has a different efficiency curve, power requirement, and capacity. The aim was to minimise the cost of power and liquid usage of the supply network whilst meeting customer gas flow demands and preventing product spill.

Mass balances of the site were produced and integrated into a Microsoft Excel spreadsheet representation of the supply network. A mixed integer nonlinear programming approach was adopted to allow machines to operate within flow limits and turn on or off based on demand. The GRG nonlinear solver method was used to minimise the cost of running the network arrangement, determined by the sum of all estimated machine powers and the cost of liquid back up usage. Constraints were programmed to maintain steady state, meet demand, and keep machine flows within bounds.

This work demonstrates that extra power requirement, liquid vapourisation and product spill caused by inefficient compression arrangements result in annual site losses of £0.6M. It is shown that through real time optimisation of the gas network a significant reduction in these financial losses can be achieved.

Keywords: *Binary, Compressors, Constraints, Minimisation, Network, Nonlinear, Optimisation, Power*

1. INTRODUCTION

BOC Gases is part of the Linde Group, a world leading supplier of industrial, process, and speciality gases. The tonnage arm of the group directly supplies customers with nitrogen, oxygen, argon, and industrial gases by pipeline. Customers whom require large volumes of gas are served by a supply network with multiple feed units to meet demand.

Changeable flow rates of medium pressure (MP) and high pressure (HP) oxygen gas are required for oxy-fuel combustion and basic oxygen steel (BOS) production respectively. The oxygen supply network compression must be manipulated on demand change to improve efficiency.

The Margam site supply network and compressor arrangement (Fig. 1) is shown opposite. Three air separation units (ASUs) supply oxygen gas to the network. ASU 1 and 2 supply Low Pressure (LP) gas and ASU 3 supplies MP and HP gas directly. Three centrifugal compressors raise LP to MP and three reciprocating compressors raise LP or MP to HP. Cross over from the HP to MP stream is managed and oxygen tank pump vapourisers (O_2 TPV) are required when HP pipeline pressure falls due to under-production.

Any tool developed must optimise the site as a whole and be flexible enough to solve for any customer requirement, adhering to all plant constraints. It must be intuitive, solve quickly, adapt to machine availability, and allow for any future changes in machine characteristics.

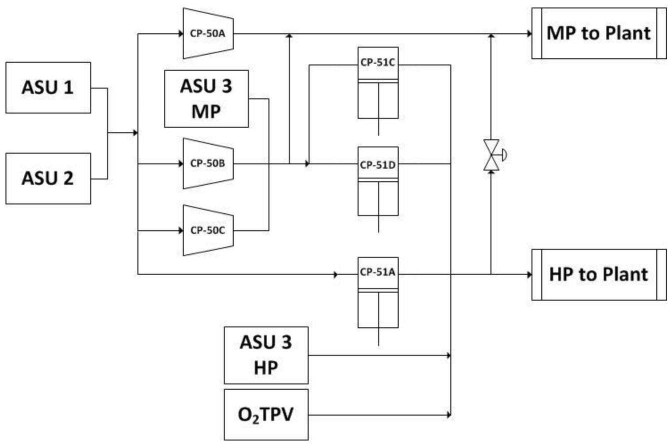

Fig. 1. Margam supply network and compressor arrangement.

Manenti and Rovaglio (2013) comprehensively describe the peculiarities of industrial gas manufacturing and carry out profit optimisation with scheduling to avoid high power prices and manage liquid levels. However, our customer demand rarely exceeds the total gas production capacity of the site therefore forward scheduling of liquid oxygen usage would yield little benefit. The focus must be to optimise the oxygen gas compression network prior to scheduling.

This paper describes the methods undertaken to improve compression arrangement management by developing a system model and using it to optimise the site as a whole.

2. MODEL DEVELOPMENT

2.1 Mass Balances

Fig. 1 showing all machines was used to develop mass balances of the network at steady state. Equations representing the MP and HP streams were expanded.

Mass balance of LP gas produced by ASU 1 and ASU 2 and compressors with LP inlet pressures.

$$LP = ASU1 + ASU2 = 50A + 50B + 50C + 51A$$

Mass balance of MP produced by network minus machines that consume it, plus let down flow from the HP stream (LD).

$$MP = 50A + 50B + 50C + ASU3MP + LD - 51C - 51D$$

Mass balance of HP produced by network minus let down flow. 51A flow has been substituted with a rearranged form of the LP equation to simplify.

$$HP = (ASU1 + ASU2 - 50A - 50B - 50C) + 51C + 51D \\ + ASU3HP + TPV - LD$$

At all times, the customer demand of MP and HP must be met by the supply network. Pipeline losses, were assumed to be a percentage of demand and thus added to the customer demand order. Average percentage losses were calculated from the difference between the total oxygen production flows from ASUs and the metered MP and HP gas flows to the customer over three months. All flows were pressure and temperature adjusted to standardise. Modelling other complexities decreases operator understanding of the network model and may increase optimisation calculation time.

2.2 Machine Flow Limits

With years of historical data available in the data historian, it was possible to produce efficiency curves and discover the flow limits for each machine numerically.

30 minute averaged data of oxygen gas flow, power usage and other key normal operation indicators, such as recycle valve opening position, were compiled over 6 months for each machine in the compression arrangement. Data was pre-screened to remove missing data and data not recorded during normal operation, e.g. at machine start up.

The minimum and maximum observed machine gas flow limits during normal operation were recorded. Where flow meters were not present, mass balances were used to estimate gas flow rates. The flow limits were stored in an array.

2.3 Efficiency Curves

Using the pre-screened data discussed in section 2.2, simple numerical regression models were used to determine the machine efficiency for a given gas flow rate. Machine efficiency is metered motor power, in kW, divided by the gas flow rate, in hundred cubic meters per hour (HCMs).

Polynomial regression produced equations of fit between the machine efficiency, in kW/HCM, and the gas flow rate. Where the compressor recycles due to anti-surge control at low through flows, increased power usage was captured by the efficiency curves. As a result, machines often run more efficiently per unit of gas when fully loaded and the polynomial curves are convex. Overload of some oxygen compressors occurs above high flows, causing inefficiency. Linear regression would not capture these complexities.

The 2nd or 3rd order polynomial equations were added to a spreadsheet to estimate machine power from machine flows.

2.4 Mixed Integer Nonlinear Programming

Numerous papers have been published describing optimisation using mixed integer nonlinear programming (MINLP) including applications to natural gas networks, Ehrhardt and Steinbach (2003), steam generation for gas treatment plants, Manesh et al. (2009), and diet strategies for salmon pigmentation, Forsberg and Guttormsen (2006). By definition, all include a combination of continuous and discrete decision variables to optimise systems exhibiting nonlinear integer, continuous or product relationships. 'Yes no' decision variables were presented as binary coefficients.

An array of binary coefficients and flows for all machines was produced in Microsoft Excel. The variable cells for flow were linked to the efficiency equations of fit of each machine. There were 11 binary coefficients, one for each ASU, compressor, Let Down, and TPV, and 13 flow coefficients – in total 24 decision variables. There were 2 more flow than binary coefficients as ASU 3 has an MP and HP stream.

For each machine an equation was formed to allow optimisation of the network. Only the flow and binary component of the equation can be altered by the optimiser as independent variables. Machine power (W_m), shown in (1), is the product of the binary coefficient (b_m), efficiency as calculated from the polynomial efficiency curve (ε_m), and machine gas flow (F_m). Where m is the machine name, ε_m is a function of gas flow rate and the gas flow rate is constrained.

$$\begin{aligned} & W_m = b_m \cdot \varepsilon_m \cdot F_m \\ & where \\ & b_m \in \{0,1\}, \\ & \varepsilon_m = f(F_m), \\ & F_{m\,\min} \le F_m \le F_{m\,\max} \end{aligned} \tag{1}$$

Constraints were programmed based on real network boundaries. In the Solver add in window, constraints were added individually for each machine and mass balance required, see Fylstra et al. (1998), starting with the 26 upper and lower bound flow coefficient constraints, as determined in section 2.2. Each flow coefficient's flow bounds have been presented in a separate array to allow for easy editing.

Equality constraints ensuring the LP, MP, and HP equations balance to prevent spill and guaranteeing the customer is supplied with the required gas flow rates were added. The loss adjusted MP and HP demands were constrained to equal the MP and HP machine mass balance equations.

The sum of estimated machine powers was multiplied by the fixed cost of power ($COST_{kW}$) to form part of the economic objective function, J. The remainder is the cost of consuming liquid oxygen stocks, the TPV flow (F_{TPV}) multiplied by the cost per HCM of liquid ($COST_{TPV}$).

$$J = COST_{kW} \cdot \sum W_m + COST_{TPV} \cdot F_{TPV} \quad (2)$$

The general algebraic formulation for MINLP problems was adapted for binary integer decision values and continuous bounded decision variables, see Floudas and Pardalos (2009).

$$\begin{cases} \min\limits_{x,y} f(F,b) \\ s.t. \\ h(F,b) = 0 \\ g(F,b) \leq 0 \\ F_{m\,\min} \leq F_m \leq F_{m\,\max} \\ b \in \{0,1\}^q \end{cases} \quad (3)$$

Vector F contains all continuous variables of flow, bounded by $F_{m\min}$ and $F_{m\max}$, vector b contains binary variables, and $f(F,b)$ is subject to all equality and inequality constraints.

2.5 Sensitivity Analysis

Coefficients of determination, or R^2 errors, of the machine polynomial regression fits were used to develop a Monte Carlo simulation of the compression arrangement power, see Doubilet et al. (1985). Normal distribution, variable independence, and constant variance were assumed.

R^2 values produced from polynomial fits of efficiency versus oxygen gas flow for flow metered oxygen compressors were around 80%, not directly flow metered oxygen compressors around 60%, and ASUs around 70%. The remaining variance not caused by oxygen gas flow through the machine $(1\text{-}R^2)$ was multiplied by the estimated machine power and square rooted to find the standard deviation. The excel function *NORMINV(rand(),μ,σ)* was used to return a randomly selected and normally distributed value within one standard deviation of the estimated machine power. The process was repeated for each machine in the compression arrangement to ensure machine errors were independent. The sum of the machine powers gave an error adjusted total site power.

Each simulation has 1000 trials and the mean and standard deviation of all trials was calculated. The standard deviation was converted into cash using power price. If an optimiser suggested an arrangement which produced smaller cash savings than two standard deviations (often around £20), a 95% confidence interval, then the optimiser should suggest that the current compression arrangement is maintained. Two sigma was assumed sufficient to change the network.

2.6 Optimisation Method Selection

Microsoft Excel 2010's built in Solver was operated to optimise the plant by minimising the objective function cell subject to programmed constraints. Nonlinearities in the machine power calculations require solving by the GRG nonlinear solution method, see Lasdon et al. (1974). The method uses simple forward difference approximations of the first partial derivate gradients of the objective function and constraints to solve nonlinear problems quickly, Ratner et al. (1978). Solver method settings were not altered from default.

Tests were carried out on a wide range of customer demand combinations to ensure the optimiser solved all possible scenarios. Solutions took around 5 seconds on an Intel Core i5-3340, 2.70GHz, 4 GB of RAM, OS MS Windows 7 Professional. As the default method was non-deterministic, different independent variable starting positions were trialled. All binary coefficients starting in an 'on' position and all flow coefficients beginning at the lower bound was successful at finding the minimum cost for all scenarios.

The multistart option was used to determine any distance from the global optimum. In all cases the multistart option with 10 starting points found the same solution as the non-deterministic method. This suggests the current starting position and method favours the best route to the optimum compression arrangement for the cases tested. Using the multistart option increased solving time above the 2 minute threshold and did not deliver any additional cost benefit.

2.7 Network Mimic

A supply network mimic was produced in Microsoft Excel as an optimiser interface (Fig. 2). The user inputs the current customer demand, which is linked to the mass balance constraint cells, to optimise the compression arrangement. A macro backed 'Solve' button was recorded in visual basic to reset the variable cells to the favoured starting positions and run the solver automatically. Flow cells were formatted to turn green when the machine is active.

The optimised flows through the machine, the upper and lower flow limits, and the estimated machine power are presented in a machine representation of the network.

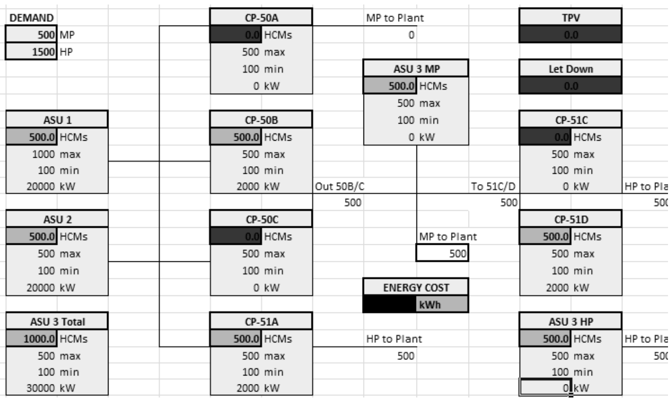

Fig. 2. Excel supply network mimic (all values false).

2.8 Machine Availability

Machines were often unavailable for periods of time during maintenance or after a machine trip. Dropdown text boxes of ‘available’ or ‘unavailable’ were positioned on the operator interface and referenced by if statements. The machine’s binary coefficient was forced to be 0 if unavailable. Altering the decision variable would therefore not affect the objective function and the optimiser had to find an alternative solution.

Adding flexibility allowed the optimiser to cater for any network configuration. The option also allowed TPV to be programmed off for most situations as favoured by liquid schedulers who wish to preserve stocks.

3. PRELIMINARY FINDINGS

3.1 Potential Financial Gains

In order to demonstrate the financial gains of running the optimised compression arrangement, current compression arrangements were recorded. The machine power curves in the optimiser were used to estimate the total site power. Compared to the optimiser output, significant power savings were found due to inefficient network management. For the recorded arrangements, the average power differential was £30 per hour, £0.26M per annum. However, some recorded arrangements were significantly further from optimum.

Inefficient network management resulted in product spill from the ASU supply lines in over supply situations and vaporisation of liquid product when under supplying. Whilst in some situations losses were unavoidable, e.g. during plant trips, the majority could have been avoided if using the optimiser. Historical data suggests that £0.23M was lost through unrequired TPV and £0.11M through ASU 1 spill.

The Monte Carlo simulation output aided operator decision making by proving beyond reasonable doubt that the new compression arrangement provided a cash saving. Where current operation was on the boundary of possible arrangements and less than two sigma, the network was not altered. The cost of network manipulation in product spill and power use during machine start and stops was assumed to be around two sigma and thus changing the network would be self-defeating in the short term. If the order is known to remain for a long time, the payback time can be interpreted.

In normal operation the optimiser did not produce an arrangement featuring a cross over flow to provide cost benefit. Its function as a safety feature remains but its use demonstrates an inefficient compression arrangement. It does not make financial sense to step up gas to HP and back down again if there is capacity to make MP elsewhere.

The optimiser did suggest TPV use where demand was too low to turn on an ASU and where demand was over maximum production of all ASUs. When the power price of the network was increased, TPV use was favoured ahead of running the larger, less efficient machines. This may improve savings if used tactically during periods of high power price.

The financial gains were corrected for recorded periods of under production; when supply did not meet the demand due to incorrect customer order or machine ramping prior to compression arrangement changeover. However, in most recorded arrangements, the supply network was over producing, resulting in higher power costs.

Pipework limitations and bottlenecks have been discovered. By producing an optimiser with manipulated mass balances offering the capacity to reopen manual valves, redundant areas of the network have been reopened to offer cost benefit. The redundant MP pipework between CP-50A and the CP-51C/D inlet area of the network is one example of this.

3.2 Demand Tracking

During installation of the optimiser on site computers, it was evident that changes in customer demand were difficult to follow. Similarly, TPV usage and product spill were hard to observe live and often occurred during changes in customer demand. The costs of these losses were not quantified.

The customer is able to order any flow rate combination of MP and HP oxygen gas at any time and BOC must supply it. However, as air flow into ASUs can only be ramped up or down at a certain rate for safety concerns, Schmidt et al. (2001), the rate of change of supply is limited by contract.

Although the customer understands the rate of change limits, they often immediately start using the new demand flow rates which, during large order increases, often causes liquid consumption. If BOC operators ensure the supply network meets the contractual ramping rate throughout the order change, consumed liquid cost is billed to the customer. At times were the ramping demand was not met by operator network manipulation, the liquid cost is charged to BOC.

To ensure the latter does not occur as often, a visual aid was produced in Microsoft Excel, (Fig. 3), and displayed in the operating centre. The demand tracker tool forward projects the contractual rate of supply change during ramps using if statements. It also plots current MP, HP, and total oxygen flows with TPV usage and product spill flows to aid network management. Totalisers sum the total plant losses for the period and convert into costs.

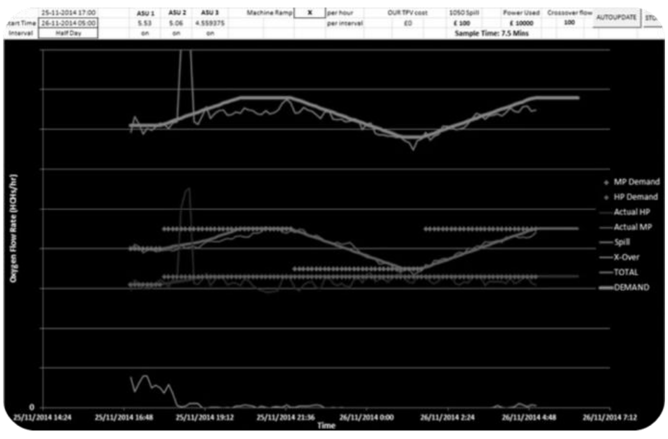

Fig. 3. Excel demand tracker tool (all values false).

4. FURTHER WORK

4.1 Optimisation

Section 2.6 concluded that developing a deterministic optimisation method had no cost benefit at current. However, as the optimiser develops and complexities such as varying power prices are added, a deterministic optimisation method may be required. Although the static optimiser was developed to improve current operation, the requirement of a dynamic, forward projecting optimiser which schedules machine stops, starts and ASU ramps to minimise losses during demand changes is the next technical challenge.

Current mass balance equality constraints state the supply network must always meet the customer demand flows. Altering the MP and HP supply equations to inequality constraints, to meet or exceed demand plus losses, allowed for over production. In some cases, over supply and spill, or under supply and TPV, can be used to deliver a larger than two sigma cost benefit. This may be useful for oxygen requests where a larger, lower loaded, and less efficient compressor is required instead of a fully loaded other.

4.2 Current Limitations

Although the two sigma rule adds confidence in the optimised results, the model remains limited by the accuracy of the polynomial regression fits of machine efficiency. Improving the data collection and pre-screening techniques may only provide a limited improvement in the value of coefficients of determination of the efficiency curves.

Model accuracy improvement will be particularly limited for ASUs if variables affecting the power requirement of the air compressor continue to be ignored by numerical modelling. Modelling of ASUs is challenging as variables including cold recovery, column pressures, and ambient conditions are all known to affect efficiency, but with a lesser influence than oxygen gas flow, Fu and Gundersen (2012). Measurements of liquid oxygen and nitrogen flows and turbine recovery can be easily recorded and used to generate multivariate models.

Current values of uncontrolled variables can be fed into models from the data historian to create better estimations of power during optimisation. Power estimation of oxygen machines can also be improved with multivariate analysis of oxygen gas flow, suction and exhaust pipeline pressures, and cooling water temperatures. Numerical modelling of the site is preferred as first principle modelling will be time consuming and not necessarily effective due to cryogenic air separation process uncertainty and nonlinearity.

4.3 Scheduling

Forward scheduling before and throughout demand changes is the natural next step in development of the optimiser and is currently a work in progress. A dynamic optimiser with the ability to schedule changes in the supply network will allow for; quantitative analysis of how many and when machine stops and starts are required, prediction of the costs of network changes in product spill, TPV, and power usage, and prevention of losses by preparing the network for change. An estimation of the payback time of changing compression arrangement will build additional confidence in the optimiser.

Scheduling further ahead will provide the facility to program machine availability and, if the customer can be persuaded to provide the information, future customer demands for optimal planning of maintenance. If the forward plans prove unreliable, forecasting of order changes by investigating trends in flows between the oxy-fuel furnace and BOS plant along with other external variables could be developed by methods such as neural network, see Zhang et al. (1998).

Development of a dynamic optimiser began with the stacking of multiple static optimisers, one for each discrete time point during a ramp. The ramp demand equations developed in section 3.2 for the demand tracker tool were used to calculate the intermediate customer demands. Mass balance constraints apply at each intermediate during the ramp but as inequality constraints to allow over production and/or spill to be modelled. Changes between intermediate compression arrangements must also be realistic. Machine binary coefficients were limited to change twice during ramps and ASU oxygen gas flow changes were limited by the speed at which LMPC safely ramps the air compressor. Limits were added to the GRG solver method as inequality constraints.

Before running the dynamic optimiser, the current network arrangement was imported to the optimiser as the starting position. The new optimiser had limited success when running but takes a lot longer due to the increased number of decision variables. The result remains non-deterministic but any reduction in losses is useful. The increase in complexity caused by the dependency on previous decisions reduced the smoothness of the model resulting in a multi-modal shape. As a result, Biegler and Grossmann (2004) suggest attempting to use global MINLP optimisation methods such as DICOPT coupled to algebraic modelling system GAMS.

Discrete time MINLP scheduling problems become large and complicated quickly, but the method can be switched to a multi period continuous time solving method, see Floudas and Lin (2004). Rather than a binary decision variable matrix determining whether a machine is running at an intermediate point, or optimising the length of time that the machine runs for, continuous variables allow the optimiser to select the start and end time of machine running periods. For each machine throughout the entire ramp there are two Excel cells formatted as times to be used as continuous time decision variables. If statements are used to reference the start and end time to determine if the machine is on for that intermediate point in the ramp. This will significantly change the mathematical formulation of the optimiser from equation (3).

Extending the compression network scheduler to include liquid make from ASUs and external liquefiers, Manenti and Rovaglio (2013) suggest increasing air compression and nitrogen injection to make liquid during low power prices and increasing TPV use during peak price times will increase the profitability of a multisite network.

Increasing the scheduling time horizon to next-day or week ahead, power price fluctuations can be predicted and capitalised upon, see Merkert et al. (2015). Baumrucker and Beigler (2010) suggest converting the optimiser to profit maximisation on stocks from network cost minimisation to allow for further advantage. A developed continuous time external liquefier scheduling tool can potentially save £500 per week versus the current load management plans. This scheduling approach will require further analysis and development with the product delivery planning team as bulk liquid customers must continue to be supplied as a priority.

4.4 Site Control and Automation

Linking the dynamic optimiser and site scheduler to the demand tracker tool could prompt operators to alter network and site configurations. If constrained effectively, Beigler and Zavala (2009) suggest bypassing the current LMPC protocols with the outputs from a simplified scheduling optimiser.

ASU product spill relates directly to the valve opening positions of the plants impurity removal and cold recovery system at the front end of the ASU, the reversing heat exchangers. Oxygen oversupply causes back pressurisation of the heat exchangers restricting oxygen gas flow into the supply network and decreasing cold recovery. Controlled decongestive methods such as periodic forced increases of valve position between limits will reduce this product spill.

The TPV system automatically starts when HP line pressure falls below a safe level. Pipeline pressure oscillates due to the BOS plant blow pattern. A pressure control system which reduces the variation will allow for the operating pressure to be lowered towards the TPV pressure constraint, lowering compressor exhaust pressures and thus power usage.

4.5 Wider Application

Steel works often require supply networks for other industrial gases such as nitrogen and argon. In South Wales, the nitrogen supply network consists of four compressors and a campaign run nitrogen liquefying unit. Including these units in the oxygen supply network optimiser will further optimise the site. The objective function could include the power for these compressions along with ASU auxiliary powers.

The optimiser could be amended and applied to other gas or liquid pipeline networks in the UK and worldwide for power price scheduling and network optimisation.

ACKNOWLEDGEMENTS

Financially supported by EPSRC grant EP/G037620/1 and BOC Gases through the Biopharmaceutical Bioprocessing Technology Centre at Newcastle University, UK.

REFERENCES

Baumrucker, B.T. and Biegler, L.T. (2010), MPEC strategies for cost optimization of pipeline operations, *Computers and Chemical Engineering*, 34, 900-913

Biegler, L.T. and Grossmann, I.E. (2004), Retrospective on Optimization, *Computers and Chemical Engineering*, 28, 1169-1192

Biegler, L.T. and Zavala, V.M. (2009), Large-scale nonlinear programming using IPOPT: An integrating framework for enterprise-wide dynamic optimization, *Computers and Chemical Engineering*, 33, 575-582

Doubilet, P., Begg, C., Weinstein, M.C., Braun, P. and McNeil, B.J. (1985), Probabilistic sensitivity analysis using Monte Carlo simulation. A practical approach, *Medical decision making : an international journal of the Society for Medical Decision Making*, 5(2), 157-177

Ehrhardt, K. and Steinbach, M.C. (2003), Nonlinear Optimization in Gas Networks. *Konrad-Zuse-Zentrum für Informationstechnik Berlin Report*. 03(46)

Floudas, C.A. and Lin, X. (2004), Continuous-time versus discrete-time approaches for scheduling of chemical processes: a review, *Computers and Chemical Engineering*, 28, 2109-2129

Floudas, C.A. and Pardalos, P.M. (2009), *Encyclopaedia of optimization*, 2236-2237, Springer, US

Forsberg, O.I. and Guttormsen, A.G. (2006), Modeling optimal dietary pigmentation strategies in fanned Atlantic salmon: Application of mixed-integer non-linear mathematical programming techniques, Aquaculture, 261(1), 118-124

Fu, C. and Gundersen, T. (2012), Using exergy analysis to reduce power consumption in air separation units for oxy-combustion processes, *Energy*, 44, 60-68

Fylstra, D., Lasdon, L., Watson, J., and Waren, A. (1998), Design and Use of the Microsoft Excel Solver, *Interfaces*, 28(5), 29-55

Lasdon, L.S., Fox R.L., and Ratner, M.W. (1974), Nonlinear Optimization Using the Generalized Reduced Gradient Method, *Revue francaise d'automatique informatique et de recherche operationnelle*, 8(3), 73-104

Manenti, F and Rovaglio, M. (2013), Market-driven operational optimsation of industrial gas supply chains, *Computers and Chemical Engineering*, 56, 128-141

Manesh, M., Motevallian, S., Amidpour, M. and Mazhari, V. (2009), Optimization of Steam Network through MINLP method: Application to Utility of KHARK Island NGL recovery Project, *Chemical Engineering Transactions*, 18, 225-230

Merkert, L., Harjunkoski, I., Isaksson, A., Säynevirta, S., Saarela, A., Sand, G. (2015), Scheduling and energy – Industrial challenges and opportunities, *Computers and Chemical Engineering*, 72, 183-198

Ratner, M., Lasdon, L.S., and Jain, A. (1978), Solving Geometric Programs Using GRG: Results and Comparisons, *Optimization Theory and Application*, 26(2), 253-264

Schmidt, W.P., Winegardner, K.S., Dennehy, M., Castle-Smith, H. (2001), Safe Design and Operation of a Cryogenic Air Separation Unit, *Process Safety Progress*, 20(4), 269-279

Zhang, G., Patuwo, B.E., Hu, M.Y. (1998), Forecasting with artificial neural networks: The state of the art, *International Journal of Forecasting*, 14, 35-62

