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Published in:
IFAC-PapersOnLine

DOI (link to publication from Publisher):
10.1016/j.ifacol.2018.06.374

Publication date:
2018

Document Version
Publisher's PDF, also known as Version of record

Citation for published version (APA):
Andreasen, A., Rasmussen, K. R., & Mandø, M. (2018). Plant Wide Oil and Gas Separation Plant Optimisation using Response Surface Methodology. *IFAC-PapersOnLine*, *51*(8), 178-184. https://doi.org/10.1016/j.ifacol.2018.06.374

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ScienceDirect

IFAC PapersOnLine 51-8 (2018) 178–184

Plant Wide Oil and Gas Separation Plant Optimisation using Response Surface Methodology

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Abstract: In this paper we will demonstrate Response Surface Methodology (RSM) applied to process simulation of an offshore oil and gas separation plant. By performing surrogate experiments according to Design of Experiment (DoE) and subsequent construction of multiple linear regression models for the chosen responses, the overall separation process is optimised in terms of power consumption under the constraints of quality specification of gas and oil export, respectively. The fluid treated in the separation plant is rich in NGL (Natural Gas Liquids) which causes challenges in meeting the export specifications. Further, the NGL causes increased condensate recycle in the compression system thereby increasing power consumption for the compressors as well as increased cooling for heat exchangers. Offshore the NGL is difficult to dispose, which makes fractionation unattractive and the NGL must be exported via the oil (partly stabilised) or via the gas (rich gas) or a combination of the two. Effectively, this violates the export specifications and the NGL must be extracted in on-shore facilities either at the oil or gas receiving facilities. By exploring different options, applying RSM, it is found that in terms of overall power consumption export of NGL with the gaseous products is more effective that exporting the NGL with the partly stabilised oil. The methodology used in the present paper can also be applied to existing production facilities as a generic optimisation tool. Due to the simplicity of the regression models mimicking the separation plant they can be coupled with the overall process control for potential on-line plant optimisation.

Keywords: Industrial Production Systems, Optimization problems, Model reduction, Process Simulators, Process parameter estimation, Regression Analysis, Statistical design

1. INTRODUCTION

Process optimisation of offshore facilities for oil and gas separation involves building a simulation model of the plant in question. The process simulation must include a representative description of the well fluid and an appropriate equation of state. By modelling all the involved unit operations the optimisation can begin by changing relevant process parameters (pressure and temperature). Often a sensitivity analysis is made to explore the importance of the different independent variables (factors) and the optimisation may be done by changing these one at a time. This can be a tedious and time consuming process. Some process simulators may have built in optimisation algorithms, however, as the process simulation grows in complexity and simulation convergence becomes time consuming, difficulties may be met. It is the authors experience that the simulator built in optimisation methods may suffer from difficulties in finding the global optimum. More elaborate optimisations may be done by coupling the process simulations with general purpose optimisation software e.g. (Adams et al., 2014).

In this paper we will use a different approach in which the optimisation part is de-coupled from the complex process simulation. This is done by applying response surface methodology (RSM) and using the process simulation to perform virtual or surrogate experiments (Grimstad, 2015; Grimstad et al., 2016). Optimisation is subsequently performed on the formulated response surface(s).

To demonstrate the application of RSM to optimisation of oil and gas separation facilities a realistic model of an offshore separation plant is made using commercial process simulation software. The well fluid treated includes a significant portion of NGL (Natural Gas Liquids). The NGL challenges power consumption of the separation plant due to significant condensate recycles in the compression system. The main target in this paper is to minimise the power consumption. Part of the optimisation is also to choose the best method for disposing the NGL.

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10.1016/j.ifacol.2018.06.374

2. METHODS

2.1 Tools

Process simulations are performed with AspenTech HYSYS v8.3.

All subsequent data handling and analysis is performed in Python 2.7 with the stack of Numpy (Van Der Walt et al., 2011), Scipy (Jones et al., 2001–), Pandas (McKinney, 2010), and Matplotlib (Hunter, 2007). Regression analysis is performed using the StatsModels module (Seabold and Perktold, 2010), and subsequent constrained optimisation is performed using Sequential Least SQuares Programming (SLSQP) (Kraft, 1994) in Numpy.

2.2 Response surface methodology

The simulation experimental plan and subsequent analysis is based on theory from Design of Experiments (DoE) and Response Surface Methodology (RSM). An exhaustive presentation of the methods of DoE and RSM will not be given here. Instead the reader is referred to relevant textbooks and literature (Box et al., 1978; Myers et al., 2009). However, a very brief introduction will be given below. RSM can be thought of as a multi stage process consisting of the following steps:

(1) Lay-out of experimental test plan according to DoE and conducting experiments (in this case simulations)
(2) Building an empirical response surface model by generating linear regression model for each of the dependent variables, Y_i, of interest (also referred to as responses) as a function of independent variables, X_j
(3) Check for linear regression assumption violations, lack-of-fit etc. (normal residuals, random residuals, outliers with influence etc.)
(4) Perform regression model reduction and selection (repeat 2-4)
(5) Validate models outside training set
(6) Using the response surface model for finding the optimal operating point by (constrained) optimisation.

A number of different experimental plans and philosophies can be chosen depending on the objective of the test plan and the number of feasible experiments. The experimental design may range from 2-level full factorial experiments with a few independent variables (also referred to as factors) - enabling to estimate both main effects and all interactions between variables, to 3-level experimental designs with many factors. When the number of factors increase the number of required tests for full factorial experimental plans grow exponentially. However, usually the effect of interactions above pair-wise interactions can be ignored, whereby the number of experiments can be reduced significantly by using a fractional factorial design in which it can be assumed that higher order (above two) interaction effects are negligible. In this study we apply a face-centered central composite design (ccd).

The general second order response surface model with k factors can be expressed as

$$y = \beta_0 + \sum_{i=1}^{k} \beta_i x_i + \sum_{i=1}^{k} \beta_{ii} x_i^2 + \sum_{i=1,i<j}^{k-1} \sum_{j=2}^{k} \beta_{ij} x_i x_j \quad (1)$$

By linear regression analysis (Faraway, 2004) the coefficients (β) can be estimated. It often turns out that some of the effects (usually second-order terms) are statistically insignificant and can be excluded from the model by either e.g. step-wise linear regression or a criterion based strategy (Faraway, 2004).

Once a response surface model which fits the experimental data to a satisfactorily level has been identified for each of the responses, the response surface can be investigated. This is often done visually, at least to start with, and this is the part of the process which has given name to the methodology. By inspecting the response surface the optimum settings may be visually identified directly. However, often several constraints must be satisfied. Those can be both constraints in factors but also constraints in responses. In case of multiple factors and several constraints an optimisation algorithm is applied.

A general optimisation problem with p response equality constraints, q response inequality constraints and n bounds for factors is defined and solved:

$$\min f(x) \quad (2)$$

Subject to the constraints

$$g_i(x) = 0 \text{ for } i = 1, \ldots, p \quad (3)$$
$$h_i(x) \geq 0 \text{ for } \; i = 1, \ldots, q \quad (4)$$
$$L_r < x_r < U_r \text{ for } \; r = 1, \ldots, n \quad (5)$$

Previously response surface methodology has been applied by one of the authors to optimise fuel oil consumption and NO_x for large two-stroke diesel engines (Mayer et al., 2010), for zero-dimensional model validation (Scappin et al., 2012), and gas engine performance optimisation (Andreasen, 2012; Juliussen et al., 2011). For general application of DoE to simulations see (Law, 2014). For applications to chemical process simulations see e.g. (Wang et al., 2012; Pontes et al., 2011). To our knowledge application of response surface methodology to plant wide optimisation of an offshore oil and gas separation plant has not previously been published.

2.3 Fluid and process simulation description

The process simulated is a three stage separation process, with gradual decrease of separator pressure. A simplified flow diagram showing the modelled process is shown in Figure 1.

The gas from the 2nd and 3rd stage separators is compressed to a pressure enabling commingling with gas from the upstream 1st stage separator. Gas from the 1st stage separator, commingled with gas from the 2nd and 3rd separator, is compressed further, before cooling and dehydration. The water dry gas is routed to the dew point control and NGL treatment facilities. These facilities consist of heat exchangers and turbine-expander/re-compressor. The cold fluid leaving the turbine-expander is routed to a low temperature knock-out drum. The gas is used for cooling of the dehydrated gas (and subsequently exported via an export compressor) and the liquid is routed to a reboiled NGL splitter column. The gas from the NGL splitter is routed back to the compression system and the liquid from the reboiler is routed to the separation system.

The flow diagram does not show condensate recycle streams from compressor suction scrubbers as well as dehydration inlet scrubber. For a more detailed view please see Figure 2.

The setup of the well fluid and thermodynamics package is summarised in Table 1. The well fluid NGL content is too high in order to meet both oil and gas export specifications at the same time.

Table 1. Dry fluid and Equation of State (EOS) data. Minor fractions of N_2 and CO_2 have been omitted. GOR is the gas-to-oil ratio. Water cut is 53%.

Parameter	Unit	Value
GOR	Sm^3/Sm^3	200
C1 content	mole %	48.83
C2-C4 content	mole %	17.23
C5-C10 content	mole %	20.08
C10+ content	mole %	13.86
Oil density	kg/m^3	853.5
Gas density	kg/m^3	1.030
EOS	–	Soave-Redlich-Kwong
Liquid density method	–	COSTALD
Enthalpy method	–	From EOS

3. RESULTS AND DISCUSSION

Based on a preliminary sensitivity analysis the following factors (independent variables) are found to be of special interest:

X_1 Pressure at turbine expander outlet (P_{exp})
X_2 Reboiler temperature (T_{reboil})
X_3 Pressure in 3rd stage separator (P_{sep})
X_4 Booster compressor discharge pressure ($P_{booster}$)
X_5 Temperature at the inlet to the dehydration facilities (T_{dehyd})

The factor level settings for each simulation experiment are summarised in Table 2. The full experimental plan of the applied face-centered central composite design (see e.g. (Croarkin and Tobias, 2017)) is given in Table 3.

Table 2. Factor level settings

Level	P_{exp} (bar)	T_{reboil} (°C)	P_{sep} (bar)	$P_{booster}$ (bar)	T_{dehyd} (°C)
High (+1)	45	35	2.5	95	35
Mid (0)	35	25	2.3	90	30
Low (-1)	25	15	2.1	85	25

The following responses (dependent variables) are recorded after convergence of each process simulation according to the simulation experimental plan:

Y_1 Export gas dew point (°C)
Y_2 Export gas Wobbe index (MJ/Nm^3)
Y_3 Export gas higher heating value, HHV (MJ/Nm^3)
Y_4 Export gas specific gravity, SG (–)
Y_5 Export oil Reid Vapour Pressure, RVP (psia)
Y_6 Total power consumption (kW)

The results of conducting process simulation experiments for each of the simulations defined by the experimental plan are summarised in Table 3.

For each of the responses linear regression models are built. Insignificant terms are removed in a manual backwards selection process removing terms with P-values > 0.05. Using this approach the following reduced regression models are derived (HHV, dew point, and Power not shown):

$$
\begin{aligned}
Y_2 &= 0.0862X_1 + 0.3914X_3 - 0.1072X_4 + 0.1550X_5 \\
&\quad - 0.0006X_1X_4 + 0.0006X_1X_5 - 0.0184X_3X_5 \\
Y_4 &= 0.0029X_1 + 0.0159X_2 - 0.0035X_4 \\
&\quad + 0.0048X_5 - 9.06\cdot10^{-5}X_1X_3 \\
&\quad - 1.887\cdot10^{-5}X_1X_4 + 1.838\cdot10^{-5}X_1X_5 \qquad (6) \\
&\quad - 0.0006X_3X_5 - 2.25\cdot10^{-5}X_4X_5 \\
&\quad + 2.204\cdot10^{-5}X_4^2 + 0.6699 \qquad (7) \\
Y_5 &= -0.3862X_1 + 0.0903X_2 - 0.1227X_4 - 0.9514X_5 \\
&\quad + 0.0031X_1X_4 - 0.0007X_2X_4 + 0.0163X_3X_4 \\
&\quad + 0.0490X_3X_5 + 0.0027X_4X_5 - 0.0009X_2^2 \\
&\quad + 0.0060X_5^2 + 38.31 \qquad (8) \\
&\qquad (9)
\end{aligned}
$$

The performance of the reduced regression models are visualised in Figures 3–6. As seen from the figures the derived regression models provides excellent fit to the simulation data. Validation simulations have been done separately both inside and outside the factor level settings used in the DoE with satisfactory results (not shown). For each of the regression models the usual assumptions (e.g. homoscedasticity, random and normal distributed residuals) are checked and found to be within normal acceptance criteria.

The response surface of power as a function of X_1 and X_5 is depicted in Figure 7.

Once the regression model is derived it is possible to define optimisation objectives. The overall objective is to minimise the plant power requirements. Three cases are defined with the constraints showed in Table 4. Case 1 considers gas export which meets all specifications for pipeline transport and receiving facilities, but allowing the oil export not to be fully stabilised i.e. a higher portion of NGL can be exported via the oil export. Case 2 is a variation of Case 1 where the Wobbe index constraint for the gas export has been removed. Case 3 considers export of fully stabilised oil but where the gas quality in terms of energy content and density (HHV, Wobbe index and SG) is allowed to exceed the gas specifications, yet with specifications for hydrocarbon dew point.

The results of the optimisation, and benchmarking the results against full process simulations using identical factor settings are summarised in Table 5.

First of all, it is observed that the regression models applied yield results which matches the process simulations quite well. Thus, even despite the great complexity of the process simulations including fluid phase behaviour and vast amount of different unit operations modelled, the very simple regression models capture these effects adequately.

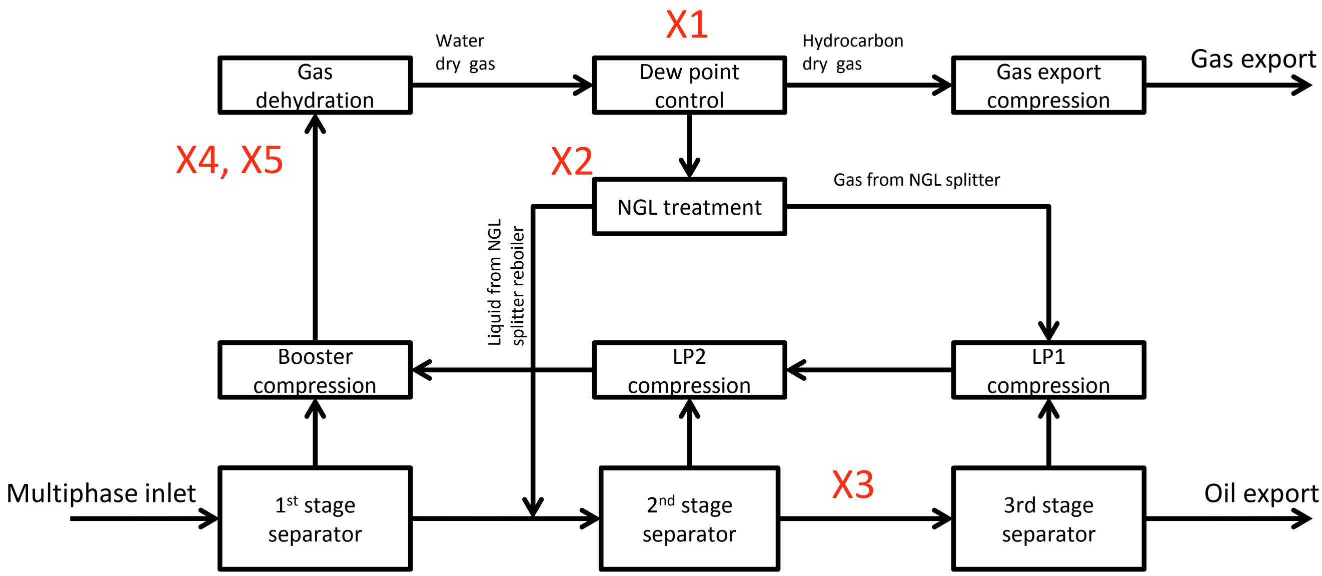

Fig. 1. Simplified process flow diagram of the process simulation model. Location of factors are indicated with red text.

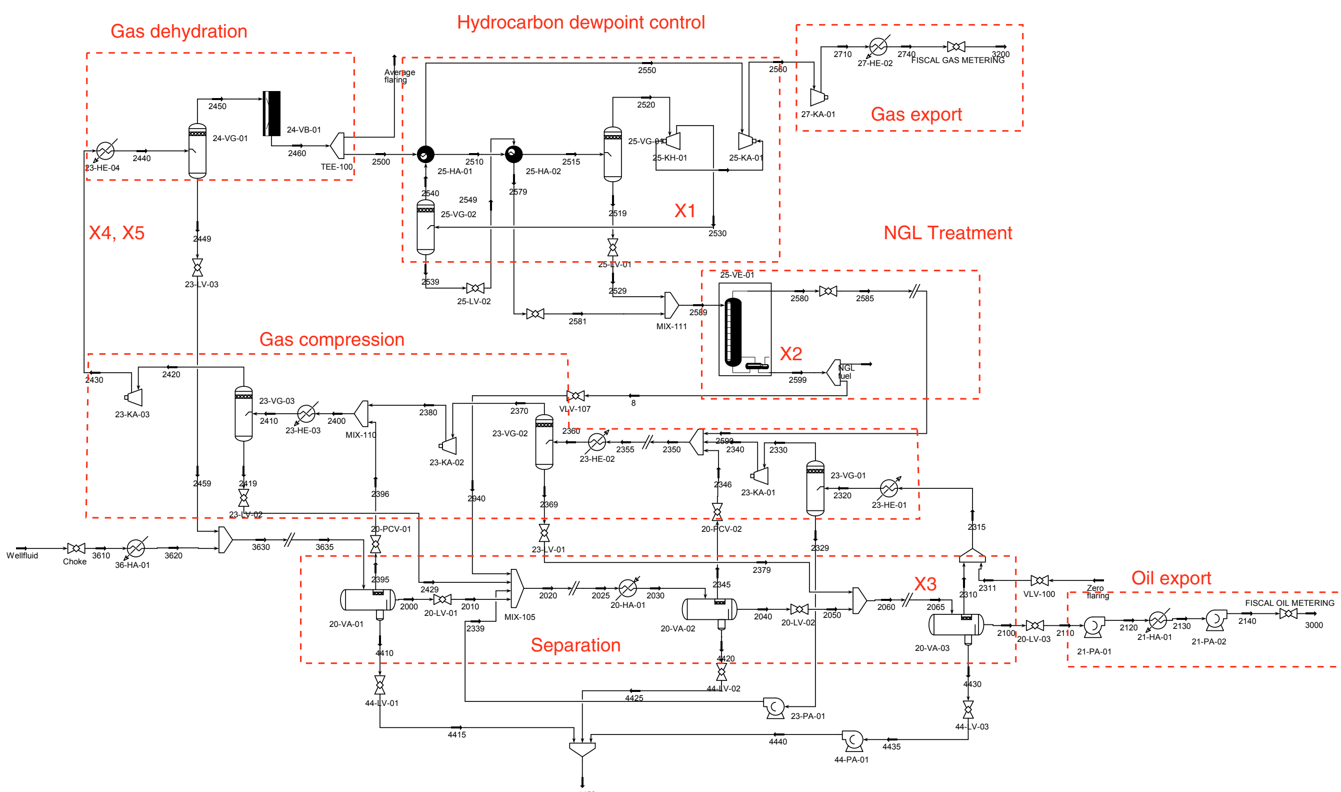

Fig. 2. Process flow diagram of the process simulation model.

Table 3. Simulation experimental plan factor level settings and process simulation responses to experimental plan. 1 = high value, 0 = mid value and -1 = low value.

No.	Factors					Responses					
	P_{exp}	T_{reboil}	P_{sep}	$P_{booster}$	T_{dehyd}	Wobbe (MJ/Nm^3)	SG (–)	HHV (MJ/Nm^3)	Dew (C°)	Power (kW)	RVP (psia)
1	0	0	0	0	0	56.56	0.663	43.64	-22.89	8670	14.71
2	-1	-1	-1	-1	-1	55.85	0.6419	42.39	-37.37	10130	16.41
3	1	-1	-1	-1	-1	56.88	0.6724	44.17	-17.38	8439	13.82
4	-1	1	-1	-1	-1	55.84	0.6417	42.38	-37.46	10160	15.95
5	1	1	-1	-1	-1	56.86	0.6718	44.16	-17.55	8453	13.44
6	-1	-1	1	-1	-1	55.82	0.641	42.33	-38	9012	17.32
7	1	-1	1	-1	-1	56.82	0.6707	44.09	-18.09	7591	14.83
8	-1	1	1	-1	-1	55.83	0.6416	42.37	-37.81	9158	17.15
9	1	1	1	-1	-1	56.81	0.6704	44.07	-18.2	7605	14.41
10	-1	-1	-1	1	-1	55.62	0.6354	42	-42.69	11440	16.72
11	1	-1	-1	1	-1	56.55	0.6626	43.61	-22.34	9550	15.06
12	-1	1	-1	1	-1	55.64	0.6358	42.03	-42.32	11600	16.23
13	1	1	-1	1	-1	56.55	0.6625	43.61	-22.37	9577	14.51
14	-1	-1	1	1	-1	55.63	0.6357	42.02	-42.57	10190	17.9
15	1	-1	1	1	-1	56.51	0.6613	43.53	-23.11	8478	16.01
16	0	0	0	0	0	56.52	0.6618	43.57	-23.45	8629	14.52
17	-1	1	1	1	-1	55.58	0.6341	41.92	-43.04	10070	17.25
18	1	1	1	1	-1	56.53	0.662	43.57	-22.73	8553	15.67
19	-1	-1	-1	-1	1	56.54	0.6623	43.6	-23.97	9127	13.76
20	1	-1	-1	-1	1	57.68	0.6965	45.62	-4.154	7643	11.32
21	-1	1	-1	-1	1	56.52	0.6617	43.56	-24.24	9143	13.35
22	1	1	-1	-1	1	57.67	0.6963	45.6	-4.198	7660	11.07
23	-1	-1	1	-1	1	56.44	0.6593	43.42	-25.55	8300	14.88
24	1	-1	1	-1	1	57.58	0.6933	45.43	-5.428	7017	12.53
25	-1	1	1	-1	1	56.42	0.6589	43.39	-25.64	8307	14.5
26	1	1	1	-1	1	57.58	0.6933	45.43	-5.346	7025	12.24
27	-1	-1	-1	1	1	56.26	0.6541	43.11	-28.6	10120	14.49
28	1	-1	-1	1	1	57.3	0.6851	44.94	-9.965	8372	12.54
29	-1	1	-1	1	1	56.27	0.6544	43.13	-28.39	10180	14.01
30	1	1	-1	1	1	57.28	0.6842	44.89	-10.22	8398	12.14
31	-1	-1	1	1	1	56.17	0.6515	42.95	-30.42	9184	15.95
32	1	-1	1	1	1	57.17	0.6805	44.67	-12.6	7592	13.88
33	-1	1	1	1	1	56.17	0.6514	42.95	-30.4	9232	15.41
34	1	1	1	1	1	57.14	0.6803	44.66	-12.15	7620	13.44
35	0	0	0	0	0	56.52	0.6617	43.56	-23.43	8602	14.52
36	-1	0	0	0	0	56.03	0.6474	42.71	-33.17	9569	15.72
37	1	0	0	0	0	57.05	0.6775	44.49	-14.08	7960	13.46
38	0	-1	0	0	0	56.52	0.6618	43.56	-23.46	8597	14.68
39	0	1	0	0	0	56.52	0.6617	43.56	-23.45	8640	14.29
40	0	0	-1	0	0	56.52	0.6617	43.56	-23.4	9108	13.95
41	0	0	1	0	0	56.53	0.6619	43.57	-23.44	8275	15.32
42	0	0	0	-1	0	56.71	0.6673	43.89	-20.54	8261	14.19
43	0	0	0	1	0	56.39	0.6577	43.32	-25.55	9068	14.84
44	0	0	0	0	-1	56.17	0.6515	42.95	-29.76	9137	15.86
45	0	0	0	0	1	56.92	0.6735	44.25	-16.84	8249	13.6
46	0	0	0	0	0	56.51	0.6613	43.53	-23.67	8615	14.52

In terms of the minimisation of the power requirements for process equipment drivers, mainly compressors, it is obvious comparing Case 1 and Case 3, that meeting export requirements for the gas is much more demanding in terms of energy than meeting oil export specifications. In other words exporting NGL mainly in the gas export is less energy intensive than exporting the NGL mainly in the oil export. Case 2 which is Case 1 without the Wobbe index constraint also shows that the minimiser finds a minimum which is in favour of pushing the NGL towards the gas export and removing constraints on both Wobbe index and RVP gives the lowest power requirement.

Table 4. Constraints applied in power optimisation.

Response	Case 1	Case 2	Case 3
Export gas dew point	≤ -2	≤ -2	≤ -2
Export gas Wobbe index	≤ 56.2	–	–
Export gas HHV	≤ 46	≤ 46	–
Export gas SG	≤ 0.7	≤ 0.7	–
Export oil RVP	–	–	12

It is also worth mentioning that for all cases many factors tends to be at their applied bounds which means that further reduction of the power requirement is possible if the bounds are expanded. The minimum power for all cases is achieved with the discharge pressure of the booster compressor at the lower bound. Further, the pressure after the turbine-expander seems to be the most important

Table 5. Optimisation results. Factors are bounded by the level settings used in the experimental plan for fitting regression models.

	Case 1			Case 2			Case 3		
Response	RSM	HYSYS	Error (%):	RSM	HYSYS	Error (%):	RSM	HYSYS	Error (%)
Power	8841	8832	-0.1	7008	7017	0.13	7129	7084	-0.63
Dew	-36.13	-36.05	-0.22	-6.23	-5.428	-12.87	-6.03	-5.439	-10.58
Wobbe	56.2	55.9	-0.54	57.87	57.58	-0.5	57.88	57.57	-0.54
HHV	42.3	42.47	0.4	45.15	45.43	0.62	45.18	45.41	0.51
SG	0.647	0.6433	-0.57	0.697	0.6933	-0.53	0.6975	0.6931	-0.63
RVP	17.05	17.02	-0.18	12.45	12.53	0.64	12	12.02	0.17
Factors									
P_{exp}	26.95	26.95		45	45		45	45	
T_{reboil}	15	15		15	15		35	35	
$P_{3^{rd}Sep.}$	2.5	2.5		2.5	2.5		2.45	2.45	
$P_{booster}$	85	85		85	85		85	85	
T_{dehyd}	25	25		35	35		35	35	

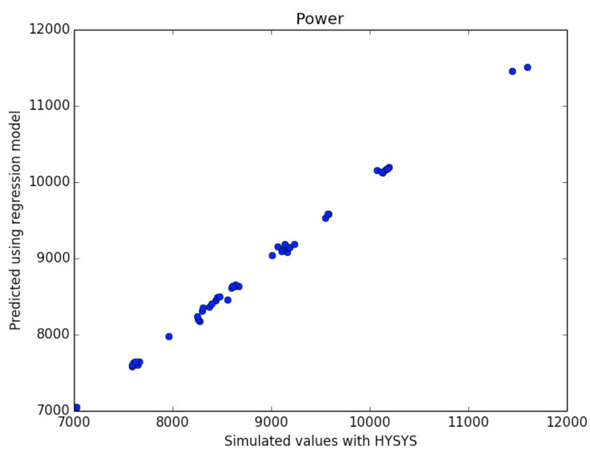

Fig. 3. Total plant power requirements (kW). Regression model prediction vs. process simulation results.

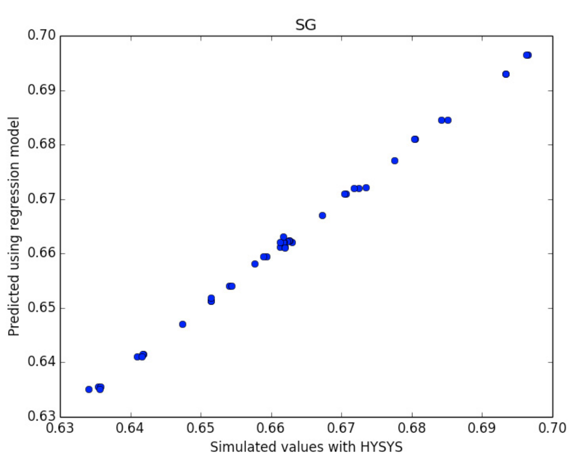

Fig. 4. Export gas specific gravity. Regression model prediction vs. process simulation results.

control parameter for determining the amount of NGL in the gas export as well as the total power requirement.

4. CONCLUSION

In this paper it has been demonstrated that RSM can be a powerful tool for optimising oil and gas separation facilities

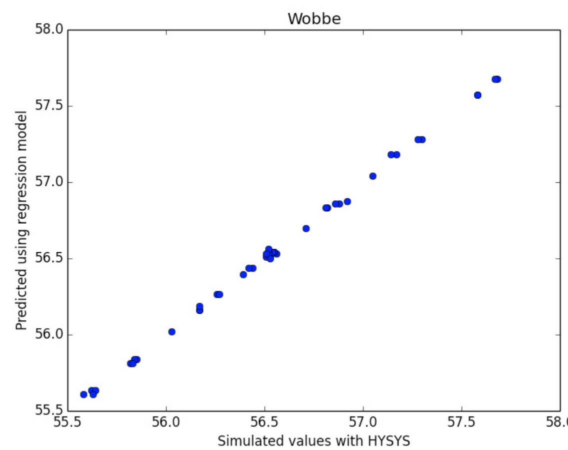

Fig. 5. Export gas Wobbe Index (MJ/Nm^3). Regression model prediction vs. process simulation results.

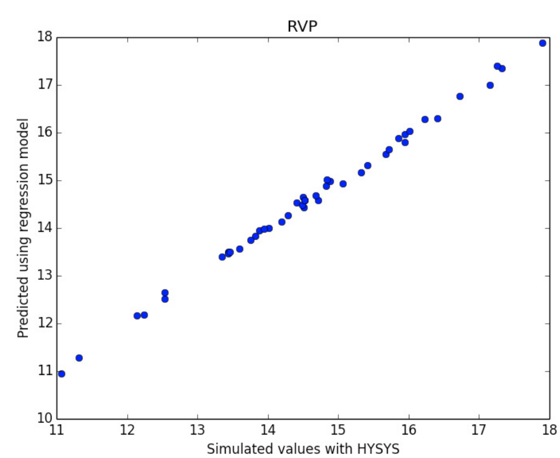

Fig. 6. Export oil RVP (psia). Regression model prediction vs. process simulation results.

by using process simulations as a surrogate model of a real plant. The regression models derived from DoE closely resembles the results from process simulations. Due to the simplicity of these models, they hold potential for being coupled to the control of the real physical process and could be used for on-line process control and optimisation.

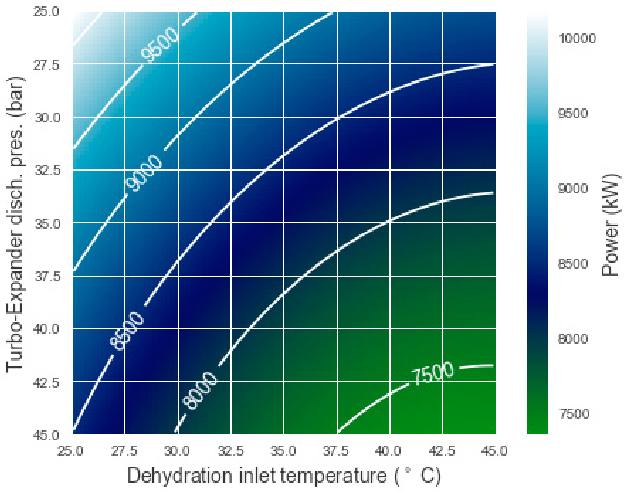

Fig. 7. Response surface of total power requirement as a function of turbine-expander discharge pressure and dehydration inlet temperature. Factor settings for reboiler temperature, booster compressor discharge pressure, and 3rd stage separator pressure is 25, 90, and 2.3, respectively.

The chosen example in the present paper, is a process with a fluid containing a significant amount of NGL, where it is challenging to meet oil and gas export specifications. The results clearly shows that it is much less energy demanding to export the NGL mainly with the gas export rather than with the oil export. Further, allowing NGL to exceed key export specifications for both oil and gas, the energy requirement can be reduced even further.

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