AALBORG UNIVERSITET

Optimisation of Central Offshore Process Equipment and Weight Estimations

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EN7-2

Bachelor Thesis

In collaboration with:

RAMBØLL

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Abstract

When processing the retrieved multiphase fluid from the wells, the many types of equipment used consume a great amount of energy during the separation of oil, gas and water. Specific oil and gas export quality has to be met before the products can be exported to the consumer. Achieving the export quality and minimising the power consumption is a complex system to predict.

This projects deal with an approach were Design of Experiment and Response Surface Methodology has been used in order to create a regression model of a given HYSYS separation simulation, with five independent high influence variables, which can predict a global minimum with export constraints applied. An optimisation algorithm was created in the programming language Python and it was verified to perform well inside the experimental training set. The optimisation model was found suitable to future industry usage, in order to find the lowest possible power consumption and still maintaining the strictly demanded export quality constraints.

In the extension of the optimisation model, the HYSYS separation simulation was used to determine a regression model, estimating the central process equipment used, based on the variety of the flow rates for oil, gas and water. This set the foundation for a Monte Carlo model, which predict the total topside weight by using correlation factors. All contributions in the Monte Carlo model are independent randomly picked, within a normal distribution uncertainty applied to all aspects in the model. The model is intended to be used in future early phase projects for a less time consuming and more precise result, than the methods used at the moment.

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Project Period: 31st of October 2014 – 15th of January 2015
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Preface

This bachelor thesis was written in the fall of 2014 by *Kasper Rønn Rasmussen*, enrolled in the thermal processes and combustion study program, within sustainable energy technologies at Aalborg University Esbjerg.

The project is in made in co-operation with Ramboll Oil & Gas, a multi-disciplinary engineering consultancy company and is based on the work done during the internship in the process department from may until end October. A special thanks to Ramboll Oil & Gas and the process department for providing the opportunity and guidance of this study.

Referencing to the bibliography, which is found in the back of the report on page 57, are enclosed in brackets as (x). The number inside the bracket corresponds to the reference number in the bibliography. Figures without reference are self-made.

For improved understanding of the methods used, it is advised to read the referred procedure appendices, starting at page 58. Most abbreviations are explained in the text when occurring, but some are only explained in the abbreviation list at page 3.

Abbreviations

Abbreviation	**Meaning**
LP	Low Pressure
IP	Intermediate Pressure
TEG	Tri Ethylene Glycol
LT	Low Temperature
NGL	Natural Gas Liquids
ppm	Part per Million
BS&W	Basic Sediment and Water
HHV	Higher Heating Value
RVP	Reid Vapour Pressure
SG	Specific Gravity
CCD	Central Composite Design
RSM	Response Surface Methodology
DOE	Design of Experiment
MEL	Master Equipment List
PFD	Process Flow Diagram
CSV-file	Comma Separated Values file
HC	Hydrocarbon

Content

Introduction

Due to the large quantity of energy consuming process equipment placed on offshore production platforms it is necessary to optimise the process facility in order to minimize the energy consumption. Oil and gas separation is a complex process, where lots of factors interact making it difficult to separate effects and distinguish trends. The oil and gas export qualities are to meet certain demands before being sent through pipelines to the on-shore refineries and in the end received by the consumer. The process department in Ramboll Oil & Gas uses HYSYS to model and optimise central process equipment in projects for their clients. HYSYS is a comprehensive process modelling system used by the world's leading oil & gas producers, refineries and engineering companies to optimise process design and operations from Aspen Technology, Inc..

The absolute minimum energy consumption, when constrained by the export quality demands, is still definitively to be found. It would be interesting to find the best composition of variable values in the process assembly to achieve the lowest possible energy consumption and still preserving the oil and gas export quality.

In connection with modelling and sizing estimates of process equipment in early phase studies, uncertainties of 30 to 50 % is applied to each piece of equipment and to the total weight. The interaction between the 200+ item uncertainties is not taking into account. Adding this aspect to modelling would indeed be relevant and it all leads to the following initiating problem:

How can the oil and gas separation be optimised more effectively and can the optimisation for the equipment be used to give better and more accurate weight estimations?

Ramboll is multi-disciplinary engineering, design and consultancy company who provides knowledge based solutions within construction, transportation, environment, energy, oil & gas, telecom and management consulting. Ramboll was founded in 1945 as the *Rambøll & Hannemann* partnership in Copenhagen, and has since then expanded to an international corporation employing 12.500 specialist. Ramboll has nearly 200 offices worldwide represented in 21 countries. Their five values are absolute and form the foundation of the company – Empathy, Enjoyment, Empowerment, Insight and Integrity. Combined, they constitute a unique point of reference in all their decisions and actions.

Ramboll has many years of experience as a consulting company in the oil and gas industry and it started with their comprehensive work in the Danish part of the North see, which now also is applied internationally. Ramboll's oil and gas experts take care of the entire project – from the initial feasibility studies about structural design, safety systems and environmental assessments to commissioning, adjustment and final decommissioning. Projects are completed by a high quality standard with great focus on safety and environmental interest, along with a principle of sustainable development. Ramboll's expertise is within piping, projecting of platforms, environment and maintenance. The biggest clients for Ramboll Oil & Gas are Maersk Oil, Statoil, Dong Energy, Nord Stream, Qatar Petroleum and EU.

A collaboration between Ramboll Oil & Gas' process department in Esbjerg and *Kasper Rønn Rasmussen*, student of sustainable energy technology at Aalborg University Esbjerg, has been set up on the basis of the internship that took place from 1st of May through October 2014 to research the described issues.

1 Background

In this chapter the basic knowledge about oil and gas separation and Ramboll's weight estimation methods is described and analysed. Optimisation methods for possible use are reviewed.

1.1 Oil and Gas Separation

The multiphase fluid from the wells, which consist of crude oil, gas, condensates, water and various contaminants, is separated into desirable fractions and treated by the process equipment to deliver stabilised marketable products. Facilities to test products and clean waste products such as produced water are also present components of the process. An example of the main equipment of the process, shown in Figure 1-2 page 9, will be described in this section. Other designs of process flow diagram, PFD, can be possible depending on the design criteria's and objectives for the production.

1.1.1 Separators

The first three main separators are gravity separators, in this case with a horizontal orientation. The multiphase fluid enters the 1st stage separator with a pressure of 30-35 barg. A choke valve carries out a possible reduction of the pressure between the well and separator. The separated water is lead out at the bottom of the vessel to the produced water treatment unit along with water separated from the 2nd and 3rd stage separators. The gas is lead out in the top and the oil to the 2nd stage separator. The pressure is now reduced to about 10 barg. Again the gas is lead out through the top in the 2nd stage separator and the oil is forwarded to the 3rd stage separator where the pressure is from 0-2 barg. The oil is lead through the metering station and then exported by pipes or stored in tanks. The purpose of the pressure reduction in several stages is to achieve maximum oil recovery and stabilize the oil and gas, and separate water. A large sudden pressure reduction in a single separator will cause a quick vaporisation, which leads to instabilities and safety hazards.

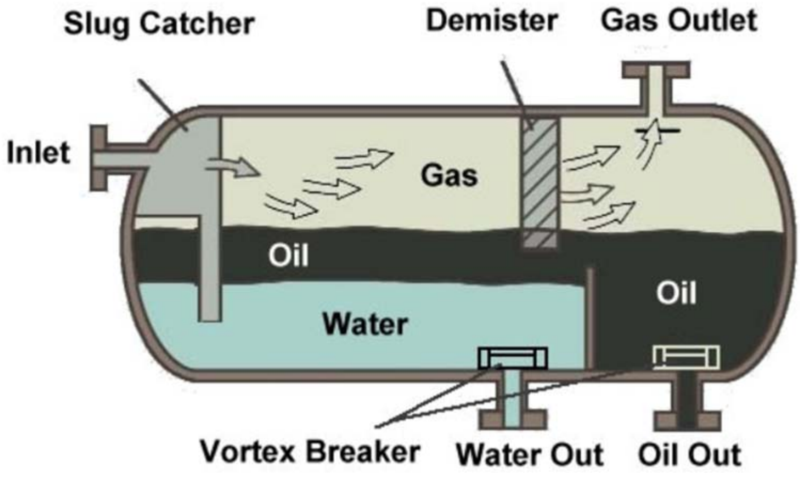


Figure 1-1: Sketch of a typical gravity separator (1).

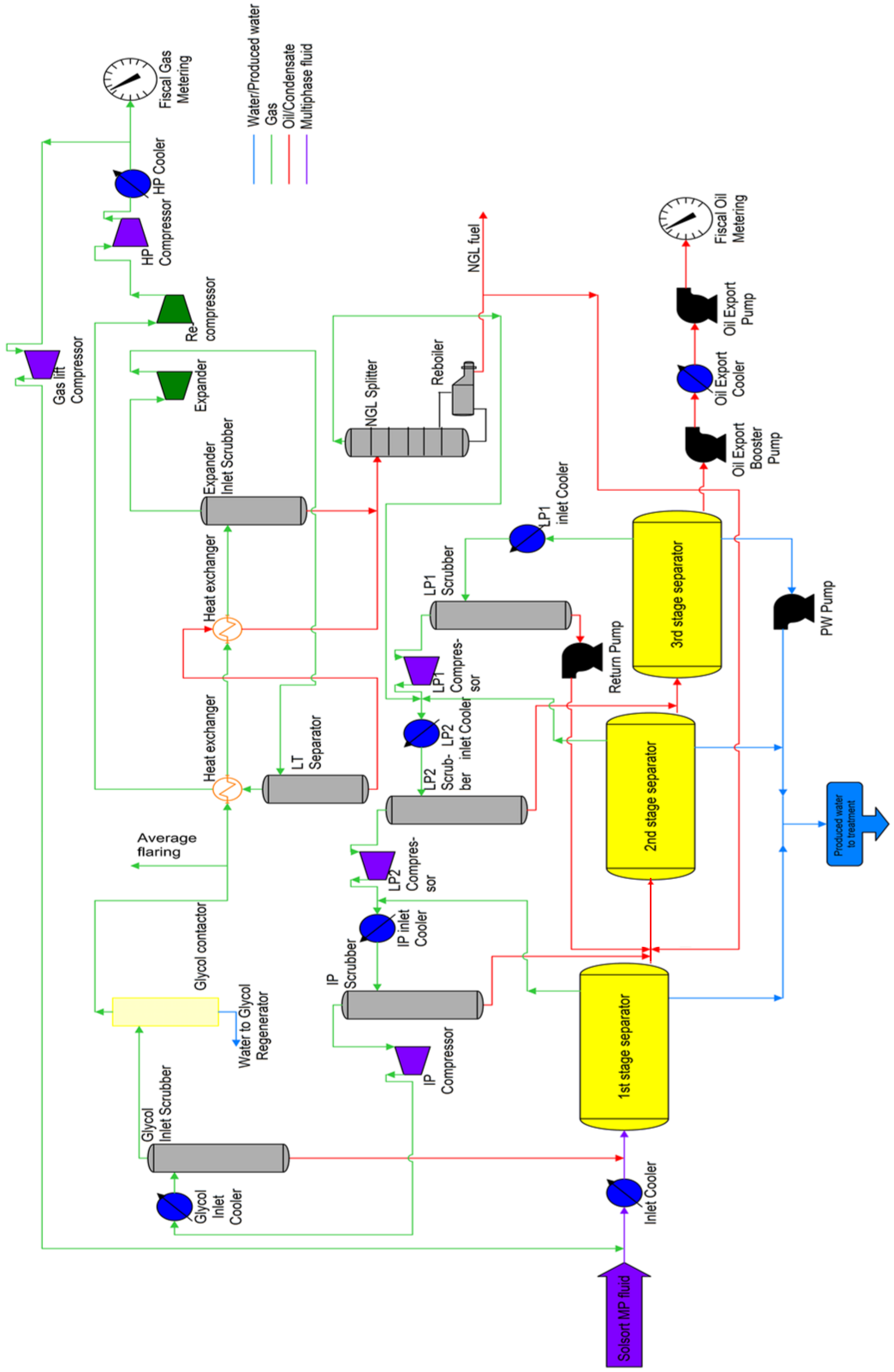


Figure 1-2: Process Flow Diagram, PFD, of an oil & gas separation and treatment process.

The retention time in a gravity separator, shown in Figure 1-1 page 8, is typically 5 minutes according to GPSA, *Gas Processors Suppliers Association* (2). This time allows the gas to bubble out, water to settle at the bottom and the oil to be taken out in the middle. At the inlet there is a baffle slug catcher. Slugs are large gas bubbles and liquid plugs, and the effect of this reduced by the catcher. Between the water and oil outlet is the weir plate located. It has the function of keeping the settled heavier water separated in bottom, so the lighter oil can skim over the plate and be lead out. The oil and water outlet is equipped with a vortex breaker to reduce disturbance on the liquid. Any vortex formation is broken to ensure that only separated liquid is tapped of and not mixed with the unwanted liquid. Similarly the gas outlet is equipped with demisters, where filters will remove liquid droplets in the gas.

1.1.2 Gas Treatment and Compression

The gas from the 3rd stage separator is sent to the LP1 compressor. Before entering the compressor the gas is cooled by a heat exchanger and passes through the LP1 scrubber in order to remove liquid. The lower the temperature of the gas, the less energy will be used to compress the gas for a given final pressure. When exiting the LP1 compressor the gas is mixed with the gas from the 2nd stage separator, along with the excess gas from the NGL splitter, before being cooled and passed through the LP2 scrubber and compressor. The gas is compressed up to approximately 30 barg by the LP2 compressor. The LP2 outlet gas is now mixed with the gas from the 1st stage separator before it is cooled. It is then forwarded to the IP scrubber and leaves the IP compressor at a pressure of approximately 50 barg. The LP and IP compressors are often centrifugal compressors driven by an electrical motor. Larger compressors are turbine driven.

Before the gas enters the glycol contactor, also called TEG, it goes through the glycol cooler and scrubber. A glycol contactor is an absorber where the gas gets absorbed in the glycol. The glycol is boiled so the water evaporates.

1.1.3 Heat Exchangers

The dry gas that leaves the glycol contactor enters first a gas-gas heat exchanger as the heating medium, leaves it and then enters a gas-condensate heat exchanger also as the heating medium. It then enters the expander inlet scrubber to extract condensate. The gas is lead out through the top to the expander-compressor, which are an expander and a compressor driven on the same axis. A large amount of the energy can therefore be recovered. After the gas has been expanded it is applied to the LT separator, and the gas now enters the gas-gas heat exchanger as the cooling medium before being compressed, cooled and then lead to the metering station. The condensate extracted from the LT separator is used as cooling medium for the gas-condensate heat exchanger before being forwarded to the NGL splitter along with the condensate from the expander inlet scrubber.

Tube and shell heat exchangers are most often to be used, but also plate heat exchanger is used at low pressure operating conditions.

1.1.4 NGL Splitter

NGLs are valuable by-products of natural gas processing. NGLs are sold separately and consist of ethane, propane, butane, iso-butane and natural gasoline. They are used at on-shore oil refineries or petrochemical plants as sources of energy and for enhancing oil recovery in oil wells. It is a challenge to export it as a by-product off-shore because of the requirement of extra infrastructure on-shore.

The splitter is separating the lighter components at the top and heavier component in the bottom. The reboiler attached is used as an item to control the export oil and gas qualities by separating further lighter components.

1.1.5 Produced Water Treatment

Environmental legislation in most countries is strict and in the North-East Atlantic the OSPAR convention protects the marine environment. For produced water disposal the platform has to comply with the *OSPAR Recommendation 2001/1 for the Management of Produced Water from Offshore Installations* (3). It emphasizes that produced water discharged into sea should not contain a higher amount of oil than 30 mg/l, corresponding to 30 ppm. Figure 1-3 shows a simple produced water system.

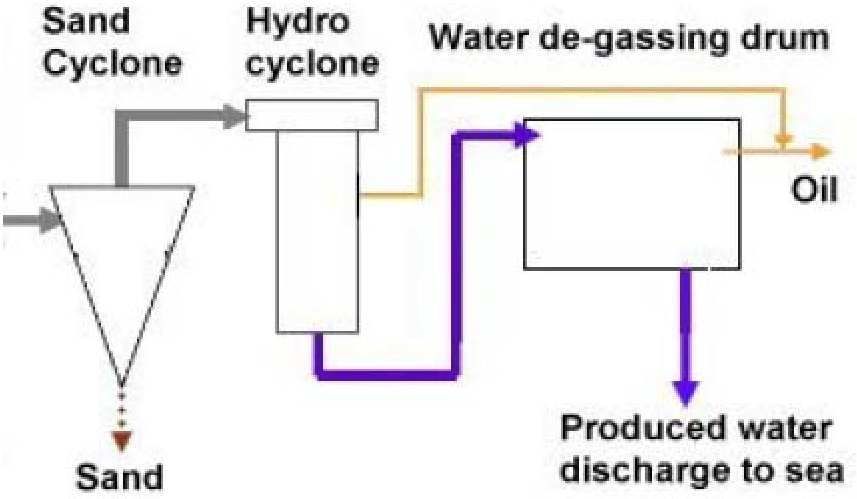


Figure 1-3: Typical water treatment system (1).

The produced water from the separators first goes through a sand cyclone, if sand is present, which removes most of sand. Before the sand is discharged it is washed clean. Then the water enters the hydrocyclone, both cyclones are technology based on high centrifugal forces and the difference between the specific gravity of oil and water, causing the lighter oil to separate from the heavier water and solids. The produced water is injected tangentially under pressure. The speed then increases because of the conical shape of the cyclone as the diameter narrows. Heavier solids and water moves in a vortex near the wall towards the exit, whereas the lighter oil will move in a secondary vortex in the center of the cyclone towards the inlet. A typical hydrocyclone unit consists of 70 – 80 hydrocyclone liners. Each liner is based on the above described hydrocyclone principle. To achieve the desired optimal flow through the hydrocyclone unit, liners can be replaced by dummies, which block the flow to give a higher flow in the remaining liners. The water is at last collected in the water de-gassing drum. Here the remaining gas will slowly rise to the surface and attract oil droplet to surface by flotation. The surface oil is drained and the produced water is ready to be discharged into sea. Oil recovered in the system is often recycled back to the 3rd stage separator.

1.2 Oil and Gas Export Quality

Oil and gas is measured very accurate, before it is sent off the platform into pipes or tank on ships for treatment at the refineries. The measuring takes place at an oil metering station and at a gas metering station. The oil and gas has to fulfil certain export demands qualities.

1.2.1 Metering Stations

There are several purposes of the metering stations. At first it is the direct billing of the sold products – oil, condensate and gas. There is a high focus on the metering from multiple participants, i.e. the operator and the partners in the license off the production field. Also billing of hydrocarbons taxes are conducted at the metering stations. These metering stations are designed according to NORSOK standards (4).

The oil metering station operates most commonly by turbine meters with dual pulse outputs. The metering is split into several runs depending on the flow to cover the full range with sufficient accuracy. From measuring volume, number of pulses, pressure and temperature the flow computer provides accurate flow measurements using formulas from industry standards. Typically an accuracy of +/- 0.3 % is achieved (1). The gas metering station measures by an ultrasonic meters or orifice meters. The pressure differential is measured over the orifice plates along with pressure, temperature, and mass. Ultrasonic meters work by sending beams across the path and measure the Doppler Effect. Several gas metering stations is provided with equipment for measurement of hydrocarbon, HC, dew point, H_2S concentration, specific gravity and a chromatograph to determine the gas composition. An accuracy of +/- 1.0 % is achieved (1).

1.2.2 Achieving Export Quality Specifications

The export of oil and gas has certain specifications that need to be retained, shown in Table 1-1. The specifications may act as constraints and can be difficult or even impossible to comply with simultaneously.

Dry export gas specifications		
Wobbe index (max/min)	50.8 / 55.8	MJ/Nm^3
HHV value (max/min)	40.2 / 46.0	MJ/Nm^3
Specific gravity (min/max)	0.55 / 0.70	-
H_2S content (max)	5	Mg/Nm^3
CO_2 content (max)	2.5	Mole %
O_2 content (max)	0.1	Mole %
Water dew point (max)	-8	°C @ 70 bar
HC dew point (max)	-2	°C @ 70 bar
Export oil specifications		
Methane content	Max. RVP 12 psia	
Ethane content		
Propane content		

Butane content		
Produced water content (max)	2.5	Vol. %
BS&W (max)	2.5	Vol. %

Table 1-1: Oil & Gas export specifications (5).

RVP, Reid Vapour Pressure, is a process used in the petroleum industry to measure the volatility of petroleum crude oil, gasoline and other petroleum products. The RVP value has to be at a certain level to make sure the oil does not create bobbles and boils in the pipe lines. Too high RVP values causes too much steam. To make sure the gas does not condensate in the pipeline, the dew point cannot be higher than -2 degrees Celsius. The gas also has to satisfy the HHV and Wobbe index limits.

When designing a process facility all these factors are investigated for the expected production rates to find out which specification can be meet in a HYSYS simulation. It is then decided where to focus lies for the production according to the oil and gas quality.

1.3 Optimisation Methods

Possible optimisation techniques for setting the variable values at a level in the process so a minimum of power consumed, and the oil and gas export quality demands are meet at the same time, are described in this section. The basis for the methods is according to a HYSYS simulation of a given oil and gas separation process.

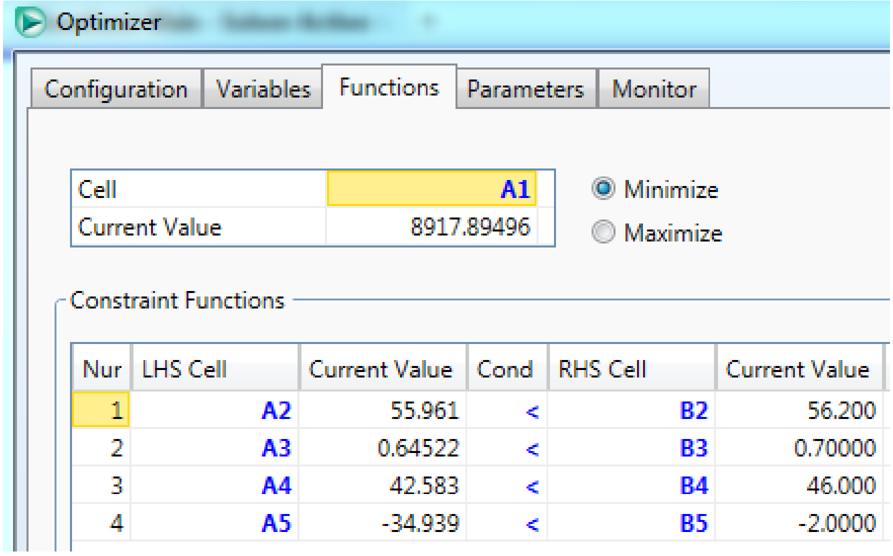
1.3.1 Manual Adjustment – Trial and Error

When adjusting the equipment variables manually by trial and error to achieve a specific export quality the interaction effects of the variables are not taking into account. This method will also result in many simulations or experiments for even a few independent variables.

It is possible to get a rather good result by this method. Through trial and error, experiences are achieved on which variable/variables causes the most impact in order to minimise the power consumption for the HYSYS simulation. Even if achievement of a good result from many trails and simulations, it is not certain that the global optimum is found.

1.3.2 HYSYS Built in Optimiser

In HYSYS there is a built in optimisation tool, where it is possible to minimise or maximise a chosen parameter in the entire process simulation. Constraint functions can be applied to the optimisation so any desired possible case can be investigated. This is shown in Figure 1-4, where the wanted objective function to be optimised is the A1 cell and the constraint functions below. To the right in the B cells wanted values for the constraint functions is given.



Optimizer [redacted]

Cell	A1
Current Value	8917.89496

● Minimize
○ Maximize

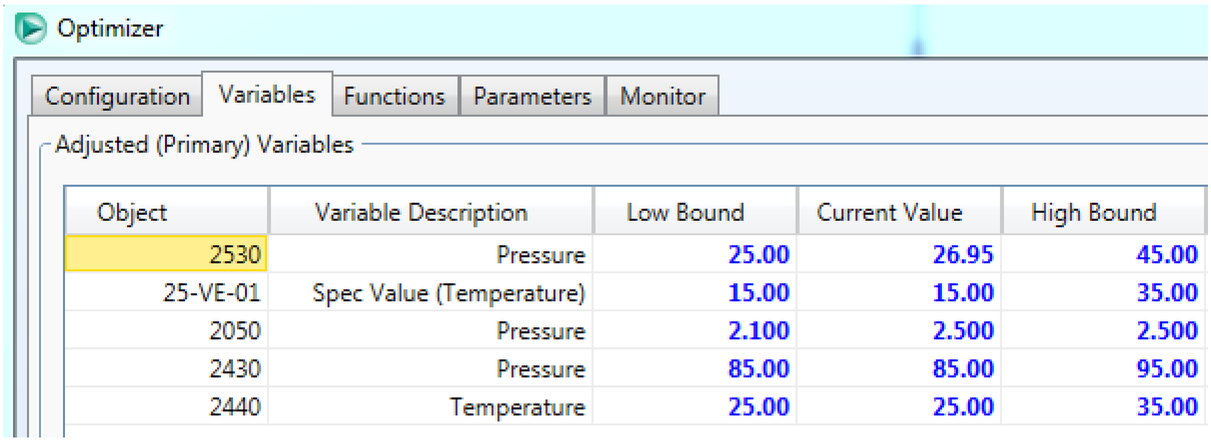
Constraint Functions

Nur	LHS Cell	Current Value	Cond	RHS Cell	Current Value
1	A2	55.961	<	B2	56.200
2	A3	0.64522	<	B3	0.70000
3	A4	42.583	<	B4	46.000
4	A5	-34.939	<	B5	-2.0000

Figure 1-4: Screen shot of HYSYS built in optimisation tool.

The simulation is then proceeding with these settings and a result to the objective function is given.

A list of the variable values for the given case is then given by the optimisation tool, seen in Figure 1-5.



Optimizer

Adjusted (Primary) Variables

Object	Variable Description	Low Bound	Current Value	High Bound
2530	Pressure	25.00	26.95	45.00
25-VE-01	Spec Value (Temperature)	15.00	15.00	35.00
2050	Pressure	2.100	2.500	2.500
2430	Pressure	85.00	85.00	95.00
2440	Temperature	25.00	25.00	35.00

Figure 1-5: Variable values given by the optimisation case – HYSYS screenshot.

The data in the two figures will not further be described. This is only intended for information about the HYSYS built in optimisation tool.

1.3.3 Design of Experiment and Response Surface Methodology

Applying boundaries to the independent variables will narrow the amount of possible settings, but it still gives a tremendous number of experiment combinations, which then will require almost an unmanageable amount of time to complete for a hand full of variables. Therefor a more intelligent and systematic method is needed that decreases the number of experiments – Design of Experiment, DOE.

Two fundamental types of variables are present in DOE, i.e. factors and responses, shown graphically in Figure 1-6. Responses are the objective of the experiment or properties that reveal if the system behaves in a healthy or unhealthy manner. The factors are tools for manipulating the system, since they apply an influence on the system.

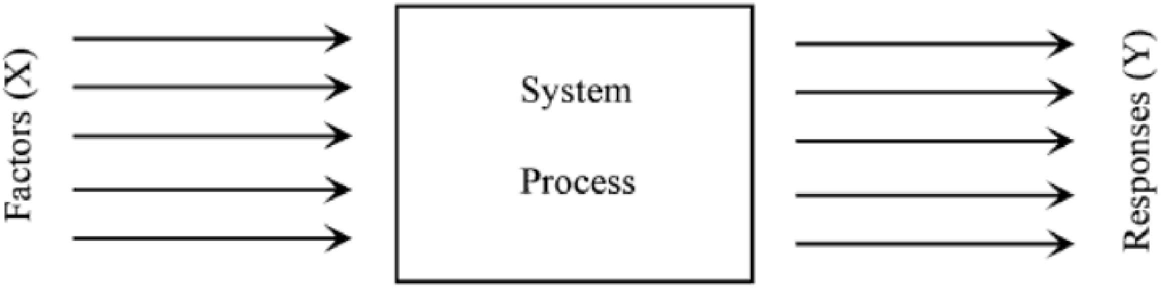


Figure 1-6: Factor and responses overview (6).

DOE is used to find the optimum conditions in industrial research, development and production. As the name indicates, DOE is dedicated for applications where systems are studied by running, in an educated way, a series of similar test. The objects of study are complex products and processes, defined with a multitude of independent variables, which usually interact in the effects on certain dependent parameters. The main advantage of using DOE in test series lie in the massive reduction in the number of necessary experiments for a specific study. This benefit is possible by keeping the focus only on detected main effects, and is enhanced by taking in consideration of the interactions appearing between the studied parameters.

The experiments are laid out in symmetrical fashion around the standard reference experiment. Hence, the standard reference experiment is usually called the center-point. For example experiments that consist of 5 variables and has a center point set to mid-level within their respective chosen range. The experiment then becomes a 5 factor 3 level experiment – low, mid and high level. If a full factorial experimental design is to be studied it would result in 3^5 = 243 experiments. By choosing a face-centered central composite design, CCD, the number of experiments can be significantly reduced.

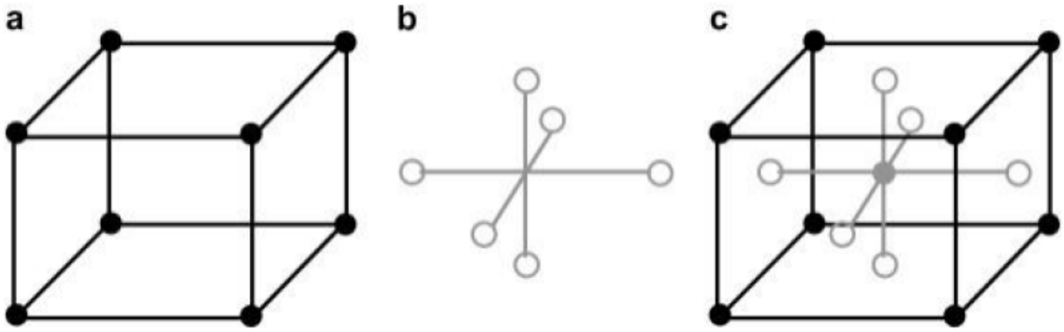


Figure 1-7: Three level three factor face centered composite design (7).

Figure 1-7 page 15 shows, a) Points in factorial portion of the design, b) Points in axial, star, portion of the design and c) the factorial and axial portions to give the CCD with center point. A total of 46 different experiments are to be carried out, including 4 recommended replicates or control points usually at the center. The low level is assigned with -1, the high level +1 and the center point 0 for a given value for each independent variable in their respective range. A simulation plan is the created based on the number of variables and levels. For a 5 factor 3 level experiment the simulations are as in Table 1-2.

Sim. #	**X_1**	**X_2**	**X_3**	**X_4**	**X_5**	**Point**
1	0	0	0	0	0	Center
2	-1	-1	-1	-1	-1	Factorial
3	1	-1	-1	-1	-1	Factorial
4	-1	1	-1	-1	-1	Factorial
5	1	1	-1	-1	-1	Factorial
6	-1	-1	1	-1	-1	Factorial
7	1	-1	1	-1	-1	Factorial
8	-1	1	1	-1	-1	Factorial
9	1	1	1	-1	-1	Factorial
10	-1	-1	-1	1	-1	Factorial
11	1	-1	-1	1	-1	Factorial
12	-1	1	-1	1	-1	Factorial
13	1	1	-1	1	-1	Factorial
14	-1	-1	1	1	-1	Factorial
15	1	-1	1	1	-1	Factorial
16	0	0	0	0	0	Center
17	-1	1	1	1	-1	Factorial
18	1	1	1	1	-1	Factorial
19	-1	-1	-1	-1	1	Factorial
20	1	-1	-1	-1	1	Factorial
21	-1	1	-1	-1	1	Factorial
22	1	1	-1	-1	1	Factorial
23	-1	-1	1	-1	1	Factorial
24	1	-1	1	-1	1	Factorial
25	-1	1	1	-1	1	Factorial
26	1	1	1	-1	1	Factorial
27	-1	-1	-1	1	1	Factorial
28	1	-1	-1	1	1	Factorial
29	-1	1	-1	1	1	Factorial
30	1	1	-1	1	1	Factorial
31	-1	-1	1	1	1	Factorial
32	1	-1	1	1	1	Factorial
33	-1	1	1	1	1	Factorial
34	1	1	1	1	1	Factorial
35	0	0	0	0	0	Center
36	-1	0	0	0	0	Axial

37	1	0	0	0	0	Axial
38	0	-1	0	0	0	Axial
39	0	1	0	0	0	Axial
40	0	0	-1	0	0	Axial
41	0	0	1	0	0	Axial
42	0	0	0	-1	0	Axial
43	0	0	0	1	0	Axial
44	0	0	0	0	-1	Axial
45	0	0	0	0	1	Axial
46	0	0	0	0	0	Center

Table 1-2: CCD simulation plan for 5 factorial 3 level experiment.

The number of simulation is significantly reduced, 46 runs, compared to a full factorial simulation plan of 243 runs. After completion of the experimental plan the responses data must be analysed in order to find out which factors influence the responses. This is usually done by fitting a polynomial model to the data. The general second order response surface model can expressed as (8):

$$Y = \beta_0 + \sum_{i=1}^{k} \beta_i X_i + \sum_{i=1}^{k} \beta_{ii} X_{ii}^2 + \sum_{i<} \sum_{j=2}^{k} \beta_{ij} X_i X_j \qquad [1]$$

Y is the investigated response. X's the independent variables. By linear regression analysis the β_0 constant term and the coefficient, β's, 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 step-wise linear regression or a criterion based strategy.

Response Surface Methodology, RSM, can be thought of as a process consisting of the following steps:

1. Generate a DOE probing the expected parameter space (constraints in independent variables – physical, practical etc.).
2. Perform the corresponding simulations/experiments.
3. For each dependent variable, Y_i, generate a linear regression model as function of independent variables, X_j's.
4. Check for linear regression assumption violations, lack-of-fit etc.
(Normal residuals, "random residuals", outliers with influence etc.).
5. Perform regression model selection (repeat 3-5)
6. Validate models outside training set
7. Optimise

The models that will be created are approximations, which simplify the study of the reality. 100 % perfection will never be achieved by a model, but can still be very useful.

1.4 Weight Estimations

In early phase studies, uncertainties are applied to estimates for dimension and weight. It is given to each piece of equipment by the involved engineering disciplines. The estimates are calculated by specific design criteria, i.e. flow rates, pressures, temperatures, medium to be processed and power demands. Principles on how to indicate a better combined uncertainty is described in this section.

1.4.1 Equipment Estimations

When sizing most process equipment in feasibility and concept studies, uncertainties is applied to the estimates. The uncertainty is typically about +/- 30-50 % depending on the detail level of the project phase. Several methods are used for equipment sizing. Ramboll has their own *Estimation Manual*, which is a correlation of data from known offshore installations and experiences. In the manual it is possible to look up weight and size for a various type of equipment depending on certain design parameters. The sizing is also done by spread sheets, where known data is applied to calculate size and weight and by collecting data from multiple vendors in order to create scaling factors or correlations. All equipment sized is listed in a Master Equipment List, MEL, with known data for the design criteria, dimension and weight. The total weight is given with another uncertainty of +/- 10-30 %. To achieve a total weight for a topside structure including all necessary engineering disciplines, the work process could be divided into two approaches, as seen in Figure 1-8. The path chosen is depending on the project phase, which decides the level of detail.

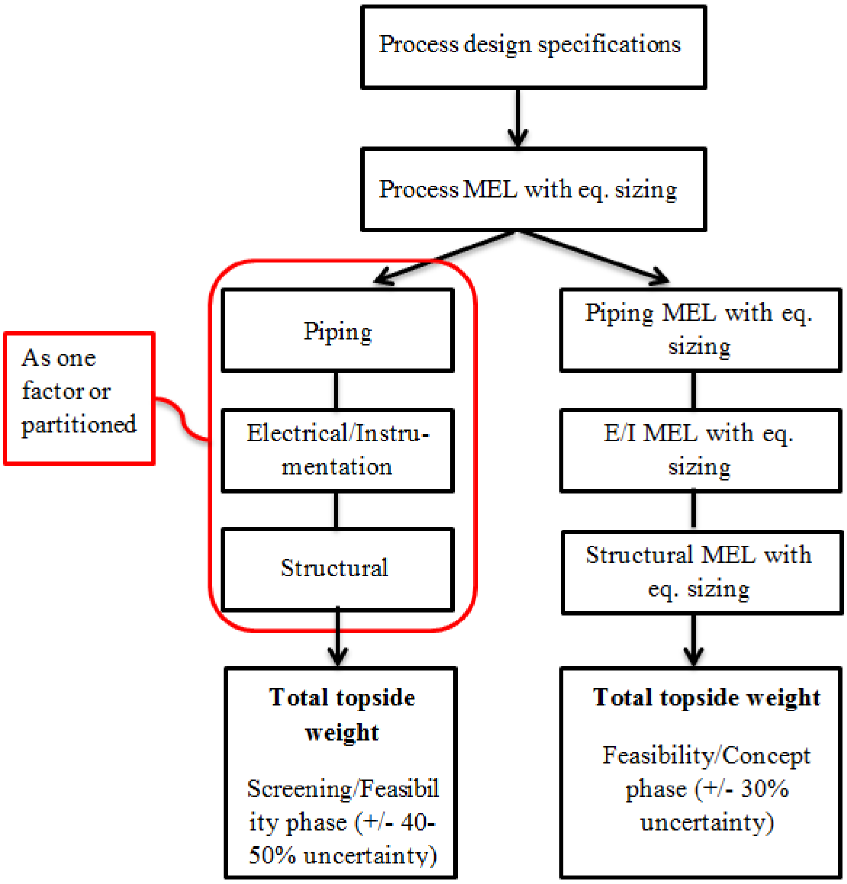

Process design specifications
Process MEL with eq. sizing
As one factor or partitioned
Piping
Electrical/Instru-mentation
Structural
Piping MEL with eq. sizing
E/I MEL with eq. sizing
Structural MEL with eq. sizing
Total topside weight
Screening/Feasibility phase (+/- 40-50% uncertainty)
Total topside weight
Feasibility/Concept phase (+/- 30% uncertainty)

Figure 1-8: Work flow diagram.

In the early project phases, screening and feasibility, the process equipment sizing can set the foundation for correlations factors based on known off-shore installation for the relation between the process weight and piping, electrical/instrument and structural. In a higher level of feasibility study or concept study, each engineering discipline will create a detailed MEL with design specification and equipment sizing for each type of equipment used in their respective field of work.

Oil, gas and water flow rates uncertainties are also present in a given reservoir. The most likely possibility is chosen through thorough analysis as the design criteria and is used for designing and sizing the equipment. The combination of equipment estimations, flow rates and factors applied can give a total weight estimate for an entire topside production platform.

1.4.2 Error Propagation

A method of describing the combined uncertainty and giving a more precise estimate when dealing with multiple variable uncertainties is by using error propagation. It is defined as the effects on a function by the uncertainties from variables and is designed to provide an accurate measurement of the uncertainty.

The method now used for the total weight in a MEL is by adding the uncertainty, depending on the project phase, to the total combined equipment weight as a worst case and can be described as:

$$Weight_{MEL} = \left(a_{weight} + b_{weight} + c_{weight} \dots + n_{weight}\right) \cdot \left(1 + \frac{Uncertainty_{percentage}}{100}\right) \qquad [2]$$

The calculated weight for each piece of equipment a, b, c… etc. with uncertainties δa, δb, δc,… etc. is desired to be combined into the quantity Q with uncertainty δQ. In order to calculate δQ, the total span of the uncertainty must be taken into account, i.e. from the lowest to the highest possible value for each quantity. This is due to the normal distribution of an uncertainty, which is an important statistical data distribution pattern occurring in many natural phenomena such as height, blood pressure, lengths of objects produced by machines etc. (9). Normally a normal distributed uncertainty represents 68% possibility (1 and -1 standard deviation), which means that the uncertainty is 16% likely (from 1 and -1 to 3 and -3 standard deviation) to be of value outside the range bounded by a +/- δa. See Figure 1-9 page 20 for further graphical details.

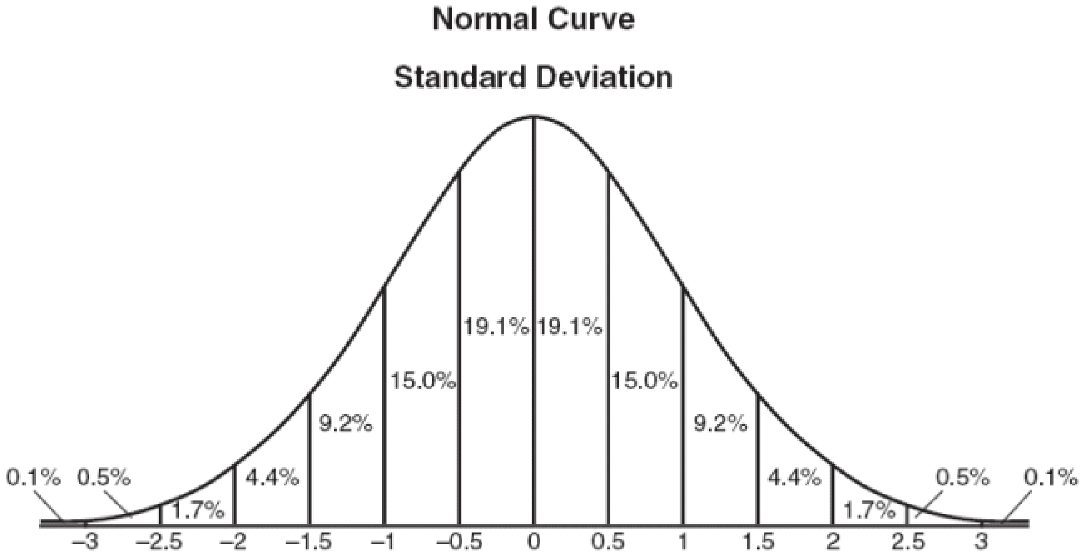


Figure 1-9: Normal distribution graphed as a bell curve with standard deviation percentages (9).

Standard deviation, σ, is controlling the spread of the normal distribution. A small standard deviation gives a more concentrated data set and bell curve. The value at the peak is called the mean. By approaching the uncertainties as normal distributed the combined uncertainty δQ, where the uncertainties depend on each other is:

$$\delta Q = \sqrt{(\delta a)^2 + (\delta b)^2 + (\delta c)^2 \ldots + (\delta n)^2} \tag{3}$$

The uncertainties add in quadrature, i.e. the square root of the sum of squares. (10)

1.4.3 Monte Carlo Method

In order to compile the multiple aspects with their respective uncertainties and get a mathematical approximation of the outcome, total weight, Monte Carlo Simulation has to be applied. Monte Carlo is a problem solving technique to approximate the probability of outcomes by running a series of simulations, which rely on repeated random sampling to obtain a numerical result. The method was named after the city Monaco, where a primary attraction is casinos.

2 Problem Delimitation and Definition

Through the analysis issues concerning oil & gas separation, weight estimations and their respective optimisation possibilities is described. The further work will not contain a deriving of the error propagation formula, equation [3], and neither a higher detail level of the equipment description in the PFD. The problem definition is on behalf of the analysis and delimitation of the problem chosen to be:

Can the energy consumption of a hypothetical HYSYS process simulation be minimised and is it possible to create a model which can estimate the total weight of a production platform?

Furthermore the following goals and methods to be used are set for the project:

- By a DOE and RSM approach, create a model possible for Ramboll to use for optimisation of a HYSYS simulation in future projects.
- Design and create a combined weight estimations Excel sheet, which uses Ramboll's estimation methods to give a total weight estimate of the central process equipment, based on data from HYSYS simulations.
- The combined weight estimation sheet is intended to set the basis for the total weight of production topside, which depends on uncertainties and factors.
- Intelligent and easy access data processing software is needed in order to apply DOE and RSM to the large amount data and perform Monte Carlo simulations.

3 Solutions and Modelling

This chapter consist of 2 sections. One concerns process optimisation of central process equipment simulated in HYSYS, by a DOE and RSM approach. The other about improvement of weight estimation methods and creating a model that estimates the total topside weight by using Monte Carlo simulations.

3.1 Process Optimisation

A HYSYS simulation of an oil and gas separation process is intended to be optimised. The purpose of the optimisation is to consume the lowest possible power and at the same time fulfil given export quality demands.

3.1.1 Experimental Setup

In the HYSYS simulation five variable factors, which is known to have an impact to the desired responses, is chosen to be included in the experiment.

The five major independent variable factors examined in this experiment are:

- X1 - Pressure after the expander
- X2 - Temperature reboiler
- X3 - Pressure 3rd stage separator
- X4 - Pressure after booster
- X5 - TEG inlet temperature

Objective responses:

- Y1 – Gas export quality (Multiple)
- Y2 – Oil export, RVP
- Y3 – Total power consumption

The PFD shown in Figure 3-1 on page 23 indicates where the variables, X1 to X5, and objectives, Y1 to Y3, are located in the process.

Applying a DOE and RSM approach to the setup, the five variables results in a 5 factor 3 level experiment. The experiment plan described on page 17 in Table 1-2 can therefore be implemented.

Variable →	P after expander [bar]	T reboiler [Celsius]	P 3. stage separator [bar]	P after booster [bar]	TEG inlet T [Celsius]
High (+1)	45	35	2.5	95	35
Mid (0)	35	25	2.3	90	30
Low (-1)	25	15	2.1	85	25

Table 3-1: DOE variable low, mid and high level values.

Table 3-1 shows the chosen value range for each of the five variables with low (-1), mid (0) and high (+1) indicators.

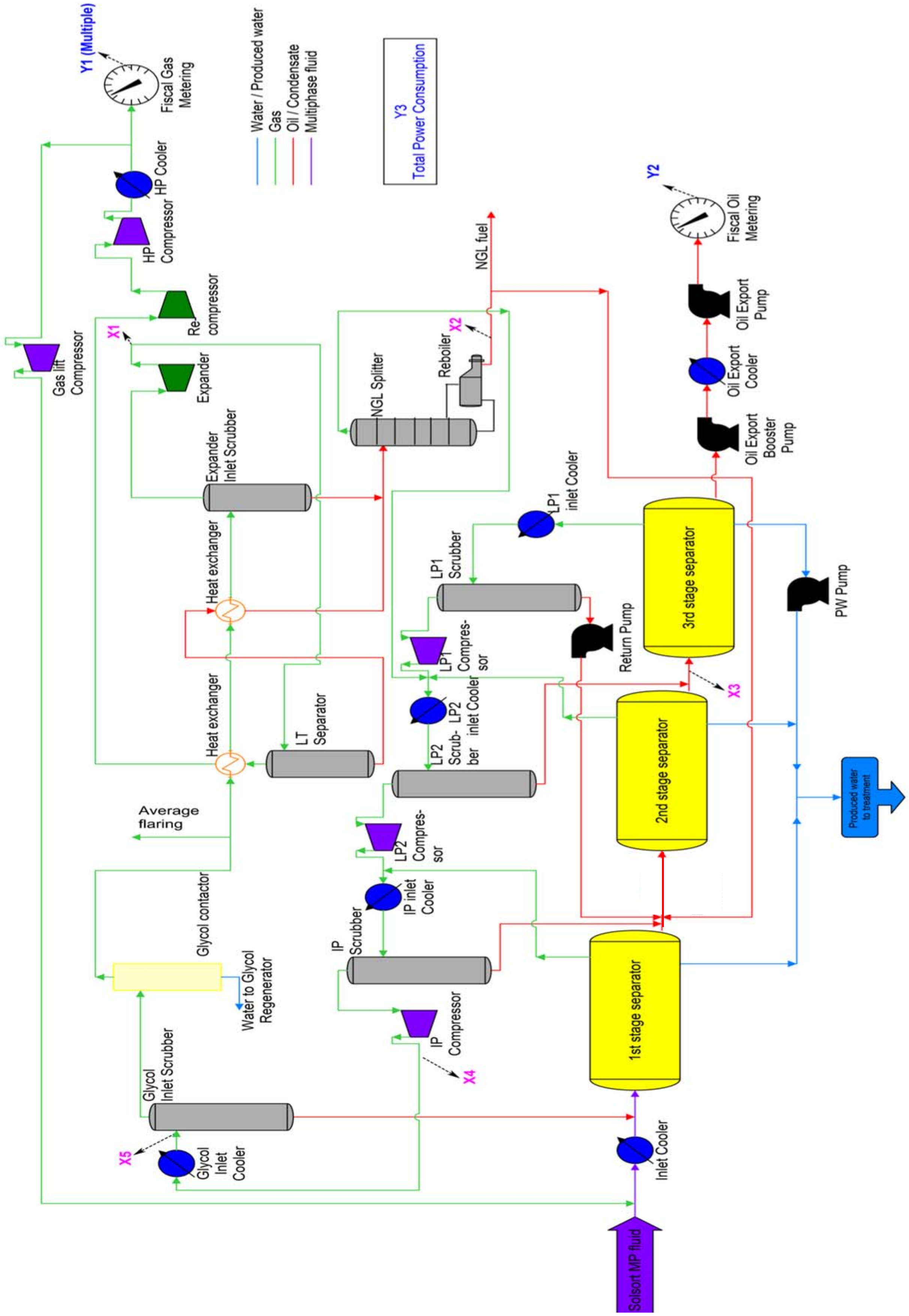


Figure 3-1: PFD of HYSYS simulation process assembly with indicators for variables and objectives.

The values are applied in the experiment plan where -1, 0 and +1 is indicated and each variable value combination is simulated in HYSYS one by one. The objective results are noted.
Specifications for the objective responses are:

Wobbe index	[MJ/m^3]
SG	[rel_to_air]
HHV	[MJ/m^3]
HC dew point	[C]
Power	[kW]
RVP	[psia]
NGL	[kg/h]

The experimental results from each simulation are listed in Table 3-2.

Simulation no.	Wobbe	SG	HHV	Dew	Power	RVP	NGL
1	56.56	0.663	43.64	-22.89	8670	14.71	2379.758
2	55.85	0.6419	42.39	-37.37	10130	16.41	2803.044
3	56.88	0.6724	44.17	-17.38	8439	13.82	2169.874
4	55.84	0.6417	42.38	-37.46	10160	15.95	2702.104
5	56.86	0.6718	44.16	-17.55	8453	13.44	2092.44
6	55.82	0.641	42.33	-38	9012	17.32	2973.121
7	56.82	0.6707	44.09	-18.09	7591	14.83	2354.133
8	55.83	0.6416	42.37	-37.81	9158	17.15	2947.571
9	56.81	0.6704	44.07	-18.2	7605	14.41	2230.665
10	55.62	0.6354	42	-42.69	11440	16.72	2862.628
11	56.55	0.6626	43.61	-22.34	9550	15.06	2455.664
12	55.64	0.6358	42.03	-42.32	11600	16.23	2758.642
13	56.55	0.6625	43.61	-22.37	9577	14.51	2334.314
14	55.63	0.6357	42.02	-42.57	10190	17.9	3101.522
15	56.51	0.6613	43.53	-23.11	8478	16.01	2621.408
16	56.52	0.6618	43.57	-23.45	8629	14.52	2334.442
17	55.58	0.6341	41.92	-43.04	10070	17.25	2857.83
18	56.53	0.662	43.57	-22.73	8553	15.67	2563.984
19	56.54	0.6623	43.6	-23.97	9127	13.76	2198.805
20	57.68	0.6965	45.62	-4.154	7643	11.32	1613.457
21	56.52	0.6617	43.56	-24.24	9143	13.35	2108.059
22	57.67	0.6963	45.6	-4.198	7660	11.07	1563.388
23	56.44	0.6593	43.42	-25.55	8300	14.88	2412.122
24	57.58	0.6933	45.43	-5.428	7017	12.53	1836.089
25	56.42	0.6589	43.39	-25.64	8307	14.5	2339.432
26	57.58	0.6933	45.43	-5.346	7025	12.24	1779.434

27	56.26	0.6541	43.11	-28.6	10120	14.49	2372.166
28	57.3	0.6851	44.94	-9.965	8372	12.54	1886.848
29	56.27	0.6544	43.13	-28.39	10180	14.01	2268.746
30	57.28	0.6842	44.89	-10.22	8398	12.14	1807.463
31	56.17	0.6515	42.95	-30.42	9184	15.95	2671.94
32	57.17	0.6805	44.67	-12.6	7592	13.88	2148.688
33	56.17	0.6514	42.95	-30.4	9232	15.41	2559.392
34	57.14	0.6803	44.66	-12.15	7620	13.44	2054.316
35	56.52	0.6617	43.56	-23.43	8602	14.52	2331.488
36	56.03	0.6474	42.71	-33.17	9569	15.72	2635.426
37	57.05	0.6775	44.49	-14.08	7960	13.46	2073.842
38	56.52	0.6618	43.56	-23.46	8597	14.68	2361.171
39	56.52	0.6617	43.56	-23.45	8640	14.29	2287.376
40	56.52	0.6617	43.56	-23.4	9108	13.95	2219.807
41	56.53	0.6619	43.57	-23.44	8275	15.32	2499.151
42	56.71	0.6673	43.89	-20.54	8261	14.19	2267.329
43	56.39	0.6577	43.32	-25.55	9068	14.84	2418.469
44	56.17	0.6515	42.95	-29.76	9137	15.86	2641.978
45	56.92	0.6735	44.25	-16.84	8249	13.6	2127.423
46	56.51	0.6613	43.53	-23.67	8615	14.52	2332.33

Table 3-2: Experimental results for the seven objective responses.

A step by step guide on how the HYSYS simulations are executed and how the results are achieved is given in *Appendix 1.1 – HYSYS Experiment Procedure*.

The goal is to be able to create a linear regression model for each objective, which can be used to predict the variable values in different cases and at the same time minimise the power consumption for the separation process. Two main cases are set up for investigation – one focusing on the gas export and one for the oil export.

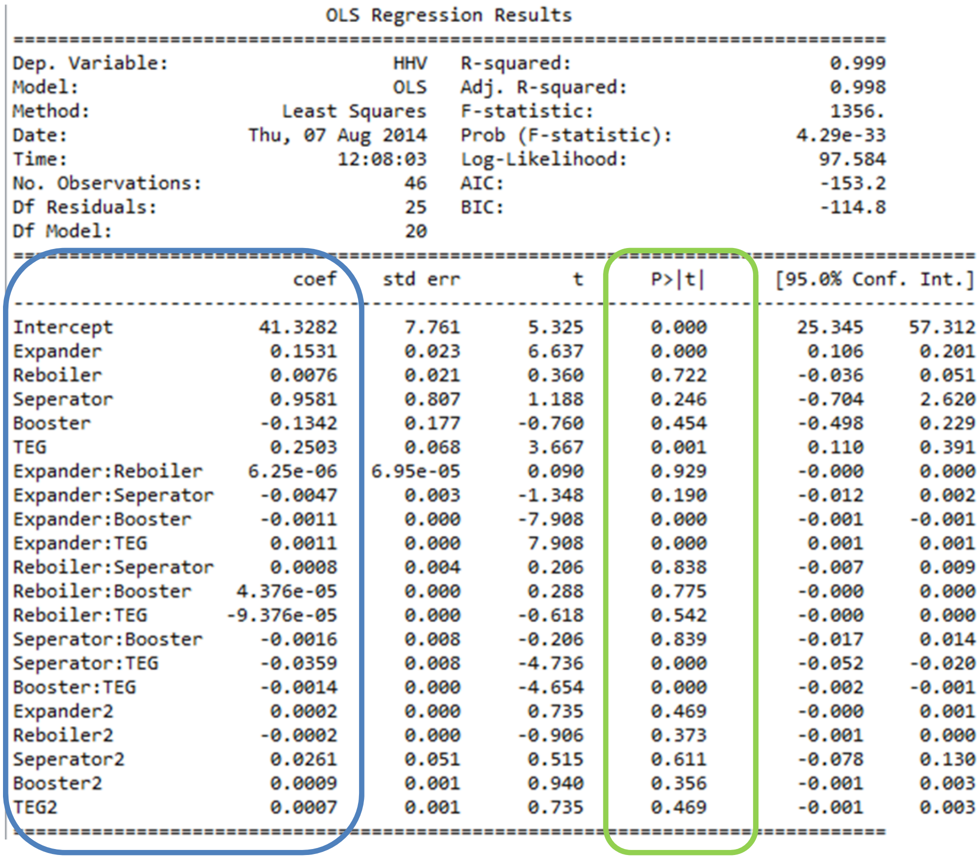
Case 1	**Case 2**
Minimise power when:	Minimise power when:
HC dew point ≤ -2 [C]	HC dew point ≤ -2 [C]
Wobbe index ≤ 58.2 [MJ/m^3]	
HHV ≤ 46 [MJ/m^3]	RVP ≤ 12 [psia]
SG ≤ 0.7 [rel_to_air]	

Table 3-3: Overview of desired optimisation cases.

3.1.2 Data Processing

Intelligent and easy accessible calculation software is needed to handle and process the large amount of data from the simulations. Through supervision from the Ramboll supervisor, Python programming language was chosen. Python is a free distributed add-on and there are several options for the environmental development interface. In this case Spyder was used, it has advanced editing, interactive testing, debugging and introspection features.

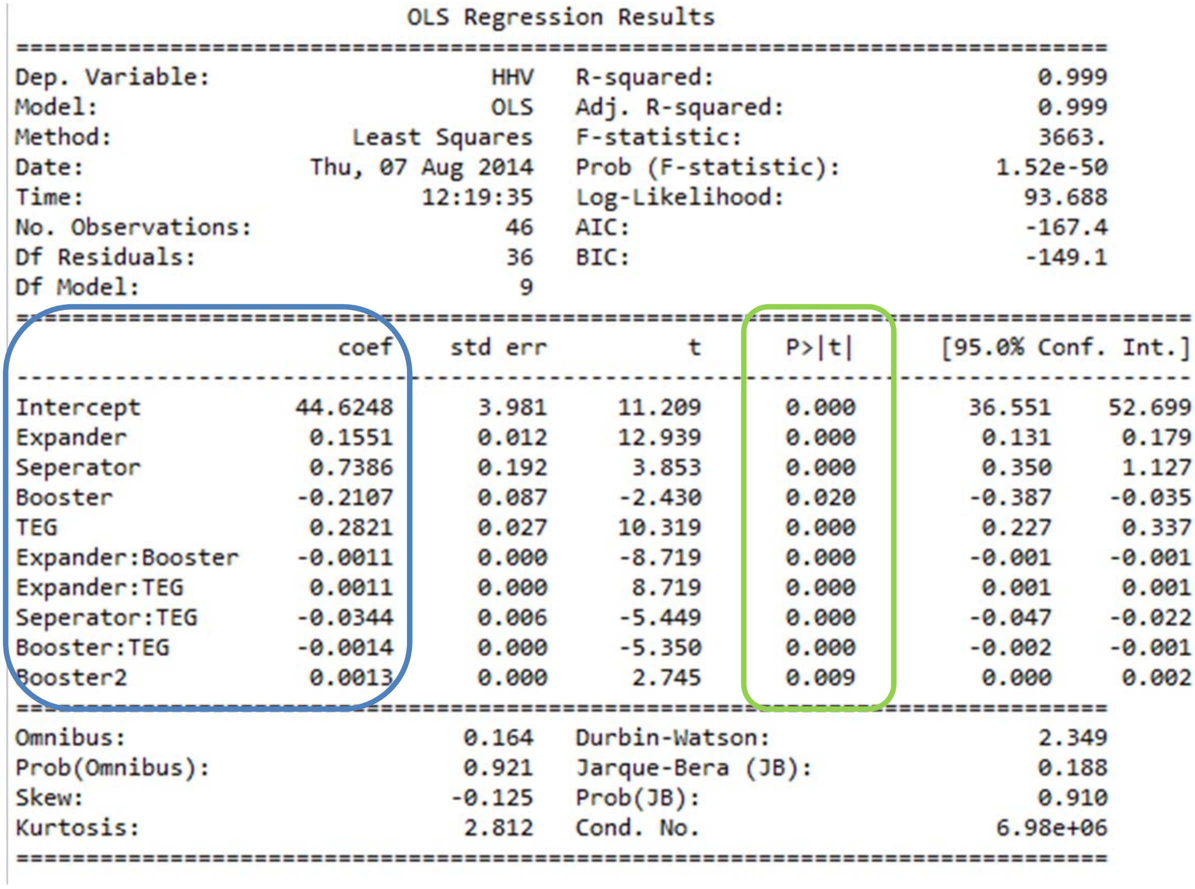
The data is listed in an Excel CSV-file to simplify the document format, so no disturbances occur when retrieving the data from the file in the program. The simulation combination values are listed with their respective results in columns. Before starting to create the code for the linear regression models, the needed libraries and scientific packages are included or imported in the beginning of the code script. In order to create the regression models in Python, the module *statsmodels* is used among other. It gives an overview of the importance, by $P > | t |$, of the coefficients for each possible variable and their interactions. Several coefficients can be excluded from the models, since they have no or an insignificant influence. A method called backward elimination. An example of the HHV regression model is given in Figure 3-2 and Figure 3-3. Figure 3-2 shows, in the blue box, the start conditions for the model with coefficients for every possible variable, variable interactions and second order terms.



```
                            OLS Regression Results
==============================================================================
Dep. Variable:                    HHV   R-squared:                       0.999
Model:                            OLS   Adj. R-squared:                  0.998
Method:                 Least Squares   F-statistic:                     1356.
Date:                Thu, 07 Aug 2014   Prob (F-statistic):           4.29e-33
Time:                        12:08:03   Log-Likelihood:                 97.584
No. Observations:                  46   AIC:                            -153.2
Df Residuals:                      25   BIC:                            -114.8
Df Model:                          20
=========================================================================================
                           coef    std err          t      P>|t|      [95.0% Conf. Int.]
-----------------------------------------------------------------------------------------
Intercept               41.3282      7.761      5.325      0.000        25.345    57.312
Expander                 0.1531      0.023      6.637      0.000         0.106     0.201
Reboiler                 0.0076      0.021      0.360      0.722        -0.036     0.051
Seperator                0.9581      0.807      1.188      0.246        -0.704     2.620
Booster                 -0.1342      0.177     -0.760      0.454        -0.498     0.229
TEG                      0.2503      0.068      3.667      0.001         0.110     0.391
Expander:Reboiler      6.25e-06   6.95e-05      0.090      0.929        -0.000     0.000
Expander:Seperator      -0.0047      0.003     -1.348      0.190        -0.012     0.002
Expander:Booster        -0.0011      0.000     -7.908      0.000        -0.001    -0.001
Expander:TEG             0.0011      0.000      7.908      0.000         0.001     0.001
Reboiler:Seperator       0.0008      0.004      0.206      0.838        -0.007     0.009
Reboiler:Booster      4.376e-05      0.000      0.288      0.775        -0.000     0.000
Reboiler:TEG         -9.376e-05      0.000     -0.618      0.542        -0.000     0.000
Seperator:Booster       -0.0016      0.008     -0.206      0.839        -0.017     0.014
Seperator:TEG           -0.0359      0.008     -4.736      0.000        -0.052    -0.020
Booster:TEG             -0.0014      0.000     -4.654      0.000        -0.002    -0.001
Expander2                0.0002      0.000      0.735      0.469        -0.000     0.001
Reboiler2               -0.0002      0.000     -0.906      0.373        -0.001     0.000
Seperator2               0.0261      0.051      0.515      0.611        -0.078     0.130
Booster2                 0.0009      0.001      0.940      0.356        -0.001     0.003
TEG2                     0.0007      0.001      0.735      0.469        -0.001     0.003
==============================================================================
```

Figure 3-2: HHV Ordinary Least Squares regression model - all term included.

After removing insignificant terms one by one with values for $P > | t |$ higher than 0.05, represented in the green box, in order to make sure the model is not giving misleading results. Figure 3-3 shows the remaining terms and their coefficients after the backward elimination. The adjusted R-squared value has also been increased, which indicates an improved model.



```
                            OLS Regression Results
==============================================================================
Dep. Variable:                    HHV   R-squared:                       0.999
Model:                            OLS   Adj. R-squared:                  0.999
Method:                 Least Squares   F-statistic:                     3663.
Date:                Thu, 07 Aug 2014   Prob (F-statistic):           1.52e-50
Time:                        12:19:35   Log-Likelihood:                 93.688
No. Observations:                  46   AIC:                            -167.4
Df Residuals:                      36   BIC:                            -149.1
Df Model:                           9
====================================================================================
                       coef    std err          t      P>|t|      [95.0% Conf. Int.]
------------------------------------------------------------------------------------
Intercept           44.6248      3.981     11.209      0.000        36.551    52.699
Expander             0.1551      0.012     12.939      0.000         0.131     0.179
Seperator            0.7386      0.192      3.853      0.000         0.350     1.127
Booster             -0.2107      0.087     -2.430      0.020        -0.387    -0.035
TEG                  0.2821      0.027     10.319      0.000         0.227     0.337
Expander:Booster    -0.0011      0.000     -8.719      0.000        -0.001    -0.001
Expander:TEG         0.0011      0.000      8.719      0.000         0.001     0.001
Seperator:TEG       -0.0344      0.006     -5.449      0.000        -0.047    -0.022
Booster:TEG         -0.0014      0.000     -5.350      0.000        -0.002    -0.001
Booster2             0.0013      0.000      2.745      0.009         0.000     0.002
==============================================================================
Omnibus:                        0.164   Durbin-Watson:                   2.349
Prob(Omnibus):                  0.921   Jarque-Bera (JB):                0.188
Skew:                          -0.125   Prob(JB):                        0.910
Kurtosis:                       2.812   Cond. No.                     6.98e+06
==============================================================================
```

Figure 3-3: Final HVV Ordinary Least Squares regression model result.

A procedure description of every step in the HHV regression model example is given in *Appendix 1.2 – Python Regression Model Procedure.*

The HHV model with respect to the five variables from Table 3-1 page 22, X1 to X5, is formed:

$$\begin{aligned} HHV = {} & 0.1551 \cdot X1 + 0.7386 \cdot X3 - 0.2107 \cdot X4 + 0.2821 \cdot X5 \\ & - 0.0011 \cdot X1 \cdot X4 + 0.0011 \cdot X1 \cdot X5 - 0.0344 \cdot X3 \\ & \cdot X5 - 0.0014 \cdot X4 \cdot X5 + 0.0013 \cdot X4 \cdot X4 + 44.6248 \end{aligned} \qquad [4]$$

Each regression model for the objective responses has been created through this procedure. The Python code script can be found in *Appendix 1.3 – Entire Python Code Script.*

3.1.3 Model Improvement and Verification

Each model for the objective responses has to be verified in order to implement them in optimisation case 1 and 2 and to determine their reliability. Several methods are used to check if the model fits.

Python provides the opportunity to create a variety of statistical plots that indicates outliers, which indicates where mistakes could be located and if they have any influence on the model. The HHV model is for an example checked by plotting the predicted values up against data set simulated in HYSYS, see Figure 3-4. For a good model fit the dots should form a linear line, which is does.

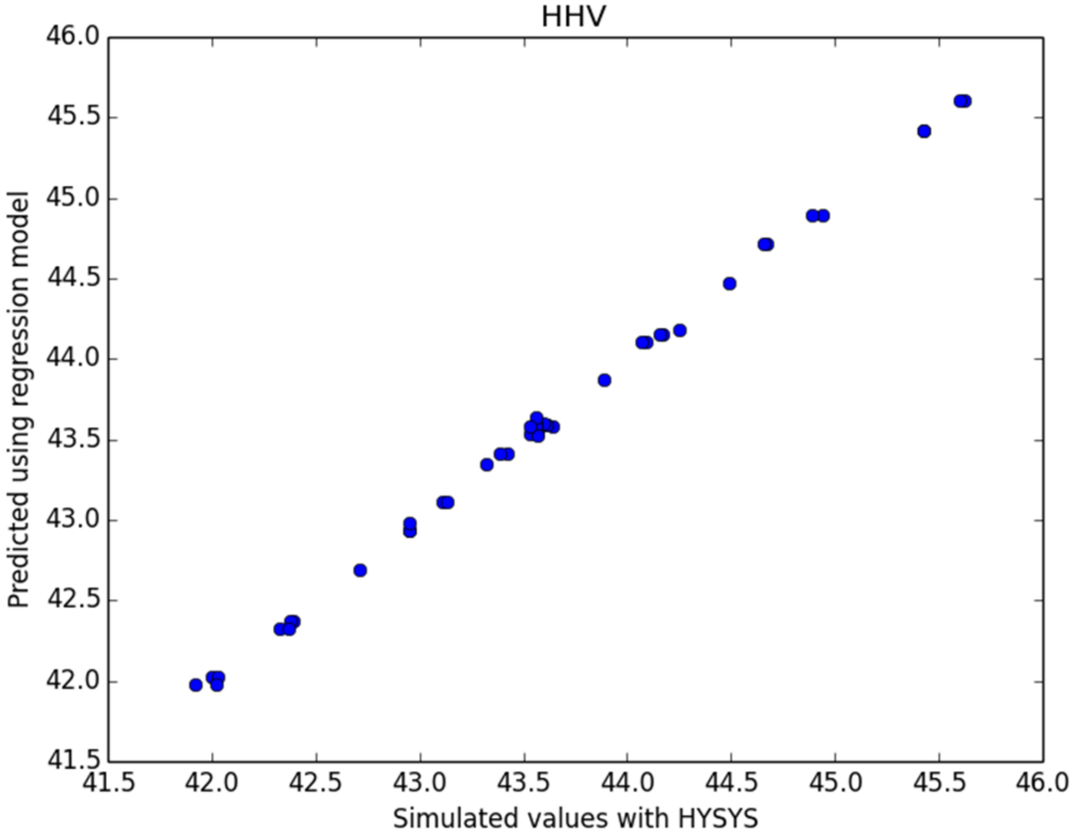


Figure 3-4: HHV model predicted vs. HYSYS simulated values.

If a point obviously lies outside the linear line, further investigation of the model could be necessary. Several plots are suitable to check possible outliers. The residual vs. fitted values plot in Figure 3-5 page 29 show the points from the HYSYS simulations. Residuals are used to control the models adaptation of the data. A large residual indicates a bad adaptation of the model to a data point. The spread of the data points should look like they are randomly placed, but should also be symmetric vertically about 0 and indicate a normalised distribution. In this plot one should look for non-constant variance and nonlinearity, which would indicate that some change in model is necessary (11). A good fit will result in a more or less linear line across the scatter. When taking the very low residual values at the y-axis in consideration for Figure 3-5, the regression model represented by the blue line, is good fit and showing a linear line.

These plots among a few others were applied to each model and the outliers present investigated. For some plots, outliers are indicated by a number. This number represents the simulation number from the CSV-file. These simulations were then reviewed to see if the data was entered probably. If so, the combination for the given simulation can be executed again to compare the entered values. It resulted in location of a few mistakes. Some simulations had to be done again, where the simulation results varied from the first entered. The most significant mistake was a wrong placement of a decimal separator. The regression model creation had to be repeated after applying the correction to the CSV-file, which gave a more accurate result.

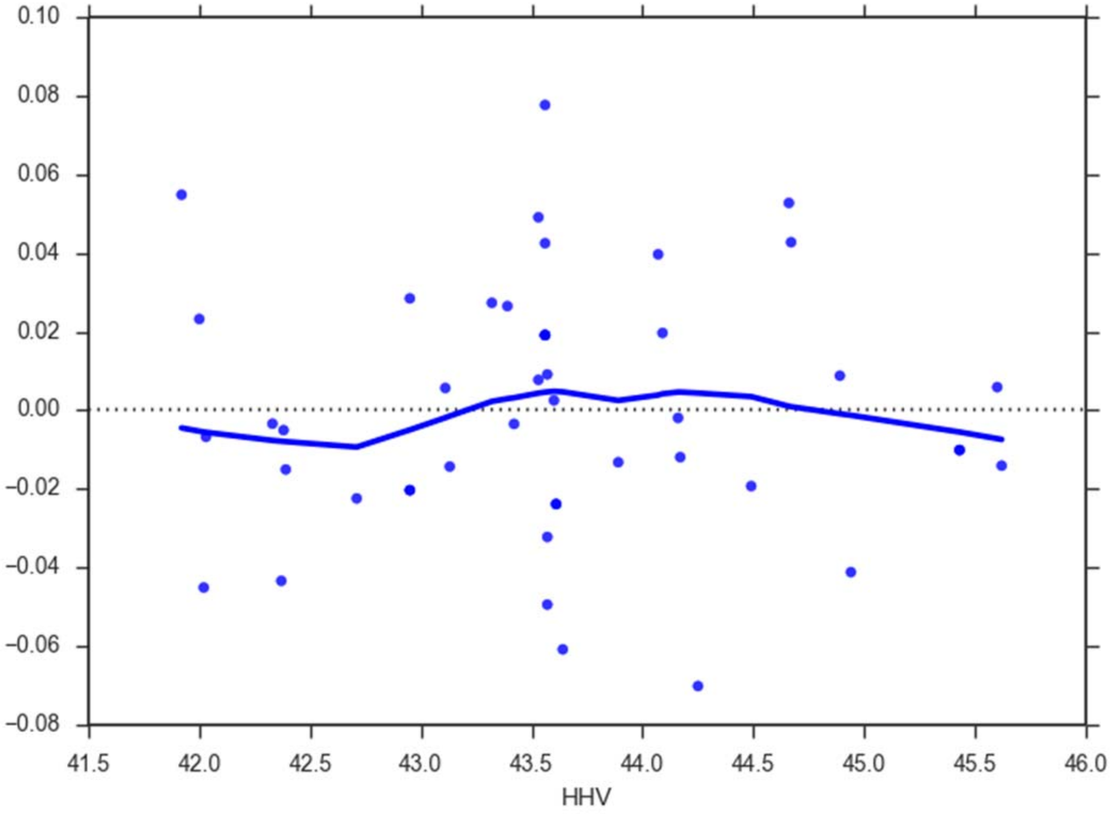


Figure 3-5: Residual vs. fitted values plot of the HHV model.

To verify the model further values for variables that have not been used in the experiment is applied both in each of the Python regression models and HYSYS for comparison. Levels that lie in between the mid-level and high/low level (+0.5 & -0.5) and outside the experimented range (+1.5 & -1.5) are compared.

Python/HYSYS variable values = (40, 30, 2.4, 92.5, 32.5)					
Python results:		**HYSYS results:**		**Error %**	**Error # diff.**
Wobbe:	57.20	**Wobbe:**	56.83	-0.65	-0.37
SG:	0.6758	**SG:**	0.6709	-0.7287	-0.0049
HHV:	43.87	**HHV:**	44.1	0.52	0.23
Dew:	-17.65	**Dew:**	-17.61	-0.25	0.04
RVP:	13.91	**RVP:**	13.78	-0.93	-0.13
NGL:	2195.5	**NGL:**	2147.2	-2.20	-48.25
Power:	8072.9	**Power:**	8063.0	-0.12	-9.93

Table 3-4: Model verification, +0.5 variable value comparison.

Python/HYSYS variable values = (30, 20, 2.2, 87.5, 27.5)					
Python results:		**HYSYS results:**		**Error %**	**Error # diff.**
Wobbe:	56.50	**Wobbe:**	56.18	-0.56	-0.32
SG:	0.6556	**SG:**	0.6516	-0.61	-0.004
HHV:	42.75	**HHV:**	42.96	0.50	0.21
Dew:	-30.47	**Dew:**	-30.11	-1.18	0.36
RVP:	15.32	**RVP:**	15.44	0.81	0.12
NGL:	2554.9	**NGL:**	2558.9	0.15	3.93
Power:	9311.0	**Power:**	9308.0	-0.032	-2.95

Table 3-5: Model verification, -0.5 variable value comparisons.

Table 3-4 and Table 3-5 shows the comparison of the +0.5 and -0.5 values applied to the models and HYSYS. The percentage errors and the numerical differences are given. In general the percentage errors are very low for all models in both scenarios.

Same comparison is done for values outside the experimented range. That is for values at +1.5 and -1.5 in Table 3-6 and Table 3-7.

Python/HYSYS variable values = (50, 40, 2.6, 100, 40)					
Python results:		**HYSYS results:**		**Error %**	**Error # diff.**
Wobbe:	57.98	**Wobbe:**	57.38	-1.03	-0.60
SG:	0.6969	**SG:**	0.6873	-1.37	-0.01
HHV:	45.04	**HHV:**	45.07	0.074	0.033
Dew:	-6.89	**Dew:**	-7.90	14.58	-1.01
RVP:	13.28	**RVP:**	13.06	-1.63	-0.22
NGL:	1990.4	**NGL:**	1955.5	-1.75	-34.89
Power:	7419.2	**Power:**	7209.0	-2.83	-210.17

Table 3-6: Model verification, +1.5 variable value comparisons.

Python/HYSYS variable values = (20, 10, 2.0, 80, 20)					
Python results:		**HYSYS results:**		**Error %**	**Error # diff.**
Wobbe:	55.62	**Wobbe:**	N/A	N/A	N/A
SG:	0.6303	**SG:**	N/A	N/A	N/A
HHV:	41.37	**HHV:**	N/A	N/A	N/A
Dew:	-49.01	**Dew:**	N/A	N/A	N/A
RVP:	18.24	**RVP:**	N/A	N/A	N/A

NGL:	3226.70	**NGL:**	N/A	N/A	N/A
Power:	11126.8	**Power:**	N/A	N/A	N/A

Table 3-7: Model verification, -1.5 variable value comparisons.

In HYSYS it was not physical possible to run the simulations in the process design with values at -1.5 and therefor no results are compared in Table 3-7. The percentage errors in Table 3-6 are for most parameters larger, compared to the results in Table 3-4 and Table 3-5. The HC dew point model has a high percentage error of almost 15 %, but since the numerical error is only 1 degree Celsius, it is still an acceptable result.

The regression models fit the HYSYS results and are ready to be implemented in the optimisation code, where the function to be optimised can be constraint by one or more of the others.

3.1.4 Results

Case 1 and 2 are calculated in Python and the results are compared to a HYSYS simulation applied with the variable values found from the Python calculation in order to verify each case.

The code script for optimisation:

```
from scipy.optimize import minimize

def f1(x):
# Dew - Constrain function
return -1*(1.8594*x[0] + 13.6961*x[2] + 2.6635*x[4] - 0.0043*x[0]*x[3] - 0.0040*x[0]*x[4] - 0.0801*x[2]*x[3] - 0.3040*x[2]*x[4] - 0.0063*x[3]*x[4] - 0.0055*x[0]*x[0] - 121.1210) – 2

def f2(x):
# Wobbe - Constrain function
return -1*(0.0862*x[0] + 0.3914*x[2] - 0.1072*x[3] + 0.1550*x[4] - 0.0006*x[0]*x[3] + 0.0006*x[0]*x[4] - 0.0184*x[2]*x[4] - 0.0007*x[3]*x[4] + 0.0007*x[3]*x[3] + 56.6857) + 56.2

def f3(x):
# HHV - Constrain function
return -1*(0.1551*x[0] + 0.7386*x[2] - 0.2107*x[3] + 0.2821*x[4] - 0.0011*x[0]*x[3] + 0.0011*x[0]*x[4] - 0.0344*x[2]*x[4] - 0.0014*x[3]*x[4] + 0.0013*x[3]*x[3] + 44.6248) + 46

def f4(x):
# SG - Constrain function
return -1*(0.0029*x[0] + 0.0159*x[2] - 0.0035*x[3] + 0.0048*x[4] - 9.062e-05*x[0]*x[2] - 1.887e-05*x[0]*x[3] + 1.838e-05*x[0]*x[4] - 0.0006*x[2]*x[4] - 2.25e-05*x[3]*x[4] + 2.204e-05*x[3]*x[3] + 0.6699) + 0.7

def objectivefun(x):
#Function to be minimized (Power)
return -162.7289*x[0] - 1823.7320*x[2] - 166.4767*x[4] + 28.6875*x[0]*x[2] - 1.2327*x[0]*x[3] + 0.7800*x[0]*x[4] + 0.0258*x[1]*x[3] - 43.7112*x[2]*x[3] + 67.0597*x[2]*x[4] -
```

```
3.2682*x[3]*x[4] + 1.4819*x[0]*x[0] + 93.7959*x[2]*x[2] + 1.8744*x[3]*x[3] +
3.0675*x[4]*x[4] + 1.72e+04

‘Constraints’
cons = ({'type': 'ineq', 'fun': f1},
{'type': 'ineq', 'fun': f2},
{'type': 'ineq', 'fun': f3},
{'type': 'ineq', 'fun': f4})

‘Bounds’
bnds = ((25, 45), (15, 35), (2.1, 2.5), (85, 95), (25, 35))

'Initial guess independt variables'
x0 = [35, 25, 2.3, 90, 30]

res = minimize(objectivefun, x0, method='SLSQP', bounds=bnds, constraints=cons)

print res
print "Dew =", Dew(res['x'][0],res['x'] [1],res['x'][2],res['x'][3],res['x'][4])
print "Wobbe =", Wobbe(res['x'][0],res['x'][1],res['x'][2],res['x'][3],res['x'][4])
print "SG =", SG(res['x'][0],res['x'][1],res['x'][2],res['x'][3],res['x'][4])
print "HHV =", HHV(res['x'][0],res['x'][1],res['x'][2],res['x'][3],res['x'] [4])
```

The boundaries can be changed to see how the optimisation function performs - for example outside the training set. As well can the constraint functions values or the composition of them be changed to apply a desired case.

For case 1 it was necessary to set the wobbe index constraint to ≤ 56.2 [MJ/m^3], because the wobbe index data collected from the simulations are close to 55.8 [MJ/m^3] as the minimum value. The optimisation function had difficulties in finding the optimum before changing it.

Case 1
Minimise power when:

- HC dew point ≤ -2 [C]
- Wobbe index ≤ 56.2 [MJ/m^3]
- HHV ≤ 46 [MJ/m^3]
- SG ≤ 0.7 [rel_to_air]

Optimisation Results:		**HYSYS Results (Validation):**		**Error %:**	**Error # difference:**
Power consumption	8841	**Power consumption**	8832	-0.10	-9
HC dew point	-36.13	**HC dew point**	-36.05	-0.22	0.08
Wobbe	56.2	**Wobbe**	55.9	-0.54	-0.3

HHV	42.3	**HHV**	42.47	0.40	0.17
SG	0.6470	**SG**	0.6433	-0.57	-0.0037
RVP	17.05	**RVP**	17.02	-0.18	-0.03
Variables found:		**Variables from optim.:**			
P Expander	26.95	**P Expander**	26.95	N/A	
T Reboiler	15	**T Reboiler**	15	N/A	
P 3rd Sep.	2.5	**P 3rd Sep.**	2.5	N/A	
P Booster	85	**P Booster**	85	N/A	
T TEG	25	**T TEG**	25	N/A	

Table 3-8: Case 1 optimisation results vs. HYSYS comparison.

The optimisation function for case 1 is finding the almost exact same values as the HYSYS simulation applied the, by Python, found variable values. The numerical error difference does more or less not exist and the percentage errors spans only from 0.1 to 0.57.

Throughout the experimental plan and working with the simulations in HYSYS and Python, it is obtained that the wobbe index has a high influence to the energy consumption. To see the effect of the wobbe index, it is omitted from the optimisation constraints.

Case 1-b
Minimise power when:

- HC dew point ≤ -2 [C]
- HHV ≤ 46 [MJ/m^3]
- SG ≤ 0.7 [rel_to_air]

Optimisation Results:		**HYSYS Results (Validation):**		**Error %:**	**Error # difference:**
Power consumption	7008	**Power consumption**	7017	0.13	9
HC dew point	-6.23	**HC dew point**	-5.428	-12.87	0.802
Wobbe	57.87	**Wobbe**	57.58	-0.50	-0.29
HHV	45.15	**HHV**	45.43	0.62	0.28
SG	0.6970	**SG**	0.6933	-0.53	-0.0037
RVP	12.45	**RVP**	12.53	0.64	-0.08
Variables found:		**Variables from optim.:**			
P Expander	45	**P Expander**	45	N/A	
T Reboiler	15	**T Reboiler**	15	N/A	
P 3rd Sep.	2.5	**P 3rd Sep.**	2.5	N/A	
P Booster	85	**P Booster**	85	N/A	
T TEG	35	**T TEG**	35	N/A	

Table 3-9: Case 1-b optimisation without wobbe index as a constraint results vs. HYSYS comparison.

When not taking demands for the wobbe index into consideration it minimises the power consumption by more than 1800 kW, compared to case 1. The percentage errors are also in this case in general very low. The HC dew point percentage error is high, but the numerical error difference is still acceptable.

Case 2
Minimise power when:

- HC dew point ≤ -2 [C]
- RVP ≤ 12 [psia]

Optimisation Results:		HYSYS Results (Validation):		Error %:	Error # difference:
Power consumption	7129	**Power consumption**	7084	-0.63	-45
HC dew point	-6.03	**HC dew point**	-5.439	-10.58	0.638
Wobbe	57.88	**Wobbe**	57.57	-0.54	-0.31
HHV	45.18	**HHV**	45.41	0.51	0.23
SG	0.6975	**SG**	0.6931	-0.63	-0.0044
RVP	12.00	**RVP**	12.02	0.17	0.02
Variables found:		**Variables from optim.:**			
P Expander	45	**P Expander**	45	N/A	
T Reboiler	35	**T Reboiler**	35	N/A	
P 3rd Sep.	2.45	**P 3rd Sep.**	2.45	N/A	
P Booster	85	**P Booster**	85	N/A	
T TEG	35	**T TEG**	35	N/A	

Table 3-10: Case 2 optimisation results vs. HYSYS comparison.

The dew point percentage error is again high for this case, but it is still acceptable because of the low numerical difference. The errors for the other parameters are very low or almost not existing.

Within the boundaries used in the experimental test, the optimisation model predicts the almost exact same results as the HYSYS simulations does with the variable input, provided by Python for all cases.

How the model performs when the high low boundaries are increased by a factor is investigated in order to try finding an even better optimum.

The new boundaries applied to code script are:

'Bounds'
bnds = ((15, 55), (5, 45), (1.9, 2.7), (75, 105), (15, 45))

The Python calculations give a warning when applying these boundaries, but the constraints are often still met. Therefor a comparison is yet still interesting.

Case 1 – new boundaries
Minimise power when:

- HC dew point ≤ -2 [C]
- Wobbe index ≤ 56.2 [MJ/m^3]
- HHV ≤ 46 [MJ/m^3]
- SG ≤ 0.7 [rel_to_air]

Optimisation Results:		HYSYS Results (Validation):		Error %:	Error # difference:
Power consumption	7859	**Power consumption**	7818	-0.52	-41
HC dew point	-35.5	**HC dew point**	-34.92	-1.63	0.58
Wobbe	56.2	**Wobbe**	55.95	-0.44	-025
HHV	42.5	**HHV**	42.57	0.16	0.07
SG	0.6498	**SG**	0.645	-0.74	-0.0048
RVP	18.73	**RVP**	18.04	-3.68	-0.69
Variables found:		**Variables from optim.:**			
P Expander	31.48	**P Expander**	31.48	N/A	
T Reboiler	5	**T Reboiler**	5	N/A	
P 3rd Sep.	2.7	**P 3rd Sep.**	2.7	N/A	
P Booster	75	**P Booster**	75	N/A	
T TEG	17.61	**T TEG**	17.61	N/A	

Table 3-11: Case 1 - new boundaries, results vs. HYSYS comparison.

Compared to the results for case 1 in Table 3-8, the percentage errors in this case are slightly larger for some parameters, but still very low in general. The power consumption when increasing the boundaries is almost 1000 kW lower.

Case 1-b – new boundaries
Minimise power when:

- HC dew point ≤ -2 [C]
- HHV ≤ 46 [MJ/m^3]
- SG ≤ 0.7 [rel_to_air]

Optimisation Results:		HYSYS Results (Validation):		Error %:	Error # difference:
Power consumption	6544	**Power consumption**	7235	10.56	691
HC dew point	-6.14	**HC dew point**	-1.87	-69.59	4.27
Wobbe	57.9	**Wobbe**	58.07	0.29	0.17
HHV	45.42	**HHV**	46.31	1.96	0.89
SG	0.699	**SG**	0.7081	1.17	0.0082

RVP	12.59	**RVP**	15.42	22.48	2.83
Variables found:		**Variables from optim.:**			
P Expander	47.82	**P Expander**	47.82	N/A	
T Reboiler	5	**T Reboiler**	5	N/A	
P 3rd Sep.	2.7	**P 3rd Sep.**	2.7	N/A	
P Booster	76.2	**P Booster**	76.2	N/A	
T TEG	28.87	**T TEG**	28.87	N/A	

Table 3-12: Case 1-b new boundaries, optimisation results vs. HYSYS comparison.

The error differences are now more inconsistent and the constraints are not maintained. Power consumption, HC dew point and the RVP errors are too large and unacceptable.

Case 2 – new boundaries
Minimise power when:

- HC dew point ≤ -2 [C]
- RVP ≤ 12 [psia]

Optimization Results:		**HYSYS Results (Validation):**		**Error %:**	**Error # difference:**
Power consumption	6494	**Power consumption**	7180	10.56	686
Dew	-2	**Dew**	3.817	-290.85	5.817
Wobbe	58.2	**Wobbe**	58.54	0.58	0.34
HHV	45.94	**HHV**	47.16	2.66	1.22
SG	0.71	**SG**	0.7225	1.76	0.0125
RVP	11.77	**RVP**	15.42	31.01	3.65
Variables found:		**Variables optim:**			
P Expander	50.27	**P Expander**	50.27	N/A	
T Reboiler	5	**T Reboiler**	5	N/A	
P 3rd Sep.	2.7	**P 3rd Sep.**	2.7	N/A	
P Booster	75.31	**P Booster**	75.31	N/A	
T TEG	30.1	**T TEG**	30.1	N/A	

Table 3-13: Case 2 - new boundaries, optimisation results vs. HYSYS comparison.

Again the error differences are too high and unacceptable for power consumption, HC dew point and RVP. No constraints are met.

3.1.5 Optimisation by HYSYS

HYSYS has a build in optimiser function where it is possible to apply the parameter to be optimised along with the wanted constraints. Several tests were performed in order to determine the accuracy of the optimiser.

Minimize power without any constraints

- All variables set to lowest values before start.

Optimiser failed after several resets of an adjuster's iteration since it reached its maximum of 100 and several activations of the optimisation process was needed, since an inconsistency warning occurred and paused the process.

- All variables set to highest values before start.
  The optimiser comes out successful and converged faster than any of the other test. The power consumption ended up at 7400 kW.

- All variables set to mid values before start.
  Successful outcome again, but the power consumption is at 7950 kW. Several activations of the optimisation process were once again needed.

In comparison the regression model in Python calculates the power consumption to be 7008 kW. Applying the variable values found by the model in HYSY, gave almost the exact same result, 7017 kW.

Minimize power case 1 and 2 applied

- All variables set to lowest values before start
- All variables set to highest values before start
- All variables set to mid values before start
- All variables set to high-low-high-low-high before start
- All variables set to low-high-low-high-low before start

The majority of the cases tested above failed in the optimisation process. The ones that had a successful HYSYS outcome were in fact not successful, since not all constraints were fulfilled. As an example case 1 with mid-level variable values entered before starting the optimisation process, found a power consumption of 8014 kW, but the wobbe constraint were too high. The other three constraints were met.

The HYSYS optimiser needs a value for each variable before being apple to perform the optimisation. The results were very inconsistent for all tests. When trying to minimise the power consumption, even without any constraints applied, each simulation gave a different result regarding power consumption and the found variables. The same inconsistencies apply to the results when adding the constraints, which rarely were met. In general the function is very slow compared to the regression model and it takes between 1-4 minutes to complete one optimisation scenario. HYSYS are looping the simulations until it has found a local optimum, which causes the long converging time and inconsistencies depending on the starting variable values. Whereas the regression model is finding a global optimum and is fulfilling the constraints.

3.1.6 Manually Adjusting

To achieve the desired output for the wobbe index only, it would be interesting to see the result for power consumption. By manually adjusting only one or two main variables, i.e. P after expander and TEG inlet T, it resulted in a power consumption of 9807 kW. The variable values started at mid-level and it took several tries before reaching the goal. Especially the final small adjustment to reach exactly 56.2 took the most. The adjustments were done in Python and checked in the HYSYS model, which was almost identical. If applying the optimisation model in Python to the same case – Wobbe constraint at 56.2 – the power consumption is only 8840 kW. If adding more constraints this process of manually adjusting the variables to meet the desired constraints will take a tremendous amount of time - a comprehensive trial and error session.

3.1.7 Summary

The concept of DOE has been applied to tests performed on a HYSYS oil and gas separation process. An experimental plan of 46 tests with a 3 level variation in 5 factors with 7 parameter responses has been executed. The data output has been processed in Python, where a variety of libraries and modules has been used to analyse the data. A regression model for each parameter was created and verified by plots and calculations comparing them to HYSYS results. An optimisation algorithm was used to minimise the power consumption and maintaining desired export constraints at the same time. The variables values found in each case was applied to HYSYS and the results compared. In general the errors of the cases are very small or not existing, which show that with the DOE and RSM methods, it is possible to predict the variable values for minimising the power consumption and preserving the constraints within the experimental boundaries. When increasing the boundaries by a factor the model showed some inconsistencies and larger percentage errors, which makes it almost unusable outside the boundaries. Along with the optimisation possibility the DOE concept also reduces the number of required experiments radically.

HYSYS' own optimiser function was tested and found impractical because of its inconsistencies in the results and requires a larger amount of time.

By manually adjusting the parameters to meet the demanded constraints the power consumption becomes significantly larger and required lots of trial and error runs to complete. This emphasizes the effect of the DOE optimisation model in saved power consumption and the time spent on manually adjusting the variables to meet the constraints given.

3.2 Weight Estimation Modelling

The error propagation method is applied to a Master Equipment List, MEL, from a previous Ramboll project, in order to investigate the possibilities of the method. The investigation also comprises which parameters affect the combined uncertainty.

The Monte Carlo method is applied to multiple parameters in order to determine a total topside production weight. Central process equipment that depends on a combination of oil, gas and water flow rates is simulated in HYSYS - same separation set-up used in the process optimisation section. The weight estimation of the equipment is depending on values, i.e. pressure, flow, temperature, etc. provided by HYSYS for each piece of equipment in the simulation. This weight estimation of the most central process equipment is the foundation for calculating the total topside weight. Monte Carlo simulation is used in order to randomly select values for flow rates and factors within a calculated standard deviation.

3.2.1 Error Propagation Applied to Existing MEL

The MEL used consist of more than 150 pieces of equipment. For several types there are needed 2 or 3 of the same. These sets are considered as one unit since the uncertainty are the same for them all. The weight of one is multiplied with 2 or 3 to achieve the unit's weight.

The span of +/- 30 % is calculated for each piece of equipment and units of the same type in the MEL. The span is then squared and the square root of the sum is the span of the combined uncertainties, in accordance with equation [3]. The MEL with all the error propagation calculations can be found in *Appendix 2.1 – Error Propagation Applied to STA-3 MEL.*

The combined uncertainty span is calculated to be 188.34 tonnes, which is a lot smaller than the +/- 30 % of 675.85 tonnes. The total weight of the MEL is 1126.42 tonnes and the span of 188.34 tonnes corresponds to a combined uncertainty of only +/- 8.36 %.

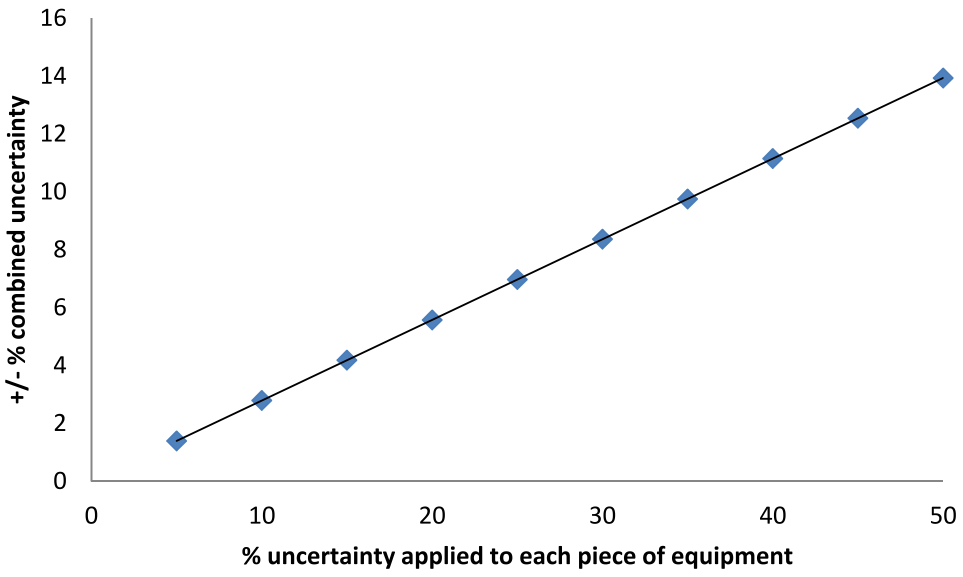


Figure 3-6: Combined uncertainty graph as a function of applied % uncertainty to each piece of equipment.

As shown by Figure 3-6, the combined uncertainty percentage error is linear depending on the applied uncertainty percentage to each piece of equipment. If a single type of equipment is extremely heavy compared to the rest, it has a great influence on the combined uncertainty. As an example there are 3 main power generators, which whey 258.6 tonnes combined. If their weight doubled, the combined uncertainty would increase from 8.36 % to 11.85 %.

To prepare a MEL for the HYSYS simulation of central process equipment, the MEL in *Appendix 2.1* is cut down so it represents almost the same types and number of equipment as the HYSYS model. The new smaller MEL is calculated in the same way as before, to see how the combined uncertainties react. When applying a +/- 30 % uncertainty to each type or unit of equipment, the combined uncertainty is higher than before, +/- 12.38 %, which is an increase of roughly 50 %. The MEL has been cut by approximately one third. In *Appendix 2.2 – Error Propagation Applied to Cut Down STA-3 MEL* calculations for both +/- 30 % and +/- 50% applied is given. When comparing the original MEL and the cut down MEL, it is observed that in the shorter MEL most of the equipment has all different weights. In the original MEL several types of equipment are of the same weight. If the weights for some of the equipment in the cut down MEL, are changed to be more alike the combined +/- percentage uncertainty drops.

3.2.2 Combined Weight Estimation Based on HYSYS Data

When designing a process plant the flow rates combined with temperature and pressure are the major influential factors. It is possible to change the flow rates in HYSYS according to a plausible range. In order to easily apply the simulated HYSYS values into the calculating weight estimation spread sheets, the calculation methods are combined into one spread sheet. The equipment weight can then be calculated for each simulation with a given combination of the flow rates for oil, gas and water, to see how the variation in the flow rates affect the duty, temperature and pressure etc. required for pumps, compressors, coolers & heat exchangers, separators and scrubbers along with several more types of equipment. These parameters are used for the weight estimations.

An example of a simulation result is given in *Appendix 2.3 – HYSYS Equipment List Data*. These data, among other known design criteria for the equipment, are then applied to combined weight estimation sheet, which can be found in *Appendix 2.4 – Combined Excel Weight Estimation Sheet.*

3.2.3 Simulation Plan and Modelling

The approach for modelling a function for the weight estimate depending on the flow rates for oil, gas and water is almost the same as the one used in the process optimisation section. A full factorial experiment plan is carried out in HYSYS. The variable values for the levels are given in Table 3-14.

Variable →	**Oil [barrel/day]**	**Gas [m^3/hr]**	**Water [barrel/day]**
High (+1)	25300	32090	37740
Mid (0)	23000	29170	31450
Low (-1)	20700	26250	25160

Table 3-14: Variable values and levels used in HYSYS

The ranges for oil, gas and water has been determined by Ramboll's chief consultant, Anders Andreasen.

The variables from the process optimisation section are set to their originally designed mid-level values.

The experiment is a 3 factor 3 level experiment equals to $3^3 = 27$ simulation combinations. The simulation results can be found in Table 3-15.

Sim. no.	X1	X2	X3	Wobbe index	SG	HHV	HC Dew	Power	RVP	Eq. weight
1	0	0	0	56.57	0.6631	43.65	-22.79	8937	13.94	558.1
2	1	1	1	56.53	0.6619	43.57	-23.31	10030	13.81	598.0
3	-1	-1	-1	56.59	0.6637	43.68	-22.52	7777	13.98	516.9
4	0	0	1	56.52	0.6617	43.56	-23.33	9425	13.64	581.1
5	0	0	-1	56.54	0.6621	43.59	-23.22	8268	13.84	536.0
6	1	1	0	56.54	0.6622	43.59	-23.20	9450	13.89	571.2
7	1	1	-1	56.55	0.6624	43.60	-23.15	8871	14.05	550.2
8	-1	-1	0	56.56	0.6626	43.62	-23.04	8364	13.83	537.7
9	-1	-1	1	56.55	0.6624	43.61	-23.09	8954	13.73	564.9
10	1	0	0	56.54	0.6621	43.59	-23.24	9233	13.63	567.8
11	-1	0	0	56.57	0.6631	43.64	-22.80	8869	14.64	556.7
12	0	1	1	56.54	0.6623	43.60	-23.12	9973	14.45	596.3
13	-1	1	1	56.58	0.6634	43.66	-22.60	9952	15.30	595.3
14	0	-1	-1	56.56	0.6627	43.62	-23.00	7822	13.33	519.5
15	1	-1	-1	56.53	0.6619	43.57	-23.41	7902	12.80	522.5
16	0	1	0	56.56	0.6628	43.63	-22.97	9410	14.57	569.6
17	0	-1	0	56.56	0.6627	43.62	-22.94	8428	13.28	540.6
18	1	0	1	56.50	0.6609	43.52	-23.69	9475	13.04	582.9
19	1	-1	1	56.53	0.6619	43.57	-23.33	9082	12.66	569.5
20	-1	0	-1	56.57	0.6631	43.64	-22.82	8264	14.67	535.7
21	-1	1	-1	56.60	0.6639	43.69	-22.47	8781	15.56	544.6
22	-1	0	1	56.59	0.6637	43.68	-22.51	9515	14.71	582.4
23	0	1	-1	56.57	0.6631	43.65	-22.81	8827	14.71	549.3
24	1	-1	0	56.51	0.6612	43.53	-23.70	8460	12.65	541.7
25	1	0	-1	56.54	0.6620	43.58	-23.32	8351	13.31	537.4
26	-1	1	0	56.59	0.6635	43.67	-22.60	9394	15.52	565.8
27	0	-1	1	56.48	0.6603	43.48	-24.05	8935	12.88	562.8

Table 3-15: Experimental plan, HYSYS results and eq. weight estimate.

As seen in the table the only objectives impacted by the variation in the flow rates are the power consumption and the equipment weight estimation. The other has little or no deviation in their outcome.

The goal for the experiment is to create a regression model for the equipment weight estimations. The same procedure when creating the regressions models for the process optimisation is used.

The equipment weight regression model was found to be:

$$EqWeight = 0.0010 \cdot X1 + 0.0278 \cdot X2 + 0.0037 \cdot X3 - 3.896 \cdot 10^{-7} \cdot X2 \cdot X2 - 58.2391 \qquad [5]$$

Improvement of the model is done by analysing outliers etc. as done similar in the process optimisation experiment.

A graph showing the simulated HYSYS values vs. the predicted values calculated by the model can be found in Figure 3-7. The points form a decent linear line and the model is good fit.

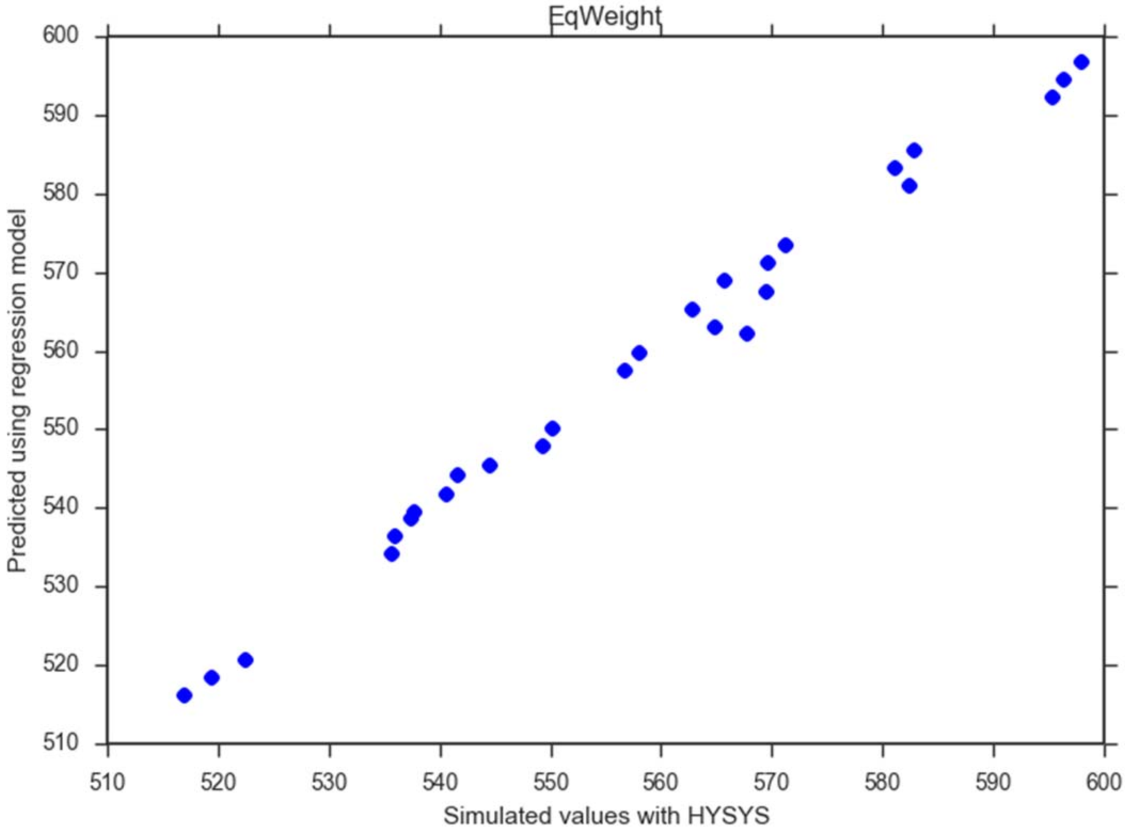


Figure 3-7: Simulated HYSYS values vs. Predicted regression model values.

The model is verified by comparing the regression model calculation of mid, low and high level values and the corresponding HYSYS simulation results for the same combinations. Table 3-16 page 43 shows that the percentage error and numerical percentage are very low for all comparisons.

Python/HYSYS variable mid values = (23000, 29170, 31450)					
Python results:		HYSYS results applied to EqWeight spread sheet:		Error %	Error # diff.
EqWeight:	560.55	EqWeight:	558.1	0.44	2.45
Python/HYSYS variable low values = (20700, 26250, 25160)					
Python results:		HYSYS results applied to EqWeight spread sheet:		Error %	Error # diff.
EqWeight:	516.84	EqWeight:	516.9	-0.01	-0.06
Python/HYSYS variable high values = (25300, 32090, 37740)					
Python results:		HYSYS results applied to EqWeight spread sheet:		Error %	Error # diff.
EqWeight:	597.6	EqWeight:	598.0	-0.07	-0.4

Table 3-16: EqWeight model verification for mid, low and high levels.

Verification for values between mid to high and mid to low values and values outside training set has also been made.

Python/HYSYS variable mid-high values = (24150, 30630, 34595)					
Python results:		HYSYS results applied to EqWeight spread sheet:		Error %	Error # diff.
EqWeight:	579.9	EqWeight:	578.5	0.24	1.4
Python/HYSYS variable mid-low values = (21850, 27710, 28305)					
Python results:		HYSYS results applied to EqWeight spread sheet:		Error %	Error # diff.
EqWeight:	539.53	EqWeight:	535.1	0.82	4.43
Python/HYSYS variable high-high values = (26450, 3550, 40885)					
Python results:		HYSYS results applied to EqWeight spread sheet:		Error %	Error # diff.
EqWeight:	613.64	EqWeight:	677.7	-10.44	-64.06
Python/HYSYS variable low-low values = (19550, 24790, 22015)					
Python results:		HYSYS results applied to EqWeight spread sheet:		Error %	Error # diff.
EqWeight:	492.5	EqWeight:	500.4	-1.6	-7.9

Table 3-17: Verification of the model with values not used to create the model.

Table 3-17 shows the comparison errors of the values applied to the model and to the equipment estimation spread sheet through HYSYS. When testing the model above the ranges for the flow rates in the high-high level case, the percentage error are getting to high. Otherwise the model performs really well and can be used as the foundation to calculate a total weight for a production platform.

Factors for all of the additional equipment are to be calculated and found from known offshore platform data and equipment lists. The different factors needed are:

- The rest of the remaining process equipment not sized by HYSYS data.
- A combined factor for the remaining equipment, i.e. electrical/instrumentation, piping and structural.
- Accommodation.

By reviewing existing process MELs an imperial factor, F_{rest}, of 1.283 is found by isolating the weight of the central process equipment, similar to the equipment used in the HYSYS simulation and the weight of the remaining equipment in relation to each other. From equation [5] the contribution of the rest can be written as:

$$Weight_{rest} = EqWeight(oil, gas, water) \cdot F_{rest} \qquad [6]$$

Where oil, gas and water are the flow rates applied from Table 3-14 page 40, corresponding to X1, X2 and X3 in equation [5]. The total weight of the process equipment is found by combining equation [5] and [6] and can be written as:

$$Weight_{process} = EqWeight + Weight_{rest} \qquad [7]$$

Through weight data from known offshore installations, where the weights for electrical/instrumentation, piping, structural and process equipment are indicated, along with the module weight. An average factor, F_{total}, where the process equipment related to the total weight is found to be 4.08, see Table 3-20 and Table 3-21 page 47 and 48 for further information.

The accommodation facility is as standard set to weigh 800 tonnes, $Weight_{accommodation}$. The total weight for a production platform can then be written as:

$$Weight_{total} = Weight_{process} \cdot F_{total} + Weight_{accommodation} \qquad [8]$$

Applying mid-level rates to oil, gas and water the total weight becomes:

$$\begin{aligned} Weight_{total} &= ((560.55 + (560.55 * 1.283)) \cdot 4.08) + 800 \\ &= \boldsymbol{6021.3\ tonnes} \end{aligned} \qquad [9]$$

This is however a result where no uncertainties is applied to any contribution in the equation.

When applying a conservative uncertainty of 50% to each piece of equipment in the MEL calculated by mid-level rates for oil, gas and water, the result of equation [9] becomes:

$$Weight_{total,50} = ((837.1 + (837.1 * 1.283)) \cdot 4.08) + 800 \\ = \mathbf{8597.3\ tonnes} \qquad [10]$$

Uncertainties could also be applied for F_{rest}, F_{total} and $Weight_{accommodation}$ to give an even more conservative result.

3.2.4 Monte Carlo Method Applied

When uncertainties are taking into account one could easily choose the worst case scenario for each factor. To have a more realistic result, where the uncertainties applied to each contribution in the model are randomly picked within a normal distribution curve, the Monte Carlo method is needed. The random selected value for one contribution is totally independent from the other. The model can be applied a given number of runs, where each contribution are randomly selected and summed together. A few runs will give an inaccurate result, since it is unlikely to have hits that cover the normal distribution. A large amount of trials is therefore required and using Python as the program to compile the large amount of samples will be suitable.

Adding Uncertainties

Uncertainties need to be added to every single contribution which includes:

- Oil flow rate.
- Gas flow rate.
- Water flow rate.
- The $EqWeight$, equation [5].
- The $Weight_{rest}$, equation [6].
- The combined factor for the remaining equipment.
- Accommodation weight.

The uncertainties applied to the list above are converted into a standard deviation, which is a measure of dispersion from the mean value. Ramboll's approach to the uncertainties, are that they covers the middle 80 % under the normal distribution curve and is corresponding to +/- 2 standard deviations. This deviates from the example given in Figure 1-9 page 20, where +/- 1 standard deviation corresponds to 68.2% and +/- 2 corresponds to 95.4%. When calculating the standard deviation an adjustment is therefore needed, in accordance with equation [11].

$$X = \mu + Z \cdot \sigma \qquad [11]$$

Where μ is the mean and σ the standard deviation of the variable X, and Z is the value from the standard normal distribution for the desired percentile. To adjust the standard deviation it has to be divided by the z-value of the 90th percentile of the distribution. From a z-score table or by using Python, the z-value is found to be +/-1.28. The 90th percentile indicates that 40% from the mean value to the boundary is covered.

Flow rates

The standard deviations, σ, for each flow rate are the range from level 0 to +1. This range is then divided by the z-value of 1.28. In Table 3-18 the σ for oil, gas and water are listed.

Flow rate of:	Standard deviation, σ:
Oil	$\sigma_{Oil} = \frac{25300 - 23000}{1.28} = 1796.9$
Gas	$\sigma_{Gas} = \frac{32090 - 29170}{1.28} = 2281.3$
Water	$\sigma_{Water} = \frac{37740 - 31450}{1.28} = 4914.1$

Table 3-18: Standard deviations of oil, gas and water flow rates.

***EqWeight* and *Weight$_{rest}$* added 50% uncertainty**

For the central process equipment weight, calculated by the combined weight estimation sheet, each piece of equipment are added a 50% uncertainty in each of the 27 simulations. The combined standard deviation is calculated by squaring each σ related to each piece of equipment and taking the square root of the sum. Example of the method is applied to *Appendix 2.4* and is listed in Table 3-19.

Equipment	Span (+/- 50%)	Span squared	$\sigma = \frac{Span/2}{1.28}$	σ^2
Inlet cooler	12.51	156.47	4.89	23.88
Oil export cooler	0.33	0.11	0.13	0.02
LP1 inlet cooler	1.58	2.51	0.62	0.38
LP2 inlet cooler	35.21	1239.45	13.75	189.12
IP inlet cooler	30.90	954.69	12.07	145.67
Glycol inlet cooler	11.66	135.94	4.55	20.74
HP cooler	6.21	38.59	2.43	5.89
Interstage heater	4.27	18.21	1.67	2.78
1st stage separator	9.73	94.66	3.80	14.44
2nd stage separator	4.74	22.43	1.85	3.42
3rd stage separator	4.32	18.64	1.69	2.84
LT separator	1.50	2.26	0.59	0.34
LP1 scrubber	0.91	0.83	0.36	0.13
LP2 scrubber	1.74	3.01	0.68	0.46
IP scrubber	3.90	15.22	1.52	2.32
Glycol inlet scrubber	7.63	58.23	2.98	8.89
Expander inlet scrubber	6.95	48.31	2.72	7.37
Glycol contactor	6.90	47.59	2.69	7.26
LP1 compressor	6.98	48.78	2.73	7.44
LP2 compressor	15.75	247.92	6.15	37.83
IP compressor	25.15	632.33	9.82	96.49

HP compressor	16.43	270.04	6.42	41.20
Gas lift compressor	0.00	0.00	0.00	0.00
Expander	9.28	86.15	3.63	13.15
Re compressor	9.28	86.15	3.63	13.15
Return pump	0.22	0.05	0.08	0.01
PW pump	0.22	0.05	0.08	0.01
Oil booster pump	1.10	1.21	0.43	0.18
Oil pump	7.88	62.09	3.08	9.47
WI pump 3 x 50%	41.22	1699.30	16.10	259.29
Heat exchanger 1	24.66	607.98	9.63	92.77
Heat exchanger 2	12.15	147.56	4.75	22.52
NGL splitter	6.19	38.33	2.42	5.85
Power generator 2 x 100%	172.36	29707.97	67.33	4533.08
Fine filter x 2 (2 micron)	4.10	16.78	1.60	2.56
SRP package	39.16	1533.54	15.30	234.00
CIP Package	7.50	56.23	2.93	8.58
Vacuum dearerator	3.78	14.32	1.48	2.18
Vacuum pump x 2	0.92	0.85	0.36	0.13
Vacuum pump skid x 2	2.77	7.65	1.08	1.17
	558.1	195.25	-	$\sqrt{\sigma^2} = 76.27$

Table 3-19: Appendix 2.4 combined standard deviation example.

The average combined standard deviation of the 27 simulation, 76.46 tonnes, is used as the final standard deviation in the Monte Carlo model.

The same approach is applied to the $Weight_{rest}$ MEL's and an average of 43.1 tonnes is found to be the standard deviation.

Factor for the remaining equipment

The F_{total} factor is created by comparing weight data from known offshore installations listed in Table 3-20.

Platform	Total Weight [tonnes]	Process Weight [tonnes]	Rel. (factor)
A	1106	225	4.92
B	1190	338	3.52
C	1385	346	4.00
D	1676	546	3.07
E	1205	232	5.19
F	1612	530	3.04
G	805	141	5.71

Table 3-20: Weight data of offshore installations (12).

Low factor	High factor	Span	$\sigma = \dfrac{Span/2}{1.28}$
3.04	5.71	2.67	**1.04**
Mid f	**4.08**		

Table 3-21: Factor, rest mid-level and standard deviation.

A standard deviation of 1.04 tonnes is applied to the factor contribution of the Monte Carlo model.

Accommodation

The living quarters is set to whey 800 tonnes and it is applied a +/- 20% uncertainty. Table 3-21 shows the calculation.

Span (+/- 20%)	$\sigma = \dfrac{Span/2}{1.28}$
320	**125.0**

Table 3-22: Accommodation standard deviation.

3.2.5 The Monte Carlo Model

The different contributions from section 3.2.4 are joined together into one model. The model can then be applied with a given number of randomly picked samples from each contribution – Monte Carlo Simulation. The Python model sample is written as:

```
'Model with uncertainties'
Samples = 100000
X = Samples

'Rates at 10%, 10% and 20% uncertainties (used in HYSYS sim)'
oil = (np.random.normal(23000, 1796.9, X))
gas = (np.random.normal(29170, 2281.3, X))
water = (np.random.normal(31450, 4914.1, X))

Weight = EqWeight(oil, gas, water)
Weight_uncertainty = (np.random.normal(0, 76.46, X))
Weight_plus_uncertainty = Weight + Weight_uncertainty
Rest = (EqWeight(oil, gas, water)*1.283)
Rest_uncertainty = (np.random.normal(0, 43.1, X))
Rest_plus_uncertainty = Rest + Rest_uncertainty
Weight_total = Weight_plus_uncertainty + Rest_plus_uncertainty

factor = (np.random.normal(4.08, 1.04, X))

'Total weight multiplied by combined factor + accommondation'
Weight_total_factor = Weight_total * factor + (np.random.normal(800, 125, X))
```

The entire code script can be found in *Appendix 2.5 – Monte Carlo Code Script*.

3.2.6 Monte Carlo Simulation Results

The model is run several times with a various number of samples in order to find the required amount where the model is performing well with an acceptable calculation time for the program.

Simulations with samples of 100, 1.000, 10.000, 100.000, 1.000.000 and 10.000.000 are carried out and the results of the following are noted:

- Mean
- Minimum
- Maximum
- Standard deviation

The results are listed in *Appendix 2.6 – Monte Carlo Results, Samples Variety* where it can be obtained that from 100.000 samples and beyond, the histograms fits the normal distribution curve more or less perfectly. The mean and standard deviation values do not vary by more than a few tonnes as they are converging around the 100.000 sample mark, shown in Figure 3-8.

The minimum and maximum values are increasing, when simulating more than 100.000 samples in the model. Hitting these extreme outer limits is very unlikely and is close to a chance of 0%. Some of the minimum results are negative, which is caused by the high uncertainties that results in high standard deviations relative to the mean values in the contributions. The 100.000 samples results are shown in Table 3-23 and Figure 3-9 page 50.

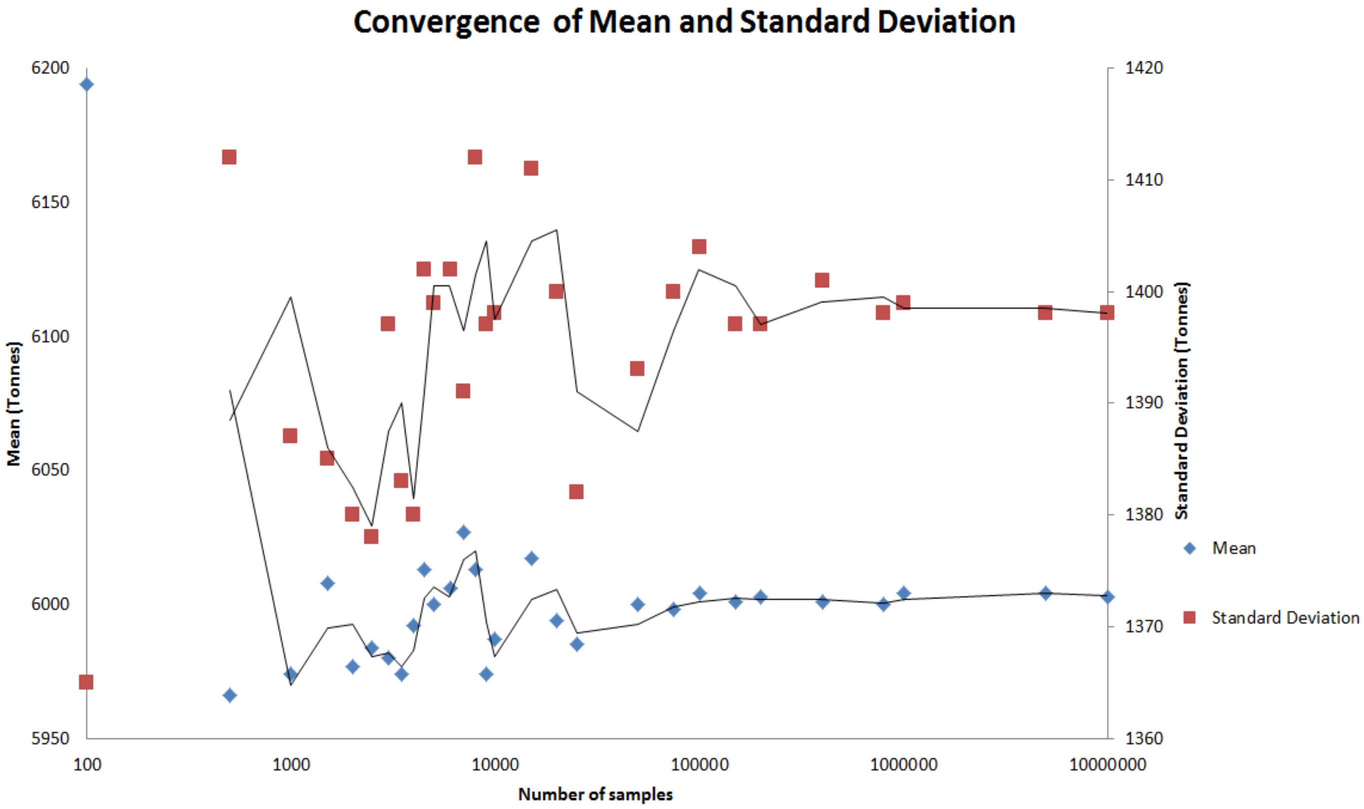


Figure 3-8: Convergence plot of the values for mean and standard deviation.

100.000 samples results:	**Weight [tonnes]:**
Mean	6006
Minimum	496
Maximum	13077
Standard deviation	1395

Table 3-23: Monte Carlo results when simulating 100000 samples.

The estimated weights of offshore equipment are by experiences very rarely to be less than the estimated weight without uncertainties applied, i.e. the mean value. The mean value is therefore the best possible outcome. Worst case scenario is expected to be within 2 standard deviations and there is only a 10% chance of hitting a value above mean + 2 standard deviations.

The x-axis of Figure 3-9 is the weight in tonnes of the topside structure randomly picked by the Monte Carlo simulation and the blue columns, which there is 100 of, represents all of the 100.000 simulations. The higher the column is the more hits of the value is simulated by the Monte Carlo model at that weight interval for the given column. The y-axis is the probability of hitting a value in a given column. The total area within the normal distribution curve, green line, sums up the probabilities to be 100%.

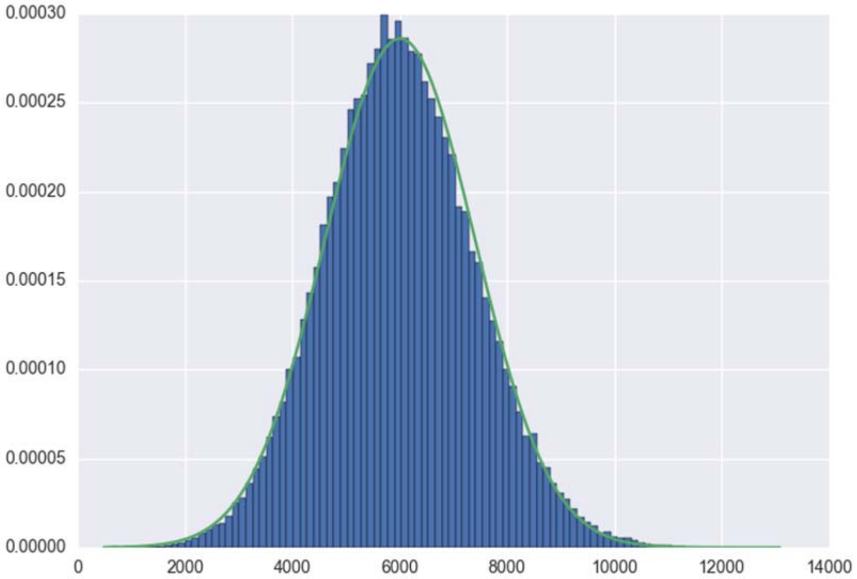


Figure 3-9: Histogram with a normal distribution curve of the Monte Carlo results of 100.000 samples.

The mean value added only 1 standard deviation multiplied 1.28, represents only a 15.9% chance of hitting a value that is above and is considered a reasonable scenario, which is not as conservative as the mean added 2 standard deviation.

$$6006 + 1395 \cdot 1.28 = \mathbf{7792\ tonnes} \qquad [12]$$

The result in equation [12] is an increase of 29.7% from the mean value.

To distinguish the affect each contributions has to the Monte Carlo models combined standard deviation. Simulations where one contribution's uncertainty is removed and instead mid-level or mean values are applied and reviewed. The remaining 4 contributions are applied their uncertainties in the same way as before and it results in 5 simulations cases, conducted again with 100.000 samples.

Case	Uncertainty set to mid/mean value	Minimum weight [tonnes]	Maximum weight [tonnes]	Standard deviation [tonnes]
1	Accommodation	468	12733	1389
2	**Factor, F_{total}**	**4078**	**8102**	**428**
3	Rest_uncertainty	208	12074	1383
4	Weight_uncertainty	177	11829	1358
5	Rates	178	12473	1387

Table 3-24: Uncertainty cases results.

From Table 3-24 it can be seen that only case 2 differs from the rest. The factor uncertainty for F_{total}, is impacting the models standard deviation and is decreasing it significantly, ref. equation [8] page 44. It also shows that the other uncertainties have little or almost no impact on the combined standard deviation compared to the result from Table 3-23. The mean values are for all cases around 6000 tonnes.

The F_{total} factor uncertainty consists of three contributions. These are split up and their respective standard deviations are calculated. The model is then applied three factor uncertainties instead of one combined to see the influence it will have for the results.

100000 samples results (partitioned factor uncertainty):	Weight [tonnes]:
Mean	6141
Minimum	163
Maximum	13181
Standard deviation	1440

Table 3-25: Monte Carlo result, when the factor uncertainty is partitioned.

Table 3-25 shows the results. Comparing them to Table 3-23 the mean and standard deviation are slightly larger, 2-3 %. For both the Monte Carlo simulation results the mean and standard deviation values are consistent, only differing a few tonnes, when running the simulation multiple times. The minimum and maximum values are more varying and can easily be +/- 600 tonnes. Even for simulations conducted with one million samples.

To roughly investigate how the model performs up against a real life study, the Ramboll STA-3 study total topside weight result is compared to the Monte Carlo model result. The flow rates from the STA-3 study are applied to the Monte Carlo model without any uncertainty. Uncertainties for the remaining contributions are still preserved. The total weight of the STA-3 topside was in the study calculated to be 9247 tonnes. The mean of the Monte Carlo model is converged at 6177 tonnes and the standard deviation at 1425 tonnes. If adding 2 standard deviations to the mean value it results in a total weight of 9027 tonnes. The difference is only 220 tonnes, which is considered to be a good result, when taking the large amount of work done by the other disciplines into account.

3.2.7 Summary

By using error propagation to combine the uncertainties for MELs in study phases, it will give a better more precise and lower weight estimate. The method could easily be applied to the existing MEL templates at Ramboll and the result can be held up against the current conservative weight estimates. One should be aware of the lists size and composition of weights. If one piece is significantly heavier compared to the rest, it will have a large impact on the combined uncertainty. As well, if the weights in the MEL are all very different or alike, it will either increase or decrease the combined uncertainty.

Ramboll's weight estimation methods have been combined into one spread sheet, where the central process equipment is present. Data from a HYSYS separation process simulation can easily be copied to the spreadsheet in order to obtain the influence to the weight estimations caused by changes in the simulation set-up. A regression model of the equipment weight depending on variation in oil, gas and water flow rates was created by carrying out full factorial experiment plan. This model set the foundation for a combined model to estimate the total topside weight and is intended to be used in early phase studies at Ramboll. Every contribution in the combined model is applied with normal distributed uncertainties and the Monte Carlo method is used to simulate randomly picked values.

The model performs well and calculates fast for a large amount of samples – within seconds for all simulations. The factor contribution for electrical/instrumentation, piping and structural weight has the largest impact to the combined standard deviation and when partitioning the F_{total} factor, the mean and standard deviation values increases. If the model where to be improved, it is crucial that more data from each contribution in the factor has to be at a higher detail level. It is easy to apply new inputs or changes to the model in Python to test different scenarios and cases. This has helped indicate the behaviours of the model. It is also possible to adapt other uncertainties to the model depending on the project study or phase that need to be processed.

The model performs well up against up against the STA-3 study. The opportunity of saving time in early phase project by only letting the process department create their fundamental design of the central process equipment could be plausible.

Sources of errors

Process Optimisation
In order for this method to be successful, it has to be thoroughly and strictly executed. A lot of manually entered data in HYSYS and excel is needed, which often can lead to mistakes. The simulations have to be performed one by one in HYSYS and the results transferred to excel. For each simulation it is important to be aware of if any errors occurring during the HYSYS simulation and resetting the adjusters or number of iteration in order to get the right results. The results were often displayed even if errors occurred.

During the creation of the Python code and model, a lot of debugging took place, as well as trying different possibilities of code scripts found by research, for a given aspect in the model. This process contained several mistakes and errors, which was analysed and solved. The final code script is intended to be used by whom it could be useful to in future studies at Ramboll. The code script then has to be changed in order to adapt it for a given case. This would require a remake of any needed regression models and renaming the elements in the code script. Future creation of a thorough step by step guideline is therefore relevant in order to minimise the chance of errors occurring and mistakes made by the user.

Weight Estimation – Monte Carlo
Once again the large amount of manually performed data processing can lead to mistakes and the method has to be executed strictly to give a successful outcome. Besides entering the simulation plan into HYSYS and the results to excel, like in the process optimisation method, a lot of data has to be entered into the combined weight estimation spread sheet. This is another factor where mistakes can be made before being able to apply the CSV-file into Python.

Because of the need to only create one regression model, where the central process equipment weight depends on the flow rates, and renaming a few elements in the code script. The usage of the model is easier and less demanding for the person adapting it to future studies compared to process optimisation procedure.

Inaccuracy lies in the factors used in the model and their respective uncertainties. These are based on data from known offshore installations. To improve the result these data, is done by collecting more data from other installations and reviewing the relations between the process equipment and the remaining equipment in a higher level of detail. Another option is to create separate models for piping, electrical/instrumentation and structural in the same way as for the process equipment. Such model could be applied in the more detailed phases of a project.

Future Work

Process Optimisation

For further verification and improvement of the method, it would be interesting to test the optimisation model on other HYSYS simulations set-ups. These HYSYS set-ups could be from other completed studies or even from production platforms in use, to investigate if a saving in the energy consumption would be possible.

The method could also be used in other stages at the platform, than the oil and gas separation, i.e. water treatment, chemical units or any other units where it could be an advantage to save energy.

Weight Estimation – Monte Carlo

The level of detail in several aspects of the model could be improved in order to achieve a better estimate. At first the weight estimation methods for each type of equipment could be improved by collecting vendor information for newer equipment technologies instead of using the older Ramboll Estimation Manual. By reviewing more data for the factors found from known offshore installations and Master Equipment Lists, would contribute to an improvement of the accuracy of the general model as well. For a more detailed and accurate result it would be interesting to adapt the model with data only from installations very similar to the topside design in the given study. This requires more work in each project, since each time the model and the used data are unique in every aspect of the model. The improvement of the weight estimation methods and factors would also result in an improvement of the uncertainties used. Verification and comparison up against other completed studies would be relevant. In order to make sure the comparison made to the STA-3 study is not a one hit wonder.

In general for both methods, it is very relevant in the future to create detailed user guidelines for the procedure and usage of the methods, in order to make other Ramboll employees being able to adapt it to their future projects. The cost for a topside structure is linked to the weight and dimension of each piece of equipment. Adding a cost element into the model would be a great and relevant expansion in the future.

Conclusion

This bachelor thesis is based on selected issues worked upon during the internship at Ramboll Oil & Gas by the energy engineering student, *Kasper Rønn Rasmussen*. The problems described in the analysis are set to be part of the annual development goal for Ramboll. Development studies are done each year at Ramboll in order to optimise their way of working or finding new and innovative methods to the oil and gas industry.

When designing an offshore oil and gas separation facility, it is difficult to predict the lowest possible energy consumption, when at the same time the export quality constraints have to be met. The many interactions between the large varieties of equipment make it almost impossible to distinguish trends among them. In order to optimise a given HYSYS process simulation in reference to the power consumption, five variables which was known to have a large impact, were investigated by a DOE and RSM approach. These methods made it possible, on behalf of a systematically experiment plan, to create regression models for each of the desired export outputs and the power consumption. The optimisation model could be set up to minimise the power in accordance to export constraints depending on a given scenario. By the verification of the model it showed the best results, when using it inside the experimental training set boundaries. The model provides large energy savings in the investigated cases compared to a traditional manual adjustment of the variables and proves that the approach and method is suitable for future use in the industry for study projects or to existing platforms.

In early phase projects the essential work lies in the creating the MEL and determine the weight for each piece of equipment. The total weight of the MELs are added an uncertainty percentage depending on the phase and detail level of the project. By error propagation the uncertainties was added to each piece of equipment instead and it resulted in a combined uncertainty, which was lower than the initial applied uncertainty. This approach proved to give a better and more precise weight estimate and together with the modelling of a regression model of the central process equipment, it set the foundation for a total topside weight. This was done by using the HYSYS simulation results, which depended on the variation in the oil, gas and water rates, and applying them to the combined weight estimation spreadsheet. Factors for the rest of the process equipment and the remaining piping, electrical/instrumentation and structural weight were created by correlation of data from known installations. By using the Monte Carlo method to predict a result within the normal distribution for each uncertainty applied to every contribution in the model. It was possible to give a weight estimate for a total topside platform, where the randomly picked contributions in the model are independent. The major influence in the model comes from the F_{total} factor. To improve the models accuracy the contribution in the F_{total} factor are to be created in a higher detail level. This would be an advantage if the model were to be applied in a concept phase study. If the improvements of the model are verified to be sufficient, this tool could in the future save a lot of man hours in early phase project.

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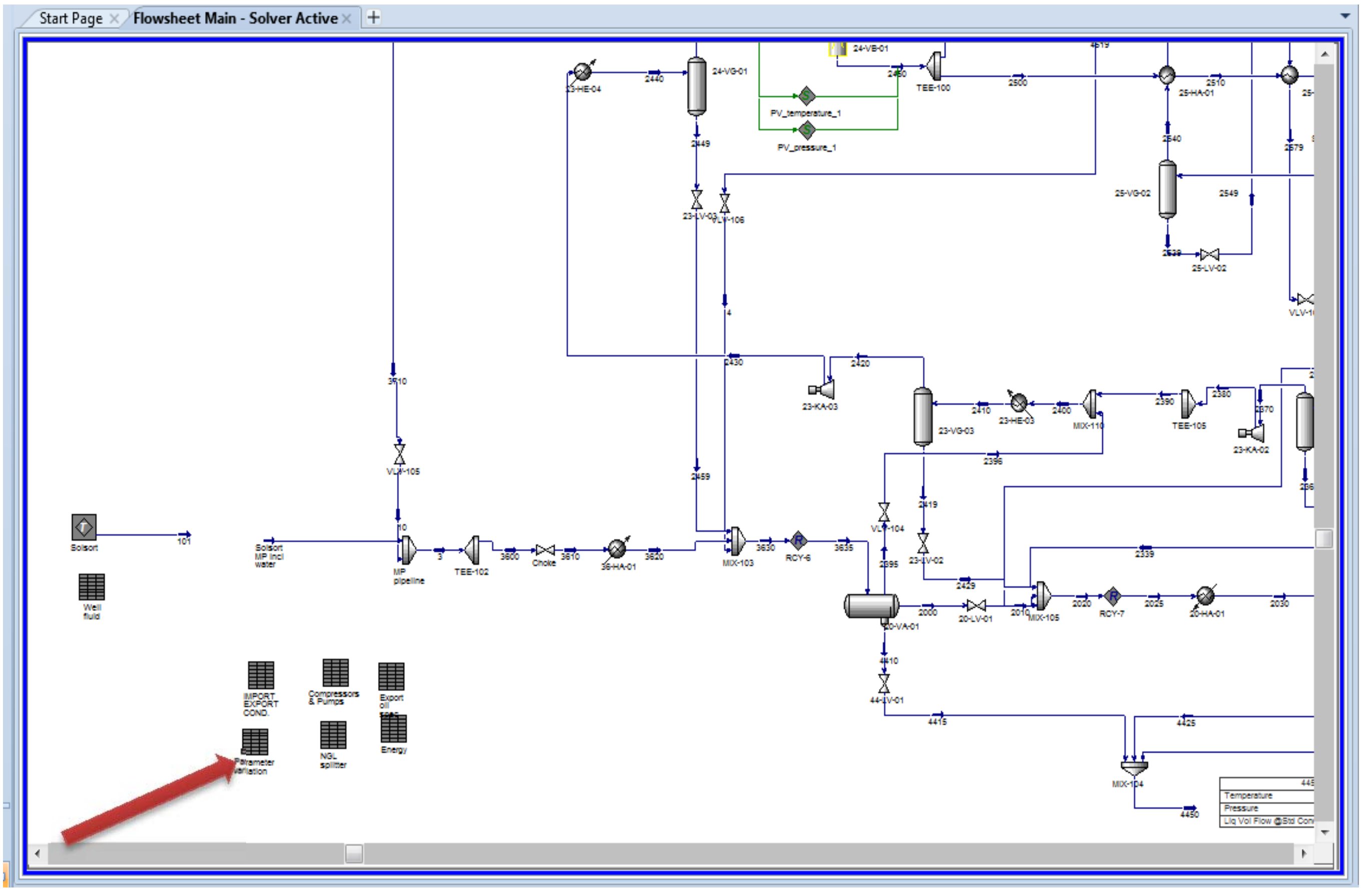
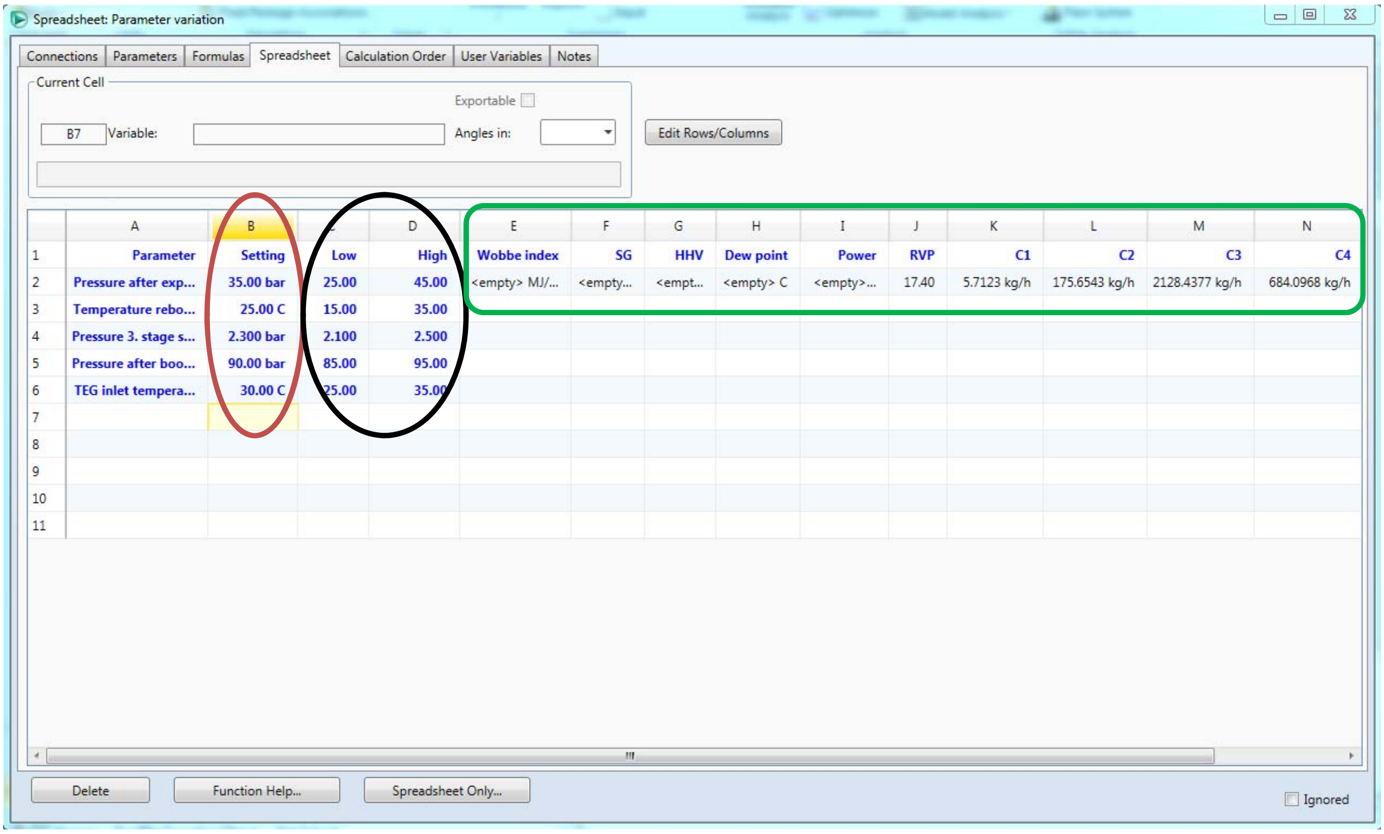
Appendices

Appendix 1.1 – HYSYS Experiment Procedure

The spread sheet ‘*Parameter Variation’* is entered in order to set the variable values according to the experiment plan.



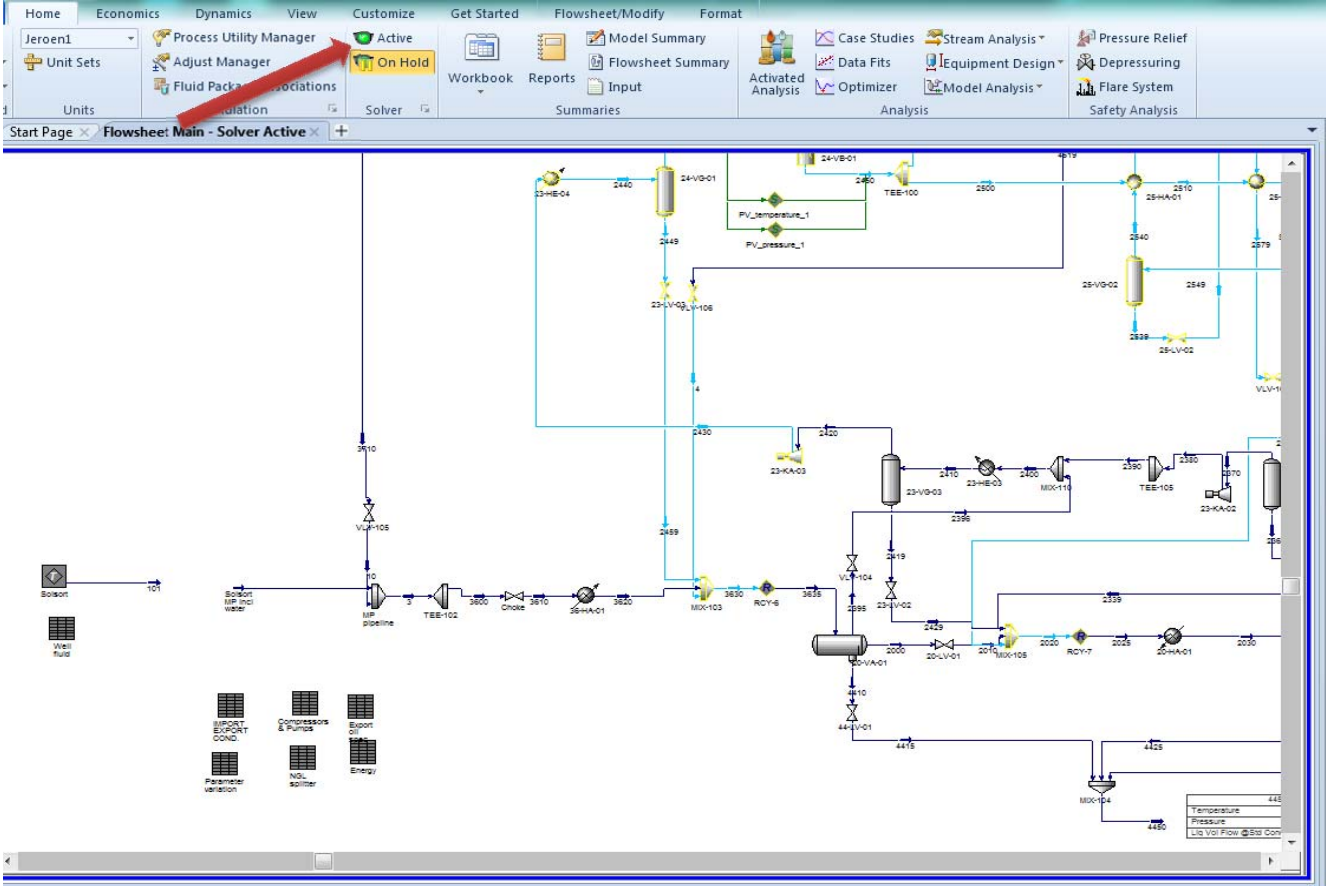
When entering the spread sheet the given values for the simulation are applied in row *B* (red circle). Row *C* and *D* are the variable boundaries (black circle) and are only present in the spread sheet in order to remember them and make it easier to apply simulation combinations. From row *E* to *N* are the objective responses to the given simulation (green box). In this example all variables are set to mid-level (0).



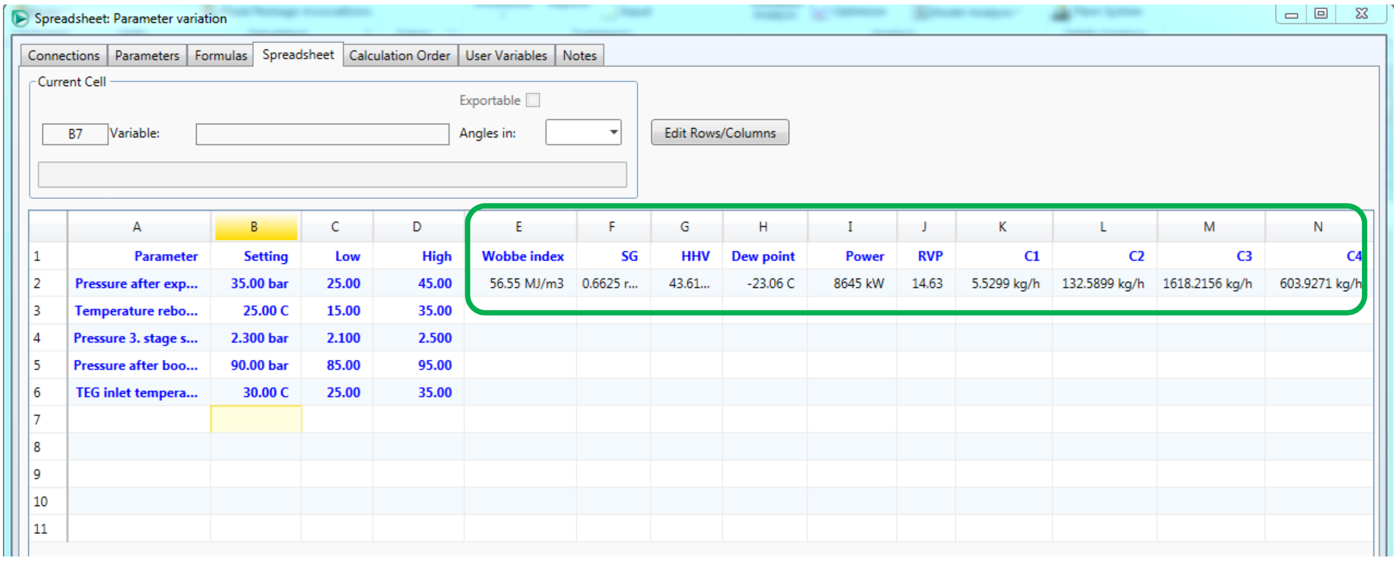
Current Cell: B7 Variable: Angles in:

	A	B	C	D	E	F	G	H	I	J	K	L	M	N
1	Parameter	Setting	Low	High	Wobbe index	SG	HHV	Dew point	Power	RVP	C1	C2	C3	C4
2	Pressure after exp...	35.00 bar	25.00	45.00	<empty> MJ/...	<empty...	<empt...	<empty> C	<empty>...	17.40	5.7123 kg/h	175.6543 kg/h	2128.4377 kg/h	684.0968 kg/h
3	Temperature rebo...	25.00 C	15.00	35.00										
4	Pressure 3. stage s...	2.300 bar	2.100	2.500										
5	Pressure after boo...	90.00 bar	85.00	95.00										
6	TEG inlet tempera...	30.00 C	25.00	35.00										
7														
8														
9														
10														
11														

HYSYS then needs to be *active* to perform the simulation.



When the simulation has converged and no warning has occurred the results can be read and copied. If any error should occur in the simulation a message is shown, and then it is possible to quickly locate where there is a problem in the simulation. Often a few clicks can reset and recalculate the simulation without the problem occurring again.

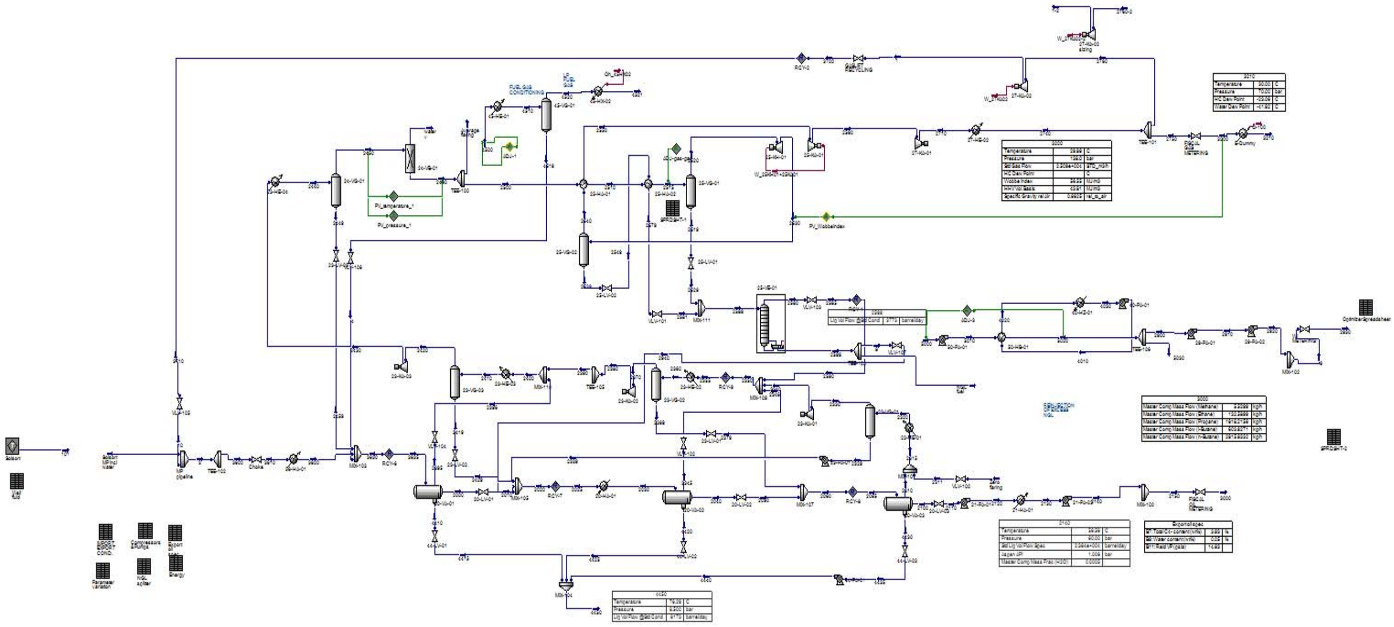


B7 Variable: Angles in:

Exportable □

	A	B	C	D	E	F	G	H	I	J	K	L	M	N
1	Parameter	Setting	Low	High	Wobbe index	SG	HHV	Dew point	Power	RVP	C1	C2	C3	C4
2	Pressure after exp...	35.00 bar	25.00	45.00	56.55 MJ/m3	0.6625 r...	43.61...	-23.06 C	8645 kW	14.63	5.5299 kg/h	132.5899 kg/h	1618.2156 kg/h	603.9271 kg/h
3	Temperature rebo...	25.00 C	15.00	35.00										
4	Pressure 3. stage s...	2.300 bar	2.100	2.500										
5	Pressure after boo...	90.00 bar	85.00	95.00										
6	TEG inlet tempera...	30.00 C	25.00	35.00										
7														
8														
9														
10														
11														

C1, C2, C3 and C4 are summed together and are combined the amount of NGL. The data for the simulation is then applied in an Excel spread sheet. The next simulation combination from the experiment plan is entered and the procedure repeats itself until the experiment plan is done. An overview of the total HYSYS simulation is shown below.



Appendix 1.2 – Python Regression Model Procedure

HHV Model Example

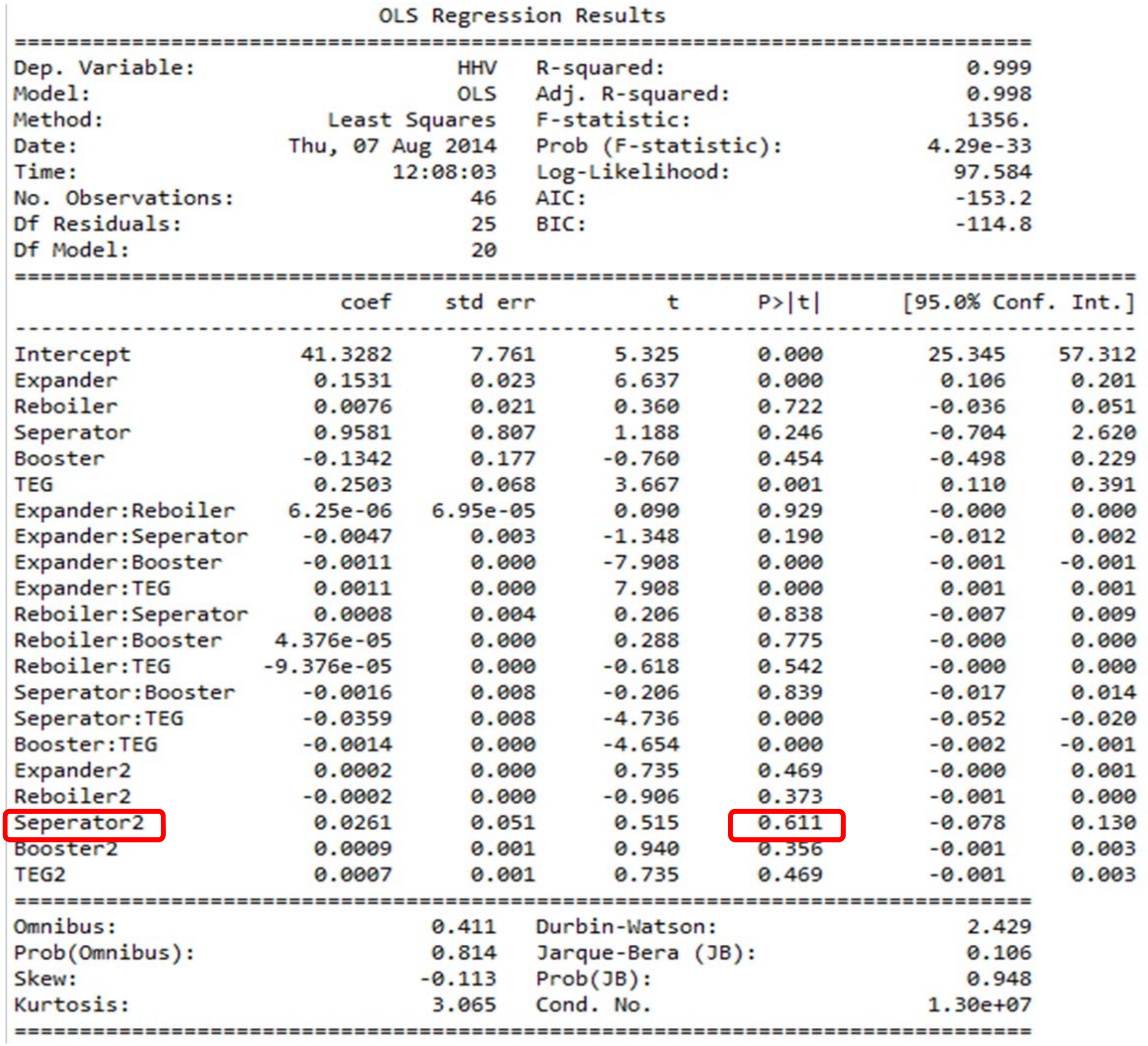
Python code script example – HHV regression model:

*#Start conditions: results2 = sm.ols('HHV ~ (Expander+Reboiler+Seperator+Booster+TEG)**2 +Expander2 + Reboiler2 + Seperator2 + Booster2 + TEG2', data=df).fit()*

*results2 = sm.ols('HHV ~ (Expander+Reboiler+Seperator+Booster+TEG)**2 - Reboiler:Seperator - Reboiler:Booster - Expander:Reboiler - Seperator:Booster - Reboiler:TEG - Reboiler - Expander:Seperator + Booster2', data=df).fit()*

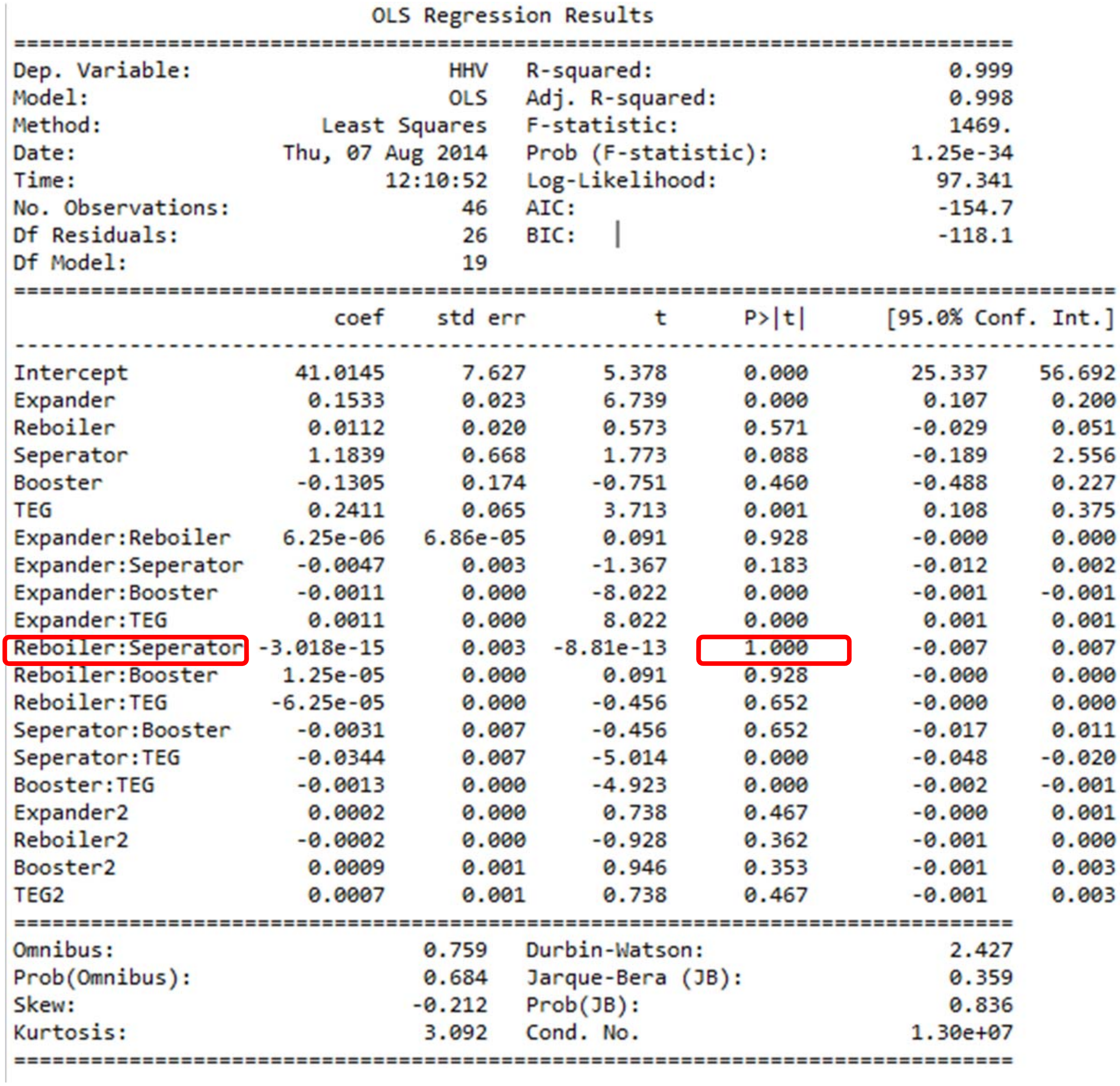
print results2.summary()

1st regression summery run includes every possible variable, variable interactions and second order terms from the start the conditions.



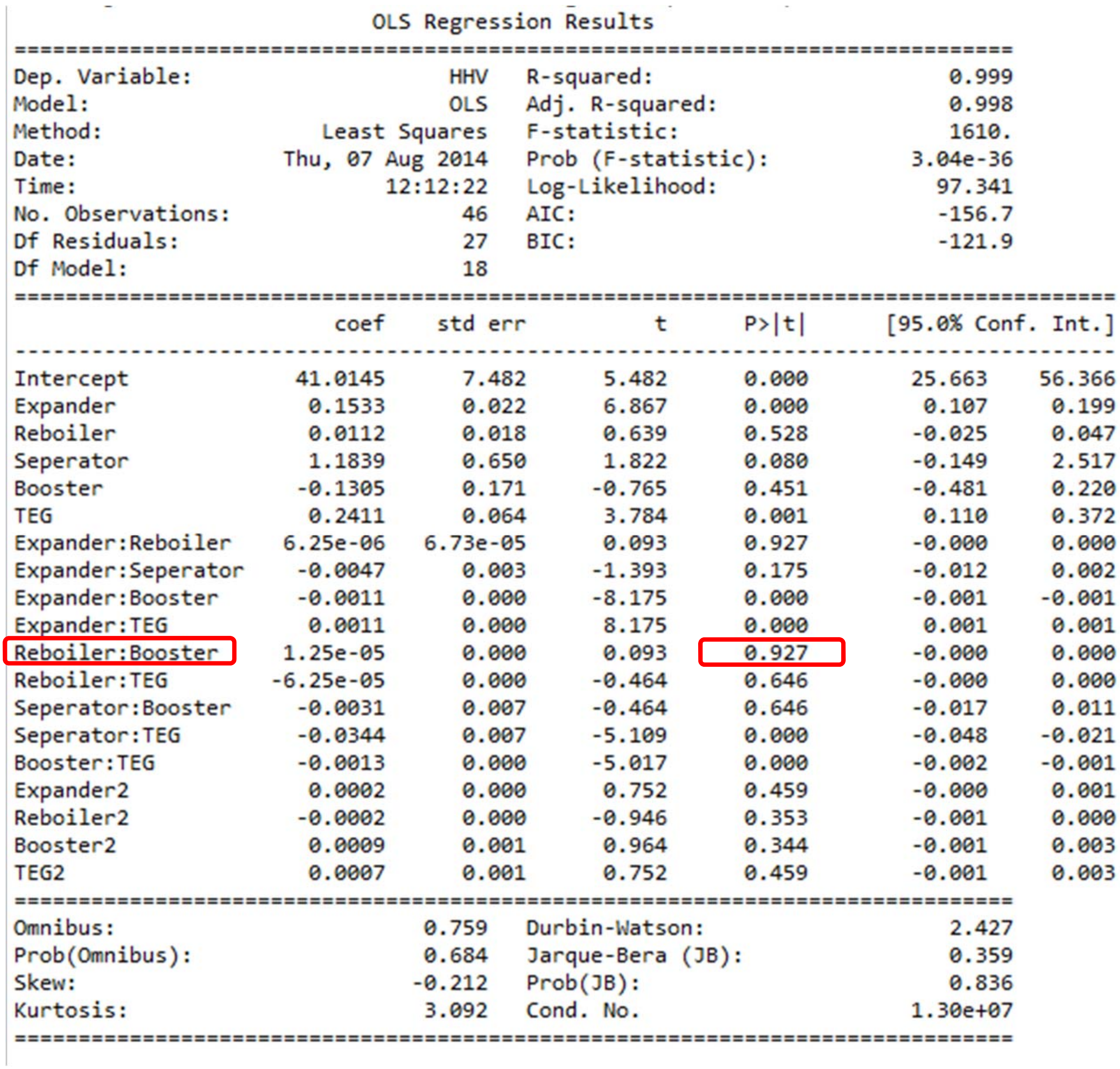
```
                            OLS Regression Results
==============================================================================
Dep. Variable:                    HHV   R-squared:                       0.999
Model:                            OLS   Adj. R-squared:                  0.998
Method:                 Least Squares   F-statistic:                     1356.
Date:                Thu, 07 Aug 2014   Prob (F-statistic):           4.29e-33
Time:                        12:08:03   Log-Likelihood:                 97.584
No. Observations:                  46   AIC:                            -153.2
Df Residuals:                      25   BIC:                            -114.8
Df Model:                          20
======================================================================================
                         coef    std err          t      P>|t|      [95.0% Conf. Int.]
--------------------------------------------------------------------------------------
Intercept             41.3282      7.761      5.325      0.000        25.345    57.312
Expander               0.1531      0.023      6.637      0.000         0.106     0.201
Reboiler               0.0076      0.021      0.360      0.722        -0.036     0.051
Seperator              0.9581      0.807      1.188      0.246        -0.704     2.620
Booster               -0.1342      0.177     -0.760      0.454        -0.498     0.229
TEG                    0.2503      0.068      3.667      0.001         0.110     0.391
Expander:Reboiler    6.25e-06   6.95e-05      0.090      0.929        -0.000     0.000
Expander:Seperator    -0.0047      0.003     -1.348      0.190        -0.012     0.002
Expander:Booster      -0.0011      0.000     -7.908      0.000        -0.001    -0.001
Expander:TEG           0.0011      0.000      7.908      0.000         0.001     0.001
Reboiler:Seperator     0.0008      0.004      0.206      0.838        -0.007     0.009
Reboiler:Booster    4.376e-05      0.000      0.288      0.775        -0.000     0.000
Reboiler:TEG       -9.376e-05      0.000     -0.618      0.542        -0.000     0.000
Seperator:Booster     -0.0016      0.008     -0.206      0.839        -0.017     0.014
Seperator:TEG         -0.0359      0.008     -4.736      0.000        -0.052    -0.020
Booster:TEG           -0.0014      0.000     -4.654      0.000        -0.002    -0.001
Expander2              0.0002      0.000      0.735      0.469        -0.000     0.001
Reboiler2             -0.0002      0.000     -0.906      0.373        -0.001     0.000
Seperator2             0.0261      0.051      0.515      0.611        -0.078     0.130
Booster2               0.0009      0.001      0.940      0.356        -0.001     0.003
TEG2                   0.0007      0.001      0.735      0.469        -0.001     0.003
==============================================================================
Omnibus:                        0.411   Durbin-Watson:                   2.429
Prob(Omnibus):                  0.814   Jarque-Bera (JB):                0.106
Skew:                          -0.113   Prob(JB):                        0.948
Kurtosis:                       3.065   Cond. No.                     1.30e+07
==============================================================================
```

$P > | t |$ values above 0.05 are removed one by one, starting usually with a second order terms. In the 2nd run *Seperator2* is removed.



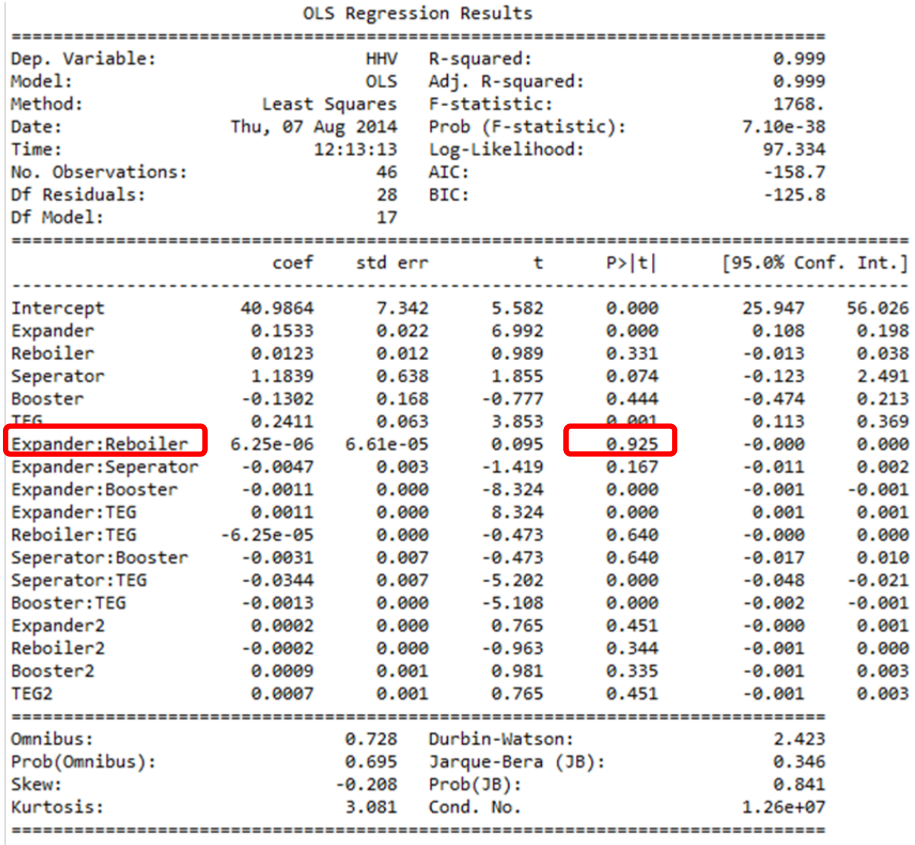
```
                            OLS Regression Results
==============================================================================
Dep. Variable:                    HHV   R-squared:                       0.999
Model:                            OLS   Adj. R-squared:                  0.998
Method:                 Least Squares   F-statistic:                     1469.
Date:                Thu, 07 Aug 2014   Prob (F-statistic):           1.25e-34
Time:                        12:10:52   Log-Likelihood:                 97.341
No. Observations:                  46   AIC:                            -154.7
Df Residuals:                      26   BIC:                            -118.1
Df Model:                          19
======================================================================================
                         coef    std err          t      P>|t|      [95.0% Conf. Int.]
--------------------------------------------------------------------------------------
Intercept             41.0145      7.627      5.378      0.000        25.337    56.692
Expander               0.1533      0.023      6.739      0.000         0.107     0.200
Reboiler               0.0112      0.020      0.573      0.571        -0.029     0.051
Seperator              1.1839      0.668      1.773      0.088        -0.189     2.556
Booster               -0.1305      0.174     -0.751      0.460        -0.488     0.227
TEG                    0.2411      0.065      3.713      0.001         0.108     0.375
Expander:Reboiler    6.25e-06   6.86e-05      0.091      0.928        -0.000     0.000
Expander:Seperator    -0.0047      0.003     -1.367      0.183        -0.012     0.002
Expander:Booster      -0.0011      0.000     -8.022      0.000        -0.001    -0.001
Expander:TEG           0.0011      0.000      8.022      0.000         0.001     0.001
Reboiler:Seperator -3.018e-15      0.003  -8.81e-13      1.000        -0.007     0.007
Reboiler:Booster     1.25e-05      0.000      0.091      0.928        -0.000     0.000
Reboiler:TEG        -6.25e-05      0.000     -0.456      0.652        -0.000     0.000
Seperator:Booster     -0.0031      0.007     -0.456      0.652        -0.017     0.011
Seperator:TEG         -0.0344      0.007     -5.014      0.000        -0.048    -0.020
Booster:TEG           -0.0013      0.000     -4.923      0.000        -0.002    -0.001
Expander2              0.0002      0.000      0.738      0.467        -0.000     0.001
Reboiler2             -0.0002      0.000     -0.928      0.362        -0.001     0.000
Booster2               0.0009      0.001      0.946      0.353        -0.001     0.003
TEG2                   0.0007      0.001      0.738      0.467        -0.001     0.003
==============================================================================
Omnibus:                        0.759   Durbin-Watson:                   2.427
Prob(Omnibus):                  0.684   Jarque-Bera (JB):                0.359
Skew:                          -0.212   Prob(JB):                        0.836
Kurtosis:                       3.092   Cond. No.                     1.30e+07
==============================================================================
```

Reboiler:*Seperator* is removed in the 3rd run since it has a maximum value for *P* > | *t* |.



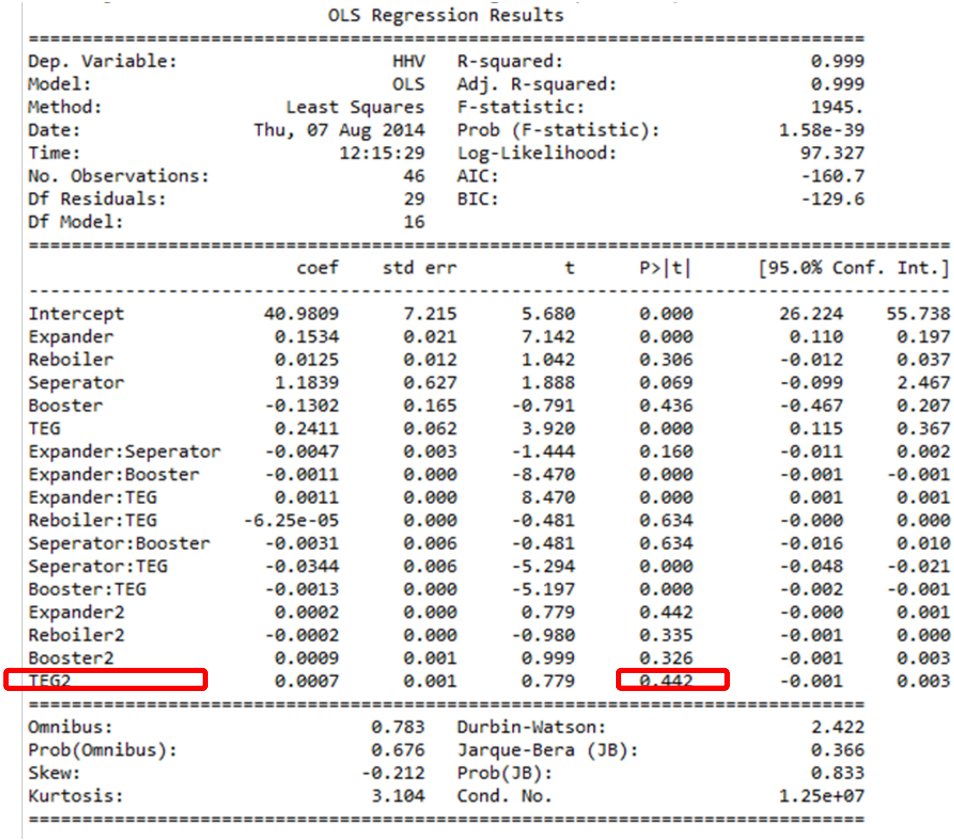
```
                            OLS Regression Results
==============================================================================
Dep. Variable:                    HHV   R-squared:                       0.999
Model:                            OLS   Adj. R-squared:                  0.998
Method:                 Least Squares   F-statistic:                     1610.
Date:                Thu, 07 Aug 2014   Prob (F-statistic):           3.04e-36
Time:                        12:12:22   Log-Likelihood:                 97.341
No. Observations:                  46   AIC:                            -156.7
Df Residuals:                      27   BIC:                            -121.9
Df Model:                          18
======================================================================================
                         coef    std err          t      P>|t|      [95.0% Conf. Int.]
--------------------------------------------------------------------------------------
Intercept             41.0145      7.482      5.482      0.000        25.663    56.366
Expander               0.1533      0.022      6.867      0.000         0.107     0.199
Reboiler               0.0112      0.018      0.639      0.528        -0.025     0.047
Seperator              1.1839      0.650      1.822      0.080        -0.149     2.517
Booster               -0.1305      0.171     -0.765      0.451        -0.481     0.220
TEG                    0.2411      0.064      3.784      0.001         0.110     0.372
Expander:Reboiler    6.25e-06   6.73e-05      0.093      0.927        -0.000     0.000
Expander:Seperator    -0.0047      0.003     -1.393      0.175        -0.012     0.002
Expander:Booster      -0.0011      0.000     -8.175      0.000        -0.001    -0.001
Expander:TEG           0.0011      0.000      8.175      0.000         0.001     0.001
Reboiler:Booster     1.25e-05      0.000      0.093      0.927        -0.000     0.000
Reboiler:TEG        -6.25e-05      0.000     -0.464      0.646        -0.000     0.000
Seperator:Booster     -0.0031      0.007     -0.464      0.646        -0.017     0.011
Seperator:TEG         -0.0344      0.007     -5.109      0.000        -0.048    -0.021
Booster:TEG           -0.0013      0.000     -5.017      0.000        -0.002    -0.001
Expander2              0.0002      0.000      0.752      0.459        -0.000     0.001
Reboiler2             -0.0002      0.000     -0.946      0.353        -0.001     0.000
Booster2               0.0009      0.001      0.964      0.344        -0.001     0.003
TEG2                   0.0007      0.001      0.752      0.459        -0.001     0.003
==============================================================================
Omnibus:                        0.759   Durbin-Watson:                   2.427
Prob(Omnibus):                  0.684   Jarque-Bera (JB):                0.359
Skew:                          -0.212   Prob(JB):                        0.836
Kurtosis:                       3.092   Cond. No.                     1.30e+07
==============================================================================
```

Reboiler:Booster is removed for the 4th run.



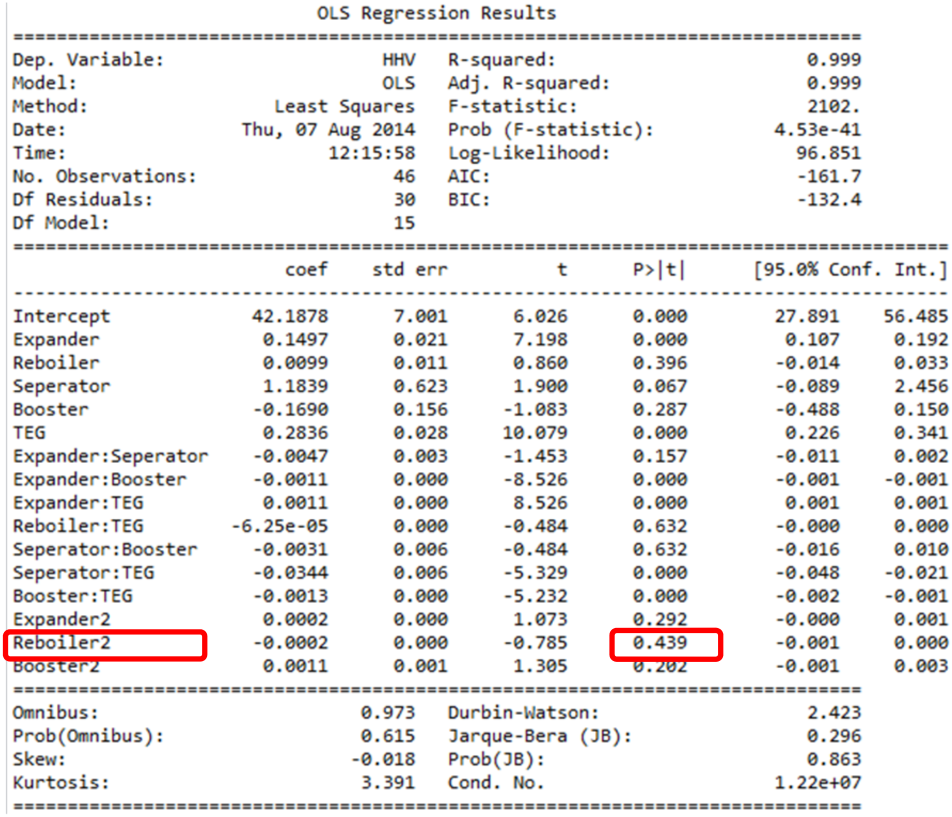
```
                            OLS Regression Results
==============================================================================
Dep. Variable:                    HHV   R-squared:                       0.999
Model:                            OLS   Adj. R-squared:                  0.999
Method:                 Least Squares   F-statistic:                     1768.
Date:                Thu, 07 Aug 2014   Prob (F-statistic):           7.10e-38
Time:                        12:13:13   Log-Likelihood:                 97.334
No. Observations:                  46   AIC:                            -158.7
Df Residuals:                      28   BIC:                            -125.8
Df Model:                          17
=====================================================================================
                        coef    std err          t      P>|t|      [95.0% Conf. Int.]
-------------------------------------------------------------------------------------
Intercept            40.9864      7.342      5.582      0.000        25.947    56.026
Expander              0.1533      0.022      6.992      0.000         0.108     0.198
Reboiler              0.0123      0.012      0.989      0.331        -0.013     0.038
Seperator             1.1839      0.638      1.855      0.074        -0.123     2.491
Booster              -0.1302      0.168     -0.777      0.444        -0.474     0.213
TEG                   0.2411      0.063      3.853      0.001         0.113     0.369
Expander:Reboiler   6.25e-06   6.61e-05      0.095      0.925        -0.000     0.000
Expander:Seperator   -0.0047      0.003     -1.419      0.167        -0.011     0.002
Expander:Booster     -0.0011      0.000     -8.324      0.000        -0.001    -0.001
Expander:TEG          0.0011      0.000      8.324      0.000         0.001     0.001
Reboiler:TEG       -6.25e-05      0.000     -0.473      0.640        -0.000     0.000
Seperator:Booster    -0.0031      0.007     -0.473      0.640        -0.017     0.010
Seperator:TEG        -0.0344      0.007     -5.202      0.000        -0.048    -0.021
Booster:TEG          -0.0013      0.000     -5.108      0.000        -0.002    -0.001
Expander2             0.0002      0.000      0.765      0.451        -0.000     0.001
Reboiler2            -0.0002      0.000     -0.963      0.344        -0.001     0.000
Booster2              0.0009      0.001      0.981      0.335        -0.001     0.003
TEG2                  0.0007      0.001      0.765      0.451        -0.001     0.003
==============================================================================
Omnibus:                        0.728   Durbin-Watson:                   2.423
Prob(Omnibus):                  0.695   Jarque-Bera (JB):                0.346
Skew:                          -0.208   Prob(JB):                        0.841
Kurtosis:                       3.081   Cond. No.                     1.26e+07
==============================================================================
```

5th run - *Expander:Reboiler* removed.



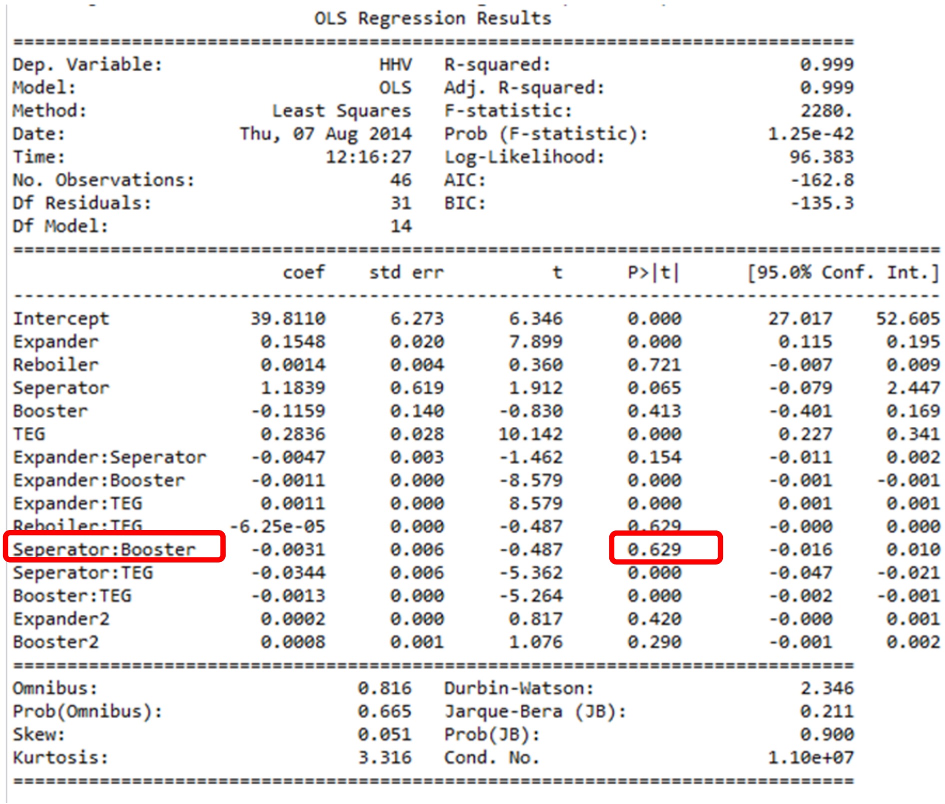
```
                            OLS Regression Results
==============================================================================
Dep. Variable:                    HHV   R-squared:                       0.999
Model:                            OLS   Adj. R-squared:                  0.999
Method:                 Least Squares   F-statistic:                     1945.
Date:                Thu, 07 Aug 2014   Prob (F-statistic):           1.58e-39
Time:                        12:15:29   Log-Likelihood:                 97.327
No. Observations:                  46   AIC:                            -160.7
Df Residuals:                      29   BIC:                            -129.6
Df Model:                          16
=====================================================================================
                        coef    std err          t      P>|t|      [95.0% Conf. Int.]
-------------------------------------------------------------------------------------
Intercept            40.9809      7.215      5.680      0.000        26.224    55.738
Expander              0.1534      0.021      7.142      0.000         0.110     0.197
Reboiler              0.0125      0.012      1.042      0.306        -0.012     0.037
Seperator             1.1839      0.627      1.888      0.069        -0.099     2.467
Booster              -0.1302      0.165     -0.791      0.436        -0.467     0.207
TEG                   0.2411      0.062      3.920      0.000         0.115     0.367
Expander:Seperator   -0.0047      0.003     -1.444      0.160        -0.011     0.002
Expander:Booster     -0.0011      0.000     -8.470      0.000        -0.001    -0.001
Expander:TEG          0.0011      0.000      8.470      0.000         0.001     0.001
Reboiler:TEG       -6.25e-05      0.000     -0.481      0.634        -0.000     0.000
Seperator:Booster    -0.0031      0.006     -0.481      0.634        -0.016     0.010
Seperator:TEG        -0.0344      0.006     -5.294      0.000        -0.048    -0.021
Booster:TEG          -0.0013      0.000     -5.197      0.000        -0.002    -0.001
Expander2             0.0002      0.000      0.779      0.442        -0.000     0.001
Reboiler2            -0.0002      0.000     -0.980      0.335        -0.001     0.000
Booster2              0.0009      0.001      0.999      0.326        -0.001     0.003
TEG2                  0.0007      0.001      0.779      0.442        -0.001     0.003
==============================================================================
Omnibus:                        0.783   Durbin-Watson:                   2.422
Prob(Omnibus):                  0.676   Jarque-Bera (JB):                0.366
Skew:                          -0.212   Prob(JB):                        0.833
Kurtosis:                       3.104   Cond. No.                     1.25e+07
==============================================================================
```

The second order term *TEG2* is removed for the 6th run.



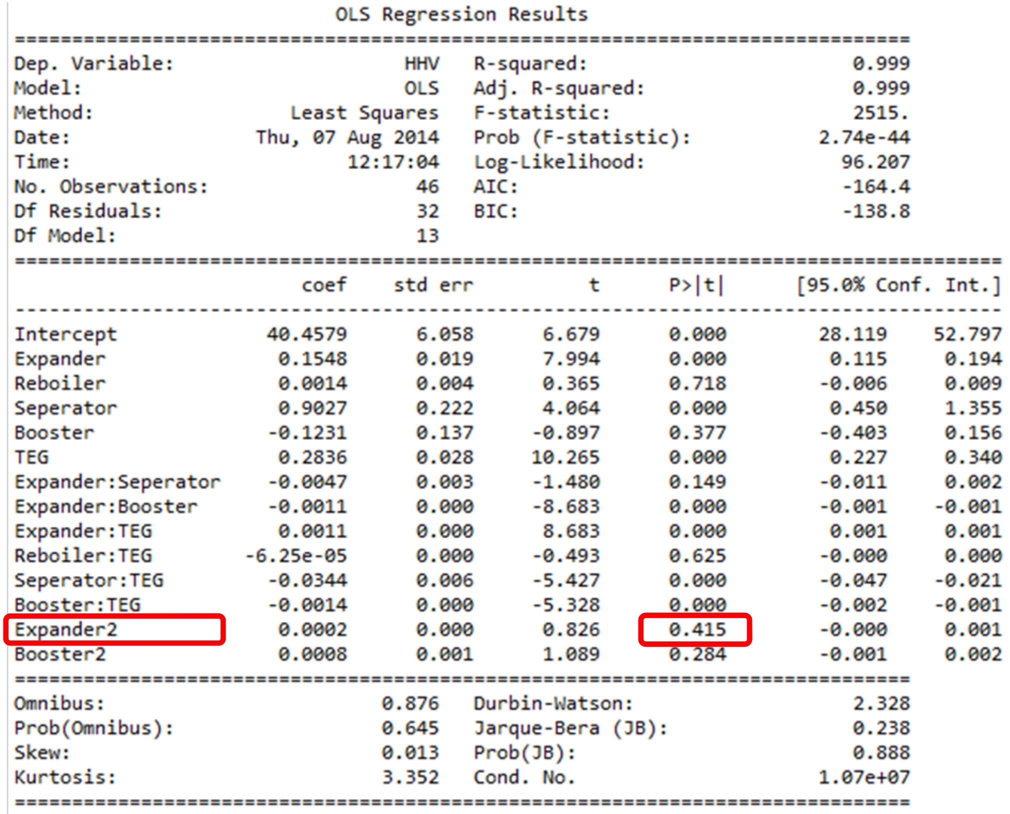
```
                            OLS Regression Results
==============================================================================
Dep. Variable:                    HHV   R-squared:                       0.999
Model:                            OLS   Adj. R-squared:                  0.999
Method:                 Least Squares   F-statistic:                     2102.
Date:                Thu, 07 Aug 2014   Prob (F-statistic):           4.53e-41
Time:                        12:15:58   Log-Likelihood:                 96.851
No. Observations:                  46   AIC:                            -161.7
Df Residuals:                      30   BIC:                            -132.4
Df Model:                          15
=====================================================================================
                        coef    std err          t      P>|t|      [95.0% Conf. Int.]
-------------------------------------------------------------------------------------
Intercept            42.1878      7.001      6.026      0.000        27.891    56.485
Expander              0.1497      0.021      7.198      0.000         0.107     0.192
Reboiler              0.0099      0.011      0.860      0.396        -0.014     0.033
Seperator             1.1839      0.623      1.900      0.067        -0.089     2.456
Booster              -0.1690      0.156     -1.083      0.287        -0.488     0.150
TEG                   0.2836      0.028     10.079      0.000         0.226     0.341
Expander:Seperator   -0.0047      0.003     -1.453      0.157        -0.011     0.002
Expander:Booster     -0.0011      0.000     -8.526      0.000        -0.001    -0.001
Expander:TEG          0.0011      0.000      8.526      0.000         0.001     0.001
Reboiler:TEG       -6.25e-05      0.000     -0.484      0.632        -0.000     0.000
Seperator:Booster    -0.0031      0.006     -0.484      0.632        -0.016     0.010
Seperator:TEG        -0.0344      0.006     -5.329      0.000        -0.048    -0.021
Booster:TEG          -0.0013      0.000     -5.232      0.000        -0.002    -0.001
Expander2             0.0002      0.000      1.073      0.292        -0.000     0.001
Reboiler2            -0.0002      0.000     -0.785      0.439        -0.001     0.000
Booster2              0.0011      0.001      1.305      0.202        -0.001     0.003
==============================================================================
Omnibus:                        0.973   Durbin-Watson:                   2.423
Prob(Omnibus):                  0.615   Jarque-Bera (JB):                0.296
Skew:                          -0.018   Prob(JB):                        0.863
Kurtosis:                       3.391   Cond. No.                     1.22e+07
==============================================================================
```

7th run – *Reboiler2* removed



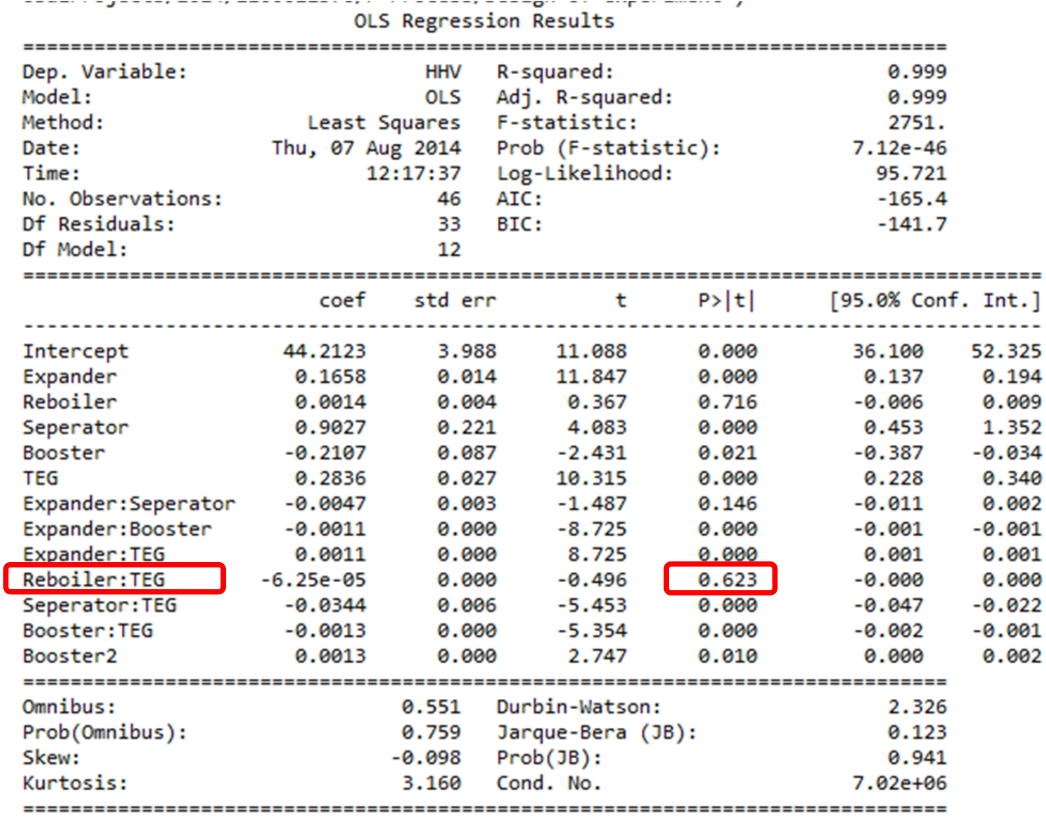
```
                            OLS Regression Results
==============================================================================
Dep. Variable:                    HHV   R-squared:                       0.999
Model:                            OLS   Adj. R-squared:                  0.999
Method:                 Least Squares   F-statistic:                     2280.
Date:                Thu, 07 Aug 2014   Prob (F-statistic):           1.25e-42
Time:                        12:16:27   Log-Likelihood:                 96.383
No. Observations:                  46   AIC:                            -162.8
Df Residuals:                      31   BIC:                            -135.3
Df Model:                          14
=====================================================================================
                        coef    std err          t      P>|t|      [95.0% Conf. Int.]
-------------------------------------------------------------------------------------
Intercept            39.8110      6.273      6.346      0.000        27.017    52.605
Expander              0.1548      0.020      7.899      0.000         0.115     0.195
Reboiler              0.0014      0.004      0.360      0.721        -0.007     0.009
Seperator             1.1839      0.619      1.912      0.065        -0.079     2.447
Booster              -0.1159      0.140     -0.830      0.413        -0.401     0.169
TEG                   0.2836      0.028     10.142      0.000         0.227     0.341
Expander:Seperator   -0.0047      0.003     -1.462      0.154        -0.011     0.002
Expander:Booster     -0.0011      0.000     -8.579      0.000        -0.001    -0.001
Expander:TEG          0.0011      0.000      8.579      0.000         0.001     0.001
Reboiler:TEG       -6.25e-05      0.000     -0.487      0.629        -0.000     0.000
Seperator:Booster    -0.0031      0.006     -0.487      0.629        -0.016     0.010
Seperator:TEG        -0.0344      0.006     -5.362      0.000        -0.047    -0.021
Booster:TEG          -0.0013      0.000     -5.264      0.000        -0.002    -0.001
Expander2             0.0002      0.000      0.817      0.420        -0.000     0.001
Booster2              0.0008      0.001      1.076      0.290        -0.001     0.002
==============================================================================
Omnibus:                        0.816   Durbin-Watson:                   2.346
Prob(Omnibus):                  0.665   Jarque-Bera (JB):                0.211
Skew:                           0.051   Prob(JB):                        0.900
Kurtosis:                       3.316   Cond. No.                     1.10e+07
==============================================================================
```

8th run – *Seperator:Booster* removed.



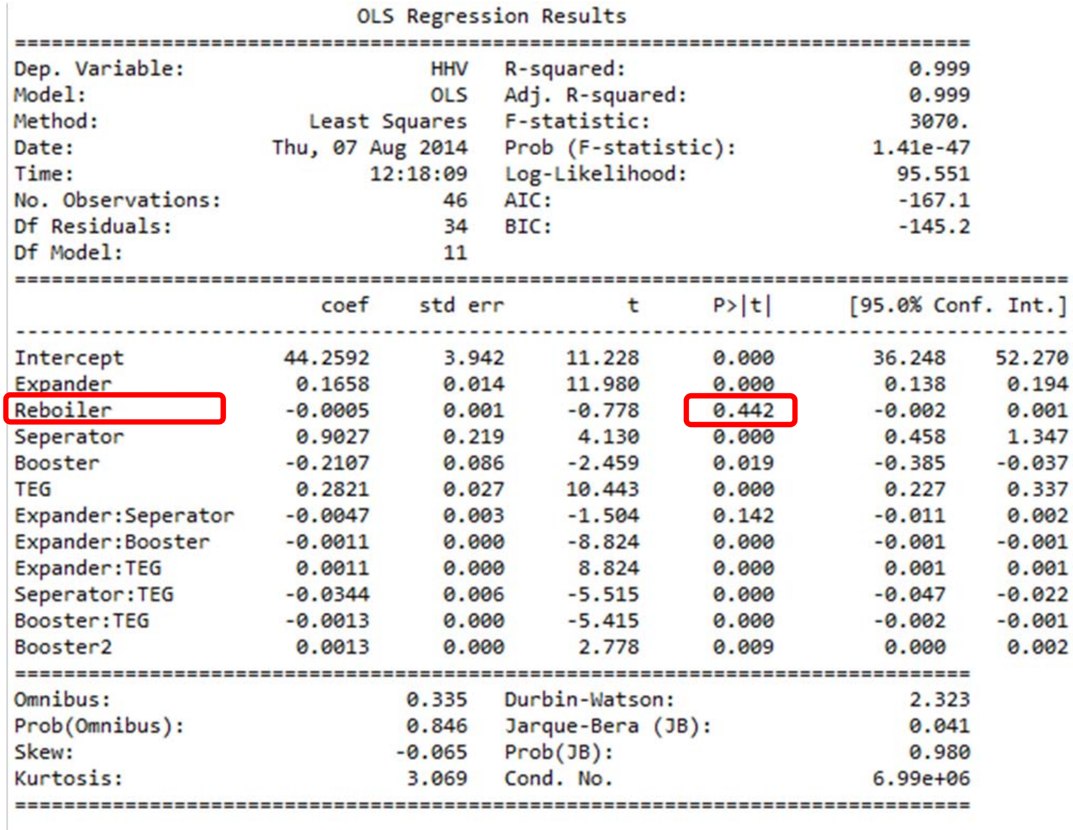
```
                            OLS Regression Results
==============================================================================
Dep. Variable:                    HHV   R-squared:                       0.999
Model:                            OLS   Adj. R-squared:                  0.999
Method:                 Least Squares   F-statistic:                     2515.
Date:                Thu, 07 Aug 2014   Prob (F-statistic):           2.74e-44
Time:                        12:17:04   Log-Likelihood:                 96.207
No. Observations:                  46   AIC:                            -164.4
Df Residuals:                      32   BIC:                            -138.8
Df Model:                          13
=====================================================================================
                        coef    std err          t      P>|t|      [95.0% Conf. Int.]
-------------------------------------------------------------------------------------
Intercept            40.4579      6.058      6.679      0.000        28.119    52.797
Expander              0.1548      0.019      7.994      0.000         0.115     0.194
Reboiler              0.0014      0.004      0.365      0.718        -0.006     0.009
Seperator             0.9027      0.222      4.064      0.000         0.450     1.355
Booster              -0.1231      0.137     -0.897      0.377        -0.403     0.156
TEG                   0.2836      0.028     10.265      0.000         0.227     0.340
Expander:Seperator   -0.0047      0.003     -1.480      0.149        -0.011     0.002
Expander:Booster     -0.0011      0.000     -8.683      0.000        -0.001    -0.001
Expander:TEG          0.0011      0.000      8.683      0.000         0.001     0.001
Reboiler:TEG       -6.25e-05      0.000     -0.493      0.625        -0.000     0.000
Seperator:TEG        -0.0344      0.006     -5.427      0.000        -0.047    -0.021
Booster:TEG          -0.0014      0.000     -5.328      0.000        -0.002    -0.001
Expander2             0.0002      0.000      0.826      0.415        -0.000     0.001
Booster2              0.0008      0.001      1.089      0.284        -0.001     0.002
==============================================================================
Omnibus:                        0.876   Durbin-Watson:                   2.328
Prob(Omnibus):                  0.645   Jarque-Bera (JB):                0.238
Skew:                           0.013   Prob(JB):                        0.888
Kurtosis:                       3.352   Cond. No.                     1.07e+07
==============================================================================
```

9th run – *Expander2* removed.



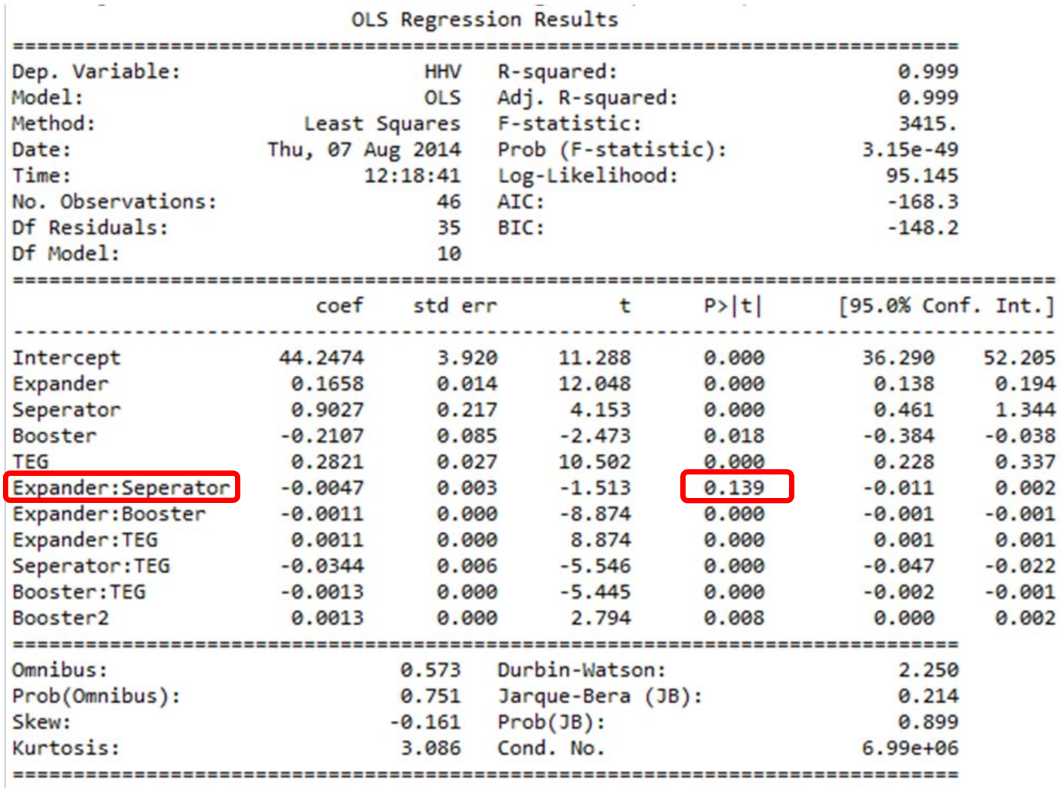
```
                            OLS Regression Results
==============================================================================
Dep. Variable:                    HHV   R-squared:                       0.999
Model:                            OLS   Adj. R-squared:                  0.999
Method:                 Least Squares   F-statistic:                     2751.
Date:                Thu, 07 Aug 2014   Prob (F-statistic):           7.12e-46
Time:                        12:17:37   Log-Likelihood:                 95.721
No. Observations:                  46   AIC:                            -165.4
Df Residuals:                      33   BIC:                            -141.7
Df Model:                          12
=====================================================================================
                        coef    std err          t      P>|t|      [95.0% Conf. Int.]
-------------------------------------------------------------------------------------
Intercept            44.2123      3.988     11.088      0.000        36.100    52.325
Expander              0.1658      0.014     11.847      0.000         0.137     0.194
Reboiler              0.0014      0.004      0.367      0.716        -0.006     0.009
Seperator             0.9027      0.221      4.083      0.000         0.453     1.352
Booster              -0.2107      0.087     -2.431      0.021        -0.387    -0.034
TEG                   0.2836      0.027     10.315      0.000         0.228     0.340
Expander:Seperator   -0.0047      0.003     -1.487      0.146        -0.011     0.002
Expander:Booster     -0.0011      0.000     -8.725      0.000        -0.001    -0.001
Expander:TEG          0.0011      0.000      8.725      0.000         0.001     0.001
Reboiler:TEG       -6.25e-05      0.000     -0.496      0.623        -0.000     0.000
Seperator:TEG        -0.0344      0.006     -5.453      0.000        -0.047    -0.022
Booster:TEG          -0.0013      0.000     -5.354      0.000        -0.002    -0.001
Booster2              0.0013      0.000      2.747      0.010         0.000     0.002
==============================================================================
Omnibus:                        0.551   Durbin-Watson:                   2.326
Prob(Omnibus):                  0.759   Jarque-Bera (JB):                0.123
Skew:                          -0.098   Prob(JB):                        0.941
Kurtosis:                       3.160   Cond. No.                     7.02e+06
==============================================================================
```

10th run – *Reboiler:TEG* removed.



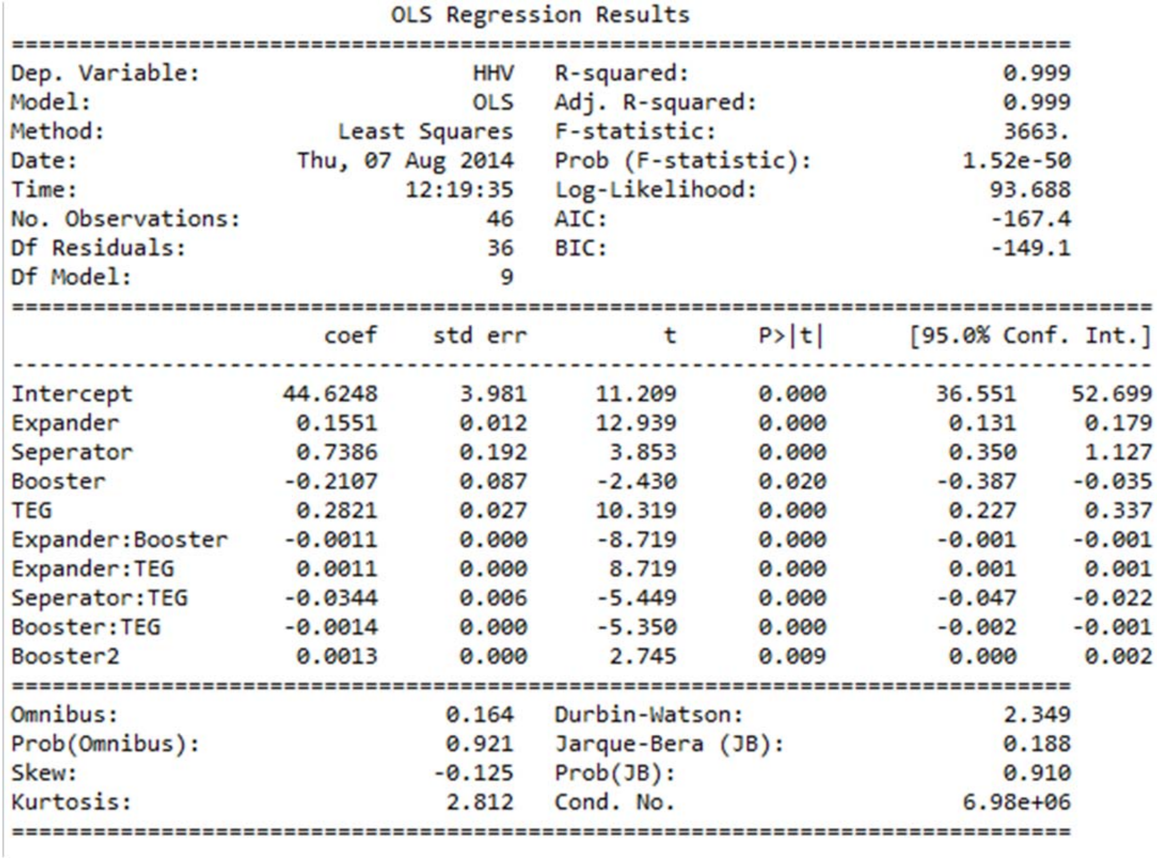
```
                            OLS Regression Results
==============================================================================
Dep. Variable:                    HHV   R-squared:                       0.999
Model:                            OLS   Adj. R-squared:                  0.999
Method:                 Least Squares   F-statistic:                     3070.
Date:                Thu, 07 Aug 2014   Prob (F-statistic):           1.41e-47
Time:                        12:18:09   Log-Likelihood:                 95.551
No. Observations:                  46   AIC:                            -167.1
Df Residuals:                      34   BIC:                            -145.2
Df Model:                          11
======================================================================================
                         coef    std err          t      P>|t|      [95.0% Conf. Int.]
--------------------------------------------------------------------------------------
Intercept             44.2592      3.942     11.228      0.000        36.248    52.270
Expander               0.1658      0.014     11.980      0.000         0.138     0.194
Reboiler              -0.0005      0.001     -0.778      0.442        -0.002     0.001
Seperator              0.9027      0.219      4.130      0.000         0.458     1.347
Booster               -0.2107      0.086     -2.459      0.019        -0.385    -0.037
TEG                    0.2821      0.027     10.443      0.000         0.227     0.337
Expander:Seperator    -0.0047      0.003     -1.504      0.142        -0.011     0.002
Expander:Booster      -0.0011      0.000     -8.824      0.000        -0.001    -0.001
Expander:TEG           0.0011      0.000      8.824      0.000         0.001     0.001
Seperator:TEG         -0.0344      0.006     -5.515      0.000        -0.047    -0.022
Booster:TEG           -0.0013      0.000     -5.415      0.000        -0.002    -0.001
Booster2               0.0013      0.000      2.778      0.009         0.000     0.002
==============================================================================
Omnibus:                        0.335   Durbin-Watson:                   2.323
Prob(Omnibus):                  0.846   Jarque-Bera (JB):                0.041
Skew:                          -0.065   Prob(JB):                        0.980
Kurtosis:                       3.069   Cond. No.                     6.99e+06
==============================================================================
```

11th run – *Reboiler* removed



```
                            OLS Regression Results
==============================================================================
Dep. Variable:                    HHV   R-squared:                       0.999
Model:                            OLS   Adj. R-squared:                  0.999
Method:                 Least Squares   F-statistic:                     3415.
Date:                Thu, 07 Aug 2014   Prob (F-statistic):           3.15e-49
Time:                        12:18:41   Log-Likelihood:                 95.145
No. Observations:                  46   AIC:                            -168.3
Df Residuals:                      35   BIC:                            -148.2
Df Model:                          10
======================================================================================
                         coef    std err          t      P>|t|      [95.0% Conf. Int.]
--------------------------------------------------------------------------------------
Intercept             44.2474      3.920     11.288      0.000        36.290    52.205
Expander               0.1658      0.014     12.048      0.000         0.138     0.194
Seperator              0.9027      0.217      4.153      0.000         0.461     1.344
Booster               -0.2107      0.085     -2.473      0.018        -0.384    -0.038
TEG                    0.2821      0.027     10.502      0.000         0.228     0.337
Expander:Seperator    -0.0047      0.003     -1.513      0.139        -0.011     0.002
Expander:Booster      -0.0011      0.000     -8.874      0.000        -0.001    -0.001
Expander:TEG           0.0011      0.000      8.874      0.000         0.001     0.001
Seperator:TEG         -0.0344      0.006     -5.546      0.000        -0.047    -0.022
Booster:TEG           -0.0013      0.000     -5.445      0.000        -0.002    -0.001
Booster2               0.0013      0.000      2.794      0.008         0.000     0.002
==============================================================================
Omnibus:                        0.573   Durbin-Watson:                   2.250
Prob(Omnibus):                  0.751   Jarque-Bera (JB):                0.214
Skew:                          -0.161   Prob(JB):                        0.899
Kurtosis:                       3.086   Cond. No.                     6.99e+06
==============================================================================
```

12th and final run – *Expander:Seperator* removed



```
                            OLS Regression Results
==============================================================================
Dep. Variable:                    HHV   R-squared:                       0.999
Model:                            OLS   Adj. R-squared:                  0.999
Method:                 Least Squares   F-statistic:                     3663.
Date:                Thu, 07 Aug 2014   Prob (F-statistic):           1.52e-50
Time:                        12:19:35   Log-Likelihood:                 93.688
No. Observations:                  46   AIC:                            -167.4
Df Residuals:                      36   BIC:                            -149.1
Df Model:                           9
====================================================================================
                      coef    std err          t      P>|t|      [95.0% Conf. Int.]
------------------------------------------------------------------------------------
Intercept          44.6248      3.981     11.209      0.000        36.551    52.699
Expander            0.1551      0.012     12.939      0.000         0.131     0.179
Seperator           0.7386      0.192      3.853      0.000         0.350     1.127
Booster            -0.2107      0.087     -2.430      0.020        -0.387    -0.035
TEG                 0.2821      0.027     10.319      0.000         0.227     0.337
Expander:Booster   -0.0011      0.000     -8.719      0.000        -0.001    -0.001
Expander:TEG        0.0011      0.000      8.719      0.000         0.001     0.001
Seperator:TEG      -0.0344      0.006     -5.449      0.000        -0.047    -0.022
Booster:TEG        -0.0014      0.000     -5.350      0.000        -0.002    -0.001
Booster2            0.0013      0.000      2.745      0.009         0.000     0.002
==============================================================================
Omnibus:                        0.164   Durbin-Watson:                   2.349
Prob(Omnibus):                  0.921   Jarque-Bera (JB):                0.188
Skew:                          -0.125   Prob(JB):                        0.910
Kurtosis:                       2.812   Cond. No.                     6.98e+06
==============================================================================
```

The number of terms has been reduced and the R-squared value is very close to 1, which indicates a good fitted model. These runs are performed multiple times for each model, where the chosen first terms are varying in some extend to see if another results would occur. The *P* > | *t* | values are changing depending on the term excluded from the model.

Appendix 1.3 – Entire Python Code Script

```
# -*- coding: utf-8 -*-
"""
Created on Mon Aug 04 10:04:30 2014

@author: KARR
"""
import matplotlib.pyplot as plt
import pandas as pd
import numpy as np
from pandas import DataFrame
import statsmodels.formula.api as sm
import statsmodels.api as smapi
import statsmodels.graphics.regressionplots as regplot
from statsmodels.graphics.regressionplots import *
import seaborn as sns

Location = r'\\ramoil.ramboll-group.global.network\Common\GlobalProjects\2014
'\1100011376\P-Process\Design of experiment\Sim_data.csv'
df = pd.read_csv(Location, sep=";")
print df

'Regression models'
#Start conditions: results = sm.ols('Power ~ (Expander+Reboiler+Seperator+
#Booster+TEG)**2 +Expander2 + Reboiler2 + Seperator2 + Booster2 + TEG2',
#data=df).fit()

'First results before correcting dataset'
results = sm.ols('NGL ~ (Expander+Reboiler+Seperator+Booster+TEG)**2 -
'Expander:Reboiler - Expander:TEG - Reboiler:Booster - Reboiler:Seperator -
'Reboiler:TEG - Expander:Seperator - Seperator -Seperator:Booster - Booster:TEG
' + Reboiler2 + Booster2', data=df).fit()

results1 = sm.ols('RVP ~ (Expander+Reboiler+Seperator+Booster+TEG)**2 -
'Reboiler:Booster - Expander:TEG - Expander:Seperator - Reboiler:Seperator -
'Expander:Reboiler - Reboiler:TEG - Booster:TEG - Seperator:TEG -
'Seperator:Booster - Seperator - Booster - Reboiler + Reboiler2 +
'Seperator2', data=df).fit()

results2 = sm.ols('HHV ~ (Expander+Reboiler+Seperator+Booster+TEG)**2 -
'Expander:Reboiler - Reboiler:Seperator - Reboiler:TEG - Reboiler:Booster -'
'Seperator:Booster - Expander:Seperator - TEG - Reboiler - Seperator+Expander2
'+ Booster2 + TEG2', data=df).fit()

results3 = sm.ols('SG ~ (Expander+Reboiler+Seperator+Booster+TEG)**2 -
'Reboiler:TEG - Reboiler:Seperator - Expander:Reboiler - Reboiler:Booster -
'Seperator:Booster - Expander:Seperator - TEG - Reboiler - Seperator +Expander2
'+ Booster2 + TEG2', data=df).fit()

results4 = sm.ols('Wobbe ~ (Expander+Reboiler+Seperator+Booster+TEG)**2 -
'Reboiler:TEG - Reboiler:Booster - Expander:Reboiler - Reboiler:Seperator -
'Seperator:Booster - Expander:Seperator - TEG - Reboiler - Seperator + Expander2
'+ Booster2 + TEG2', data=df).fit()

results5 = sm.ols('Power ~ (Expander+Reboiler+Seperator+Booster+TEG)**2 -
'Expander:Reboiler - Reboiler:Seperator - Booster:TEG - Expander:TEG -
'Reboiler:TEG - Reboiler:Booster - Expander:Seperator - Seperator:Booster -
'Expander:Booster - Reboiler + Booster2', data=df).fit()

results6 = sm.ols('Dew ~ (Expander+Reboiler+Seperator+Booster+TEG)**2 -
'Expander:Reboiler - Reboiler:Seperator - Reboiler:Booster - Expander:Seperator
'- Reboiler:TEG - TEG - Booster:TEG - Seperator:Booster - Expander:Booster -
'Seperator - Expander:TEG - Reboiler + Booster2 + TEG2', data=df).fit()

'Second go :-)'
results = sm.ols('NGL ~ (Expander+Reboiler+Seperator+Booster+TEG)**2 -
'Reboiler:Seperator - Expander:TEG - Reboiler:TEG - Expander:Seperator -
'Expander:Reboiler - Reboiler:Booster - Seperator:Booster - Seperator',
data=df).fit()

results1 = sm.ols('RVP ~ (Expander+Reboiler+Seperator+Booster+TEG)**2 -
'Expander:TEG - Reboiler:Seperator - Reboiler:TEG - Expander:Seperator -
'Expander:Reboiler - Seperator + Reboiler2 + TEG2', data=df).fit()

results2 = sm.ols('HHV ~ (Expander+Reboiler+Seperator+Booster+TEG)**2 -
'Reboiler:Seperator - Reboiler:Booster - Expander:Reboiler - Seperator:Booster
'- Reboiler:TEG - Reboiler - Expander:Seperator + Booster2', data=df).fit()

results3 = sm.ols('SG ~ (Expander+Reboiler+Seperator+Booster+TEG)**2 -
'Expander:Reboiler - Reboiler:Booster - Reboiler:Seperator - Reboiler:TEG
'-Seperator:Booster - Reboiler + Booster2', data=df).fit()

results4 = sm.ols('Wobbe ~ (Expander+Reboiler+Seperator+Booster+TEG)**2 -
'Expander:Reboiler - Reboiler:Booster - Reboiler:Seperator - Seperator:Booster
'- Reboiler:TEG - Reboiler - Expander:Seperator + Booster2', data=df).fit()

results5 = sm.ols('Power ~ (Expander+Reboiler+Seperator+Booster+TEG)**2 -
'Booster - Reboiler:Seperator - Reboiler - Expander:Reboiler - Reboiler:TEG
'+Expander2 + Seperator2 + Booster2 + TEG2', data=df).fit()

results6 = sm.ols('Dew ~ (Expander+Reboiler+Seperator+Booster+TEG)**2 -
'Reboiler:TEG - Reboiler - Expander:Reboiler - Booster - Reboiler:Seperator -
'Expander:Seperator - Reboiler:Booster +Expander2', data=df).fit()

print results.summary()
print results1.summary()
print results2.summary()
print results3.summary()
print results4.summary()
print results5.summary()
print results6.summary()

def Power(Expander, Reboiler, Seperator, Booster, TEG):
    ExpC=-162.7289
    SepC=-1823.7320
    TEGC=-166.4767
    ExpSepC=28.6875
    ExpBoosC=-1.2327
    ExpTEGC=0.7800
    RebBoosC=0.0258
    SepBoosC=-43.7112
    SepTEGC=67.0597
    BoosTEGC=-3.2682
    Exp2C=1.4819
    Sep2C=93.7959
    Boos2C=1.8744
    TEG2C=3.0675
    Int=1.72e+04

    respower = ExpC*Expander + SepC*Seperator + TEGC*TEG + ExpSepC*Expander*
    Seperator + ExpBoosC*Expander*Booster + ExpTEGC*Expander*TEG + RebBoosC*
    Reboiler*Booster + SepBoosC*Seperator*Booster + SepTEGC*Seperator*TEG +
    BoosTEGC*Booster*TEG + Exp2C*Expander*Expander + Sep2C*Seperator*Seperator
    + Boos2C*Booster*Booster + TEG2C*TEG*TEG + Int
    return respower

def Wobbe(Expander, Reboiler, Seperator, Booster, TEG):
    ExpC=0.0862
    SepC=0.3914
    BoosC=-0.1072
    TEGC=0.1550
    ExpBoosC=-0.0006
    ExpTEGC=0.0006
    SepTEGC=-0.0184
    BoosTEGC=-0.0007
    Boos2C=0.0007
    Int=56.6857

    reswobbe = ExpC*Expander + SepC*Seperator + BoosC*Booster + TEGC*TEG +
    ExpBoosC*Expander*Booster + ExpTEGC*Expander*TEG + SepTEGC*Seperator*TEG
    + BoosTEGC*Booster*TEG + Boos2C*Booster*Booster + Int
    return reswobbe

def SG(Expander, Reboiler, Seperator, Booster, TEG):
    ExpC=0.0029
    SepC=0.0159
    BoosC=-0.0035
    TEGC=0.0048
    ExpSepC=-9.062e-05
    ExpBoosC=-1.887e-05
    ExpTEGC=1.838e-05
    SepTEGC=-0.0006
    BoosTEGC=-2.25e-05
    Boos2C=2.204e-05
    Int=0.6699

    ressg = ExpC*Expander + SepC*Seperator + BoosC*Booster + TEGC*TEG +
    ExpSepC*Expander*Seperator + ExpBoosC*Expander*Booster + ExpTEGC*Expander
    *TEG + SepTEGC*Seperator*TEG + BoosTEGC*Booster*TEG + Boos2C*Booster*
    Booster + Int
    return ressg

def HHV(Expander, Reboiler, Seperator, Booster, TEG):
    ExpC=0.1551
    SepC=0.7386
    BoosC=-0.2107
    TEGC=0.2821
    ExpBoosC=-0.0011
    ExpTEGC=0.0011
    SepTEGC=-0.0344
    BoosTEGC=-0.0014
    Boos2C=0.0013
    Int=44.6248

    reshhv = ExpC*Expander + SepC*Seperator + BoosC*Booster + TEGC*TEG +
    ExpBoosC*Expander*Booster + ExpTEGC*Expander*TEG + SepTEGC*Seperator*TEG +
    BoosTEGC*Booster*TEG + Boos2C*Booster*Booster + Int
    return reshhv

def RVP(Expander, Reboiler, Seperator, Booster, TEG):
    ExpC=-0.3862
    RebC=0.0903
    BoosC=-0.1227
    TEGC=-0.9514
    ExpBoosC=0.0031
    RebBoosC=-0.0007
    SepBoosC=0.0163
    SepTEGC=0.0490
    BoosTEGC=0.0027
    Reb2C=-0.0009
    TEG2C=0.0060
    Int=38.3067

    resrvp = ExpC*Expander + RebC*Reboiler + BoosC*Booster + TEGC*TEG +
    ExpBoosC*Expander*Booster + RebBoosC*Reboiler*Booster + SepBoosC*Seperator*
    Booster + SepTEGC*Seperator*TEG + BoosTEGC*Booster*TEG + Reb2C*Reboiler*
    Reboiler + TEG2C*TEG*TEG + Int
    return resrvp

def NGL(Expander, Reboiler, Seperator, Booster, TEG):
    ExpC=-97.5646
    RebC=-4.6692
    BoosC=-31.7798
    TEGC=-164.7876
    ExpBoosC=0.7904
    SepTEGC=18.2413
    BoosTEGC=0.7947
    Int=7797.0129

    resngl = ExpC*Expander + RebC*Reboiler + BoosC*Booster + TEGC*TEG +
    ExpBoosC*Expander*Booster + SepTEGC*Seperator*TEG + BoosTEGC*Booster*
    TEG + Int
    return resngl

def Dew(Expander, Reboiler, Seperator, Booster, TEG):
    ExpC=1.8594
    SepC=13.6961
    TEGC=2.6635
    ExpBoosC=-0.0043
    ExpTEGC=-0.0040
    SepBoosC=-0.0801
    SepTEGC=-0.3040
    BoosTEGC=-0.0063
    Exp2C=-0.0055
    Int=-121.1210

    resdew = ExpC*Expander + SepC*Seperator + TEGC*TEG + ExpBoosC*Expander*
    Booster + ExpTEGC*Expander*TEG + SepBoosC*Seperator*Booster + SepTEGC*
    Seperator*TEG + BoosTEGC*Booster*TEG + Exp2C*Expander*Expander + Int
    return resdew

print Wobbe(35, 25, 2.3, 90, 30)
print SG(35, 25, 2.3, 90, 30)
print HHV(35, 25, 2.3, 90, 30)
print Dew(35, 25, 2.3, 90, 30)
print Power(35, 25, 2.3, 90, 30)
print RVP(35, 25, 2.3, 90, 30)
print NGL(35, 25, 2.3, 90, 30)

'Optimization'
from scipy.optimize import minimize

def f1(x):
    # Dew - Constrain function
    return -1*(1.8594*x[0] + 13.6961*x[2] + 2.6635*x[4] - 0.0043*x[0]*x[3] -
    0.0040*x[0]*x[4] - 0.0801*x[2]*x[3] - 0.3040*x[2]*x[4] - 0.0063*x[3]*x[4]
    - 0.0055*x[0]*x[0] - 121.1210) - 2

def f2(x):
    # Wobbe - Constrain function
    return -1*(0.0862*x[0] + 0.3914*x[2] - 0.1072*x[3] + 0.1550*x[4] -
    0.0006*x[0]*x[3] + 0.0006*x[0]*x[4] - 0.0184*x[2]*x[4] - 0.0007*x[3]*x[4]
    + 0.0007*x[3]*x[3] + 56.6857) + 56.2

def Wobbe2(x):
    return 0.0862*x[0] + 0.3914*x[2] - 0.1072*x[3] + 0.1550*x[4] - 0.0006*x[0]
    *x[3] + 0.0006*x[0]*x[4] - 0.0184*x[2]*x[4] - 0.0007*x[3]*x[4] + 0.0007
    *x[3]*x[3] + 56.6857

def f3(x):
    # HHV - Constrain function
    return -1*(0.1551*x[0] + 0.7386*x[2] - 0.2107*x[3] + 0.2821*x[4] -
    0.0011*x[0]*x[3] + 0.0011*x[0]*x[4] - 0.0344*x[2]*x[4] - 0.0014*x[3]*x[4]
    + 0.0013*x[3]*x[3] + 44.6248) + 46

def f4(x):
    # SG - Constrain function
    return -1*(0.0029*x[0] + 0.0159*x[2] - 0.0035*x[3] + 0.0048*x[4] -
    9.062e-05*x[0]*x[2] - 1.887e-05*x[0]*x[3] + 1.838e-05*x[0]*x[4] -
    0.0006*x[2]*x[4] - 2.25e-05*x[3]*x[4] + 2.204e-05*x[3]*x[3] + 0.6699) + 0.7

def f5(x):
    # RVP - Contrain function
    return -1*(-0.3862*x[0] + 0.0903*x[1] - 0.1227*x[3] - 0.9514*x[4] +
    0.0031*x[0]*x[3] - 0.0007*x[1]*x[3] + 0.0163*x[2]*x[3] + 0.0490*x[2]*x[4]
    + 0.0027*x[3]*x[4] - 0.0009*x[1]*x[1] + 0.0060*x[4]*x[4] + 38.3067) + 12

def objectivefun(x):
    #Function to be minimized
    return -162.7289*x[0] - 1823.7320*x[2] - 166.4767*x[4] + 28.6875*x[0]*x[2]
    - 1.2327*x[0]*x[3] + 0.7800*x[0]*x[4] + 0.0258*x[1]*x[3] - 43.7112*x[2]
    *x[3] + 67.0597*x[2]*x[4] - 3.2682*x[3]*x[4] + 1.4819*x[0]*x[0] + 93.7959
    *x[2]*x[2] + 1.8744*x[3]*x[3] + 3.0675*x[4]*x[4] + 1.72e+04

cons = ({'type': 'ineq', 'fun': f1},
{'type': 'ineq', 'fun': f2},
{'type': 'ineq', 'fun': f3},
{'type': 'ineq', 'fun': f4})
#{'type': 'ineq', 'fun': f5})

bnds = ((25, 45), (15, 35), (2.1, 2.5), (85, 95), (25, 35))
#bnds = ((0.1, 200), (0.1, 200), (0.1, 200), (0.1, 200), (0.1, 200))
#bnds = ((20, 50), (10, 40), (2.0, 2.6), (80, 100), (20, 40))
'Initial guess independt variables'
x0 = [35, 25, 2.3, 90, 30]
#x0 = [0, 0, 0, 0, 0]

res = minimize(objectivefun, x0, method='SLSQP', bounds=bnds, constraints=cons)

print res
print f1(res['x'])
print f2(res['x'])
print f3(res['x'])
print f4(res['x'])
print "Dew =", Dew(res['x'][0],res['x'][1],res['x'][2],res['x'][3],res['x'][4])
print "Wobbe =",
Wobbe(res['x'][0],res['x'][1],res['x'][2],res['x'][3],res['x'][4])
print "SG =", SG(res['x'][0],res['x'][1],res['x'][2],res['x'][3],res['x'][4])
print "HHV =", HHV(res['x'][0],res['x'][1],res['x'][2],res['x'][3],res['x'][4])
print "RVP =", RVP(res['x'][0],res['x'][1],res['x'][2],res['x'][3],res['x'][4])

#print objectivefun(x0)

'Plots'
plt.figure(01)
sns.set(style="whitegrid")
sns.set_style("ticks")
sns.residplot(df.Wobbe, results4.fittedvalues, color="blue", lowess=True)
plt.savefig("Wobbe_resid.png")

plt.figure(02)
sns.set(style="whitegrid")
sns.set_style("ticks")
sns.residplot(df.SG, results3.fittedvalues, color="blue", lowess=True)
plt.savefig("SG_resid.png")

plt.figure(03)
sns.set(style="whitegrid")
sns.set_style("ticks")
sns.residplot(df.RVP, results1.fittedvalues, color="blue", lowess=True)
plt.savefig("RVP_resid.png")

plt.figure(04)
sns.set(style="whitegrid")
sns.set_style("ticks")
sns.residplot(df.HHV, results2.fittedvalues, color="blue", lowess=True)
```

```
plt.savefig("HHV_resid.png")

plt.figure(05)
sns.set(style="whitegrid")
sns.set_style("ticks")
sns.residplot(df.NGL, results.fittedvalues, color="blue", lowess=True)
plt.savefig("NGL_resid.png")

plt.figure(06)
sns.set(style="whitegrid")
sns.set_style("ticks")
sns.residplot(df.Power, results5.fittedvalues, color="blue", lowess=True)
plt.savefig("Power_resid.png")

plt.figure(07)
sns.set(style="whitegrid")
sns.set_style("ticks")
sns.residplot(df.Dew, results6.fittedvalues, color="blue", lowess=True)
plt.savefig("Dew_resid.png")

plt.show()

plt.figure(1)
plt.plot(df.NGL,results.fittedvalues, 'bo')
plt.title('NGL')
plt.xlabel("Simulated values with HYSYS")
plt.ylabel("Predicted using regression model")
plt.savefig("NGL_predicted_vs_simulated.png")

plt.figure(8)
plt.hist(results.norm_resid())
plt.ylabel('Count')
plt.xlabel('Normalized residuals')
plt.title('NGL')
plt.savefig("NGL_hist_residuals.png")

plt.figure(15)
res=results.resid
fig=smapi.qqplot(res)
plt.title('NGL')
plt.savefig("NGL_qqplot.png")
plot_leverage_resid2(results)
plt.savefig("NGL_leverage_vs_residuals.png")
influence_plot(results)
plt.savefig("NGL_influence.png")

plt.figure(2)
plt.plot(df.RVP,results1.fittedvalues, 'bo')
plt.title('RVP')
plt.xlabel("Simulated values with HYSYS")
plt.ylabel("Predicted using regression model")
plt.savefig("RVP_predicted_vs_simulated.png")

plt.figure(9)
plt.hist(results1.norm_resid())
plt.ylabel('Count')
plt.xlabel('Normalized residuals')
plt.title('RVP')
plt.savefig("RVP_hist_residuals.png")

plt.figure(16)
res1=results1.resid
fig=smapi.qqplot(res1)
plt.title('RVP')
plt.savefig("RVP_qqplot.png")
plot_leverage_resid2(results1)
plt.savefig("RVP_leverage_vs_residuals.png")
```

```
influence_plot(results1)
plt.savefig("RVP_influence.png")

plt.figure(3)
plt.plot(df.HHV,results2.fittedvalues, 'bo')
plt.title('HHV')
plt.xlabel("Simulated values with HYSYS")
plt.ylabel("Predicted using regression model")
plt.savefig("HHV_predicted_vs_simulated.png")

plt.figure(10)
plt.hist(results2.norm_resid())
plt.ylabel('Count')
plt.xlabel('Normalized residuals')
plt.title('HHV')
plt.savefig("HHV_hist_residuals.png")

plt.figure(17)
res2=results2.resid
fig=smapi.qqplot(res2)
plt.title('HHV')
plt.savefig("HHV_qqplot.png")
plot_leverage_resid2(results2)
plt.savefig("HHV_leverage_vs_residuals.png")
influence_plot(results2)
plt.savefig("HHV_influence.png")

plt.figure(4)
plt.plot(df.SG,results3.fittedvalues, 'bo')
plt.title('SG')
plt.xlabel("Simulated values with HYSYS")
plt.ylabel("Predicted using regression model")
plt.savefig("SG_predicted_vs_simulated.png")

plt.figure(11)
plt.hist(results3.norm_resid())
plt.ylabel('Count')
plt.xlabel('Normalized residuals')
plt.title('SG')
plt.savefig("SG_hist_residuals.png")
plt.figure(18)
res3=results3.resid
fig=smapi.qqplot(res3)
plt.title('SG')
plt.savefig("SG_qqplot.png")
plot_leverage_resid2(results3)
plt.savefig("SG_leverage_vs_residuals.png")
influence_plot(results3)
plt.savefig("SG_influence.png")

plt.figure(5)
plt.plot(df.Wobbe,results4.fittedvalues, 'bo')
plt.title('Wobbe')
plt.xlabel("Simulated values with HYSYS")
plt.ylabel("Predicted using regression model")
plt.savefig("Wobbe_predicted_vs_simulated.png")
plt.figure(12)
plt.hist(results4.norm_resid())
plt.ylabel('Count')
plt.xlabel('Normalized residuals')
plt.title('Wobbe')
plt.savefig("Wobbe_hist_residuals.png")
plt.figure(19)
res4=results4.resid
fig=smapi.qqplot(res4)
plt.title('Wobbe')
plt.savefig("Wobbe_qqplot.png")
```

```
plot_leverage_resid2(results4)
plt.savefig("Wobbe_leverage_vs_residuals.png")
influence_plot(results4)
plt.savefig("Wobbe_influence.png")

plt.figure(6)
plt.plot(df.Power,results5.fittedvalues, 'bo')
plt.title('Power')
plt.xlabel("Simulated values with HYSYS")
plt.ylabel("Predicted using regression model")
plt.savefig("Power_predicted_vs_simulated.png")
plt.figure(13)
plt.hist(results5.norm_resid())
plt.ylabel('Count')
plt.xlabel('Normalized residuals')
plt.title('Power')
plt.savefig("Power_hist_residuals.png")
plt.figure(20)
res5=results5.resid
fig=smapi.qqplot(res5)
plt.title('Power')
plt.savefig("Power_qqplot.png")
plot_leverage_resid2(results5)
plt.savefig("Power_leverage_vs_residuals.png")
influence_plot(results5)
plt.savefig("Power_influence.png")

plt.figure(7)
plt.plot(df.Dew,results6.fittedvalues,'bo')
plt.title('Dew')
plt.xlabel("Simulated values with HYSYS")
plt.ylabel("Predicted using regression model")
plt.savefig("Dew_predicted_vs_simulated.png")
plt.figure(14)
plt.hist(results6.norm_resid())
plt.ylabel('Count')
plt.xlabel('Normalized residuals')
plt.title('Dew')
plt.savefig("Dew_hist_residuals.png")
plt.figure(21)
res6=results6.resid
fig=smapi.qqplot(res6)
plt.title('Dew')
plt.savefig("Dew_qqplot.png")
plot_leverage_resid2(results6)
plt.savefig("Dew_leverage_vs_residuals.png")
influence_plot(results6)
plt.savefig("Dew_influence.png")

plt.show()
```

Appendix 2.1 – Error Propagation Applied to STA-3 MEL

STA-3
MEL

Equipment:	**Weight (tonnes)**	**(-30%)**	**(+30%)**	**Span**	**Span squared**
2 x Inlet Cooler (Tube side)	24.80	17.36	32.24	14.88	221.41
Test Separator Inlet Cooler	9.00	6.30	11.70	5.40	29.16
1st Stage Separator	27.00	18.90	35.10	16.20	262.44
2nd Stage Separator	12.60	8.82	16.38	7.56	57.15
3rd Stage Separator	8.40	5.88	10.92	5.04	25.40
Test Separator	10.50	7.35	13.65	6.30	39.69
2 x Crude Oil Booster Pump A/B	2.15	1.50	2.79	1.29	1.66
Crude Oil Export Cooler	2.52	1.76	3.28	1.51	2.29
2 x Crude Oil Export Pump A/B	15.26	10.68	19.84	9.16	83.83
Oil Fiscal Meter	9.00	6.30	11.70	5.40	29.16
Combined Oil and Gas Analyzer House	3.00	2.10	3.90	1.80	3.24
Oil Metering Proofer	9.00	6.30	11.70	5.40	29.16
Oil Pig Launcher	2.00	1.40	2.60	1.20	1.44
1st Stage LP Inlet Cooler	5.50	3.85	7.15	3.30	10.89
1st Stage LP Suction Scrubber	1.50	1.05	1.95	0.90	0.81
2 x LP Suction Drum Pump A/B	1.00	0.70	1.30	0.60	0.36
1st Stage LP Compressor	17.00	11.90	22.10	10.20	104.04
2nd Stage LP Compressor		0.00	0.00	0.00	0.00
2nd Stage LP Inlet Cooler	5.50	3.85	7.15	3.30	10.89
2nd Stage LP Suction Scrubber	4.00	2.80	5.20	2.40	5.76
Booster Inlet Cooler	33.60	23.52	43.68	20.16	406.43
Booster Suction Scrubber	1.20	0.84	1.56	0.72	0.52
Booster Compressor	28.60	20.02	37.18	17.16	294.47
HP Compressor		0.00	0.00	0.00	0.00
Dehydration Inlet Cooler	15.90	11.13	20.67	9.54	91.01
Dehydration knock out scrubber	1.60	1.12	2.08	0.96	0.92
Glycol Contactor	4.90	3.43	6.37	2.94	8.64
Gas / Gas Exchanger	17.40	12.18	22.62	10.44	108.99
Gas / Liquid Exchanger	16.20	11.34	21.06	9.72	94.48
Expander Inlet Scrubber	3.80	2.66	4.94	2.28	5.20
Turbo Expander	4.50	3.15	5.85	2.70	7.29
LT Separator	7.40	5.18	9.62	4.44	19.71
NGL Splitter	19.80	13.86	25.74	11.88	141.13
Reboiler	2.60	1.82	3.38	1.56	2.43
HP suction scrubber	2.30	1.61	2.99	1.38	1.90
HP After cooler	6.20	4.34	8.06	3.72	13.84
Gas lift suction scrubber	1.40	0.98	1.82	0.84	0.71
Gas lift compressor	5.40	3.78	7.02	3.24	10.50
Gas lift recycle cooler	2.00	1.40	2.60	1.20	1.44
Gas lift meter	0.30	0.21	0.39	0.18	0.03
Gas Fiscal Meter	18.00	12.60	23.40	10.80	116.64
Gas Pig Launcher	2.10	1.47	2.73	1.26	1.59
Glycol Regeneration Package	9.90	6.93	12.87	5.94	35.28
3 x Cooling Medium Cooler	11.70	8.19	15.21	7.02	49.28
Cooling Medium Expansion Tank	1.60	1.12	2.08	0.96	0.92
3 x Cooling Medium Pump	13.02	9.11	16.93	7.81	61.03
Cooling Medium Filter	1.10	0.77	1.43	0.66	0.44
Cooling Medium Storage Tank	10.00	7.00	13.00	6.00	36.00

Cooling Medium Make up Pump	1.00	0.70	1.30	0.60	0.36
Chemical Injection Package	16.00	11.20	20.80	9.60	92.16
Storage capacity all chemicals	30.00	21.00	39.00	18.00	324.00
Chemical collection tank	7.00	4.90	9.10	4.20	17.64
Chemical collection pump	0.10	0.07	0.13	0.06	0.004
HP Flare Knock out Drum	8.35	5.85	10.86	5.01	25.11
HP flare metering package	0.50	0.35	0.65	0.30	0.09
LP flare metering package	0.25	0.18	0.33	0.15	0.02
Flare ignition package	0.50	0.35	0.65	0.30	0.09
LP flare gas ejector	0.25	0.18	0.33	0.15	0.02
HP Hydro cyclone	2.20	1.54	2.86	1.32	1.74
LP Hydro cyclone	0.60	0.42	0.78	0.36	0.13
2 x Produced Water treatment Unit	27.20	19.04	35.36	16.32	266.34
2 x Water Return Pump	0.20	0.14	0.26	0.12	0.01
Fuel Gas Scrubber	0.70	0.49	0.91	0.42	0.18
Fuel Gas Superheater	1.00	0.70	1.30	0.60	0.36
Fuel Gas Inlet Cooler	1.80	1.26	2.34	1.08	1.17
Hypochlorite Package	1.30	0.91	1.69	0.78	0.61
Hypochlorite storage tank	3.87	2.71	5.03	2.32	5.39
2 x Seawater Lift Pump	10.15	7.11	13.20	6.09	37.12
3 x Coarse Filter	18.90	13.23	24.57	11.34	128.60
2 x Fine Filter	5.60	3.92	7.28	3.36	11.29
Sulphate Removal Package Skid	47.00	32.90	61.10	28.20	795.24
Clean In Place Package	9.00	6.30	11.70	5.40	29.16
Vacuum Deaerator	7.60	5.32	9.88	4.56	20.79
2 x Vacuum Pump	1.00	0.70	1.30	0.60	0.36
3 x Seawater Injection Booster Pump	1.50	1.05	1.95	0.90	0.81
3 x Produced Water Injection Booster Pump	1.50	1.05	1.95	0.90	0.81
3 x Water Injection Pump	32.40	22.68	42.12	19.44	377.91
Fresh Water Generation Package	3.00	2.10	3.90	1.80	3.24
Fresh Water Storage Tank	0.00	0.00	0.00	0.00	0.00
2 x Fresh Water Distribution Pump	0.60	0.42	0.78	0.36	0.13
Hazardous Open Drain Tank	2.00	1.40	2.60	1.20	1.44
2 x Hazardous Open Drain Pump	0.60	0.42	0.78	0.36	0.13
Drain caisson pump	0.50	0.35	0.65	0.30	0.09
Non Hazardous Open Drain Tank	0.50	0.35	0.65	0.30	0.09
2 x Non Hazardous Open Drain Pump	0.60	0.42	0.78	0.36	0.13
Drain caisson pump	0.50	0.35	0.65	0.30	0.09
Closed Drain / LP Flare Knock out Drum	4.00	2.80	5.20	2.40	5.76
2 x Closed Drain Pump	1.00	0.70	1.30	0.60	0.36
3 x Heli Fuel Tank	6.00	4.20	7.80	3.60	12.96
2 x Diesel Tank	0.00	0.00	0.00	0.00	0.00
Diesel Filter	0.50	0.35	0.65	0.30	0.09
2 x Diesel Pump	0.60	0.42	0.78	0.36	0.13
2 x Diesel Filter	1.00	0.70	1.30	0.60	0.36
2 x Air Compressor	4.00	2.80	5.20	2.40	5.76
2 x Air Dryer Package	5.00	3.50	6.50	3.00	9.00
Air Receiver	5.00	3.50	6.50	3.00	9.00
2 x Inert Gas Generator	12.00	8.40	15.60	7.20	51.84
Sewage Macerator Package	0.50	0.35	0.65	0.30	0.09
3 x Firewater Pump Package	135.00	94.50	175.50	81.00	6561.00
Deluge Valve Skids	14.00	9.80	18.20	8.40	70.56
2 x Firewater Jockey Pump	1.20	0.84	1.56	0.72	0.52
3 x Main Power Generator	258.60	181.02	336.18	155.16	24074.63
Emergency Diesel Generator	16.00	11.20	20.80	9.60	92.16

Wellhead Control Panel		4.00	2.80	5.20	2.40	5.76
Total	**Square root of the sum**	***1126.42***	***788.50***	***1464.35***	***675.85***	**188.34**
					= # +-	**94.17**
					+/- %	8.360144

Appendix 2.2 – Error Propagation Applied to Cut Down STA-3 MEL

STA-3
MEL Cut down to central process equipment

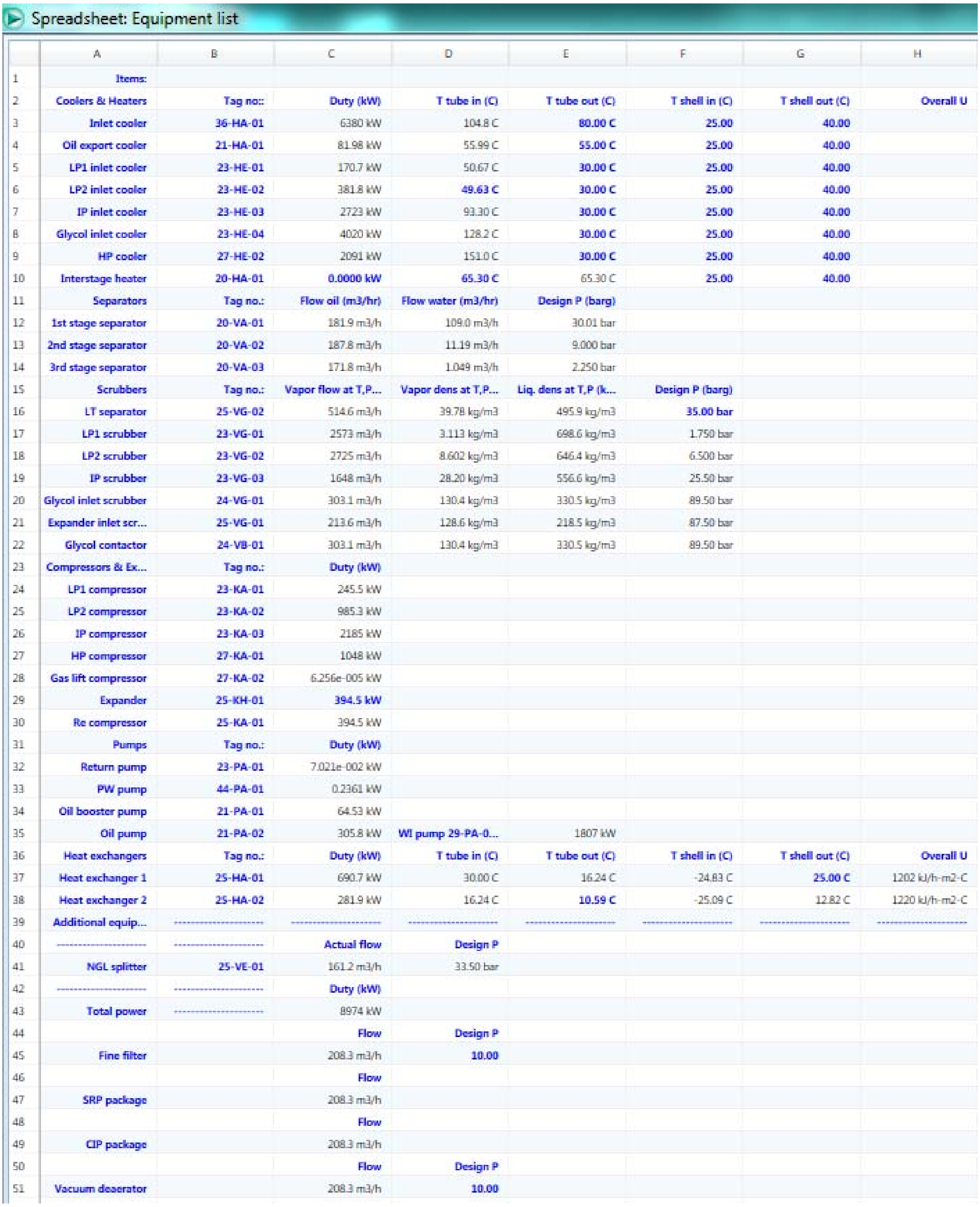
Equipment	**Weight**	**(-30%)**	**(+30%)**	**Span**	**Span squared**
2 x Inlet Cooler (Tube side)	24.80	17.36	32.24	14.88	221.41
1st Stage Separator	27.00	18.90	35.10	16.20	262.44
2nd Stage Separator	12.60	8.82	16.38	7.56	57.15
3rd Stage Separator	8.40	5.88	10.92	5.04	25.40
2 x Crude Oil Booster Pump A/B	2.15	1.50	2.79	1.29	1.66
Crude Oil Export Cooler	2.52	1.76	3.28	1.51	2.29
2 x Crude Oil Export Pump A/B	15.26	10.68	19.84	9.16	83.83
1st Stage LP Inlet Cooler	5.50	3.85	7.15	3.30	10.89
1st Stage LP Suction Scrubber	1.50	1.05	1.95	0.90	0.81
2 x LP Suction Drum Pump A/B	1.00	0.70	1.30	0.60	0.36
1st Stage LP Compressor	17.00	11.90	22.10	10.20	104.04
2nd Stage LP Compressor		0.00	0.00	0.00	0.00
2nd Stage LP Inlet Cooler	5.50	3.85	7.15	3.30	10.89
2nd Stage LP Suction Scrubber	4.00	2.80	5.20	2.40	5.76
Booster Inlet Cooler	33.60	23.52	43.68	20.16	406.43
Booster Suction Scrubber	1.20	0.84	1.56	0.72	0.52
Booster Compressor	28.60	20.02	37.18	17.16	294.47
HP Compressor		0.00	0.00	0.00	0.00
Glycol Contactor	4.90	3.43	6.37	2.94	8.64
Gas / Gas Exchanger	17.40	12.18	22.62	10.44	108.99
Gas / Liquid Exchanger	16.20	11.34	21.06	9.72	94.48
Expander Inlet Scrubber	3.80	2.66	4.94	2.28	5.20
Turbo Expander	4.50	3.15	5.85	2.70	7.29
LT Separator	7.40	5.18	9.62	4.44	19.71
NGL Splitter	19.80	13.86	25.74	11.88	141.13
Reboiler	2.60	1.82	3.38	1.56	2.43
HP suction scrubber	2.30	1.61	2.99	1.38	1.90
HP After cooler	6.20	4.34	8.06	3.72	13.84
Gas lift compressor	5.40	3.78	7.02	3.24	10.50
2 x Main Power Generator	172.40	120.68	224.12	103.44	10699.83
Total **Square root of the sum**	***453.53***	***317.47***	***589.59***	***272.12***	**112.26**
				= # +-	**56.13**
				+/- %	12.3763

Equipment	**Weight**	**(-50%)**	**(+50%)**	**Span**	**Span squared**
2 x Inlet Cooler (Tube side)	24.80	12.40	37.20	24.80	615.04
1st Stage Separator	27.00	13.50	40.50	27.00	729.00
2nd Stage Separator	12.60	6.30	18.90	12.60	158.76
3rd Stage Separator	8.40	4.20	12.60	8.40	70.56
2 x Crude Oil Booster Pump A/B	2.15	1.07	3.22	2.15	4.61
Crude Oil Export Cooler	2.52	1.26	3.78	2.52	6.35
2 x Crude Oil Export Pump A/B	15.26	7.63	22.89	15.26	232.87
1st Stage LP Inlet Cooler	5.50	2.75	8.25	5.50	30.25
1st Stage LP Suction Scrubber	1.50	0.75	2.25	1.50	2.25
2 x LP Suction Drum Pump A/B	1.00	0.50	1.50	1.00	1.00

1st Stage LP Compressor		17.00	8.50	25.50	17.00	289.00
2nd Stage LP Compressor			0.00	0.00	0.00	0.00
2nd Stage LP Inlet Cooler		5.50	2.75	8.25	5.50	30.25
2nd Stage LP Suction Scrubber		4.00	2.00	6.00	4.00	16.00
Booster Inlet Cooler		33.60	16.80	50.40	33.60	1128.96
Booster Suction Scrubber		1.20	0.60	1.80	1.20	1.44
Booster Compressor		28.60	14.30	42.90	28.60	817.96
HP Compressor			0.00	0.00	0.00	0.00
Glycol Contactor		4.90	2.45	7.35	4.90	24.01
Gas / Gas Exchanger		17.40	8.70	26.10	17.40	302.76
Gas / Liquid Exchanger		16.20	8.10	24.30	16.20	262.44
Expander Inlet Scrubber		3.80	1.90	5.70	3.80	14.44
Turbo Expander		4.50	2.25	6.75	4.50	20.25
LT Separator		7.40	3.70	11.10	7.40	54.76
NGL Splitter		19.80	9.90	29.70	19.80	392.04
Reboiler		2.60	1.30	3.90	2.60	6.76
HP suction scrubber		2.30	1.15	3.45	2.30	5.29
HP After cooler		6.20	3.10	9.30	6.20	38.44
Gas lift compressor		5.40	2.70	8.10	5.40	29.16
2 x Main Power Generator		172.40	86.20	258.60	172.40	29721.76
Total	**Square root of the sum**	***453.53***	***317.47***	***589.59***	***272.12***	**187.10**

= # +-	**93.55**
+/- %	20.62717

Appendix 2.3 – HYSYS Equipment List Data



Spreadsheet: Equipment list

	A	B	C	D	E	F	G	H
1	Items:							
2	Coolers & Heaters	Tag no::	Duty (kW)	T tube in (C)	T tube out (C)	T shell in (C)	T shell out (C)	Overall U
3	Inlet cooler	36-HA-01	6380 kW	104.8 C	80.00 C	25.00	40.00	
4	Oil export cooler	21-HA-01	81.98 kW	55.99 C	55.00 C	25.00	40.00	
5	LP1 inlet cooler	23-HE-01	170.7 kW	50.67 C	30.00 C	25.00	40.00	
6	LP2 inlet cooler	23-HE-02	381.8 kW	49.63 C	30.00 C	25.00	40.00	
7	IP inlet cooler	23-HE-03	2723 kW	93.30 C	30.00 C	25.00	40.00	
8	Glycol inlet cooler	23-HE-04	4020 kW	128.2 C	30.00 C	25.00	40.00	
9	HP cooler	27-HE-02	2091 kW	151.0 C	30.00 C	25.00	40.00	
10	Interstage heater	20-HA-01	0.0000 kW	65.30 C	65.30 C	25.00	40.00	
11	Separators	Tag no.:	Flow oil (m3/hr)	Flow water (m3/hr)	Design P (barg)			
12	1st stage separator	20-VA-01	181.9 m3/h	109.0 m3/h	30.01 bar			
13	2nd stage separator	20-VA-02	187.8 m3/h	11.19 m3/h	9.000 bar			
14	3rd stage separator	20-VA-03	171.8 m3/h	1.049 m3/h	2.250 bar			
15	Scrubbers	Tag no.:	Vapor flow at T,P...	Vapor dens at T,P...	Liq. dens at T,P (k...	Design P (barg)		
16	LT separator	25-VG-02	514.6 m3/h	39.78 kg/m3	495.9 kg/m3	35.00 bar		
17	LP1 scrubber	23-VG-01	2573 m3/h	3.113 kg/m3	698.6 kg/m3	1.750 bar		
18	LP2 scrubber	23-VG-02	2725 m3/h	8.602 kg/m3	646.4 kg/m3	6.500 bar		
19	IP scrubber	23-VG-03	1648 m3/h	28.20 kg/m3	556.6 kg/m3	25.50 bar		
20	Glycol inlet scrubber	24-VG-01	303.1 m3/h	130.4 kg/m3	330.5 kg/m3	89.50 bar		
21	Expander inlet scr...	25-VG-01	213.6 m3/h	128.6 kg/m3	218.5 kg/m3	87.50 bar		
22	Glycol contactor	24-VB-01	303.1 m3/h	130.4 kg/m3	330.5 kg/m3	89.50 bar		
23	Compressors & Ex...	Tag no.:	Duty (kW)					
24	LP1 compressor	23-KA-01	245.5 kW					
25	LP2 compressor	23-KA-02	985.3 kW					
26	IP compressor	23-KA-03	2185 kW					
27	HP compressor	27-KA-01	1048 kW					
28	Gas lift compressor	27-KA-02	6.256e-005 kW					
29	Expander	25-KH-01	394.5 kW					
30	Re compressor	25-KA-01	394.5 kW					
31	Pumps	Tag no.:	Duty (kW)					
32	Return pump	23-PA-01	7.021e-002 kW					
33	PW pump	44-PA-01	0.2361 kW					
34	Oil booster pump	21-PA-01	64.53 kW					
35	Oil pump	21-PA-02	305.8 kW	WI pump 29-PA-0...	1807 kW			
36	Heat exchangers	Tag no.:	Duty (kW)	T tube in (C)	T tube out (C)	T shell in (C)	T shell out (C)	Overall U
37	Heat exchanger 1	25-HA-01	690.7 kW	30.00 C	16.24 C	-24.83 C	25.00 C	1202 kJ/h-m2-C
38	Heat exchanger 2	25-HA-02	281.9 kW	16.24 C	10.59 C	-25.09 C	12.82 C	1220 kJ/h-m2-C
39	Additional equip...	--------------------	--------------------	--------------------	--------------------	--------------------	--------------------	--------------------
40	--------------------	--------------------	Actual flow	Design P				
41	NGL splitter	25-VE-01	161.2 m3/h	33.50 bar				
42	--------------------	--------------------	Duty (kW)					
43	Total power	--------------------	8974 kW					
44			Flow	Design P				
45	Fine filter		208.3 m3/h	10.00				
46			Flow					
47	SRP package		208.3 m3/h					
48			Flow					
49	CIP package		208.3 m3/h					
50			Flow	Design P				
51	Vacuum deaerator		208.3 m3/h	10.00				

Appendix 2.4 – Combined Excel Weight Estimation Sheet

Combined equipment sizing sheet

*Copy values from HYSYS and known parameters corresponding to the cells marked with GREEN

Items:

For convenience if needed:								+/- percantage error
*Convert BPD to m3/hr				*Converrt MMSCFD to m3/hr:				X %:
BPD:	31450	m3/hr =	208.356	MMSCFD:	1	m3/hr:	1118.9	50

Coolers & Heaters	Tag no.:	Duty (kW):	T tube in (°C):	T tube out (°C):	T shell in (°C):	T shell out (°C):	LMTD (°C):	Tube shell (#):	U (W/m2/C):	Area (m2):	ID (m):	Length (m):	Weight (t):	Weight + X%	Weight - X%
Inlet cooler	36-HA-01	6379.7	104.8	80.0	25.0	40.0	59.8	150/300	470.0	227.1	0.88	6.83	**12.51**	**18.76**	**6.25**
Oil export cooler	21-HA-01	82.0	56.0	55.0	25.0	40.0	22.3	150/150	300.0	12.3	0.28	2.68	**0.23**	**0.34**	**0.11**
LP1 inlet cooler	23-HE-01	170.7	50.7	30.0	25.0	40.0	7.5	150/150	300.0	76.1	0.65	5.94	**1.60**	**2.40**	**0.80**
LP2 inlet cooler	23-HE-02	381.8	49.6	30.0	25.0	40.0	7.1	150/150	200.0	270.3	0.97	7.03	**35.06**	**52.59**	**17.53**
IP inlet cooler	23-HE-03	2723.2	93.3	30.0	25.0	40.0	20.4	150/300	300.0	444.8	1.40	7.54	**31.37**	**47.06**	**15.69**
Glycol inlet cooler	23-HE-04	4020.1	128.2	30.0	25.0	40.0	29.0	150/600	450.0	308.1	0.76	7.11	**11.87**	**17.80**	**5.93**
HP cooler	27-HE-02	2090.5	151.0	30.0	25.0	40.0	34.2	150/600	450.0	135.9	0.54	5.73	**6.22**	**9.33**	**3.11**
Interstage heater	20-HA-01	0.0	65.3	65.3	25.0	40.0	32.2	150/300	450.0	0.0	0.15	1.49	**4.27**	**6.40**	**2.13**

Separators	Tag no.:	Flow oil (m3/hr):	Flow water (m3/hr):	Reten. Time (min.):	% Full:	L/D Ratio:	Design P (barg):	Allow. Stress (N/mm2)	Corr. allow. (mm):	ID (m):	T/T (m):	W/T req.:	W/T select:	Shell (t):	Head (t):	Weight (t):	Weight + X%	Weight - X%
1st stage separator	20-VA-01	181.889394	109.0	5	65	4	30.0	300	3	2.26	9.05	15.98	15.98	8.22	1.51	**9.73**	**14.60**	**4.87**
2nd stage separator	20-VA-02	187.779909	11.1936612	5	65	4	9.0	300	3	2.00	7.99	6.67	10.00	4.00	0.74	**4.74**	**7.11**	**2.37**
3rd stage separator	20-VA-03	171.780555	1.05	5	65	4	2.25	300	3	1.91	7.62	4.13	10.00	3.65	0.67	**4.32**	**6.48**	**2.16**

Scrubbers	Tag no.:	Vapor flow at (m3/hr):	Vapor dens. at (kg/m3):	Liquid dens. at (kg/m3):	K factor (m/s):	Corrected K factor:	L/D Ratio:	Design P (barg):	Allow. Stress (N/mm2)	Corr. allow. (mm):	ID (m):	T/T (m):	W/T req.:	W/T select:	Shell (t):	Head (t):	Weight (t):	Weight + X%	Weight - X%
LT separator	25-VG-02	514.582744	39.780964	495.9	0.1	0.058	3.5	35.0	160	3	0.97	3.38	15.22	15.22	1.25	0.26	**1.51**	**2.26**	**0.75**
LP1 scrubber	23-VG-01	2573.3	3.11263324	698.6	0.1	0.070	3.5	1.8	160	3	0.93	3.27	3.90	10.00	0.77	0.16	**0.93**	**1.39**	**0.46**
LP2 scrubber	23-VG-02	2725.1	8.60215279	646.4	0.1	0.068	3.5	6.5	160	3	1.29	4.50	6.24	10.00	1.45	0.31	**1.76**	**2.64**	**0.88**
IP scrubber	23-VG-03	1647.6	28.2015216	556.6	0.1	0.060	3.5	25.5	160	3	1.49	5.22	16.68	16.68	3.27	0.68	**3.95**	**5.92**	**1.97**
Glycol inlet scrubber	24-VG-01	303.1	130.43696	330.5	0.1	0.053	3.5	89.5	160	3	1.28	4.48	44.46	44.46	6.39	1.31	**7.70**	**11.55**	**3.85**
Expander inlet scrubber	25-VG-01	213.6	128.611142	218.5	0.1	0.053	3.5	87.5	160	3	1.31	4.58	44.44	44.44	6.69	1.37	**8.06**	**12.09**	**4.03**
Glycol contactor	24-VB-01	303.1	130.43696	330.5	0.1	0.057	3.5	89.5	160	3	1.24	4.32	43.06	43.06	5.78	1.18	**6.96**	**10.44**	**3.48**

Compressors & Expanders	Tag no.:	Duty (kW):	Lenght (m):	Height (m):	Width (m):	Weight (t):	Weight + X%	Weight - X%
LP1 compressor	23-KA-01	245.5	3.33	1.48	2.19	**7.04**	**10.56**	**3.52**
LP2 compressor	23-KA-02	985.3	5.33	1.98	2.37	**15.86**	**23.78**	**7.93**
IP compressor	23-KA-03	2184.7	6.99	2.34	2.48	**25.24**	**37.86**	**12.62**
HP compressor	27-KA-01	1048.2	5.45	2.01	2.38	**16.44**	**24.66**	**8.22**
Gas lift compressor	27-KA-02	6.26E-05	0.02	0.06	0.93	**0.00**	**0.00**	**0.00**
Expander	25-KH-01	394.5	3.91	1.64	2.25	**9.29**	**13.94**	**4.65**
Re compressor	25-KA-01	394.5	3.91	1.64	2.25	**9.29**	**13.94**	**4.65**

Pumps	Tag no.:	Duty (kW):	Additional kW (if needed automatically included in eq.):		Duty applied in main eq. (min 4 kW & max 789 kw)	Lenght (m):	Height (m):	Width (m):	Weight (t):	Weight + X%	Weight - X%
Return pump	23-PA-01	0.1	0		4	1.34	0.67	0.64	**0.22**	**0.33**	**0.11**
PW pump	44-PA-01	0.2	0		4	1.34	0.67	0.64	**0.22**	**0.33**	**0.11**
Oil booster pump	21-PA-01	64.5	0		64.5	1.82	0.82	0.60	**1.10**	**1.65**	**0.55**
Oil pump	21-PA-02	305.8	0	**Real duty WI pump:**	305.8151227	4.42	1.52	1.71	**7.89**	**11.84**	**3.95**
WI pump 3 x 50%	29-PA-02	1807.0	114.5	903.5	789	6.92	1.97	2.32	**41.22**	**61.83**	**20.61**

Heat exchangers	Tag no.:	Duty (kW):	T tube in (°C):	T tube out (°C):	T shell in (°C):	T shell out (°C):	LMTD (°C):	Tube shell (#):	Overall U (kJ/hr/m2/C)	U (W/m2/C):	Area (m2):	OD (m):	Length (m):	Weight (t):	Weight + X%	Weight - X%
Heat exchanger 1	25-HA-01	690.7	30.0	16.2	-24.8	25.0	17.1	600/600	1201.7	333.8	120.80	0.46	5.19	**24.65**	**36.98**	**12.33**
Heat exchanger 2	25-HA-02	281.9	16.2	10.6	-25.1	12.8	13.8	600/600	1220.0	338.9	60.44	0.41	4.77	**12.84**	**19.25**	**6.42**

Additional equipment	**Tag no.:**																
		Actual flow (m3/hr):	Reten. Time (min.):	% Full:	L/D Ratio:	Design P (barg):	Allow. Stress (N/mm2)	Corr. allow. (mm):	ID (m):	T/T (m):	W/T req.:	W/T select:	Shell (t):	Head (t):	Weight (t):	Weight + X%	Weight - X%
NGL splitter	25-VE-01	161.2	5	65	3.5	33.5	300	3	1.95	6.81	15.49	15.49	5.16	1.08	**6.24**	**9.36**	**3.12**

		kW Needed (max. 19570):	Generator Taurus 60 chosen for power demand up to 5100 kW	Generator Taurus 70 chosen for power demand between 5101 and 7160 kW	Generator Mars 100 chosen for power demand between 7161 and 10215 kW	Generator Titan 250 chosen for power demand between 10216 and 19570 kW	Lenght for one generator (m):	Height for one generator (m):	Width for one generator (m):	Total weight of the two generators (t):	Weight + X%	Weight - X%
Power generator 2 x 100%	N/A	8974.23671	0	0	3	0	14.2	3.8	2.8	**172.36**	**258.54**	**86.18**

		Flow (m3/hr):	Design P (barg):	Allow. Stress (N/mm2)	Corr. allow. (mm):	ID (m):	T/T (m):	W/T req.:	W/T select:	Shell (t):	Head (t):	Weight of two(t):	Weight + X%	Weight - X%
Fine filter x 2 (2 micron)	N/A	208.3	10	160	3	2.28	1.5	11.3	11.3	0.96	1.09	**4.10**	**6.14**	**2.05**

		Flow (m3/hr):	Lenght (m):	Height (m):	Width (m):	Weight (t):	Weight + X%	Weight - X%
SRP package	N/A	208.3	6.7	5.8	3.7	**39.16**	**58.74**	**19.58**

		Flow (m3/hr):	Lenght (m):	Height (m):	Width (m):	Weight (t):	Weight + X%	Weight - X%
CIP Package	N/A	208.3	2.9	5.8	2.5	**7.50**	**11.25**	**3.75**

		Flow (m3/hr):	Design P (barg):	Allow. Stress (N/mm2)	Corr. allow. (mm):	ID (m):	T/T (m):	W/T req.:	W/T select:	Shell (t):	Head (t):	Weight (t):	Weight + X%	Weight - X%
Vacuum dearerator	N/A	208.3	10	160	3	1.5	9	8.7	10.0	3.35	0.43	**3.78**	**5.68**	**1.89**

		Duty (kW):	Additional kW (if needed automatically included in eq.):	Duty applied in main eq. (min 4 kW & max 789 kw)	Lenght (m):	Height (m):	Width (m):	Weight of two(t):	Weight + X%	Weight - X%
Vacuum pump x 2	N/A	10.4	0	10.4	1.25	0.62	0.39	**0.92**	**1.38**	**0.46**

		Vacuum pump weight (t):	Lenght (m):	Height (m):	Width (m):	Weight of two(t):	Weight + X%	Weight - X%
Vacuum pump skid x 2	N/A	0.46	1.98	0.99	0.62	**2.77**	**4.15**	**1.38**
TOTAL						**560.9**	**841.4**	**280.5**

Appendix 2.5 – Monte Carlo Code Script

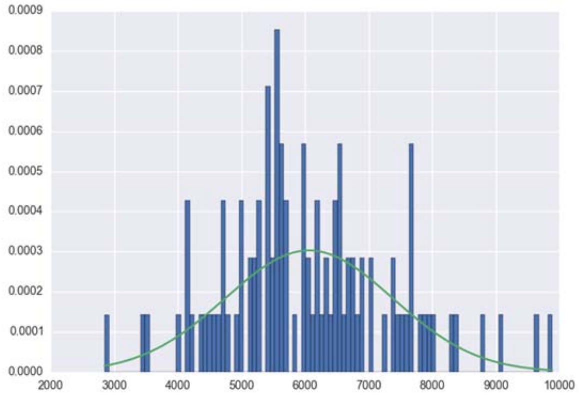
```
# -*- coding: utf-8 -*-
"""
Created on Fri Oct 10 10:56:13 2014

@author: KARR
"""

# -*- coding: utf-8 -*-
"""
Created on Thu Oct 09 14:47:35 2014

@author: KARR
"""

import matplotlib.pyplot as plt
import pandas as pd
import numpy as np
import array
import pylab as p
from numpy import genfromtxt
from pandas import DataFrame
from scipy.stats import stats
from scipy.stats import norm
from numpy.random import normal
import matplotlib.mlab as mlab
from pandas import DataFrame
import statsmodels.formula.api as sm
import statsmodels.api as smapi
import statsmodels.graphics.regressionplots as regplot
from statsmodels.graphics.regressionplots import *
import seaborn as sns

Location = r'\\ramoil.ramboll-group.global.network\Common\GlobalProjects\2014
'\1100011376\P-Process\DOE & Weight-Cost estimation\Full factorial
'\FF_sim_data_CSV.csv'
df = pd.read_csv(Location, sep=",")
print df

data = np.genfromtxt(Location, dtype=float, delimiter=',', names=True)

print data
print data['Wobbe']
print data['SG']
print data['HHV']
print data['Dew']
print data['Power']
print data['RVP']
print data['NGL']
print data['EqWeight']
print data['EqWeightpos']
print data['EqWeightneg']
print data['sumS2']

'Regression models'
Start conditions: results = sm.ols('Power ~ (Oil+Gas+Water)**2 + Oil2 + Gas2
+ Water2', data=df).fit()

results = sm.ols('Power ~ (Oil+Gas+Water)**2 - Gas:Water - Oil:Gas - Oil:Water
'+ Water2', data=df).fit()
results1 = sm.ols('EqWeight ~ (Oil+Gas+Water)**2 - Oil:Gas- Oil:Water -
'Gas:Water + Gas2', data=df).fit()

print results.summary()
print results1.summary()

'Models'

def Power(Oil, Gas, Water):
    OilC = 0.0238
    GasC = 0.1705
    WaterC = 0.1708
    Water2C = -1.244e-06
    IntC = -713.2169

    respower = OilC*Oil + GasC*Gas + WaterC*Water + Water2C*Water*Water + IntC
    return respower

def EqWeight(Oil, Gas, Water):
    OilC = 0.0010
    GasC = 0.0278
    WaterC = 0.0037
    Gas2C = -3.896e-07
    IntC = -58.2391

    reseqweight = OilC*Oil + GasC*Gas + WaterC*Water + Gas2C*Gas*Gas + IntC
    return reseqweight

'Mid level'
print Power(23000, 29170, 31450)
print EqWeight(23000, 29170, 31450)

'High level'
print Power(25300, 32090, 37740)
print EqWeight(25300, 32090, 37740)

'Low level'
print Power(20700, 26250, 25160)
print EqWeight(20700, 26250, 25160)

'mid-high'
print EqWeight(24150, 30630, 34595)

'mid-low'
print EqWeight(21850, 27710, 28305)

'high-high'
print EqWeight(26450, 33550, 40885)

'low-low'

print EqWeight(19550, 24790, 22015)

plt.figure(0)
sns.set(style="whitegrid")
sns.set_style("ticks")
sns.residplot(df.EqWeight, results1.fittedvalues, color="blue", lowess=True)
plt.savefig("EqWeight_resid.png")

plt.figure(1)
plt.plot(df.EqWeight,results1.fittedvalues, 'bo')
plt.title('EqWeight')
plt.xlabel("Simulated values with HYSYS")
plt.ylabel("Predicted using regression model")
plt.savefig("EqWeight_predicted_vs_simulated.png")

plt.figure(2)
res=results1.resid
fig=smapi.qqplot(res)
plt.title('EqWeight')
plt.savefig("EqWeight_qqplot.png")

plt.figure(3)
plot_leverage_resid2(results1)
plt.savefig("EqWeight_leverage_vs_residuals.png")

plt.figure(4)
influence_plot(results1)
plt.savefig("EqWeight_influence.png")

'Model with uncertainties'
Samples = 1000000
X = Samples

'Rates at 10%, 10% and 20% (used in HYSYS sim)'
oil = (np.random.normal(23000, 1796.9, X))
gas = (np.random.normal(29170, 2281.3, X))
water = (np.random.normal(31450, 4914.1, X))

'Rates at 40%'
oil = (np.random.normal(23000, 7187.5, X))
gas = (np.random.normal(29170, 9115.6, X))
water = (np.random.normal(31450, 9828.1, X))

'Rates at 30%'
oil = (np.random.normal(23000, 5390.6, X))
gas = (np.random.normal(29170, 6836.7, X))
water = (np.random.normal(31450, 7371.1, X))

'Rates at 20%'
oil = (np.random.normal(23000, 3593.8, X))
gas = (np.random.normal(29170, 4557.8, X))
water = (np.random.normal(31450, 4914.1, X))

'Rates at 10%'
oil = (np.random.normal(23000, 1796.9, X))
gas = (np.random.normal(29170, 2281.3, X))
water = (np.random.normal(31450, 2457, X))

'Rates at mid/mean values'
oil = 23000
gas = 29170
water = 31450

Weight = EqWeight(oil, gas, water)
Weight_uncertainty = (np.random.normal(0, 76.46, X))
Weight_plus_uncertainty = Weight + Weight_uncertainty
Rest = (EqWeight(oil, gas, water)*1.283)
Rest_uncertainty = (np.random.normal(0, 43.1, X))
Rest_plus_uncertainty = Rest + Rest_uncertainty
Weight_total = Weight_plus_uncertainty + Rest_plus_uncertainty
```

```
'Factors combinded'
factor = (np.random.normal(4.08, 1.04, X))
factor_mean = 4.08
'Factors partitioned'
factor_EI = (np.random.normal(0.46, 0.36, X))
factor_piping = (np.random.normal(0.45, 0.31, X))
factor_structure = (np.random.normal(2.28, 0.96, X))


'Total weight multiplied by combined factor + accommondation'
Weight_total_factor = Weight_total * factor + 800
Accommodation = (np.random.normal(800, 125, X))
Weight_total_factor = Weight_total * factor + Accommodation
Weight_plain = (Weight + Rest) * factor_mean + 800

WWW = (Weight_plus_uncertainty + Rest) * factor + 800

print Weight_plain
print 'Mean', np.mean(WWW)
print 'Minimum', np.min(WWW)
print 'Maximum', np.max(WWW)
print 'stddev', np.std(WWW)

'Total weight added partitioned factors'
Weight_total_partitioned_factors = Weight_total + Weight_total * factor_EI +
Weight_total * factor_piping + Weight_total * factor_structure + Accommodation

'Prints'
print oil
print gas
print water
print Weight
print Weight_uncertainty
print Weight_plus_uncertainty
print Rest
print Rest_uncertainty
print Rest_plus_uncertainty
print Weight_total
print factor
print Accommodation
print Weight_total_factor

print 'min weight', np.min(Weight)
print 'min weight_uncer', np.min(Weight_uncertainty)
print 'min weigt_plus_unc', np.min(Weight_plus_uncertainty)
print 'min rest', np.min(Rest)
print 'min rest_uncer', np.min(Rest_uncertainty)
print 'min rest_plus_unc', np.min(Rest_plus_uncertainty)
print 'min weight_tot', np.min(Weight_total)
print 'min factor', np.min(factor)

print 'Mean', np.mean(Weight_total_factor)
print 'Minimum', np.min(Weight_total_factor)
print 'Maximum', np.max(Weight_total_factor)
print 'stddev', np.std(Weight_total_factor)

print 'Mean', np.mean(Weight_total_partitioned_factors)
print 'Minimum', np.min(Weight_total_partitioned_factors)
print 'Maximum', np.max(Weight_total_partitioned_factors)
print 'stddev', np.std(Weight_total_partitioned_factors)
```

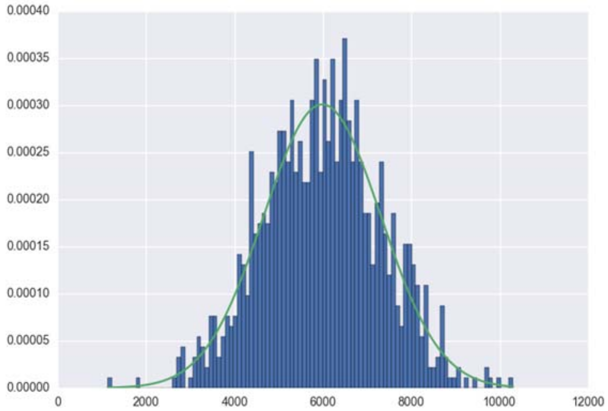
```
'Histogram and normal distribution plot'
plt.figure(5)
Weight_total_factor.sort()
WTFmean = np.mean(Weight_total_factor)
WTFstd = np.std(Weight_total_factor)
plt.hist(Weight_total_factor, bins=100, normed=True)
x = np.linspace(np.min(Weight_total_factor), np.max(Weight_total_factor),1000)
plt.plot(x, mlab.normpdf(x, WTFmean, WTFstd))
plt.savefig("X_samples")

'Histogram and normal distribution plot partitioned factors'
plt.figure(6)
Weight_total_partitioned_factors.sort()
WTPFmean = np.mean(Weight_total_partitioned_factors)
WTPFstd = np.std(Weight_total_partitioned_factors)
plt.hist(Weight_total_partitioned_factors, bins=100, normed=True)
x = np.linspace(np.min(Weight_total_partitioned_factors),
np.max(Weight_total_partitioned_factors),1000)
plt.plot(x, mlab.normpdf(x, WTPFmean, WTPFstd))
plt.savefig("XP_samples")

plt.figure(7)
Rest_uncertainty.sort()
RUmean = np.mean(Rest_uncertainty)
RUstd = np.std(Rest_uncertainty)
plt.hist(Rest_uncertainty, bins=100, normed=True)
x = np.linspace(np.min(Rest_uncertainty), np.max(Rest_uncertainty),1000)
plt.plot(x, mlab.normpdf(x, RUmean, RUstd))
plt.savefig("X_samples")

'Combined factor'
mean + 1.28 stddev
mean_plus = WTFmean + 1.28*WTFstd
mean - 1.28 stddev
mean_minus = WTFmean - 1.28*WTFstd

print 'mean+1.28std', mean_plus
print 'mean-1.28std', mean_minus

'Partitioned factors'
mean + 1.28 stddev
mean_plus = WTPFmean + 1.28*WTPFstd
mean - 1.28 stddev
mean_minus = WTPFmean - 1.28*WTPFstd

print 'mean+1.28std', mean_plus
print ' mean-1.28std', mean_minus

plt.show()
```

Appendix 2.6 – Monte Carlo Results, Samples Variety

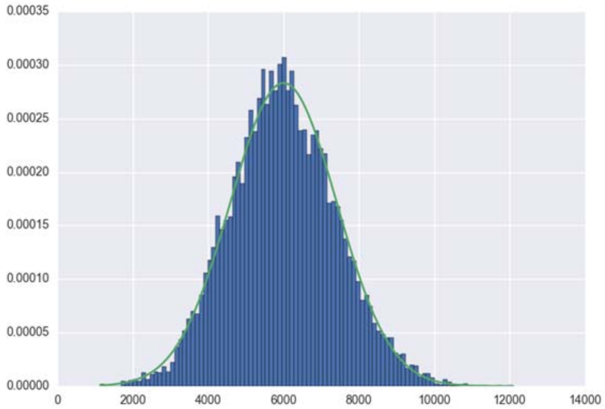
100 samples results:	Weight [Tonnes]:
Mean	6064
Minimum	2852
Maximum	9887
Standard deviation	1317



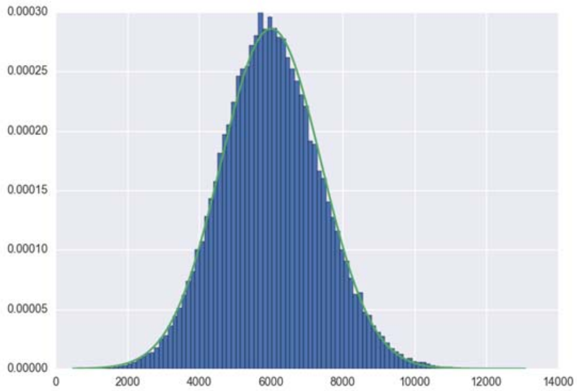
1000 samples results:	Weight [Tonnes]:
Mean	5986
Minimum	1134
Maximum	10300
Standard deviation	1325



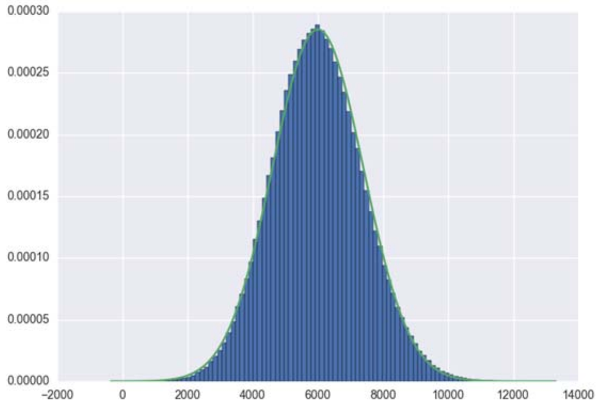
10000 samples results:	Weight [Tonnes]:
Mean	6001
Minimum	1140
Maximum	12086
Standard deviation	1409



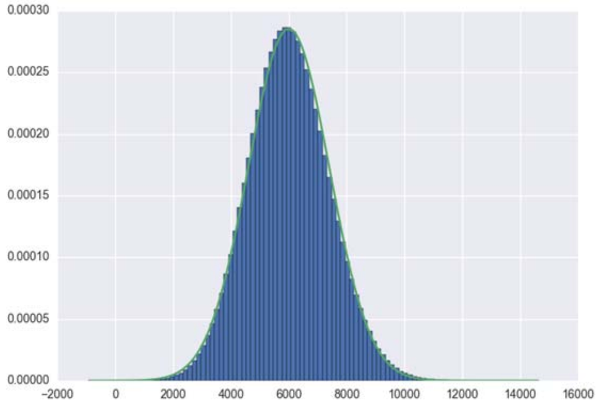
100000 samples results:	Weight [Tonnes]:
Mean	6006
Minimum	496
Maximum	13077
Standard deviation	1395



1000000 samples results:	Weight [Tonnes]:
Mean	6003
Minimum	-354
Maximum	13302
Standard deviation	1398



10000000 samples results:	Weight [Tonnes]:
Mean	6001
Minimum	-904
Maximum	14621
Standard deviation	1398



CD-ROM Content

EN7-2 Bachelor Thesis – *Optimisation of Central Offshore Process Equipment and Weight Estimations*

Combined Weight Estimation Excel Spreadsheet Example – *Equipment sizing for FF_1*

Optimisation Code Script PDF – *DOE_code_script*

Monte Carlo Code Script PDF – *FullFactorial50_for_PDF*

PDF Book – *ABB OIL AND GAS PRODUCTION HANDBOOK*

PDF Book – *Practical Regression and Anova using R, Julian J. Faraway, 2002*

PDF Article – *Use of Design of Experiment principles to develop a dose-response function for colour photographs, Ann Fenech, Tom Fearn, Matija Strlic, 2012.*