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A PROBABILISTIC APPROACH FOR COMPRESSOR SIZING AND PLANT DESIGN

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Abstract

Equipment sizing decisions in the Oil and Gas Industry often have to be made based on incomplete data. Often, the exact process conditions are based on numerous assumptions about well performance, market conditions, environmental conditions and others. Since the ultimate goal is to meet production commitments, the traditional way of addressing this is, to use worst case conditions, and often adding margins onto these. This will invariably lead to plants that are oversized, in some instances by large margins. In reality, the operating conditions are very rarely the assumed worst case conditions, but they are

usually more benign most of the time. Plants designed based on worst case conditions, once in operation, will therefore usually not operate under optimum conditions, have reduced flexibility, and therefore cause both higher capital expenses and operating expenses.

The authors outline a new probabilistic methodology that provides a framework for more intelligent process-machine designs. A standardized framework using Monte Carlo simulation and risk analysis is presented that more accurately defines process uncertainty and its impact on machine performance .

This paper describes a new method for the design of efficient plants. The use of statistical and probabilistic tools allows to better take the unpredictability of component performance, as well as ambient conditions and demand, into account. Using the methodology allows to design plants that perform best under the most likely scenarios, as opposed to traditional designs that tend to work best under unlikely worst case scenarios. A study was performed for a relatively simple scenario, but the method is not limited, and can easily be adapted to scenarios involving entire pipeline systems, complete plants, or platform operations. Based on these considerations, significant cost reductions are possible in many cases.

INTRODUCTION

During Front End Engineering Design (FEED) Process engineers often make blanket assumptions on pressure losses across process exchangers, vessels, control valves, etc. which can vary significantly from individual losses as defined in the manufacturer's specifications. Certain license processes will also recommend that a + 10% margin on flow be added to accommodate uncertainty during operation. These have been found to result in vast discrepancies between what was specified in a design office and what is found during start up in the field. Due to uncertainties in the actual design conditions for most oil and gas compression applications, compression units often are needlessly oversized. Therefore they are more expensive, and generate higher operating expenses than units that are sized closer to the actual operating conditions. The argument for oversizing is often, that these oversized units will always provide enough power to meet the operating conditions under any circumstances. However, the probability that all difficult circumstances occur at the same time is very small. Kurz et al (2013) have made this argument for pipeline operations.

Taher and Meher-Homji (2012) have pointed out the necessity for realistic margins between compressor absorbed power and gas turbine available power. All too often , these margins are applied, while looking at the equipment performance under the most extreme conditions, that is, the compressor at its highest power operating point, and the gas turbine at the highest possible ambient temperature. Needless to say that, even without the margin, the probability that the gas turbine can ever use its maximum power is virtually nil. Rather, the units, including the process valves, and process separators are oversized for practical operation purposes. Operating oversized equipment is usually a challenge: Valves tend to have poor controllability, and separators may operate at low separation efficiency if the flow they actually have to handle is much smaller than what they were designed for. Compressors may run in recycle, or very close to the control line.

Despite expensive company specifications and upper quartile maintenance practices, off design operation continues to plague the industry with catastrophic failures and inefficient plant operation. Recent data taken from 1 major Petrochemical producer indicated that over 80% of the pumps surveyed operated away from their intended design point by up to 20%. One estimate, places this cost at over 5 billion dollars per year to the global energy and petrochemical industries largely stemming from failure and operational inefficiency . The methodology has been used for other purposes related to turbomachinery. For example, Singh (1985) and Singh et al. (2004) have discussed probabilistic approaches to individual equipment items, for example turbine blades or impellers. In addition, the Monte Carlo analysis approach has been widely applied in Risk Assessment. It also has been broadly applied for logistical modeling of process plants, working on gross plant building blocks. On a smaller scale, the methodology has been applied to electrical systems, including reliability data on individual sensors of electrical components.

BACKGROUND

In the early years of the 19th century industrial quality was limited to inspecting finished products and removing defective items. Shewhart's (1939) work pointed out the importance of reducing variation in a manufacturing process and the understanding that continual process-adjustment in reaction to non-conformance actually increased variation and degraded quality. Shewhart (1939) framed the problem in terms of assignable-cause and chance-cause variation and introduced the control chart as a tool for distinguishing between the two. He concluded that while every process displays variation, some processes display controlled variation that is natural to the process, while others display uncontrolled variation that is not present in the process causal system at all times. Taguchi (1995), stressed the importance of addressing variance during product design phases by developing a framework for statistical experiments. He suggested that the design process consists of three phases: system design, parameter design, and tolerance design. In the system design phase basic concept is decided using theoretical knowledge and experience to calculate the basic parameter values to provide the required performance. Parameter design involves refining the output values in relation to control and noise factors not under the effective control of the designer. Tolerance design, he asserted, is the final stage, in which the effects of random variation of manufacturing processes and environments are evaluated to determine whether the design and processes can be further optimized.

Unfavorable variances within the Taguchi meta-model (1995) translate to greater operational risk with critical machinery. Both Barringer (2003), and Bloch (1998) have documented machinery failures that have occurred as a result of off design operation resulting from variances in the specified operating conditions. One major petrochemical manufacturer recently surveyed over 100 pumps in a process unit and found over 80% operated up to 20% away from their design point. Europump and Hydraulic Institute publications (2001) have noted that nearly 20% percent of the world's electrical energy demand and over 25% of energy usage in certain industrial plant operations account for pumping systems alone. Off design operation of pumps and turbomachinery is estimated to cost the process industry over $ 5 billion per year in failures and inefficiency.

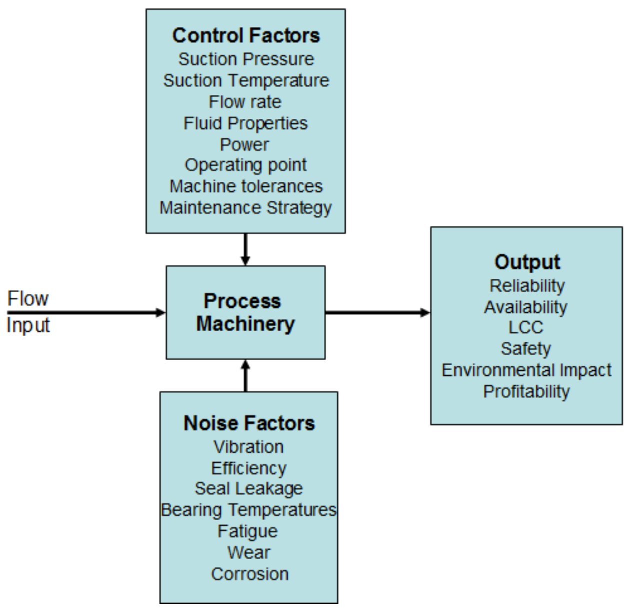

Figure 1: Meta-Model for Machinery (Taguchi, 1995)

PROCESS-MACHINERY INTERFACE

The oil, gas and petrochemical industries are a network of highly integrated production processes where products from one process may have an end use or may also represent raw materials for other processes. Operational flexibility is required to enable operators to constantly respond to changing market conditions. The impact of uncertainty is unavoidable. In production planning, sources of system uncertainties can be categorized as short or long-term. The former uncertainties involve operational variations, for example those resulting from catastrophic equipment failure. Whereas, long-term uncertainty may include supply and demand rate variability and price fluctuations that manifest themselves over a longer time line.

The optimization of down-stream process facility networks involves a broad range of aspects varying from economical and environmental analysis to strategic selection of processes . Most process engineering optimizations begin with deterministic models which will define the production capacities within the various processes. Acknowledging the shortcomings of deterministic models, parameter (process yield, raw material and product prices, and lower product demand) uncertainty is then computed using stochastic models. The results of these models in the literature have been shown to yield very different network configurations and plant capacities.

Having established technologies, processes and production capacities engineering efforts within major capital projects then develop flow diagrams. The determination of flow and pressure loss calculations are derived from non-specific assumptions based on similar equipment types or more often times on rules of thumb. Factors of safety are applied to account for long term fouling, wear or aging of equipment. Other factors of safety may be added to also account for computational uncertainty. Licensor requirements may additionally mandate a supplemental adder of 10% of flow to accommodate future expansion or operational flexibility. Machinery engineers are then provided process conditions confirmed by modeling runs expressed as deterministic normal and design points. These are used as a basis of selection for FEED engineering design. Eventually, this equipment will be specified using API Standards that may require tolerances on power of additional + 4% . In certain cases , users will size drivers on the basis of end of the curve power requirements despite falling outside allowable operating ranges or alternatively based on a future presumed increases of + 5% head in the case of API-610 centrifugal pumps. In other words, instead of proceeding in an orderly sequence of successively more precise designs as prescribed by Tagushi (1995) in the last century, the current process industry model follows a divergent path of increasing variance until it ultimately culminates in equipment purchase and start up. Figure 2 illustrates the increasing precision from conceptual design to FEED study, and to the detailed design.

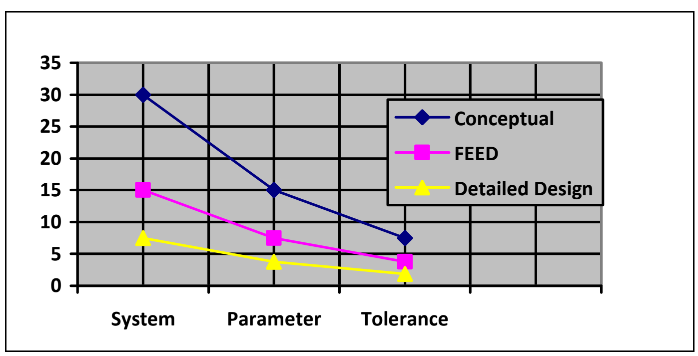

Figure 2: Maximum Process-Machine Variance

METHODS TO ACCOUNT FOR UNCERTAINTY

Two principal methods to describe the probabilistic nature of design data, and their influence on possible plant performance are perturbation methods and the Monte Carlo Analysis. Of the two methods, we have selected the Monte Carlo analysis for this study.

Using a Monte Carlo simulation, we will describe a new method, whereby one accounts for the probability that certain conditions occur. Ambient conditions, factors that influence operating conditions, or equipment performance, and others are treated as probabilistic. At the core, this is an application of the Monte Carlo method, to demonstrate the advantages of a probabilistic station design. Several examples, based on typical project requirements, will be provided.

Numerical methods that are known as Monte Carlo methods can be loosely described as statistical simulation methods, where statistical simulation is defined in quite general terms to be any method that utilizes sequences of random numbers to perform the simulation (Oakridge National Laboratory, 1995). Monte Carlo methods have been used for centuries, but only in the past several decades has the technique gained the status of a full-fledged numerical method capable of addressing the most complex applications.

Statistical simulation methods may be contrasted to conventional numerical discretization methods, which typically are applied to ordinary or partial differential equations that describe some underlying physical or mathematical system. In many applications of Monte Carlo, the physical process is simulated directly, and there is no need to even write down the differential equations that describe the behavior of the system. The only requirement is that the physical (or mathematical) system be described by probability density functions (pdf's). Once the pdf's are known, the Monte Carlo simulation can proceed by random sampling from the pdf's. Many simulations are then performed (multiple ``trials'' or ``histories'') and the desired result is taken as an average over the number of observations (which may be a single observation or perhaps millions of observations). In many practical applications, one can predict the statistical error (the ``variance'') in this average result, and hence an estimate of the number of Monte Carlo trials that are needed to achieve a given error.

CASE STUDY

The different outcomes, comparing the traditional stacking of tolerances and a probabilistic approach are demonstrated in the following example. It is based on realistic data, based on a typical scenario encountered in gas gathering operations. For gas gathering operation, either onshore or offshore, suction and discharge pressures my stay reasonably constant, especially when the application is combined with export compression.

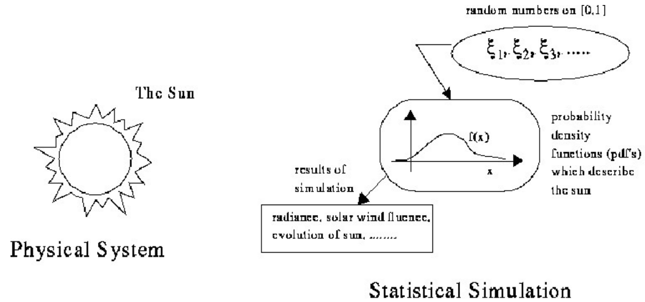

Figure 3: Monte Carlo Simulation of a physical system (Oakridge National Laboratory, 1995).

For the compressors, this means that the required head stay about the same, regardless of flow. Therefore, in general, the compressor operating points will move from the control line (and lower speed) to the choke region (and higher speed), depending on available power (Figure 4). As a result, the compressor efficiency sees significant fluctuations. If little power is available (hot days or degraded engine), the unit will go into recycle and thus off –line. The traditional design methodology would require to size the unit to produce 5% more than the design flow, at the highest ambient temperature conditions. Since there is usually some uncertainty about the gas composition that needs to be compressed, the lightest gas will be assumed for sizing the machines. For our example, we assumed a 5% variation of specific gravity around the nominal gas composition. As will be shown later, assuming the lighter gas will add about 1.4% to the compressor consumed power. This forces one to design a compressor that operates at this condition at its best efficiency, since this operating condition determines the size of the driver. Driver sizing traditionally requires to assume a 4% positive tolerance on the compressor absorbed power, and an additional tolerance between the compressor absorbed power and the driver power, to allow for engine degradation, typically in the range of 3 to 9% (for our study, we have assumed 9%). One of the reasons is the concern that the unit will go off line if the driver does not produce sufficient power to stay on line. The driver will usually be assumed with a tolerance from its nominal performance of 3%. In our example, the highest site temperature is 45C, while the most likely site temperature is 37.8C (that will be the temperature for sizing the 'probabilistic' engine). This means, that the new driver will be oversized by about 33% , compared to a driver sized strictly based on nominal values.

The gas which has to be compressed usually consists of mixtures of light hydrocarbons (alkanes), nitrogen, and carbon dioxide. In many applications, especially midstream pipeline and storage applications, but also in many upstream applications, the dominant component is Methane. Often, especially in upstream applications near the well, the gas is saturated with water. Hydrogen sulfide may also be present. The conversion of process variables (temperature, pressure, flow, gas composition) into variables relevant for the compressor (enthalpy, entropy, density) is performed using equations of state (EOS). Frequently applied EOS include Redlich-Kwong, Redlich-Kwong-Soave, Peng-Robinson , Lee-Kesler-Ploecker , the Starling version of the Benedict-Webb-Rubin model , and the AGA 8 adaptation in ISO20765-1 (Rasmussen et al, 2009).

The probabilistic design uses nominal data. We also added a case were we, arbitrarily, assumed an engine with 10% more power than in the previous probabilistic design. This margin allows to control the desired probability to be able to deliver the design flow.

Parameter	Traditional	Probabilistic	Probabilistic, 10% margin
Specific Gravity	0.7315	0.77	0.77
Compressor power consumption	110.6%	100%	110%
Design Ambient Temperature	45 C	37.8°C	37.8°C
Degradation after 4 years	9%	0%	0%
Nominal power, new engine, at 37.8 C	133.35	100%	110%
Nominal, new engine, at 45 °C	124.27%	93.19%	102.51%
Relative size	+ 33.35%	0	+ 10%

Table 1: Different design assumptions for the same application.

The Monte Carlo simulation is performed using commercially available software (@Risk®,2012).
The questions to be answered are:

- What is probability that the design flow can be met at all times , assuming a degraded engine in year 4.
- What is the average flow that will be met

The limitation in choices is acknowledged, since equipment, in this case gas turbines, come in discrete power ratings. How close the plant design matches the size of a selected driver has therefore a significant impact on the outcome of the study. However, this does not impose a limitation to the concept.

Cases where the traditional design would exactly load a certain gas turbine, while the probabilistic sizing would require the same driver, but only partially loaded, would skew the results. To eliminate this bias, it was assumed that two different gas turbines exist, that meet exactly the requirements for either the probabilistic sizing requirements or the traditional sizing requirements. Moreover, it was assumed that efficiency, part load behavior and the slope of the power-temperature relationship are the same for each driver. In the economic discussion, we will assume that both drivers have the same \$/kW cost. In reality, all these assumptions are reasonably realistic.

For the traditional plant design, the parameters are outlined in Table 1. No probabilities are applied at this stage, but rather, the design includes the typically required design margins.
For the probabilistic plant design , we assign probabilities to the following parameters:

-gas turbine available power: normal distributed around a nominal value. This is in line with typical manufacturing tolerance seen from industrial gas turbine manufacturers. The gas turbine available power variation due to manufacturing tolerances: normal distribution around a nominal value. This is in line with typical manufacturing tolerance seen from industrial gas turbine manufacturers. It is general practice to reduce the acceptance criteria for the power of engines by a certain percentage from the predicted value, for example by 3%. The same would be done for driver efficiency. Most evaluations would use the acceptance value , rather than the nominal value, for evaluations. Therefore, we assume a standard deviation of $\sigma = 1.5\%$ for the manufacturing tolerances.

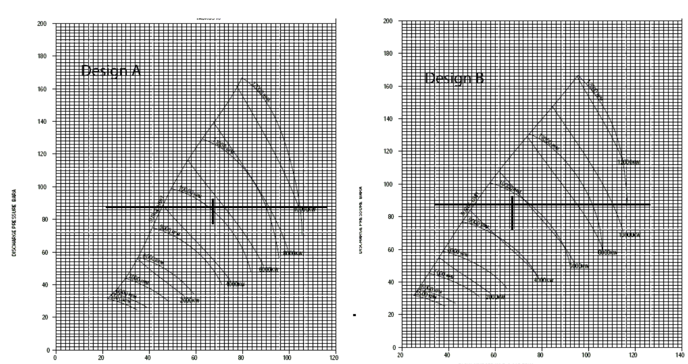

Figure 4: Compressor Map, Design A(left) and Design B (right). Design Flow and Discharge pressure are indicated. All operating points are assumed to be at constant discharge pressure, and are thus located on the horizontal line. Design B has a slightly better efficiency (+2%) at its design point than Design A, because it uses impellers with a higher flow coefficient. Impeller diameters, and number of impellers are identical for both designs.

-Ambient temperature: we assumed a triangular distribution with a most probable temperature of 37.8 C, a maximum temperature of 45C and a minimum temperature of 10C. The variation in ambient temperature serves as a surrogate for the impact of all ambient conditions that influence the available engine power.

-Gas compressor power consumption: With fixed head, the power consumption is only a function of flow and efficiency. The efficiency is assumed to be normal distributed around a nominal value. This is in line with typical manufacturing tolerance seen from industrial gas turbine manufacturers. Using an actual compressor map, the nominal efficiency of the compressor is known for any flow, along a path of constant head (Figure 6a). The model sets the station flow to zero if the compressor goes into recycle (because it crosses the control line) due to lack of power.
API 617 in general allows the compressor on the test bed to consume 4% more power than predicted above, and the driver sizing has to be appropriate for this scenario. For the purpose of this study, we did not assume that the head-flow characteristic of the compressor is subject to deviations.

-Gas Composition, expressed by gas specific gravity. One of the key problems in any plant designs is the uncertainty of the actual operating parameters of the compressors. Since we have fixed the suction and discharge conditions we are using the uncertainty in the gas composition as a surrogate for all effects on the compressor operating requirements (Figure 6b). It is acknowledged that there are many other factors, such as gas temperature, required suction or discharge pressure and others. Based on a normal distribution for gas specific gravity, and all other parameters fixed, this allows to calculate the probability distribution for the compressor absorbed power.

-Degradation: In many instances, the applied tolerances are to cover effects of engine degradation. We evaluated the performance over 4 years, with increasing levels of degradation. The level of degradation is subject to uncertainty, and we assume a normal distribution around a mean value. We look into degradation after 4 years, with a normal distribution for the degradation values. The power degradation after four years is nominal 6%, with $\sigma = 1.5\%$. (Kurz et al. (2009), Morini et al., (2010)).

-Flow capability: Based on the probabilities above, it is possible to calculate the flow the compression train can generate (Figure 6a).

To illustrate the issue, this is a possible scenario for a probabilistic plant design study. We selected a pipeline compressor example (others are equally possible), because a probabilistic element can easily be incorporated (in this case the friction losses in the pipeline). We can also easily define the required performance (delivering a certain amount of flow at a certain pressure). We also can introduce the variation in equipment performance (compressor efficiency and driver output), as well as ambient conditions.

Figure 5 shows the nominal site available power versus ambient temperature for a new engine. The power demand for the compressor, between traditional design parameters and probabilistic design parameters is increased by over 33%. This constitutes a significant increase in CAPEX and OPEX, the latter due to the fact that maintenance cost roughly tracks with power. Although gas turbine ratings are only available in discrete sizes, and increase of 33% in power output usually means the difference between at least one driver size. We will not take size mismatch into account for the calculations for the larger driver, since this mismatch could affect the sizing of both the smaller and the larger driver. We therefore assume a driver exists, that exactly meets at full load the project requirements, and has the same manufacturing tolerances and non-dimensional efficiency versus load behavior regardless of size.

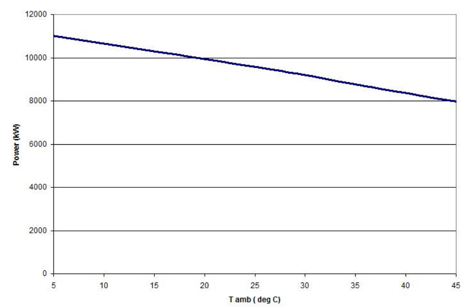

Figure 5: Nominal site available power for new gas turbine driver.

For the situation at hand, we also have to consider that we have different options of sizing the compressor. To show this, we have actually created two compressor designs, that operate a somewhat different surge margin at the design point. Design A has about 25.6% surge margin at the design point, while Design B has about 17.1 % surge margin at the design point (Figure 4). This means, that the chance that the compressor goes into recycle (and the flow goes to zero) is higher for Design B. On the other hand, it will show better performance at higher flows, that is, when the engine produces more than design power.

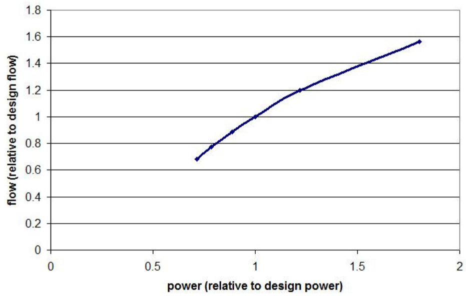

Figure 6a Relationship between compressor power consumption and compressor flow for a constant head application (Design A).

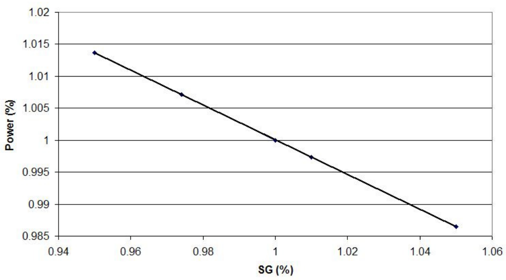

Figure 6b: Impact on change of gas composition on compressor power consumption

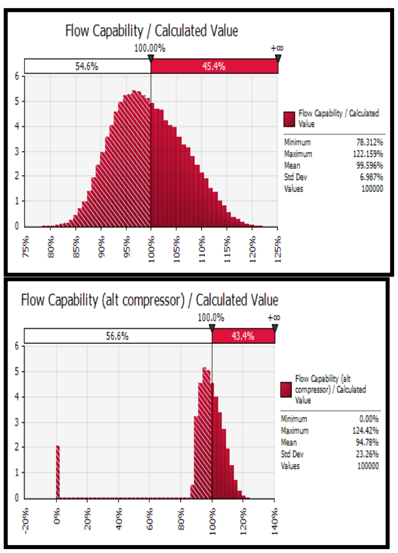

Figure 7: Probability of meeting the design flow demand (100%) with a selection based on nominal data in year 4. Design A compressor selection left, Design B compressor selection, right. Due to its lower design surge margin, the Design B compressor may go into recycle, and thus the flow becomes zero. The mean achieved flow (99.6%) of Design A is clearly better, and almost meets the required design flow.

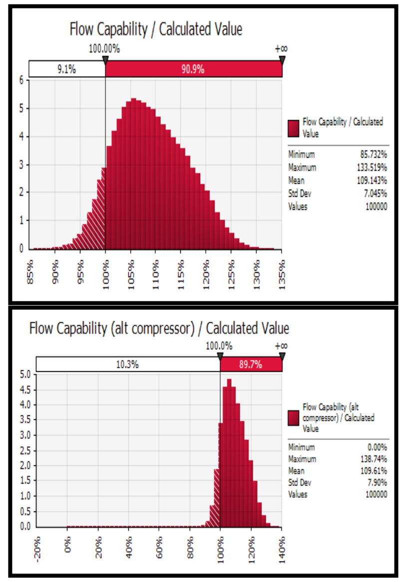

Figure 8: Probability of meeting the design flow demand (100%) with a selection based on nominal data and 10% power margin in year 4. Design A compressor selection left, Design B compressor Selection, right. Design B still has to resort to recycle at a few instances. However, the mean achieved flow is almost identical for both designs, and exceeds the required design flow.

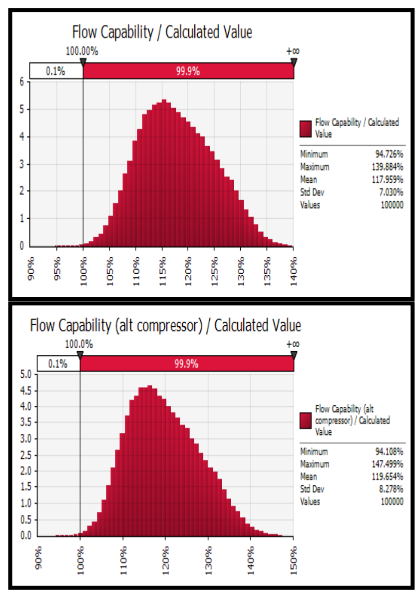

Figure 9: Probability of meeting the design flow demand (100%) with a selection based on nominal data and 20% power margin in year 4. Design A compressor selection left, Design B compressor Selection, right. Design B provides a slightly better average flow (119.7%). Both designs meet the full demand over 99.9% of the time.

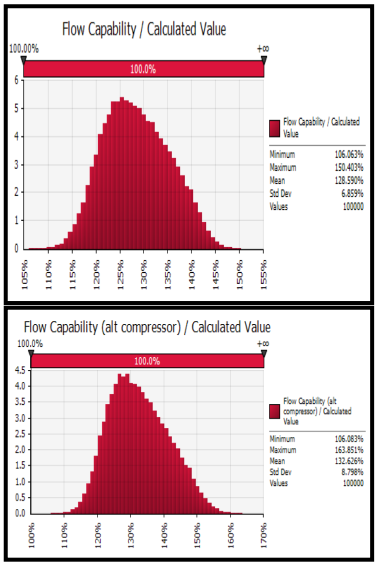

Figure 10: Probability of meeting the design flow demand (100%) with a selection based on nominal data and 33.35% power margin in year 4. This would be the performance of a traditionally sized compressor train. Design A compressor selection left, Design B compressor selection, right. Both designs exceed the 100% demand at all times. Design B provides a higher average flow (132.6%) than Design A.

The result of the Monte Carlo Simulation is a probability distribution for the delivered flow (Figures 7 to 10), always assuming engines that are in their 4th year of operation, with the associated engine power degradation. For an engine sized strictly for nominal requirements, that is without margins for gas turbine and compressor performance, no allowance for degradation, the nominal specific gravity, and the most frequently occurring temperature, the package only reaches (assuming Design A) the required flow 45.4% of the time. However, the average flow this configuration can achieve is still 99.6% (Figure 7). Design B shows one of the problems resulting from the lower design surge margin: The machine goes occasionally off line, because the recycle control line is crossed. It therefore only flows on average 94.8% of the flow, and meets the full demand 43.4% of the time.

Figures 8 and 9 show the behavior for engines sized for 10% and 20% more power than the nominal configuration shown in Figure 6. In these cases, the average flow is above 100%, with a slight advantage for design B. Moreover, the design with 20% margin meets the design flow practically always (over 99.9% of the time).

For the results in Figure 10, the engine was sized to meet the traditional approach. In other words, it is sized with margins for gas turbine and compressor performance, an allowance for degradation, the highest ambient temperature, and the lightest gas. This adds up to a 33.5% power margin over the nominal design shown in Figure 7. Obviously, this configuration will meet and exceed the design flow demand at all times, for both compressor designs. The Design B is advantageous is this case, due to its higher flow capability, and can, on average, achieve over 132% of the design flow.

We therefore see, that the probability to meet the flow demand at all times, with an engine, designed for nominal and most likely process conditions, is about 45%. On the other hand, if we just add 20% margin (as opposed to the 33.5% that would result from the traditional design), the probability becomes about 99.9%. It should be noted, that we state the probability for not meeting the flow demand. Even in cases where the flow demand is not met (situations where the power margin is negative), the station will still flow gas. It just will be somewhat less than the design demand. Therefore it is important to evaluate the average flow capability, which takes into account that the shortfall in flow at certain times can be compensated by excess flow at other time- assuming the process equipment is designed to make use of this capability. It also must be mentioned that this example describes the situation after the engine has been running for 4 years. In earlier years, with less degradation, the margins become more favorable.

The biggest influence on the capability of the train to meet the flow requirements is in the ambient temperature (Figure 11). This indicates that even if all other factors mentioned in this study are neglected, a careful consideration of actual site temperature distributions alone can give good insights into the sizing requirements.

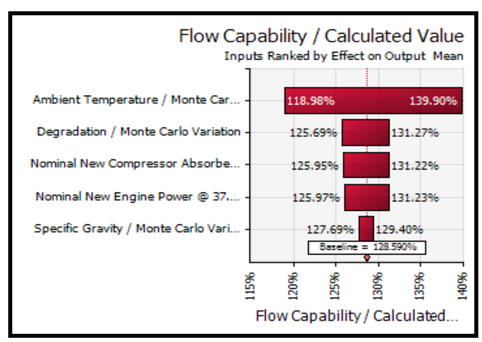

Figure 11: Inputs ranked by effect on output mean. This chart is for design A with 33.5% margin, but it is typical for all examples.

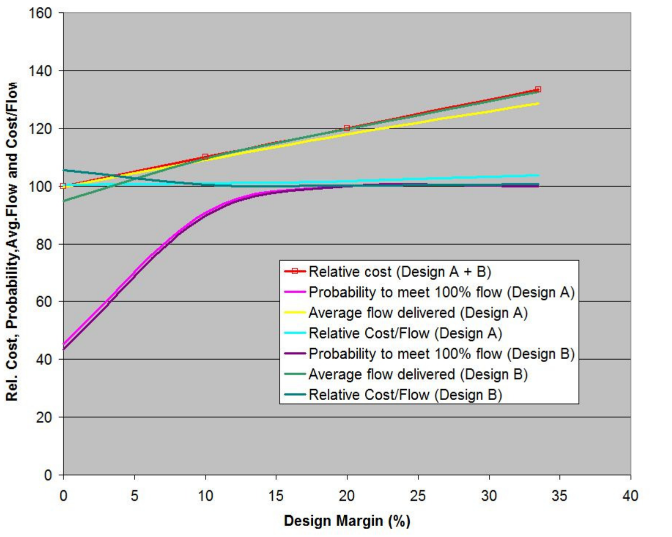

Figure 12: Comparison of cost, probability to meet the design flow, average flow delivered and cost per flow delivered, for Designs A and B.

The overall results are shown in Figure 12. We show the cost of oversizing the engine based on the assumption of a constant $/kW cost. The traditionally sized driver, in our example, would be about 33.5% more expensive than the driver sized based on nominal conditions. Maintenance costs scale also at an approximately constant $/kW value, so they also would be about 33.5% higher. This has considerable impact in particular for CAPEX and OPEX constrained projects. If the project specifics allow to satisfy the design flow on average, virtually no power margin is necessary. An increase in driver size yields improvements, but this assumes that the rest of the station equipment, and the gas supply are sufficient to use that capability. A power margin of about 20% can assure that the flow demand is met even in the 4th year of driver operation. It also must be mentioned that, while the increase in average flow for higher margins looks attractive, it will look significantly less attractive in the earlier years. This is due to the fact that the compressor will operate further near choke, and at decreasing efficiencies if large amounts of surplus power is available. Eventually, the compressor will become speed limited, and cannot absorb additional power.

This becomes clear when we look at the cost for a certain amount of flow delivered. Here, Design A, with no design margin, and Design B with 10 to 20% margin tie for the lowest cost per flow delivered. Design A is clearly better than Design B for low power margins, while Design B is favorable for high flow margins.

Again, it needs to be emphasized that gas turbine drivers are not manufactured in a continuum of power ratings. The other results show the capability of the train to always deliver the required flow, as well as the average flow that can be delivered.

The argument for this type of study does not include the impact on fuel consumption, which has been covered in other studies (Kurz et al., 2013).

APPLICATIONS

The example was used to highlight the significant savings that can be accomplished by more appropriate plant designs. As shown, the savings in installed power can be significant. In evaluating potential savings, the user must be clear about the goal of the optimization. For example, if the value of production is very high, the value of incremental production will always outweigh incremental cost of the equipment – up to the point where incremental production is limited by other factors, such as the capacity of the facility, the capacity of the recipient of the production, or the capacity of the wells. However, we have to assume that the overall design flows for the project are realistic, and the goal is to meet these flows with a limited amount of expense.

Another important application is based on the fact that gas turbines are available only in discrete sizes. Many compression installations are sized to meet certain process needs (Rasmussen et al., 2009). For example, a gas injection application may be sized on a certain flow requirement (to meet the desired oil recovery), and to meet a certain discharge pressure (based on a predicted reservoir pressure). Similarly, a gas export application would be based on the amount of gas available (an estimate), and the pressure drop in the pipeline (just as in the example above, subject to uncertainty). The suction and discharge requirements for a pipeline compressor, sized to meet certain flow demands, are subject to the friction losses in the pipeline (Kurz et al, 2013) . All these values are subject to uncertainty. So is the distribution of ambient temperature, as well as the degradation behavior of the driver, the driven equipment, the process equipment and the pipeline. If the nominal values and tolerances are used, the application would require a certain power from the driver, that may be between available driver sizes. The probabilistic method can, in this case, be used to determine the probable economic impact of a slightly smaller (and less expensive) or an oversized driver.

The simulation can also be used to determine the capability of an existing plant. Again, in that case the parameters for the existing units (possibly based on test data, or based on prognostics (Venturini et al, 2012) would be entered. The results allow determining the firm output commitments that can be made. Further, it is possible to determine the allowable performance deterioration before the delivery commitments are jeopardized. Thus, maintenance and overhaul decisions can be made on a more rational basis.

CONCLUSION

This paper defines a new method to design efficient and safe plants. The use of statistical and probabilistic tools allows to better take the unpredictability of component performance, as well as ambient conditions and (although not demonstrated in this paper) demand, into account. Using the methodology allows to design plants that perform best under the most likely scenarios, as opposed to traditional designs that tend to work best under unlikely worst case scenarios. This study was performed for a relatively simple scenario, but the method is not limited, and can easily be adapted to scenarios involving entire pipeline systems, complete plants, or platform operations. New approaches to the discussion of spare units are possible. Based on these considerations, significant cost reductions are possible in many cases.

The other 'new' concept follows from the fact, that neither the equipment manufacturers, nor the engineering contractors (or end user) have all information by themselves. Thus, the methodology described requires close collaboration during project development.

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