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Reliability based performance modelling and evaluation: A case study of heat exchanger

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Abstract
This paper presents an approach that combines First Order Reliability Method (FORM) with Monte Carlo Simulation (MCS) to solve constrained stochastic optimization problems in a proficient way. Based on FORM/MCS, this paper shows how parametric uncertainties can be characterized, modelled, propagated across the life cycle of an engineering system and then obtain a wide range of performance measures that can support engineers as they seek to improve design/operational robustness, safety and cost efficiency. A case study involving counter flow heat exchanger is performed to illustrate applicability and usefulness of the approach. Impacts of uncertainties on the worth of energy to be recovered by the heat exchanger from waste process fluid are represented through probability distributions, bounds and a number of performance measures. Sensitivity of the performance target, in this case, financial gain, to each of the basic variables is determined, both in magnitude and direction. Two sets of specifications are also considered to demonstrate that the approach can be used to conduct reliability based performance improvement without attracting disproportionate cost.

Keywords: Reliability analysis; Uncertainty modelling; Heat exchanger; Energy recovery; Stochastic optimization.

1. Introduction
Engineering facilities have to be designed to withstand certain degree of variability in physical operating conditions and market forces. After the traditional steady state design, control systems are usually added to help keep the system within some acceptable limits; the controllers must be suitable and optimally tuned to serve some specific functions. In addition, selection of design materials, equipment sizing, prediction of production in both quantity and quality, estimation of total investment costs including operating cost during the life cycle of the facility and impact of inflation/interest rates have to be done, preferably at the early design phase. But all these vital decisions have to be made in the presence of uncertainties which come from a number of sources such as: Mathematical Modelling (usually due to oversimplification, lack of knowledge or wrong/misapplication of the model), statistical uncertainty (due to lack of good data), human factors (due to differences in perception/interpretations) and physical uncertainty (due to random input/process variations). Thus, chance of over or under design is always expected; while the former implies overspending, under design may compromise system performance

and general efficiency; ideally, neither is acceptable. In the presence of these kinds of uncertainties, the engineers are expected to design facilities that are fit for purpose, predict overall performance/cash flows, ensure cost efficiency, including safety of lives, equipment and the environment. This calls for more research into stochastic approaches for uncertainty modelling and analysis [1, 2]. In their works, Whiting *et al* [3], Clarke *et al* [4] and Wakeham *et al* [5] gave some insights into uncertainties, their preponderance in engineering systems and some of the factors affecting modelling approaches in terms of accuracy, time consumption and computational difficulties. These problems suggest that refined approaches to uncertainty quantification would be of benefit to engineers and other stakeholders such as managers and regulatory bodies. Subsequently, research began to concentrate on application of specific aspects of reliability engineering to process systems engineering. For instance, Arellano-Garcia & Wozny [6] and Al-Qahtani & Elkamel [7] have proposed some methodologies for process optimization under uncertainty. These works highlight advantages of stochastic approaches over the deterministic methods which often fail to capture low probability events that may well be of high consequence. Stochastic approaches aim to integrate more realistic service/operating settings into the analysis. Furthermore, Abdelaziz & Radermacher [8] proposed a theoretical methodology for modelling heat exchanger performance under uncertainty. However, application of the methodology is limited to air-water heat exchangers. This paper combines one of the advanced structural reliability techniques, termed, First Order Reliability Method (FORM) with Monte Carlo Simulation (MCS) to optimise designs and enhance performance predictions based on a wide range of stochastic performance measures in a simpler way. Problem formulation strategy and solution procedure featuring FORM and MCS are discussed. Also, for illustrative purposes, a case study involving heat exchanger performance and economic evaluation is considered. Ignoring the uncertainties, Teke *et al* [9] and Ağra [10] used this case study to demonstrate a deterministic model that can be used to determine the right heat exchanger type to achieve a given saving - investment ratio.

2. Methodology

2.1 Uncertainty modelling: Mathematical formulation

First, Key variables governing performance of the candidate system, a heat exchanger in this case, have to be identified. Each of these variables having significant uncertainty, set of which is denoted by the vector $\underline{X}$, is characterized in terms of bound/range and appropriate probability density function. Next, an objective function is developed to capture a design/operational target. This can be achieved in a number of ways including real experimentation, (especially when looking at an in-service system) and analytical mathematical modelling involving mass & energy balances, thermodynamic principles and/or reaction kinetics, among others. In a situation where the objective function is overly complex, absent or available in an implicit form, response surface methodology [11] could be employed to construct a surrogate or the so called black box model; this approach has been found to give functions that are fairly accurate for reliability analyses [12]. Having built the objective function, $\Psi(x)$, a threshold, Ω, for the design/operation target is then decided guided by experience, deterministic optimization results, market data or regulatory requirements such as the need to minimize production of certain pollutant, etc. Another mathematical function, $G_{\underline{X}}(\underline{x})$, usually termed Limit State Function (LSF), is set up and mapped from the physical space (X) to standard normal space (Z), [such that: $Z \sim N(0,1)$], which is a space of uncorrelated standard normal variables, depicted in Figure 1. The transformation is achieved thus:

$$Z_i = \frac{X_i - \mu_{X_i}}{\sigma_{X_i}} \tag{1}$$

where μ_{X_i} and σ_{X_i} are the first and second moments respectively, X_i is a given realization of the uncertain variable. It is worth to note that non Gaussian variables can also be handled through the normal tail transformation as discussed by Melchers [13]. Such transformation is necessary in order to normalize the design/operation space about the mean value of the objective function. In the physical (X) space, some of the problems that could affect the analysis include effects of different units-sets on the coefficients of the surrogate model and possible correlation among the uncertain variables. This transformation also ensures that the point closest to the origin from the failure domain is where the highest probability density portion is located and the design/operation target is most sensitive to this point [14].

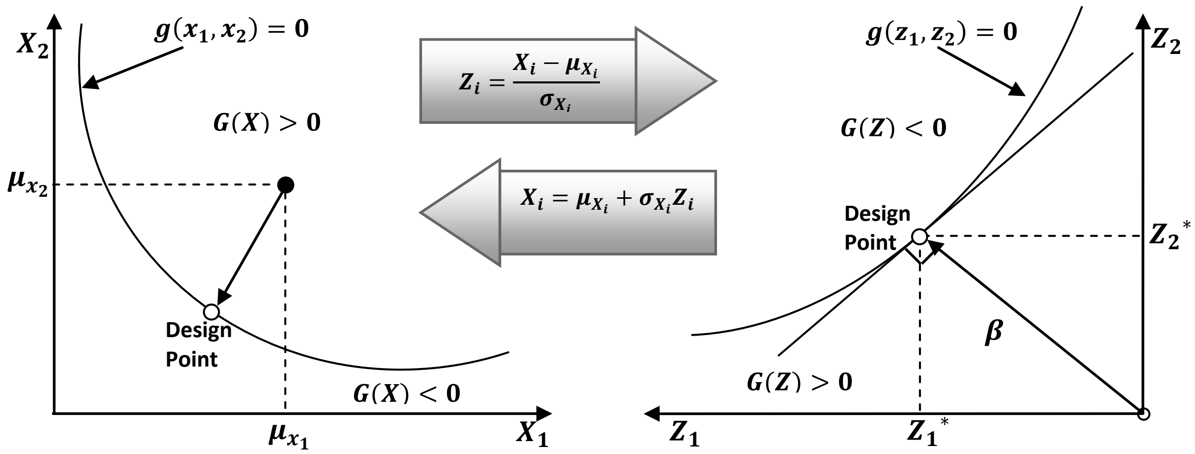

Figure 1. Failure surface transformation from physical (X) to standard normal space (Z) for a non-linear safety margin involving two independent Gaussian variables

The LSF is defined to split the performance space of the system into success (feasible) and failure (infeasible) regions in the standard normal space. Geometrically, the limit state surface can be visualised as an $(n-1)-$ dimensional hyper-surface in the space of the basic variables $\underline{X}$ [15]. As illustrated in Figure 1, this surface divides the design or operation domain into failure and non failure regions. Hence, giving a system under uncertainty, we may, for instance, wish to determine the chance that the system assumes a value equal to or less than the threshold Ω, thus:

$$P_f = P[\Psi(x) \leq \Omega] = P\left[G_{\underline{X}}(\underline{x}) \leq 0\right] \tag{2}$$

where P_f is the probability of "failure" to achieve indented design/operation target. The LSF may be built such that failure is deemed to have occurred whenever $G_{\underline{X}}(\underline{x}) \leq 0$, consequently, $G_{\underline{X}}(\underline{x}) \geq 0$ implies success, safety or non failure. The reverse of this definition may also be true depending on the physical meaning of the design/operation target. Therefore, strictly speaking, P_f does not always quantify failure probability, it could be the other way round. The reliability value can be obtained from, $R_p = 1 - P_f$, (if P_f denotes failure probability). In terms of the joint density function, the probability value can be expressed thus:

$$P_f = \int \dots \int_{G_{\underline{X}}(\underline{x}) \leq 0} \dots \int f_{X_1, X_2, \dots X_n}(x_1, x_2, \dots, x_n) . dx_1 . dx_2 . , \dots, dx_n \tag{3}$$

where $f_{X_1, X_2, \dots, X_n}(.)$ is the joint probability density function for the n uncertain variables.

2.2 Solution techniques

In practice, Eq.3 could be quite complex featuring non Gaussian variables, high dimensionality and interacting/correlated variables with response surface displaying significant nonlinearity. In a simple and efficient way, this paper shows how non linear programming problems can be solved by combining both MCS and FORM analysis. MCS is a well known technique, hence will only be briefly highlighted here. On the other hand, FORM analysis, which is relatively new especially in chemical engineering applications [13], will be described at length in what follows. To solve Eq.3 based on MCS method, first, an indicator function, $I(x)$, defined in Eq.4, is introduced to shift integration domain of Eq.3 into real space.

$$I(x) = \begin{cases} 1, & G_{\underline{X}}(\underline{x}) \leq 0 \\ 0, & G_{\underline{X}}(\underline{x}) > 0 \end{cases} \tag{4}$$

Simple Matlab code can be scripted to execute the computation steps. In this case, a computer program was written to index the in/output data and extract responses satisfying the prescribed constraint, $G_{\underline{X}}(\underline{x}) \leq 0$. Total sample size, n_T and the indicator function counts were then used to estimate P_f, thus:

$$P_f \cong \frac{1}{n_T}\sum_{i=1}^{n} I(x_i) \tag{5}$$

Extensive literature on MCS methods including illustrative case studies are given in Thoft-Christensen & Baker [15], Labeau & Zio [16] and Naess *et al* [17]. As mentioned earlier, First Order Reliability Method (FORM) can be employed to solve the optimization problem. FORM analysis seeks to determine the most probable design/performance point ($\underline{Z}^*$) and the corresponding success/failure probability. Other performance measures, such as sensitivity indices α_i and reliability index β, can also be obtained through FORM analysis.

After the transformation, Taylor series expansion is then employed to linearize the objective function at the design point ($Z_1{}^*$, $Z_2{}^*$), where highest probability density is located. This point corresponds to the intersection between a line segment from the origin (β) and the failure surface, ($G(Z_1, Z_2) = 0$), shown in Figure 1.This line segment is the shortest distance from the origin to the surface and is termed reliability index, β. Ignoring higher order terms of the Taylor series, the linear function (a hyper-plane for higher dimensional systems) at the most probable design point ($\underline{Z}^*$) in the standard normal is given by:

$$G(\underline{Z}) \approx \|\nabla G(\underline{Z}^*)\|(\beta - \alpha^T Z_i) \tag{6}$$

where α_i are the sensitivity indices, i.e. the direction cosines of β along the respective coordinates evaluated at $\underline{Z}^*$ and give quantitative measures of the sensitivity of the system performance to perturbations in the basic variables, It can be shown that [14, 18]:

$$\alpha_i = \frac{Z_i{}^*}{\beta} = \frac{-\nabla G(Z_i)}{\|\nabla G(Z_i)\|} \tag{7}$$

Therefore, the problem has essentially reduced to a constrained optimization problem, seeking to minimize β which is orthogonal to the surface, $G(\underline{Z}) = 0$, it can be shown that:

$$\underline{Z}^* = arg\ min\left\{\|\underline{Z}\| \mid G(\underline{z}) = 0\right\} \tag{8}$$

where $\|\underline{Z}\|$ is the norm of the vector $\underline{Z}$ in the Euclidean space representing the distance from the origin to the failure surface in standard normal space, β can thus be expressed as:

$$\beta = min\sqrt{\sum_{i=1}^{N} Z_i{}^2}\ \ , \text{ Subject to } G(Z) = 0 \tag{9}$$

and the probability of failure given by:

$$P_f = \Phi(-\beta) \tag{10}$$

where $\Phi(.)$ is the standard normal cumulative distribution function. Eq.10 gives an exact solution if the LSF is linear [14].

A number of algorithms have been proposed to search for the design/operation point, $\underline{Z}^*$, details on these search schemes can be found elsewhere [19]. In this paper, we used improved Hasofer - Lind - Rackwitz - Fiessler (iHLRF) iterative algorithm. More details on iHLRF can be found in [13, 15]. After the transformation from X to Z −Space, iHLRF algorithm is used to search for the design/operation point, a general search scheme is given by:

$$Z_{m+1} = Z_m + S_m.\Delta \tag{11}$$

where m is the iteration counter, Δ is the search direction and S_m is the step size corresponding to the m^{th} iteration. The initial trial point is usually selected to be the mean point on the limit state surface in physical space which corresponds to zero in the standard normal space since $Z \sim N(0,1)$. Both α_i and the $G_{\underline{Z}}(\underline{z})$ are evaluated at trial design point, $\underline{Z}^{*'}$ to give $\alpha_i{}^0$ and $G_{\underline{Z}}(\underline{z}^0)$ respectively. The vector, $Z_i{}^*$ (given by Eq.12), is evaluated a number of times and in each case the corresponding value of the LSF $G_{\underline{Z}}(\underline{z})$ is computed until convergence is achieved, i.e. until $G(\underline{z}) = 0$ or ≈ 0.

$$Z_i{}^* = \alpha_i{}^0 \times [(\alpha_j{}^0 Z_j{}^0)^T - G(\underline{Z}^{*'})]/\left(\alpha_j{}^{0^2}\right)^T \tag{12}$$

The resulting coordinate $\underline{Z}^*$, is used to calculate the required minimum distance β, defined by Eq.9. Some of the mathematical expressions given earlier can be employed to compute other performance measures depending on the level of details required. Note that Eq.1 can be used to map the design point $\underline{Z}^*$ back to the physical space $\underline{X}^*$. The resulting stochastic performance measures can then be used by the engineer to support uncertainty-laden decisions. As in the case of MCS, the FORM analysis can be simplified by scripting some computer codes to execute the procedure described above.

In the next section, a case study involving heat exchanger performance and economic evaluation will be considered. The case is adopted from Teke *et al* [9] and Ağra [10] where the financial performances of six different heat exchangers were modelled deterministically. Although the model ignores both epistemic and aleatory uncertainties, it provides a reasonable basis for comparative analysis assuming that all the heat exchangers are subject to the same level of noise. As expected, out of the six heat exchanger configurations, the study showed that counter flow exchanger is the best for the situation at hand; resulting in a net gain of about $\$1.3$ in the 15 year life-cycle of the equipment. Parallel flow configuration was ranked least accruing a net gain of about \$930,238. Obviously, a number of factors can affect these estimates including random variation in operating temperatures and flowrates of both fresh and waste streams, uncertainty in the value of the overall heat transfer coefficient which could be up to [20] $\pm 50\%$, changes in pressure drop across the heat exchanger, uncertainties in inflation rates, interest rates, fuel prices and fatigue/wear/ageing effects on both boiler and heat exchanger which can affect their respective efficiencies. On the other hand, investment cost estimates are significantly affected by uncertainties emanating from the basic costs due to delivered equipment, equipment erection, piping, instrumentation/control, utilities, off-sites, engineering design/construction and working capital, all these cost estimates are associated with some degree of uncertainties especially at the initial design stage where in-depth detail is unavailable. Deterministic estimates may not provide adequate information on the degree of uncertainties associated with the results [21, 22], decision makers such as engineers, operators and managers are left with incomplete information; hence the need for stochastic modelling, which is the main goal of this paper. A wide range of valuable decision measures will be computed based on both FORM and MCS methods.

3. Sample application and discussion

3.1 A case Study of counter flow heat exchanger

For illustrative purposes, stochastic modelling and analysis of a counter flow heat exchanger, which was modelled deterministically by Teke *et al* [9] and Ağra [10], will be conducted in this section. Stochastic approach is needed to make the modelling more realistic, providing valuable performance measures that can be used to support critical decisions on the heat exchanger during the design phase and over its 15 year life-time. Detail on this case study is given in Table 1. The work involves derivation of two functions, one for modelling energy recovery and the other for estimating the total financial investment covering initial equipment costs, freight, installation, operation and maintenance, among others. The difference between these two functions, which are to be evaluated based on the given specifications, gives the net gain due to the counter flow heat exchanger.

Based on the resulting cost function, A LSF is then set up to capture the deterministic net gain, which is the target threshold in this case. Subject to constraints, system of the equations is then solved using both FORM and MCS frameworks to obtain the required information. For this particular case study, a major target is the net financial gain from the heat exchanger assuming a nominal life of 15 years. It can be shown that the Net Present Value of the Gain, $NPVG$ is given by:

$$NPVG = 3600.\mathcal{E}_{hex}.C_P M_{ww} \int_0^{8760} (T_{hi} - T_{ci}).dt \frac{F}{\eta_{blr}.Hu}\left[\frac{1}{r-e_r}\right]\left[1-\left(\frac{1+e_r}{1+r}\right)^n\right] - I_c A$$
$$= Q\frac{F}{\eta_{blr}.Hu} PWF - I_c NTU * C_{min}/U \quad (13)$$

where $\mathcal{E}_{hex}$, η_{blr} are the heat exchanger and boiler effectiveness/efficiency respectively; C_P is the specific heat capacity of water (J/kg °C), (assumed to apply to both fresh and waste water streams, hence the ratio, $C_r = C_P.M_{ww}/C_P.M_{fw} = M_{ww}/M_{fw}$); T_{hi}, T_{ci} are the temperatures of the hot (waste) and cold (fresh) water streams respectively; M_{ww} is the Mass flow rate of waste fluid (kg/s); F is the fuel Price, $(\$/kg)$; Hu is the lower calorific value of fuel, (J/kg) and f is the fuel price rate, (%); while [10, 23]:

Table 1. (a) Heat exchanger performance specifications, adopted from [10, 23]

Parameter	Symbol	Specification
Temperature of waste fluid	T_{hi}	40°C
Mass flow rate of waste fluid	M_{ww}	3.8 kg/s
Mass flow rate of fresh water	M_{fw}	7.59 kg/s
Lower calorific value of fuel	Hu	$41e+06\, J/kg$
Boiler efficiency	η_{blr}	0.85
Operation time per year	t	$8300h$
Life of heat exchanger	n	$15year$
Overall heat transfer coefficient	U	1200 W/m^2K
Heat exchanger cost per unit area	I_c	$350\$/m^2$
Fuel Price	F	$0.5\$/kg$
Specific heat of cold and hot fluid	C_p	4186 $J/kg\ C$
Inflation rate	G	0.2 (%)
Interest rate	I	0.32 (%)
Fuel price rate	F	0.25 (5)
Number of Transfer Units	NTU	4

Table 1. (b) Average water temperature – time records for the heat exchanger in one year, adopted [10, 23]

Water Temp. (°C)	10	14	17	20	25
Temp. Change ΔT (°C)	30	26	23	20	15
Operating, time Δt (hrs)	1000	1500	1800	3000	1000

Real interest rate (%),

$$r = (i-g)/(1+g) \quad (14)$$

Real price rate (%),

$$e_r = (f-g)/(1+g) \quad (15)$$

Present Worth Factor,

$$PWF = \left[\frac{1}{r-e_r}\right]\left[1-\left(\frac{1+e_r}{1+r}\right)^n\right] \quad (16)$$

And the recovered energy from waste water per annum Q given as,

$$Q = 3600.\mathcal{E}_{hex}.C_{min}\int_0^{8760}(T_{hi}-T_{ci}).dt \tag{17}$$

Next, to reflect the uncertainties in the heat exchanger performance, $\mathcal{E}_{hex}$, η_{blr}, M_{ww} and I_c are assumed to be stochastic. For brevity, the other variables are assumed to be fairly well known or represented by the four uncertain variables being modelled. Each of these uncertain variables is characterized by a range, $[a, b]$ and a probability distribution. $\mathcal{E}_{hex}$, η_{blr} and M_{ww} are assumed to be governed by Gaussian distribution while I_c is modelled by uniform/rectangular distribution. First and second moments of each of the variables are then evaluated. For the Gaussian variables, the second moment corresponding to a $100(1-\alpha)\%$ confidence level can be is estimated from a modified version of Eq.1, thus:

$$\sigma_{X_i} \cong \frac{L_i-\mu_{X_i}}{Z_{i(1-\alpha)}} \tag{18}$$

Where $L_i = |a| = |b|$ (true for Gaussian variables) and $Z_{i(1-\alpha)} = 2.575$ is the Z −score corresponding to 99% confidence level, which can be read from standard normal distribution table. For the rectangular distribution, the first two moments are respectively given by:

$$\mu_i = (a+b)/2; \quad \sigma_i = \sqrt{(b-a)^2/12} \tag{19}$$

For a counter flow heat exchanger, the deterministic effectiveness value is calculated using:

$$\boldsymbol{\mathcal{E}_{hex}} = \frac{\mathbf{1-exp[-NTU(1-Cr)]}}{\mathbf{1+Cr.exp[-NTU(1-Cr)]}} \tag{20}$$

where $C_r = M_{ww}/M_{fw}$ (assuming that same specific heat capacity value applies to both fresh and waste water streams). Table 2 summarizes the preliminary data which will be used for further analysis. Next, after developing the objective function (Eq.13), a limit state function is set up to capture the deterministic Net Present Value of the Gain, $NPVG_{Det} = \$1.3M$, thus:

$$G_{\underline{X}}(\underline{x}) = NPVG - NPVG_{Det} \quad \text{so that:} \quad P_f = P[NPVG - NPVG_{Det} \leq 0] \tag{21}$$

Table 2. Performance and cost data for a counter flow heat exchanger

Parameter	Bound $[a, b]$	Mean	Stdev	Distribution
Mass flow rate of waste fluid, M_{ww} (kg/s)	3.2 – 4.4	3.8	0.233	Gaussian
Heat exchanger effectiveness, $\mathcal{E}\_hex$ (%)	70.93 – 90.93	80.93	3.883	Gaussian
Boiler efficiency, η_{blr} (%)	79 – 91	85	2.330	Gaussian
Heat exchanger cost per unit area, I_c (\$/m^2)	310 – 390	350	23.094	Rectangular

The LSF is then transformed from the physical space (X) to standard normal Space (Z) using Eq.1. FORM along with MCS analysis method, as described earlier, is then used to compute the desired performance measures, presented in Tables 3, 4 and Figures 2-4.

Table 3. Scenario A- Performance measures characterizing the nominal performance specifications

FORM Analysis			Monte Carlo Analysis
Parameter($\underline{X}$)	α_i	Design Point ($\underline{X}^*$)	$\mu_{NPVG} = \$1.162 * 10^6$
η_{blr}	−0.352	0.839	$\sigma_{NPVG} = \$9.776 * 10^4$
$\mathcal{E}_{hex}$	0.585	0.841	$[a, b]_{NPVG} \cong [\$7 * 10^5, \$1.7 * 10^6]$
I_c	−0.016	349.285	$skewness = -0.149$
M_{ww}	0.731	4.035	$kurtosis = 3.03$
HL – Index, $\beta = 1.38$			HL – Index, $\beta = 1.4115$
$P[NPVG_{Det} - NPVG \leq 0] = 0.0839$			$P[NPVG_{Det} - NPVG \leq 0] = 0.0821$

Table 4. Scenario B- Reliability based performance measures

FORM Analysis			Monte Carlo Analysis
Parameter$(\underline{X})$	α_i	Design Point $(\underline{X}^*)$	$\mu_{NPVG} = \$1.264 * 10^6$
η_{blr}	-0.349	0.842	$\sigma_{NPVG} = \$1.177 * 10^5$
$\mathcal{E}_{hex}$	0.565	0.866	$[a,b]_{NPVG} \cong [\$7 * 10^5, \$2 * 10^6]$
I_c	-0.016	350.792	$skewness = -0.137$
M_{ww}	0.747	3.933	$kurtosis = 3.02$
HL – Index, $\beta = -1.53$			HL – Index, $\beta = -1.51$
$P[NPVG_{Det} - NPVG \leq 0] = 0.937$			$P[NPVG_{Det} - NPVG \leq 0] = 0.936$

3.2 Discussion

In the presence of uncertainties, stochastic methods can be used to intensify designs and obtain more realistic design and economic measures. For instance, given the degree of noise associated with mass flow rate of waste fluid, M_{ww}, heat exchanger effectiveness, $\mathcal{E}_{hex}$, boiler efficiency, η_{blr} and heat exchanger cost per unit area, I_c as presented in Table 2, it can be seen that a more realistic value for the net gain is $\$1.162 * 10^6$, as shown in Table 3, this is the most probable Net gain as suggested by Figure 2. However, even at this lower gain, based on the indicated design point, there is only about 8.4% chance of achieving that net gain, a probabilistic measure like this can be used to assess credibility of design specifications. For instance, this low probability value suggests that better performance specification needs to be sought, i.e. specifications that ensure higher business reliability without entailing disproportionate cost. As demonstrated in this paper, stochastic approaches could be quite helpful in addressing this kind of optimization problems. Also, based on the α_i values under scenario A, given in Table 3, it can be seen that the net present value of the gain, $NPVG$, is most sensitive to mass flowrate of the waste fluid, followed by heat exchanger effectiveness, then boiler efficiency and finally the total investment cost during the 15year- life time of the heat exchanger. Also, note that the alpha values corresponding to heat exchanger effectiveness and Mass flowrate are positive which suggests that values of one or both of these variables may have to be increased in order to step up business reliability which in this case has to do with achieving higher gain. As an example, scenario B is presented (in Table 2) where performance specifications are now adjusted to achieve higher probability of success, i.e. about 94% instead of 8.4% in scenario A. FORM analysis was used to determine the new design points, given in Table 4. Note the close agreement between FORM and MCS results in terms of β and $P[NPVG_{Det} - NPVG \leq 0]$ values. Also, note that to achieve this level of performance reliability, the average gain is now $\$1.264 * 10^6$ instead of $\$1.162 * 10^6$ obtained in scenario A, where very poor reliability was recorded. With modelling methods like this, set of various specifications and the corresponding reliability indices can be determined for an engineering system right at the design phase, this information, including merits and demerits of each option, can be presented to project sponsors to make a final decision. Also, note that, going by the problem formulation and solution strategies described in this paper, the term reliability index (β), in this context, is a probabilistic measure of the possibility of designing/operating the heat exchanger in a variety of conditions/specifications while meeting the intended financial gain. In a way, the index gauges robustness, resilience or flexibility of the heat exchanger in the face of random basic variables.

On the other hand, based on the MCS data, it is possible to write a computer code that builds an entire design/operations space for a given engineering system, providing an opportunity for visualizing a potential performance space for the system, an example is shown in Figure 3. The code can also be extended to index and extract all those design specifications that lead to failure or poor performance. For instance, Figure 4 shows a set of coordinates that lead to low financial gain, thus preferably, no specification should be drawn from this space.

Finally, the resulting performance plots/measures can also be used as a basis for identifying optimum control strategy/tuning necessary to hold an engineering system within some acceptable limits. Stochastic modelling techniques like the one presented in this paper, are needed to shift system models closer to reality, they can be used to support general engineering decisions affecting safety, reliability and cost efficiency.

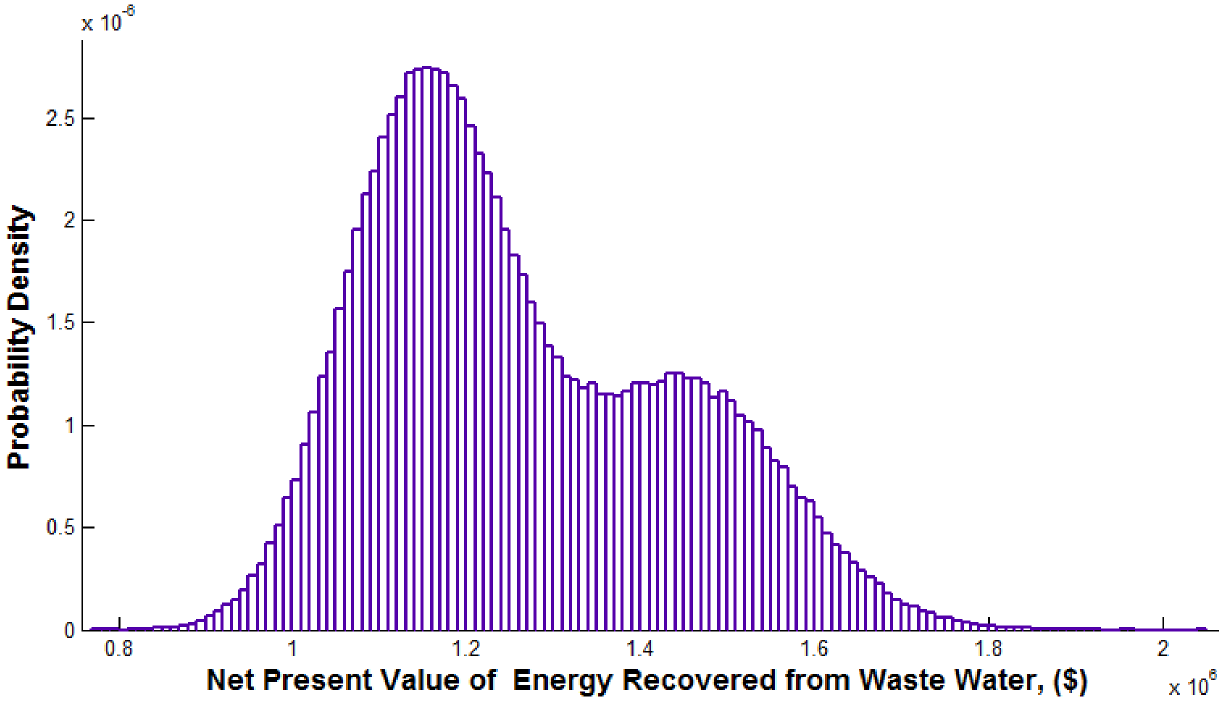

Figure 2. Distribution of financial gain from heat exchanger as induced by uncertainty in some of the basic variables

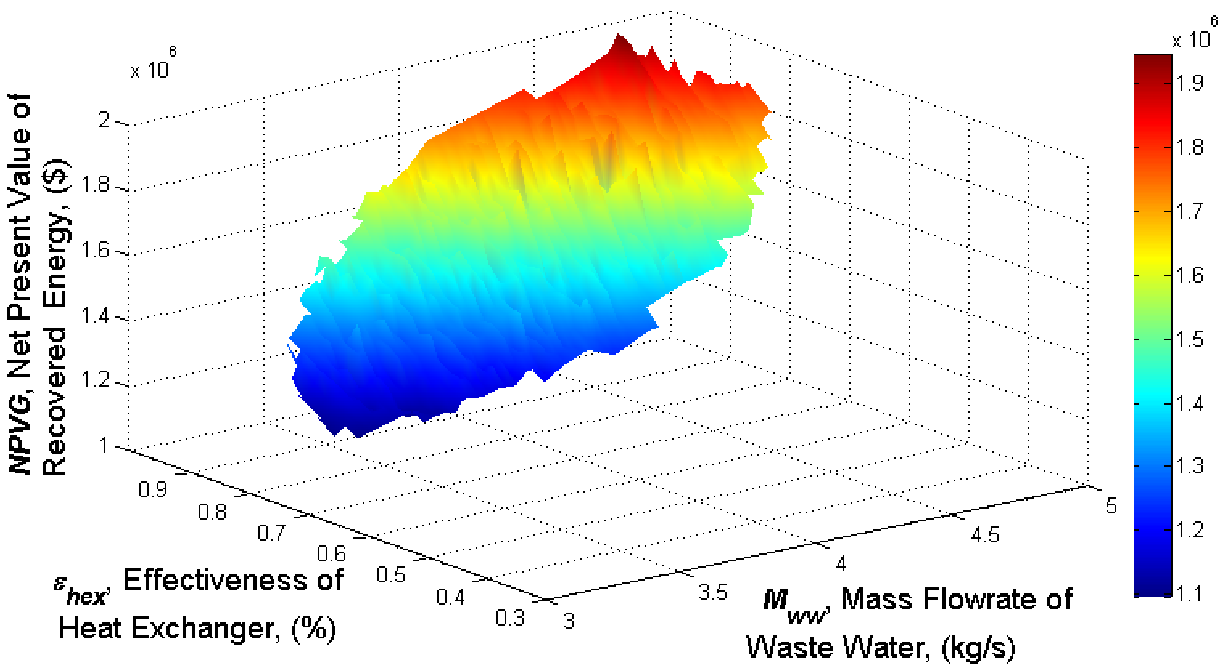

Figure 3. Overall performance space showing the expected net present value of the recovered energy during the life cycle of a heat exchanger

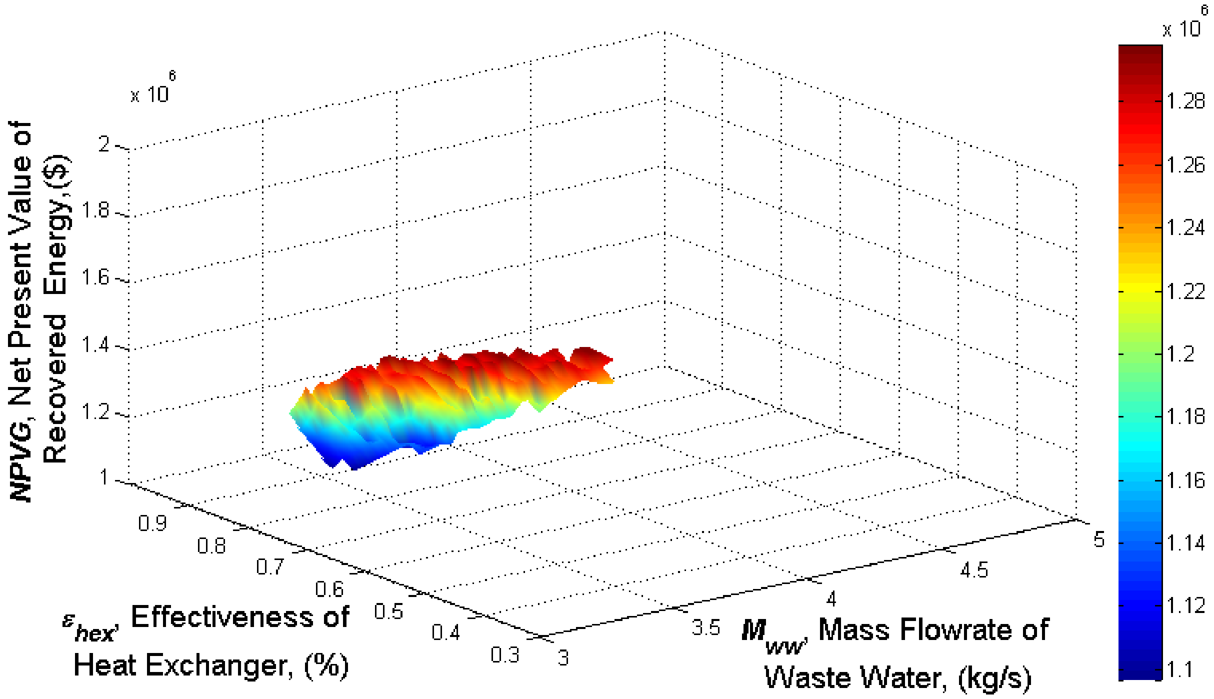

Figure 4. Set of performance points with potential to result in low financial gain

4. Conclusions

A method for conducting reliability based performance optimization has been presented. Combining FORM and MCS provides a simple way of generating a wide range of stochastic performance measures which can be used to improve design/operational robustness in the face of uncertainty which is inherent in engineering applications. The approach is general; it can be used to address engineering systems other than the heat exchanger which has been considered for illustrative purposes in this paper. In any case, an objective function would have to be constructed analytically, through response surface modelling or some other means. In the presence of credible stochastic performance measures, a range of uncertainty-laden decisions can be supported; these include decisions on equipment sizing & geometry, controller choice & tuning, production/cash flow prediction as well as resource allocation and budgeting.

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