Chapter 6

Case studies

6.1 INTRODUCTION

This chapter presents two examples that illustrate the application of uncertainty analysis, in combination with process models, to inform decisions on treatment plant design and operations. These case studies illustrate how these tools can be utilised to quantitatively define the risks and opportunities in different design and operational decisions, and thus how a utility might select the appropriate levels of cost and risk. The examples include a steady state and a dynamic application.

6.2 STEADY-STATE UNCERTAINTY ANALYSIS EXAMPLE: OPERATION OF THE DURHAM WRRF

6.2.1 Project objectives

In this example, Clean Water Services (CWS) (Tigard, Oregon, USA) was exploring how to best operate their Durham Advanced Wastewater Treatment Facility (Figure 6.1) in anticipation that the local regulatory authority would require it to nitrify year around (Menniti *et al.*, 2014). Their permit at the time only required nitrification during the summer (dry) season. In reality, the dry season extends to a large part of the year and during this period the plant contributes a significant fraction of the river flow. Nitrification is needed to dilute the plant's effluent ammonia. However, the expected winter (wet) season effluent permit ammonia would be based in part on the receiving river flow, with lower river flows requiring higher levels of nitrification.

Operations staff wished to understand what operating sludge age they would need to target in the winter that would allow them to reliably achieve the required winter effluent ammonia targets.

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Figure 6.1 Durham advanced wastewater treatment facility.

6.2.2 Conventional design approach using safety factors

As discussed previously, design safety factors are normally based on industry experience for developing a design robust enough to accommodate: (1) future variability (2) uncertainty in operating conditions and (3) uncertainty in effluent requirements. The nitrification safety factor (NSF) is a widely applied heuristic ('rule of thumb') used to estimate the design sludge retention time (SRT) of a nitrifying activated sludge system (Scheible *et al*, 1993). The safety factor lumps together various performance-related uncertainties including vulnerability to inhibitory substances in the influent wastewater, pH swings, and difficulties in maintaining adequate dissolved oxygen.

The EPA Nitrogen Control Manual notes that safety factors are ultimately expressions of design confidence. For example, in the 1993 USEPA Manual on Nitrogen Control (Scheible *et al.*, 1993), as part of a design approach for a nitrifying suspended growth system the following is mentioned: 'the anticipated variations in process conditions and the uncertainty in the kinetic coefficients warrant a safety factor of 2.0' (Scheible *et al*, 1993). An overly conservative choice of a safety factor can lead to an unnecessarily expensive design. Conversely, a safety factor that is too low can lead to a plant that frequently fails to achieve its effluent ammonia target. The 1993 USEPA (Scheible *et al*, 1993) document defines the minimum sludge age (SRT) as the SRT at which nitrifiers are just about to wash out of the system. The equation they provide for the washout SRT (SRT_{MIN}, for pH values <7.2) is given in equation 6.1. The NSF is defined in equation 6.2.

$$SRT_{\mathrm{MIN}} = \frac{1}{\mu_{\max} \times \theta_{\mu,\max}^{(T-20)} \times \left(\dfrac{DO}{DO + K_{OA}}\right) \times [1 - 0.833 \times (7.2 - pH)] - b \times \theta_b^{(T-20)}} \qquad (6.1)$$

where:

SRT_{MIN} = washout sludge age for nitrifiers (days)
$\mu_{\max}$ = maximum specific growth rate at 20°C (1/d)
$\theta_{\mu,\max}$ = maximum specific growth rate temperature adjustment

DO = dissolved oxygen concentration (mg/L)
K_{OA} = oxygen half-saturation value for autotrophs (mg/L)
b = autotrophic decay rate (1/d)
θ_b = decay rate temperature adjustment
T = temperature in °C

$$NSF = \frac{SRT_{\text{Aerobic}}}{SRT_{\text{MIN}}} \tag{6.2}$$

where:

NSF = nitrification safety factor
SRT_{Aerobic} = actual (or design) operating SRT

6.2.3 Probabilistic design approach

CWS chose to use a probabilistic approach to determine a suitable NSF for wet weather operations. The approach used is described below.

Firstly (step 1), the anticipated wet weather ammonia effluent requirements were determined from an analysis performed by CWS based on calculations of ammonia toxicity in the river. Ammonia toxicity is based on river flows, pH, temperature and ammonia concentrations. These effluent ammonia requirements were expected to decrease as the flow in the Tualatin River (discharge location) decreased (i.e., increasing impact of plant effluent ammonia on lower river flows). Figure 6.2 shows these values. At river flows above 21.24 m^3/s (750 ft^3/s), the target effluent ammonia is actually higher than the plant effluent ammonia when not nitrifying, thus eliminating the need for nitrification.

Secondly (step 2), historical data were analysed, to estimate the frequency at which the combination of river flow and plant influent water temperature would require the plant to nitrify to meet the anticipated effluent ammonia limits. When river flow is high, there is greater capacity in stream to dilute the

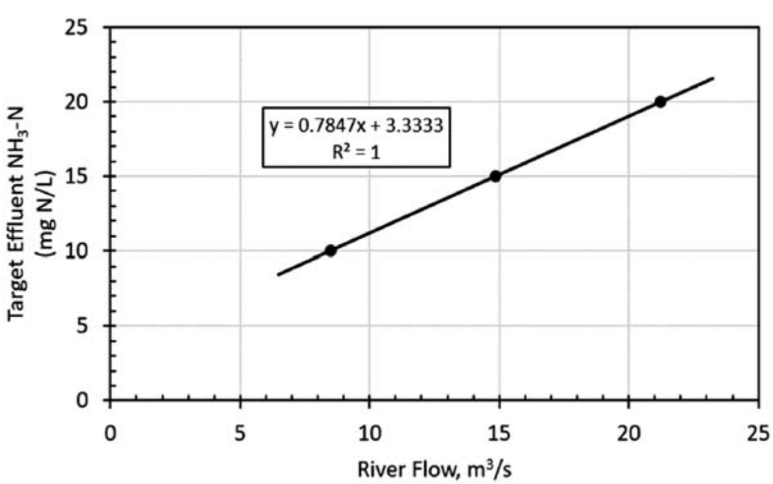

Figure 6.2 Target effluent ammonia requirements as a function of river flow.

ammonia received from the plant effluent. This lessens the extent of nitrification that must be accomplished within the plant. Influent temperature figures into the calculation because at higher temperature, nitrification proceeds at higher rates and sufficient nitrification can be achieved at lower aerobic SRT.

Thirdly (step 3), the results from step 2 were reviewed in order to select for planning purposes, the most appropriate target NSF. USEPA's Nitrification Safety Factor calculation (equation 6.2, Scheible *et al*, 1993) was used to determine the probability of achieving nitrification when river flows were low.

A Monte Carlo analysis was used for the probabilistic analysis. In a Monte Carlo analysis, the sources of uncertainty and variability in the parameters of a deterministic calculation are identified. For this project, the deterministic calculation is the NSF as described previously. The model input parameters considered variable or uncertain, defined by probability distribution functions (PDFs) and correlated against each other were:

- Wastewater influent temperature.
- Operating SRT. While determining this SRT was the goal of the work, the ability of operational staff to maintain this exactly is limited, therefore a normal distribution with a standard deviation of 1 day was set up around the target SRT.
- Nitrifier kinetic parameters. The maximum specific growth rate, $\mu_{\max}$ ($0.77 \pm 5\%$ 1/d), oxygen half-saturation coefficient, K_{OA} ($0.05 \pm 25\%$ mg/l) and decay rate, b ($0.5 \pm 25\%$ 1/d) were estimated through model calibration. These parameters were not measured directly and could vary over time. Therefore, their uncertainty and variability were accounted for in the probabilistic analysis using a uniform distribution following Sin *et al.* (2009).

Additionally, the river flow rate was correlated with the wastewater temperature. A probability density function is applied to those sources of uncertainty and variability to describe the range of possible parameter values. When possible, the probability density functions are fitted to historical data to ensure they describe actual conditions as accurately as possible. The influent temperature and operating SRT were fitted to historical data. These probability density functions are sampled hundreds or thousands of times to generate hundreds or thousands of possible parameter sets. The deterministic calculation is performed with each parameter set and the results are analysed to estimate the probability of different outcomes occurring. The impact of pH was also evaluated as described below.

Once the target NSF was determined, the sources of variability and uncertainty in the calculation of the NSF were identified, and this variability and uncertainty was quantified with PDFs.

Finally (step 4), to determine the design SRT, a Monte Carlo probability-based analysis was used. First, the reliability criteria were set with CWS's input to determine the acceptable level of risk assumed in the design. Then the design SRT was chosen for the planning alternatives to ensure the reliability criteria were satisfied. These risk criteria were:

- For a system pH of 7.2 (or for an assumption of no pH inhibition), the reliability criterion is that the NSF must be 1.3 or greater 95% of the time for the entire wet weather season.
- For a system pH of 7.0 (or for an assumption of nitrification inhibition due to low pH), the reliability criteria are that the NSF must be 1.3 or greater 95% of the time when the river flow is less than 21.24 m^3/s (750 ft^3/s), (the first benchmark river flow) and the NSF must be greater than 1.3, 75% of the time for the entire wet weather season.

Steps 1−4 described above did not involve a full plant simulation but, instead, used an NSF spreadsheet calculation with river input flows and temperatures (both wastewater and river) to determine the needed operating SRT, with the goal of running as low a SRT possible while minimising the probability of washing out nitrifiers during the winter period. For the final determination of the target minimum NSF, the SRT for nitrifier washout was also estimated with a steady state whole plant simulator based on IWA's ASM2d model and compared to the minimum SRT predicted from the EPA NSF equation.

For NSF calculations using the whole plant simulator, the model input SRT and the aerobic fraction of the plug flow basins were used to determine the NSF. The equation for SRT_{MIN} shown above was used to determine the washout SRT.

6.2.4 Results and discussion

The results from step 4 indicated that the nitrifiers start allowing significant ammonia in the effluent (begin to wash out of the system) just below an NSF of 1.3. This change in nitrification happens abruptly in the simulated plant, with the effluent ammonia increasing from around 1 mg-N/L to around 20 mg-N/L when the NSF decreased from 1.3 to 1.2. The fact that the model indicates loss of nitrification above an NSF of 1 indicates that the EPA approach and the simulation are not exactly in alignment, which is not surprising in light of the simple approach of the EPA equation vs. the ASM2d model. In reality, however, there is a wider band of operating conditions where nitrification is unstable, but the nitrifiers do not wash out. This is due to variability in SRT control, wastewater temperature, and other operating factors.

Imminent nitrifier washout in the operating plant was defined to occur when the plant effluent ammonia concentration increased above 1.0 mg-N/L. Nitrifier washout was predicted by the ASM2d-based simulator at an NSF of 1.3, indicating that the EPA NSF equation predicts nitrifier washout at a lower SRT than that predicted by the whole plant simulator. The same parameter values were used in NSF calculation as were used in the ASM2d model, accounting for the differences in the ASM2d death/regeneration approach.

The minimum target NSF of 1.3 was also confirmed with actual plant operating data (Figure 6.3), which further supports the idea that the EPA equation does not quite reflect actual kinetics. However, even in light

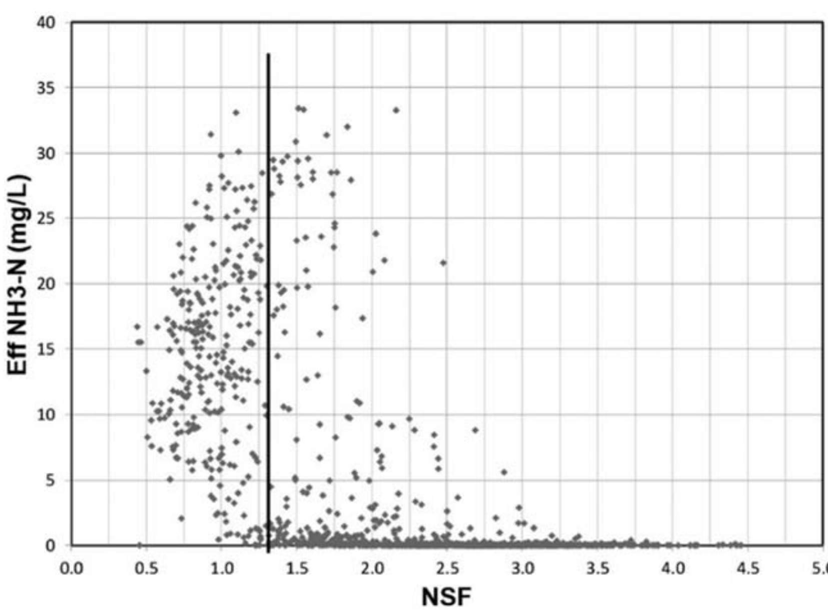

Figure 6.3 Durham AWTF operational results for determining the target NSF.

of this discrepancy, once adjusted for observed operations (i.e., 1.3 vs. 1.0 NSF), the NSF calculation provides a simple approach for understanding how close nitrification is to failure within an activated sludge system.

The wastewater influent temperature was found to be negatively correlated with the river flows. As the river flows went down (and decreased the target effluent ammonia, the wastewater influent temperature was found to increase. Figure 6.4 shows the measured values of river flow vs. the wastewater temperature as well as the equivalent sampled values from the probability model correlation that was set up between these two parameters.

In the absence of the probabilistic analysis, a 'rule of thumb' NSF, based on engineering and operations experience of 1.5 would have been applied to operation at the minimum week wastewater temperature, resulting in a design SRT of 8.5 days. This probabilistic analysis resulted in a design SRT of 8.0 days as this SRT satisfied the reliability criterion (NSF >1.3 95% of the time) as shown in Figure 6.5. In Figure 6.5, the 5% bar (i.e., 95% reliability) shows that at 8 days the NSF was at 1.34, while at 8.5 days it was at 1.44 (results not shown), which was unnecessarily high. The comparison of these two SRTs illustrates the level of unnecessary conservatism inherently saved by quantifying the uncertainties with probability analysis. The lower design SRT maximises existing infrastructure investment because it increases the rated capacity of the secondary process at a lower SRT while, very importantly, providing CWS with confidence that the system will perform under critical wet weather conditions.

The data set was also sorted so only parameter sets with river flows less than 21.24 m^3/s (the river flow triggering the need for nitrification) were evaluated (Figure 6.5 right). These results demonstrate that the NSF is greater than the minimum target value of 1.3, more than 99% of the time when nitrification is required, providing CWS further assurance (a level of conservatism) that the secondary process will be able to reliably nitrify under critical wet weather conditions.

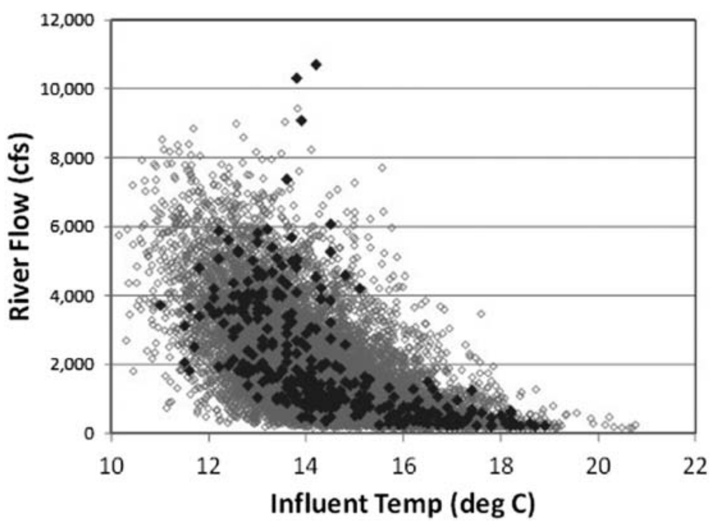

Figure 6.4 Correlation between influent temperature and river flow. Data in black are actual values, data in grey are results from PDF sampling.

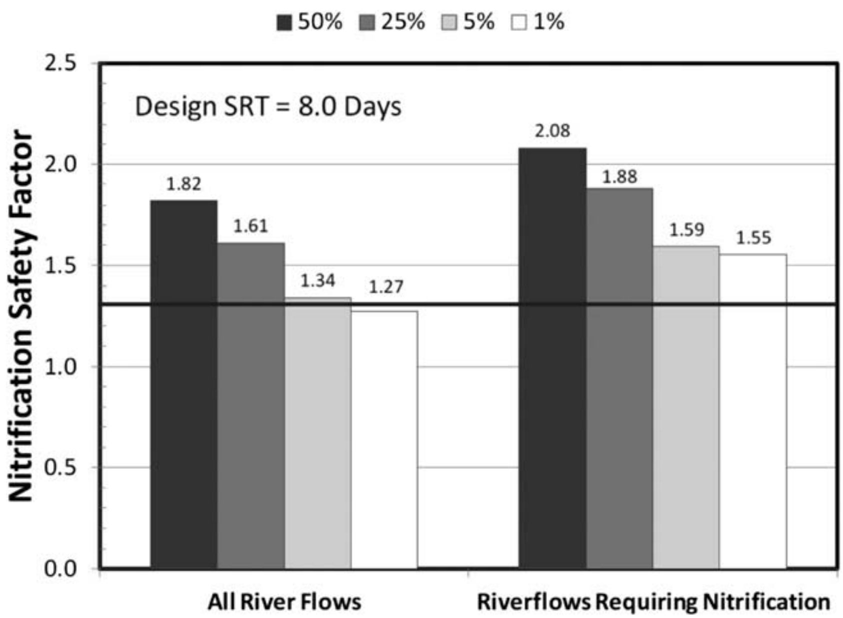

Figure 6.5 Durham AWTF NSF results showing the 50th, 25th, 5th, and 1st percentile NSF values for the chosen design SRT of 8.0 days and the results at 8.5 days SRT.

6.3 DYNAMIC UNCERTAINTY ANALYSIS EXAMPLE: DESIGN UPGRADE FOR THE EINDHOVEN WRRF

6.3.1 Project objectives

The Eindhoven WRRF (Figure 6.6) has a design capacity of 750 000 population equivalent (PE) and is the third largest WRRF in the Netherlands. Wastewater entering the plant is screened and de-gritted before going through primary treatment. The maximum design flow of the influent pumping station, preliminary treatment and primary clarifiers is 35 000 m^3/h (343 ft^3/s). However, the secondary treatment design flow is 26 250 m^3/h (258 ft^3/s). During high flow rates, excess flow is diverted to a storm storage tank. The biological treatment comprises three activated sludge tanks with anaerobic, anoxic, and aerated zones. Each activated sludge tank sends flow to four secondary clarifiers. The final effluent is discharged to the Dommel River. A detailed description of the plant can be found in Cierkens *et al.* (2012). Information on the plant effluent permit, as well as the basic characteristics of the connected sewershed can be found in Schilperoort (2011) and Belia *et al.* (2012).

Between 2003 and 2006 the Eindhoven WRRF underwent an upgrade to comply with new, more stringent, nutrient effluent limits (e.g., daily average flow proportional ammonia of 2 mg-N/L) and also to increase the hydraulic capacity of the secondary treatment from 20 000 to 26 250 m^3/hr (196–258 ft^3/s).

The objective of this study was to use the probabilistic design methodology presented in Chapter 5 and summarised in Figure 6.7 to determine the area and depth of the secondary clarifiers and the total bioreactor volume (aerobic, anaerobic and anoxic) for this upgrade.

Figure 6.6 Arial view of the Eindhoven WWPT.

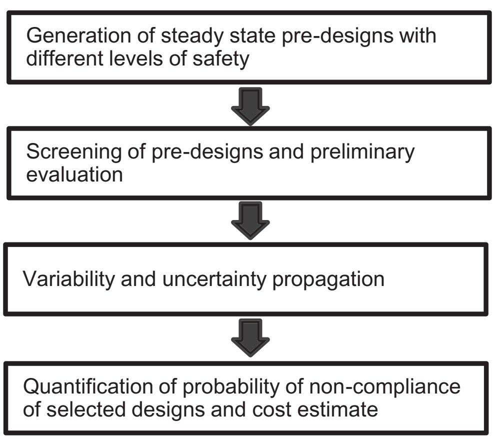

Figure 6.7 Proposed design methodology.

6.3.2 Generation and screening of steady-state pre-designs

The German ATV (2000) guidelines were used as a steady-state design tool for the generation of the pre-designs. A uniform uncertainty range was assigned to each input of the ATV design guideline parameters and the design outputs were generated by Monte Carlo simulation. The ranges of uncertainty were derived using the information obtained from the previous studies on the Eindhoven WRRF (Belia *et al.*, 2012; Schilperoort, 2011), ATV (2000) design guideline recommendations, effluent standards (imposed by regulations), and expert opinion. Table 6.1 shows a selection of the uncertain parameters for each major category. The complete list can be found in Talebizadeh (2015).

Table 6.1 Range of values assigned to the ATV design inputs (lower and upper limits of the uniform distribution).

ATV Design Inputs	Lower Limit	Upper Limit	Units
Influent constituents			
Primary effluent COD[1,2]	200	400	mg/L
Primary effluent nitrogen[1,2]	30	50	mgN/L
Maximum hourly wet weather flow rate as 2-h mean[1,2]	45 000	65 000	m^3/h
Inert particulate COD fraction of particulate COD[3]	0.2	0.35	%
Inorganic TSS fraction of total TSS[3]	0.2	0.3	%
Safety factors			
Safety factor for nitrification[3]	1.45	1.5	-
Safety factor applied to the effluent inorganic nitrogen[3]	0.6	0.8	-
Safety factor applied to the effluent phosphorous[3]	0.6	0.7	-
Operation parameters			
Minimum contact time in anaerobic tanks[1,2]	0.9	1.1	hr
Effluent concentrations			
Total nitrogen concentration in the effluent[4]	10	10	mgP/L
Phosphorous concentration in the effluent[4]	1	1	mgP/L

Notes: 1: Expert opinion, 2: Previous studies on the Eindhoven WRRF, 3: ATV design guideline, 4: Effluent standards.

Five thousand pre-designs were generated by random sampling of 5000 sets of ATV inputs. The ATV standards were applied to each of the 5000 sets to generate unit process dimensions for the aerobic, anoxic and anaerobic volume of the bioreactors and the area and depth of the secondary clarifiers. This resulted in 5000 alternative designs. The number of alternatives to be evaluated with a model run under dynamic conditions was reduced to the seven most representative ones by k-means clustering.

These seven design alternatives were representative of the overall design space of the outputs. The reduction of design alternatives for further evaluation through the k-clustering method keeps the computational load for the overall analysis at a manageable level.

The histograms on the diagonal panels in Figure 6.8 represent the distribution of design outputs (SST area and depth, total and anaerobic bioreactor volume) that were generated according to the ATV design guidelines. The red dots in the scatter plots of the other panels represent cluster centroids that were calculated using the *k*-means clustering method. For instance, the total activated sludge tank volume in the seven design alternatives varied between 71 000 and 107 000 m^3.

The selected design alternatives were further evaluated with a year-long influent time series, representing a typical year (Talebizadeh *et al.*, 2016). The simulation was performed using the ASM2d biological model (Henze *et al.*, 1999) and the Bürger *et al.* (2011) secondary settling model. For this set of simulations, the model parameters were given 'best estimate' values.

For each alternative a simulated effluent time series was generated. This effluent time series was processed to produce 24-hour mean values for COD, NH4-N, TSS and TN. Cumulative distribution functions (CDFs) were constructed for the four constituents. The objective of this step was to flag and eliminate alternatives that did not meet the desired performance criteria for a typical intra-annual variability. This step also identified alternatives that had very similar performance. Following this evaluation step five alternatives were selected for further analysis (Table 6.2).

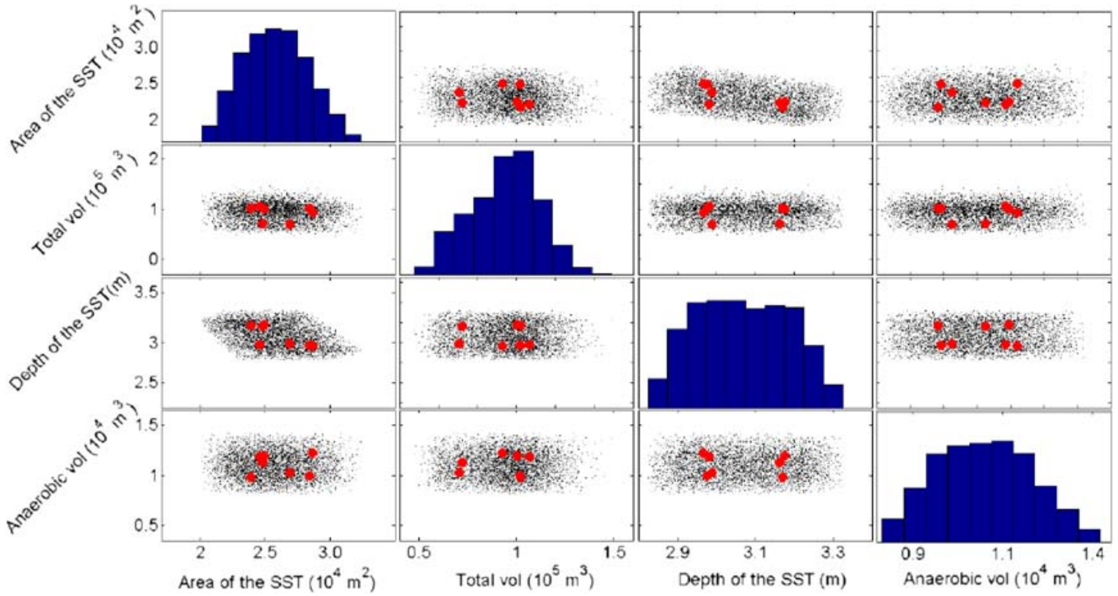

Figure 6.8 Distribution of the generated 5000 pre-designs and the centroids locations corresponding to the k-means clustering with seven centroids (i.e., the red dots). Total volume refers to total reactor volume.

Table 6.2 Dimensions of the design alternatives selected for further evaluation.

Design Alternatives	Total Reactor Volume (m^3)	Anaerobic Volume (m^2)	Depth of Secondary Clarifier (m)	Area of Secondary Clarifier (m^2)
Alt1	47 850	12 200	3.1	27 250
Alt2	59 400	11 100	3.0	25 250
Alt3	70 650	10 250	3.0	26 900
Alt4	106 650	11 850	3.0	24 600
Alt5	118 700	9500	3.1	26 250

6.3.3 Variability and uncertainty propagation

For the five alternatives selected for further evaluation, a pragmatic Monte Carlo simulation was performed, aimed at evaluating the impact of influent variability and parametric uncertainty on the performance of each design.

6.3.3.1 Influent variability

For the influent variability evaluation, as described in Section 5.3.5.1, *N* influent time series were generated by an influent generator calibrated using available weather, catchment and plant data. Details of the influent generator are described in Talebizadeh *et al.* (2016).

The influent data used for the calibration of the influent generator included flow, and sensor data for ammonia, soluble COD, total COD and TSS. Long-term daily rainfall data and also rainfall data with finer temporal resolution provided were used for estimating the parameters of the weather generator.

With the weather generator an indefinite number of rainfall intensity time series can be generated, each leading to one of the *N* influent time series.

6.3.3.2 Model parameter uncertainty

The uncertainty in the model parameters was characterised by assigning uniform distributions to uncertain model parameters. In this study all of the ASM2d model kinetic and stoichiometric parameters were considered uncertain. The lower and upper limits of the distribution of each parameter were calculated using a Nominal value (most likely value) multiplied by a percentage of the Nominal value as described in Brun *et al.* (2002). The Nominal values and uncertainty ranges were based on a combination of expert opinion, modelling experience and previous studies. Random sampling (RS) with no-correlation was selected for sampling from the distribution of uncertain model parameters. The choice of random sampling of model parameters was based on the study of Hauduc *et al.* (2011) in which no strong correlation was reported between the parameters of the ASM2d model.

The 'pragmatic' Monte Carlo method (for details see Chapter 5, Section 5.3.7.1) was implemented for the propagation of variability and uncertainty. The following sets of parameters were used:

(1) The lower limit of the uniform distributions
(2) The upper limit of the uniform distributions
(3) The Nominal set of model parameters
(4) The 'Worst Case' set of model parameters

Table 6.3 includes a sub-set of the model parameters considered uncertain. It shows the lower and upper limits of the uniform distributions used to describe the uncertainty surrounding the parameter values as well as the Nominal and 'Worst Case' values used in the uncertainty propagation simulations. The 'Worst Case' set of model parameters was selected to represent a very unfavourable condition for removal of ammonia and other parameters of interest. The 'Worst Case' set of model parameters corresponded to 95% confidence for the NH_4 effluent standards (i.e., 2 mg/l) and a higher than 95% for other pollutant concentrations. For a complete table see Talebizadeh (2015).

Table 6.3 Selected uncertain model parameters with their upper, lower limits, Nominal, and Worst-Case values.

Model Parameters	Lower Limit	Upper Limit	Nominal	Worst Case
Reference temperature of the activated sludge	20	20	20	20
Decay rate	0.075	0.225	0.15	0.224
Rate constant for lysis and decay	0.32	0.48	0.4	0.419
Hydrolysis rate constant	1.5	4.5	3	2.856
Maximum growth rate	0.8	1.2	1	0.862
Anoxic reduction factor for decay of autotrophs	0.165	0.495	0.33	0.386
Anoxic reduction factor for decay of heterotrophs	0.4	0.6	0.5	0.428
SVI	100	140	120	125

6.3.4 Quantification of probability of non-compliance (PONC)

From the simulated effluent time series of BOD, COD, and NH_4 (with 15-min temporal resolution) 24-h daily flow-proportional average concentrations were calculated. This matched the sampling frequency used for compliance. The plant also has discharge standards for TN and TSS that it must meet on an annual basis. Therefore, annual average concentrations for these water quality measures were calculated from the simulated effluent time series. Once the convergence of the effluent distributions was achieved, the CDFs of the different effluent constituents were derived and their corresponding PONC values were calculated.

For each design alternative, several PONC values were derived. Table 6.4 includes the PONC corresponding to the pragmatic Monte Carlo simulation at the Nominal and 'Worst Case' set of model parameters (refer to Chapter 5, Section 5.3.7.1 for discussion of the pragmatic Monte Carlo simulation). The PONC values calculated using the pragmatic Monte Carlo with model parameters set to the Nominal values correspond to the most likely behaviour of the plant. The PONCs calculated with model parameters set to the 'Worst Case' set of model parameters, correspond to a possible (but less likely compared to the Nominal set of model parameters) condition. As expected, the calculated PONC values are larger compared to the case of Nominal model parameters.

Table 6.4 also includes the expected number of days that the effluent ammonia and TN concentrations are expected to exceed the effluent standards. The metrics shown in Table 6.3 can be used to compare the behaviour of the design alternatives. As expected, an increase in bioreactor volume results in a reduction of PONC.

To better explore the relationship between the total volume of the bioreactors and the PONC, the PONC values for NH_4 of each design alternative were plotted against the total bioreactor volume (Figure 6.9).

The NH_4 PONC values for all of the design alternatives, calculated using the pragmatic Monte Carlo simulation at the Nominal set of model parameters are below 5%. However, the NH_4 PONC values for Alt1, Alt2, and Alt3 calculated at the 'Worst Case' set of model parameters (i.e., corresponding to a possible but conservative set of model parameters) are very high (i.e., 86.4, 78.7, and 29 expected days of non-compliance in a year, respectively), which may render them unacceptable due to their poor expected performance in NH_4 removal. In contrast to alternatives Alt1, Alt2 and Alt3, alternatives Alt4 and Alt5 have near zero PONCs at the Nominal set of model parameters and small values at the 'Worst

Table 6.4 PONC values for different design alternatives calculated using the pragmatic Monte Carlo simulation for two sets of model parameters ('Nominal' and 'Worst Case') (Talebizadeh, 2015).

Alternatives		Alt1	Alt2	Alt3	Alt4	Alt5
Total bioreactor volume		47 850	59 400	70 650	106 650	118 700
Pragmatic Monte Carlo simulation with Nominal parameter set						
NH_4	PONC	0.04	0.02	0.01	0.003	0.001
	Days[1]	15.1	6.2	3.4	1	0.2
TN	PONC	0.08	0.023	0	0	0
	Per cent[2]	8.00%	2.20%	0.00%	0.00%	0.00%
Pragmatic Monte Carlo simulation with Worst-Case parameter set						
NH_4	PONC	0.24	0.13	0.08	0.03	0.01
	Days[1]	86.4	48.7	29	7.8	5.1
TN	PONC	0.8	0.52	0.4	0.02	0.04
	Per cent[2]	80%	52%	40%	4%	2%

[1]Expected number of days with non-compliance event in a year (i.e., PONC $\times$ 365).
[2]Expected percentage of years with non-compliance events.

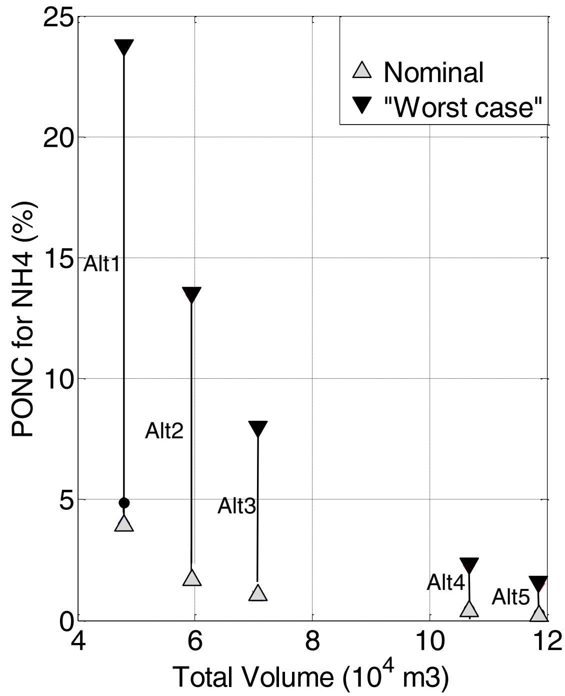

Figure 6.9 Relationship between PONC values (calculated using the pragmatic Monte Carlo simulation for the Nominal and 'Worst-Case' parameter sets) and the total bioreactor volume of the five design alternatives (Talebizadeh, 2015).

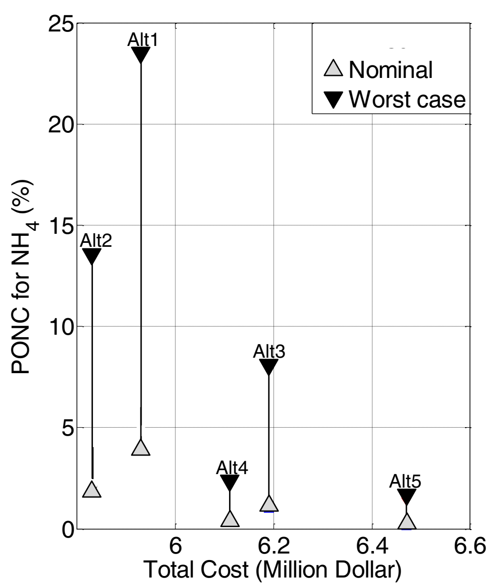

Figure 6.10 Relationship between PONC values (calculated using the pragmatic Monte Carlo simulation for the Nominal and 'Worst-Case' parameter sets) and the total cost of the five design alternatives included in Table 6.2.

Case' set of model parameters (i.e., 7.8 and 5.1 expected days of non-compliance in a year corresponding to Alt4 and Alt5, respectively).

6.3.5 Total cost estimates

The CapdetWorks (CapdetWorks, 2018; Harris *et al.*, 1982) software was used for calculation of the total cost corresponding to the different design alternatives. The calculated costs are based on the costing database for 2013 in the United States with 8% interest rate and 40 years for the lifetime of the project. They include operational, maintenance, materials and energy and capital costs. Figure 6.10 illustrates the relationship between the PONC values and the corresponding total cost for the different design alternatives.

Plotting the variation of PONC against the total cost can help designers identify those regions in design space for which the ratio of reduction in PONC to the increase in the total cost is at its highest and the effluent standards are met with a tolerable PONC. For example, if designers were interested in a NH_4 PONC value of less than 5% and a total cost in the range of 6 million dollars for the 'Worst Case' set of model parameters, Alt4 would be selected as the best design alternative.

6.4 SUMMARY

The application of the methods illustrated in this chapter provides additional insights into traditional approaches. The advantage of the proposed methods can be summarised as follows:

(1) They reduce subjectivity in the selection of design values, especially in situations where the engineers do not have enough experience (e.g., not enough knowledge on the effect of different process configurations on treatment performance).
(2) They provide an explicit, quantitative measure of compliance to effluent standards.
(3) They assist design engineers in identifying the limits of a specific treatment technology or process configuration as well as the design regions where the increase in certain process unit size would not result in a significant increase in the probability of compliance.

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