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Assessing the use of activated sludge process design guidelines in wastewater treatment plant projects: A methodology based on global sensitivity analysis

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ABSTRACT

Design inputs (wastewater characteristics, operational settings, effluent requirements or safety factors,...) need to be supplied when using activated sludge process design guidelines (ASPDG) to determine the design outputs (biological reactor volume, the dissolved oxygen demand or the different internal/external recycle flow-rates). The values of the design inputs might have strong effects on the future characteristics of the plant under study. For this reason, there is a need to determine how both design inputs and outputs are linked and how they affect wastewater treatment plant (WWTP) designs. In this paper we assess ASPDG with a methodology based on Monte Carlo (MC) simulations and Global Sensitivity Analysis (GSA). The novelty of this approach relies on working with design input and output ranges instead of single values, identifying the most influential design inputs on the different design outputs and improving the interpretation of the generated results with a set of visualization tools. The variation in these design inputs is attributed to epistemic uncertainty, natural variability as well as operator, owner and regulator decision ranges. Design outputs are calculated by sampling the previously defined input ranges and propagating this variation through the design guideline. Standard regression coefficients (SRC), cluster analysis (CA) and response surfaces (RS) are used to identify/interpret the design inputs that influence the variation on the design outputs the most. The illustrative case study uses the widely recognized Metcalf & Eddy guidelines and presents a didactic design example for an organic carbon (C) and nitrogen (N) removal pre-denitrifying activated sludge plant. Results show that the proposed GSA can satisfactorily decompose the variance of the design outputs ($R^2 > 0.7$): aerobic (V_{AER}) and anoxic (V_{ANOX}) volume, air demand (Q_{AIR}) and internal recycle flow rate (Q_{INTR}). Response surfaces are proposed to facilitate the visualization of *how*, *when* and *why* the design outputs may change when the most influential design inputs are modified. Finally, it is demonstrated that the proposed method is useful for process engineers providing a regional instead of a local picture of a design problem.

Software availability

Name of the software: PROcess DEsign Guidelines ANalyzer (PRODEGAN)
Developers: modelEAU, Département de génie civil et de génie des eaux, Université Laval
Program language: MatLab 7.1
Hardware required: Personal computer. Intel Pentium
Availability: The source code for generating the Activated Sludge Designs using Metcalf & Eddy guidelines (the example documented in this paper) as well as for MC simulations and GSA analysis can be obtained for free. Contact Prof. Peter A Vanrollghem. Département de génie civil et de génie des eaux, Université Laval, 1065, Avenue de la Médecine, Québec G1V 0A6, QC, Canada. Peter.Vanrolleghem@gci.ulaval.ca

Nomenclature[1]

A: Vector of design inputs
AER: Aerobic zone
ANOX: Anoxic zone

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[1] The nomenclature used in this article is in accordance with the new stan- dardized framework for wastewater treatment modelling notation (Corominas et al., 2010)

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ASPDG: Activated sludge process design guideline
b_k: Slopes in the SRC regression model
b_0: Offset in the SRC regression model
CA: Cluster analysis
f_S_B: Influent soluble biodegradable organics fraction [-]
f_S_U: Influent soluble undegradable organics fraction [-]
f_XC_B: Influent particulate biodegradable organics fraction [-]
f_X_{OHO}: Influent ordinary heterotrophic organisms fraction [-]
$f\_X_{U,inf}$: Influent particulate undegradable organics from the influent fraction [-]
GSA: Global sensitivity analysis
HRT: Hydraulic retention time [hours]
LHS: Latin hypercube sampling
MC: Monte Carlo
MLE: Modified Ludzack-Ettinger
MLSS: Mixed liquor suspended solids [g TSS m^{-3}]
PDF: Probability density function
Q1: First quartile
Q3: Third quartile
Q_{AIR}: Aeration flow rate [m^3 day^{-1}]
Q_{INTR}: Internal recycle flow rate [m^3 day^{-1}]
RSA: Response surface analysis
S: Scenario
S_B: Soluble biodegradable organics [g COD m^{-3}]
SF_{AER}: Safety factor in AER [-]
SF_{ANOX}: Safety factor in ANOX [-]
$S_{NHX,e}$: Effluent ammonium requirement [g N m^{-3}]
$S_{NOX,e}$: Effluent nitrate requirement [g N m^{-3}]
SO2: Dissolved oxygen concentration in AER [g (-COD) m^{-3}]
SRC: Standardized regression coefficients
SRT: Sludge retention time [days]
S_U: Soluble undegradable organics [g COD m^{-3}]
TSS: Total suspended solids [g TSS m^{-3}]
V_{AER}: Aerobic volume [m^3]
V_{ANOX}: Anoxic volume [m^3]
WWTP: Wastewater treatment plant
X: Vector of design outputs
XC_B: Particulate biodegradable organics [g COD m^{-3}]
X_{OHO}: Ordinary heterotrophic organisms [g COD m^{-3}]
$X_{U,inf}$: Particulate undegradable organics from the influent [g COD m^{-3}]

1. Introduction

Activated sludge process design guidelines (ASPDG) comprise a set of equations that computed in a sequential manner are used to quantify a number of design outputs as a function of design inputs. The design inputs include influent characteristics, operational settings, safety factors, kinetic and stoichiometric parameters and effluent requirements. The design outputs comprise aerobic, anoxic, anaerobic volumes, dissolved oxygen demand; internal and external recycle flow-rates, settling areas and dosage of chemicals (external carbon source, metal salts, and alkalinity). Most of the ASPDG are based on mechanistic approaches (Ekama et al., 1984; Grady et al., 1999; Tchobanoglous et al., 2003; WEF, 2009) which are reduced/modified/simplified versions of the International Water Association (IWA) Activated Sludge Models (ASM) (Henze et al., 2000). However, there are other ASPDG based on more empirical principles (ATV, 2000; Ten States Standards, 2004) where the sizing procedure relies more on the process knowledge/experience of wastewater engineers.

Independently of the selected ASPDG, the values of the design outputs have a direct link to the design inputs. For example, in some guidelines the biodegradable fraction is important for evaluating oxygen demand, process sludge production and aeration volume requirements. Also, the stricter effluent requirements and the higher level of safety will increase aerobic/anoxic volumes requirements, external/internal recycle rates and the oxygen demand. After all, design outputs will somehow determine characteristics (reactor configuration, blowers' capacity, pumping stations' size, storage tank volume) of the future plant as well as the associated construction and operating costs of the wastewater treatment plant (WWTP) project. For this reason it is important for process engineers to keep in mind why, when and how design outputs will change when the design inputs are modified for each particular case study.

Most of the research carried out on ASPDG is based on: 1) improving the quantification procedure (Bixio et al., 2002; Plósz, 2007), 2) selection of alternatives (Poch et al., 2004) and 3) reactor optimization (Moles et al., 2003; Flores et al., 2007; Rivas et al., 2008). However, the previously mentioned approaches do not give an answer to posted problems: How do the values of the design inputs determine the design outputs? How does the uncertainty about influent biodegradability interact with the choice of selecting an operational MLSS concentration when calculating the oxygen demand? How do the two choices of specifying a safety factor and setting the effluent requirements determine the plant's pumping system?

The objective of this paper is to present a methodology to assess ASPDG in WWTP projects based on Monte Carlo (MC) simulations and Global Sensitivity Analysis (GSA). The main novelty of this approach relies on: i) working with design input and output ranges instead of single values, ii) identifying the most influential design inputs on the different design outputs and finally iii) improving the interpretation of the generated results to a set of visualization tools. There are several successful applications of the Monte Carlo simulation technique in the field of wastewater engineering (von Sperling and Lumbers, 1991; von Sperling, 1996; Abusam et al., 2002; Bixio et al., 2002; Al-Redhwan et al., 2005; Benedetti et al., 2008). Most of these works are based on studying the effects of different types of input uncertainties (Bixio et al., 2002; Neumann et al., 2007; Benedetti et al., 2008; Flores-Alsina et al., 2008; Sin et al., 2009; Belia et al., 2009). In some cases MC simulations are combined with GSA techniques to prioritize sources of uncertainty (Flores-Alsina et al., 2009; Neumann et al., 2009; Sin et al., 2011).

In contrast to these previous studies, this approach not only considers epistemic uncertainty (influent fractionation, kinetics & stoichiometry, settling parameters….) but also includes value ranges due to temporal and spatial variability (temperature, influent loads) as well as decision ranges that reflect desires and preferences (regulator requirements, operational settings, and safety levels). Therefore we express design inputs as i) constants; ii) probability density functions due to lack of knowledge (epistemic uncertainty), natural variability or decision ranges or finally iii) scenarios. For example, if an engineer is using the presented methodology for a specific site and the effluent requirements are non-negotiable they would enter the analysis as constants. If a utility is operating several WWTP in a watershed they may have flexibility in load allocation (e.g. Total Maximum Daily Loads, TMDL) and might therefore consider a range of values for the effluent requirement of a single treatment plant. The effect of a future change in legislation could be studied by the use of scenario analysis.

The paper is organized as follows. First, the developed methodology is presented. The different steps are detailed and the implemented techniques briefly described. Next, a simple and didactical case study is presented where an activated sludge plant is designed to remove organic carbon (C) and nitrogen (N) using the Metcalf & Eddy guidelines (Tchobanoglous et al., 2003). The results show both local (deterministic) and regional visualization of the design outputs. Finally, the analysis is complemented with a scenario analysis and a thorough discussion of the results.

2. Methods

This section gives a general overview of the methodology presented in this study. The methodology is comprised of three main blocks: 1) definition of the design problem and scope of the study, 2) Monte Carlo (MC) simulations and 3) Global Sensitivity Analysis (GSA) (see flow diagram in Fig. 1). The main characteristics of each block are described in the following sections.

2.1. Definition of the design problem and scope of the study

This step includes the gathering of information such as influent wastewater evolution and composition, the specification of the plant configuration, the determination of effluent limits, specification of safety factors, characterization of desired operational settings etc…Hereby the framing of the study is defined (Sin et al., 2009). The framing consists of identifying design input ranges that reflect i) epistemic uncertainty, ii) natural variability or iii) stakeholders' decision ranges.

For the present case study, the influent wastewater composition is the same as that proposed in the Benchmark Simulation Model No1 (BSM1) (Copp, 2002). The average dry weather wastewater to be treated has a flow rate is 18,500 $m^3 \cdot day^{-1}$ (62% corresponds to households, 13% is industrial and the remaining 25% is infiltration) with an organic and nitrogen load of 6500 kg $COD \cdot day^{-1}$ and 680 kg $N \cdot day^{-1}$ respectively (Gernaey et al., 2011) i.e. typical municipal wastewater. The treatment goal is to remove C and N. The selected configuration is a Modified Ludzack-Ettinger process (MLE). In MLE configurations, the initial contact of the influent wastewater and return activated sludge occurs in an anoxic zone (ANOX), which is followed by an aerobic zone (AER) (see process layout in Fig. 2). The process relies on the nitrate – formed in the aerobic zone – being returned via an internal recycle to the anoxic zone to be denitrified. Default values of the effluent requirements, safety factors when designing the reactors and the preferred operational conditions are summarized in Table 1.

In this illustrative case study, ranges of the design inputs are attributed to the following: i) epistemic uncertainty about the influent fractionation and the decision ranges for ii) effluent requirements, iii) operational dissolved oxygen concentration and iv) safety factors (see Fig. 2). The authors are aware of other parameters with a strong impact on plant design such as influent loads, temperature, kinetics, stoichiometry, MLSS concentration in the reactor, settling properties among others. Some of these influences are further investigated in the scenario analysis while others are assumed to be constant. The reader must be aware that this is an illustrative case study to test the methodology and that a full-fledged application is beyond the scope of this paper. Therefore, for full scale engineering projects the «framing» referred to above needs to be specified in detail.

2.2. Monte Carlo simulations

MC simulation methods are a class of computational algorithms that rely on repeated random sampling. MC simulation involves four steps: (1) Specifying ranges for the design inputs [*A*], (2) sampling from the design input ranges and (3) propagating the sampled values through the ASPDG to obtain a range of values for each of the design outputs and (4) analysis of the results.

2.2.1. Specification of the inputs

For the present case study, the design inputs with value ranges [*A*] are characterized using uniform probability density functions (PDF) (Table 1). PDFs due to epistemic uncertainty are limited to the COD influent fractionation parameters. The total organic load is assumed to be known, but the different biodegradable (f_S_B, f_X_B and f_X_{OHO}) and non-biodegradable (f_S_U and $f\_X_{U,inf}$) fractions are considered to be uncertain. An uncertainty range of default value ±50% is assumed (Flores-Alsina et al., 2008). f_XC_B (slowly biodegradable fraction) is not included in the table because it is calculated as the difference between 1 and the sum of the other organic fractions: $f\_XC_B = 1 - (f\_S_B + f\_X_{OHO} + f\_S_U + f\_X_{U,inf})$.

The design inputs that reflect decision ranges include: the effluent requirements (effluent ammonium $S_{NHX,e}$ and nitrate $S_{NOX,e}$), the safety factors for the aerobic and the anoxic sections (SF_{AER} and SF_{ANOX}) and the operational conditions (the desired oxygen concentration in the bioreactor S_{O_2}). On this occasion the value ranges of the different PDFs were defined according to feasible decision ranges.

In all cases we used uniform PDFs to map the possible ranges. No systematic method was used to study the effect of alternative shapes (Beinat, 1997). Researchers and engineers applying this methodology need to define which interactions they want to explore and the appropriate limits and shapes of the used distributions.

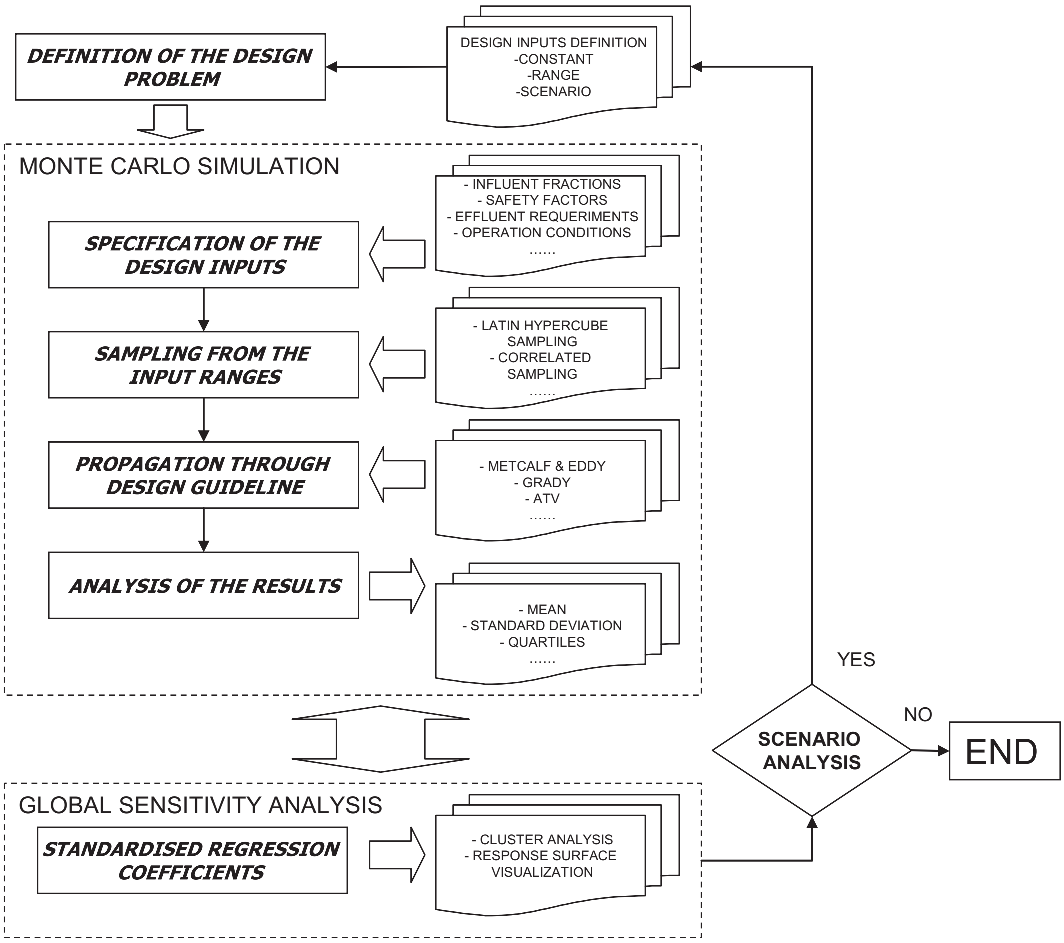

Fig. 1. Flow diagram of the proposed methodology.

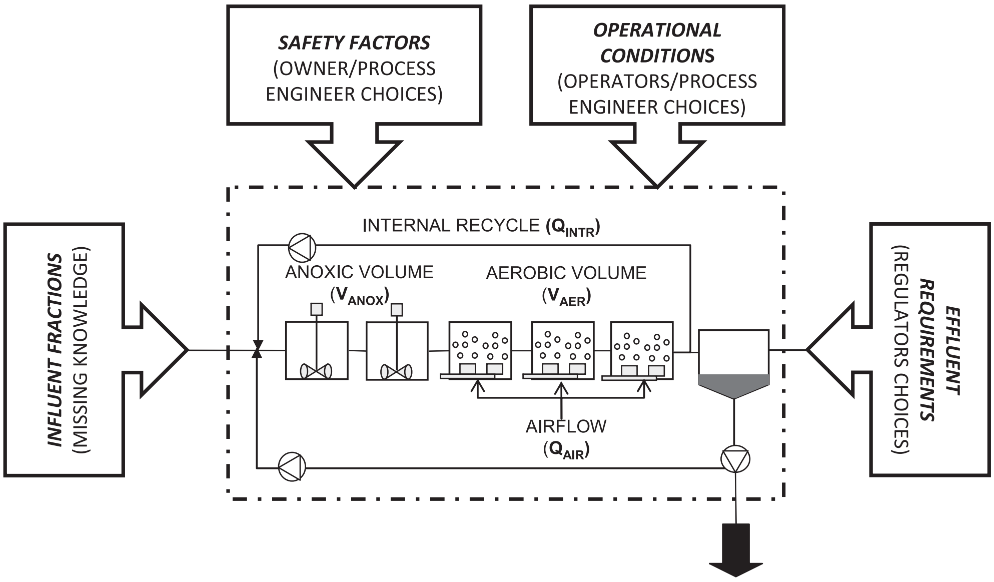

Fig. 2. Sources of uncertainty (influent fractions) and choices (safety factors, operational conditions, effluent requirements) that determine the final activated sludge plant design.

2.2.2. Sampling from the input factor ranges

The design input space is sampled using the Latin hypercube method (LHS) (McKay et al., 1979; Iman et al., 1981). The LHS method is a stratified sampling technique that enables covering the entire analyzed space with a lower number of samples compared to random sampling. In this study, a sample size of 1000 is applied. Each Latin hypercube sample contains one randomly selected value from each of the previously defined probability distributions. Even though the methodology also contemplates the potential of performing correlated sampling, in this case study input ranges are assumed to be independent (Clemen and Reilly, 1999). The authors are aware that some correlation is possible between the design inputs e.g. stringent effluent requirements for $S_{NHX,e}$ and $S_{NOX,e}$. Nevertheless, for simplicity purposes the design inputs are assumed to be independent from each other.

2.2.3. Propagation of the sampled values through the model to obtain a range of values for the output

For each sample of [*A*] the different design outputs [*X*] are computed with the Metcalf & Eddy equations: $[X] = f([A])$. The vector [*X*] includes the aerobic volume (V_{AER}), the anoxic volume (V_{ANOX}), the internal recycle (Q_{INTR}) and the aeration flow (Q_{AIR}). To obtain [*X*] the 20 non-linear implicit algebraic equations of the Metcalf & Eddy guidelines are implemented as an m-file in MatLab. The aerobic volume (V_{AER}) is sized on the basis of the net specific growth rate of nitrifying organisms, the design solids retention time, the desired mixed liquor suspended solids (MLSS) concentration and the total mass of solids that has to be removed to maintain the chosen sludge residence time. Next, the required internal recycle flow rate (Q_{INTR}) is calculated through a mass balance which includes the nitrate produced in the aerobic zone, the nitrate in the return activated sludge and the desired nitrate level in the effluent. The anoxic volume (V_{ANOX}) is designed by comparing the nitrate produced in the aerobic zone to the nitrate which can potentially be removed for a given hydraulic retention time and the available biodegradable organic matter. Finally, the airflow rate (Q_{AIR}) is quantified based on the difference between the oxygen required (for carbon removal and nitrification) and the oxygen saved (by denitrification). Although the usefulness of using MC simulations and GSA is illustrated with the Metcalf and Eddy guidelines, the developed methodology can be applied to any ASPDG. In fact, it is has been implemented in a way that allows to be adapted for other guidelines such as the Grady, ATV guidelines, US EPA CAPDET or HSA.

Table 1
Range of values of design inputs [*A*] expressed as uniform probability distributions characterised by mean, lower and upper values (In order to fulfil the mass balance $f\_XC_B = 1 - (f\_S_U + f\_S_B + f\_X_{U,inf} + f\_X_{OHO})$).

Initial assumption [*A*]	Symbol	Mean value	Lower value	Upper value	Units
Influent fractions					
Fraction of soluble undegradable organics	f_S_U	0.09	0.05	0.14	–
Fraction of soluble biodegradable organics	f_S_B	0.16	0.08	0.24	–
Fraction of influent particulate undegradable organics	$f\_X_{U,inf}$	0.12	0.06	0.18	–
Fraction of heterotrophic organisms	f_X_{OHO}	0.11	0.06	0.17	–
Effluent requirements					
Effluent ammonium	$S_{NHX,e}$	2	0.5	6	gN m^{-3}
Effluent nitrate	$S_{NOX,e}$	6	5	10	gN m^{-3}
Safety factors					
Aerobic section	SF_{AER}	1.25	1	1.5	–
Anoxic section	SF_{ANOX}	1.25	1	1.5	–
Operational conditions					
Dissolved oxygen in the aerobic zone	S_{O_2}	2	0.5	4	(-gCOD) m^{-3}

2.2.4. Analysis of the results

The solution of the model, for all the design input combinations, results in a PDF of the desired design outputs [*X*]. The last step of the MC procedure consists of analyzing the distribution of [*X*]. Using descriptive statistics the mean, standard deviation, quartiles, etc. are extracted.

2.3. Global sensitivity analysis (GSA)

2.3.1. Standardized regression coefficients (SRC)

GSA using SRCs involves performing a linear regression on the output of the MC simulation (here 1000 simulations), revealing the (linear) relationships between the design inputs [*A*] and the design outputs [*X*]. The regression that is conducted for each design output is represented by the following equation (Eq. (1))

$$\hat{X}_j = b_0 + \sum_{k=1}^{n} b_k A_k \tag{1}$$

where $\hat{X}_j$ is the regression model prediction for design output *j*, b_0 is the offset, b_k are the slopes and *n* is the number of design inputs A_k. The subindex *k* and *j* represent a particular design input and output respectively. The standardized regression coefficients (SRC) are obtained by normalisation of the slopes by their standard deviations of the design inputs σ_{A_k} and outputs $\sigma_{\hat{X}_j}$ as stated in Eq. (2)

$$SRC_{j,k} = b_k \frac{\sigma_{A_k}}{\sigma_{\hat{X}_j}} \tag{2}$$

According to Saltelli et al. (2004) the SRC are a valid measure of sensitivity if the coefficient of determination $R^2 > 0.7$. The higher the absolute values of the SRC, the stronger the influence of the corresponding input [*A*] on determining the output *X*.

2.3.2. Cluster analysis and response surfaces

The absolute values of the regression coefficients are then ranked and categorized according to «strong», «medium» and «weak» influence by k-means cluster analysis (CA). K-means clustering is a classification method which aims to partition observations into clusters in which each observation belongs to the cluster with the nearest mean (Hair et al., 1998). The response surfaces for the different design outputs are plotted as a function of selected design inputs with «strong» influence.

2.4. Scenario analysis

Finally a scenario analysis is performed to investigate how the results from MC simulations and GSA are affected by changing some of the constants. The scenario analysis allows evaluating possible future or hypothetical events by considering alternative possible outcomes (scenarios). These scenarios can be formulated at the beginning of the design process or iteratively as new opportunities are envisaged as the design process advances (See Fig. 1) In this case, the value of the design inputs assigned as constant is modified and the entire analysis is repeated. The results of the second analysis are compared with the default case. It must be said that in this case study the different scenarios are formulated in a kind of arbitrary way, but cover realistic situations.

3. Results

3.1. Local analysis of the design outputs

The results applying default design inputs are presented in the first row of Table 2. The total hydraulic retention time is 10.6 h with an anoxic retention time around 3 h (V_{ANOX}) and an aerobic retention time of 7 h (V_{AER}). In both cases, HRT is within the limits (HRT_{AER} = 4–12 h, HRT_{ANOX} = 1–3) as recommended by engineering manuals. The anoxic volume is especially high, mainly due to the low content of (biodegradable) organic matter in the influent, which makes big volumes necessary to denitrify all the nitrogen according the required effluent standards. The internal recycle is 400% of the influent flow which is higher than the ranges recommended by literature (100–200% of the influent flow). This is due to: 1) the high nitrogen load in the influent, 2) the strict nitrate limits in the effluent.

3.2. Regional analysis of the design outputs

3.2.1. Monte Carlo analysis

Table 2 summarizes the ranges of the design outputs [*X*] obtained from propagating the design inputs [*A*] from Table 1 in the MC simulation. The ranges are characterised by average value, maximum and minimum values as well as the first and third quartile (Q1, Q3). For example, the designed aerobic volume (V_{AER}) can vary between 5100 (Q1) and 6800 (Q3) m^3. It is important to highlight that the difference between the maximum and the minimum value are far more extreme, but that these values are very sensitive to the sampled parameter sets and may therefore differ considerably between repeated analyses. The average time to run this analysis (1000 MC simulations) on a duo-core processor at 3 GHz is less 1 min.

Table 2
Default values (local analysis), mean values, maximum and minimum values, quartiles Q1 and Q3 and Q3-Q1 (regional analysis) for the design variables [*X*] obtained in the Monte Carlo analysis (rounded to 2 significant digits).

	Design variable [*X*]			
	V_{AER} (m^3)	V_{ANOX} (m^3)	Q_{AIR} ($m^3\ min^{-1}$)	Q_{INTR} ($m^3\ day^{-1}$)
Local analysis				
Value	5600	2500	61	76,000
Regional analysis				
Mean value	6200	3300	65	88,000
Maximum value	18,000	5100	85	140,000
Minimum value	3500	2000	52	56,000
Percentile 25 (Q1)	5100	2900	59	68,000
Percentile 75 (Q3)	6800	3700	70	107,000
Q3-Q1	1700	850	11	39,000

Table 3
Standardized regression coefficients (SRC) for the different design variables. Bold values have been identified as strong by k-means. $R^2 > 0.7$, indicates that the variance of design outputs is well described by the model and the SRCs are valid measures of sensitivity.

Design input [*A*]	Design output [*X*]							
	V_{AER}		V_{ANOX}		Q_{AIR}		Q_{INTR}	
	$R^2 = 0.72$		$R^2 = 0.94$		$R^2 = 0.96$		$R^2 = 0.95$	
	SRC	Rank	SRC	Rank	SRC	Rank	SRC	Rank
f_S_U	−0.03	7	0.18	5	−0.20	3	0.013	2
f_S_B	−0.12	4	**−0.37**	**3**	−0.01	8	0.000	9
$f\_X_{U,inf}$	0.11	5	**0.48**	**2**	−0.27	2	0.003	6
f_X_{OHO}	−0.03	8	0.01	9	−0.01	7	0.012	3
$S_{NHX,e}$	**−0.54**	**1**	−0.17	6	−0.18	4	−0.008	7
$S_{NOX,e}$	0.04	6	−0.30	4	0.17	5	**−0.984**	**1**
SF_{AER}	**0.38**	**3**	0.13	8	0.14	6	0.004	5
SF_{ANOX}	−0.01	9	**0.64**	**1**	0.00	9	0.001	8
S_{O_2}	**−0.54**	**2**	−0.17	7	**0.85**	**1**	0.008	4

3.2.2. Global sensitivity analysis

The SRCs from the GSA (Eq. (1) and Eq. (2)) for the four design outputs are reported in Table 3. The coefficients of determination are above $R^2 > 0.7$, indicating that the variance of design outputs is well described by the linear model and the SRCs are a valid measure of sensitivity. The signs specify whether the linear relationship between the design output and the design input is positive or negative. The design inputs which in the k-means clustering are classified as having a «strong» influence on determining the design output are highlighted in bold.

Both the effluent requirement for ammonium ($S_{NHX,e}$) and the oxygen concentration set-point in the reactor (S_{O_2}) have a strong influence on determining the aerobic zone tank volume (V_{AER}) (Table 3). This is mainly due to net specific growth rate of the nitrifying organisms which is based on Monod kinetics and thus depends on the ammonium and the oxygen concentration within the reactor. The lower the specific growth rate, the higher the required design sludge retention time and consequently the larger the aerobic volumes are required. An increase in the biodegradability of the influent COD (high f_S_B and low $f\_X_{U,inf}$) decreases the anoxic volume (V_{ANOX}), because the nitrate reduction rates are higher (organic matter is the electron donor during denitrification) and it is possible to reduce the same quantity of nitrate with a lower hydraulic retention time. Design airflow (Q_{AIR}) is dominated by the desired oxygen concentration set-point in the reactor (S_{O_2}) and is only moderately influenced by the uncertainty about the influent biodegradability and the effluent ammonium requirements imposed in the case study. The choice of nitrate requirement ($S_{NOX,e}$) has a strong influence on the internal recycle flow (Q_{INTR}). In fact, it will determine the quantity of nitrified nitrogen that has to be transported from the aerobic to the anoxic section in order to achieve the desired effluent concentration. The range of considered safety factors (SF_{AER} and SF_{ANOX}) significantly affects the reactor volumes (V_{AER} and V_{ANOX}).

3.2.3. Response surface analysis

The results of this regional analysis also enable the creation of higher-dimensional response surfaces (one for each design output), which represent the design output *X* as a function of the design inputs [*A*]. Fig. 3 shows a 3D scatter plot which displays the combined influence of the two most influential design inputs for both aerobic (V_{AER}) and anoxic (V_{ANOX}) volumes. Combinations of strict effluent requirements ($S_{NHX,e}$) and low operational oxygen concentration (S_{O_2}) lead to large aerobic volumes (V_{AER}) and vice versa (see Fig. 3a,c). On the other hand, high influent biodegradability (high f_S_B and low $f\_X_{U,inf}$) leads to small anoxic volumes

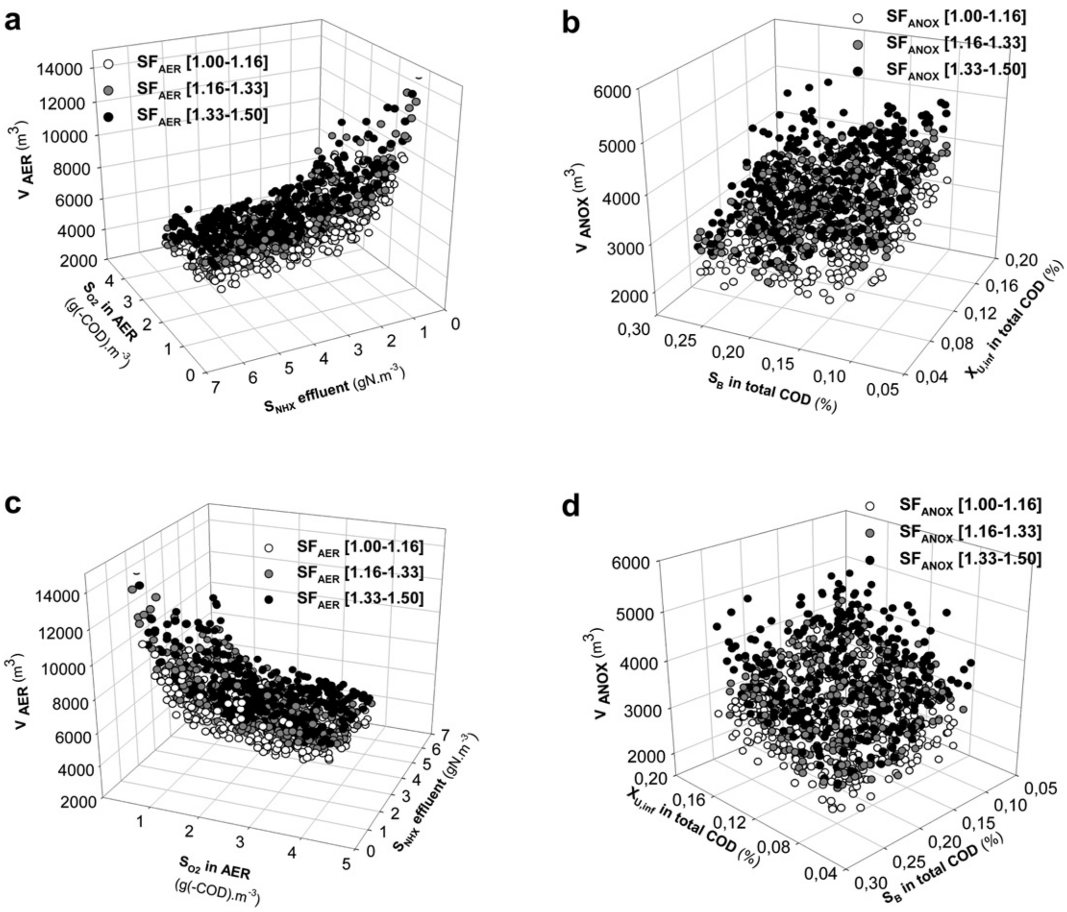

Fig. 3. Different views of the combined influence of the most influential design inputs for (V_{AER}) aerobic (a,c) and (V_{ANOX}) anoxic (b,d) volume.

(V_{ANOX}) (see Fig. 3b,d). For both cases the effect of the safety factor choice (SF_{AER} and SF_{ANOX}) is highlighted (Fig. 3). Another interesting result is the identification of correlations between different design outputs *X*. For example, high anoxic volumes (V_{ANOX}) are related to higher pumping capacities for the internal recirculation (Q_{INTR}). From Table 3 it is possible to see that both design variables (V_{ANOX} and Q_{INTR}) exhibit negative correlation with $S_{NOX,e}$ (effluent limits for nitrate): The stricter the nitrate limits ($S_{NOX,e}$) the larger the anoxic volume (V_{ANOX}) and the recycle flow (Q_{INTR}) will be. V_{ANOX} and Q_{AIR} present positive and negative correlation with $f\_X_{U,inf}$. The latter indicates that some energy savings in aeration flow (Q_{AIR}) are possible at higher denitrification volumes (V_{ANOX}). This is mainly due to the use of nitrate instead of oxygen as electron acceptor for organic matter degradation. Consequently, the quantity of oxygen required in the aerobic phase to remove the organic matter is lower as is therefore the aeration demand.

3.3. Scenario analysis

Scenario *S0* denotes the base case described above. Three further scenarios (*S1, S2 & S3*) are suggested and studied in this section:

- In scenario 1 (*S1*) the design temperature is reduced from 15 to 10 deg C.
- In scenario 2 (*S2*) the nitrogen load is reduced by 50%.

Table 4
Results of the scenario analysis (rounded to 2 significant digits).

	Design variable [*X*]			
	V_{AER} (m^3)	V_{ANOX} (m^3)	Q_{AIR} (m^3min^{-1})	Q_{INTR} (m^3day^{-1})
S0: Default case				
Mean value	6200	3300	65	88,400
Most influential parameters	S_{O_2} & $S_{NHX,e}$	SF_{ANOX}, $f\_X_{U,inf}$ & S_B	S_{O_2}	$S_{NOX,e}$
S1: Decrease of the design operating temperature down from 15 to 10 °C				
Mean value	8400	4000	74	88,400
Most influential parameters	S_{O_2} & $S_{NHX,e}$	SF_{ANOX}, $f\_X_{U,inf}$ & S_B	S_{O_2}	$S_{NOX,e}$
S2: 50% reduction of the nitrogen influent load				
Mean value	6100	990	58	35,000
Most influential parameters	S_{O_2} & $S_{NHX,e}$	$S_{NOX,e}$, SF_{ANOX} & $f\_X_{U,inf}$	S_{O_2}	$S_{NOX,e}$
S3: Increase of the design operating MLSS 3000 *to* 4000 g m^{-3}				
Mean value	4600	2500	65	81,500
Most influential parameters	S_{O_2} & $S_{NHX,e}$	SF_{ANOX}, $f\_X_{U,inf}$ & $S_{B,}$	S_{O_2}	$S_{NOX,e}$

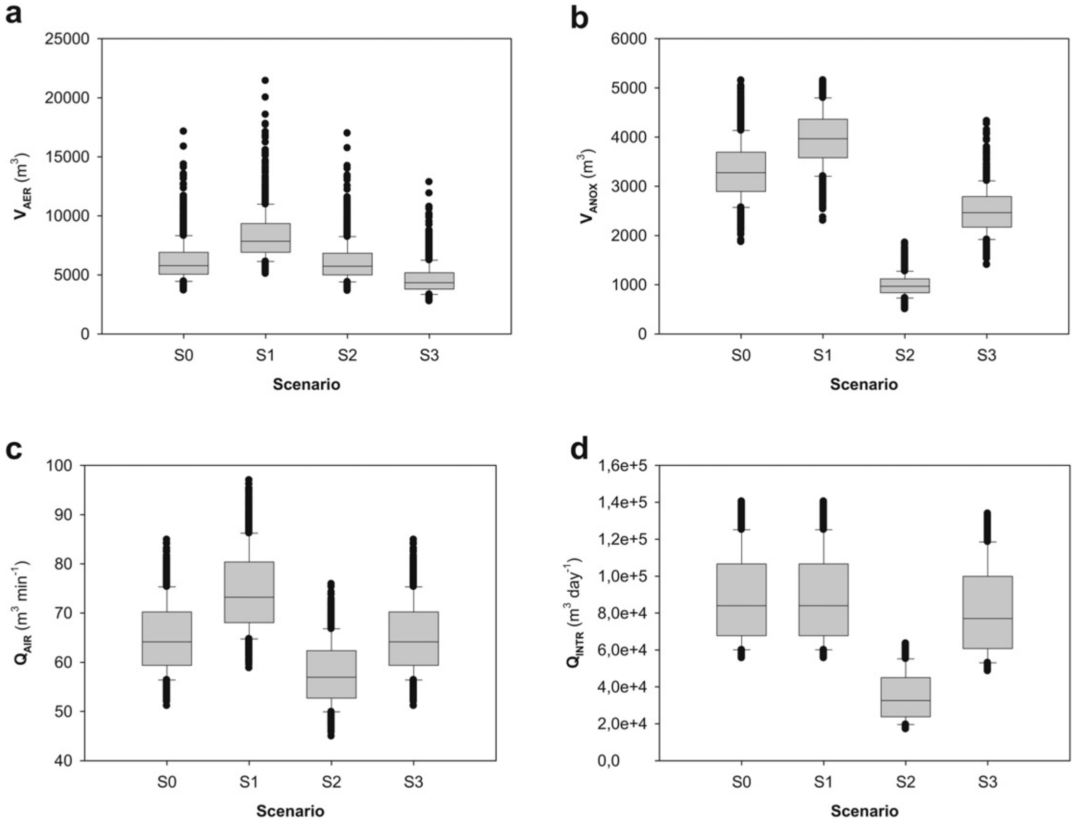

Fig. 4. Multiple box plots of the design outputs *X* for the different scenarios (*S0* = default, *S1* = decrease temperature, *S2* = decrease N load and *S3* = increase the MLSS concentration): a) aerobic volume (V_{AER}), (b) anoxic volume (V_{ANOX}), airflow (Q_{AIR}) and (d) internal recycle (Q_{INTR}).

- In scenario 3 (*S3*) the MLSS concentration in the reactor is increased from 3000 to 4000 g TSS·m^{-3}.

The effects of the temperature decrease (*S1*) are automatically captured by the temperature dependent kinetics included in the design equations. This situation leads to a substantial increase of the aerobic volume (V_{AER}), the anoxic volume (V_{ANOX}) and the airflow (Q_{AIR}) as well as their associated variance (see Table 4 and Fig. 4). The contrary effect (decrease volume and associated variance), but at lower magnitude, is achieved with an increase of the operational MLSS concentration in the reactor (*S3*). Finally, when the nitrogen load is reduced (*S2*) the aerobic zone (V_{AER}) remains practically equal while the anoxic zone (V_{ANOX}) and the aeration (Q_{AIR}) and internal recirculation (Q_{INTR}) flow rate are reduced in both mean and variance.

Compared to the base case (*S0*) the results of the GSA practically remain unchanged (Table 4). The main difference can be observed in *S2*, with a re-ranking of the influence of design inputs with respect to V_{ANOX}: In this case, the most influential design input is the effluent nitrate requirement ($S_{NOX,e}$) while the anoxic safety factor (SF_{ANOX}) and the influent biodegradability ($f\_X_{U,inf}$) move to second and third rank respectively. With a reduced influent nitrogen load, even with low organic matter content, the design input that will determine the total anoxic volume (V_{ANOX}) is the effluent requirement for nitrate ($S_{NOX,e}$) and not the composition of organic matter in the influent.

4. Discussion

The methodology proposed to assess the ASPDG for WWTP projects has a set of advantages and opens the door to several discussions:

4.1. Regional instead of local analysis of a design problem

The GSA comprising calculation of SRCs, CA and RSA allows a "regional" instead of a "local" analysis of a design problem. For example, when comparing the results of Table 2, the aerobic and anoxic volumes (V_{AER} and V_{ANOX}), the aeration flow rate (Q_{AIR}) and the internal recirculation (Q_{INTR}) are lower in the local analysis than the averages calculated after running the Monte Carlo simulations. In addition the PDF of V_{AER} is highly skewed (there is 17% increase and 9% decrease between the mean values and Q3 and Q1) compared to the other design outputs with a higher degree of symmetry. These regional analyses show the relative impact of different input ranges and how a small number of them may drastically affect the dimensioning and therefore the cost of the WWTP project.

The study also shows the variation of the different design outputs (V_{AER}, V_{ANOX}, Q_{AIR} and Q_{INTR}) as function of: epistemic uncertainty (lack of knowledge), natural variability (due to time or space) or decision ranges (desires or preferences) (Table 3). This allows a better understanding of the relative importance of the role of the agents involved in the decision making (regulators, plant owners, operators, process engineers…) will have on a WWTP project to develop. After running these analyses process engineers should keep in mind that for example, i) the selection of the effluent requirements set by the regulator, ii) the way that the plant operator wants to run the plant or iii) the degree of safety that the owner (water utility) wants to have for his/her plant will strongly affect the cost of the aerobic section (Table 3). On the other hand, the uncertainty in the influent fractionation seems to have a very poor relevance when organic carbon and nitrification reactors have to be designed (Table 3).

The results of the GSA provide information about *why*, *when* and *how* the different construction volumes, air blower characteristics or pumping station capacities may vary when the design inputs are modified. For this case study it was identified that strict effluent requirements (low $S_{NHX,e}$) and a low operational oxygen concentration (S_{O_2}) in the bioreactor were the main *cause* of large aerobic volumes (V_{AER}) (Fig. 3a,c). Similarly, it was shown that poor organic matter biodegradability (low f_S_B & high $f\_X_{U,inf}$) increased the anoxic tank volumes (V_{ANOX}) (Fig. 3b,d). Also, it was possible to identify the situations *when* the changes were more pronounced and *how* these changes occur. For example, the aerobic volume (V_{AER}) increased almost exponentially when the effluent requirements ($S_{NHX,e}$) were lowered from 4 to 1 g m^{-3}. The exponential behaviour of V_{AER} can also explain the lower R^2 values (see Table 3) compared the other design outputs. On the other hand, the anoxic volume (V_{ANOX}) linearly doubled or tripled when the biodegradable fraction is reduced.

4.2. Improvements of designs due to knowledge gain

Secondly, the paper shows that analyzing the effects that input variations might have on the design outputs leads to more reliable designs due to the knowledge gain. From the results reported in Fig. 3b and d, one may conclude that it is useful to perform a detailed characterization of the influent organic matter, particularly if lower nitrate effluent concentrations are demanded. In particular, important savings could be obtained through smaller anoxic volumes (V_{ANOX}) when reducing the uncertainty on the influent fractionation. In case one is certain that one has a readily biodegradable influent, less conservative approaches can be applied when sizing the anoxic reactor (for example selecting lower safety factors). Also, the existing synergies and trade-offs among cost for construction (larger volumes), cost for equipment (smaller aeration system) and cost for operation (lower aeration energy) could be brought to light. Previous results show the interconnection of these three different aspects (V_{AER} and Q_{AIR}) and thorough analyses should be conducted in which one tries balancing construction costs, aeration costs and costs of possible effluent violations. The analysis shows that some opportunities can be identified through the design process, which can be further studied using scenario analysis (See schematics in Fig. 1).

4.3. Scenario analysis to answer what-if questions

Thanks to the scenario analysis it was possible to complement the entire evaluation process and to answer *what-if* questions permitting to evaluate changes in the design and the relative importance of the design inputs. For example, if the plant is constructed in a location with very low minimal temperatures (*S1*), higher averages and larger ranges have to be expected for both aerobic (V_{AER}) and anoxic (V_{ANOX}) volumes. Nevertheless, the results of the GSA showed that V_{AER} and V_{ANOX} were also sensitive to S_{O_2} and S_B and $X_{U,inf}$. For this reason, if an additional investment is made into a good aeration system or if the occasional addition of an external carbon source is considered, the biological volumes (V_{AER} and V_{ANOX}) could be significantly reduced. Scenario 2 revealed that the default influent wastewater does not have a suitable C/N ratio. This fact could be suspected from the anoxic zone hydraulic retention times obtained in *S0* ($HRT_{ANOX} \approx 3$ h), which is higher than the values suggested in literature (HRT = 1–3 h). The scenario analysis revealed that a substantial reduction in construction (V_{ANOX}) and operational costs (Q_{INTR} and Q_{AIR}) occur at a lower nitrogen load. The results of this analysis can warn the plant manager not to accept some high N-strength industrial influent, encouraging the implementation of source control measures. In scenario 3 (*S3*), it was possible to see a substantial reduction of the biological volumes when the design MLSS concentration was allowed to increase. Keeping this idea in mind, some designers may want to invest in a larger secondary clarifier, thus avoiding possible solids separation problems which are more likely to occur at such high MLSS concentrations. Finally, with the scenario analysis it is also possible to deduce general properties of the design guidelines that can be applied to a wide range of cases. For example *S1* and *S3* do not lead to changes in the importance ranking of the inputs. Nevertheless, there are always special cases that will have to be treated separately *e.g. S2* (which leads to a change in the rankings).

4.4. Methodology as support tool for designers

At this stage of the paper the readers must be aware that process knowledge is essential to analyze the information provided by the proposed methodology. However, the pre-selection made by CA and the combined input–output visualization in the same plot can facilitate the analysis. For experienced designers some of the highlighted points are obvious. Nevertheless, especially when nonlinearity increases or in the presence of interactions between design inputs, estimating how input ranges influence the design outputs may not be trivial. The methodology is expected to be useful to design engineers, regulators, operators and students/junior engineers as it lets them explore how design outputs are influenced by input ranges. The reader is reminded that this case study only shows the effect of a selected number of design inputs on a simple guideline and that an analysis of a full scale design problem is out of scope of the paper.

4.5. Guideline comparison

The modular structure of the methodology allows to plug-in any design guideline (Grady et al., 1999). This is a topic of current research that evaluates how sensitive the different guidelines react to the same design input ranges for the same project. In this way, one may know if these design guidelines use more or less conservative approaches.

4.6. Underlying assumptions

Finally it is important to highlight that the conclusions of the present case study are as good as the underlying assumptions. The selection of the design guideline is crucial and will determine the values of the design outputs. In the same way, the definition of the design problem, the scope of the study and the definition of the input ranges strongly affect the results and the conclusions of the analysis. The reader is reminded that the description of important factors such as the characteristics of input ranges for the design inputs, the assigned PDFs (uniform) and the sampling methodology (non-correlated) are kept rather general in this generic case study. A modification in all these points could lead to a different interpretation of the results. The results of the analysis like the one presented herein have to be interpreted in the context that has been formulated.

5. Conclusions

The paper presents a methodology and the supporting tools to assess the use of ASPDG in WWTP design projects. The proposed methodology is based on MC simulations and GSA and enables process engineers to better understand the relationships between design input and design output ranges. The main novelty of this approach relies on: i) working with input and output ranges, ii) identifying the most influential design inputs on the different design outputs and finally iii) improving the interpretation of the generated results by a set of visualization tools. The key findings of the presented investigation can be summarized as follows:

- The paper contributes to the field of wastewater engineering with a method that allows a "regional" instead of a "local" use of a design procedure.
- MC & GSA (SRC, CA and RSA) are useful tools to identify which design inputs influence the design outputs the most.
- The proposed set of methods provide a better understanding about when, how and why design outputs change as a function of design input ranges.
- Additionally, the results generated during the study would allow to a junior/senior process engineer to gain a deeper insight into the design guideline and deduce general properties improving his/her understanding.

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