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Model development and simulation for predicting risk of foaming in anaerobic digestion systems

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ABSTRACT

Although there is not a complete agreement on the causes of foaming in anaerobic digestion, experts and operators do have valuable empirical knowledge of key factors. Based on this knowledge, a model for calculating the risk of foaming in anaerobic digestion systems due to microbiological causes has been developed. Organic loading rate, variation in organic loading rate, and the presence of filamentous microorganisms in the activated sludge system, used as a feed source for the digester, have been selected as the inputs of a knowledge-based model designed to provide as output the risk of foaming in an anaerobic digester. The performance of the model is demonstrated by means of a case study using the IWA Benchmark Simulation Model No. 2 as a framework, where risk of foaming is used as a new evaluation criterion. The simulated results of an open-loop configuration and two closed-loop control strategies illustrate the usefulness of this knowledge-based approach as a means of estimating the risk of foaming in anaerobic digestion.

1. Introduction

Deterministic models have been widely used to describe anaerobic digestion (AD) processes, mainly for very specific purposes. For instance, in Mu et al. (2007), an AD model is used to describe the growth of hydrogen producing microorganisms, the consumption of substrate and the formation of product. Bernard et al. (2001) propose a two-step model that can be easily used for closed-loop control and optimisation of AD processes. Other studies have focused on sulphate reduction in AD (Knobel and Lewis, 2002). Specifically, one of the motivating factors behind the development of the Anaerobic Digestion Model No. 1 (ADM1) was to focus on setting up a more complete and versatile model, based on the first AD models (Batstone et al., 2002).

However, none of these AD modelling approaches is able to overcome one of the limitations of deterministic modelling, an inability to properly describe the population dynamics responsible for operational imbalances (e.g. the presence of foam caused by filamentous bacteria). There have been a few promising studies about the modelling of microbial diversity, such as the work by Ramirez et al. (2009), where the significant role of microbial diversity regarding the modelling and control of AD processes is highlighted. Nevertheless, this advance does not provide a comprehensive, general model of the mechanisms involved in the development of foaming in anaerobic digestion systems and therefore other approaches have to be studied. Indeed, among the various operating problems that affect AD in wastewater treatment plants, foaming is the most extensive and problematic. The consequences of foaming are numerous: blockage of the gas mixing devices, fouling of gas collection pipes, decrease in volatile solids reduction, loss of effective digester volume, low biogas production, etc. For this reason, several studies have been published on causes of foaming in anaerobic digestion (FAD). According to the review by Ganidi et al. (2009) causes of FAD are related to two main sources, the feed sludge characteristics (including surface active agents, organic loading rates and filamentous microorganisms) and the digesters design and operating characteristics (shape, temperature, mixing). Therefore different types of process data combined with heuristic knowledge of the operators are exploited to detect this microbiology-related operational problem on full-scale systems: on-line data, off-line analytical data reflecting the feed sludge quality and quantity, off-line microbiological information (floc and sludge aspects, filamentous bacteria species identification, etc.) and in situ visual observations are all taken into account. However, the usefulness for prediction is limited: it only provides a warning when the

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problem is already in a developed stage. The presence of heuristics and qualitative knowledge on complex phenomena such as anaerobic digestion foaming stands in sharp contrast with the lack of basic mechanistic knowledge on the population dynamics of the microorganisms causing these phenomena.

The complexity involved in the description of operational problems of microbiological origin can be tackled by Knowledge-Based Systems (KBSs), as complementary tools to mechanistic models. KBSs use heuristic knowledge and human experience to apply reasoning to the problems that can affect a system. Enhanced description of complex operational problems can be achieved by linking numerical models and knowledge-based systems into integrated tools, which allow for management and active use of essential knowledge related to these problems. Literature examples on the application of knowledge-based tools (e.g. expert systems, fuzzy logic or qualitative modelling) or data-based models (e.g. neural networks or data-driven models) complementing mechanistic models in anaerobic digestion modelling are also already available (e.g. Puñal et al., 2003). For example, in Puñal et al. (2003) a KBS is applied to the monitoring and diagnosis of an AD plant. The system is able to identify the current state of the process (i.e. normal, hydraulic overload, organic overload, etc.); it can also predict its trend, failures in the instrumentation and propose control actions. The results of validation show that the system can present valuable solutions that end up in recovering normal operation. Data mining techniques have also shown to be useful tools to determine the relevance of the process variables on AD foaming. Recently, the work presented in Dalmau et al. (2010) presented an example of how a wrapper approach is applied to select the most relevant variables to foaming in AD. Besides, a knowledge-based risk assessment model for settling problems of microbiological origin in activated sludge systems (filamentous bulking, foaming and rising sludge) has been successfully developed and applied (Comas et al., 2008).

The aim of this paper is to present a knowledge-based risk model, which integrates expert knowledge with the mechanisms of AD in standard deterministic models, to infer foaming of microbiological origin during the simulation of anaerobic digestion systems. First, the development of the risk model is presented including the knowledge embodied in the risk model and its implementation in fuzzy logic. Then, the performance of the risk model in different case studies is discussed, using the IWA Benchmark Simulation Model No. 2 (BSM2) as the simulation platform of wastewater treatment plants (Jeppsson et al., 2007). The case study scenarios include an open-loop scenario to show the general performance of the AD risk model and a case study in which the open-loop case study and two control strategies are compared. Finally, conclusions are drawn based on model simulations results using the risk model developed.

2. Risk model development

The development of the risk model for foaming simulation is divided in four steps: knowledge acquisition, selection of key variables, implementation, and simulation. For the knowledge acquisition, the literature related to foaming in AD is reviewed considering the most relevant causes for foaming. In the second step, the suitable variables for foaming simulation are selected taking into account their availability in the current mechanistic models and ability to control them to minimise/remediate foaming problems. The third step involves the implementation of the risk model in a fuzzy logic rule-based system, presenting the different membership functions and the rules embodied in the risk model. The last step is the design of the model outcomes used for simulation evaluation.

2.1. Knowledge acquisition

Fig. 1 presents a scheme of the current knowledge on possible causes for foaming in AD that are reviewed in the work by Ganidi et al. (2009). It has been divided between the feed sludge characteristics and the anaerobic digester design and operational conditions. Three groups of causes for foaming were identified including the input sludge characteristics (surface active agents, organic loading rates (OLR) and filamentous bacteria). Mixing energy, temperature, and VFA levels (as a main surface active agent present in the anaerobic digester) and shape of the digester were identified as the other main causes for foaming related to the anaerobic digester design and operational conditions.

Ganidi et al. (2009) stated that surface active agents in anaerobic digestion feed act as foaming initiators when a concentration threshold (still unknown) is exceeded. They also point out that accumulation of surface active agents is related to their degradability. Therefore, lipids contribution to foaming is less when compared to proteins due to a faster degradability of the former, which are less likely to accumulate in the bulk phase and cause foaming. In terms of detergents, their low degradability under anaerobic conditions, which implies an increased surface activity of the anaerobic sludge, can be related to foaming. But there is no confirmation of foaming events due to this factor in the literature.

With regard to filamentous bacteria (*Microthrix parvicella and Gordonia* spp.) many studies point to their direct involvement in foaming events (Pagilla et al., 1997; Westlund et al., 1998; Eikelboom, 2000; Moen, 2003; Barber, 2005). Ganidi et al. (2009), following the example of Davenport and Curtis (2002) in terms of foaming in AS, stated that foaming in AD can be regarded as a 3-phase system comprising of gas, liquid and solid particles. The gas and liquid phases contain the surface active agents responsible for foam initiation and the solid phase contains the particles (hydrophobic bacteria such as *M. parvicella* and *Gordonia* spp.) responsible for foam stabilisation.

The relationship between OLR and foaming is supported by many authors as shown in Fig. 1. In Ganidi et al. (2009), it was suggested that the residual feed organic constituents, not fully degraded in the digester, leads to the accumulation of hydrophobic substances that can promote foaming. However, there is still a lack of information on the critical concentrations for hydrophobic substances. Some authors propose 'safe' ranges of OLR although they are broad and probably each digester would have its own critical organic loading threshold. Overloading and fluctuation of digester loading should be avoided by daily and weekly monitoring of solids loading rates and the digester's performance. Intermittent loading rates lead to intermittent levels of gas production and if the gas collection piping is not of adequate capacity, there is potential for onset of foaming during higher gas production periods.

In terms of the digester design and operational conditions, gas mixing is pointed out by some authors (Pagilla et al., 1997; Barber, 2005; Moen, 2003) as a cause of foaming. With regard to the mixing energy, poor and excessive mixing can both cause foaming (Pagilla et al., 1997; Brown, 2002; Moen, 2003). Concerning the digester shape, no information so far has suggested a relationship between digester shape and foaming occurrence (Metcalf and Eddy, 2003). Both conventional and egg shaped digesters have experienced foaming problems in the recent years. In relation to temperature, higher temperatures reduce surface tension and viscosity of sludge increasing the foaming risk. However, the only experimental evidence on the effect of temperature in digestion is from Chae et al. (2008), but no reference to foaming events is made in the paper. Surface active agents accumulation in the digester (mainly VFA) has also been pointed out as a foaming cause, however, there is no experimental or quantitative evidence in the literature to

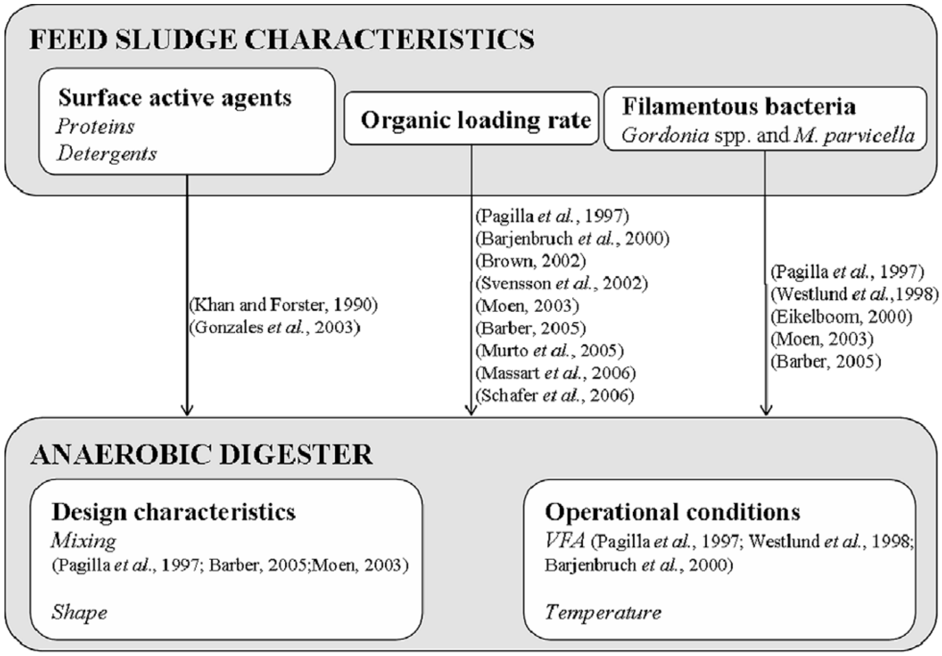

Fig. 1. Schematic representation of the possible causes for FAD (See above-mentioned references for further information.)

support the interpretation that accumulation of acetic acid leads to foaming (Ganidi et al., 2009).

2.3. Selection of related variables

With regard to the selection of the most relevant variables to identify foaming (i.e. the inputs for the risk model), some considerations were made to take into account variables or factors depending on whether or not they are usually modelled, and are key factors that cause and can be used to control foaming.

The first one highlights the relevance of controlling loading rates, as previously stated, overloading and fluctuation in digester loading should be avoided by daily and weekly monitoring of solids loading rates and the digesters performance. Besides, the literature has many examples of studies and full-scale plant experiences relating foaming and poor operational practices in terms of loading rates (as shown in Fig. 1). Thus, to consider the effect of unstable and high loading rates as potential foaming causing factors, OLR and its daily variations have to be two of the risk model inputs.

Since filamentous bacteria are also related to foaming in anaerobic digesters, as many studies point to *Gordonia* spp. (formerly *Nocardia* sp.) as initiators of foaming, and responsible for foam stabilisation, the presence of filamentous bacteria in the AD feed (i.e. waste activated sludge from foaming-plagued activated sludge systems) should be taken into account in the risk model. This is possible given that the risk model for the activated sludge by Comas et al. (2008) provides the risk of foaming due to *M. parvicella*. The risk of foaming in activated sludge (FAS) is included as a contributing factor in the AD foaming risk model.

Concerning the surface active agents present in the AD inflow (mainly proteins and detergents; Fig. 1), in general these substances represent mostly low biodegradable substrates (described as particulate substrates in standard anaerobic digestion models). Detergents are not usually specifically described as state variables unless they are used for very specific purposes, and therefore, they cannot be taken into account directly. Nonetheless, in Ganidi et al. (2009) it is stated that the detergents contribution to foaming is linked to the surface tension of the liquid phase. Since the surface tension in the liquid phase is usually not measured or modelled in AD models and it will not be considered in the risk model. Nevertheless, the role of proteins as surface active agents is taken into account without including additional variables by including them in the particulate substrate calculations and therefore, in the OLR calculation.

Considering the anaerobic digester mixing, as commented, both excessive and poor mixing can cause foaming if a critical concentration of surface active agents is present. Since the mixing energy is only calculated in some ADM1 implementations, the mixing energy effect has not been considered. Besides, the distinction between gas and mechanically mixed digesters is not considered in the risk model since it is not commonly modelled.

The effect of temperature oscillations on foaming in mesophilic conditions has not been studied. For thermophilic conditions, the effect is only supposed to be on viscosity and surface tension of the liquid phase. However, despite the fact that temperature effect would be of great interest for a mechanistic model of foaming in AD, it is not included in this risk model because standard anaerobic digestion models do not consider temperature as a state variable.

As pointed out in the knowledge acquisition, there is no proven effect of the digester's shape on foaming (Metcalf and Eddy, 2003). Therefore, it has not been considered in the risk model.

With regard to the effect of VFA accumulation in the digester as a cause for foaming, many works link VFA accumulation to foaming, but no experimental or quantitative evidence has been reported in this regard. Besides, accumulation of VFAs is generally considered to be a result of organic loading rate imbalances, which is already included in the risk model as a variable. Thus, VFA levels as a distinct variable has not been considered for the risk model.

To summarise, OLR (considering proteins, lipids and inert material), daily OLR variation, and the presence of filamentous bacteria in the influent (related to FAS risk) will be the input variables of the risk model. Although the selection of these three input variables from the possible variables may restrict a broader applicability of the risk model proposed, it still provides valuable information about the risk of foaming when simulating anaerobic digestion processes.

2.4. Implementation

The description of expert knowledge is tackled using the principles of fuzzy decision theory (Bellmann and Zadeh, 1970). Due to its simplicity and efficiency, this theory is already widely used in environmental modelling applications. The risk model estimates the risk of occurrence of microbiology-related anaerobic digestion foaming by processing the data used by the mechanistic model (not only simulation outputs but also influent data and operational parameters). In this work, the fuzzy toolbox by MATLAB® (MathWorks Inc.) has been used to implement the risk model.

The risk estimation implies three main steps:

(i) *fuzzification*, where the crisp values of numerical data are converted into linguistic labels (i.e. low, high, etc.) by means of corresponding membership functions. Membership functions are defined for each input and output variable used (i.e. OLR, OLR daily variation, risk of foaming in the AS – FAS risk – and FAD risk). Triangular or pseudo-trapezoidal functions are used to define the membership functions.Limits for the different membership functions were proposed (e.g. what values represent a very low, low, medium, high and very high OLR). Concerning OLR limits, Metcalf (2003) state that the appropriate OLRs for anaerobic digesters are between 1.6 and 4.8 kg VS m^{-3} d^{-1}. The manual of operation of the Water Environment Federation (1996) suggests an OLR between 1.6 and 6.2 kg VS m^{-3} d^{-1}. For instance, Massart et al. (2006) state that to prevent FAD, the OLR should be maintained between 1.6 and 2.4 kg VS m^{-3} d^{-1}. Murto et al. (2005) found that an OLR higher than 2.6 kg VS m^{-3} d^{-1} can produce excessive foaming. Regarding OLRvar, Massart et al. (2006) recommended a daily variation of 5–10%. These limits, once related to Fig. 2, result in the membership function features listed in Table 1. A last consideration was made given that the OLR limits that appear in the bibliography do not distinguish between proteins, lipids, carbohydrates and other surface agents as the usual AD models can do. Hence, in OLR calculation from simulation results carbohydrates where included. OLRvar will be calculated on a daily basis as the percentage of variation of the average OLR for one day with respect to the average OLR of the previous day. A customization of the parameters related to the fuzzy approach such as the limits or overlapping of the membership functions is left to the final user (the same OLR, OLRvar or presence of filamentous organisms in the aeration basins do not affect in the same way – in terms of microbiology-related foaming – in all the anaerobic digestion systems).

(ii) *fuzzy inference*, in order to obtain an output for the FAD risk, a set of rules were defined including the knowledge acquired (presented in Fig. 2). This set of rules will form the knowledge base of the risk model. The basic decision matrix is the front layer of Fig. 2 that takes into account the OLR (left axis of Fig. 2) and its variation on a daily basis (bottom axis in Fig. 2). From this basic decision matrix the FAD risk increases as the FAS risk (right axis in Fig. 2) increases (second and third layers in Fig. 2). Each box corresponds to the result of a rule. e.g. ⟨IF OLR is very low AND OLR variation is medium AND FAS risk is high THEN FAD risk is medium (grey box)⟩. To concatenate the set of rules, the Mamdani method was selected as the fuzzy inference method (Mamdani and Assilan, 1975). Again the limits for the qualitative ranges of the three decision matrices are left for calibration to the end user according to site specific conditions.

(iii) *Defuzzification*, in which the linguistic label obtained from the inference is converted into a numerical value for the only output of the risk model 'FAD risk'. Again, this is performed by means of the above mentioned membership functions. The method used to obtain the numerical value for the FAD risk is the centre of gravity (Fiter et al., 2005).

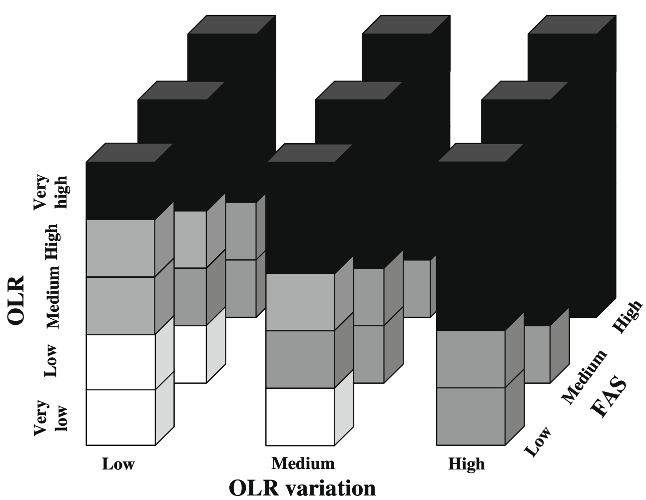

Fig. 2. Decision matrices of the risk model. Degree of FAD risk indicated by colours: white boxes indicate low FAD risk, grey boxes are for medium FAD risk and black boxes represent high FAD risk.

2.5. Model outcomes

The outcome of the model, the FAD risk, indicates the potential for development of foaming in the anaerobic digester. The FAD risk value provided by the model ranges from 0 (very low possibility) to 1 (most likely). The risk model outputs are the FAD risk profile vs. time and the percentage of time over the whole simulation period at high (>0.8) FAD risk. Fig. 3 shows the response surfaces for FAD risk depending on OLR and OLRvar for each FAS risk membership function (i.e. Fig. 3a for low, Fig. 3b for medium and Fig. 3c for high FAS risk). Fig. 3 illustrates how the high FAD risk zone (top) of the surfaces becomes wider as FAS risk increases from low to high. The inverse effect is shown for the low FAD risk zone (bottom).

To consider the low dynamics of foaming development, the outcome risk is filtered by means of an exponential filter with a time constant of three days (Comas et al., 2008) although it can be customised by the user of the risk model. This filter prevents unrealistic sudden changes from very high to very low values for FAD risk.

Table 1
Membership function features of the risk model.

Variable		Very low	Low	Medium	High	Very high
OLR (kg VS m^{-3} d^{-1})	Shape	Trapezoidal	Triangular	Triangular	Triangular	Trapezoidal
	Range	[−0.1,0,1,1.8]	[1.2,1.8,2.4]	[1.8,2.6,3.4]	[2.4,3.4,4.4]	[3.4,4.4,5,10]
OLRvar (%)	Shape	–	Trapezoidal	Triangular	Trapezoidal	–
	Range	–	[−0.1,0,10,15]	[10,15,20]	[15,20,30,100]	–
FAS risk (from 0 to 1)	Shape	–	Trapezoidal	Triangular	Trapezoidal	–
	Range	–	[−0.1,0,0.3,0.5]	[0.2,0.6,0.8]	[0.6,0.8,1]	–
FAD risk (from 0 to 1)	Shape	–	Triangular	Triangular	Triangular	–
	Range	–	[−0.2,0,0.2]	[0.2,0.5,0.8]	[0.8,1,1.2]	–

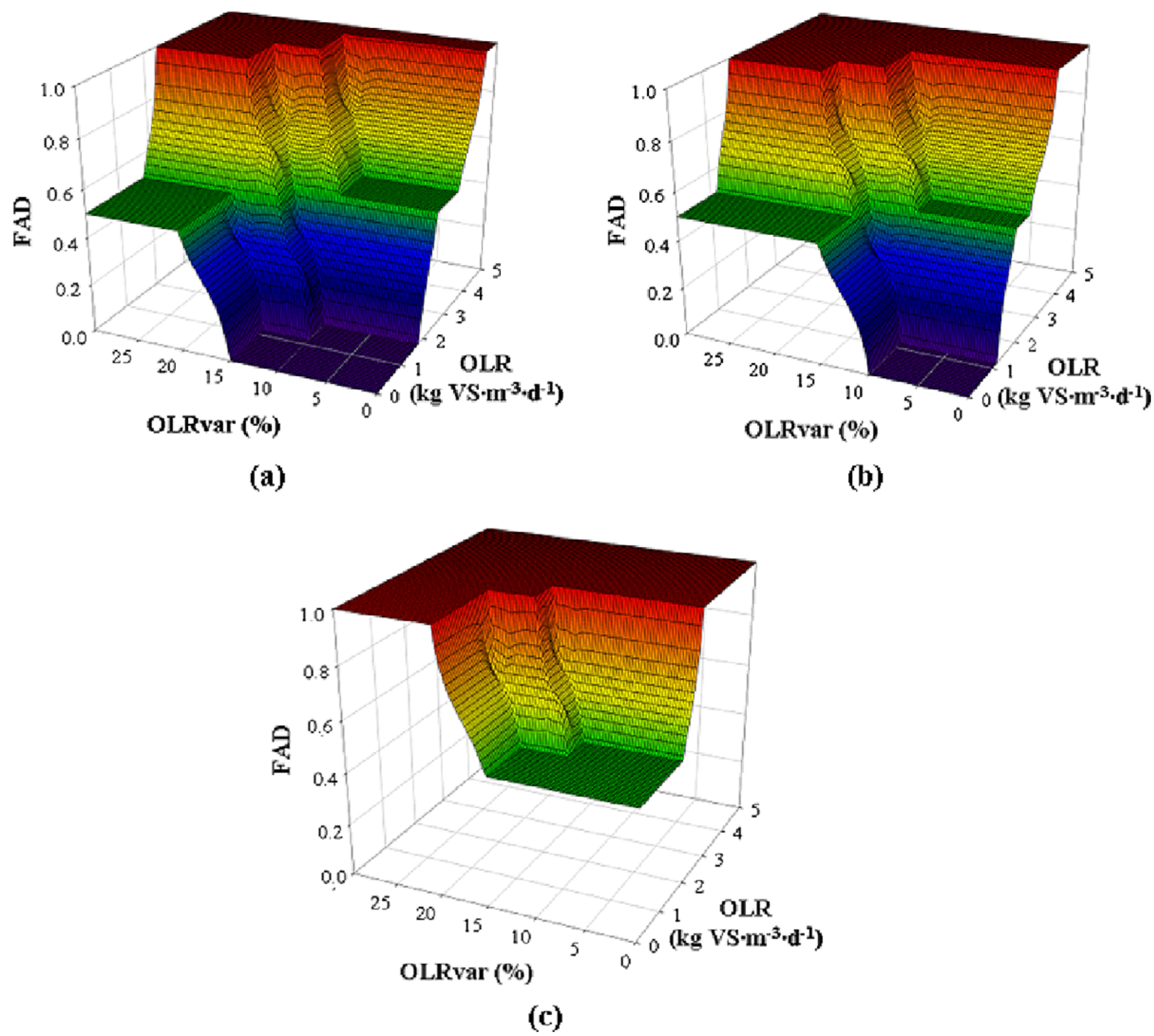

Fig. 3. Response surfaces for FAD risk for each FAS risk membership function value: (a) low; (b) medium and (c) high FAS risk.

Obviously, risk model outputs also depend on the limits of the fuzzy membership functions. As a compromise, these limits were chosen from standard values, as described in the implementation section. However, it is worth remembering that users can change these limits according to their own AD configuration since the limits for OLR that can cause foaming may vary from one digester to another.

3. Performance of the risk model

This section presents the performance of the risk model in a case study using the BSM2 as a framework to illustrate the usefulness of the knowledge-based approach for estimating the AD risk. After the BSM2 has been introduced, the section is divided into two parts. The first is dedicated to the results of the risk model from open-loop simulations. The second is devoted to a comparison of WWTP control strategies related to FAD risk through simulation studies.

3.1. Framework: the IWA Benchmark Simulation Model No. 2

BSM2 is a standardised simulation protocol for testing and validating control strategies applied to wastewater treatment plants. It is a plant-wide layout and model composed of seven components: (i) a primary clarifier based on the description of Otterpohl and Freund (1992) and Otterpohl et al. (1994); (ii) a five-reactor (two anoxic plus three aerobic) nitrogen removal activated sludge configuration based on ASM1 (Henze et al., 1987); (iii) a secondary clarifier based on the double exponential model of Takács et al. (1991); (iv) an ideal gravity thickening unit; (v) anaerobic digestion based on ADM1 (Batstone et al., 2002); (vi) an ideal dewatering unit and, (vii) a storage tank. A BSM2 simulation is run for a total of 809 days. The initial 200 days are used to reach a steady state with constant input data, while 245 of the remaining 609 days are used to reach a quasi-steady-state using dynamic input data and to provide adaptive controllers with enough time to estimate parameter values. Therefore, only the last 364 days are available to be used for evaluation purposes. The evaluation criteria of the BSM2 encompass, among others, an effluent quality index (EQI in kg of pollutant units d^{-1}) which is a weighted sum of the pollutants in the effluent, and an operational cost index (OCI, dimensionless) which includes costs accrued from pumping energy, aeration, mixing, sludge disposal, external carbon source addition and methane production. A detailed description of the whole layout, simulation protocol, sensor models, control handles and evaluation criteria calculations for the BSM2 can be found in Jeppsson et al. (2007) and Nopens et al. (2008).

3.2. Open-loop case

An open-loop case study with constant values for the main plant-wide WWTP operational parameters was simulated to

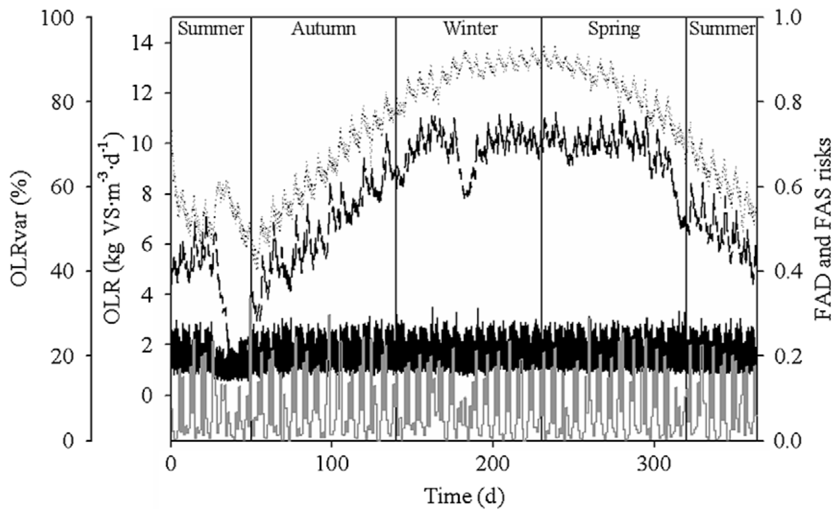

Fig. 4. Simulated results of the risk model for the open-loop case for a one-year simulation (from July 1st). OLR (solid line); OLRvar (grey line); FAS risk (dotted black line); FAD risk (dashed line).

illustrate the performance of the risk model. In terms of operational parameters related to the FAD risk, the waste activated sludge (WAS) flow rate, Qw, was fixed at 300 $m^3\,d^{-1}$ and the return activated sludge flow rate, Qr, was equal to the influent wastewater flow rate, Q. Fig. 4 shows the FAD risk profile as a function of time over different seasons together with OLR, OLRvar, and FAS risk profiles.

In general, the FAD risk trend is similar to that for FAS risk. However, at the end of the summer (days 30–50, approximately), there is a divergence in FAD risk with respect to the FAS risk due to a greater decrease in both OLR and OLRvar, which compensates for the increase in FAS risk during the same period. From approximately day 170 until the onset of summer (day 310), FAD risk stabilises satisfactorily at around 0.7. In this period FAD risk has the highest values possible with low OLR (1.2–2.4 kg VS $m^{-3}\,d^{-1}$) and between low and medium OLRvar (5–20%). In other words, FAD risk does not increase further (unlike the FAS risk) because it has reached its maximum value with the current values of OLR and OLRvar. FAD risk would only increase, at these levels of FAS risk, with higher OLR and/or OLRvar. Around day 185, FAD risk drops considerably for a few days, in line with OLRvar values, even though FAS risk is relatively high at this time. From day 270, the trend is for FAD risk to decrease in line with the FAS risk, and drop more sharply around day 320 due to another sharp decrease in OLRvar values around the same time.

3.3. Operational parameters influence

According to the definition of the risk model, two main operational parameters influence the FAD risk: Qw and Qr. Qw influences the amount of solids going to the anaerobic digester, and changes the OLR accordingly. Qr has a direct effect on the amount of solids in the activated sludge tanks, which is directly related to the F/M ratio on which the FAS risk depends. In other words, low Qr keeps solids concentration lower in the aerated tanks by not returning the activated sludge from the clarifiers at high enough rate, so the F/M is increased temporarily, thereby lowering the FAS risk, and vice versa.

For both Qr and Qw simulations the previously presented open-loop case was used. For each Qr simulation Qw was kept at 300 $m^3\,d^{-1}$, and for each Qw simulation Qr was kept at 1.0 times the inflow rate (Qin). Qw was tested from 100 to 700 $m^3\,d^{-1}$ in 100 $m^3\,d^{-1}$ steps, whereas Qr was tested from 0.25 times to 1.5 times Qin in 0.25 steps.

3.4. Effect of Qr

Table 2 summarises the average FAD risk, FAS risk, OLR and OLRvar for each Qr. Table 2 shows how FAD risk increases from 0.412 for a Qr value of 0.25 times Qin to 0.571 for a Qr value of 1.0 times Qin. From this point, on average FAD risk remains constant at 0.574 for higher Qr values. As noted previously, at low Qr, FAS risk is low as well, in accordance with FAD risk. At higher Qr the inverse effect takes place, and average FAD risk increases. Average OLRvar increases at the same rate that the average OLR decreases as Qr increases. This trend can be explained by the fact that lower values of OLR and similar values of OLR increments give a higher percentage of OLRvar.

3.5. Effect of Qw

Table 3 shows the average FAD risk, FAS risk, OLR and OLRvar for each Qw. When Qw increases, average FAD risk also increases slightly at first, from 0.548 to 0.572, but then descends to 0.432. The increase in average OLR explains the rise in average FAD risk for Qw from 100 to 200 $m^3\,d^{-1}$. Afterwards, it descends to 0.432 (for Qw equal to 700 $m^3\,d^{-1}$), given that FAS risk decreases drastically from 0.766 to 0.475 with the increase in Qw (from 200 to

Table 2
Average FAD risk, FAS risk, OLR and OLRvar for each Qr.

Qr ($m^3\,d^{-1}$)	0.25 Qin	0.5 Qin	0.75 Qin	1 Qin	1.25 Qin	1.5 Qin
av. FAD risk	0.412	0.545	0.565	0.571	0.574	0.574
av. FAS risk	0.438	0.655	0.701	0.725	0.739	0.748
av. OLR (kgVS $m^{-3}\,d^{-1}$)	1.85	1.76	1.72	1.69	1.67	1.66
av. OLRvar (%)	7.14	7.40	7.49	7.53	7.55	7.58

Table 3
Average FAD risk, FAS risk, OLR and OLRvar for each Qw.

Qw ($m^3\ d^{-1}$)	100	200	300	400	500	600	700
av. FAD risk	0.548	0.572	0.571	0.559	0.534	0.496	0.432
av. FAS risk	0.779	0.766	0.725	0.679	0.633	0.581	0.475
av. OLR (kgVS $m^{-3}\ d^{-1}$)	1.39	1.61	1.69	1.74	1.79	1.82	1.85
av. OLRvar	9.01	7.76	7.53	7.52	7.55	7.53	7.51

700 $m^3\ d^{-1}$, respectively). Above Qw equal to 200 $m^3\ d^{-1}$, OLR does not increase enough to become significant compared to the FAS risk. Regarding average OLRvar, it decreases in line with the increase in the average OLR, as in the previous case (i.e. Qr study), although this time the effect is greater for the Qw of 100 $m^3\ d^{-1}$, given the low average OLR. Thus, for a given daily OLR oscillation it is important not to have too low OLR, since OLRvar could increase the FAD risk.

3.6. Closed-loop control strategies

Two closed-loop cases with automatic controllers involving manipulation of variables related to the risk model inputs were used to test the model's performance.

The first control strategy (CS1) involves the BSM2 default DO controller (Nopens et al., 2008), which consists of a proportional-integral (PI) DO controller with a set point of 2 g $O_2\ m^{-3}$ in reactor 4 by manipulating the overall oxygen transfer rate coefficient, K_La. For reactors 3 and 5, the same K_La is applied with a gain of 1 and 0.5, respectively. CS1 also includes a TSS controller with a setpoint of 4400 gTSS m^{-3} (3400 gTSS m^{-3} if $T < 15$ °C) mixed liquor suspended solids (MLSS) concentration, which manipulates Qw. This CS shows the effect of controlling the solids inventory in the activated sludge process on the digester. The variability of Qw is also reflected in the OLRvar value.

The second control strategy (CS2) involves the same DO controller plus an ideal PI OLR controller which manipulates Qw using an OLR setpoint of 1.75 kg VS $m^{-3}\ d^{-1}$. The effect of such a controller on the FAD risk in this strategy is interesting.

Fig. 5 shows the simulated results for CS1. The OLR range is in the same range as in the open-loop case. During the winter period (days from 150 to 240 approximately), the general FAD risk trend is similar to the open-loop case, although this time the manipulation of Qw causes more peaks in OLRvar, which is also reflected in the peaks appearing in the FAD risk profile. Likewise, noticeable changes in the OLR profile are reflected in FAD risk as well. For instance, during the summer period (days from 0 to 50 and 320 to 364 approximately) the same effect as seen in Fig. 4 is present here (i.e. the decrease in FAD risk linked to the decrease in OLR and OLRvar). As a result, keeping the solids inventory constant in the activated sludge tanks in fact causes more instability to the anaerobic digester in terms of FAD risk.

Fig. 6 shows the profile of the risk model input variables for CS2 together with the FAD risk. It can be clearly seen how the OLR controller drastically reduces OLRvar, the effect of which can also be appreciated in the OLR since oscillations have almost disappeared. This low OLRvar causes the FAD risk to stabilise around 0.45 even though FAS risk is high, especially during the winter and early spring period. The only exception to this almost constant FAD risk is during the summer period, with its low MLSS concentration associated with the summer season, which is also the reason for the low FAS risk.

Table 4 shows the benchmark evaluation criteria (i.e. EQI, OCI) together with average time at high FAD risk (>0.8) and average FAD risk for the three cases presented (i.e. open-loop, CS1 and CS2).

While the highest FAD risk corresponds to the open-loop case, the lowest FAD risk corresponds to CS2 since the OLR controller regulates the OLR to a safe setpoint (1.75 kg VS $m^{-3}\ d^{-1}$). The average time at high FAD risk is higher for CS1 due to the control of the MLSS in the activated sludge. For example, whenever MLSS is high the automatic controller increases Qw, which increases the feed OLR to the anaerobic digester. Effluent quality is slightly worse for CS2 than for open-loop and CS1 due to the fact that the OLR control is performed regardless of the MLSS concentration in the sludge system. Thus MLSS concentration in the activated sludge tanks could be lower than the concentration required to achieve optimal treatment efficiency. Operational cost is lower for CS2 due to the low OLRvar linked to low Qw variations, as can be seen in the OLRvar profiles in Figs. 5 and 6. Moreover, OLR is slightly higher in CS2 than in CS1, leading to higher methane production

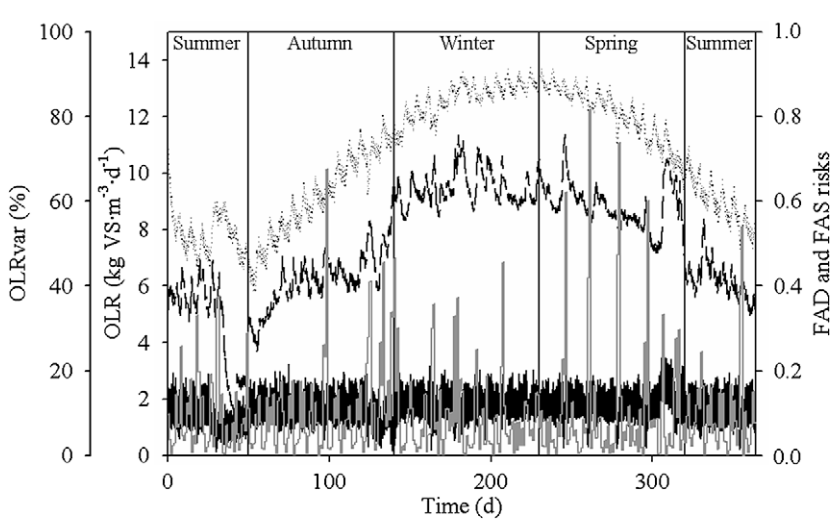

Fig. 5. Risk model CS1 results for a one-year simulation (from July 1st). OLR (solid line); OLRvar (grey line); FAS risk (dotted line); FAD risk (dashed line).

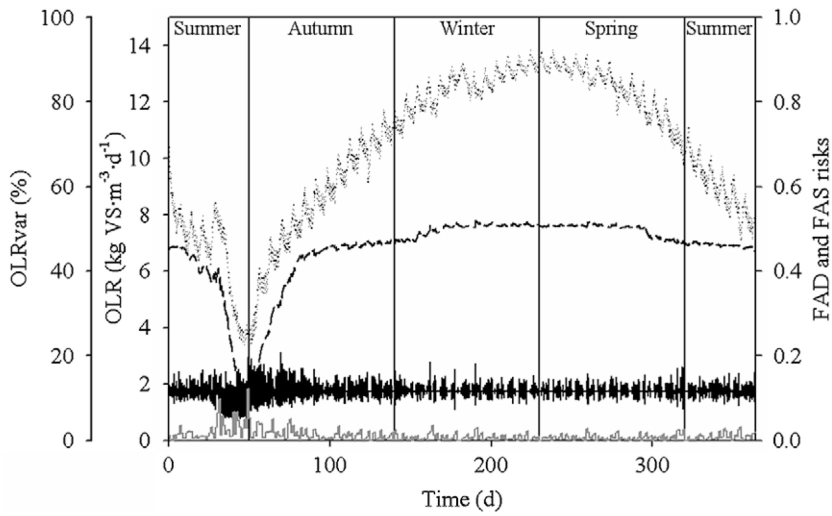

Fig. 6. Risk model CS2 results for a one-year simulation (from July 1st). OLR (solid line); OLRvar (grey line); FAS risk (dotted line); FAD risk (dashed line).

Table 4
Average FAD risk, percentage of time at high FAD risk and benchmark evaluation criteria for open-loop, CS1 and CS2.

	Average FAD risk	Average time at high FAD risk (%)	EQI (kg pollutant units d^{-1})	OCI
Open-loop	0.58	0	5657	9208
CS1	0.54	0.34	6499	6812
CS2	0.45	0	6677	6735

and, therefore, a decrease in operating costs. As is evident, there is a trade-off between the optimal performance in the activated sludge and anaerobic digester regarding effluent quality and costs. The results of the risk model emphasise the need for plant-wide supervisory control strategies to minimise trade-off effects, which at the same time is an aim for sustainable sludge and wastewater treatment.

4. Discussion

Recent research advances in population dynamics and mechanistic modelling provide valuable knowledge for future development of a general deterministic model of the filamentous bacteria and related operational problems of microbiological origin. Nevertheless, a complete general mechanistic model is yet to be determined. Thus, a risk model provides a complementary tool which can be applied to any general or specific models.

Regarding the results of the risk model, it is important to highlight that the aim is not to diagnose operational problems of microbiological origin with absolute certainty but to quantify whether the simulated control strategies bring about a severe risk for leading the system towards a situation with operational problems of microbiological origin. In order to calculate the evaluation indices it was necessary to quantify the risk index initially with a scope to improve later with more mechanistic factors included. For this reason, a threshold value of 0.8 was fixed to indicate severe risk of operational foaming problems of microbiological origin.

Validation is still an open question since it is difficult even in the case of the risk model used in this research. A validation of the risk model based on real data from a pilot plant or a full-scale WWTP is very difficult due to the fact that the model is giving the risk of a particular operational problem of microbiological origin but this risk is seldom recorded in real plants (common monitoring programs do not even register the occurrence of those problems). Moreover, the risk model is not developed to be applied in full-scale facilities directly by itself but to complement dynamic simulations when comparing operational procedures and control strategies.

A sensitivity analysis can enhance the customization of the risk model offering the possibility to identify the most sensitive variables. Afterwards, a customization process based on those variables could provide a more reliable risk model for adaptation to specific anaerobic digestion systems. Performing a detailed and complete sensitivity and uncertainty analysis of the risk assessment model, not only to study the effect of the fuzzy parameters (limits, ranges and shape of membership functions) but also to understand and analyse the knowledge embodied in the decision matrices and to highlight the relevance and linearity of the variables, is high on our priority list of future work.

5. Conclusions

The risk model for anaerobic digestion foaming together with a risk model for problems related to activated sludge systems provide an overall approach for the plant-wide evaluation of microbiology-related problems, allowing model users to have a complete set of criteria and thereby avoid biased evaluations of the simulation results.

This tool is complementary to existing criteria related to removal efficiencies and to operational costs, meaning that new conclusions can be drawn from the simulation evaluation process when microbiology-related problems are included. Some simulated control strategies which can have a positive impact in terms of environmental and/or economic criteria may prove to be not suitable when anaerobic digester performance is evaluated.

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