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Identification of critical operational hazards in a biogas upgrading pilot plant through a multi-criteria decision-making and FTOPSIS-HAZOP approach

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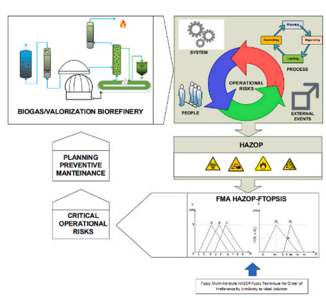
HIGHLIGHTS

- FTOPSIS Method was implemented in a biogas upgrading plant.
- Major risks were identified in the desulfurization biofilter and bioreactors.
- Preventive maintenance could be improved after fuzzy logic risks analysis.
- MCDM-HAZOP and FTOPSIS are used to identify hazards and determine risk values.
- Analytical hierarchy process was effectively used for criteria weighting.

GRAPHICAL ABSTRACT



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ABSTRACT

The hazard and operability analysis (HAZOP) is one of the most popular approaches for risk management, although weaknesses such as the limited number of risk factors considered, the inaccuracy of experts' opinions or the limited process knowledge might compromise the quality of the results. In this context, conventional HAZOP analysis can be improved via a Fuzzy Multi-Attribute HAZOP technique. Under a fuzzy logic, Analytic Hierarchy Process and the Technique for Order of Preference by Similarity to Ideal Solution can be combined with Fuzzy Multi-Attribute HAZOP to determine the weight of risk factors and to rank critical hazards. The inherent risks biogas upgrading, such as explosiveness, overpressure, or premature deterioration of equipment, should be identified for planning of critical control points and for enabling a proper maintenance plan. Previous models were applied to a photosynthetic biogas upgrading and a biogas-to-polyhydroxyalkanoates production pilot plant in order to identify and get more information about associated risks of the operation of these valorization biotechnologies, sometimes not fully provided by HAZOP analysis. Biotrickling filter and the polyhydroxyalkanoates production tank were identified as the most critical subsystems, with contributions of 33.3% and 17.8% to the overall risk, respectively (within quartile 1, Q_1). Additionally, biogas and recycling/feeding streams clustered a large number of operational risks (up to 83.4% of total risk within Q_1). The sensibility analysis demonstrated the reliability and robustness of the final ranking. The results of this analysis will support preventive maintenance by identifying critical monitored points when scaling-up biological biogas upgrading processes.

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Abbreviation

AC	Associated Cost
ACS	Ant Colony System methodology
AHP	Analytic Hierarchy Process
ANP	Analytic Network Process
ATEX	Explosive atmosphere
BWM	Best Worst Method
CC	Closeness Coefficient
CI	Consistency Index
CoCoSo	Combined Compromise Solutions
CR	Consistency Ratio
DE	Domino Effect
DEMATEL	Decision Making Trial and Evaluation Laboratory
DMRA	Decision-Matrix Risk Assessment
EDAS	Evaluation Based on Distance from Average Solution
EFMEA	Environmental Failure Modes and Effects Analysis
ELECTRE	Elimination Et Choix Traduisant la REalité
F	Frequency
FAHP	Fuzzy Analytic Hierarchy Process
FMA	Fuzzy Multi-Attribute
FTOPSIS	Fuzzy TOPSIS
GRA	Grey Relational Analysis
HAZOP	Hazard and Operability
HRAP	(High Rate Algae Pond)
ISM	Interpretive Structural Modeling
MADM	Multi-Attribute Decision Making
MEREC	Method based on the Removal Efects of Criteria
MICMAC	Matriced Impacts Croisés Multiplication Appliquée à un Classement
MOORA	Multi-Objective Optimization on the basis of Ratio Analysis
OCRA	Operational Competitiveness Rating Analysis
P&ID	Detailed Piping and Instrumentation Diagram
P	Probability
PHA	Polyhydroxyalkanoates
PPEs	Personal Protection Elements
PROMETHEE	Preference Ranking Organization Method for Enrichment Evaluation
QFD	Quality Function Deployment
RF	Response to Failure
RI	Random Index
R-MULTIMOOSRAL	Multi objective Optimization by Ratio Analysis plus full multiplicative form
RPN	Risk Priority Number
R-TODIM	Interactive and multi-criteria decision making
S	Severity
SPM	Sensitivity to Preventive Maintenance
SSM	Sensitivity to Safe Measure
SWARA	Stepwise Weight Assessment Ratio Analysis
TOPSIS	Technique for Order of Preference by Similarity to Ideal Solution
U	Un-detectability
VIKOR	VIseKriterijumska Optimizacija I Kompromisno Resenje
WASPAS	Weighted Aggregated Sum Product Assessment

1. Introduction

Complex processes, multiple interconnected equipment, and sophisticated automatic control loops are used in modern large-scale chemical industries to optimize process operation, which renders them vulnerable to suffering from serious fault consequences (Kang and Guo, 2016). This also applies to modern biogas production and valorization plants. Even though the behaviour of biological processes has been observed to be less affected by failures due to their robustness and the resilience of the biological community, potential hazards must be analysed. In this context, since biogas production and valorization at industrial scale is relatively recent, the experience related to hazards and associated risks is significantly lower compared with other industrial biotechnological processes. This missing knowledge is typically obtained from similar units, mainly from the chemical industry (Kotek et al., 2020).

The so-called Hazard and Operability (HAZOP) analysis is the most widely used process hazard analysis methodology (Wang et al., 2012). HAZOP analysis represents a systematic qualitative tool to identify potential deviations from normal operation and ensures safeguards to prevent accidents, considering both process design and planned modifications (Kotek and Tabas, 2012; UNE-EN 61882, 2017). A process flow diagram or a detailed piping & instrumentation diagram (P&ID) constitutes the basis of a HAZOP analysis (Liin et al., 2010). Nonetheless, several researchers have demonstrated the limitations of using precise expert judgments, the main tool in this technique, due to the frequent inconsistencies between experts' opinions (Nilsen and Aven, 2003). Thus, the completeness of the analysis cannot be ensured, as it widely depends on the experience and commitment of the participants in the HAZOP study (Kościelny et al., 2017). In this context, fuzzy logic represents an effective approach to cope with the uncertainty caused by data scarcity and incomplete process knowledge, and has been effectively used to improve the performance and credibility of risk assessment techniques (Alidoosti et al., 2012; Sii et al., 2001). The potential of HAZOP analysis is also limited by the even weights attributed to all risk factors, resulting in similar ranks for both a low-probability high--consequence hazard and a high-probability low-consequence hazard. In this sense, the implementation of methodologies of multi-attribute decision making (MADM) such as *Analytic hierarchy process* (AHP) (Saaty, 1980) or *Technique for order of preference by similarity to ideal solution* (TOPSIS) (Hwang and Yoon, 1981), among others (DEMATEL, ELECTRE, VIKOR, PROMETHEE, etc), can be used to establish the weights and rank the different risk factors in order to improve the analysis (Kokangül et al., 2017). Therefore, integration of fuzzy logic and MADM techniques improve the accuracy and reliability of decision making under uncertainty. Both AHP and TOPSIS have been widely used in the literature, due to their simplicity and ability to order and rank alternatives (Rahim et al., 2021), flexibility, intuitive appeal to the decision makers and their ability to check inconsistencies, allowing to solve problems with several contradictory criteria (Ikwan et al., 2020).

A fuzzy AHP-TOPSIS analysis is based on a classic fuzzy logic derived from fuzzy set theory to deal with ambiguous, subjective or imprecise reasoning. Fuzzy logic allows handling uncertainty, as crisp data may be inadequate to model real-life situations (Cheraghi et al., 2019). The use of linguistic assessments (i.e., ratings and weights of the criteria in the problem are represented by means of linguistic variables) instead of numerical values constitutes a more realistic approach to model human judgements. Thus, a fuzzy environment is used both in the evaluation (AHP) and the ranking (TOPSIS) processes due to the effectiveness and robustness of the risk assessment procedure (Chen, 2000). AHP was initially developed by Saaty to conduct MADM problems examining the pair-wise comparison of decision criteria using a hierarchical structure (Saaty, 1980). The vague nature of alternative selection problems and the inherent imprecision in the pair-wise comparison process were overcome by Chang through the Fuzzy AHP methodology, which determines the weights of the criteria by decision makers (Chang, 1996), (Kannan et al., 2013; Ku et al., 2010). On the other hand, TOPSIS applied in fuzzy environment is commonly used as a robust tool to manage linguistic judgments of experts and to establish the final ranking of activities. This technique, based on hierarchical structure, is applied when a large number of alternatives has to be considered, which are classified according to their distance from a negative-ideal solution (Chen, 2000; Grassi et al., 2009). Fuzzy AHP and Fuzzy TOPSIS have been widely employed to determine the relative weight of risk factors and in hazard ranking in many industrial processes, including food processing, pipeline network for oil and natural gas transportation, assembly processes, crude-oil processing-plants, or gas wellhead facilities (Akyildiz and Mentes, 2017; Carpitella et al., 2016; Kokangül et al., 2017; Marhavilas et al., 2019). In brief, ranking analysis of causes and consequences helps identifying critical monitored points and control structures not previously defined. Besides, a high quality model enables the analysis of emergency scenarios (Košcielny et al., 2017).

Despite the implementation of AHP, HAZOP and TOPSIS under a fuzzy logic frame facilitates decision-making in the industrial context, these methodologies have never been applied to biogas production and valorization processes. In this work, a comprehensive Fuzzy Multi-Attribute HAZOP (FMA-HAZOP) analysis and Fuzzy TOPSIS modeling of two novel biological biogas valorization processes: photosynthetic biogas upgrading and biogas bioconversion into biopolymers, was developed for the first time. These processes are attracting recent attention due to the lack of competitiveness of conventional physical-chemical biogas upgrading technologies and the foreseen lack of economic viability of biogas-to-electricity in an international context of decreasing prices of solar or wind energy (Pérez et al., 2019). Thus, an improved HAZOP analysis using the aforementioned techniques of semi-industrial pilot-plants devoted to the upgrading of biogas into biomethane using microalgae and the production of polyhydroxyalkanoates (PHA) from biogas will contribute to improved decision making for the planning of preventive maintenance and control of these biological processes, identifying the riskiest stages and extrapolating the results to future biogas biorefineries.

1.1. Literature review

Research on process safety has become a very popular topic among researchers both in developed and developing countries. Most risk analysis studies develop models and simulate and introduce novel decision making methods for probabilistic safety analysis in process systems (Abdulvahitoglu and Kilic, 2022). Most studies mainly involve three research clusters including dynamic risk assessment, inherent safety, and fuzzy set theory.

Previous HAZOP analyses combined with Multi-Criteria Decision Making (MCDM) methods have been applied in different industrial areas and processes for the identification of critical hazards and risks. For example, a fuzzy-HAZOP/Ant Colony System methodology (ACS) was implemented by Solukloei et al. (2022) and Saffarian et al. (2020) applied two methods of Environmental Failure Modes and Effects Analysis (EFMEA) and Melbourne to conduct risk assessment (Saffarian et al., 2020; Solukloei et al., 2022). Additionally, Analytic Hierarchy Process (AHP) and Fuzzy Analytic Hierarchy Process (FAHP) were applied and combined with those methods aiming at a more logical and compatible analysis in order to identify risk assessment of a gas power plant. Additionally, Fine–Kinney risk analysis and AHP-TOPSIS method was applied in a medium-sized gas filling facility. A fuzzy Decision Making Trial and Evaluation Laboratory (DEMATEL) implemented with TOPSIS to assess the comprehensive risk of hydrogen generation unit was studied by Li et al. (2020) and an AHP and Preference Ranking Organization Method for Enrichment Evaluation (PROMETHEE) for predicting the risk of leakage in a storage tank in refineries was assessed by (Ikwan et al., 2020; Li et al., 2020). In a manufacturing sector, Rahim et al. (2021) developed a fuzzy-TOPSIS multi-criteria decision-making model for material selection with the integration of safety, health and environment risk assessment (Rahim et al., 2021). Mojaver et al. (2022) implemented a comparative analysis of air gasification of plastic waste and conventional biomass using a AHP/TOPSIS MCDM approach (Mojaver et al., 2022). Cheraghi et al. (2019) and Marhavilas et al. (2020) applied HAZOP fuzzy logic analysis to identify faults and propose safety recommendations in different industrial plants (Cheraghi et al., 2019; Marhavilas et al., 2020).

Alternative MCDM hybrid approaches have been combined with other methods in order to perform risk assessments of the process industry, supply chain performance, solutions for logistics barriers, manufacturing system selection and optimal maintenance strategy selection. In this sense, Keshavarz-Ghorabaee (2021) indicated the following as relevant MCDM methodologies: Decision Making Trial and Evaluation Laboratory (DEMATEL), Grey Relational Analysis (GRA), Multi-Objective Optimization on the basis of Ratio Analysis (MOORA), Elimination Et Choix Traduisant la REalité (ELECTRE), Operational Competitiveness Rating Analysis (OCRA), Analytic Network Process (ANP), Preference Ranking Organization Method for Enrichment of Evaluations (PROMETHEE), Weighted Aggregated Sum Product Assessment (WASPAS), VIseKriterijumska Optimizacija I Kompromisno Resenje (VIKOR), Combined Compromise Solutions (CoCoSo), Method based on the Removal Efects of Criteria (MEREC) and Stepwise Weight Assessment Ratio Analysis (SWARA) (Keshavarz-Ghorabaee, 2021).

Table A1 (Appendix A) compiles some recent studies in the field of industrial processes. Interestingly, no studies associated with risk analysis in biogas treatment plants have been identified.

2. Materials and methods

2.1. Description of techniques and models

The methodology used to perform the risk analysis consisted of 3 steps: a conventional HAZOP analysis (step I), a FMA-HAZOP assessment (step II), and the implementation of the Fuzzy TOPSIS model (step III). A schematic description of the methodology is provided in Appendix A Figure A1.

2.1.1. HAZOP analysis

The HAZOP technique was applied in two steps: first, the entire process was divided into “nodes” in order to address the complexity of the design (Lind and Wu, 2018). Then, a multidisciplinary team of experts, through structured brainstorming sessions, applied a set of guidewords to the different process sections in order to identify causes and consequences of behaviour deviations from reference parameters. This process included any potential risk within a particular influence ratio, revealing if the plant had sufficient control and safety measures to ensure a safe operation (Johansen and Rausand, 2014).

2.1.2. AHP-TOPSIS analysis with fuzzy logic

A fuzzy environment was defined by the most often-used triangular fuzzy number represented with three points (real numbers): a = (l, m, u) (Kutlu and Ekmekçioglu, 2012). A fuzzy set was identified by its membership function (u_m) as represented by Eq. (1) and Figure A2. A. (Appendix A) (Zadeh, 1965; Zimmerman, 2001):

$$u_m(x) = \begin{cases} 0\, x \leq l; \\ \dfrac{x-l}{m-l} l \leq x \leq m; \\ \dfrac{u-x}{u-m} m \leq x \leq u; \\ 0x \geq u \end{cases} \tag{1}$$

The main operational laws were defined as follows:

$$(l_1, m_1, u_1) \oplus (l_2, m_2, u_2) = (l_1 + l_2, m_1 + m_2, u_1 + u_2) \tag{2}$$

$$(l_1, m_1, u_1) \odot (l_2, m_2, u_2) \approx (l_1 l_2, m_1 m_2, u_1 u_2) \tag{3}$$

$$(\lambda, \lambda, \lambda) \odot (l_2, m_2, u_2) \approx (\lambda l_2, \lambda m_2, \lambda u_2), \lambda > 0, \lambda\, \varepsilon R \tag{4}$$

$$(l_1, m_1, u_1)^{-1} = (1/u_1, 1/m_1, 1/l_1) \tag{5}$$

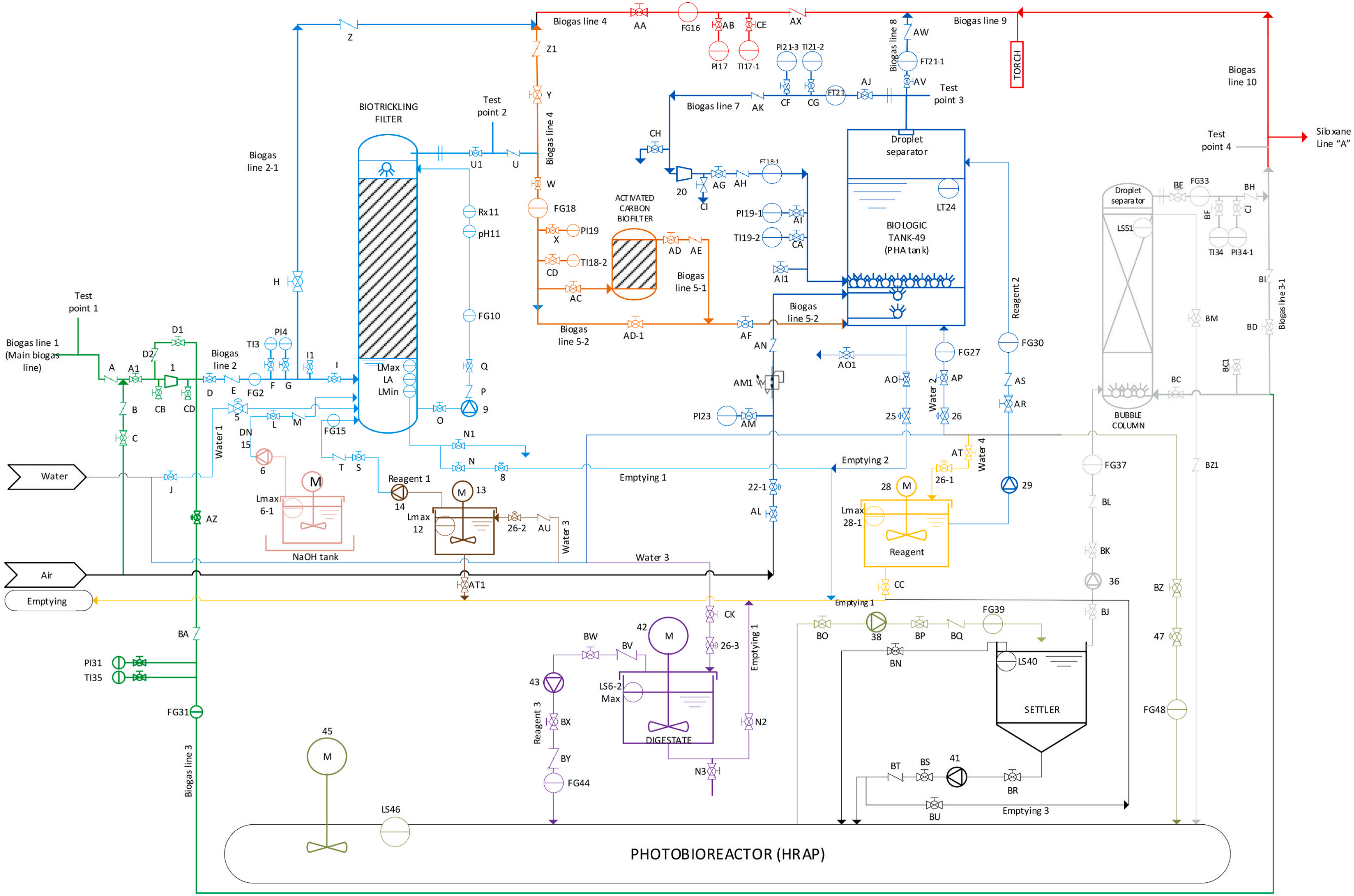

Fig. 1. P&ID of the pilot plant and main subsystems: S0 = Main biogas line (● green); S1= Biotrickling filter (● light blue); S2= Activated carbon filter (●orange); S3=Caustic soda tank and line (● pink); S4 = Mineral salt medium to biotrickling filter (● brown); S5= PHA tank and line (● blue); S6 = Mineral salt medium for PHA (●yellow); S7= Bubble column (● grey); S8= Settler (● black); S9 = Digestate to HRAP (● purple); S10 = HRAP (●moss green); S11 = Torch line (●red). (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

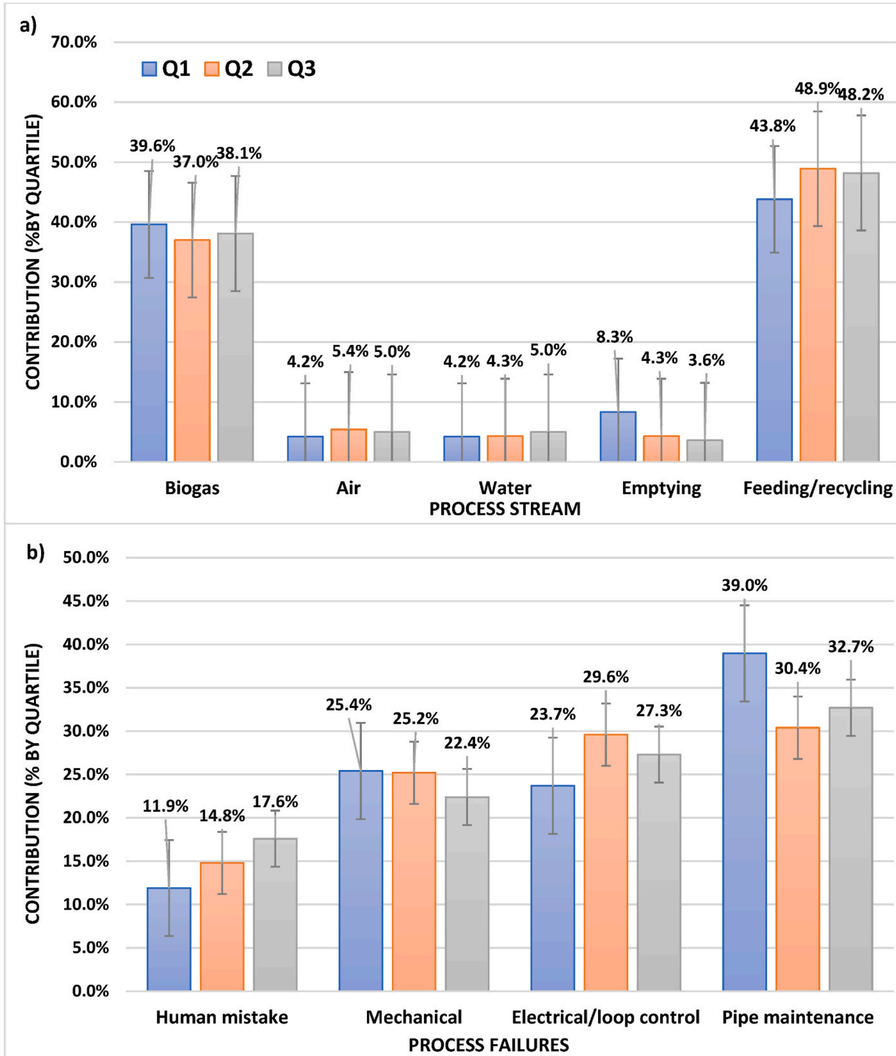

Fig. 2. a) Distribution by quartile of risks in main process streams: first quartile Q_1 (blue bars), second quartile Q_2 (orange bars), third quartile Q_3 (grey bars). b) Distribution by quartile of risks associated to process failures: first quartile Q_1 (blue bars), second quartile Q_2 (orange bars), third quartile Q_3 (grey bars). (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

And the Euclidean distance between fuzzy numbers M_1 and M_2:

$$d(\widetilde{M}_1, \widetilde{M}_2) = \sqrt{\frac{1}{3}(l_1 - l_2)^2 + (m_1 - m_2)^2 + (u_1 - u_2)^2} \tag{6}$$

The first step is to structure the decision-making problem by carrying out pairwise comparisons for each risk according to the scale of relative importance defined (the weight of the risk factors is determined using the fuzzy AHP according to (Chang, 1996)). The triangular fuzzy scales of relative importance used in pairwise comparison were defined as: complete and utter importance (2.5,3,3.5), much strong importance (2, 2.5,3), strong importance (1.5,2,2.5), low importance (1,1.5,2), approximately equal importance (0.5,1,1.5), and exactly equal importance (1,1,1) (Cheraghi et al., 2019). The elements in the main diagonal of the pairwise comparison matrix were (1, 1, 1), while the elements in the ith row and the jth column, and in the jth row and the ith column, were defined according to Eq. (7) and Eq. (8), respectively. The pairwise comparison matrix is displayed in Table 1.

$$\widetilde{M}_{gi}^{j} = \left(l_{ij}, m_{ij}, u_{ij}\right) \tag{7}$$

$$\widetilde{M}_{gj}^{j} = \left(\widetilde{M}_{gi}^{j}\right)^{-1} = \left(l_{ij}, m_{ij}, u_{ij}\right)^{-1} = \left(\frac{1}{u_{ij}}, \frac{1}{m_{ij}}, \frac{1}{l_{ij}}\right) \tag{8}$$

The second step is to determine the consistency of the resulting comparison matrix (index CI, Eq. (9)) using the consistency ratio (CR, Eq. (10)) and the random consistency index (RI) after conversion of pairwise fuzzy numbers to crisp numbers via a defuzzification process, as defined by (Saaty, 1980). The random consistency indexes for different number of factors (n) from 1 to 10 are 0, 0, 161 0.52, 0.89, 1.11, 1.25, 1.35, 1.40, 1.45, and 1.49 respectively,

$$CI = \frac{\lambda_{max} - n}{n - 1} \tag{9}$$

$$CR = \frac{CI}{RI} \tag{10}$$

where $\lambda_{\max}$ is the largest eigenvalue, and n is the number of factors compared in the matrix. The graded mean integration approach, crisp numbers, proposed by (Zimmerman, 2001), was defined by Eq. (11):

$$P(\widetilde{M}) = \frac{l + 4m + u}{6} \tag{11}$$

After defuzzification of each value in the matrix, a CR value lower than 0.10 must be obtained, otherwise different weights should be assigned.

The next step is the calculation of the risk relative weights. The

Table 1
Pairwise comparison matrix.

Risk factors	P	F	S	U	SPM	SSM	AC	RF	DE
Probability (P)	(1,1,1)	$(\frac{1}{2},1\ \frac{3}{2})$	$(1\ \frac{3}{2},2)$	$(\frac{3}{2},2\ \frac{5}{2})$	$(2\ \frac{5}{2},3)$	$(2\ \frac{5}{2},3)$	$(2\ \frac{5}{2},3)$	$(\frac{3}{2},2\ \frac{5}{2})$	$(\frac{1}{2},1\ \frac{3}{2})$
Frequency (F)	$(\frac{2}{3},1,2)$	(1,1,1)	$(1\ \frac{3}{2},2)$	$(2\ \frac{5}{2},3)$	$(2\ \frac{5}{2},3)$	$(2\ \frac{5}{2},3)$	$(1\ \frac{3}{2},2)$	$(\frac{5}{2},3\ \frac{7}{2})$	$(1\ \frac{3}{2},2)$
Severity (S)	$(\frac{1}{2}\frac{2}{3},1)$	$(\frac{1}{2}\frac{2}{3},1)$	(1,1,1)	$(\frac{5}{2},3\ \frac{7}{2})$	$(2\ \frac{5}{2},3)$	$(\frac{5}{2},3\ \frac{7}{2})$	$(2\ \frac{5}{2},3)$	$(2\ \frac{5}{2},3)$	$(\frac{1}{2},1\ \frac{3}{2})$
Un-detectability (U)	$(\frac{2}{5},\frac{1}{2},\frac{2}{3})$	$(\frac{1}{3},\frac{2}{5},\frac{1}{2})$	$(\frac{2}{7},\frac{1}{3},\frac{2}{5})$	(1,1,1)	$(\frac{1}{2},1\ \frac{3}{2})$	$(\frac{1}{2},1\ \frac{3}{2})$	$(1\ \frac{3}{2},2)$	$(\frac{3}{2},2\ \frac{5}{2})$	$(2\ \frac{5}{2},3)$
Sensitivity to preventive maintenance (SPM)	$(\frac{1}{3},\frac{2}{5},\frac{1}{2})$	$(\frac{1}{3},\frac{2}{5},\frac{1}{2})$	$(\frac{1}{3},\frac{2}{5},\frac{1}{2})$	$(\frac{2}{3},1,2)$	(1,1,1)	$(\frac{1}{2},1\ \frac{3}{2})$	$(1\ \frac{3}{2},2)$	$(2\ \frac{5}{2},3)$	$(\frac{1}{2},1\ \frac{3}{2})$
Sensitivity to safe measure (SSM)	$(\frac{1}{3},\frac{2}{5},\frac{1}{2})$	$(\frac{1}{3},\frac{2}{5},\frac{1}{2})$	$(\frac{2}{7},\frac{1}{3},\frac{2}{5})$	$(\frac{2}{3},1,2)$	$(\frac{2}{3},1,2)$	(1,1,1)	$(\frac{1}{2},1\ \frac{3}{2})$	$(\frac{1}{2},1\ \frac{3}{2})$	$(1\ \frac{3}{2},2)$
Associate cost (AC)	$(\frac{1}{3},\frac{2}{5},\frac{1}{2})$	$(\frac{1}{2}\frac{2}{3},1)$	$(\frac{1}{3},\frac{2}{5},\frac{1}{2})$	$(\frac{1}{2}\frac{2}{3},1)$	$(\frac{1}{2}\frac{2}{3},1)$	$(\frac{2}{3},1,2)$	(1,1,1)	$(\frac{5}{2},3\ \frac{7}{2})$	$(\frac{1}{2},1\ \frac{3}{2})$
Response to failure (RF)	$(\frac{2}{5},\frac{1}{2},\frac{2}{3})$	$(\frac{2}{7},\frac{1}{3},\frac{2}{5})$	$(\frac{1}{3},\frac{2}{5},\frac{1}{2})$	$(\frac{2}{5},\frac{1}{2},\frac{2}{3})$	$(\frac{1}{3},\frac{2}{5},\frac{1}{2})$	$(\frac{2}{3},1,2)$	$(\frac{2}{7},\frac{1}{3},\frac{2}{5})$	(1,1,1)	$(1\ \frac{3}{2},2)$
Domino effect (DE)	$(\frac{2}{3},1,2)$	$(\frac{1}{2},1\ \frac{3}{2})$	$(\frac{2}{3},1,2)$	$(\frac{1}{3},\frac{2}{5},\frac{1}{2})$	$(\frac{2}{3},1,2)$	$(\frac{1}{2},1\ \frac{3}{2})$	$(\frac{2}{3},1,2)$	$(\frac{1}{2},1\ \frac{3}{2})$	(1,1,1)

weighing process was performed according to the Chang's extent analysis method, resulting in m extent analysis values for each object $\widetilde{M}_{g1}^{1}$, $\widetilde{M}_{g2}^{2}, \widetilde{M}_{g3}^{3}, \ldots, \widetilde{M}_{gn}^{m}$, where $\widetilde{M}_{gi}^{j}$ are triangular fuzzy numbers. The value of fuzzy synthetic extent with respect to the ith object is itself a triangular fuzzy number that can be defined as Eq. (12):

$$\widetilde{S}_i = \sum_{j=1}^{m} \widetilde{M}_{gi}^{j} \odot \left[\sum_{i}^{n} \sum_{j}^{m} \widetilde{M}_{gi}^{j} \right]^{-1} \tag{12}$$

Since $\widetilde{M}_1 = (l_1, m_1, u_1)$ and $\widetilde{M}_2 = (l_2, m_2, u_2)$ are fuzzy numbers, the possibility degree of $\widetilde{M}_1 \geq \widetilde{M}_2$ is defined as (Eq. (13)):

$$V(\widetilde{M}_2 \geq \widetilde{M}_1) = \begin{cases} 1 \ if \ m_2 > m_1; \\ 0 \ if \ l_1 > u_2; \\ \mu_{\widetilde{M}_1}(d) = \dfrac{l_1 - u_2}{(m_2 - u_2) - (m_1 - l_1)} \ otherwise \end{cases} \tag{13}$$

where d is the ordinate of the highest intersection point D between fuzzy numbers (Figure A2. B, Appendix A). Thus, a fuzzy number will be greater than k fuzzy numbers if $\widetilde{M} \geq \widetilde{M}_1, \widetilde{M}_2, \ldots, \widetilde{M}_k$, with a possibility degree defined by Eq. (14):

$$V(\widetilde{M} \geq \widetilde{M}_1, \widetilde{M}_2, \ldots, \widetilde{M}_k) = min V(\widetilde{M} \geq \widetilde{M}_i), \ \mathrm{i} = 1, 2, \ldots, \ \mathrm{n}; \mathrm{k} \neq \mathrm{i} \tag{14}$$

The weight vector W was $d(A_i) = min V(\widetilde{S}_i \geq \widetilde{S}_k) k = 1, 2, \ldots, n; k \neq i$, and the normalized result was defined according to Eq. (15):

$$W = (d(A_1), d(A_2), \ \ldots, d(A_n))^T \tag{15}$$

The triangular fuzzy numbers used for evaluation of risk factors are shown in Table 2.

Finally, FTOPSIS is implemented in the last step in order to determine the most critical risk, which corresponds to the one that is nearest to the positive-ideal solution and farthest to the negative ideal solution. The fuzzy rating of the decision maker about the ith alternative A_i based on the jth criterion C_j can be presented as a matrix, where the weight of the criterion C_j was calculated using Eq. (15):

$$D = \begin{array}{c} \\ A_1 \\ A_2 \\ \vdots \\ A_i \\ \vdots \\ A_m \end{array} \begin{array}{c} \begin{array}{cccccc} C_1 & C_2 & \ldots & C_j & \ldots & C_n \end{array} \\ \begin{pmatrix} \tilde{X}_{11} & \tilde{X}_{12} & \ldots & \tilde{X}_{1j} & \ldots & \tilde{X}_{1n} \\ \tilde{X}_{21} & \tilde{X}_{22} & \ldots & \tilde{X}_{2j} & \ldots & \tilde{X}_{2n} \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ \tilde{X}_{i1} & \tilde{X}_{i2} & \ldots & \tilde{X}_{ij} & \ldots & \tilde{X}_{in} \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ \tilde{X}_{m1} & \tilde{X}_{m2} & \ldots & \tilde{X}_{mj} & \ldots & \tilde{X}_{mn} \end{pmatrix} \end{array}$$

where A_i are the hazards in this study, and C_j are the criterion (risk factors in this study). The normalized matrix from D matrix, R, is defined according to Eq. (16):

$$\widetilde{R} = [\widetilde{r}_{ij}]_{mxn} \tag{16}$$

where,

$$\widetilde{r}_{ij} = \begin{cases} \left(\dfrac{a_{ij}}{c_j^+}, \dfrac{b_{ij}}{c_j^+}, \dfrac{c_{ij}}{c_j^+} \right) j \in B; \\ \left(\dfrac{a_j^-}{c_{ij}}, \dfrac{a_j^-}{b_{ij}}, \dfrac{a_j^-}{a_{ij}} \right) j \in C; \end{cases} \tag{17}$$

B and C are the benefit and cost criteria, respectively, $c_j^+ = \max c_{ij}$ if j ∊ B and $a_j^- = \min a_{ij}$ if j ∊ C. Considering the different relevance of each criterion, the weighted normalized fuzzy decision matrix can be constructed as $\widetilde{V} = [\widetilde{v}_{ij}]_{mxn}, i = 1, 2, 3, \ldots, m, j = 1, 2, 3, \ldots, n; where \ \widetilde{v}_{ij} = \widetilde{r}_{ij}.\widetilde{w}_j$. Finally, the closeness coefficient (CC) was used to determine the rank order of the different alternatives (Eq. (18)):

$$CC_i = \frac{d_i^-}{d_i^+ + d_i^-}, i = 1, 2, 3, \ldots, m \tag{18}$$

where d_i^+ is the distance of fuzzy positive ideal solution $A^+ = (\widetilde{v}_1^+, \widetilde{v}_2^+, \ldots, \widetilde{v}_j^+, \ldots, \widetilde{v}_n^+)$ and d_i^- the distance of fuzzy negative ideal solution $A^- = (\widetilde{v}_1^-, \widetilde{v}_2^-, \ldots, \widetilde{v}_j^-, \ldots, \widetilde{v}_n^-)$, being $\widetilde{v}_j^+ = (1,1,1)$ and $\widetilde{v}_j^- = (0,0,0)$. Distances were defined according to Eq. (19) and Eq. (20):

$$d_i^+ = \sum_{j=1}^{n} d\left(\widetilde{v}_{ij}, \widetilde{v}_j^+\right), i = 1, 2, \ldots, m \tag{19}$$

Table 2
Triangular fuzzy scales of relative importance.

Linguistic variable	Symbol	Triangular fuzzy number
Negligible	NE	(0,0,1)
Very low	VL	(0,1,2)
Low	LO	(1,2,3)
Medium low	ML	(2,3,4)
Fair	FA	(3,4,5)
Medium high	MH	(4,5,6)
High	HI	(5,6,7)
Very high	VH	(6,7,8)
Absolutely high	AH	(7,8,9)
Maximum	MA	(8,9,9)

$$d_i^- = \sum_{j=1}^{n} d\left(\widetilde{v}_{ij}, \widetilde{v_j^-}\right), i = 1, 2, \ldots, m \tag{20}$$

2.2. Main evaluated criteria

A conventional HAZOP analysis only covers causes and consequences where the variability of actions can be interpreted as risks. However, fundamental aspects of risks such as workplace characteristics, human factors, reaction capacity facing risks, awareness towards personal protective equipment, maintenance or number of persons exposed, should be included as risk factors (Cheraghi et al., 2019; Grassi et al., 2009; McDermott et al., 2009). Thus, nine criteria were analysed in order to improve the quality of risk evaluation:

1. Occurrence probability (P): this criterion explored the likelihood of an identified risk to occur. Variations of measured variables from all relevant equipment and facilities were also analysed. Safety and protection measures such as ATEX protection (explosive atmosphere), the use of personal protection elements (PPEs) by staff, alarms and regulation requirements were considered (Giardina and Morale, 2015).
2. Severity (S): the severity of the resulting consequences such as injuries and fatalities, damage to the equipment, environmental impact, measurements failures, and business interruption were considered when evaluating this factor.
3. Frequency (F): this factor considered the incidence of a specific consequence of a hazard. Failure of safety measures and imperfect maintenance can affect the frequency of certain consequences. In this study it was assumed that all safety measures were operational, and scheduled maintenance activities were conducted. Frequency was estimated as the rate of occurrence of an event expressed as the number of occurrences of an event in a given time (Jung, 2005).
4. Sensitivity of security measures (SSM): failures related to security measures can increase the probability of accidents (Cheraghi et al., 2019).
5. Sensitivity of preventive maintenance (SPM): imperfect maintenance of equipment can increase both the frequency and the severity of hazards (Grassi et al., 2009).
6. Sensitivity to undetectability (U): the inability to foresee or detect a failure hinders the prevention of the accident. This factor was related to the interaction between the operator and the working environment such as machines and equipment (Giardina and Morale, 2015; Grassi et al., 2009).
7. Associated cost (AC): this parameter accounted for the cost of managing risks and incurring losses. Total cost of risk included retained (uninsured) losses and related loss adjustment expenses, risk control costs, transfer costs and administrative costs.
8. Response to failure (RF): the capacity to effectively manage the variability of processes and associated risks in order to reduce the impact on components (facilities, streams, human resources, etc.). In this case, all variations were analysed as findings regardless of the associated hazard.
9. Domino effect (DE): domino accidental events are accidents in which a primary event propagates to nearby equipment, triggering one or more secondary events resulting in overall consequences more severe than those caused by the primary events (Kadri and Chatelet, 2013). The accidents caused by a domino effect typically induce the most catastrophic consequences.

2.3. Description of the model case scenario

The semi-industrial scale plant herein assessed included two novel processes for the valorization of the biogas produced in an anaerobic digester: a photosynthetic upgrading unit and a bioreactor for the production of PHA (Fig. 1). The first experimental module, aiming at producing 8 m^3d^{-1} of biomethane from biogas, consisted of an open photobioreactor (High Rate Algal Pond, HRAP) of 280 m^2 inoculated with a microalgal-bacterial consortium and interconnected to an external 0.5 m^3 biogas absorption column via a 5.5 m^3 conical settler. Preliminary results at laboratory scale have demonstrated the capacity of this biotechnology to provide a high quality biomethane fulfilling the requirements for injection into natural gas grids (CH_4 >95%, CO_2 < 2%, O_2 < 0.3% and traces of H_2S) at lower operating costs and environmental impacts than their physical/chemical counterparts (Rodero et al., 2018). The second experimental module consisted of a two steps process to produce PHA from 108 m^3d^{-1} of biogas: a biotrickling filter devoted to the anoxic desulfurization of raw biogas, followed by a 9 m^3 bubble bioreactor where methanotrophic organisms accumulate up to 40% w/w of PHA using CH_4 as the carbon source under nutrient limited conditions (García Pérez et al., 2018). The pilot plants were operated at URBASER facilities in Zaragoza (Spain) within the BBI-JU H2020 project URBIOFIN (detailed description of the process is included in Appendix A: Process Description).

3. Results and discussion

3.1. HAZOP analysis

A HAZOP analysis was carried out using information of existing facilities, legal requirements, and experts' opinions regarding reactors construction and operation of biological processes. Start up and operation of the biorefinery were considered in the HAZOP evaluation. The P&ID of the pilot plant was divided into eleven subsystems, represented in different colours in Fig. 1: S0 = Main biogas feeding line; S1= Biotrickling filter for the desulfurization of biogas; S2= Activated carbon filter for H_2S removal in case of S1 failure; S3= NaOH for pH regulation in S1; S4 = Mineral salt medium (MSM) feeding to S1; S5= PHA production unit; S6 = MSM feeding to S5; S7= Bubble column for biogas upgrading in the photosynthetic unit; S8= Settler for biomass separation and recycling to the HRAP; S9 = Digestate feeding to the HRAP; S10 = Photobioreactor (HRAP) in the photosynthetic unit; S11 = Biogas torch. The deviations of parameters were analysed considering both main streams and control alternatives including the biogas line, freshwater line, airline, recycling and feeding line, human control, mechanical control, signal of control loops and preventive maintenance. From the eleven subsystems, fifty-eight nodes were identified after a variability analysis of the above-mentioned parameters.

The main parameters considered in the HAZOP analysis were:

- Variables: Pressure, Temperature, Signal transduction, Redox signal, Level signal, pH signal, Liquid/Gas ratio (L/G), Flame (presence/absence);
- Composition: % biogas, % nutrients, % H_2S, % methane;
- Flow rates: Biogas, Water, Air, Leachate, Caustic soda;
- Signals: Electrical, Mechanical, Signal of control loops.

The detailed results of the HAZOP analysis can be found in Tables A2 and A.3. in Appendix A. The main hazards were associated to the complexity of the control loops and the lack of response in case of failure (control on/off), especially those of the biogas-to-PHA reactor and the biotrickling filter. The operation of these bioreactors was affected by a large number of parameters (i.e. redox potential, pH, temperature, pressure, level, etc.) and control loops (level control, pH control, redox control, over-pressure or low-pressure control, etc.). Additionally, leaks from multiple connections, the high liquid recycling velocity in the PHA production reactor, the fluctuation of flow rates of biogas and MSM recycling due to clogging, and the explosion limits of biogas/air mixtures (1.5 mol O_2/1 mol CH_4 ratio), were identified as key sources of risk in the biotrickling filter and PHA tank (Table A2.). Clogging of the pipelines, pumps or valves also entailed a relevant impact on the performance of both the photosynthetic HRAP and the PHA production unit, especially due to residual waste from the landfill located near the plant that accumulated inside the HRAP and the settler. A filter and a contention mesh placed in the HRAP, together with the periodical cleaning of the floating waste, were implemented as prevention measures.

Manual or human control represented another key parameter to be considered. Prevention of control failure, and therefore of the subsequent detrimental effects on process performance, can only be accomplished via an effective *in-situ* identification and comprehension of equipment and pipelines, a continuous revision and monitoring of critical process parameters, and ultimately, a deep knowledge of the process. Typical routine control, revision of operating parameters (including level of tanks and HRAP, recycling and dosage flow, temperature and dissolved oxygen in the cultivation broth of the HRAP, biogas and air flowrates, pressure inside line and vessels or pH) and monitoring check lists can be implemented in order to reduce the impacts associated to manual and human control errors.

The use of biogas, digestate and caustic soda entailed an associated risk that required a specific analysis. In the particular case of biogas, and despite the operational CH_4/O_2 ratio might avoid the risk of explosion, a low pressure switch on the main biogas compressor and on the blower of the internal recycling line of the PHA tank (in case of low or no pressure inside the biogas and air feeding lines, respectively), and a flame arrestor were installed to avoid the critical consequences of deflagration. Similar safety devices were implemented in the airline. In this context, typical accidents occurring in biogas plants were considered when the HAZOP analysis of the pilot plant was carried out (INERIS, *Institut National de l'Environnement Industriel et des Risques*, France): leakages in the storage tank and/or distribution network of biogas, leakages following the completion of work on site, accidental release of H_2S, corrosion of equipment, water pollution caused by effluent discharge, overflow in sewage systems or storm-water control due to exceptional downpours, equipment failures in the event of massive influx of fire-water suppression, presence of dangerous products in the raw material used to produce biogas, overflow in vessels, freezing of valves, high pressure inside the digester or vessels due to clogging, etc. (Salvi and Delsinne, 2011).

The main risk associated with the storage and use of digestate to feed the HRAP can be related with clogging or plugging of pipelines and the interruption of feeding system. Additionally, bioaerosols can be emitted from the digestate, thus reducing the contact time during control and transport operations is of utmost importance from a health point of view (Chen and Reniers, 2018). In a previous evaluation of working conditions at this URBASER facility, a limited generation of bioaerosols was observed, with a contact frequency less than 20% of a workday. Additionally, the pipelines from the digestate storage vessel to the HRAP were designed minimizing the pipe length and ensuring discharge over panel to reduce splatters.

3.2. Implementation of the fuzzy AHP-TOPSIS model

The weight values obtained for the different risk factors were P: 0.18446, F: 0.19568, S: 0.19379, U: 0.1011, SPM: 0.08855, SSM: 0.06764, AC: 0.08081, RF: 0.00952, and DE: 0.07843. A consistency index of comparison matrix of 0.07 was calculated, complying with the maximum value of 0.1 as stated by (Saaty, 1980). Probability, frequency and severity were the most relevant factors according to their weight values: 0.18446, 0.19568 and 0.19379, respectively. On the contrary, sensitivity to safety measures (0.06764), domino effect (0.07843) and response to failures (0.00952) exhibited the lowest weights. These results were in accordance with the robustness of the system and the lack of drastic consequences derived from a short period of uncontrolled conditions. Similar results have been reported by other authors in gas wellhead facilities (Cheraghi et al., 2019; Grassi et al., 2009).

The hazards identified in the HAZOP analysis were ranked using the Closeness Coefficients (CC_i) according to TOPSIS model. The CC_i values ranged between 0.82442 and 0.88347 (Table 3, Table A3.). After ranking, the hazards were clustered in quartiles (Q_1, Q_2 and Q_3) in order to identify the main groups of risk factors.

3.2.1. Risks associated to process streams

The main biogas feeding line accounted for 39.6% of the failure scenarios ranked in the first quartile, while biomass recycling and feeding lines represented ~43.8% of the identified hazards. Water feeding, airline, and draining lines only represented between 4 and 8% of total potential failures in the plant. A similar contribution of the identified hazards was found within quartiles 2 and 3 (Fig. 2a).

These preliminary results can be explained by the large number of pipelines, singular points, and control loops installed in the recycling and feeding lines, the risk increasing when increasing the numbers of connections, valves and electrical signals. The hazards inherent to the biogas line increased the significance of some criteria factors related to explosion impacts, although the proposed protection mechanisms (i.e., ATEX protections), the low working pressure (below 1 bar) and the use of internal guidelines for controlling and planning works, reduced the weight of the calculated risk. In our particular plant, only six possible explosive atmospheric formation points were identified and categorized as non-dangerous zones due to the high ventilation in the installation

Table 3
First twenty hazards ranked according to the TOPSIS model.

Ranking	System	Node	Parameter deviation	CCi
1	PHA production	30	Presence of water in the biogas stream	0.88347
2	Main biogas feeding	1	No flowrate.	0.88250
3	PHA production	29	Presence of water in the biogas stream	0.88110
4	Biotrickling filter	10	The pH and Redox signals are incorrect or undetected.	0.88088
5	Main biogas feeding	1	Variation in the composition.	0.88037
6	Main biogas feeding	1	No flowrate.	0.88022
7	PHA production	29	Increase in methane concentration	0.87999
8	PHA production	30	Lower flowrate from tank compared with normal working conditions.	0.87959
9	Biotrickling filter	12	H_2S is detected.	0.87956
10	PHA production	29	Increase in methane concentration	0.87920
11	PHA production	28	Level system failure	0.87919
12	Biogas upgrading	38	Variation in the composition of the upgraded biogas	0.87911
13	PHA production	28	Mixing is not sufficient.	0.87873
14	Biotrickling filter	10	Flow rate is not enough.	0.87829
15	Settler	43	Lower flow than under normal working conditions.	0.87826
16	Biotrickling filter	10	No signal from signal converter.	0.87747
17	Torch	58	There is not flame.	0.87687
18	MSM feeding to biofilter	22	Less flow rate.	0.87674
19	Biotrickling filter	7	Flow rate is not enough.	0.87672
20	Biogas upgrading	39	There is not flow when the called BM valve is opened	0.87617

(located outdoors), (UNE-EN 60079–10, 2004): main biogas pipeline, main biogas compressor, biotrickling filter, recycling blower in the PHA production reactor, PHA production reactor, and bubble biogas absorption column in the photosynthetic unit. Similar analyses have been carried out by other authors in gas wellhead facilities (Cheraghi et al., 2019) or in a pilot-scale high-pressure CO_2-hydrocarbon absorption systems (Aziz et al., 2017). When assessing explosion hazards, the power of an explosion is proportional to the total mass of explosive material to the power of 1/3 (Díaz Alonso et al., 2006). Moreover, an explosion might propagate and impact nearby vessels, which can contain hazardous starting materials or products. Therefore, it is crucial during process design that the right safety measures are taken to prevent explosion propagation. This can be accomplished by using check valves to avoid back flow and by incorporating a suitable quench stream to smother the hazardous reaction mixture (e.g. diluting oxygen with a nitrogen stream) (Kockmann et al., 2017). Additional devices such as pressure switches acting on compressors, and flame arrestors before torch or biogas feeding to avoid the domino effect of deflagration were included in the semi-industrial scale plant herein analysed.

3.2.2. Clustering failures

The risks associated with connections leaks and general maintenance of pipelines represented 39% of the identified hazards, while 25% were associated to likely mechanical failures in equipment such as pumps, engines, control instruments and valves. Additionally, 23% of failures were clustered under control loops and 12% were attributed to human control failures. These results were similar for quartiles 2 and 3, although the contribution of human failures to Q_3 increased up to 17% (Fig. 2b).

The impact of mechanical breakdowns or leaks in pumps, engines, pipes, valves and process control instrumentation was of major relevance due to the associated cost, the long detection time and the detrimental effect on the system performance. Therefore, despite the low occurrence probability, a high calculated risk value was estimated during the weighting decision process. In our particular demo plant, preventive measures to retain wastes from the nearby landfill were implemented to avoid collision of materials on pumps and pipelines (i.e. installation of a containment net). Similar results have been reported by MARS (Major Accidents Reporting System) and MIDHAS (Major Hazards Incident Data Service), who concluded that the highest incidence of accidents in chemical and biofuel plants were associated to malfunctioning and mechanical breakdowns of equipment (Rivera et al., 2015; Sabador, 1995). The negligible impact of human control identified in the URBIOFIN demo plant was associated to the robustness of the process and control program previously defined.

Regarding the use of chemicals, caustic soda (25% w/w) entails a corrosive and toxicological risk. The storage tank was vented to the atmosphere, thus piping downstream of the flush pump was unpressurized. Pipe rupture caused by inappropriate connections might result in a spray leak of caustic soda, however, the low dosage flowrate significantly reduces the associate risks. Additionally, the elapsed time between two loads of the caustic soda tank was relatively high, and a tailored pump (anti-corrosion) together with a strict verification supply program was employed.

Biological risks constitute another source of risk analysed in this study. Biological hazards related to biological agents may be present in biotechnological production facilities. Hazard analyses in the industrial biotechnology sector typically consider two categories: biological hazards mainly associated to occupational health and environment, and "traditional" hazards (non-biological hazards). Both biological and traditional hazards are essential for risk assessment of processes and products in industrial biotechnology, and widely depend on the characteristics of the production plants (Chen and Reniers, 2018). In our case study, biological factors were related with the biological reactors (HRAP, PHA production bioreactor and desulfurization biotrickling filter), but no pathogenic risk for workers was identified.

3.2.3. Subsystem contribution to risks

Within the first quartile (Q_1, 25% of hazards), 33% of failures were related to the biotrickling filter (desulfurization unit), 18% to the PHA production tank and line, 11% to the main biogas line, 8.9% to the activated carbon filter and 6.7% to the bubble column (Fig. 3a). The novel Redox-pH-level control loop implemented in the biotrickling filter was a crucial aspect when risks associated to the desulfurization performance were analysed. In the particular case of PHA production unit, risk of explosion due to inappropriate mixture air/methane was a decisive hazard.

On the contrary, caustic soda feeding was not represented in Q_1 due to the strict and intrinsic security measurements previously described, including a contention tray and a level control system, together with the low requirements of this chemical to maintain the pH in the biotrickling filter (drain valves and transferring under safety protection). A similar contribution of risks was observed in quartiles 2 and 3 (Fig. 3b and c, respectively).

3.3. Comparative and sensitivity analysis

A comparative and sensitivity analyses were conducted to assess the reliability of the final ranking obtained, which depends on the weightings of each risk criterion analysed. For this purpose, two analysis methodologies have been applied: WASPAS, and The Evaluation Based on Distance from Average Solution (EDAS) developed by Ghorabaee et al. (2015). In terms of process failures, both methods present similar results of distribution by quartile compared to the methodology applied in the present study. However, a slight increase in the contribution to failures associated with human mistakes is observed with the EDAS method. Similarly to the contribution by streams, the distribution remains practically the same for the three methodologies. The analysis graphs are included in Appendix A.

Regarding sensitivity analysis, 9 scenarios were defined. In each of them, one of the 9 risk criterion was considered to be the most important, with a weight equal to 75%. For each scenario, the effect on the risk ranking was evaluated, clustered by process streams and type of process failures assigned to the first quartile. The analysis of the results revealed that the biogas and feeding/recycling lines remain as the process streams with the highest associated risks in Q_1 regardless of the scenario analysed (Fig. 4a). Similarly, pipe maintenance was the process failure with a higher associated risk in most of the scenarios evaluated, with a contribution increasing up to 60% when SPM was considered as the risk criterion with the highest weight (Fig. 4b). On the contrary, electrical/loop control or mechanical failures showed a contribution below 30%. Only human error arose as the process failure with an increased shared to the total risk in all the scenarios analysed, likely due to the high impact of preventive maintenance and costs. Overall, the results of the sensitivity analysis demonstrated that, in the majority of the scenarios, a relative percentage change of 75% in the weighting of the criteria does not affect the risk ranking obtained within Q_1.

3.4. Additional considerations

The fuzzy-HAZOP technique enhances the evaluation of process deviation risks by incorporating multiple aspects of risk. The identification of the importance of each criterion, through the multi-criteria analysis, allows overcoming the limitation of giving similar importance to the analysis criteria when implementing the traditional HAZOP technique (Cheraghi et al., 2019). The ranking of significance of the findings (FTOPSIS) allows focusing and reducing the complexity of the decision-making process. In the present analysis, the clustering by process lines facilitates the planning of control and preventive maintenance. However, this clustering has a limited advantage since the importance of each particular hazard and its implication for the plant's operability should not be underestimated. Another weakness of the analysis is associated with the lack of specificity of the risks. Specific risks could be

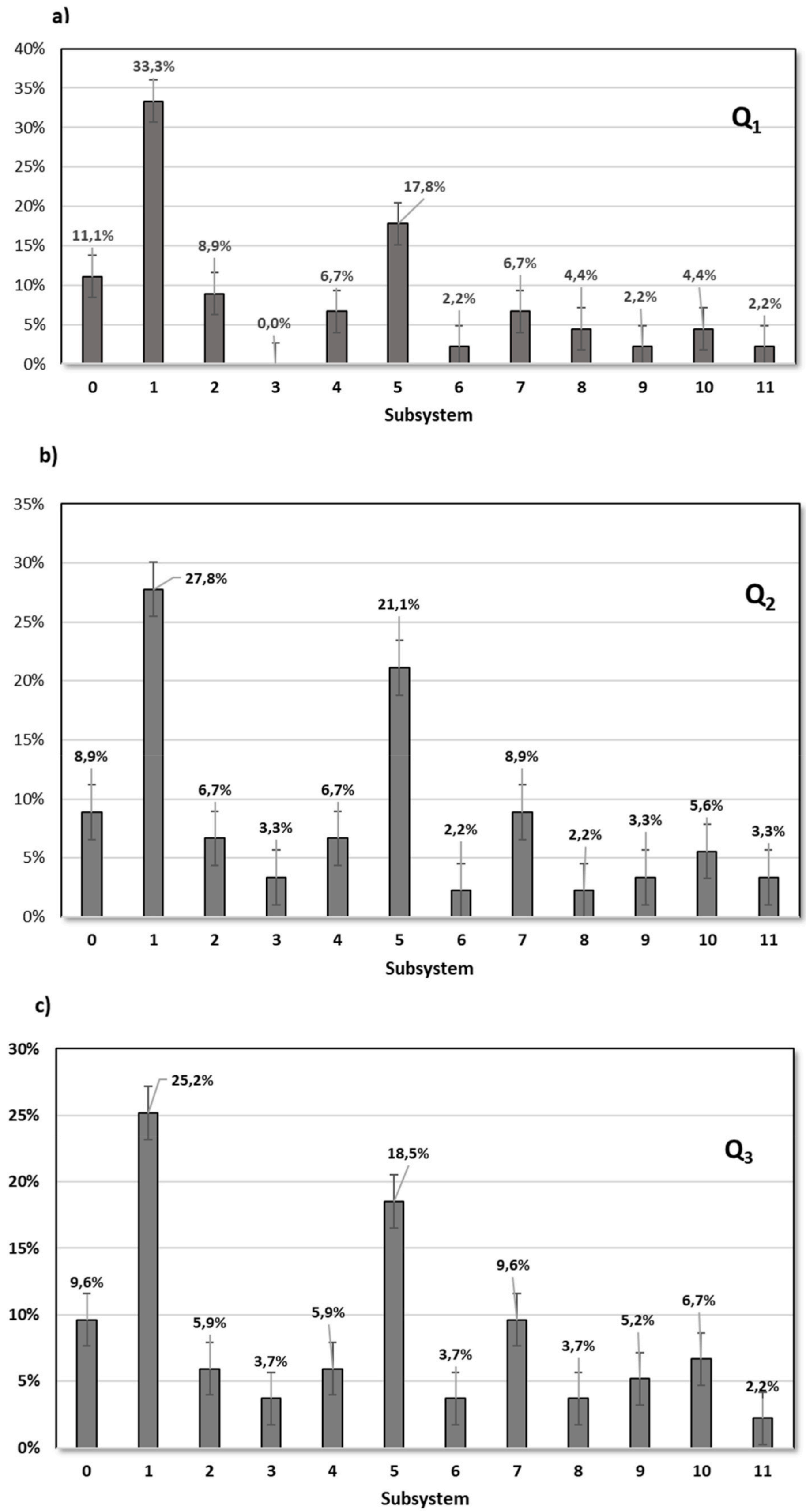

Fig. 3. Contribution of subsystems to risks within quartiles a) Q1, b) Q_2 and c) Q_3. S0: Main biogas line, S1: Biotrickling filter, S2: Activated carbon filter, S3: NaOH tank and line, S4: Mineral salt medium (MSM) for biofilter, S5: PHA tank and line, S6: MSM to PHA, S7: Bubble column, S8: Settler, S9: Digestate to HRAP, S10: HRAP, S11: Torch line.

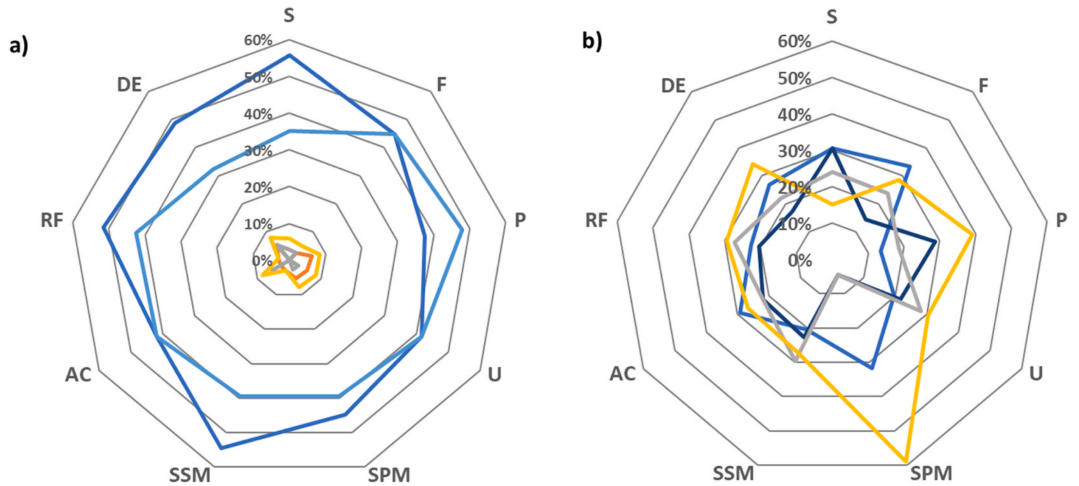

Fig. 4. Sensitivity analysis for the different risk criteria within first quartile (Q1) a) Process streams: Biogas (● blue), Feeding/recycling (● light blue), Emptying (●yellow), Air (●red), Water (● grey); b) Process failures: Human error (● blue), Pipe maintenance (●yellow), Electrical/loop control (● grey); Mechanical (● dark blue). (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

included in future studies, i.e. risk factors for accidents (working at height, working under explosive atmosphere, working with equipment), chemical and toxic substances (solvents, oils, cleaners), and physical factors (noise, vibration, thermal conditions, lighting).

4. Conclusions

The use of Fuzzy AHP-TOPSIS models improves the outcome and impact of traditional HAZOP analyses. Thus, strategically better results were obtained when additional risk criteria were introduced in the risk assessment. In this case study, severity, frequency, and probability were determined as the most significant criteria when hazards were analysed, with calculated weight values of 0.19568, 0.19379, and 0.18446, respectively. These criteria provided an enhanced reliability when assessing significant deviations of the target biogas valorization processes herein evaluated. The most relevant risks were identified in the biotrickling filter unit (33.3% within Q_1) and were associated to the biogas and liquid recycling streams, and the Redox-pH-level control loop. Other critical control points were identified in the PHA production unit and associated lines, mainly related to the mixture and high recycling flow rate of biogas and air streams, increasing explosion risks (contribution of 17.8% to overall risk within Q1). Regarding process failures, a low significance of human error was calculated (17.6% in Q3), mainly due to the robustness of the biorefinery. On the contrary, pipe maintenance emerged as the most critical process failure, with a share of 32.7% within Q3. The implementation of the acquired knowledge during the design and operation of biogas upgrading plants will assist management decisions related to planning preventive maintenance or defining critical monitored points. In this regard, particular attention should be paid to control loops and to those units with a significant number of equipment (the biotrickling filter and the PHA tank in our particular case study), which require a strict maintenance in order to avoid a negative impact to entire subsystems. Finally, the sensitivity analysis confirmed the consistency of the results and consequently the reliability of the established ranking of risks obtained through the implemented methodology.

Overall, this study contributes to the design of management strategies to reduce significant hazards and to the integrated management of biogas treatment plants. This evaluation represents the embryo for risk and hazard analysis in other bio-based processes. Furthermore, it should be emphasized that there is a wide range of decision techniques that incorporate expert knowledge and allow prioritisation of risks and response to decision making, among which TOPSIS and AHP are widely used in the widely used in the literature.

Author statement

Cristian A. Severi: Conceptualization, Investigation, Methodology, Writing – original draft preparation. **Víctor Perez:** Visualization, Methodology. **Celia Pascual:** Visualization, Methodology. **Raúl Muñoz:** Supervision, Reviewing. **Raquel Lebrero:** Supervision, Writing- Reviewing and Editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.chemosphere.2022.135845.

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