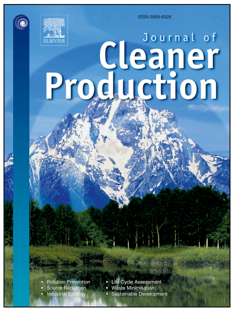
Accepted Manuscript



Analysis of a wastewater treatment plant using fuzzy goal programming as a management tool: A case study

M. Díaz-Madroñero, Pérez-Sánchez, J.R. Satorre, J. Mula, P.A. López-Jiménez

PII: S0959-6526(18)30151-3

DOI: 10.1016/j.jclepro.2018.01.129

Reference: JCLP 11809

To appear in: *Journal of Cleaner Production*

Received Date: 14 October 2017

Revised Date: 13 January 2018

Accepted Date: 17 January 2018

Please cite this article as: Díaz-Madroñero M, Pérez-Sánchez , Satorre JR, Mula J, López-Jiménez PA, Analysis of a wastewater treatment plant using fuzzy goal programming as a management tool: A case study, *Journal of Cleaner Production* (2018), doi: 10.1016/j.jclepro.2018.01.129.

Analysis of a wastewater treatment plant using fuzzy goal programming as a management tool: a case study

Díaz-Madroñero M[a], Pérez-Sánchez[b], Satorre JR [b], Mula, J[a*], López-Jiménez PA [b]

a. Research Centre on Production Management and Engineering (CIGIP), Universitat Politècnica de València, Escuela Politécnica Superior de Alcoy, Plaza Ferrándiz y Carbonell, Alcoy, Spain..

b. Hydraulic and Environmental Engineering Department. Universitat Politècnica de València. Camino de Vera s/n. Spain.

Correspondence: fmula@cigip.upv.es

Abstract: Water management is currently a priority in all integrated water cycle sections when a close relation between water and energy is considered. Wastewater treatment plants are high-energy consumers and, therefore, energy reduction is necessary to improve the energy footprint and to also reduce operating costs. This research presents a combined strategy using linear mathematical programming which, in turn, employs current treatment techniques with dilution through regenerated water at the treatment plant. The strategy used a new model that was adapted to minimise exploitation costs. The strategy also obtained a global solution by considering the uncertainty of the different variables, which are included in the treatment process. This uncertainty was considered by fuzzy goal programming, which allowed water managers to optimise treatment according to energy costs, contaminant loads, and the inlet and outlet concentrations. A mathematical tool was applied to a real case study located in a township in the province of Alicante (Spain). The solution showed a 49.47% reduction in economic cost when comparing the optimised solution to the deterministic solution. This energy reduction was 803 GWh/year and the theoretical reduction of greenhouse emissions was 586.2 tCO_2/year.

Keywords: Fuzzy goal programming; water management; wastewater treatment; combined strategy

Table 1 List of acronyms

BOD	Biological oxygen demand
DM	Decision maker
FGP	Fuzzy goal programming
FMOMILP	Fuzzy multiobjective mixed integer linear programming
MILP	Mixed integer linear programming
MIP	Mixed integer programming
MOMILP	Multiobjective mixed integer linear programming
UV	Ultraviolet
WWTP	Wastewater treatment plant

1 Introduction

Sustainability is a well-known concept that focuses on reducing inputs in different processes to reduce the use of non-renewable resources and emissions. Sustainability criteria are related in environmental,

economic, social-cultural and health-hygiene terms (Romero et al., 2017). Wastewater plants also present them in both their positive and negative forms. On the one hand, treatment plants can regenerate the wastewater to be used in irrigation or for freshwater purposes, which has a positive impact on the environmental and makes water re-use possible. This is very important if lack of an available resource is considered in some areas in particular, and the need to save it globally (Padilla-Rivera et al., 2016). On the other hand, this benefit is made by increasing energy use and CO_2 emissions. The need to reduce these negative impacts encourages water management companies to change their practices to improve the situation (Morera et al., 2015).
Energy use is one of the most important (economic and environmental) costs to be paid by water managers (Castellet and Molinos-Senante, 2016). Therefore, optimising the distribution of the flows between processes, and correctly selecting operating processes according to the inlet flows of sewer systems, and therefore designing and ultimately controlling wastewater plants, depend on a profound understanding of the inter-relationships of process variables (Huang and Wang, 1999). Waste water treatment plants (WWTPs) are processes that reveal the complexity between different variables and processes (*e.g.*, inflow of wastewater, inlet and outlet concentrations of the contaminants in each process, economic cost of energy use) (Poch et al., 2004). The variation in these variables, and the capacity of facilities, both determine the performance of each process.

Therefore, optimisation is key to reduce energy use and CO_2 emissions in treatment plants. Increased performance is related to knowing the influence of the variables inside regeneration treatments and to developing optimisation techniques that help water managers increase sustainability. In line with this, computer modelling is a powerful tool for such designs and operational control, where models are well performed and validated. Nevertheless, in recent decades, evolutionary and numerical techniques, such as mathematical programming, have emerged within the learning tools framework that complement empirical models from databases.

These optimisation techniques have been applied to different areas, such as the design and determination of operating parameters in wastewater plants, and the selection of treatment processes in such facilities. The design area can be associated with technological and economic feasibility assessments of future planned WWTPs (Panepinto et al., 2016), while the operational area can be related to data supervision in WWTPs (Poch et al., 2004), energy benchmarking (Longo et al., 2016) and savings by using proper DSSs (Torregrossa et al., 2018). One of the first studies in this field was proposed by (Huang et al., 1999), who developed a mathematical programming model for optimal water usage and treatment networks in any chemical plant in order to minimise total fresh water use and wastewater treatment capacity. Later, Bagajewicz (2000) and Bagajewicz and Savelski (2001) dealt with designing water networks in refineries and process industries, and focused on minimum freshwater use. Bagajewicz et al. (2002) complemented the previous proposals by minimising energy use by using a mixed-integer linear programming model.

Several research works on wastewater treatment have been conducted since 1980. Takama et al. (1980) applied an optimisation approach using non-convex nonlinear programming to integrate the wastewater volume into industrial processes. Doyle and Smith (1997) proposed a methodology by linearising Takama's approach, although the proposal did not always obtain the best solution between processes. In 1998, mixed-integer non-linear programming was first proposed to analyse the regeneration water process and to obtain the global solution (Galán and Grossmann, 1999; Zamora and Grossmann, 1998). Linear programming was used to optimise recycle water systems by considering only one contaminant (Savelski and Bagajewicz, 2000) or different ones (Savelski and Bagajewicz, 2003). The fuzzy technique was implemented to analyse uncertainty when the contaminant mass load was considered, which was applied to different plants (Tan, 2011; Tan and Cruz, 2004). In relation to this analysis, different techniques (*e.g.*, Montecarlo Method (Tan et al., 2007), particle swarm optimization (Hul et al., 2007), adaptive random search (Jeżowski et al., 2007), among others) were used successfully to analyse the sensitivity of solutions when the mass load was considered. Ng et al. (2009) optimised water recovery in a milling process, while Ramos et al. (2014) developed water recovery for the recycled paper industry. Along this line, Khor et al. (2012) formulated a mixed-integer nonlinear programme to determine the optimal interconnections in total flow rates and contaminant concentrations without considering uncertainty.

Other contributions to optimise water networks in industrial processes, multipurpose batch plants and the optimisation of water discharge solutions in the process industry can be found in de Faria et al. (2009), Majozi, (2005) and Koppol et al. (2004), respectively. In contrast, Rivas et al. (2008) presented a non-linear mathematical programming model for the automatic calculation of the design and operating parameters for WWTPs with different effluent requirements or wastewater characteristics. Ouyang et al. (2015) proposed a fuzzy analytical hierarchy process to select a wastewater treatment by integrating sustainability factors (*i.e.*, environmental, economic, ecological and social). In line with this, Sujak et al. (2017) proposed a holistic approach based on mathematical programming approaches to design cost-optimal water networks by taking into account different issues such as elimination, reduction, reuse, outsourcing and regeneration, as well as cost constraints to improve payback periods and annual savings.

An accurate assessment of the relationship between parameters should involve decision support systems, in which the techniques that implement uncertainty become a powerful tool to model different processes by optimising water management according to defined objective functions. To deal with such problems, fuzzy goal programming (FGP) approaches have emerged to reflect the imprecision of input data, which cannot be known with complete certainty. Besides, FGP enables a trade-off between conflicting objectives in the decision making of processes. Hence, although the literature presents several relevant works about optimization models for wastewater management by mathematical programming, to the best of our knowledge, some of the analysed references have considered optimising energy use under fuzzy conditions (Torregrossa et al., 2016). A few real cases contemplate the inherent uncertain conditions along with energy use and the variables of the process.

As a novelty, this paper presents a combined strategy in which current water regeneration techniques (*e.g.,* microfiltration, ultrafiltration) were combined with the dilution of the contaminant load by using the flows that come from regeneration units of the treatment plant. In this scenario, wastewater managers have to make several and interrelated decisions using many variable, inaccurate or imprecise data. These data have to be considered to obtain a profitable global solution. This research focused on three objectives: (1) modifying the optimisation model to incorporate uncertain conditions; (2) adapting the mode to operate in water lines in WWTPs; (3) applying the model to a real case study. This strategy combines current wastewater regeneration techniques with dilution by optimising exploitation costs (by considering minimum freshwater use and energy costs). Besides, the strategy obtained the global solution by considering the uncertainty of the different variables, which are included in the treatment process. Therefore, the main contribution of this research was to help water managers and practitioners to develop more sustainable water systems.

This paper is structured as follows: the Introduction is described in the present section. The second section describes the problem defined in the research. Section 3 defines the mathematical model that lists the necessary equations and constraints of the model to optimise the process. Section 4 defines the fuzziness levels, the ranking fuzzy numbers and the fuzzy goal programming (FGP) method. Section 5 presents the case study and the results when the mathematical model was applied. Section 6 offers the main conclusions.

2 Problem description

All urban and industrial volumes must be treated before spillages to natural beds (European Comission, 2016), and WWTPs must be used to prevent environmental pollution and real diseases. Water treatment plants are, therefore, designed to reduce the contaminant concentration present in the circulating flows along the different treatment parts. Water decontamination occurs when water enters the plant and an efficient combination of treatments is implemented. In an initial stage (pretreatment), big solids and other physical floating materials present in the water are eliminated. As a secondary treatment, settlers are designed so that organic materials are separated by sedimentation and biological processes that intend to remove any dissolved and suspended organic compounds in the water (Fig. 1).

Although a primary treatment is considered, this process was not included in the analysed case study. When air circulation is lengthy, no anaerobic digester is installed (those plants whose treated volume is below 50,000 m^3/day). Besides, when both lengthy air circulation and nitrification-denitrification processes exist, decantation (primary treatment) usually presents problems since a BOD is consequently removed as the anoxic stage does not have enough carbonaceous matter.

When the primary treatment is an active process, it is located between the pre-treatment and the secondary treatment. Figure 1 shows only the water line, and the different discharges of the processes that derive from the sludge line (not analysed in this research).

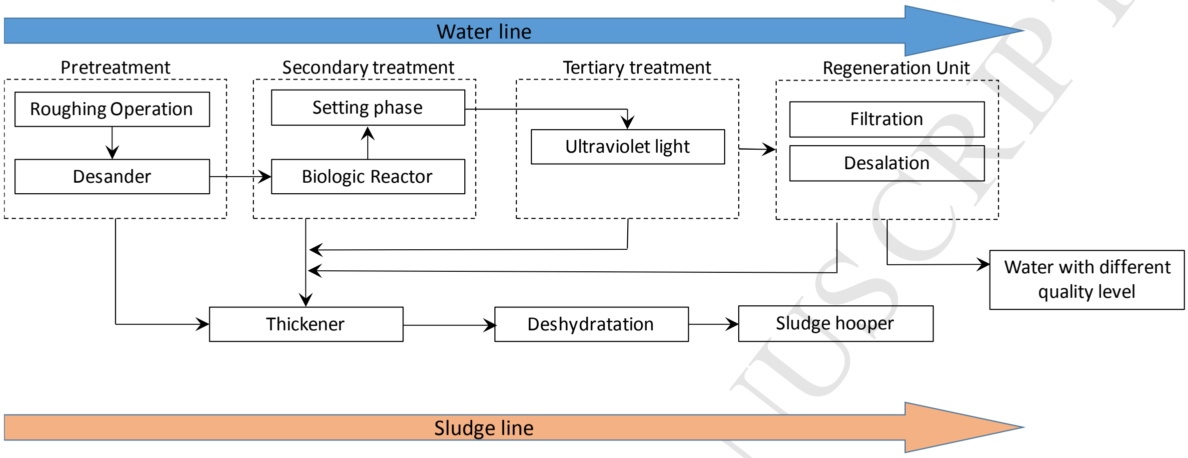


Fig. 1 Stages in the water treatment process

In secondary treatments, the presence of microbes is crucial as they consume organic matter and convert it into carbon dioxide, energy and more water (Cheremisinoff, 2002). The biologic process operation causes variability as a result of the biologic cycle of microorganisms. Therefore, some hysteresis considered in the outlet parameter and in the inlet parameters (concentration) causes variations in the performance, although the biologic process has its inertia.

After secondary, tertiary treatments are designed to improve water quality before it is reused or discharged to other receiving waters. Tertiary treatment is a physiochemical process that is conditioned by variations in the inlet load, and reactive doses depend on the inlet concentration, with variations in the outlet-water quality, which are motivated by a physical (e.g., temperature) or a chemical (e.g., pH, redox potential). Different techniques can be applied, such as various sorts of filtrations, ammonia or other specific contaminant removals or disinfections. Among them all, different regeneration units, such as filtration by sand, mesh filtration, microfiltration and ultrafiltration, can be used to increase water quality. The applied technique depends on the final water use (e.g., irrigation, ecologic flow, washing down in urban areas). These techniques, together with UV disinfection, are different technologies for reclaimed water.

3 Model formulation

In order to incorporate uncertainty related to operating parameters into a WWTP and to improve deterministic planning tools, a fuzzy multiobjective mixed integer linear programming (FMOMILP) model is presented in this study, which is based on the previous work by Ramos et al. (2014). The proposed model considers fuzzy goals and fuzzy data related to maximum and minimum concentrations of contaminant loads in the inlet and outlet in processes (*i.e.*, secondary and tertiary), as well as in the inlet of the contaminant load in the secondary process. The nomenclature defines the sets of indices, parameters and decision variables for the FMOMILP model (Table 2).

Table 2 Nomenclature (a tilde ~ denotes the fuzzy parameters)

Indices	
I,J	Processes (*i=1,…P; j=1,…,P*)
R,M	Regeneration units (*r=1,…,R; m=1,...,R*)
C	Components (*c=w,…C*) (*w* corresponds to water)
Parameters	
$cp_{i,j}$	Cost of connecting process *i* and process *j* (€)
cw_i	Cost of freshwater used in process *i* (€)
$cpr_{i,r}$	Cost of connecting process *i* and regeneration unit *r* (€)
$crp_{r,i}$	Cost of connecting regeneration unit *r* and process *i* (€)
$cr_{r,m}$	Cost of connecting regeneration unit *r* and regeneration unit *m* (€)
$\widetilde{M}_i^c$	Contaminant load in process *i* (t/day)
β_i	Discharge ratio in process *i* (%)
$\widetilde{cout}_i^{max}$	Maximum concentration allowed at the outlet of process *i* (ppm)
$\widetilde{cin}_i^{max}$	Maximum concentration allowed at the inlet of process *i* (ppm)
c_r^{out}	Maximum concentration allowed at the outlet of regeneration unit *r* (ppm)
c_r^{in}	Maximum concentration allowed at the inlet of regeneration unit *r* (ppm)
minf	Minimum flow rate between any kind of processes and/or regeneration unit (t/day)
maxf	Maximum flow rate between any kind of processes and/or regeneration unit (t/day)
Decision variables	
$FINP_i^c$	Inlet of contaminant *c* of process *i* (t/day)
$FOUTP_i^c$	Outlet of contaminant *c* of process *i* (t/day)
$FINR_r^c$	Inlet of contaminant *c* of regeneration unit *r* (t/day)
$FOUTR_r^c$	Outlet of contaminant *c* of regeneration unit *r* (t/day)
FW_i	Freshwater used in process *i* (t/day)
$FP_{i,j}^c$	Flow of component *c* between process *i* and process *j* (t/day)
$FPR_{i,r}^c$	Flow of component *c* between process *i* and regeneration unit *r* (t/day)
$FRP_{r,i}^c$	Flow of component *c* between regeneration unit *r* and process *i* (t/day)
$FR_{r,m}^c$	Flow of component *c* between regeneration unit *r* and regeneration unit *m* (t/day)
FD_i^c	Discharge of component *c* in process *i* (t/day)
YW_i	Binary variable indicating the freshwater use in process *i*
$YP_{i,j}$	Binary variable indicating the existence of flow between process *i* and process *j*
$YPR_{i,r}$	Binary variable indicating the existence of flow between process *i* and regeneration unit *r*
$YRP_{r,i}$	Binary variable indicating the existence of flow between regeneration unit *r* and process *i*
$YR_{r,m}$	Binary variable indicating the existence of flow between regeneration unit *r* and regeneration unit *m*

The FMOMILP model is formulated as follows:

Objective functions

Equations (1) to (3) represent the minimisation of the total connections costs (Z_1), total freshwater use (Z_2) and total regenerated freshwater use (Z_3) according to the decision maker's (DM) preferences.

$$Min\, Z_1 \cong \sum_{i,j\in P, i\neq j} cp_{i,j} YP_{i,j} + \sum_{i\in P} cw_i YW_i + \sum_{i\in P, r\in R} cpr_{i,r} YPR_{i,r} + \sum_{i\in P, r\in R} crp_{r,i} YRP_{r,i} + \sum_{r\in R, m\in R} cr_{r,m} YR_{r,m} \quad (1)$$

$$Min\, Z_2 \cong \sum_{i\in P} FW_i \quad (2)$$

$$Min\, Z_3 \cong \sum_{r\in R, i\in P} FRP_{r,i}^{c=w} \quad (3)$$

Subject to:

Constraints for water mass balance in processes

$$FINP_i^{c=w} = FW_i + \sum_{j\in P, j\neq i} FP_{j,i}^{c=w} + \sum_{r\in R} FRP_{r,i}^{c=w} \qquad \forall i \in P \qquad (4)$$

$$FOUTP_i^{c=w} = FD_i^{c=w} + \sum_{j\in P, j\neq i} FP_{i,j}^{c=w} + \sum_{r\in R} FPR_{i,r}^{c=w} \qquad \forall i \in P \qquad (5)$$

$$FINP_i^{c=w} = FOUTP_i^{c=w} \qquad \forall i \in P \qquad (6)$$

The total inlet of water in each process is determined in Constraint (4) as the sum of the freshwater, the flow of water from other processes and the flow of water from regeneration units. Constraint (5) calculates the total outlet of water in each process, which consists of the water sent to discharge, to other processes and to regeneration units. Constraint (6) establishes the balance between the inlet and outlet of mass water in each process.

Constraints for contaminant mass balance in processes

$$FINP_i^c = \sum_{j\in P, j\neq i} FP_{j,i}^c + \sum_{r\in R} FRP_{r,i}^c \qquad \forall i \in P \qquad (7)$$

$$FOUTP_i^c = FD_i^c + \sum_{j\in P, j\neq i} FP_{i,j}^c + \sum_{r\in R} FPR_{i,r}^c \qquad \forall i \in P \qquad (8)$$

$$FINP_i^c + \widetilde{M}_i^c = FOUTP_i^c \qquad \forall i \in P \qquad (9)$$

Constraint (7) represents the inlet of the contaminant mass in each process, composed of the contaminant mass received from other processes and from regeneration units. The outlet of contaminant mass is similar to Constraint (5). In Constraint (9), the contaminant mass balance is determined by taking into account the contaminant load at the inlet of the process.

Constraints for process performance

$$FD_i^c = \beta_i \widetilde{M}_i^c \qquad i = 1 \qquad (10)$$

$$FD_i^c = \beta_i \widetilde{M}_i^c + \sum_{j\in P, j\neq i} FP_{j,i}^c \qquad \forall i \neq 1 \qquad (11)$$

Constraints (10) and (11) impose the deleted performance of the first and the other processes, respectively, as a proportion of the contaminant load.

Constraints for the water mass balance in regeneration units

$$FINR_r^{c=w} = \sum_{m\in R, m\neq r} FR_{m,r}^{c=w} + \sum_{i\in P} FPR_{i,r}^{c=w} \qquad \forall r \in R \qquad (12)$$

$$FOUTR_r^{c=w} = \sum_{i\in P} FRP_{r,i}^{c=w} + \sum_{m\in R, m\neq r} FR_{r,m}^{c=w} \qquad \forall r \in R \qquad (13)$$

$$FINR_r^{c=w} = FOUTR_r^{c=w} \qquad \forall r \in R \qquad (14)$$

Similarly to Constraints (4) to (6), the water mass balance in each regeneration unit is represented by Constraints (12) to (14). The total amount of water that enters the regeneration unit is the sum of the amounts of water received from other regeneration units and all the processes, as stated by Constraint (12). Similarly, the total outlet is determined in Constraint (13) as the sum of water flows to processes and the water flows to other regeneration units, while Constraint (14) represents the balance between inlet and outlet.

Constraints for the contaminant mass balance in regeneration units

$$FINR_r^c = \sum_{m \in R, m \neq r} FR_{m,r}^c + \sum_{i \in P} FPR_{i,r}^c \quad \forall r \in R \quad (15)$$

$$FOUTR_r^c = \sum_{i \in P} FRP_{r,i}^c + \sum_{m \in R, m \neq r} FR_{r,m}^c \quad \forall r \in R \quad (16)$$

$$FINR_r^c = FOUTR_r^c + FRD_r^c \quad \forall r \in R \quad (17)$$

Constraints (15) and (16) calculate the inlet and outlet of the contaminant in regeneration units similarly as Constraints (12) and (13) do for the water component. Moreover, Constraint (17) establishes the mass balance of the contaminant by adding the proportion to be sent to discharge.

Processes equations to connect other processes, regeneration units or discharge

$$FP_{i,j}^c - \widetilde{cout}_i^{max} FP_{i,j}^{c=w} = FOUTP_i^c - \widetilde{cout}_i^{max} FOUTP_i^{c=w} \quad \forall i, \forall j \in P, i \neq j \quad (18)$$

$$FPR_{i,r}^c - \widetilde{cout}_i^{max} FPR_{i,r}^{c=w} = FOUTP_i^c - \widetilde{cout}_i^{max} FOUTP_i^{c=w} \quad \forall i \in P, \forall r \in R \quad (19)$$

$$FD_i^c - \widetilde{cout}_i^{max} FD_i^{c=w} = FOUTP_i^c - \widetilde{cout}_i^{max} FOUTP_i^{c=w} \quad \forall i \in P \quad (20)$$

Constraints (18) to (20) define the relation between the outlet flow among processes, as well as the relation between processes and regeneration units. These flows depend on the outlet concentration of the different processes.

Regeneration units equations for recirculating to processes

$$FRP_{r,i}^c - c_r^{out} FRP_{r,i}^{c=w} = FOUTR_r^c - c_r^{out} FOUTR_i^{c=w} \quad \forall i \in P, \forall r \in R \quad (21)$$

$$FR_{r,m}^c - c_r^{out} FR_{r,m}^{c=w} = FOUTR_r^c - c_r^{out} FOUTR_i^{c=w} \quad \forall r, \forall m \in R \quad (22)$$

Constraints (21) and (22) define the flow circulation between regeneration units and processes when the flow is used to lower the contaminant concentration. These flows depend on the outlet concentration of the different regeneration units.

Operating constraints

$$FINP_i^c \leq \widetilde{cin}_i^{max} FINP_i^{c=w} \quad \forall i \in P \quad (23)$$

$$FOUTP_i^c \leq \widetilde{cout}_i^{max} FOUTP_i^{c=w} \quad \forall i \in P \quad (24)$$

$$FINR_r^c \leq c_r^{in} FINR_r^{c=w} \quad \forall r \in R \quad (25)$$

$$FOUTR_r^c = c_r^{out} FOUTR_r^{c=w} \quad \forall r \in R \quad (26)$$

In this group, Constraints (23) and (24) limit the concentration allowed at the inlet and outlet of each process, while Constraint (25) limits the concentration at the inlet of each regeneration unit and Constraint (26) fixes the corresponding outlet concentration.

Disjunctive constraints

$minf \cdot YW_i \leq FW_i$ $\quad \forall i \in P$ (27)

$FW_i \leq maxf \cdot YW_i$ $\quad \forall i \in P$ (28)

$minf \cdot YP_{i,j} \leq FP_{i,j}^{c=w}$ $\quad \forall i, \forall j \in P$ (29)

$FP_{i,j}^{c=w} \leq maxf \cdot YP_{i,j}$ $\quad \forall i, \forall j \in P$ (30)

$minf \cdot YD_i \leq FD_i^{c=w}$ $\quad \forall i \in P$ (31)

$FD_i^{c=w} \leq maxf \cdot YD_i$ $\quad \forall i \in P$ (32)

$minf \cdot YPR_{i,r} \leq FPR_{i,r}^{c=w}$ $\quad \forall i \in P, \forall r \in R$ (33)

$FPR_{i,r}^{c=w} \leq maxf \cdot YPR_{i,r}$ $\quad \forall i \in P, \forall r \in R$ (34)

$minf \cdot YRP_{r,i} \leq FRP_{r,i}^{c=w}$ $\quad \forall i \in P, \forall r \in R$ (35)

$FRP_{r,i}^{c=w} \leq maxf \cdot YRP_{r,i}$ $\quad \forall i \in P, \forall r \in R$ (36)

$minf \cdot YR_{r,m} \leq FR_{r,m}^{c=w}$ $\quad \forall r, \forall m \in R$ (37)

$FR_{r,m}^{c=w} \leq maxf \cdot YR_{r,m}$ $\quad \forall r, \forall m \in R$ (38)

In order to model the decision as to whether connections exist among processes, regeneration units, processes, and among regenerations units, regeneration units and processes, and between processes and the discharge, binary variables are activated by using Constraints (27) to (38) if the corresponding flows take values between the minimum and maximum allowable limits.

Binary constraints for decision variables

$YW_i, YP_{i,j}, YPR_{i,r}, YRP_{r,i}, YR_{r,m} \in \{0,1\}$ $\quad \forall i, \forall j \in P, \forall r, \forall m \in R$ (39)

Constraint (39) provides the binary condition for the decision variables.

It is necessary to point out that Constraints (10), (11) and (25) were added to the original model by Ramos et al. (2014). As a novelty in the model, the deleted performance of processes, as well as the inlet operating concentration conditions at the regeneration units, were also considered. The original model by Ramos et al. (2014) concentrates the inlet load to extract the water during process. In this research, the model minimised freshwater use by carrying out the dilution of the inlet load (solids suspension) during the regeneration treatment. This dilution was considered by Constraint (25) for both regeneration units and processes (Constraint (23)).

The imprecise aspiration levels of the DM for each objective function were included by using the symbol '≅', which is the fuzzified version of '='. Accordingly, Equations (1)–(3) are fuzzy. In this case, the DM has to simultaneously optimise these conflicting objectives within the framework of imprecise aspiration levels by a fuzzy goal programming (FGP) approach (Díaz-Madroñero et al., 2014a). FMOMILP and FGP methodologies have been discussed in different research works (e.g., Díaz-Madroñero et al. (2017), Ebrahimnejad and Verdegay (2016), Hegeman et al. (2014), Mula et al. (2014), Naderi et al. (2016).

4 Solution methodology

In this section, to address the fuzziness related to contaminant loads and concentrations, and the fuzziness in the aspiration levels that correspond to the objective functions, the ranking fuzzy numbers approach by Jiménez (1996) and Jiménez et al. (2007), and the FGP method by Torabi and Hassini (2008), were applied, respectively. This FGP approach transforms the original FMOMILP model into an equivalent MILP model that be solved by using a standard MIP solver. Moreover, an interactive solution procedure based on Díaz-Madroñero et al. (2014b) was applied.

4.1 Addressing constraints with fuzzy numbers

As in several previous research works (Díaz-Madroñero et al., 2014a; Peidro et al., 2010), the uncertainty inherent to input parameters was modelled by using trapezoidal fuzzy numbers in a similar way to that applied in Peidro et al (2010) and Díaz-Madroñero et al. (2014a).

Let's consider the following multiobjective linear programming problem with fuzzy parameters:

$$\text{Min } \tilde{z} = (z_1, z_2, ..., z_k)$$

subject to:

$$x \in N(\tilde{A}, \tilde{b}) = \{x \in R^n \ / \tilde{a}_i x \le \tilde{b}_i, \ i = 1,...,m, \ x \ge 0\} \tag{40}$$

where z_1, z_2, …, z_k are the objective functions of the multi-objective linear programming problem, defined as $z_k = c_k^t \cdot x$ for the each objective function; $c_k = (c_1, c_2, ... c_n)$ are the associated coefficient costs for the corresponding objective function; x is the crisp decision vector. Moreover, $\tilde{A} = [\tilde{a}_{ij}]_{mxn}$ and $\tilde{b} = (\tilde{b}_1, \tilde{b}_2, ..., \tilde{b}_m)^t$ represent the fuzzy parameters involved on both sides of the constraints and x is the crisp decision vector. The possibility distribution of the fuzzy parameters is assumed to be characterised by fuzzy numbers. So this problem can be transformed by applying the approach by Jiménez (1996) and Jiménez et al. (2007) to a crisp equivalent parametric problem, as follows:

$$\text{Min } \tilde{z} = (z_1, z_2, ..., z_k)$$

subject to:

$$[(1-\sigma)E_1^{a_i} + \sigma E_2^{a_i}]x \le \sigma E_1^{b_i} + (1-\sigma)E_2^{b_i}, i = 1, ..., m, x \ge 0, \sigma \in [0,1] \tag{41}$$

where σ represents the degree to which, at least, all the constraints are fulfilled; that is, σ is the feasibility degree of a decision x. The expected interval of a fuzzy trapezoidal (Fig. 2) number (a_1,a_2,a_3,a_4), noted as $EI(\tilde{a})$, is calculated according to Heilpern (1992) as follows:

$$EI(\tilde{a}) = [E_1^a, E_2^a] = \left[\frac{1}{2}(a_1 + a_2), \frac{1}{2}(a_3 + a_4)\right] \tag{42}$$

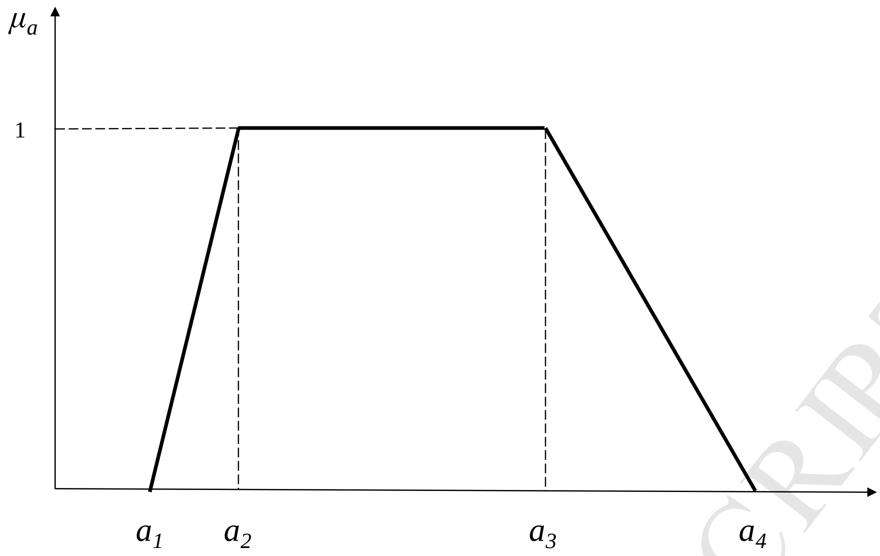


Fig. 2 Trapezoidal fuzzy number $\tilde{a}$

If (40) is an equality type constraint, this could be transformed into two equivalent crisp constraints:

$$\left[\left(1-\frac{\sigma}{2}\right)E_1^{a_i}+\frac{\sigma}{2}E_2^{a_i}\right]x \le \frac{\sigma}{2}E_1^{b_i}+\left(1-\frac{\sigma}{2}\right)E_2^{b_i},\ i=1,\ldots,m,\ x\ge 0,\ \sigma\in[0,1]$$

$$\left[\left(1-\frac{\sigma}{2}\right)E_2^{a_i}+\frac{\sigma}{2}E_1^{a_i}\right]x \ge \frac{\sigma}{2}E_2^{b_i}+\left(1-\frac{\sigma}{2}\right)E_1^{b_i},\ i=1,\ldots,m,\ x\ge 0,\ \sigma\in[0,1] \qquad (43)$$

So by applying this approach to the previously defined FMOMILP model, and by considering trapezoidal fuzzy numbers for the uncertain parameters, we obtained an auxiliary crisp multiobjective mixed-integer linear programming model (MOMILP) as follows:

Objective functions

$$Min\ Z_1 \cong \sum_{i,j\in P, i\neq j} cp_{i,j} YP_{i,j} + \sum_{i\in P} cw_i YW_i + \sum_{i\in P, r\in R} cpr_{i,r} YPR_{i,r} + \sum_{i\in P, r\in R} crp_{r,i} YRP_{r,i} + \sum_{r\in R, m\in R} cr_{r,m} YR_{r,m} \qquad (44)$$

$$Min\ Z_2 \cong \sum_{i\in P} FW_i \qquad (45)$$

$$Min\ Z_3 \cong \sum_{r\in R, i\in P} FRP_{r,i}^{w} \qquad (46)$$

Subject to:

Constraints for the water mass balance in processes

Constraints (4) to (6)

Constraints for the contaminant mass balance in processes

Constraints (7) to (8)

$$FOUTP_i^c - FINP_i^c \leq \frac{\sigma}{2} \cdot \frac{M_{i1}^c + M_{i2}^c}{2} + \left(1 - \frac{\sigma}{2}\right) \cdot \frac{M_{i3}^c + M_{i4}^c}{2} \qquad \forall i \in P \qquad (47)$$

$$FOUTP_i^c - FINP_i^c \geq \frac{\sigma}{2} \cdot \frac{M_{i3}^c + M_{i4}^c}{2} + \left(1 - \frac{\sigma}{2}\right) \cdot \frac{M_{i1}^c + M_{i2}^c}{2} \qquad \forall i \in P \qquad (48)$$

Constraints (47) and (48) correspond to the two equivalent crisp constraints regarding Constraint (9).

Constraints for process performance

$$FD_i^c \leq \beta_i \cdot \left[\frac{\sigma}{2} \cdot \frac{M_{i1}^c + M_{i2}^c}{2} + \left(1 - \frac{\sigma}{2}\right) \cdot \frac{M_{i3}^c + M_{i4}^c}{2}\right] \qquad i = 1 \qquad (49)$$

$$FD_i^c \geq \beta_i \cdot \left[\frac{\sigma}{2} \cdot \frac{M_{i3}^c + M_{i4}^c}{2} + \left(1 - \frac{\sigma}{2}\right) \cdot \frac{M_{i1}^c + M_{i2}^c}{2}\right] \qquad i = 1 \qquad (50)$$

$$FD_i^c - \sum_{j \in P, j \neq i} FP_{j,i}^c \leq \beta_i \cdot \left[\frac{\sigma}{2} \cdot \frac{M_{i1}^c + M_{i2}^c}{2} + \left(1 - \frac{\sigma}{2}\right) \cdot \frac{M_{i3}^c + M_{i4}^c}{2}\right] \qquad \forall i \neq 1 \qquad (51)$$

$$FD_i^c - \sum_{j \in P, j \neq i} FP_{j,i}^c \geq \beta_i \cdot \left[\frac{\sigma}{2} \cdot \frac{M_{i3}^c + M_{i4}^c}{2} + \left(1 - \frac{\sigma}{2}\right) \cdot \frac{M_{i1}^c + M_{i2}^c}{2}\right] \qquad \forall i \neq 1 \qquad (52)$$

Constraints (49) and (50) correspond to the two equivalent crisp constraints regarding equality type Constraint (10), as well as Constraints (51) and (52) for Constraint (10).

Constraints for the water mass balance in regeneration units

Constraints (12) to (14)

Constraints for the contaminant mass balance in regeneration units

Constraints (15) to (17)

Process splitter equations

$$\left[\left(1 - \frac{\sigma}{2}\right) \cdot \frac{cout_{i1}^{max} + cout_{i2}^{max}}{2} + \frac{\sigma}{2} \cdot \frac{cout_{i3}^{max} + cout_{i4}^{max}}{2}\right] \cdot FOUTP_i^{c=w} - \left[\left(1 - \frac{\sigma}{2}\right) \cdot \frac{cout_{i1}^{max} + cout_{i2}^{max}}{2} + \frac{\sigma}{2} \cdot \frac{cout_{i3}^{max} + cout_{i4}^{max}}{2}\right] \cdot FP_{i,j}^{c=w} \leq FOUTP_i^c - FP_{i,j}^c \qquad \forall i, \forall j \in P, i \neq j \qquad (53)$$

$$\left[\left(1 - \frac{\sigma}{2}\right) \cdot \frac{cout_{i3}^{max} + cout_{i4}^{max}}{2} + \frac{\sigma}{2} \cdot \frac{cout_{i1}^{max} + cout_{i2}^{max}}{2}\right] \cdot FOUTP_i^{c=w} - \left[\left(1 - \frac{\sigma}{2}\right) \cdot \frac{cout_{i3}^{max} + cout_{i4}^{max}}{2} + \frac{\sigma}{2} \cdot \frac{cout_{i1}^{max} + cout_{i2}^{max}}{2}\right] \cdot FP_{i,j}^{c=w} \geq FOUTP_i^c - \qquad \forall i, \forall j \in P, i \neq j \qquad (54)$$

$FP_{i,j}^{c}$

$$\left[\left(1-\frac{\sigma}{2}\right)\cdot\frac{cout_{i1}^{max}+cout_{i2}^{max}}{2}+\frac{\sigma}{2}\cdot\frac{cout_{i3}^{max}+cout_{i4}^{max}}{2}\right]\cdot FOUTP_i^{c=w}-\left[\left(1-\frac{\sigma}{2}\right)\cdot\frac{cout_{i1}^{max}+cout_{i2}^{max}}{2}+\frac{\sigma}{2}\cdot\frac{cout_{i3}^{max}+cout_{i4}^{max}}{2}\right]\cdot FPR_{i,r}^{c=w}\leq FOUTP_i^{c}-FPR_{i,r}^{c} \quad \forall i\in P,\ \forall r\in R \tag{55}$$

$$\left[\left(1-\frac{\sigma}{2}\right)\cdot\frac{cout_{i3}^{max}+cout_{i4}^{max}}{2}+\frac{\sigma}{2}\cdot\frac{cout_{i1}^{max}+cout_{i2}^{max}}{2}\right]\cdot FOUTP_i^{c=w}-\left[\left(1-\frac{\sigma}{2}\right)\cdot\frac{cout_{i3}^{max}+cout_{i4}^{max}}{2}+\frac{\sigma}{2}\cdot\frac{cout_{i1}^{max}+cout_{i2}^{max}}{2}\right]\cdot FPR_{i,r}^{c=w}\geq FOUTP_i^{c}-FPR_{i,r}^{c} \quad \forall i\in P,\ \forall r\in R \tag{56}$$

$$\left[\left(1-\frac{\sigma}{2}\right)\cdot\frac{cout_{i1}^{max}+cout_{i2}^{max}}{2}+\frac{\sigma}{2}\cdot\frac{cout_{i3}^{max}+cout_{i4}^{max}}{2}\right]\cdot FOUTP_i^{c=w}-\left[\left(1-\frac{\sigma}{2}\right)\cdot\frac{cout_{i1}^{max}+cout_{i2}^{max}}{2}+\frac{\sigma}{2}\cdot\frac{cout_{i3}^{max}+cout_{i4}^{max}}{2}\right]\cdot FD_i^{c=w}\leq FOUTP_i^{c}-FD_i^{c} \quad \forall i\in P \tag{57}$$

$$\left[\left(1-\frac{\sigma}{2}\right)\cdot\frac{cout_{i3}^{max}+cout_{i4}^{max}}{2}+\frac{\sigma}{2}\cdot\frac{cout_{i1}^{max}+cout_{i2}^{max}}{2}\right]\cdot FOUTP_i^{c=w}-\left[\left(1-\frac{\sigma}{2}\right)\cdot\frac{cout_{i3}^{max}+cout_{i4}^{max}}{2}+\frac{\sigma}{2}\cdot\frac{cout_{i1}^{max}+cout_{i2}^{max}}{2}\right]\cdot FD_i^{c=w}\geq FOUTP_i^{c}-FD_i^{c} \quad \forall i\in P \tag{58}$$

Constraints (53) to (58) represent the crisp formulation of Constraints (18) to (20) by applying the approach by Jiménez (1996) and Jiménez et al. (2007).

Regeneration unit splitter equations

Constraints (21) to (22)

Operating constraints

$$FINP_i^{c}\leq\left[\sigma\cdot\frac{cin_{i1}^{max}+cin_{i2}^{max}}{2}+(1-\sigma)\cdot\frac{cin_{i3}^{max}+cin_{i4}^{max}}{2}\right]\cdot FINP_i^{c=w} \quad \forall i\in P \tag{59}$$

$$FOUTP_i^{c}\leq\left[\sigma\cdot\frac{cout_{i1}^{max}+cout_{i2}^{max}}{2}+(1-\sigma)\cdot\frac{cout_{i3}^{max}+cout_{i4}^{max}}{2}\right]FOUTP_i^{c=w} \quad \forall i\in P \tag{60}$$

and Constraints (25) to (26).

Constraints (59) and (60) are the defuzzified versions of Constraints (23) and (24).

Disjunctive constraints

Constraints (27) to (38)

Binary constraints for the decision variables

Constraint (39)

4.2 Fuzzy goal programming as a solution method

The literature provides several methodologies to solve mathematical programming models with multiple conflicting objectives. Among them, fuzzy goal programming, and specially weighted approaches have emerged as a useful method to incorporate the DM's preferences and trade-offs aspiration levels between objectives (Lai and Hwang, 1993; Tiwari et al., 1987; Torabi and Hassini, 2008; Yaghoobi et al., 2008).

In these approaches, each fuzzy objective is described by a membership function that reflects the DM's degree of satisfaction about achieving the target. Among the different forms of membership functions, the linear type is the most convenient compared to other more complicated membership functions because it provides equivalent, efficient and computationally tractable linear models (Verdegay, 2015). Indeed as the three goals are of the minimizing type, the corresponding no increasing continuous linear membership functions are formulated as follows:

$$\mu_{Z_k}=\begin{cases} 1 & Z_k < Z_k^l \\ \frac{Z_k^u - Z_k}{Z_k^u - Z_k^l} & Z_k^l < Z_k < Z_k^u \\ 0 & Z_k > Z_k^u \end{cases} \tag{61}$$

where μ_{Z_k} is the membership function of objective Z_k, while Z_k^l and Z_k^u are the lower and upper bounds of objective function Z_k. This kind of linear membership function is graphically represented in Figure 3. According to Liang and Cheng (2009), the values for Z_k^l and Z_k^u can be determined by asking the DM to specify the fuzzy objective value interval by taking into account his/her managerial preferences, or by solving the three single objective problems independently and then taking their optimistic and pessimistic values (Torabi and Hassini, 2008)

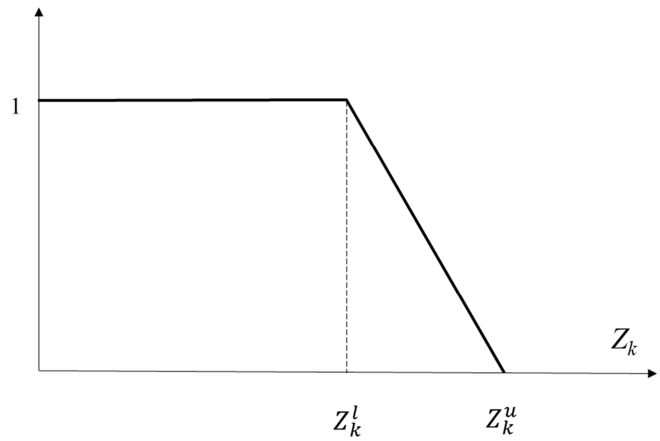


Fig. 3 *Membership function of* Z_k

The FGP approach by Torabi and Hassini (2008), is based on the convex combination of the lower bound for the degree of satisfaction of objectives, plus the weighted sum of these degrees of achievement. This FGP solution method transforms a multiobjective mathematical programming problem into an equivalent single objective model, as follows:

$$\text{Max } \lambda(x) = \gamma\lambda_0 + (1-\gamma)\sum_k w_{Z_k}\mu_{Z_k}(x)$$

Subject to: $\lambda_0 \leq \mu_{Z_k}(x) \quad k=1, 2, \ldots, N$

$$x \in F(x)$$

$$\lambda_0, \gamma \in [0,1] \tag{62}$$

where μ_{Z_k} and $\lambda_0 = min\{\mu_{Z_k}\}$ denote the satisfaction degree or membership function of the *k*th objective and the minimum satisfaction degree of the objectives, respectively. Moreover, w_{Z_k} and γ indicate the relative importance of the *k*th objective function and the coefficient of compensation which controls the compromise degree among the objectives, respectively. These parameters are determined by the DM's preferences.

By using the previous FGP approach, the complete equivalent crisp single-goal equivalent MILP model is formulated as follows:

$$Max\ \lambda(x) = \gamma \cdot \lambda_0 + (1-\gamma) \cdot \left(w_{Z_1} \cdot \mu_{Z_1} + w_{Z_2} \cdot \mu_{Z_2} + w_{Z_3} \cdot \mu_{Z_3}\right) \tag{63}$$

Subject to:

$$\mu_{Z_1} \leq \frac{Z_1^u - Z_1}{Z_1^u - Z_1^l} \tag{64}$$

$$\mu_{Z_2} \leq \frac{Z_2^u - Z_2}{Z_2^u - Z_2^l} \tag{65}$$

$$\mu_{Z_1} \leq \frac{Z_3^u - Z_3}{Z_3^u - Z_3^l} \tag{66}$$

$$0 \leq \lambda_0 \leq 1 \tag{67}$$

$$0 \leq \mu_{Z_1} \leq 1 \tag{68}$$

$$0 \leq \mu_{Z_2} \leq 1 \tag{69}$$

$$0 \leq \mu_{Z_3} \leq 1 \tag{70}$$

and Constraints (4) to (8), (12) to (17), (21), (22), (25) to (39) and (47) to (60).

4.3 Solution procedure

Here the interactive solution procedure proposed by Díaz-Madroñero et al. (2014b), based on Liang and Cheng (2009), was adapted to solve the WWTP performance optimisation problem. This procedure facilitated the decision-making process in a fuzzy scenario because it allowed the DM to adjust the search direction during the solution procedure interactively to obtain a preferred satisfactory solution. Figure 4 summarises the proposed interactive solution procedure that is defined in the following steps:

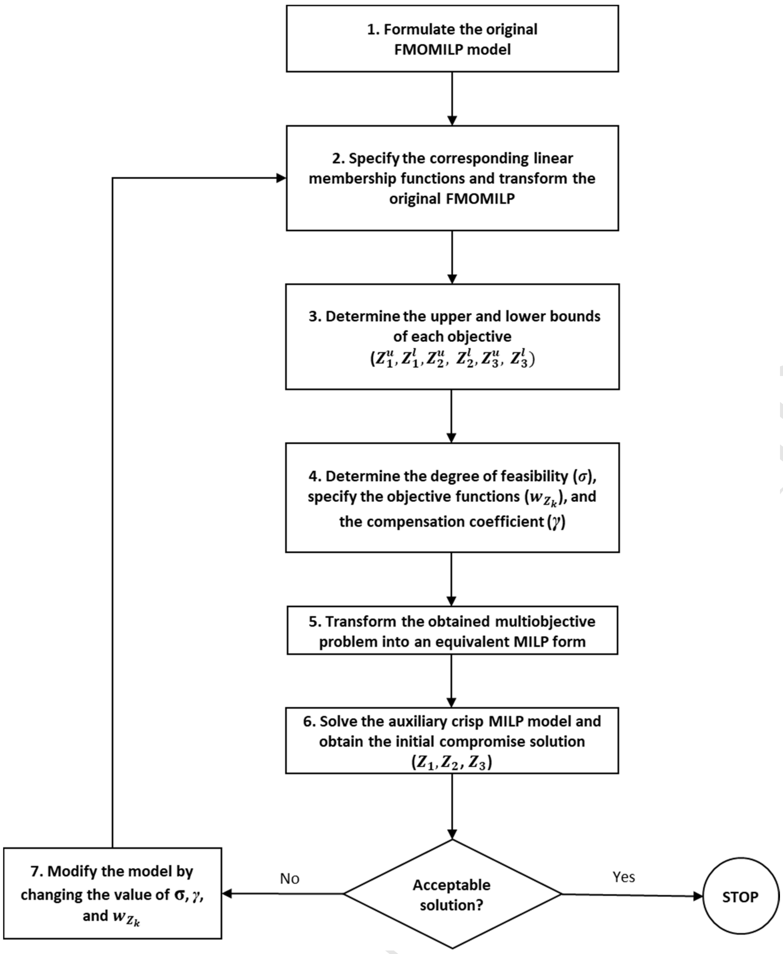


Fig. 4 *The proposed interactive solution procedure*

- Step 1. Formulate the original FMOMILP model for the WWTP problem according to Eqs. (1)–(39).
- Step 2. Specify the corresponding linear membership functions for all the fuzzy parameters and transform the original FMOMILP into a crisp model using (41) and (43).
- Step 3. Determine the upper and lower bounds of each objective function and specify their corresponding linear membership function according to (61).
- Step 4. Determine the feasibility degree, σ, for Constraints (47) to (60) and specify the corresponding relative importance of the objective functions, w_{Z_k}, and the compensation coefficient, γ, in (63).
- Step 5. Transform the obtained multiobjective problem into an equivalent MILP form by using the FGP-based methodology presented above.
- Step 6. Solve the proposed auxiliary crisp single objective model by the MIP solver and obtain the initial compromise solution for the WWTP problem.
- Step 7. If the DM is satisfied with this current efficient compromise solution, stop. Otherwise, go back to Step 2 and provide another efficient solution by changing the value of the controllable parameters (σ, γ, and w_{Z_k}).

Parameters σ, γ, and w_{Z_k} are customisable by the DM depending on his/her preferences. By adjusting the feasibility degree (σ), the DM can determine the degree that the constraints with fuzzy parameters are fulfilled. However, according to Jiménez (1996) and Jiménez et al. (2007), these authors approached the highest level of fulfilment of constraints, and the lowest degree of satisfaction related to the objective function was obtained. Therefore, the DM has to balance the value of the feasibility degree (σ) to obtain better results for the objective functions. Parameters w_{Z_k} are also adjustable and can be used by the DM to determine the relative importance of each objective function according to his/her priorities, and to hence address the solution process to obtain values for the most important objective functions. Moreover, the compensation coefficient (γ) can be used to emphasise these relative weights if lower values are selected or to obtaining a more symmetric solution if higher values are set.

5 Results

5.1 Case study

The WWTP case study is located in a township in the province of Alicante (Spain) (Fig. 5a). This WWTP is small and treats the water generated by 2,500 inhabitants as well as the water generated by the industrial companies that are located in this village. Figure 5b shows that the WWTP only has secondary and tertiary treatment and contains four regeneration units (*i.e.*, sand filter, mesh filter, microfilter, and ultrafilter). The possible connections among them are observed in Figure 5, with 27 different possible combinations. The flow lines from 1 to 12 represent the flow between processes and/or regeneration units. The flow lines from 13 to 20 show the recirculation lines and are used to reduce the concentration in processes. Finally from line 21 to 27, the discharge flow is established from processes or regeneration units to the sludge line.

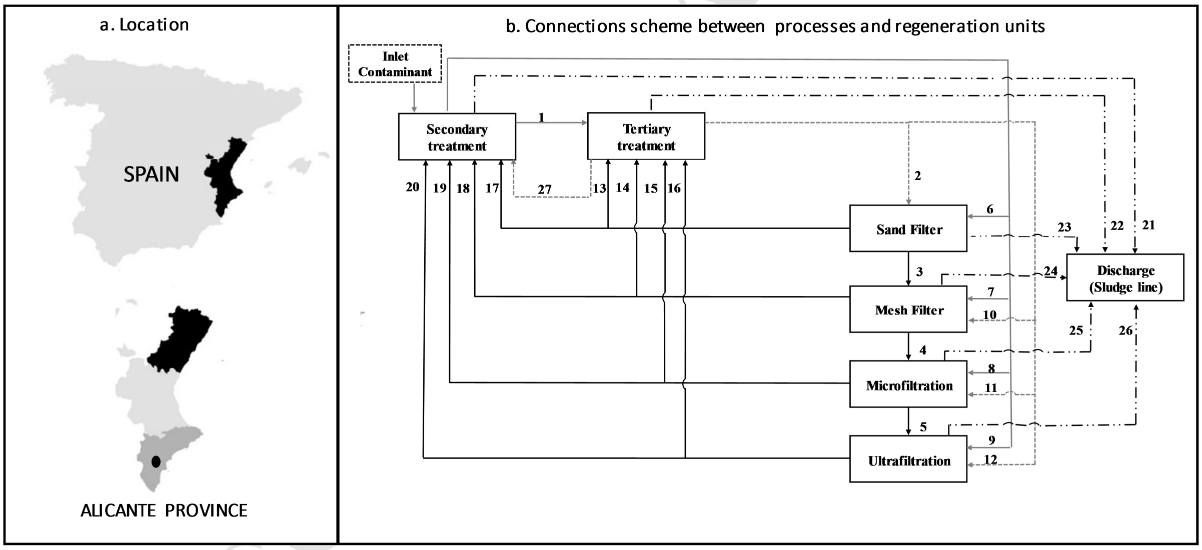


Fig. 5 Location of the WWTP (a). Connections scheme between processes and regeneration units (b)

According to the analysed case study, the inlet and outlet limits of the different processes are defined below by considering in each process only the concentration of suspension solids, while other contaminants (*e.g.*, nitrogen, phosphorus) are not contemplated in this case as a result of the model being programming using one contaminant. However, the mathematical programming can consider other different contaminant to suspension solid.

1. Secondary treatment: this does not have any restrains in the inlet contaminant load because the facility is designed to process wastewater. If the suspension solid concentration is considered, the outlet flow must be a smaller concentration than 35 mg/l. This value is established by current legislation.
2. Tertiary treatment: this process receives flows from the secondary one. Inlet contaminant loads are variable and depend on secondary treatment performance, with a maximum value of 5 mg/l. If

the outlet values are above 5 mg/l, the tertiary process operating will be wrong. The reasons for this can differ, and can be related to how the treatment is managed (e.g., incorrect dose of the reagents, excessive velocity in the lamellar clarification).

3. Regeneration units. The established limits in each regeneration unit are:
    - Sand Filter: maximum inlet limit: 5 mg/l; maximum outlet limit: 2 mg/l
    - Rotating filter: maximum inlet limit: 2 mg/l; maximum outlet limit: 1 mg/l
    - Microfiltration: maximum inlet limit: 1 mg/l; maximum outlet limit: 0.5 mg/l
    - Ultrafiltration: maximum inlet limit: 0.5 mg/l; maximum outlet limit: 0 mg/l

The costs considered between connections are defined in Table 3. These costs consider the energy cost (€/(t/h)) to transfer the different flows between processes. The cost associated with line 27 is set with an infinite value (computationally expressed with a very big number compared to other costs) to avoid the circulation from the tertiary to the secondary treatment. Although the regeneration units (i.e., microfiltration and ultrafiltration) are not common in treatment plants, there are cases in which they are necessary to obtain regenerated water that can be used to water green vegetables. However, if the use of these processes is not necessary, they can be removed from the mathematical proposal.

Table 3. Considered energy cost per connection

Line	Energy Cost (€/(t/day))	Line	Energy Cost (€/(t/day))	Line	Energy Cost (€/(t/day))	Line	Energy Cost (€/(t/h))
1	0.080	8	0.100	15	0.050	22	0.000
2	0.050	9	0.130	16	0.060	23	0.000
3	0.020	10	0.030	17	0.030	24	0.000
4	0.050	11	0.070	18	0.040	25	0.000
5	0.010	12	0.080	19	0.060	26	0.000
6	0.070	13	0.010	20	0.060	27	∞
7	0.050	14	0.020	21	0.000	--	--

5.2. Fuzzy goal programming results

In this section, the FGP decision model results obtained for wastewater plant management and the methodology of the proposed solution are evaluated. Three different scenarios were considered depending on the uncertainty associated with the different input parameters. The first scenario only considers uncertainty in relation to the contaminant load. In contrast, the second scenario incorporates the fuzziness inherent to the inlet and outlet concentrations, but by considering the deterministic contaminant load. Finally, the third scenario considers all the previous fuzzy parameters. Tables 4, 5 and 6 provide the results obtained for each objective function (Z_1, Z_2, Z_3), their corresponding values of membership functions or degree of fulfilment according to the DM's preferences (μ_{Z_1}, μ_{Z_2}, μ_{Z_3}), as well as the global degree of satisfaction $\lambda(x)$ for each scenario. Moreover, Tables 4, 5 and 6 also present input data values, such as the upper and lower limits of each objective function ($[Z_1^u, Z_1^l]$, $[Z_2^l, Z_2^l]$ and $[Z_3^u, Z_3^l]$) and the FGP approach parameters, such as the weights considered for the objective functions and coefficient γ, according to the DM's preferences.

Table 4. Comparison of the results when the contaminant load is fuzzy

	σ=0	**σ=0.1**	**σ=0.2**	**σ=0.3**	**σ=0.4**	**σ=0.5**	**σ=0.6**	**σ=0.7**	**σ=0.8**	**σ=0.9**
Z_1 (€/day)	46.00	47.00	47.00	46.00	46.00	46.00	46.00	46.00	46.00	46.00
Z_2 (t/day)	506.00	526.70	547.40	568.10	588.80	609.50	630.20	650.90	671.60	692.30
Z_3 (t/day)	4000.00	4000.00	4000.00	4001.40	4147.20	4293.00	4438.80	4584.60	4730.40	4876.20
λ_0	0.74000	0.70550	0.67100	0.63650	0.60200	0.56750	0.53300	0.49850	0.46400	0.42950
μ_{Z_1}	0.97347	0.97245	0.97245	0.97347	0.97347	0.97347	0.97347	0.97347	0.97347	0.97347
μ_{Z_2}	0.74000	0.70550	0.67100	0.63650	0.60200	0.56750	0.53300	0.49850	0.46400	0.42950
μ_{Z_3}	1.00000	1.00000	1.00000	0.99977	0.97547	0.95117	0.92687	0.90257	0.87827	0.85396
$\lambda(x)$	0.80781	0.782535	0.757350	0.732215	0.702656	0.673097	0.643538	0.613979	0.584420	0.558760
$[Z_1^u, Z_1^l]$	$Z_1^u = 1000, Z_1^l = 20$									
$[Z_2^l, Z_2^l]$	$Z_2^u = 950, Z_2^l = 350$									
$[Z_3^u, Z_3^l]$	$Z_3^u = 10000, Z_3^l = 4000$									
FGP parameters	w_{Z_1}=0.15; w_{Z_2}=0.55; w_{Z_3}=0.3; γ=0.4									
Variable connection costs (€/day)	802.76	822.78	876.34	929.71	963.58	997.46	1025.03	1058.70	1092.37	1126.04

Z_1: total connections costs; Z_2: total freshwater use; Z_3: total regenerated freshwater use
λ_0: minimum satisfaction degree of the objectives;
μ_{Z_1}: satisfaction degree of objective Z_1; μ_{Z_2}: satisfaction degree of objective Z_2; μ_{Z_3}: satisfaction degree of objective Z_3
$\lambda(x)$: objective function of the crisp single−goal equivalent MILP model according to Torabi and Hassini's approach
$[Z_1^u, Z_1^l]$: upper and lower bound of the objective function Z_1; $[Z_2^u, Z_2^l]$: upper and lower bound of the objective function Z_2;$[Z_3^u, Z_3^l]$: upper and lower bound of the objective function Z_3
w_{Z_1}: relative importance of the Z_1 objective function; w_{Z_2}: relative importance of the Z_2 objective function; w_{Z_3}: relative importance of the Z_3 objective function
γ: coefficient of compensation to control the compromise degree among the objectives

Table 5. Comparison of results when the inlet and outlet concentrations are fuzzy

	σ=0	**σ=0.1**	**σ=0.2**	**σ=0.3**	**σ=0.4**	**σ=0.5**	**σ=0.6**	**σ=0.7**	**σ=0.8**	**σ=0.9**
Z_1 (€/day)	46.00	46.00	46.00	46.00	46.00	46.00	46.00	46.00	53.00	56.00
Z_2 (t/day)	350.00	350.00	350.00	350.00	350.00	350.00	350.00	350.00	350.00	350.00
Z_3 (t/day)	4777.68	4787.63	4797.63	4807.65	4817.72	4827.82	4838.39	4854.93	4869.22	4980.23
λ_0	0.87038	0.86872	0.86706	0.86539	0.86371	0.86203	0.86026	0.85751	0.85513	0.83662
μ_{Z_1}	0.97347	0.97347	0.97347	0.97347	0.97347	0.97347	0.97347	0.97347	0.97347	0.97347
μ_{Z_2}	1.00000	1.00000	1.00000	1.00000	1.00000	1.00000	1.00000	1.00000	1.00000	1.00000
μ_{Z_3}	0.87039	0.86873	0.86706	0.86539	0.86371	0.86203	0.86027	0.85751	0.85513	0.83662
$\lambda(x)$	0.922437	0.921474	0.92051	0.919539	0.918566	0.917590	0.916568	0.914969	0.912945	0.901938
$[Z_1^u, Z_1^l]$	$Z_1^u = 1000, Z_1^l = 20$									
$[Z_2^l, Z_2^l]$	$Z_2^u = 950, Z_2^l = 350$									
$[Z_3^u, Z_3^l]$	$Z_3^u = 10000, Z_3^l = 4000$									
FGP parameters	w_{Z_1}=0.15; w_{Z_2}=0.55; w_{Z_3}=0.3; γ=0.4									
Variable connection costs (€/day)	1072.58	1072.68	1072.78	1072.88	1077.37	1103.28	1132.13	1089.32	1112.09	1117.81

Z_1: total connections costs; Z_2: total freshwater use; Z_3: total regenerated freshwater use
λ_0: minimum satisfaction degree of the objectives;
μ_{Z_1}: satisfaction degree of objective Z_1; μ_{Z_2}: satisfaction degree of objective Z_2; μ_{Z_3}: satisfaction degree of objective Z_3
$\lambda(x)$: objective function of the crisp single−goal equivalent MILP model according to Torabi and Hassini's approach
$[Z_1^u, Z_1^l]$: upper and lower bound of the objective function Z_1; $[Z_2^u, Z_2^l]$: upper and lower bound of the objective function Z_2;$[Z_3^u, Z_3^l]$: upper and lower bound of the objective function Z_3
w_{Z_1}: relative importance of the Z_1 objective function; w_{Z_2}: relative importance of the Z_2 objective function;w_{Z_3}: relative importance of the Z_3 objective function
γ: coefficient of compensation to control the compromise degree among the objectives

Regarding the first scenario shown in Table 4, the best results for the global satisfaction value (λ(x)) were obtained for the lower values of σ. Moreover, the best objective function values for Z_2 and Z_3 were also obtained for the lower values of the feasibility degree, which became worse with the increment of σ. However, objective function Z_1 remained constant (46€/day) for all the values of the feasibility degree, except for 0.1 and 0.2, in which a cost of 47€/day was obtained in both cases. In contrast, these constant connection costs were given from σ=0 to σ=0.7 for the second scenario, while they were higher for the other values of the feasibility degree. When the contaminant load, inlet and outlet concentrations were considered fuzzy, the dispersion of values for the objective function was greater. The results were better for the small values of the feasibility degree, but were worse for the higher values of σ.

Freshwater use increased from 506 t/day (σ=0) to 692.30 t/day (σ=0.9) with the feasibility degree in the first scenario. For the second and the third scenarios, the values obtained for the second objective function (Z_2) were constant in relation to the feasibility degree. The maximum degree of satisfaction was obtained for all the σ values according to the DM's preferences. Regenerated freshwater use (Z_3) presented the best values for low feasibility degrees, especially in the first and the third scenarios. Z_3 became worse with the increase oin the σ values. Hence the different DM's degrees of satisfaction for each σ were always lower than 87% in the second scenario, while the regenerated freshwater involved a degree of satisfaction above 90% in the other scenarios, except for the two higher feasibility degree values.

Tables 4, 5 and 6 show the satisfaction values. The best results for the global satisfaction value ($\lambda(x)$) were obtained for the lower values of σ in all the scenarios. The variation inthe global degree of satisfaction was higher in the first scenario, in which only the contaminant load was considered fuzzy. Moreover, the achievement of the global degree of satisfaction was higher than 90% for the whole range of feasibility degrees for the second and third scenarios. For the first and the deterministic scenarios (that did not consider any uncertain parameter), the global degree of satisfaction became significantly worse (Fig. 6). According to Díaz-Madroñero et al. (2014a), regarding the risk level, the DM can choose between risky solutions with σ ≤ 0.5, average or neutral solutions with σ = 0.5 and conservative solutions, which are not willing to admit high risks for σ ≥ 0.5.

Table 6. Comparison of the results when contaminant load, inlet and outlet concentrations are fuzzy

	σ=0	**σ=0.1**	**σ=0.2**	**σ=0.3**	**σ=0.4**	**σ=0.5**	**σ=0.6**	**σ=0.7**	**σ=0.8**	**σ=0.9**
Z_1 (€/day)	33.00	40.00	42.00	43.00	45.00	46.00	53.00	46.00	53.00	63.00
Z_2 (t/day)	350.00	350.00	350.00	350.00	350.00	350.00	350.00	350.00	350.00	350.00
Z_3 (t/day)	4034.97	4000.00	4000.00	4000.00	4000.00	4099.01	4285.91	4480.88	4675.33	4972.64
λ_0	0.98674	0.97959	0.97755	0.97653	0.97449	0.97347	0.95235	0.91985	0.88744	0.83789
μ_{Z_1}	0.98674	0.97959	0.97755	0.97653	0.97449	0.97347	0.96633	0.97347	0.96633	0.95612
μ_{Z_2}	1.00000	1.00000	1.00000	1.00000	1.00000	1.00000	1.00000	1.00000	1.00000	1.00000
μ_{Z_3}	0.99417	1.00000	1.00000	1.00000	1.00000	0.98350	0.95235	0.91985	0.88745	0.83789
$\lambda(x)$	0.99245	0.990000	0.989000	0.988500	0.987500	0.984030	0.969332	0.951127	0.931687	0.902030
$[Z_1^u, Z_1^l]$	$Z_1^u = 1000, Z_1^l = 20$									
$[Z_2^l, Z_2^l]$	$Z_2^u = 950, Z_2^l = 350$									
$[Z_3^u, Z_3^l]$	$Z_3^u = 10000, Z_3^l = 4000$									
FGP parameters	w_{Z_1}=0.15; w_{Z_2}=0.55; w_{Z_3}=0.3; γ=0.4									
Variable connection costs (€/day)	465.28	741.79	768.64	774.00	870.41	981.59	1009.62	1039.64	1068.06	1115.59

Z_1: total connections costs; Z_2: total freshwater use; Z_3: total regenerated freshwater use
λ_0: minimum satisfaction degree of the objectives;
μ_{Z_1}: satisfaction degree of objective Z_1; μ_{Z_2}: satisfaction degree of objective Z_2; μ_{Z_3}: satisfaction degree of objective Z_3
$\lambda(x)$: objective function of the crisp single−goal equivalent MILP model according to Torabi and Hassini's approach
$[Z_1^u, Z_1^l]$: upper and lower bound of the objective function Z_1; $[Z_2^u, Z_2^l]$: upper and lower bound of the objective function Z_2;$[Z_3^u, Z_3^l]$: upper and lower bound of the objective function Z_3
w_{Z_1}: relative importance of the Z_1 objective function; w_{Z_2}: relative importance of the Z_2 objective function;w_{Z_3}: relative importance of the Z_3 objective function
γ: coefficient of compensation to control the compromise degree among the objectives

Figure 6 shows variation in the global degree of satisfaction according to the feasibility degree for the different fuzzy parameters considered (only load, inlet and outlet concentration, and all the parameters). These values can be compared with the deterministic results, which are also shown in the figure.

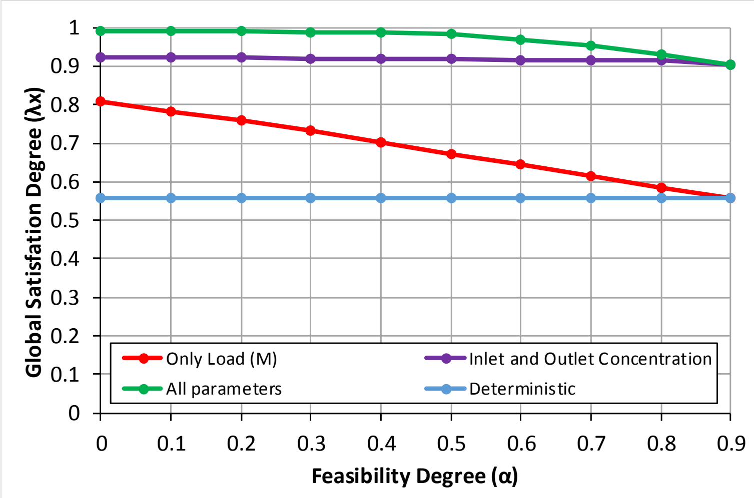


Fig. 6 Variation in global satisfaction according to feasibility degree

The previous values contain the recirculation values of water for each assumption. This recirculation contributed to modify the inlet load in the different processes and regenerations units in order to search for the most feasible solution in the water treatment process. If recirculation was not considered, the economic cost to perform the complete treatment was 1,887€/day (when the contaminant load was 30,000 kg/day with an average volume of 5,500 m^3/day), including the four regeneration units (Table 3). In contrast, when the best proposed solution was considered with fuzzy goal programming, the economic cost was 953.59€/day for a neutral DM. The economic reduction was 49.47% compared to the complete treatment without recirculation, and was 28.44% when the neutral solution was compared to the deterministic solution. The cost is related directly to the circulating flows between processes and regeneration units because each volume unit needs energy to move inside the process. As an example, Table 7 shows the values obtained for the proposed solution (considering a feasibility degree of 0.5). In this table, the contaminant load and recirculated water are quantified per line.

Table 7. Comparison of the results when contaminant load, inlet and outlet concentrations are fuzzy and σ=0.5

Line	Contaminant Load (kg/day)	Recirculated Water (t/day)	Line	Contaminant Load (kg/day)	Recirculated Water (t/day)
1	28099.41	1794.16	15	0.00	0.00
2	20495.06	4099.01	16	0.00	2304.85
3	8198.02	4099.01	17	0.00	0.00
4	4099.01	4099.01	18	0.00	0.00
5	2049.50	4099.01	19	0.00	0.00
6	0.00	0.00	20	0.00	1794.16
7	0.00	0.00	21	3550.00	8.75
8	0.00	0.00	22	2454.94	341.25
9	0.00	0.00	23	12297.03	0.00
10	0.00	0.00	24	4099.01	0.00
11	0.00	0.00	25	2049.50	0.00
12	0.00	0.00	26	2049.50	0.00
13	0.00	0.00	27	1599.40	0.00
14	0.00	0.00	--	--	--

Optimisation of the wastewater process when considering the recirculation of regenerated water is interesting for both economic indicators and other sustainability indicators which improve in parallel. The necessary volume of regenerated water is obtained in the plant. Therefore, if wastewater managers wish to work by dilution, regenerated water can be used whose cost is lower than freshwater (i.e., drinking water). This reduction in freshwater, which lowers to zero in the case study, decreases the consumption of natural resources and, therefore, also the energy used in the catchment and distribution. In this case study, when the daily regenerated volume was 4,099 m^3, the used energy reduced by 803 GWh/year when considering the non-recirculation of regenerated water. This reduction is the equivalent to 586.2 tCO_2/year, according to (Spadaro et al., 2000), who defined an average reduction of 730 gCO_2/kWh. This reduction in the used volume of water, as well as CO_2 emission, contribute to improve the sustainability of the WWTP when WWTP size enables the plant to be treated by dilution to be developed.

The proposed strategy presents both advantages and limitations. On the one hand, dilution can be considered a good solution in WWTPs with small or medium treatment capacities to reduce the energy use needed when biological treatments are used. Moreover, the used modelling approach allowed us to address two of the main problems faced by a DM, such as multiple conflicting objectives and fuzziness existing in the input data due to the uncertainty that is inherent in wastewater treatment processes. This solution method can also generate unbalanced and balanced solutions according to the DM's preferences by adjusting customisable parameters (σ, γ, and w_{Z_k}). Finally, the use of a linear approach to model all the objectives and constraints enabled the determination of optimal solutions in a reasonable CPU time using a desktop PC. On the other hand, the main limitations of this research include the consideration of one contaminant and only part of the total purification process in WWTPs. Some possible future research lines could contemplate multiple contaminants in an extended treatment process, although the complexity of the model could increase and, therefore, so could the CPU time needed to obtain good solutions. Thus, the development of efficient resolution algorithms based on metaheuristics or matheuristics could be another research line.

6 Conclusions

This research presents a mathematical tool that adapts one mathematical model to be used in water treatment processes by introducing regenerated water between the different treatment processes. This tool optimises the use of regenerated water according to used freshwater, the cost on each line, as well as the cost of the different regeneration processes, by considering both the inlet and outlet concentrations in each process phase. This tool enables to manage small- and medium-sized WWTPs (maximum flow of 6,000-7,000 m^3/day) by dilution. Therefore, the consideration of the dilution of the contaminant load by using regenerated water at the WWTP can be a feasible solution with this kind of treatment plant (*i.e.*, low population with a high contaminant load given industrial activity), especially if the present energy cost is considered (currently, the average value of energy cost is 0.08 €/kWh in the present case study). However, the feasibility of this operating system will depend on the volume needed in the WWTP to carry out the dilution of the contaminant load, which is not considered herein.

Hence the combination of current purification techniques (*e.g.*, microfiltration, ultrafiltration) with classical solutions (*e.g.*, dilution through regenerated water at the WWTP) for some given cases improves the treatment plant's water management by reducing energy use and, therefore, by improving the energy footprint of water in the integrated water cycle (catchment-distribution-purification). To quantify this reduction, the mathematical tool was applied to a real case study, which is located in a township in the province of Alicante (Spain). When the model was applied, the reduction in energy use was 803,000 kWh/year and the theoretical reduction in greenhouse emissions could be 586.2 tCO_2/year.

The programmed model allows water managers to consider distributing recirculation flows in each process and regeneration unit according to the average energy cost between processes and inlet contaminant loads. Therefore, this mathematical tool can be used when regenerated water is employed for different uses (e.g., irrigation, washing down urban areas) since water managers can decide the treated volume in each regeneration unit according to the use, energy cost or the need for use during the purification process at the WWTP.

In order to analyse the significance of the different variables inside the water treatment process, a fuzzy goal programming was applied to a case study. The fuzzy analysis considered variation in the inlet load, the inlet and outlet concentrations in each phase and the variation in all the parameters. By applying this technique, the reduction in the economic cost can vary between 53.47% and 39.41% according to the risk level assumed by the DM. Finally, the development of the similar model to be applied to a WWTP can contribute to improve the energy footprint in the purification phase and can also increase the sustainability indicators of the water cycle.

References

Bagajewicz, M., 2000. A review of recent design procedures for water networks in refineries and process plants. Comput. Chem. Eng. doi:10.1016/S0098-1354(00)00579-2

Bagajewicz, M., Rodera, H., Savelski, M., 2002. Energy efficient water utilization systems in process plants. Comput. Chem. Eng. 26, 59–79. doi:10.1016/S0098-1354(01)00751-7

Bagajewicz, M.J., Savelski, M.J., 2001. On the use of linear models for the design of water utilisation systems in process plants with a single contaminant. Trans. Inst. Chem. Eng. Part A, 600–610. doi:10.1205/02638760152424389

Castellet, L., Molinos-Senante, M., 2016. Efficiency assessment of wastewater treatment plants: A data envelopment analysis approach integrating technical, economic, and environmental issues. J. Environ. Manage. 167, 160–166. doi:10.1016/J.JENVMAN.2015.11.037

Cheremisinoff, N.P., 2002. Handbook of water and wastewater treatment technologies. Butterworth-Heinemann.

de Faria, D.C., Ulson de Souza, A.A., Guelli Ulson de Souza, S.M. de A., 2009. Optimization of water networks in industrial processes. J. Clean. Prod. 17, 857–862. doi:10.1016/j.jclepro.2008.12.012

Díaz-Madroñero, M., Mula, J., Jiménez, M., 2014a. Fuzzy goal programming for material requirements planning under uncertainty and integrity conditions. Int. J. Prod. Res. 52, 6971–6988. doi:10.1080/00207543.2014.920115

Díaz-Madroñero, M., Mula, J., Jiménez, M., Peidro, D., 2017. A rolling horizon approach for material requirement planning under fuzzy lead times. Int. J. Prod. Res. 55, 2197–2211. doi:10.1080/00207543.2016.1223382

Díaz-Madroñero, M., Peidro, D., Mula, J., 2014b. A fuzzy optimization approach for procurement transport operational planning in an automobile supply chain. Appl. Math. Model. 38, 5705–5725. doi:10.1016/j.apm.2014.04.053

Doyle, S.J., Smith, R., 1997. Targeting Water Reuse with Multiple Contaminants. Process Saf. Environ. Prot. 75, 181–189. doi:10.1205/095758297529020

Ebrahimnejad, A., Verdegay, J.L., 2016. A Survey on Models and Methods for Solving Fuzzy Linear Programming Problems. Springer, Cham, pp. 327–368. doi:10.1007/978-3-319-31093-0_15

European Comission, 2016. Eighth Report on the Implementation Status and the Programmes for Implementation (as required by Article 17) of Council Directive 91/271/EEC concerning urban waste water treatment. doi:doi:10.1017/CBO9781107415324.004.

Galán, B., Grossmann, I.E., 1999. Optimization strategies for the design and synthesis of distributed wastewater treatment networks. Comput. Chem. Eng. 23, S161–S164. doi:10.1016/S0098-

1354(99)80040-4

Hegeman, J., Peidro, D., del Mar Alemany, M., Díaz-Madroñero, M., 2014. A Decentralized Production and Distribution Planning Model in an Uncertain Environment. Springer, Berlin, Heidelberg, pp. 317–353. doi:10.1007/978-3-642-53939-8_14

Heilpern, S., 1992. The expected value of a fuzzy number. Fuzzy Sets Syst. 47, 81–86.

Huang, C.-H., Chang, C.-T., Ling, H.-C., Chang, C.-C., 1999. A Mathematical Programming Model for Water Usage and Treatment Network Design. Ind. Eng. Chem. Res. 38, 2666–2679. doi:10.1021/ie990043s

Huang, Y., Wang, X., 1999. Application of fuzzy causal networks to waste water treatment plants. Chem. Eng. Sci. 54, 2731–2738. doi:10.1016/S0009-2509(98)00421-7

Hul, S., Tan, R.R., Auresenia, J., Fuchino, T., Foo, D.C.Y., 2007. Water Network Synthesis Using Mutation-Enhanced Particle Swarm Optimization. Process Saf. Environ. Prot. 85, 507–514. doi:10.1205/PSEP06065

Jeżowski, J., Bochenek, R., Poplewski, G., 2007. On application of stochastic optimization techniques to designing heat exchanger- and water networks. Chem. Eng. Process. Process Intensif. 46, 1160–1174. doi:10.1016/J.CEP.2007.02.024

Jiménez, M., 1996. Ranking fuzzy numbers through the comparison of its expected intervals. Int. J. Uncertain. Fuzziness Knowl. Based Syst. 4, 379–388.

Jiménez, M., Arenas, M., Bilbao, A., 2007. Linear programming with fuzzy parameters: an interactive method resolution. Eur. J. Oper. Res. 177, 1599–1609.

Khor, C.S., Chachuat, B., Shah, N., 2012. A superstructure optimization approach for water network synthesis with membrane separation-based regenerators. Comput. Chem. Eng. 42, 48–63. doi:10.1016/J.COMPCHEMENG.2012.02.020

Koppol, A.P.R., Bagajewicz, M.J., Dericks, B.J., Savelski, M.J., 2004. On zero water discharge solutions in the process industry. Adv. Environ. Res. 8, 151–171. doi:10.1016/S1093-0191(02)00130-2

Lai, Y.J., Hwang, C.L., 1993. Possibilistic linear programming for managing interest rate risk. Fuzzy Sets Syst. 54, 135–146. doi:10.1016/0165-0114(93)90271-I

Liang, T.F., Cheng, H.W., 2009. Application of fuzzy sets to manufacturing/distribution planning decisions with multi-product and multi-time period in supply chains. Expert Syst. Appl. 36, 3367–3377. doi:10.1016/j.eswa.2008.01.002

Longo, S., d'Antoni, B.M., Bongards, M., Chaparro, A., Cronrath, A., Fatone, F., Lema, J.M., Mauricio-Iglesias, M., Soares, A., Hospido, A., 2016. Monitoring and diagnosis of energy consumption in wastewater treatment plants. A state of the art and proposals for improvement. Appl. Energy. doi:10.1016/j.apenergy.2016.07.043

Majozi, T., 2005. An effective technique for wastewater minimisation in batch processes. J. Clean. Prod. 13, 1374–1380. doi:10.1016/J.JCLEPRO.2005.04.016

Morera, S., Comas, J., Poch, M., Corominas, L., 2015. Connection of neighboring wastewater treatment plants: Economic and environmental assessment. J. Clean. Prod. 90, 34–42. doi:10.1016/j.jclepro.2014.11.047

Mula, J., Peidro, D., Poler, R., 2014. Optimization Models for Supply Chain Production Planning Under Fuzziness. Springer, Berlin, Heidelberg, pp. 397–422. doi:10.1007/978-3-642-53939-8_17

Naderi, M.J., Pishvaee, M.S., Torabi, S.A., 2016. Applications of Fuzzy Mathematical Programming Approaches in Supply Chain Planning Problems. Springer, Cham, pp. 369–402.

doi:10.1007/978-3-319-31093-0_16

Ng, D.K.S., Foo, D.C.Y., Tan, R.R., Pau, C.H., Tan, Y.L., 2009. Automated targeting for conventional and bilateral property-based resource conservation network. Chem. Eng. J. 149, 87–101. doi:10.1016/J.CEJ.2008.10.003

Ouyang, X., Guo, F., Shan, D., Yu, H., Wang, J., 2015. Development of the integrated fuzzy analytical hierarchy process with multidimensional scaling in selection of natural wastewater treatment alternatives. doi:10.1016/j.ecoleng.2014.11.006

Padilla-Rivera, A., Morgan-Sagastume, J.M., Noyola, A., Güereca, L.P., 2016. Addressing social aspects associated with wastewater treatment facilities. Environ. Impact Assess. Rev. 57, 101–113. doi:10.1016/j.eiar.2015.11.007

Panepinto, D., Fiore, S., Genon, G., Acri, M., 2016. Thermal valorization of sewer sludge: Perspectives for large wastewater treatment plants. J. Clean. Prod. 137, 1323–1329. doi:10.1016/j.jclepro.2016.08.014

Peidro, D., Mula, J., Jiménez, M., del Mar Botella, M., Botella, M.M., Jimenez, M., del Mar Botella, M., 2010. A fuzzy linear programming based approach for tactical supply chain planning in an uncertainty environment. Eur. J. Oper. Res. 205, 65–80. doi:10.1016/j.ejor.2009.11.031

Poch, M., Comas, J., Rodríguez-Roda, I., Sànchez-Marrè, M., Cortés, U., 2004. Designing and building real environmental decision support systems. Environ. Model. Softw. 19, 857–873. doi:10.1016/J.ENVSOFT.2003.03.007

Ramos, M.A., Boix, M., Montastruc, L., Domenech, S., 2014. Multiobjective Optimization Using Goal Programming for Industrial Water Network Design. Ind. Eng. Chem. Res. 53, 17722–17735. doi:10.1021/ie5025408

Rivas, A., Irizar, I., Ayesa, E., 2008. Model-based optimisation of Wastewater Treatment Plants design. Environ. Model. Softw. 23, 435–450. doi:10.1016/j.envsoft.2007.06.009

Romero, L., Pérez-Sánchez, M., Amparo López-Jiménez, P., 2017. Improvement of sustainability indicators when traditional water management changes: a case study in Alicante (Spain). AIMS Environ. Sci. 4, 502–522. doi:10.3934/environsci.2017.3.502

Savelski, M., Bagajewicz, M., 2003. On the necessary conditions of optimality of water utilization systems in process plants with multiple contaminants. Chem. Eng. Sci. 58, 5349–5362. doi:10.1016/J.CES.2003.09.004

Savelski, M.J., Bagajewicz, M.J., 2000. On the optimality conditions of water utilization systems in process plants with single contaminants. Chem. Eng. Sci. 55, 5035–5048. doi:10.1016/S0009-2509(00)00127-5

Spadaro, J. V., Langlois, L., Hamilton, B., 2000. Greenhouse Gas Emissions of Electricity Generation Chains: Assessing the Difference, in: International Atomic Energy Agency (IAEA). Vienna.

Sujak, S., Handani, Z.B., Wan Alwi, S.R., Manan, Z.A., Hashim, H., Lim Jeng Shiun, 2017. A holistic approach for design of Cost-Optimal Water Networks. J. Clean. Prod. 146, 194–207. doi:10.1016/j.jclepro.2016.06.182

Takama, N., Kuriyama, T., Shiroko, K., Umeda, T., 1980. Optimal planning of water allocation in industry. J. Chem. Eng. Japan 13, 478–483. doi:10.1252/jcej.13.478

Tan, R.R., 2011. Fuzzy Optimization Model for Source-Sink Water Network Synthesis with Parametric Uncertainties. Ind. Eng. Chem. Res. 50, 3686–3694. doi:10.1021/ie101025p

Tan, R.R., Cruz, D.E., 2004. Synthesis of robust water reuse networks for single-component retrofit problems using symmetric fuzzy linear programming. Comput. Chem. Eng. 28, 2547–2551. doi:10.1016/J.COMPCHEMENG.2004.06.016

Tan, R.R., Foo, D.C.Y., Manan, Z.A., 2007. Assessing the sensitivity of water networks to noisy mass loads using Monte Carlo simulation. Comput. Chem. Eng. 31, 1355–1363. doi:10.1016/J.COMPCHEMENG.2006.11.005

Tiwari, R.N., Dharmar, S., Rao, J.R., 1987. Fuzzy goal programming - An additive model. Fuzzy Sets Syst. 24, 27–34. doi:10.1016/0165-0114(87)90111-4

Torabi, S.A., Hassini, E., 2008. An interactive possibilistic programming approach for multiple objective supply chain master planning. Fuzzy Sets Syst. 159, 193–214. doi:10.1016/j.fss.2007.08.010

Torregrossa, D., Hernández-Sancho, F., Hansen, J., Cornelissen, A., Popov, T., Schutz, G., 2018. Energy saving in wastewater treatment plants: A plant-generic cooperative decision support system. J. Clean. Prod. 167, 601–609. doi:10.1016/j.jclepro.2017.08.181

Torregrossa, D., Schutz, G., Cornelissen, A., Hernández-Sancho, F., Hansen, J., 2016. Energy saving in WWTP: Daily benchmarking under uncertainty and data availability limitations. Environ. Res. 148, 330–337. doi:10.1016/J.ENVRES.2016.04.010

Verdegay, J.L., 2015. Progress on Fuzzy Mathematical Programming: A personal perspective. Fuzzy Sets Syst. 281, 219–226. doi:10.1016/j.fss.2015.08.023

Yaghoobi, M.A., Jones, D.F., Tamiz, M., 2008. Weighted additive models for solving fuzzy goal programming problems. Asia-Pacific J. Oper. Res. 25, 715–733. doi:10.1142/S0217595908001973

Zamora, J.M., Grossmann, I.E., 1998. Continuous global optimization of structured process systems models. Comput. Chem. Eng. 22, 1749–1770. doi:10.1016/S0098-1354(98)00244-0