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Assessing the efficiency of wastewater treatment plants in an uncertain context: a DEA with tolerances approach

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ABSTRACT

As the number of wastewater treatment plants (WWTPs) has increased, the economics associated with their management have become more relevant. The efficiency assessment is therefore a useful tool for cost reduction. For this purpose, Data Envelopment Analysis (DEA) is a highly suitable technique, since it is a holistic approach that aggregates performance indicators into a single index. However, one of the most common criticisms of DEA models is that information on uncertainty estimates is not provided. To overcome this limitation, we assess efficiency by using a DEA model with statistical tolerances for both inputs and outputs. This model is applied to a sample of Spanish WWTPs. The results show that WWTP efficiency scores change when data modifications are incorporated. In addition, we verify that not all WWTPs have the same sensitivity with respect to changes in the inputs and outputs. Moreover, WWTPs are ranked in terms of efficiency, allowing the identification of facilities with the best practices, which will serve as a reference for minimizing operating costs at other plants. This empirical application illustrates that the combination of the DEA model with uncertainty assessments provides more robust results, leading to more reliable conclusions than traditional DEA. From a policy perspective, the incorporation of uncertainty in the DEA model with tolerances allows future performance of the WWTPs to be predicted and ranked, demonstrating the usefulness of this approach.

1. Introduction

Environmental quality and sustainable development have been increasingly recognized as real social needs, which has led to the development of regulation instruments and legislation for environmental protection by industrialized countries. Thus, Directive 91/271/EEC concerns the collection, treatment, and discharge of urban wastewater. The objective of the Directive is to protect the environment from the adverse effects of wastewater discharge. This Directive has resulted in a dramatic increase in the number of wastewater treatment plants (WWTPs) in all European Union Member States over the last two decades.

Despite the environmental benefits associated with the wastewater treatment process (Hernández-Sancho et al., 2010), it involves high costs for all society (Molinos-Senante et al., 2010). For example, in Spain the total cost of sewage services is estimated at 1415.3 million euros per year, or roughly 0.2% of GDP. Likewise, the cost of the recovery rate of this service is estimated to be around 85% (MARM, 2011).

As a consequence, WWTP managers are under ever increasing pressure to tighten control and improve the pollutants removal efficiency, especially when discharged into sensitive areas, while at the same time restricting costs.

Efficiency is directly linked to cost containment and cost reduction (Zhang et al., 2011). The surprising fact is that, while the measure of efficiency is a long-standing issue of study in

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the field of economics, its implementation in the field of wastewater treatment remains very low. A review of the efficiency literature indicates that most existing studies remain limited in scope and methodology, in comparison to other related areas such as water supply (Worthington, 2011). The most widely used approach to assess the economic efficiency of WWTPs is the definition of indicators or ratios, which relates the efficiency of pollutant removal, energy consumption, and other operational variables of WWTP operational costs (Stemplewski et al., 2001; Benedetti et al., 2008; Galletti and Landon, 2009; Zhao et al., 2010). These indicators are only useful in assessing a partial or a specific area of operation. Hence, the use of these ratios to make inferences about the overall operational performance of WWTPs should be treated with caution (Zhong et al., 2011). In fact, the use of these indicators could potentially lead to incorrect policy implications (Alexander, 2009).

The information gap in the literature about this subject is evident, and there is a clear need for the use of advanced techniques for the measurement of efficiency in WWTPs. For example, the holistic approach of the Data Envelopment Analysis (DEA) technique has been applied to multiple fields of research (Gattoufi et al., 2004). DEA is a non-parametric technique that is able to estimate the production function with minimal prior assumptions. An attractive feature of DEA is that it can easily handle multiple outputs/inputs situations, even in the absence of price data. DEA is perfectly suited to our application when a WWTP is viewed as a firm that carries out a productive process, the outputs of which are the pollutants removed from wastewater and the inputs are the operational and maintenance costs of the facility. Moreover, DEA is a powerful tool that may easily aggregate performance indicators into a single performance index (Boscá et al., 2009). Furthermore, to improve the decision making process is not sufficient with identify efficient WWTPs but also they should be ranked in terms of efficiency.

While DEA has many advantages in comparison to other methodologies, it has one particular shortcoming that may lead to ambiguity in the interpretation of its results. The drawback is that estimates from conventional DEA analysis do not provide information on the uncertainty of estimates. As mentioned before, DEA is a nonparametric technique; therefore, it does not allow for any statistical inferences. The role of uncertainty is important because the conclusions derived from the efficiency analysis of the tested units are highly sensitive to data errors and the influence of external factors on the selected variables (Sin et al., 2011). To overcome this problem, regression analysis and bootstrap are the most applied methods. A third alternative to address data uncertainty is by using chance constrained DEA models. This programming was first incorporated to DEA models by Olesen and Petersen (1995). Other authors have analyzed the sensitivity of the results to changes in the variables by using superefficiency techniques (Andersen and Petersen, 1993). It should also be noted that the possibility of applying fuzzy mathematical programming for the treatment of the uncertainty has also been investigated (León et al., 2003).

As an alternative to these processes, a DEA model with statistical tolerance (also called DEA with uncertainty assessment) has been developed by Bonilla et al. (2004). In this model, the definition of certain tolerance levels for the selected inputs and outputs in the problem allows a variation interval to be obtained for each of the efficiency scores. Although bootstrap and DEA with uncertainty assessment obtain similar results, the greater simplicity and execution speed of the tolerance method is advantageous through allowing inputs and/or outputs to be subjected to possible modifications (Bonilla et al., 2004). The DEA with tolerances model allows narrowing uncertainty and making predictions about the efficiency of the units if inputs and outputs change. In relation to this second utility, Hernández-Sancho et al. (2011) show that seasonally operational treatment plants are less efficient than non-seasonally ones, which affects the possibilities of water reuse. Therefore, in cases where regenerated water is reused, the prediction of efficiency changes is very important, particularly when there is variability in the data.

This paper has three related objectives with respect to evaluating the operation of WWTPs in Spain. First, we evaluate the techno-economical efficiency for a sample of WWTPs by applying the DEA technique based on the assumption of variable returns to scale (VRS). Second, we aim to narrow the uncertainty of the results by assessing the stability of the efficiency analysis results by employing the methodology shown in Boscá et al. (2006). According to this methodology, the efficiency and tolerance study completes the deterministic efficiency analysis because the possible variation in the efficiency level is obtained when the selected input and output values vary. Third, we aimed to rank the assessed WWTP units by using the methodological approach suggested by Boscá et al. (2011), which allows ranking units according to their efficiency scores. We consider the utility of identifying the comparative strengths and weaknesses of WWTPs towards the adoption of efficient measures which in turn would reduce the costs of operation.

2. Methodology

2.1. *DEA efficiency assessment*

Traditionally, efficiency has been subject to extensive study and use from an economic perspective. The application of ratios between outputs and inputs has been, and continues to be, a method that is regularly used for measuring the efficiency of different Decision Making Units (DMUs). Nevertheless, actual situations are usually more complicated, and require more sophisticated methods (Boscá et al., 2011).

The DEA methodology developed by Charnes et al. (1978) is a non-parametric method based on linear programming for the estimation of production frontiers. Subsequently, this technique has been used for measuring comparative efficiency in a wide range of applications. In particular, this technique is one of the most powerful methods for analyzing series of production units, with multiple inputs and outputs. In this kind of study, the relative efficiency for each Decision Making Unit (DMU) is calculated by comparing its inputs and outputs in relation to the rest of the units (Bonilla et al., 2002). Basically, DEA evaluates the performance of peer DMUs, allowing the construction of a surface over the data that permits the observed behavior of a unit to be compared against the best observed practices (Lin et al., 2011). Thus, the DMUs that determine the envelope are referred to as efficient units, and those that are excluded are considered as inefficient units. Thus, when a DMU reaches the maximum output given a vector of inputs (output-oriented DEA), or uses a minimum of inputs to produce a given output (input-oriented DEA), it is placed on the production frontier (Charnes et al., 1996). Further details on DEA are provided by Färe et al. (1985), Coelli (1999), and Cooper et al. (2004).

For convenience, we adopt the input minimization assumption, because WWTPs aim to achieve an effluent level that meets discharge criteria at the lowest possible cost. In any case, the orientation of the model is not a relevant issue, since both provide some measure of resource efficiency, just from different perspectives (Chiu et al., 2011).

Based on previous works (Hernández-Sancho and Sala-Garrido, 2009; Hernández-Sancho et al., 2011), the operating and maintenance costs of WWTPs are known to be affected by economies of scale, since these authors demonstrate that the largest plants run more efficiently than smaller plants. Therefore, DEA based on the assumption of variable returns to scale (VRS) is considered to be the most appropriate form of model to apply in this situation.

According to the model DEA-VRS, given $j = 1, 2, \ldots, n$ DMUs or WWTPs, each of which uses a vector of m inputs $x_j = (x_{1j}, x_{2j}, \ldots, x_{mj},)$ to generate a vector of s outputs $y_j = (y_{1j}, y_{2j}, \ldots, y_{sj},)$, where λ is a vector of intensity. The measure of efficiency θ is obtained by solving the following linear programming problem for each DMU j_o:

$$\begin{aligned}
&\operatorname{Min} \theta \\
&\text{s.t.} \\
&\sum_{j=1}^{n} \lambda_j x_{ij} \leq \theta x_{ij_o} \quad 1 \leq i \leq m \\
&\sum_{j=1}^{n} \lambda_j y_{rj} \geq y_{rj_o} \quad 1 \leq r \leq s \\
&\lambda_j \geq 0 \quad 1 \leq j \leq n \\
&\sum_{j=1}^{n} \lambda j = 1
\end{aligned} \tag{1}$$

The measure of efficiency $E_I(y_{j_o}, x_{j_o}) = \theta$ is constrained between 0 and 1. Specifically, it is considered that a DMU (WWTP) is efficient if $\theta = 1$ and slacks are zero, while it is inefficient if $0 \leq \theta < 1$. The difference between the score θ and the value 1 may be considered as the potential reduction in inputs to obtain the same outputs.

2.2. DEA with tolerance model

As mentioned in Section 1, one of the most common criticisms of the DEA model as a deterministic mathematical model, is that it does not take uncertainty into account (Tsolas, 2010). In other words, DEA has no accommodation for noise or random error, as it uses a linear programming approach to estimate the frontier. The inefficiency scores derived from DEA and the envelopment surface are "calculated" rather than statistically "estimated" (Assaf and Matawie, 2010). To overcome this limitation, we applied DEA model with uncertainty assessment developed by Bonilla et al. (2004).

The DEA with statistical tolerance allows a variation[1] level to be defined for each of the inputs (i) and outputs (r) considered in each of the assessed DMUs. These exchange rates are denoted as $\alpha_{ij}, \alpha'_{ij}, \beta_{rj}, \beta'_{rj}$, and are a non-negative scalar expressing the changes from left and right of the values of inputs and outputs respectively. Importantly, the tolerances defined for each of the outputs and inputs may be symmetrical or may not respect to the original value.

Suppose that the values of the inputs and outputs are within the range defined by Eq. (2):

$$x_{ij} \in \left[x_{ij} - \alpha_{ij}, x_{ij} + \alpha'_{ij}\right] \quad y_{rj} \in \left[y_{rj} - \beta_{rj}, y_{rj} + \beta'_{rj}\right] \tag{2}$$

Given the breadth of possible combinations, we focus on analyzing only the extreme values and the original value of each input and output. If we assess the efficiency of the DMU j_o, the inputs and outputs may take the following values, expressed in multiplicative form:

$$\begin{aligned}
&\text{Inputs of the DMU } j_o: \quad x_{ij_o}(1-\alpha_{ij_o}), x_{ij_o}, x_{ij_o}(1+\alpha'_{ij_o}) \\
&\text{Outputs of the DMU } j_o: \quad y_{rj_o}(1-\beta_{rj_o}), y_{rj_o}, y_{rj_o}(1+\beta'_{rj_o}) \\
&\text{Inputs of the DMU } j \neq j_o: \quad x_{ij}(1-\alpha_{ij}), x_{ij}, x_{ij}(1+\alpha'_{ij}) \\
&\text{Outputs of the DMU } j \neq j_o: \quad y_{rj}(1-\beta_{rj}), y_{rj}, y_{rj}(1+\beta'_{rj})
\end{aligned} \tag{3}$$

Therefore, the number of DEA combinations[2] that require resolving when analyzing the DMU j_o is 3^4 (81). There are three situations: (i) favorable, (ii) unfavorable, and (iii) original, with four possible inputs and outputs: (i) inputs for the analyzed DMU, (ii) outputs for the analyzed DMU, (iii) inputs for the remaining DMUs, and (iv) outputs for the remaining DMUs.

By simplifying the notation of (Eq. 3), (Eq. 4) is obtained:

$$\begin{aligned}
&x_{ij_o} - \alpha_{ij_o} := x^m_{ij_o}, \quad x_{ij_o} := x^o_{ij_o}, \quad x_{ij_o} + \alpha'_{ij_o} := x^M_{ij_o} \\
&y_{rj_o} - \beta_{rj_o} := y^m_{rj_o}, \quad y_{rj_o} := y^o_{rj_o}, \quad y_{rj_o} + \beta'{}_{rj_o} := y^M_{rj_o}
\end{aligned} \tag{4}$$

where x^m_{ij} is the minimum value (m) of the input "i" for DMU "j". x^o_{ij} is the original value (o) of the input "i" for DMU "j". x^M_{ij} is the maximum value (M) of the input "i" for DMU "j". y^m_{rj} is the minimum value (m) of the output "r" for DMU "j". y^o_{rj} is the original value (o) of the output "r" for DMU "j". y^M_{rj} is the maximum value (M) of the output "r" for DMU "j".

By substituting in the original DEA model (Eq. (1)), the original values of the inputs and outputs are replaced by the modified values according to the estimated level of tolerance, from which it is possible to define the best and worst possible case scenarios that can appear for each DMU "j_o".

The best case scenario for DMU "j_o": inputs decrease with increasing outputs in this DMU, while the rest of the DMUs register inverse behavior in their variables according to tolerance levels:

$$\begin{aligned}
x_{ij} &= \begin{cases} x^m_{ij} & j = j_o \\ x^M_{ij} & j \neq j_o \end{cases} \\
Y_{rj} &= \begin{cases} y^M_{rj} & j = j_o \\ y^m_{rj} & j \neq j_o \end{cases}
\end{aligned} \tag{5}$$

[1] Methodology for the calculation of a suitable tolerance level for each input and output is described in Appendix 1.

[2] For environmental efficiency processes where there are inputs, outputs and undesirable outputs, the total number of problems to be solved is 3^6 (729).

The worst case scenario for DMU "j_o": inputs increase with decreasing outputs in the DMU under evaluation, while the rest of the DMUs inputs decrease and outputs increase:

$$x'_{ij} = \begin{cases} x^M_{ij} & j = j_o \\ x^m_{ij} & j \neq j_o \end{cases} \qquad y'_{rj} = \begin{cases} y^m_{rj} & j = j_o \\ y^M_{rj} & j \neq j_o \end{cases} \tag{6}$$

By collecting the most favorable and unfavorable case scenarios for each analyzed DMU, the X' and Y' matrices are achieved:

$$X' = [x_{ij}] \in M_{(i,j)} \qquad Y' = [y_{rj}] \in M_{(r,j)} \tag{7}$$

The matrices (7) implemented in the model (1) allow the value of the efficiency index for the "best case scenario" and for the "worst case scenario" to be attained. In other words, the maximum and minimum efficiency score is obtained for each DMU under study, thus uncertainty is narrowed.

2.3. Ranking DMUs

The WWTPs must be ranked to prioritize facilities on which actions would be carry out to improve efficiency. This objective was achieved by using the approach defined by Boscá et al. (2011). Thus, Eqs. (8) and (9) present two efficiency indicators for the j_o-th order unit (R^1_{jo} and R^2_{jo}), allowing the production units (WWTPs) to be ranked according to their relative level of efficiency.

$$R^1_{j_o} = \frac{e_{j_o}}{\tau_{j_o}} \tag{8}$$

$$R^2_{j_o} = \begin{cases} (S_{j_o} - e_{j_o})/(\tau_{j_o} - e_{j_o}) & \text{If } \tau_{j_o} \neq e_{j_o} \\ 0 & \text{If } \tau_{j_o} = e_{j_o} \end{cases} \tag{9}$$

where e_{j_o} is the number of times that DMU j_o is efficient (i.e., the efficiency score equals 1). $S_{j_o} = \sum_{a,b,c,d} E\left(x^a_{ij}, x^b_{ijo}, y^c_{rj}, y^d_{rjo}\right)$, which is the sum of the 81 efficiency scores of DMU j_o. $\tau_{j_o} = 81$, for this problem. If there are undesirable outputs, the value of τ_{j_o} is 729.

The indicator $R^1_{j_o}$ reports on the proportion of times that unit j_o has been efficient. Its value is between [0,1]. A value of 0 indicates that the DMU has been characterized as inefficient in all of the 81 scenarios. If the indicator is equal to unity, this result implies that in all the problems have been solved, and the efficiency score is equal to one. In other words, the higher the value of $R^1_{j_o}$, the greater propensity of the unit to be efficient. The indicator $R^2_{j_o}$ is used when two units have the same value for the first indicator, for which the range of values is also between [0,1].

It follows that DMU_j would be better than DMU_z if:

$$DMU_j > DMU_z \Leftrightarrow R^1_j > R^1_z \tag{10}$$

If $R^1_j = R^1_z$, the second indicator of efficiency ($R^2_{j_o}$) is used. In this case, DMU_j would be better than DMU_z if:

$$DMU_j > DMU_z \Leftrightarrow R^1_j = R^1_z \text{ and } R^2_j > R^2_z \tag{11}$$

3. Sample description

Our data consist of a sample of 45 WWTPs located in the Valencia Region, which is on the Mediterranean coast of Spain. All WWTPs carry out conventional secondary wastewater treatment with nitrogen removal. The wastewater that is treated at the facilities is residential in origin, with industrial discharge being rare. The ultimate reason for using this sample is to ensure that all WWTPs are essentially comparable, as is required when using a DEA-based distance function (Odeck, 2009). Statistical information was supplied for the year 2009 by the Regional Wastewater Treatment Authority (Entitat of Sanejament d'Aigues-EPSAR).

Accordingly, the objective of WWTPs is considered to be to perform a production process that obtains an effluent content that meets the quality criteria required by legislation at the lowest possible cost. WWTPs are considered as multi-output firms that remove three main pollutants from wastewater. Thus, as a consequence of the treatment process, three outputs are generated: (i) suspended solids (SS) (y_1), (ii) organic matter measured as chemical oxygen demand (COD) (y_2), and (iii) nitrogen (N) (y_3). The necessary inputs to carry out the process are operation and maintenance costs (x_1). It is worth highlighting that outputs are measured in physical units (grams of pollutant removal per cubic meter of treated water), while inputs are expressed in monetary units (euros per cubic meter of treated water).

A brief description of these variables is provided in Table 1.

In our research, usually outputs data accuracy is not a problem. This is because in most cases the compilation of data is characterized by the precision of analytical methods for the determination of contaminants of both the influent and the effluent, which has improved considerably in recent years. In addition, WWTP operators are legally obliged to determine the main parameters that define the quality of the treated water on a daily basis, and the Regional Administration conducts periodic checks to verify that the data provided by the companies are correct. Nevertheless, contaminated samples are occasionally present, while analytical mistakes or point pollution discharges may produce data that are not representative. The situation is more complex with respect to inputs, because it is the operators that provide the data to the Administration. Despite the fact that costs are strictly controlled by the operating companies, is very difficult to obtain such information, since neither the Administration nor companies have the legal obligation to make this information public. Furthermore, the same company is responsible for the

Table 1 – Main descriptive statistics for variables used in the study.

	VOLUME (m^3/year)	OUPUTS (g/m^3)			INPUTS (€/m^3)
		SS	COD	N	Cost
Mean	408,014	263	588	43	0.5203
Std. dev.	286,381	121	344	20	0.2112

Source: Entitat of Sanejament d'Aigues-EPSAR (Regional Government).

management of various WWTPs in most cases. Hence, accounting is conducted jointly for all plants, which makes the acquisition of information at the individual WWTP level difficult.

4. Results and discussion

4.1. *Tolerances for outputs and inputs*

Following the methodology described in Appendix 1, symmetrical gaps for each of the outputs and inputs of each WWTP have been estimated. To this end, we used output and input data for the years between 2003 and 2009, since these datasets are basically the longest time series available at present. Table 2 provides a list of the values of (symmetric) tolerance obtained for the inputs (operation and maintenance costs) and outputs (SS, COD and N removed).

The greater the amplitude of the tolerance interval, the greater the sensitivity to possible input and output changes and, in contrast, a lesser margin is shown in the strength of the efficiency index whether data varies. For this reason, despite the fact that WWTPs are not particularly plagued by data inaccuracy, it is important to assess the uncertainty in the parameters that determine efficiency to obtain reliable conclusions. For example, the values in Table 2 indicate that WWTP 4 presents a variability of ±46.3% in the removal of SS.

Our empirical results show that the average value of tolerance for the inputs is lower than for the outputs. This result is consistent with what we might expect from the theoretical point of view, because WWTP operators aim to minimize operational costs and, since our time series is recent, the majority of analyzed plants in this study have already optimized their expenses. With respect to outputs, the volume of pollutants that are removed depends, not only on how a particular WWTP is operated, but also on the characteristics of the influent. After the wastewater treatment process, effluent that meets the quality criteria required by legislation must be obtained. Therefore, if the concentration of pollutants in the influent changes over time, it is clear that the volume of pollutants that are being removed must also change. For this reason, the average exchange rates obtained for the outputs are greater than that for the inputs.

At the plant level, tolerances of the studied WWTPs are observed to be highly variable especially for outputs, which are confirmed by the standard deviation values. The variability in the tolerance for nitrogen between plants was particularly significant, as the minimum value was 1.3% (WWTP 41), while the maximum value was 70% (WWTP 25). For the other two pollutants (SS and COD), the variability in the tolerance levels may in general be justified by the fact that the influent quality had changed over time in several plants (i.e., WWTPs with high tolerance values), while others remained virtually constant (i.e., WWTPs with small tolerance values). It is also important to note that the concentration of these pollutants in the effluent should be similar because it is regulated by legislation (Directive 92/271/EEC). In addition, WWTP 4 presented the highest value of variability in both the SS and the COD removed. This is because during 2003 (at the beginning of its operation) this WWTP had operational problems for several months; hence, the removal percentage of the monitored pollutants for that year was low, while for the remaining years the removal efficiencies were considerably higher.

Table 2 – Tolerances for input and outputs in %.

WWTP	OUTPUTS (%)			INPUTS (%)
	SS	COD	N	Cost
1	8.8	12.5	11.8	23.9
2	2.4	6.6	29.1	13.5
3	2.2	6.3	10.1	6.6
4	46.3	57.1	27.3	10.7
5	11.2	3.3	10.3	13.7
6	0.3	0.6	45.9	9.5
7	6.8	1.9	24.3	29.1
8	3.4	29.9	10.8	2.3
9	40.8	2.0	6.2	12.5
10	6.0	2.6	13.3	16.8
11	2.7	2.3	9.0	1.2
12	2.3	14.0	18.6	8.9
13	1.7	3.4	16.3	4.1
14	2.5	1.0	18.9	13.1
15	7.9	3.4	5.0	11.2
16	11.4	17.4	22.1	15.8
17	0.1	2.2	23.0	4.5
18	18.6	7.5	4.4	1.8
19	1.9	3.9	28.5	12.3
20	14.9	15.9	23.8	2.8
21	4.6	1.2	8.1	3.1
22	2.8	4.4	15.5	4.2
23	12.4	18.7	18.9	6.4
24	4.1	1.7	46.7	0.9
25	42.7	15.5	70.0	19.3
26	22.7	20.3	8.5	3.4
27	9.2	1.5	4.7	5.0
28	4.0	2.2	5.6	1.9
29	2.0	1.0	14.1	8.6
30	7.3	6.9	7.6	8.9
31	21.3	9.6	8.4	9.4
32	10.1	5.5	7.8	5.4
33	3.3	2.1	11.2	8.8
34	23.4	11.2	15.8	15.0
35	2.0	9.8	31.4	3.6
36	3.6	4.5	7.1	2.7
37	6.6	2.0	4.1	14.9
38	10.7	15.3	9.0	3.6
39	13.1	9.7	6.9	2.5
40	1.4	1.5	1.4	1.5
41	1.6	1.3	1.3	1.2
42	28.0	18.8	6.9	3.5
43	14.9	21.5	21.7	23.6
44	26.2	25.4	17.3	7.0
45	4.8	14.3	22.2	12.7
Mean	10.6	9.3	16.3	8.7
Std. Dev.	11.4	10.5	13.2	6.7

4.2. *Efficiency scores*

Once the tolerances have been calculated, the next step in our analysis is to apply the DEA model (Eq. (1)) to the set of WWTPs being investigated by considering the original data, as well as gaps in the input and output. The resolution of the DEA model with uncertainty assessment leads 81 scores being obtained for each of the WWTPs, which provides the variation in the range of efficiency score values. The breadth and complexity of the resultant information is noticeable; therefore, we divide the efficiency scores obtained for each of the WWTPs into four scenarios: (i) original situation without tolerances (ORIGINAL), (ii) maximum score obtained (MAX), which corresponds to the best possible case scenario, (iii) minimum score achieved (MIN), which corresponds to the worst possible case scenario, and (iv) mean score of the 81 possible combinations of tolerances (MEAN). Along with these datasets, Table 3 provides information on the amplitude of the range (MAX–MIN) and (ORIGINAL − MEAN) percentage terms.

First, we discuss the results that were obtained when the original data was used (ORIGINAL). The mean efficiency score across the sample was 0.588. Taking into account that a DMU is efficient when its score is equal to unity (i.e., 1), the mean potential for saving inputs among the WWTPs is about 41.2%. Our empirical results are similar to that obtained by Hernández-Sancho and Sala-Garrido (2009), who estimated an average efficiency score of 0.41 for 338 WWTPs in 2004. Hence, under the most favorable scenario (MAX), the average efficiency score of the WWTPs could potentially reach 0.740, which means there could be an improvement approximately of 26%. However, under the worst case scenario, the decrease in average efficiency is also quantified as 26%. These results allow us to confirm that the tolerances calculated for each of

Table 3 – Efficient scores using DEA with uncertainty assessment.

WWTP	ORIGINAL	MEAN	MAX	MIN	AMPLITUDE (max–min) (%)	AMPLITUDE (ori-mean) (%)
1	0.790	0.794	1.000	0.540	46.0%	−0.4%
2	1.000	0.894	1.000	0.631	36.9%	10.6%
3	0.574	0.575	0.656	0.504	15.3%	−0.1%
4	0.351	0.356	0.424	0.304	12.1%	−0.5%
5	0.737	0.794	1.000	0.511	48.9%	−5.7%
6	0.654	0.747	1.000	0.511	48.9%	−9.3%
7	1.000	1.000	1.000	1.000	0.0%	0.0%
8	0.855	0.849	0.972	0.727	24.5%	0.6%
9	0.728	0.773	1.000	0.513	48.7%	−4.4%
10	0.174	0.193	0.391	0.135	25.6%	−1.9%
11	0.349	0.414	0.696	0.255	44.1%	−6.5%
12	0.334	0.335	0.390	0.287	10.4%	−0.1%
13	0.381	0.486	1.000	0.304	69.6%	−10.5%
14	1.000	0.999	1.000	0.947	5.3%	0.1%
15	0.598	0.601	0.779	0.459	32.1%	−0.3%
16	0.797	0.808	1.000	0.625	37.5%	−1.1%
17	0.380	0.379	0.432	0.330	10.2%	0.0%
18	0.468	0.516	0.843	0.333	51.0%	−4.8%
19	1.000	0.889	1.000	0.353	64.7%	11.1%
20	1.000	0.912	1.000	0.430	57.1%	8.9%
21	0.263	0.275	0.378	0.233	14.5%	−1.1%
22	1.000	1.000	1.000	1.000	0.0%	0.0%
23	0.352	0.351	0.432	0.285	14.8%	0.2%
24	0.267	0.283	0.459	0.240	21.8%	−1.6%
25	0.924	0.904	1.000	0.627	37.3%	2.0%
26	0.286	0.347	0.644	0.242	40.2%	−6.1%
27	0.159	0.159	0.175	0.145	3.0%	−0.0%
28	0.278	0.277	0.305	0.251	5.4%	0.1%
29	0.472	0.470	0.576	0.371	20.5%	0.2%
30	0.353	0.354	0.420	0.300	12.0%	−0.1%
31	0.679	0.677	0.915	0.504	41.0%	0.3%
32	1.000	0.989	1.000	0.677	32.3%	1.2%
33	0.853	0.879	1.000	0.690	31.0%	−2.5%
34	0.462	0.578	1.000	0.264	73.6%	−11.6%
35	0.794	0.853	1.000	0.640	36.0%	−5.9%
36	0.375	0.372	0.438	0.306	13.2%	0.3%
37	0.362	0.366	0.471	0.281	18.9%	−0.4%
38	1.000	0.908	1.000	0.421	57.9%	9.2%
39	0.248	0.256	0.339	0.227	11.2%	−0.8%
40	1.000	0.794	1.000	0.368	63.2%	20.6%
41	0.345	0.408	0.685	0.272	41.3%	−6.3%
42	0.270	0.272	0.316	0.245	7.1%	−0.3%
43	0.584	0.593	0.914	0.388	52.7%	−0.9%
44	0.456	0.459	0.525	0.408	11.7%	−0.4%
45	0.519	0.529	0.706	0.424	28.1%	−1.1%
Mean	0.588	0.593	0.740	0.433	30.6%	−0.4%
Std. dev.	0.283	0.266	0.281	0.217	20.2%	5.6%

the outputs and inputs are symmetrical with respect to the original value. It is important to note that the average efficiency score for the 81 analyzed cases (MEAN) is 0.593, which is practically the same as when the original data is used (i.e., the difference is less than 1%).

Table 3 shows that, aside from the efficient units, 10 WWTPs could become efficient by simply increasing their pollutants removal efficiency, or by decreasing their operation and maintenance costs. In other words, in the best-case scenario, 22% of the studied WWTPs minimize their costs given a certain level of outputs. Therefore, the measures used by these WWTPs should be undertaken by other plants to achieve an increase in outputs to improve efficiency. Nevertheless, the rest of the WWTPs (58%) would not become efficient, even in the best case scenario.

If the least favorable case scenario is analyzed (i.e., an increase in inputs with a decrease in outputs of the DMU, while the rest vary inversely), the fact that 7 of the 9 WWTPs that had an efficiency score equal to unity based on the original data are no longer efficient, should be underlined. Here, it is worth noting the plant numbers 7 and 22, both in the best and the worst scenarios, had an efficiency score equal to unity (i.e., are always efficient). Likewise, it is also important to note that the significant decrease in efficiency experienced by WWTP numbers 19, 20, 38, and 40, shifting from the efficient production frontier to having efficiency scores of below 0.6. These changes indicate that these plants should remain vigilant, as if there are small changes in the volume of pollutants removed, its efficiency will be greatly reduced.

Fig. 1 clearly shows the variation intervals (represented by bars) between the best and the worst possible case scenarios of WWTP efficiency scores, as well as the original values that were employed. The different length of the intervals denotes the level of stability (i.e., less or more) in the obtained results.

If the original value is compared with the average of the 81 scores (AMPLITUDE (ori-mean)), the average divergence is just −0.4%, for both positive and negative values. In absolute terms, the maximum amplitude is 20.6%, while the lowest amplitude is 0.0%. These results indicate that when the efficiency of a sample of WWTPs is assessed, the mean value does not differ greatly from the score that would be obtained if the confidence intervals of the original data had been used. However, when the same analysis is performed at the plant level, consideration of the gaps (uncertainty) acquires special importance since there are substantial differences between the results from original data and from the average of the 81 scenarios.

Variability is understood as the difference between the score in the best and the worst case scenario (AMPLITUDE (max–min)). Hence, large amplitude implies that a WWTP may improve or worsen significantly when their inputs and outputs change. In other words, individual WWTPs are very sensitive to possible variations in the inputs and/or outputs. In comparison, low amplitude indicates that the efficiency will change minimally, or may remain stable if the amplitude is zero, despite variation in the inputs and outputs. Hence, of the studied WWTPs, our empirical results indicate that 18% of the plants have amplitudes higher than 50%, reaching a maximum value of 74%. In other words, the efficiency of these plants would be greatly affected by changes to their inputs or outputs. In contrast, 38% of plants have amplitudes lower than 20%. This value indicates that these plants are minimally sensitive to changes in the data. Of all the evaluated WWTPs, the most ''insensitive'' were numbers 7 and 22, because both in the best and the worst scenarios are efficient, with their amplitude being 0%.

Looking at the distribution of efficiency scores across individual plants, three levels may be distinguished: (i) high efficiency, when the average efficiency score exceeds 0.7, (ii) medium efficiency, when the average efficiency scores are between 0.3 and 0.7, and (iii) low efficiency, when the average level of efficiency does not exceed 0.3. Fig. 2 shows these three groups of WWTPs with respect to the original, maximum and minimum possible scores.

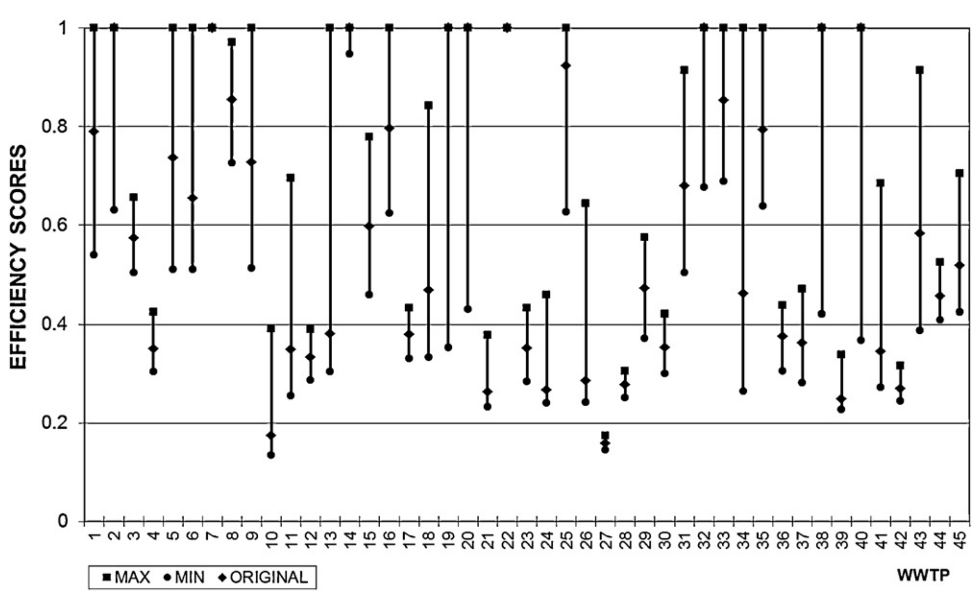

Fig. 1 – DEA with tolerances: maximum, minimum and original scores.

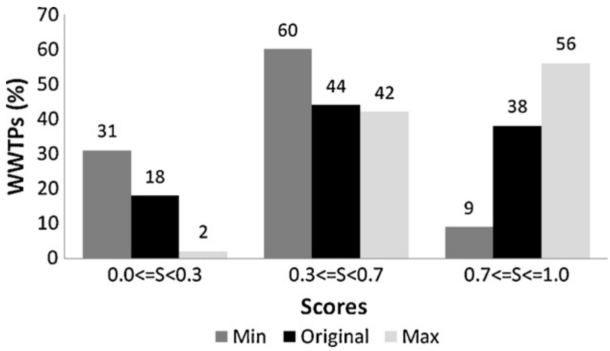

Fig. 2 – Groups of WWTPs for original, minimum and maximum.

We found that the percentage of plants that had a mean efficiency minimally changed when the efficiency was determined using either the original data or the estimated tolerances, particularly in the case of the maximum values. However, in the case of groups of plants with low and high efficiency, the differences between the best and the worst scenarios were very significant. Thus, we observed that the percentage of facilities with low efficiency was 31% when the minimum value was used, while the percentage decreased to 2% when using the maximum value. For plants with high efficiency, there was a 47% difference between the plants of this group when considering the best and the worst case scenarios.

This example clearly illustrates the advantages of measuring efficiency when taking into account the uncertainty in the inputs and outputs that characterize the production process.

4.3. *Ranking DMUs*

Once the efficiency scores were obtained, we proceeded to calculate the two efficiency indicators (R^1 and R^2) detailed in Section 2.3 for each of the evaluated WWTPs, to complete the efficiency analysis. As explained, both ratios occur in a range of values [0,1]. The more frequently that a WWTP is efficient, the closer that indicator R^1 is to unity, and would therefore occupy a higher place in the ranking.

Efficiency indicators R^1 and R^2 for each WWTP studied are reported in Appendix 2. As expected from previous analysis, the WWTP numbers 7 and 22 jointly occupy first place in the ranking. In other words, these plants are the most efficient, since indicator R^1 shows the value of its upper bound, whereby these units are efficient under the 81 possible analyzed cases. The subsequent positions in the ranking are occupied by WWTP numbers 14 and 32, which have a value very close to unity. Remember that these WWTPs were efficient when using the original data and in the best case scenario. However, in the worst case scenario their efficiency scores were reduced to 0.947 and 0.677, respectively.

Also, the ratio R^1 confirms that in the best case scenario, 19 of the 45 analyzed WWTPs would become efficient, since the value of this indicator for these plants is greater than zero. In contrast, 26 facilities could never become efficient (WWTPs R^1 equal to zero).

The results of the R^2 indicator facilitate the ranking of the WWTPs that have the same value of R^1. Specifically for our study, first the value of R^2 allow WWTP numbers 1, 5 and 6 to be ranked, which present the same value of R^1 and are greater than zero. Moreover, R^2 also allows us to classify plants that even in the best case scenario would not become efficient, such as WWTPs with an R^1 value equal to zero. In this way, we verify that this group of facilities does not form a homogeneous group, but that WWTP numbers 8, 31 or 15 occupy a higher position in the ranking. This difference in ranking occurs because when variation in the inputs and outputs leads these plants to the best possible situation, higher efficiency rates may be obtained when compared to other WWTPs for which R^1 also is zero. In comparison, plant numbers 10 and 27 would be the least efficient, even in the best possible scenario, because they had the lowest values of the ratio R^2.

In summary, we would like to highlight that evidence is provided showing that WWTP numbers 7 and 22 have the best performance from the point of view of efficiency, as all possible scenarios are efficient. In other words, these two plants represent the efficient frontier of best practice. Furthermore, the results of the efficiency indicators allow us to verify that the plant number 27 is the worst of all analyzed plants, because even in the best scenario, the efficiency of this plant would remain lower than the other assessed facilities.

The hierarchical ranking of the WWTPs is of special interest for the authorities, since compared against the results where almost all units may be considered efficient, this system facilitates discrimination. In turn, this allows plants with better efficiency values to be identified and prioritized. Thus, the authorities are provided with more complete information for the decision-making process when planning investment actions in these facilities.

5. Conclusions

The rapid increase in costs associated with WWTP management, means that performance evaluation has acquired special relevance to identify the units with the best practice for use as a reference guideline. The DEA technique has proven to be a suitable tool for evaluating the efficiency of production processes that have multiple inputs and outputs, such as wastewater treatment processes. However, one of the main disadvantages of this method is that information about uncertainty is not available.

Our analysis contributes new information about how changes in available data could cause instability in the efficiency results. We estimated the efficiency scores for a sample of 45 Spanish WWTPs by using the DEA model with uncertainty assessment, due to its guarantee of greater stability in the results. Moreover, we used obtained results to calculate the two indicators that allow the evaluated WWTPs to be ranked in terms of efficiency.

As a consequence, we derived useful insights about the efficiency of our sample of WWTPs. First, the tolerances estimated for each of the parameters show that variability in the outputs is greater than for the inputs. Second, the average efficiency scores that was obtained with both the original data and with minimum and maximum gaps indicates that there is scope for the managers of facilities to reduce their operational costs. Third, the difference between the efficiency score for the best and worst scenarios indicates that not all of the studied WWTPs had the same sensitivity to changes in their inputs and outputs. Finally, at the plant level, our analysis verifies that there are substantial changes in the number of efficient plants when data with gaps are used instead of the original data.

Concerning the ranking of WWTPs, we contribute empirical evidence verifying that two WWTPs clearly occupy first place, because in all analyzed scenarios the efficiency scores were one. Hence, these WWTPs should be considered as the best-practice. In contrast, the second indicator confirms that the plants which not will not become efficient even in the best scenario, are heterogeneous, allowing the lowest ranked WWTP to be identified.

Of note, the employment of the DEA model with uncertainty assessment facilitates the incidence of each output and input of the WWTP efficiency scores to be measured in comparison to the traditional DEA. Likewise, the inclusion of variability in the data solved the problem of inaccuracy, in addition to being used to predict changes in the efficiency of plants subject to variability in the volume of outputs and inputs. This analysis allows plants that should be on alert to be identified, because small changes in the data will cause a dramatic reduction in their efficiency. In addition, plants with the greatest potential for improvement may also be identified, and ensuring that the correct change in their operational parameters are selected to become efficient.

Finally, from a policy perspective, the results of the derived efficiency scores should be of use to both managers of WWTPs and responsible Administration, as the most efficient and innovative facilities are identified as references. Therefore, the comparative strengths and weaknesses of WWTPs may be identified, allowing the adoption of measures for the efficient allocation of available resources. The adoption of this best practice in the other WWTPs, would potentially contribute towards minimizing operation and maintenance costs, and thus increase the profits of companies.

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Appendix 1

The determination of the tolerance values is a critical aspect of the DEA model with uncertainty assessment, given the subjectivity to which it is exposed. Clearly, the arbitrary determination of possible variations in the inputs and outputs affects the results, from which unusable and/or unrealistic conclusions may be derived. According to Bonilla et al. (2004), Medal (2010), and Boscá et al. (2011), a descriptive statistical method must be selected to analyze the data. This method is based on the selection of a historical series of inputs and outputs. Considering the maximum and minimum levels reached in the review period, gaps submitted for these variables may be determined, and thus the appropriate levels of tolerance may be selected.

The method used to determine the tolerance levels follows six steps that are applied to each of the analyzed DMUs, and for each of the considered outputs and inputs. The steps are described as follows:

Step 1: Analysis of the inputs and outputs for each period of time (i).

Step 2: Calculation of the mean, maximum and minimum values for the given data of each period (i).

Step 3: Calculation of the differences between the maximum and mean (DIFMAX (i)), and the differences between the minimum and mean (DIFMIN (i)), according Eq. (A1), of each period (i) analyzed. (I = 1, 2, ..., *n*)

$$\mathrm{DIFMAX}\,(i) = \frac{\mathrm{Max}\,(i) - \mathrm{Mean}\,(i)}{\mathrm{Mean}\,(i)} \qquad \mathrm{DIFMIN}\,(i) = \frac{\mathrm{Mean}\,(i) - \mathrm{Min}\,(i)}{\mathrm{Mean}\,(i)} \tag{A1}$$

Step 4: Determination of individual tolerance levels for each period (i):

$$\mathrm{TOL}\,(i) = \frac{\mathrm{DIFMAX}\,(i) - \mathrm{DIFMIN}\,(i)}{2} \tag{A2}$$

Step 5: Determination of the global amplitude for each type of input and output tolerance as the arithmetic mean of the variables (TOL (i)):

$$\mathrm{TOL} = \mathrm{mean\,TOL}\,(i) = \frac{\sum_{i=1}^{n} \mathrm{TOL}(i)}{n} \tag{A3}$$

Step 6: The tolerance value (TOL) is divided by two. By dividing the overall amplitude into two parts, both positive and negative variations of inputs and outputs are indicated.

The described methodology allows the symmetrical tolerances to be calculated since, as shown in step 6, the overall amplitude is divided in half. However, when it is considered important that the tolerances are not symmetrical, the proposal of Bonilla et al. (2004) can be tailored to maintain steps 1 to 3, while substituting steps 4–6 as follows:

Step 4: Determination of upper individual tolerance level for each input and output.

$$\mathrm{TOL\,MAX} = \frac{\sum_{i=1}^{n} \mathrm{DIF\,MAX}\,(i)}{n} \tag{A4}$$

Step 5: Determination of lower individual tolerance level for each input and output.

$$\mathrm{TOL\,MIN} = \frac{\sum_{i=1}^{n} \mathrm{DIF\,MIN}\,(i)}{n} \tag{A5}$$

Whether symmetric or non-symmetric tolerances are calculated, the same weight is assigned to each of the time periods being analyzed. However, in the case of large historical series, it may be appropriate to assign a greater weight to more recent periods and a lower weight to those furthest from the current time.

Medal and Sala (2009) validated this approach in determining the tolerances of the variables, through the analysis of contingency tables of the distribution of scores for each of the analyzed DMU, which led to the conclusion that the selection of tolerances based on individual historical variations in the inputs and outputs leads to better results than the use of generic or random variations.

Appendix 2

Table A2 – WWTPs efficiency ranking.

WWTP	R^1	R^2
7	1.000	–
22	1.000	–
14	0.987	0.947
32	0.938	0.813
38	0.777	0.587
19	0.740	0.358
20	0.617	0.769
40	0.555	0.536
25	0.518	0.800
2	0.506	0.784
35	0.308	0.787
33	0.247	0.839
34	0.222	0.456
9	0.210	0.712
1	0.185	0.748
5	0.185	0.747
6	0.185	0.690
13	0.111	0.422
16	0.074	0.792
8	0.000	0.849
31	0.000	0.677
15	0.000	0.601
43	0.000	0.593
3	0.000	0.575
45	0.000	0.529
18	0.000	0.516
29	0.000	0.470
44	0.000	0.460
11	0.000	0.414
41	0.000	0.408
17	0.000	0.380
36	0.000	0.372
37	0.000	0.365
4	0.000	0.356
30	0.000	0.354
23	0.000	0.350
26	0.000	0.347
12	0.000	0.335
24	0.000	0.282
28	0.000	0.277
21	0.000	0.274
42	0.000	0.272
39	0.000	0.256
10	0.000	0.193
27	0.000	0.159

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