Universitat de València

Doctorado en Desarrollo Local y Cooperación Internacional

EVALUACIÓN DEL COMPORTAMIENTO ENERGÉTICO DE LAS ESTACIONES DEPURADORAS DE AGUAS RESIDUALES

Una aproximación económica

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CONTENIDO

ÍNDICE DE FIGURAS

ÍNDICE DE TABLAS

ACRÓNIMOS Y ABREVIACIONES

CE	Coste energético
DBO	Demanda Biológica de Oxígeno
DEA	Análisis Envolvente de Datos
DMA	Directiva Marco del Agua
DMU	Unidad de toma de decisión
DQO	Demanda Química de Oxígeno
EDAR	Estación Depuradora de Aguas Residuales
HE	Habitante Equivalente
J	Envejecimiento de las instalaciones
N	Nitrógeno
P	Fósforo
SBM	Medida basada en holguras
SS	Sólidos Suspendidos
V	Volumen de agua residual
WSBM	Medida basada en holguras ponderada
Z	Parámetro operacional

AGRADECIMIENTOS

Me gustaría poner fin a esta etapa agradeciendo a todas las personas que han contribuido a la realización de este trabajo.

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DOCUMENTOS ACREDITATIVOS

1. Autorización para la presentación de la tesis doctoral

VNIVERSITAT DE VALÈNCIA **Departament d'Economia Aplicada**

Valencia, 17 de octubre de 2019

Francesc Hernández Sancho, Coordinador del Grupo de Economía del Agua y Catedrático de Economía Aplicada de la Universidad de Valencia,

hace constar que:

Como director de la tesis doctoral de LLEDÓ CASTELLET VICIANO, con NIF 20486718-C, titulada "*Evaluación del comportamiento energético de las Estaciones Depuradoras de Aguas Residuales: una aproximación económica*", inscrita en el Programa de Doctorado "Desarrollo Local y Cooperación Internacional" de la Universidad de Valencia, autorizo a presentar dicha tesis mediante la modalidad de compendio de artículos, constituido por las siguientes publicaciones:

1. **Castellet-Viciano, L.**, Torregrossa, D., and Hernández-Sancho, F. (2018). The relevance of the design characteristics to the optimal operation of wastewater treatment plants: Energy cost assessment. Journal of Environmental Management, 222, 275-283.
2. **Castellet-Viciano, L.**, Hernández-Chover, V., and Hernández-Sancho, F. (2018). Modelling the energy costs of the wastewater treatment process: The influence of the aging factor. Science of the Total Environment, 625, 363-372.
3. **Castellet, L.**, and Molinos-Senante, M. (2016). Efficiency assessment of wastewater treatment plants: A data envelopment analysis approach integrating technical, economic, and environmental issues. Journal of Environmental Management, 167, 160-166.

Acreditando que dicha tesis cumple los requisitos formales al uso y presenta unos contenidos completos, fundamentados y acordes con la normativa que regula los estudios de doctorado y que se ha hecho un uso ético de la información utilizada en el proceso de investigación.

Atentamente,

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2. Impacto de las publicaciones

Departament d'Economia Aplicada

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3. **Castellet, L.**, and Molinos-Senante, M. (2016). Efficiency assessment of wastewater treatment plants: A data envelopment analysis approach integrating technical, economic, and environmental issues. Journal of Environmental Management, 167, 160-166.

han sido publicadas en dos revistas científicas JCR de alto impacto, como son *Science of the Total Environment* y *Journal of Environmental Management*, ambas de primer cuartil y con un factor de impacto de 4,610 y 4,005, respectivamente.

Atentamente,

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3. Contribución de la doctoranda en las publicaciones

VNIVERSITAT DE VALÈNCIA **Departament d'Economia Aplicada**

Valencia, 17 de octubre de 2019

Francesc Hernández Sancho, Coordinador del Grupo de Economía del Agua y Catedrático de Economía Aplicada de la Universidad de Valencia.

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3. **Castellet, L.**, and Molinos-Senante, M. (2016). Efficiency assessment of wastewater treatment plants: A data envelopment analysis approach integrating technical, economic, and environmental issues. Journal of Environmental Management, 167, 160-166.

la actual doctoranda es la principal autora de las publicaciones, y éstas no han sido utilizadas de forma directa o indirecta en otras tesis doctorales.

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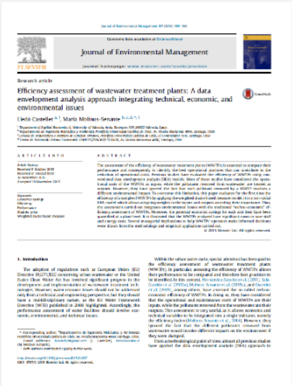
PUBLICACIONES QUE CONSTITUYEN EL COMPENDIO DE ARTÍCULOS

ARTÍCULO 1



Efficiency assessment of wastewater treatment plants: A data envelopment analysis approach integrating technical, economic, and environmental issues

Castellet, L., and Molinos-Senante

Journal of Environmental Management
Volume 167, 1 February 2016, Pages 160-166
Quartile: Q1; Impact Factor: 4.005

https://doi.org/10.1016/j.jenvman.2015.11.037

ARTÍCULO 2

The relevance of the design characteristics to the optimal operation of wastewater treatment plants: energy cost assessment

Castellet-Viciano, L., Torregrossa, D., and Hernández-Sancho, F.

Journal of Environmental Management
Volume 222, 15 September 2018, Pages 275-283
Quartile: Q1; Impact Factor: 4.005

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ARTÍCULO 3

Modelling the energy costs of the wastewater treatment process: The influence of the aging factor

Castellet-Viciano, L., Hernández-Chover, V., and Hernández-Sancho, F.

Science of The Total Environment
Volume 625, 1 June 2018, Pages 363-372
Quartile: Q1; Impact Factor: 4.610

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ABSTRACT

Wastewater Treatment Plants (WWTPs) are a basic piece of urban infrastructure as they are essential to guarantee public and the environment health. Currently, in Spain there are approximately 3,000 WWTPs that treat 4,700 hm^3 of wastewater. Approximately, 55.8% and 33.5% of the wastewater treated is discharged into river channels and the sea, respectively, while 10.4 % is reused in agriculture and garden watering, and the remaining 0.3% is infiltrated to the ground for aquifer regeneration and other purposes. Depending on the final disposal of wastewater, different quality requirements established on urban wastewater and reuse regulations must be complied, and it can be achieved thanks to the implementation of treatment technologies that require high energy consumption for its operation. Over the years, it has been observed that the energy consumption used in the wastewater treatment sector has intensified because of the increase in the number of people connected to the sewerage system, and the need to meet the environmental requirements established by European and state regulations in this matter.

The control of the energy consumption of the WWTPs has become a relevant aspect for the operators of the facilities due to the economic impact that it has on the operational costs of the process, which can represent between 30 and 40% of the total costs. Variations in energy costs depend on the technology used in the process, the size of the population served, as well as the quality of the effluent required, among many other factors. In addition, it is expected that energy consumption, and therefore the costs associated with it, will increase in the near future as a result of the publication of a new legislation that contemplates more demanding quality requirements than the current ones.

Given this situation, over the last few years, facilities with more efficient technologies and automatic control systems have been implemented to regulate the energy consumption of the facilities. Despite this, there is still a high potential for improvement in terms of optimizing the energy consumption of the facilities, as demonstrated in the paper that is part of this compendium entitled *Efficiency assessment of wastewater treatment plants: A data envelopment analysis approach integrating technical, economic, and environmental issues*. In this study it is proved that the energy cost, and, therefore, the energy consumption of the WWTPs could be reduced giving as a result a more efficient process. To carry out this study, a methodology that has aroused great interest because of its great versatility in both scientific community and in the field of wastewater treatment has been used. This is the Data Envelopement Analysis (DEA), a methodology based on linear optimization models that allows

measuring the relative efficiency of a set of production units through a non-parametric procedure.

In order to optimize the process and reduce unnecessary energy consumption it is important to identify those factors that affect the energy consumption of the plants and analyse their influence. For this purpose, the use of statistical and econometric techniques is proposed, since they allow to assess how different variables or characteristics of the facilities may affect the energy consumption. Detecting those variables or parameters closely linked to the energy consumption of wastewater treatment plants will allow managers and operators, whether public or private, to act on them and improve the efficiency of the facilities. In the light of this, the papers named *The relevance of the design characteristics to the optimal operation of wastewater treatment plants: energy cost assessment* and *Modeling the energy costs of the wastewater treatment process: The influence of the aging factor* are developed. The first of the publications mentioned above presents the differences between the design iflow and the real flow treated by the facilities as a factor that may affect the energy costs of the facilities, while the second aims to evaluate and demonstrate the negative effects that the aging of the infrastructure has on the energy cost.

With regard to the size of the facilities, there are many examples in which large differences between the real flow of the facilities and the design can be observed, either because they are oversized since the expectations of population growth considered at the time of construction were not met, or because its treatment capacity is exceeded due to the fact that the wastewater volumes treated are higher than the design flow. Whatever the reason for the mismatch between the actual and the design flow, the truth is that the equipment that constitutes the facilities is not working at the optimum, being small-sized facilities the most affected since, unlike the large, they are not usually equipped with control systems that optimize the sizing.

Regarding the aging of the facilities, we are facing a new situation that concerns both public and private managers, since these are infrastructures that must be maintained and renewed periodically to ensure their proper functioning. Since Directive 91/271 / EEC entered into force, the equipment related to the sewage system has grown remarkably, and there are many facilities that have already exceeded their useful life or are in the middle of this period, so without the existence of preventive maintenance strategies and a well-defined replacement plans, the process and the quality of wastewater can be affected, putting the health of people and the environment at risk.

The relationship between the factors mentioned previously, that is, the mismatch between the real and the design flow and the aging of the facilities, with the energy cost, is materialized through the development of different cost functions that enables the managers and operators to mode the energy cost of the WWTPs taking into account these variables, in addition to other technical variables such as the size of the facilities, the technology used and the quality of the wastewater. It is considered that this kind of tools could provide useful information to the managers, becoming a useful tool for the decision making process.

RESUMEN

Las Estaciones Depuradoras de Aguas Residuales (EDARs) son una pieza básica del conjunto de infraestructuras urbanas, ya que son indispensables para garantizar la salud pública y del medio ambiente. Actualmente, en España existen aproximadamente 3.000 EDARs que tratan 4.700 hm^3 de aguas residuales, de los cuales la mayor parte, un 55,8% y un 33,5% son vertidos a cauces fluviales y al mar, respectivamente, mientras que un 10,4% es reutilizado en la agricultura y el riego de jardines, y el 0,3% restante es infiltrado al suelo para la regeneración de acuíferos y otros fines. Según el destino del agua residual, la normativa en materia de aguas residuales urbanas y reutilización requiere el cumplimiento de unos criterios de calidad determinados, que se consiguen gracias a la implementación de tecnologías de tratamiento que requieren un elevado consumo energético para su funcionamiento. A lo largo de los años, se ha observado que el consumo energético utilizado en el sector de la depuración se ha intensificado debido a que la población conectada al sistema de alcantarillado es cada vez mayor, y a la necesidad de cumplir con las exigencias ambientales establecidas por la normativa europea y estatal en esta materia.

El control del consumo energético de las EDARs se ha convertido en un aspecto fundamental para los operadores de las instalaciones debido al impacto económico que tiene en los costes operacionales del proceso, los cuales pueden suponer entre un 30 y un 40% de los costes totales, dependiendo de la tecnología empleada en el proceso, el tamaño de la población servida, así como de la calidad del efluente exigida, entre otros muchos factores. Además, se prevé que el consumo energético, y por ende los costes asociados a éste, incrementen en los próximos años como consecuencia de la publicación de una legislación que contemple requerimientos de calidad más exigentes que los actuales.

Ante esta situación, a lo largo de los últimos años se han implementado las instalaciones con tecnologías más eficientes y sistemas de control automáticos que permiten regular su consumo energético. Pese a ello, aún existe un elevado potencial de mejora por lo que se refiere a la optimización del consumo energético de las EDARs, tal y como se demuestra en el artículo que forma parte del presente compendio titulado *"Efficiency assessment of wastewater treatment plants: A data envelopment analysis approach integrating technical, economic, and environmental issues"*. En esta publicación se prueba que el coste energético, y, por ende, el consumo energético de las EDARs presenta un gran potencial de mejora por lo que a la eficiencia del proceso se refiere. Para llevar a cabo este estudio se utiliza una metodología que ha despertado gran interés en los últimos años tanto entre la comunidad científica en general como

en el ámbito del tratamiento de las aguas residuales por su gran versatilidad. Se trata del Análisis Envolvente de Datos (DEA), una metodología basada en los modelos de optimización lineal que permite medir la eficiencia relativa de un conjunto de unidades de producción a través de un procedimiento no paramétrico.

Con el fin de optimizar el proceso y reducir consumos energéticos innecesarios es importante identificar los distintos factores que afectan al consumo energético de las plantas y ver en qué medida influyen. Para ello, se propone el uso de técnicas estadísticas y econométricas que permiten analizar distintas variables o características de las instalaciones que pueden afectar al consumo energético. Detectar aquellas variables o parámetros estrechamente ligados al consumo energético de las EDARs permitirá a los gestores y operadores, ya sean públicos o privados, actuar sobre ellas y mejorar la eficiencia de las instalaciones. Con este propósito se desarrollan los artículos *"The relevance of the design characteristics to the optimal operation of wastewater treatment plants: energy cost assessment"* y *"Modelling the energy costs of the wastewater treatment process: The influence of the aging factor"*. El primero de ellos presenta las diferencias entre el caudal de diseño y el caudal real tratado por las instalaciones como un factor que puede afectar a los costes energéticos de las instalaciones, mientras que el segundo pretende evaluar y demostrar los efectos negativos que tiene el envejecimiento de las infraestructuras en el coste energético.

Por lo que se refiere al dimensionamiento de las instalaciones son muchos los casos en los que se pueden observar grandes diferencias entre el caudal real que tratan las instalaciones y el de diseño, bien sea porque están sobredimensionadas ya que no se cumplieron las expectativas de crecimiento poblacional consideradas en el momento de construcción, o bien porque su capacidad de tratamiento se ve sobrepasada debido a que se tratan volúmenes de agua superiores a los de diseño. Sea cual sea el motivo del desajuste entre el caudal real y el de diseño, lo cierto es que los equipos que constituyen las instalaciones no están trabajando en el óptimo, siendo generalmente las instalaciones de pequeño tamaño las más afectadas ya que, a diferencia de las grandes, no suelen estar equipadas con sistemas de control que permiten optimizar el dimensionamiento.

En cuanto al envejecimiento de las instalaciones, estamos ante una nueva situación que preocupa tanto a gestores públicos como privados, ya que se trata de infraestructuras que hay que mantener y renovar periódicamente para garantizar su correcto funcionamiento. Desde que entrara en vigor la Directiva 91/271/CEE el equipamiento relacionado con el sistema de saneamiento ha crecido notablemente, y son muchas las instalaciones que ya han superado su vida útil o se encuentran a mitad de este periodo, por lo que sin la existencia de estrategias de mantenimiento preventivo y un plan de reposición bien definido, el proceso y la calidad del agua residual se pueden ver afectadas poniendo en riesgo la salud de las personas y del medio ambiente.

La relación entre los factores citados anteriormente, es decir, el desajuste entre el caudal real y el de diseño y el envejecimiento de las instalaciones, con el coste energético se materializa mediante el desarrollo de distintas funciones de coste que permiten modelizar el coste energético de las EDARs teniendo en cuenta estas variables, además de otro tipo de variables técnicas como el tamaño o la tecnología de tratamiento y la calidad del agua tratada. Se considera que este tipo de herramienta podría aportar información de gran utilidad a los gestores de las instalaciones, convirtiéndose en una herramienta útil para la toma de decisiones.

RESUM

Les Estacions Depuradores d'Aigües Residuals (EDARs) són una peça clau del conjunt d'infraestructures urbanes, ja que són indispensables per garantir la salut pública i del medi ambient. Actualment, a Espanya existixen aproximadament 3.000 EDARs que tracten 4.700 hm^3 d'aigües residuals, dels quals la major part, un 55,8% i un 33,5% són abocats a llits fluvials i al mar, respectivament, mentre que un 10,4% és reutilitzat en l'agricultura i el reg de jardins, i el 0,3% restant és infiltrat al sòl per a la regeneració d'aqüífers i altres fins. Segons el destí de l'aigua residual, la normativa en matèria d'aigües residuals urbanes i reutilització requerix el compliment d'uns criteris de qualitat determinats, que s'aconseguixen gràcies a la implementació de tecnologies de tractament que requerixen un elevat consum energètic per al seu funcionament. Al llarg dels anys, s'ha observat que el consum energètic utilitzat en el sector de la depuració s'ha intensificat pel fet que la població connectada al sistema de clavegueram és cada vegada major, i a la necessitat de complir amb les exigències ambientals establides per la normativa europea i estatal en esta matèria.

El control del consum energètic de les EDARs s'ha convertit en una matèria fonamental per als operadors de les instal·lacions a causa de l'impacte econòmic que té en els costos operacionals del procés, els quals poden suposar entre un 30 i un 40% dels costos totals, depenent de la tecnologia empleada en el procés, la quantitat de població servida, així com de la qualitat de l'efluent exigida, entre altres molts factors. A més, es preveu que el consum energètic, i per tant, els costos associats a este, incrementen en els pròxims anys com a conseqüència de la publicació d'una legislació que contemple requeriments de qualitat més exigents que els actuals.

Davant d'esta situació, al llarg dels últims anys s'han implementat les instal·lacions amb tecnologies més eficients i sistemes de control automàtics que permeten regular el seu consum energètic. A pesar d'això, encara hi ha un elevat potencial de millora pel que fa a l'optimització del consum energètic de les EDARs, tal com es demostra en l'article que forma part del present compendi titulat "Efficiency assessment of wastewater treatment plants: A data envelopment analysis approach integrating technical, economic, and environmental issues". En esta publicació es prova que el cost energètic, i, per tant, el consum energètic de les EDARs presenta un gran potencial de millora pel que a l'eficiència del procés es referix. Per dur a terme este estudi s'utilitza una metodologia que ha despertat gran interés en els últims anys tant entre la comunitat científica en general, com en l'àmbit del tractament de les aigües residuals, per la seua gran versatilitat. Es tracta de l'Anàlisi Envolvent de Dades (DEA), una metodologia basada

en els models d'optimització lineal que permet mesurar l'eficiència relativa d'un conjunt d'unitats de producció a través d'un procediment no paramètric.

Amb la finalitat d'optimitzar el procés i reduir els consums energètics innecessaris és important identificar els distints factors que afecten el consum energètic de les plantes i veure en quina mesura influïxen. Per a això, es proposa l'ús de tècniques estadístiques i economètriques que permeten analitzar distintes variables o característiques de les instal·lacions que poden afectar el consum energètic. Detectar aquelles variables o paràmetres estretament lligats al consum energètic de les estacions depuradores d'aigües residuals permetrà als gestors i operadors, ja siguen públics o privats, actuar sobre elles i millorar l'eficiència de les instal·lacions. Amb este propòsit es desenvolupen els articles "The relevance of the design characteristics to the optimal operation of wastewater treatment plants: energy cost assessment" i "Modelling the energy costos of the wastewater treatment process: The influence of the aging factor". El primer d'ells presenta les diferències entre el cabal de disseny i el cabal real tractat per les instal·lacions com un factor que pot afectar els costos energètics de les instal·lacions, mentre que el segon, pretén avaluar i demostrar els efectes negatius que té l'envelliment de les infraestructures en el cost energètic.

Pel que fa al dimensionamiento de les instal·lacions són molts els casos en què es pot observar grans diferències entre el cabal real que tracten les instal·lacions i el de disseny, bé siga perquè estan sobredimensionades ja que no es van complir les expectatives de creixement poblacional considerades en el moment de construcció, o bé perquè la seua capacitat de tractament es veu sobrepassada pel fet que es tracten volums d'aigua superiors als de disseny. Siga quin siga el motiu del desajust entre el cabal real i el de disseny, el ben cert és que els equips que constituïxen les instal·lacions no estan treballant en el seu òptim, sent generalment les instal·lacions de dimensió reduïda les més afectades ja que, a diferència de les grans, no solen estar equipades amb sistemes de control que permeten optimitzar el dimensionament.

En quant a l'envelliment de les instal·lacions, estem davant d'una nova situació que preocupa tant gestors públics com privats, ja que es tracta d'infraestructures que cal mantindre i renovar periòdicament per a garantir el correcte funcionament. Des que entrara en vigor la Directiva 91/271/CEE, l'equipament relacionat amb el sistema de sanejament ha crescut notablement, i són moltes les instal·lacions que ja han superat la seua vida útil o es troben a meitat d'este període, per la qual cosa sense l'existència d'estratègies de manteniment preventiu i un pla de reposició ben definit, el procés i la qualitat de l'aigua residual es poden veure afectats posant en risc la salut de les persones i del medi ambient.

La relació entre els factors esmentats anteriorment, és a dir, el desajust entre el cabal real i el de disseny i l'envelliment de les instal·lacions, amb el cost energètic es materialitza per mitjà del desenvolupament de distintes funcions de cost que permeten modelizar el cost energètic de les EDARs tenint en compte estes variable, a més d'un altre tipus de variables tècniques com la grandària o la tecnologia de tractament i la qualitat de l'aigua tractada. Es considera que este tipus de ferramenta podria aportar informació de gran utilitat als gestors de les instal·lacions, convertint-se en una ferramenta útil per a la presa de decisions.

DESARROLLO DE LA TESIS DOCTORAL

1. Introducción

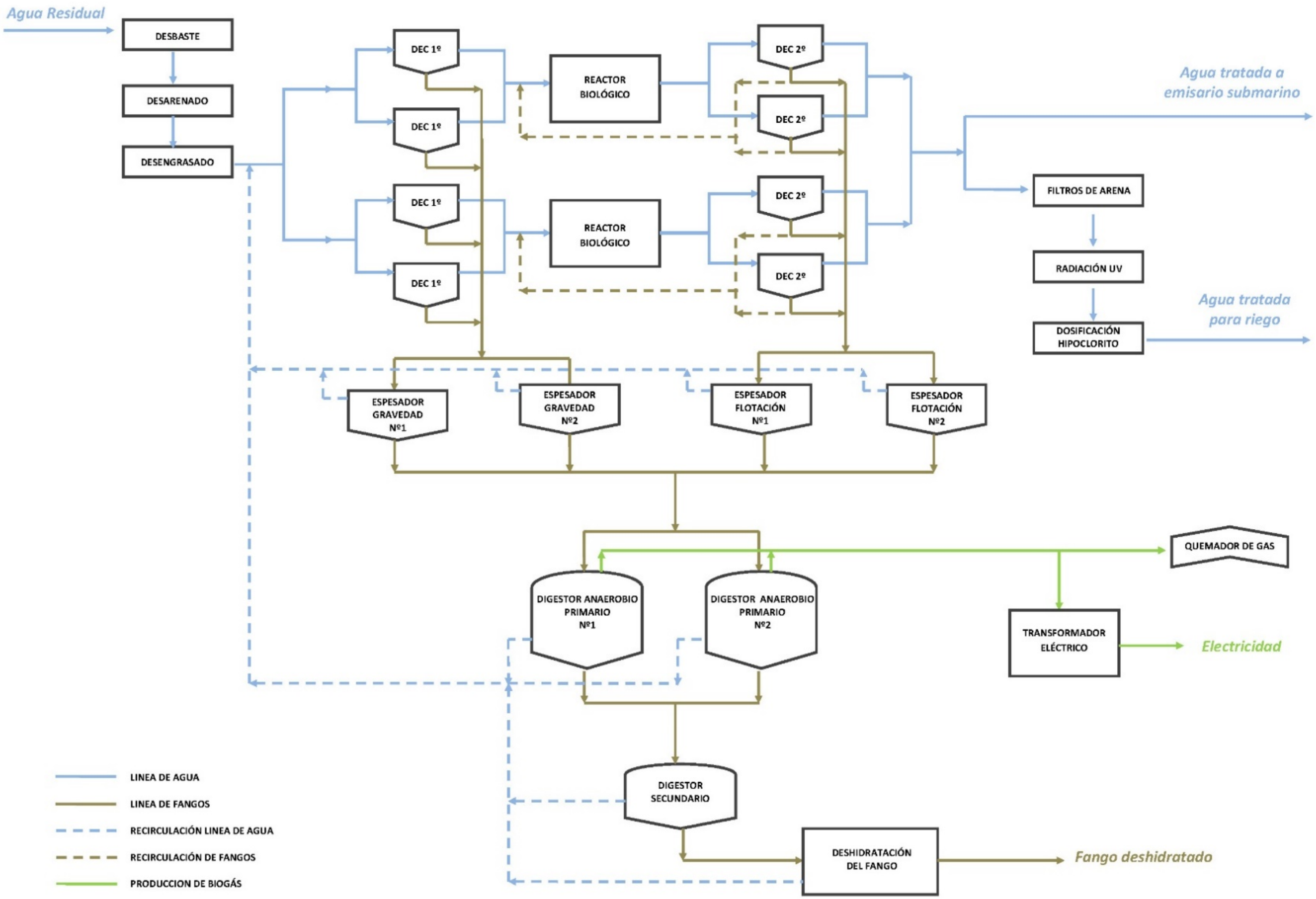
Desde que en la segunda mitad del s. XX se observase el elevado nivel de degradación y la pérdida de calidad que habían sufrido las masas de agua como consecuencia del desarrollo económico y social de las ciudades españolas, el control de las aguas residuales comenzó a ser objeto de regulación por la normativa española (Aragón, Ortega, Ferrer, & Salas, 2013; Delgado, 2012). Sin embargo, fue con la implementación de la Directiva 91/271/CE sobre el tratamiento de aguas residuales, cuando las Estaciones Depuradoras de Aguas Residuales (EDARs) se consideraron parte indispensable del ciclo urbano del agua, con el fin de garantizar la protección de la salud pública y el medio ambiente. Esta Directiva obliga a que las áreas urbanas con más de 2.000 habitantes equivalentes (h.e.) estén dotadas de instalaciones de recolección y tratamiento de aguas residuales, y además establece los parámetros de calidad que debe tener el agua tratada antes de ser devuelta al medio receptor. De esta forma las EDARs se convierten en una pieza más del conjunto de infraestructuras públicas urbanas, no solo por la función que desempeñan sino por la gran cantidad de recursos materiales y económicos que requieren para su construcción y operación (Buonocore, Mellino, De Angelis, Liu, & Ulgiati, 2018).

El objetivo del tratamiento de las aguas residuales es devolver al medio natural las aguas de consumo humano reduciendo la cantidad de carga contaminante a través de una serie de procesos fisicoquímicos y biológicos. Gracias al rápido desarrollo tecnológico de la última década estos procesos han ido evolucionando y adaptándose a las, cada vez mayores, exigencias ambientales (Lofrano & Brown, 2010). También se ha avanzado tanto técnica como legislativamente en cuanto al tratamiento y la reutilización del agua residual (Mujeriego & Asano, 1999) y de los fangos producidos en el proceso (Kelessidis & Stasinakis, 2012).

Actualmente la mayor parte de las instalaciones disponen de un tratamiento de tipo convencional, el cual consta de las siguientes fases: *i)* pretratamiento; *ii)* tratamiento primario; *iii)* tratamiento secundario o biológico, y *iv)* tratamiento terciario, este último aplicado únicamente en aquellos casos en los que el agua tratada es reutilizada (Asano, Smith, & Tchobanoglous, 1985; Tchobanoglous, Stensel, Tsuchihashi, & Burton, 2013). La fase de pretratamiento consiste en la eliminación de elementos de gran tamaño mediante un desbaste, y de arenas y grasas a través de procesos de sedimentación y flotación. Seguidamente en el tratamiento primario, el agua residual pasa a un decantador circular o rectangular, en el cual el agua fluye a muy baja velocidad, permitiendo que las partículas más pesadas se depositen en el fondo por gravedad, de donde posteriormente son extraídas y evacuadas a la línea de fangos para su posterior tratamiento. El tratamiento biológico tiene como función la eliminación o reducción de la materia orgánica del agua residual mediante el empleo de poblaciones de microorganismos diversos que utilizan la materia orgánica presente en el agua como fuente de alimentación. Algunos sistemas de tratamiento secundario requieren un aporte directo de oxígeno mediante turbinas o compresores para garantizar la oxidación de la materia. Esta fase culmina con la decantación secundaria, en la que los microorganismos se depositan en el fondo gracias a la acción de la gravedad y a la baja velocidad del agua, pudiendo así devolverlos al reactor biológico por recirculación y, eliminar los fangos en exceso. Finalmente, el tratamiento terciario comprende una serie de procesos fisicoquímicos y de desinfección que acondicionan el agua tratada para ser reutilizada, dependiendo su calidad del uso que se vaya a hacer de esta agua (Mujeriego & Asano, 1999) .

A lo largo del tratamiento del agua residual descrito anteriormente se generan una serie de fangos con un elevado contenido de agua y organismos, que hay que tratar y gestionar antes de su disposición final (Kacprzak et al., 2017). El primer proceso de tratamiento de los fangos es el espesado que puede ser por gravedad y/o flotación, lo cual permite una menor necesidad de calor en la digestión, una menor energía para mezclarlo, una menor dilución del sustrato biológico y una menor producción de sobrenadante. Y a su vez, permite trabajar con mayores cargas orgánicas disminuyendo el volumen total del digestor. A continuación, el fango es sometido a un proceso de estabilización, mediante digestión aerobia o anaerobia, cuyo objetivo es la reducción de los patógenos y la detención de la putrefacción y producción de malos olores. En esta etapa del proceso se genera metano, el cual algunas EDARs utilizan para producir biogás que convierten en energía eléctrica para abastecer a la propia instalación (Mills, Pearce, Farrow, Thorpe, & Kirkby, 2014). Y finalmente, tras la estabilización el fango es deshidratado con el fin de disminuir el contenido de humedad hasta valores que hagan posible su disposición. En los últimos años la gestión de fangos ha adquirido mayor interés, ya que es un subproducto con un elevado potencial de reutilización en la agricultura, o la recuperación de energía mencionada anteriormente o incluso de calor (Cieślik, Namieśnik, & Konieczka, 2015; Kacprzak et al., 2017). A continuación, en la Figura 1, se presenta el diagrama de flujo de un proceso de tratamiento de aguas residuales convencional con dos líneas de tratamiento.

Figura 1. Diagrama de flujo de un sistema de tratamiento de aguas residuales convencional (elaboración propia)



Para llevar a cabo el proceso descrito anteriormente se necesitan tecnologías que consumen grandes cantidades de energía, por ello muchos autores califican el proceso de tratamiento de aguas residuales como un proceso intensamente energético (Chae & Kang, 2013; Frijns, Hofman, & Nederlof, 2013; Longo et al., 2016; Power, McNabola, & Coughlan, 2014). No obstante, existen diferencias según la tipología de tratamiento y su configuración, el tamaño de la planta, su edad, así como de las exigencias de calidad del agua tratada (Gu et al., 2017; Niu, Wu, Qi, & Niu, 2019; Venkatesh & Brattebø, 2011; Westerhoff, Yoon, Snyder, & Wert, 2005).

El principal factor que determina el consumo eléctrico de las instalaciones es el tipo de tecnología utilizada, siendo las tecnologías de cultivo fijo (biodiscos, filtros percoladores) las que presentan un menor consumo energético ya que no requieren de un aporte mecánico de oxígeno (Plappally & Lienhard, 2012). Generalmente la tecnología que presenta mayores consumos energéticos son los biorreactores de membranas que consumen aproximadamente 2,91 kWh/kg $DQO_{eliminada}$, seguido de los procesos de aireación prolongada, los sistemas de eliminación biológica de nutrientes, lagunas aireadas y fangos activos convencionales con un consumo de 1,30 kWh/kg $DQO_{eliminada}$, 1,20 kWh/kg $DQO_{eliminada}$, 0,74 kWh/kg $DQO_{eliminada}$, y 0,57 kWh/kg $DQO_{eliminada}$, respectivamente (Longo et al., 2016). Además, el proceso de depuración está influenciado por la presencia de economías de escala (Fraquelli & Giandrone, 2003; Guerrini, Andrea, Romano, & Campedelli, 2013; Hernández-Chover, Bellver-Domingo, & Hernández-Sancho, 2018; Hernández-Sancho, F., Molinos-Senante, & Sala-Garrido, 2011; Longo et al., 2016; Singh, Kansal, & Carliell-Marquet, 2016) las cuales pueden observarse a través del consumo energético de las instalaciones, de modo que, para un mismo tipo de tecnología de tratamiento, cuanto mayor es volumen de agua residual tratada menor cantidad de energía consume el proceso (Mizuta & Shimada, 2010; Niu et al., 2019; Wang et al., 2016). Por ejemplo, Longo et al. (2016) presenta una variación en el consumo energético de las instalaciones de 0,69 kWh/kg $DQO_{eliminada}$ en EDARs de más de 100.000 HE a 3,01 kWh/kg $DQO_{eliminada}$ en plantas que tratan menos de 2000 HE. Sin embargo, estos consumos energéticos pueden variar según distintos países (Wang et al., 2016), ya que los requerimientos de calidad del agua exigidos pueden cambiar.

Numerosos estudios apuntan que el actual consumo energético de las EDARs se verá acrecentado en los próximos años debido al crecimiento de la población, a la introducción de una nueva regulación sobre las aguas residuales, el incremento en los parámetros de calidad del agua tratada, así como el envejecimiento y deterioro de las instalaciones (Mo & Zhang, 2013). Las razones por las que se prevé un incremento en las exigencias de calidad del agua tratada se deben principalmente a: i) la incorporación en la normativa de la extracción de contaminantes emergentes (Power et al., 2014), y ii) el cambio climático, que incrementará la necesidad de hacer uso de fuentes de agua no convencionales, como el agua regenerada, para reducir la presión sobre los recursos hídricos en zonas de estrés hídrico (Englehardt et al., 2016). Esto obligaría a implementar las instalaciones con tecnologías de tratamiento más avanzadas que, respecto a las actuales, presentan un consumo energético más elevado (Westerhoff et al., 2005; Zwiener & Frimmel, 2000). Estos dos aspectos junto con el incremento en el precio de la energía eléctrica (Bodik & Kubaská, 2013; Gikas, 2017; Teixeira, Mendes, Murta, & Nunes, 2016), ha dado lugar a que en los últimos años se haya realizado un gran esfuerzo para reducir el consumo de energía de las instalaciones, haciendo especial hincapié en aquellas etapas del proceso que requieren un mayor consumo energético como es el tratamiento biológico que representa aproximadamente un 50-60% del consumo eléctrico de la instalación y el tratamiento de fangos que puede alcanzar entre un 15 y 25% (Gu et al., 2017).

Con el objetivo de reducir la dependencia energética de aquellos sectores que consumen grandes cantidades de energía y hacer frente a la escasez de recursos energéticos, el cambio climático, y el incremento de los costes energéticos en los procesos, en el año 2012 el Parlamento Europeo publicó la Directiva 2012/27/EU, sobre eficiencia energética, con la que para el 2020 se pretende haber reducido en un 20% las emisiones de gases de efecto invernadero, incrementado en un 20% la producción de energía mediante fuentes renovables y mejorado en un 20% en la eficiencia energética (Directive, 2012). En el sector del tratamiento de aguas residuales entre las medidas aplicadas para reducir el consumo energético destacan la sustitución de sistemas de aireación de turbinas por sistemas de aireación de burbujas y sistemas de control de aireación que permiten ajustar los requerimientos de oxígeno según el volumen de agua tratada y la cantidad de materia orgánica disuelta en el agua (Frijns et al., 2013; Henriques & Catarino, 2015; Zhou, Ang, & Poh, 2008). Autores como Stiwell et al. (2010) asumen que solo mediante la optimización de los sistemas de bombeo y de aireación se podría reducir entre el 3 y el 6 % del consumo energético global en el sector de depuración, mientras que el estudio realizado por Liu et al. (2012) va un poco más allá y estima que la aplicación de medidas de eficiencia energética podrían suponer un 10-30% de ahorro energético, con un plazo de amortización de entre 1 y 5 años. Otra forma de garantizar la sostenibilidad de las instalaciones desde el punto de vista energético y que ha despertado un gran interés en las últimas décadas ha sido la aplicación de los principios de la economía circular (European Commission, 2015), de forma que un subproducto generado en el propio proceso de depuración, como son los fangos, se convierte en un recurso para la producción de energía mediante los sistemas de cogeneración (Gikas, 2017; Silvestre, Fernández, & Bonmatí, 2015). Con este aprovechamiento energético las plantas de tratamiento de aguas residuales podrían llegar a ser autosuficientes energéticamente (Gu et al., 2017; Gude, 2015) e incluso producir más energía de la consumida.

La gestión energética y el uso de tecnologías más eficientes son clave para reducir el consumo energético y los costes operacionales, y garantizar la sostenibilidad del proceso de tratamiento de aguas residuales. Sin embargo, existen otros factores menos estudiados, y que son abordados en la presente investigación, que también pueden afectar al consumo energético y los costes operacionales que no requieren de aspectos técnicos sino de un cambio en el modelo de gestión o de planteamiento en el sector, como son el sobre o infradimensionamiento y el envejecimiento de los equipos y de las instalaciones en general.

Las instalaciones de tratamiento de aguas residuales están diseñadas para tratar un volumen o una carga de contaminantes teórica, con lo cual todos los equipos, incluidos los elementos tecnológicos, los sistemas de bombeo y otros dispositivos de la planta estarán preparados para tratar con estas características iniciales. Sin embargo, en algunos casos el caudal de diseño teórico puede llegar a distar mucho del real porque las expectativas de crecimiento poblacional o desarrollo industrial no llegan a cumplirse. De forma que estas diferencias pueden causar ineficiencias en el proceso, ya que las instalaciones y los equipos que son demasiado grandes o de tamaño insuficiente pueden funcionar incorrectamente, disminuyendo la calidad del agua tratada y aumentando los costos operativos en términos de energía, reactivos, mantenimiento y personal (Campos & von Sperling, 1996). Silva y Rosa (2015) afirman que cuanto más cercano sea el volumen real tratado al de diseño, más eficiente será el proceso de depuración. Un ejemplo de este efecto suele darse EDARs de áreas turísticas, las cuales solo funcionan a su capacidad máxima durante un corto período del año, estando sobredimensionadas la mayor parte del tiempo. En consecuencia, Sala-Garrido et al. (2012) encuentran que las EDARs sometidas a estacionalidad son menos eficientes que aquellas que no lo están y tienen mayor regularidad en el caudal tratado.

Otro aspecto relevante es el envejecimiento de las instalaciones, ya que con el paso de los años los equipos se van deteriorando y pierden rendimiento, de modo que para mantener el nivel de producción requieren un mayor consumo energético (Daw, Hallett, DeWolfe, & Venner, 2012; Mo & Zhang, 2013; Rojas & Zhelev, 2012). Casi treinta años después de la publicación de la Directiva 91/271/ CE, la preocupación por el estado de estas instalaciones ha incrementado en muchos países desarrollados, ya que muchos de los elementos que conforman estas infraestructuras ya han llegado o están llegando al final de su vida útil y sin embargo existe una falta de inversión en mantenimiento y renovación de los equipos y la infraestructura (AEAS, 2014; AEAS, 2016; Davis, Sullivan, Marlow, & Marney, 2013; Salman, 2010; Tafuri & Selvakumar, 2002; Younis & Knight, 2010). Además, el deterioro también tiene un impacto directo en el proceso, ya que la calidad del servicio disminuye, lo que genera mayores quejas por parte de los usuarios (Molinos-Senante, Maziotis, & Sala-Garrido, 2016) y aumenta el riesgo de incumplimiento de los estándares de calidad del agua tratada.

Por lo tanto, las instalaciones ineficientes y deterioradas ponen en riesgo la *ecoeficiencia* definida por el Consejo Empresarial Mundial para el Desarrollo Sostenible. En consecuencia, un proceso eco-eficiente permite satisfacer las necesidades humanas a través de servicios y bienes económicos competitivos, que deben producirse haciendo un uso óptimo de los recursos al tiempo que reducen los impactos ambientales durante su ciclo de vida a niveles que deben ser iguales o inferiores a la capacidad de carga estimada de la Tierra (Iribarren, Hospido, Moreira, & Feijoo, 2011; Lorenzo-Toja et al., 2016; Schmidheiny & Zorraquin, 1998; Van Caneghem, Block, Van Hooste, & Vandecasteele, 2010).

2. Objetivos

El objetivo general de la presente tesis doctoral es el análisis de los costes energéticos de las Estaciones Depuradoras de Aguas Residuales a nivel global de la planta y su relación con distintas características físicas u operacionales de las instalaciones. Dentro del objetivo general pueden diferenciarse los siguientes objetivos específicos:

1. Evaluación de la eficiencia del proceso de depuración mediante un modelo de optimización lineal capaz de priorizar el input energético.
2. Obtención de un indicador capaz de medir el infra o sobredimensionamiento de las instalaciones y evaluar sus efectos sobre el consumo energético.
3. Analizar los efectos del paso del tiempo sobre el coste energético de las instalaciones.
4. Modelizar el coste energético teniendo en cuenta el infra o sobredimensionamiento para distintos tamaños de planta, y el envejecimiento de las instalaciones.

3. Metodología

En el año 2000, la Directiva Marco del Agua (DMA), sobre la protección y la calidad de las masas de agua, estableció la necesidad de abordar la gestión de los recursos hídricos desde un punto de vista multidisciplinar, incluyendo el uso de instrumentos económicos capaces de evaluar los beneficios ambientales y los costes asociados a la gestión del agua. En este sentido, la realización de estudios económicos para el diseño e implementación de políticas eficientes para la gestión de los recursos hídricos es una necesidad cada vez más reconocida.

En el ARTICULO 1, *"Efficiency assessment of wastewater treatment plants: A data envelopment analysis approach integrating technical, economic, and environmental issues"*, para evaluar el potencial de mejora que presentan las instalaciones en cuanto al coste energético se utiliza la metodología denominada Análisis Envolvente de Datos (DEA), la cual ha sido utilizada en distintos ámbitos como por ejemplo en la evaluación de eficiencia de bancos, aerolíneas, equipos de futbol, universidades (Casu & Molyneux, 2003; Chen, Skully, & Brown, 2005; Fandel, 2007; Kuah & Wong, 2011; Lozano & Gutiérrez, 2014; Sala-Garrido, R., Liern-Carrión, Martinez, & Boscá, 2009; Staub, da Silva e Souza, Geraldo, & Tabak, 2010), así como en la evaluación de la eficiencia del tratamiento del agua residual con distintos propósitos(Guerrini, A., Romano, Leardini, & Martini, 2015; Hernández-Chover et al., 2018; Hernández-Sancho et al., 2011; Hernández-Sancho, Francesc & Sala-Garrido, 2009; Lorenzo-Toja et al., 2018; Lozano & Gutiérrez, 2014; Sala-Garrido, Ramón, Hernández-Sancho, & Molinos-Senante, 2012). Pese a que existen números modelos DEA, la premisa de todos ellos es detectar dentro de un conjunto de unidades (unidades de toma de decisión, DMU) aquellas que sean más eficientes teniendo en cuenta la cantidad de productos consumidos (inputs) y productos generados (outputs) en el proceso.

Se trata de una metodología no paramétrica, en la que las unidades eficientes definen la llamada "frontera de eficiencia" estableciendo la cantidad mínima de recursos con los que una unidad podría operar y/o la cantidad máxima de productos que ésta podría ser capaz de generar. El nivel de eficiencia del resto de unidades se calcula midiendo la distancia a la frontera, dando como resultado un índice de eficiencia relativo que va a depender siempre de la muestra de estudio. En el caso particular del ARTICULO 1, se utiliza el modelo desarrollado por Tone (2011) denominado Medida Ponderada Basada en Holguras, también conocido por sus siglas en ingles WSBM ("Weighted Slacks Based Measure"), cuyas principales características son que asume que la reducción de inputs y outputs no son proporcionales, propio de los modelos no radiales, y además permite asignar ponderaciones a los inputs y outputs del modelo de eficiencia, permitiendo priorizar la reducción o el aumento de éstos (Barros, Managi, & Matousek, 2012). Autores como Murillo-Zamorano (2004) consideran que el hecho de poder introducir ponderaciones en el modelo aporta subjetividad a la evaluación, pero si se adopta un criterio objetivo para la determinación de los pesos, como Chen et al. (2015), esto supone una ventaja ya que permite discriminar entre las diferentes variables aportando mayor riqueza al estudio.

En este primer artículo, para evaluar la eficiencia de un grupo de $J = \{1, 2, \dots, j\}$ EDARs que utilizan *m* inputs y *s* outputs, para una EDAR$_j$ se define un vector input $x_j = \left(x_{1j}, x_{2j}, \dots, x_{mj}\right)$ y un vector output $y_j = \left(y_{1j}, y_{2j}, \dots, y_{sj}\right)$. Las variables utilizadas como input están representadas por los costes operacionales del proceso, los cuales se dividen en: (i) costes de energía, definidos como el coste del consumo eléctrico utilizado en el tratamiento del agua residual; (ii) costes de personal, incluyen los salarios de técnicos y operadores de las plantas; (iii) costes de reactivos, son todos aquellos costes en los que incurren los compuestos químicos necesarios para el tratamiento; (iv) costes de mantenimiento, comprende los costes derivados del mantenimiento de los equipos e infraestructura; (v) costes de residuos, se refieren a los costes asociados a la gestión de residuos y lodos; y (vi) otros costes, incluye diferentes tipos de costes, como material de oficina o laboratorio, gestión administrativa, entre otros. Mientras que las variables de output las constituyen los contaminantes eliminados del agua residual: (i) la cantidad de sólidos suspendidos (SS) eliminados; (ii) la cantidad de materia orgánica e inorgánica eliminada medida como Demanda Química de Oxígeno (DQO); (iii) la cantidad de nitrógeno eliminado (N); y (iv) la cantidad de fósforo extraído (P).

Una vez introducidas las variables input y output, se define el conjunto de posibilidades de producción de la siguiente manera (Tone, 2011):

$$P = \left\{(x, y) \middle| x_i \geq \sum_{j=1}^{n} x_{ij} \ (\forall i), 0 \leq y_r \leq \sum_{j=1}^{n} y_{rj} \ (\forall r),\ e\lambda = 1, \lambda \geq 0\right\} \tag{1}$$

dónde e es un vector fila en el que todos los elementos son iguales a uno y $\lambda = \left(\lambda_1, \lambda_2, \dots, \lambda_j\right)$ es un vector de intensidad.

La introducción de las holguras permite transformar las desigualdades de la Ecuación 1 en las siguientes igualdades (Tone, 2010):

$$x = \sum_{j=1}^{n} \lambda_j \, x_j + s^- \tag{2}$$

$$y = \sum_{j=1}^{n} \lambda_j \, y_j - s^+ \tag{3}$$

$$s^- \geq 0, \quad s^+ \geq 0 \tag{4}$$

Donde $s^- = (s_1^-, s_2^-, \ldots, s_m^-) \in R^m$ y $s^+ = (s_1^+, s_2^+, \ldots, s_s^+) \in R^s$ son las holguras de los inputs y outputs, respectivamente.

Según Tone (2011), el modelo WSBM se define de la siguiente manera:

$$\rho_{IO}^* = min_{\lambda, s^-, \lambda s^+} \frac{1-(\frac{1}{m})\sum_{i=1}^{m}\frac{w_i^- s_i^-}{x_{io}}}{1+(\frac{1}{s})\sum_{r=1}^{s}\frac{w_r^+ s_r^+}{y_{ro}}} \tag{5}$$

s.t:

$$x_{io} = \sum_{j=1}^{n} x_{ij}\, \lambda_j + s_i^- \qquad (i = 1, \ldots, m)$$

$$y_{ro} = \sum_{j=1}^{n} y_{rj}\, \lambda_j - s_r^+ \qquad (r = 1, \ldots, s)$$

$$\sum_{j=1}^{n} \lambda_j = 1$$

$$\lambda_j \geq 0\ (\forall j), s_i^- \geq 0\ (\forall i), s_r^+ \geq 0\ (\forall r)$$

Con $\sum_{i=1}^{m} w_i^- = m$ y $\sum_{r=1}^{s} w_r^+ = s$. Donde w_i y w_r reflejan la importancia del input i y del output r. Para definir las ponderaciones correspondientes a cada una de las variables input y output, se ha adoptado un criterio ambiental en el que inputs y outputs son ponderados según el impacto ambiental que generan. Para ello se han tomado como referencia los trabajos realizados por Hernández-Sancho et al. (2010) y Molinos-Senante et al. (2015), los cuales mediante el cálculo de los precios sombra otorgan un valor económico que simboliza el impacto ambiental que cada uno de los contaminantes del agua residual generaría si no fuese eliminado del agua tratada, y el impacto asociado a los gases de efecto invernadero resultantes del consumo energético de las instalaciones, los cuales aparecen detallados en la Tabla 1. Además, este criterio de ponderación también tiene en cuenta el destino del agua tratada, ya que el efecto de los contaminantes es distinto según la calidad del medio receptor.

Tabla 1. Precios sombra utilizados para el cálculo de las ponderaciones

Destino agua tratada	SS	DQO	N	P	GEI electricidad
Rio	0,005	0,098	16,353	30,944	0,124
Sea	0,001	0,010	4,612	7,533	0,018
Humedal	0,010	0,122	65,209	103,424	0,159
Reutilización	0,010	0,140	26,182	79,268	0,265

Fuente: Hernández-Sancho et al. (2010) and Molinos-Senante et al. (2015)

De modo que haciendo uso de los valores anteriores y conociendo el volumen y el destino del agua tratada de cada una de las EDARs se obtienen los pesos que se introducen en la ecuación para cada variable input y output. Siguiendo la función objetivo presentada en la Ecuación 5 las unidades más eficientes serán aquellas que con menos costes operacionales consigan extraer una mayor cantidad de contaminantes, priorizando aquellos con mayor impacto ambiental. De forma que una EDAR es eficiente si y solo si el índice de eficiencia es igual a 1 y la holgura (distancia a la frontera) es 0. Por el contrario, si el índice de eficiencia es menor que 1, la EDAR se considera ineficiente porque podría reducir sus costes (costes operacionales) teniendo en cuenta la cantidad de contaminantes que extrae del agua residual. Además, el modelo se aplica bajo rendimientos variables de escala, ya que debido a la presencia de economías de escala en el proceso de depuración un cambio en los inputs no produce cambios proporcionales en los outputs (Guerrini et al., 2015; Molinos-Senante, Hernández-Sancho, & Sala-Garrido, 2014; Sala-Garrido et al., 2012) .

Una vez evaluado el potencial energético de mejora que presentan las instalaciones, en los artículos *"The relevance of the design characteristics to the optimal operation of wastewater treatment plants: energy cost assessment"* y *"Modelling the energy costs of the wastewater treatment process: The influence of the aging factor",* respectivamente ARTICULOS 2 y 3 del presente compendio, se analiza qué variables y en qué medida están relacionadas con el coste energético para su posterior modelización. La obtención de una función capaz de estimar los costes operacionales del proceso de tratamiento del agua residual ha sido objeto de análisis en estudios previos como Gonzalez-Serrano et al. (2005), Guo et al. (2013) o Hernandez-Sancho et al.(2011), con el fin de obtener un mayor conocimiento de la estructura de costes del proceso y poder hacer una predicción ante distintos escenarios. Guo et al.(2013) afirman que los costes operacionales y de mantenimiento del proceso de depuración de aguas residuales pueden ser representados mediante la función de coste $C = \beta \cdot Q^{\alpha}$, donde C es el coste del proceso, Q representa la escala del proceso, y β y α son dos constantes del modelo. Se trata de una ecuación capaz de incluir el efecto de las economías de escala en la estimación de los costes. Sin embargo, el consumo energético y su coste dependen de muchas otras variables que deben tenerse en cuenta cuando se pretende hacer una modelización. Por ello, en este trabajo se utiliza la ecuación desarrollada por Hernández-Sancho et al. (2011) que reconoce la influencia de las economías de escala en el proceso y además permite introducir distintas variables explicativas del coste en el modelo de la siguiente forma $C = A \cdot Z^b \cdot e^{\sum \alpha_i x_i}$, donde C es el coste (€/año), Z y x_i son distintas variables independientes del modelo; y A, b y α son los coeficientes.

La modelización del coste energético se lleva a cabo mediante el uso de la regresión lineal, para lo cual se hace una trasformación de la ecuación mencionada anteriormente de la siguiente forma:

$$\ln C = \ln A \cdot\ b \cdot \ln Z + \sum \alpha_i x_i$$

Las técnicas de regresión permiten analizar estadísticamente la relación entre la variable dependiente, representada por el coste energético, y un conjunto de variables independientes, generalmente variables técnicas como pueden ser el volumen de agua tratada, la cantidad de contaminantes eliminados en el proceso, rendimientos, etc. De modo que mediante el uso de diferentes técnicas estadísticas se evalúa la relación de las variables con el coste energético para obtener una ecuación robusta capaz de estimar el coste energético. Para ello se utiliza el programa estadístico SPSS originalmente utilizado en el ámbito de las ciencias sociales, pero que en los últimos años se ha extendido a muchos otros ámbitos como la medicina o las finanzas. Haciendo uso de las distintas técnicas disponibles en este software se selecciona la mejor combinación de variables capaz de explicar el modelo, que vendrá definida por la siguiente información estadística: (1) el valor de significatividad de las variables, (2) la R^2 ajustada, y (3) el error estándar de las estimaciones. Las condiciones para que el modelo seleccionado sea bueno es que todas las variables del modelo sean significativas dentro de un intervalo de confianza del 95%, de modo, que el p-valor de las variables debe ser inferior a 0,05 (una cola). En cuanto a la R^2 ajustada, que representa la bondad de ajuste de la función, puede tomar valores de entre 0 y 1, siendo preferibles los modelos con la R^2 ajustada más elevada. Y finalmente, en combinación con los parámetros anteriores, el error estándar debe ser el menor posible. Además de estos tres criterios, la fiabilidad del modelo viene garantizada por el cumplimiento de una serie de hipótesis básicas que todos los modelos de regresión lineal deben cumplir, y que son:

1. No-colinealidad entre las variables, es decir, las variables explicativas deben ser independientes, de modo que no existe una relación lineal exacta entre ninguna de las ellas. Este supuesto se analiza a través del factor de inflación de la varianza (FIV), o la tolerancia, que es 1/FIV. De acuerdo con Kleinbaum et al. (1988), existen problemas de colinealidad entre las variables cuando el FIV presenta valores superiores a 10.
2. Normalidad de los residuos, los residuos de cada una de las variables o del conjunto de variables que constituyen el modelo se distribuyen normalmente con media 0. El comportamiento normal de los residuos se estudia a partir del cálculo de los residuos estandarizados y puede ser analizado gráficamente o bien estadísticamente a través del

test de Kolmogrov-Smirnof (Dodge, 2008) . Dentro de un intervalo de confianza del 95%, si el p-valor es superior a 0,025 (dos colas) no se puede rechazar la hipótesis nula, que asume normalidad en los residuos.

3. Independencia de los residuos, los residuos del modelo deben ser aleatorios e independientes entre sí. La independencia de los residuos se comprueba mediante el estadístico de Durbin-Watson (Dodge, 2008). El resultado del estadístico DW puede oscilar entre 0 y 4, y la horquilla de valores en torno a los cuales se puede asumir independencia se encuentra entre 1,5 y 2,5, mientras que valores del estadístico superiores a 2,5 indican una autocorrelación positiva, mientras que los inferiores a 1,5 indican que la autocorrelación es negativa.
4. Homocedasticidad, para cada valor de la variable independiente, la varianza de los residuos debe ser constante, si por el contrario la varianza de los residuos es aleatoria, el modelo presenta problemas de heterocedasticidad. La presencia o no de homocedasticidad en el modelo se comprueba estadísticamente mediante el Test Breusch-Pagan (Baltagi, 2008). La hipótesis nula del test es que el modelo presenta homocedasticidad, de modo que dentro de un intervalo de confianza del 95%, si el p-valor es inferior a 0,05, se rechaza la hipótesis nula, concluyendo que el modelo presenta problemas de heterocedasticidad.

4. Principales resultados

A partir del estudio de eficiencia realizado en el ARTICULO 1 para una muestra de 49 estaciones depuradoras de aguas residuales situadas en la Comunidad Valenciana se obtiene un índice de eficiencia para cada una de ellas dando máxima priorización a la reducción de costes energéticos y la eliminación de nutrientes, de modo que, aquellas instalaciones que con un menor consumo energético consigan eliminar más cantidad de nutrientes serán las más eficientes. De esta forma se consigue un indicador objetivo que permite evaluar la eficiencia del proceso de depuración considerando aspectos técnicos, económicos y ambientales.

Para ello se ha aplicado el modelo de eficiencia WSBM desarrollado por Tone (2011) que permite asignar ponderaciones a los inputs y outputs del modelo de eficiencia. En la Tabla 2 se presentan las ponderaciones calculadas utilizando los precios sombra obtenidos en los trabajos de Hernández-Sancho et al. (2010) y Molinos-Senante et al. (2015) y utilizadas para construir el indicador de eficiencia siguiendo la metodología descrita en el apartado anterior.

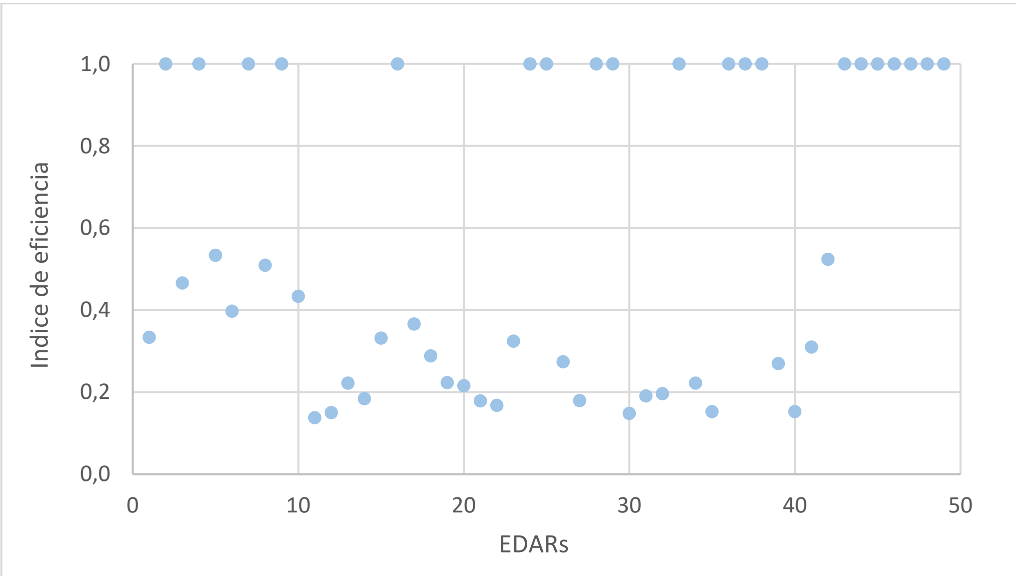
Tabla 2. Ponderaciones resultantes para las variables input y output

PONDERACIÓN INPUTS						PONDERACIÓN OUTPUTS			
ENERGÍA	PERSONAL	REACTIVOS	MANTENIMIENTO	RESIDUOS	OTROS	SS	DQO	N	P
25,3381	14,9324	14,9324	14,9324	14,9324	14,9324	0,.0095	0,1604	32,686	67,1441

Cabe tener en cuenta que la suma de las ponderaciones de las variables input y output deben sumar 100 respectivamente. Tal y como se puede observar en la Tabla 2, la variable input con mayor peso es la energía, ya que el resto de las variables bien no presentan un impacto ambiental como es el coste de personal, mantenimiento y otros, o bien porque en caso de tenerlo, como son los reactivos y los residuos, resulta difícil de evaluar de forma objetiva, lo cual constituye la principal limitación del artículo. En cuanto a las variables output se obtiene que ambos nutrientes, fósforo y nitrógeno, tienen pesos considerablemente mayores que el resto, 67,1441 y 32,6860 respectivamente, ya que una elevada concentración de estos contaminantes en el medio receptor puede causar problemas de eutrofización (Howarth, 2008; Kontas, Kucuksezgin, Altay, & Uluturhan, 2004; Smith, Tilman, & Nekola, 1999). Les siguen en importancia la DQO con un peso de 0,1604 y, finalmente, los SS con 0,0095.

Una vez aplicado el modelo, se obtiene un índice de eficiencia para cada una de las instalaciones, los cuales se representan en la Figura 2. Observamos que el 41% de la muestra es eficiente, mientras que el resto de las instalaciones son ineficientes con un índice promedio de 0,2784. Este índice de eficiencia constata el elevado potencial de mejora que presentan las EDARs de la muestra evaluada.

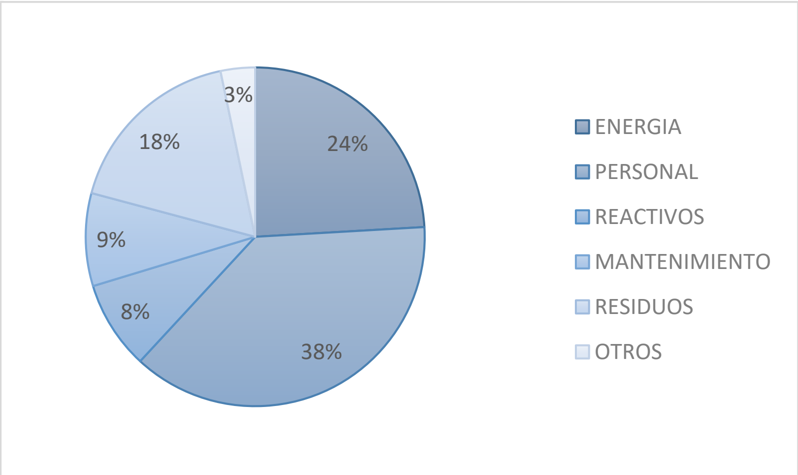
Figura 2. Índice de eficiencia para cada instalación



Para garantizar que los resultados obtenidos no están sesgados por los pesos atribuidos a cada input y output, se lleva a cabo un análisis de sensibilidad en el que se calcula la eficiencia de cada una de las EDARs con variaciones en el peso de la energía de ± 10% ± 25% ± 50% ± 75% y ± 100%. Este análisis de sensibilidad se centra en peso asociado al input energía ya que esta es la partida de costes objeto de estudio, y éste ha sido el único ítem ponderado de los inputs mediante el cálculo de los precios sombra del CO_2, y por lo tanto puede estar sometido a mayor incertidumbre. Tras realizar el análisis de eficiencia para cada uno de los escenarios propuestos anteriormente se observa que los cambios en los pesos de energía no afectan significativamente a los resultados de los índices de eficiencia de la muestra de EDARs evaluadas, siendo eficientes las mismas instalaciones que eran en el escenario original. De modo que, pese a que existen grandes variaciones en el peso otorgado al input energía, los índices de eficiencia permanecen casi constantes. Por lo que puede concluirse que los valores de eficiencia de las EDARs no dependen del peso atribuido a los costes de energía (ver anexo A).

Al tratarse de un modelo no radial, éste permite analizar individualmente el potencial de mejora de cada una de las variables del vector de inputs. Puesto que todas las instalaciones cumplen con los criterios de calidad del agua tratada establecidos en la normativa, el foco de atención se centra en los costes, es decir, cuanto se podrían reducir los costes de tratamiento si las plantas ineficientes incrementasen su eficiencia. Desde este punto de vista, la Figura 3 muestra que las partidas que mayores ahorros podrían aportar son personal y energía con un 38% y 25% respectivamente, seguidas de la gestión de residuos, mantenimiento, reactivos y otros costes con un 18%, 9%, 8% y 3%, respectivamente.

Figura 3. Potencial de ahorro por partida de costes



Los resultados anteriores muestran que el consumo energético presenta un elevado potencial de mejora, al igual que concluyen Molinos-Senante et al. (2014) y Longo et al.(2016) en los respectivos estudios. De tal forma que para poder optimizar el consumo energético es necesario conocer qué factores lo determinan y poder actuar sobre ellos.

4.1 *Análisis de la influencia del sobre o infradimensionamiento de las instalaciones en los costes energéticos*

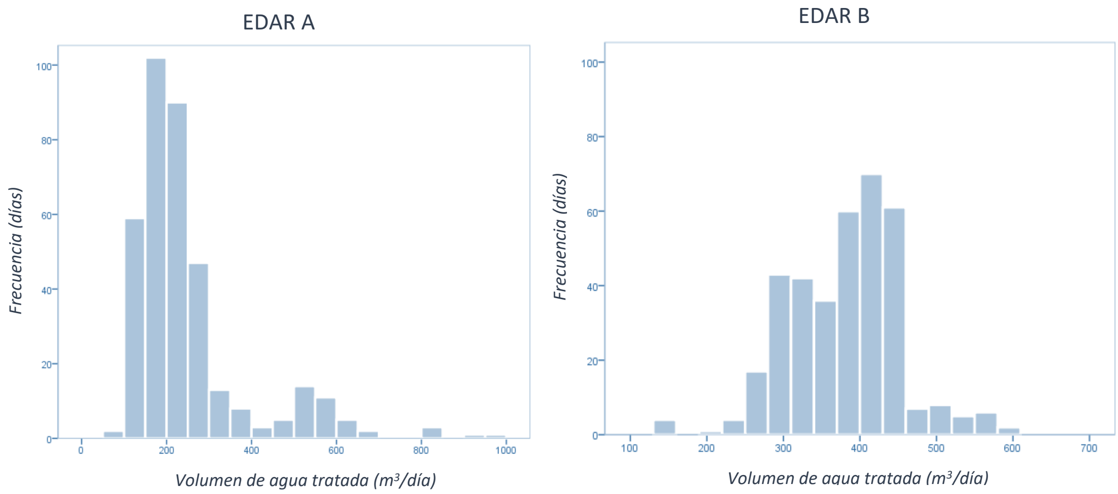
Para evaluar cómo influye el sobredimensionamiento o infradimensionamiento sobre el coste energético de las instalaciones en el ARTICULO 2, se construye un indicador operacional, cuyo objetivo es representar cuanto se aleja el caudal real del de diseño. Matemáticamente este indicador se calcula con la mediana de las diferencias diarias entre el caudal real y de diseño.

$$Z = \frac{|\, q - Q \,|}{Q} \cdot 100$$

El uso de la mediana permite detectar si la diferencia entre ambos caudales es un comportamiento habitual o puntual, ya que nos informa de cuál es la tendencia durante un periodo de 183 días, es decir, medio año. El indicador operacional puede alcanzar un valor mínimo de 0 cuando no existe diferencia entre el caudal real y el de diseño, y aumentará a medida que incrementa la diferencia entre ellos, hasta un valor máximo de 1.

Este indicador nos permite diferenciar patrones operacionales distintos, tal y como se puede observar en la Figura 4, en la cual se representa la frecuencia para el caudal real diario de la EDAR A que fue diseñada para tratar un volumen de 1.140 m^3/día, y la EDAR B, cuyo caudal de diseño es de 450 m^3/día. El indicador operacional (Z) resultante para la EDAR A es de 0,82, lo cual indica que durante la mayor parte del tiempo la planta no opera conforme a las características de diseño. Por el contrario, el caudal real diario tratado por la EDAR B es mucho más próximo al de diseño, quedando reflejado en el índice operacional Z que es de 0,16.

Figura 4. Histograma para el caudal real de dos EDARs



El índice operacional Z descrito anteriormente, como se puede observar en el ARTICULO 2, se calcula para un total de 156 EDARs, las cuales se agrupan según el número de habitantes equivalentes tratados en: i) pequeñas, consta de 58 instalaciones con menos de 2,000 habitantes equivalentes.; ii) medianas, incluye un total de 62 plantas que tratan entre 2.000 y 20.000 habitantes equivalentes; y iii) grandes, los constituyen 36 EDARs de más de 20,000 habitantes equivalentes. Para establecer los grupos se ha tomado como referencia el estudio de Benedetti et al. (2008), en el que se encuentran diferencias considerables en los costes operacionales fijos y variables de los tres grupos. En la Tabla 3 se presenta un resumen de los valores del índice Z obtenidos, destacando la gran cantidad de instalaciones (46,55 % de las pequeñas, 48,19% de las medianas y 41,67% de las grandes) que habitualmente están operando con una diferencia del 50% respecto al caudal de diseño. Otro aspecto que también cabe señalar es que el grupo de EDARs grandes son las que menores diferencias presentan y, por lo tanto, están operando en unas condiciones más próximas a las de diseño.

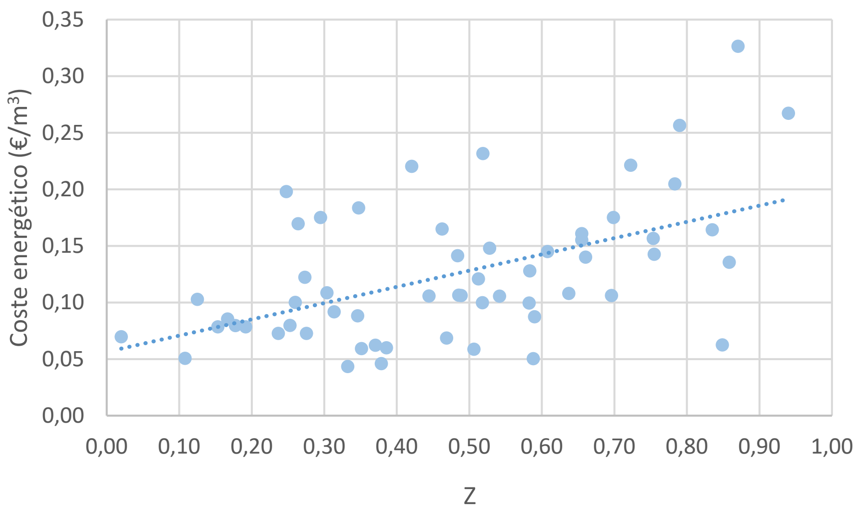
Tabla 3. Resumen de los valores obtenidos del parámetro operacional para cada una de las EDARs de la muestra

	Nº de EDARs (%)			
	Z > 0,5	**Z > 0,6**	**Z > 0,7**	**Z > 0,8**
PEQUEÑAS	46,55 %	29,31 %	17,24 %	8,60 %
MEDIANAS	48,19 %	32,25 %	14,50 %	6,45 %
GRANDES	41,67 %	25,00 %	8,33 %	0,00 %

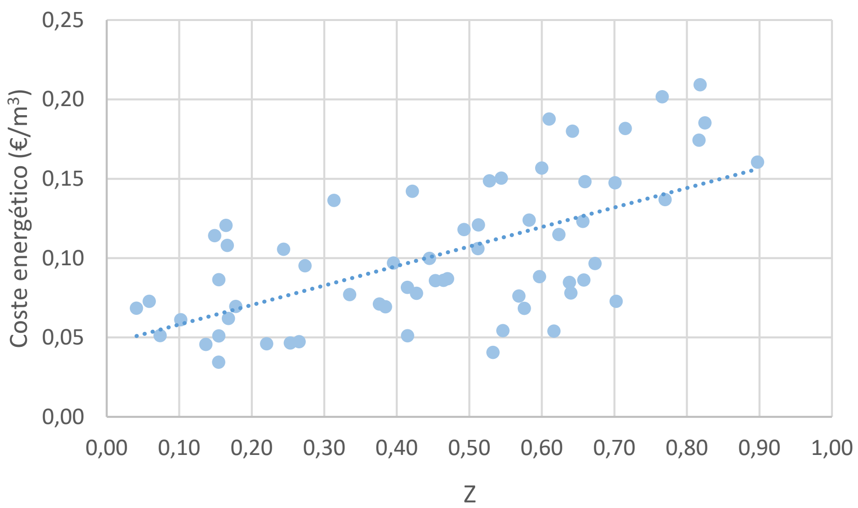
A continuación, se analiza la relación entre el índice operacional Z y el consumo energético. En primer lugar, en la Figura 5 se presenta un gráfico de dispersión para cada uno de los grupos según el tamaño de planta, en los que se puede observar que existe una tendencia lineal positiva entre ambas variables, de modo que cuanto mayor es la diferencia entre el caudal real y de diseño en condiciones habituales mayor es el coste energético de las instalaciones.

Figura 5. Relación entre el parámetro Z y el coste energético (€/m³)

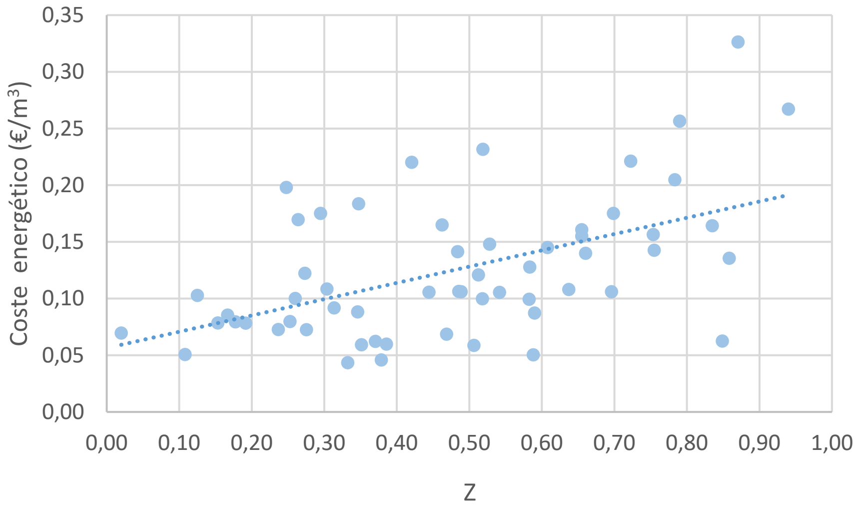
a) EDARs pequeñas



b) EDARs medianas



c) EDARs grandes



Esta relación y su intensidad son también analizadas estadísticamente (Tabla 4) mediante el test de correlación de Spearman, que permite corroborar la existencia de una correlación positiva entre el índice operacional (Z) y el consumo energético con un nivel de confianza del 99% (nivel de p-valor menor que 0,01). De acuerdo con Silva y Rosa (2015) el hecho de que el caudal real no se ajuste al de diseño de la planta hace que los equipos no operen en su óptimo, repercutiendo negativamente sobre el consumo energético y los costes. No obstante, cabe tener en cuenta que éste no es el único factor que influye en el consumo energético, lo cual explica que el grado de intensidad de la correlación sea moderado.

Tabla 4. Test de correlación entre el índice operacional Z y el coste energético (€/m^3)

	PEQUEÑAS	**MEDIANAS**	**GRANDES**
Correlación	0,481	0,597	0,552
Significatividad	0,001	0,001	0,001

Una vez se ha comprobado que los desajustes entre el caudal real y el de diseño de las instalaciones influyen en el coste energético, siguiendo la metodología descrita en el apartado *3 Metodología*, en el ARTICULO 2 se desarrolla una función de costes que modeliza el coste energético de las plantas de tratamiento de aguas residuales a través de una serie de variables técnicas del proceso como puede ser el volumen de agua tratada, la cantidad de SS eliminados, los rendimientos de DQO y/o DBO, la cantidad de nutrientes eliminados, así como el propio indicador operacional (Z). Puesto que durante el estudio se observaron diferencias estadísticamente significativas en el coste energético de instalaciones de distinto tamaño (según el número de habitantes equivalentes) se desarrolla una función de costes para cada uno de los tres tamaños de planta (Tabla 5).

Tabla 5. Funciones de coste para estimar el coste energético según el tamaño de las instalaciones

	Funciones de coste	R^2
PEQUEÑAS	$CE = 1{,}983 \cdot 10^{6} \cdot V^{0{,}717}\, e^{(-14{,}327\, DBO\, +\, 0{,}660\, Z)}$	0,599
MEDIANAS	$CE = 1{,}854 \cdot 10^{-5} \cdot V^{0{,}859}\, e^{(10{,}152\, DBO\, +\, 0{,}625\, Z)}$	0,851
GRANDES	$CE = 3{,}949 \cdot 10^{-7} \cdot V^{0{,}746}\, e^{(15{,}876\, DBO\, +\, 0{,}693\, Z)}$	0,791

Donde, CE es el coste de energía en €/año; V es el volumen de aguas residuales tratadas por una planta expresado en m^3/año; DBO es el rendimiento de eliminación de la DBO en porcentaje, y Z es el índice operacional que relaciona el caudal de diseño con el real.

Para la validación del modelo, se comprueba que se cumplen una serie de características e hipótesis. En primer lugar, todas las variables explicativas de los modelos desarrollados para cada uno de los grupos de plantas son significativas con un nivel de confianza del 95%. Y, además, se cumplen las cuatro hipótesis básicas de los modelos de regresión descritas en el apartado de metodología (Tabla 6), cuyos resultados se pueden consultar en el Anexo B.1.

Tabla 6. Cumplimiento de las hipótesis básicas del modelo (Anexo B.1)

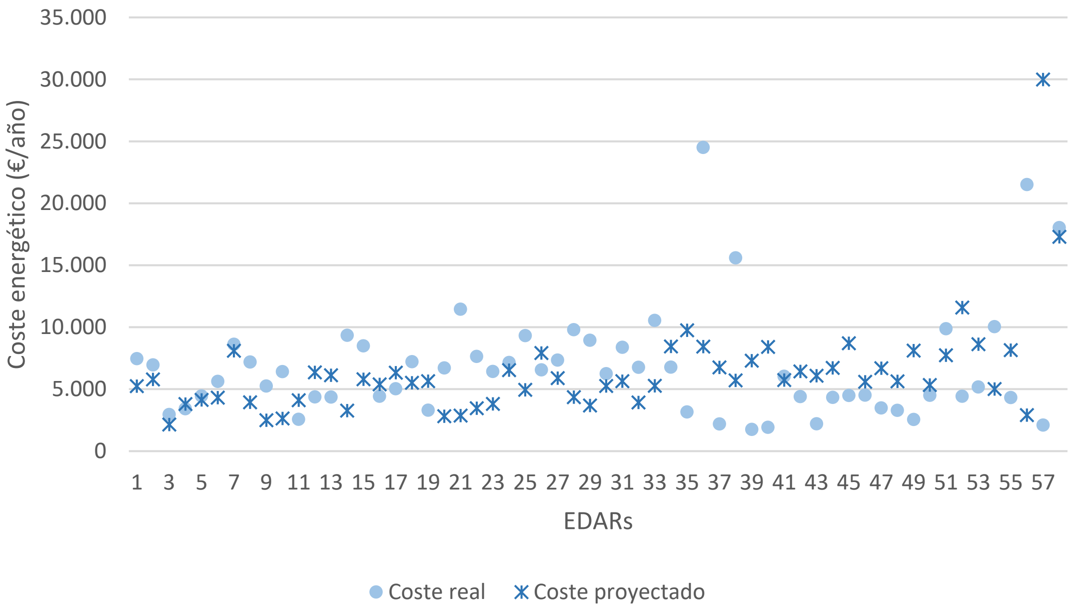
	PEQUEÑAS	MEDIANAS	GRANDES
No colinealidad entre las variables	✓	✓	✓
Normalidad de los residuos	✓	✓	✓
Independencia de los residuos	✓	✓	✓
Homocedasticidad	✓	✓	✓

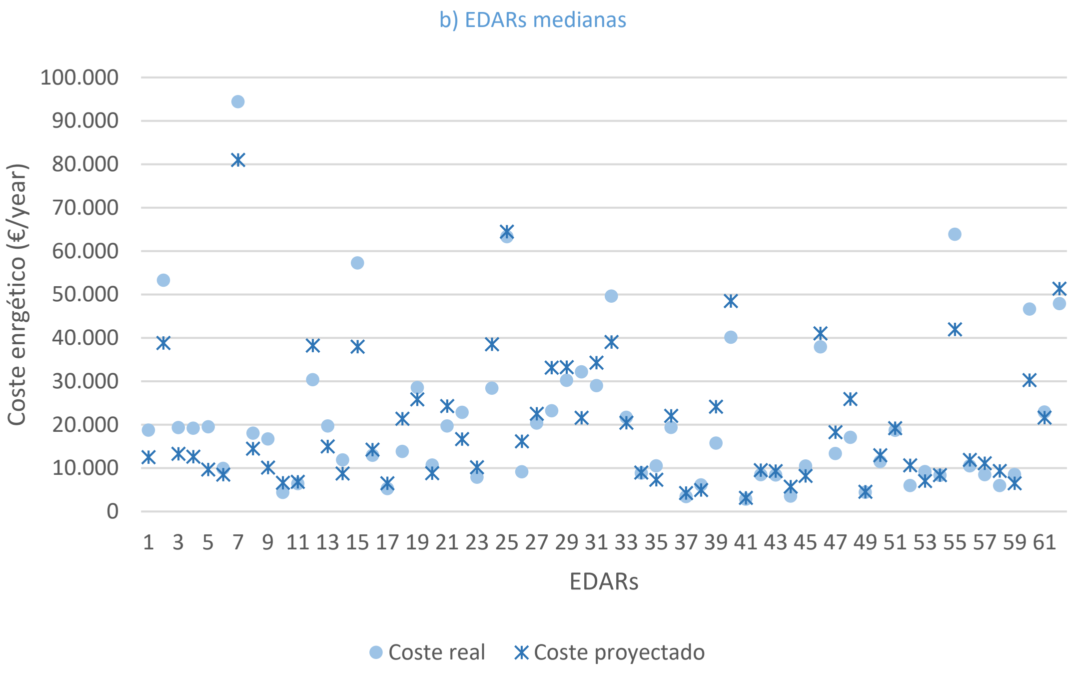
Una vez validadas todas las hipótesis se puede confirmar que el coste energético de las estaciones depuradoras depende directamente del volumen de agua tratada, la cantidad de DBO eliminada y del índice operacional que relaciona el caudal de diseño con el real, pero lo hacen en proporciones distintas según se trate de plantas pequeñas, medianas o grandes (Tabla 5). Si bien, cabe destacar que las plantas pequeñas muestran mayor heterogeneidad en cuanto al comportamiento del coste energético, lo cual queda reflejado a través del coeficiente de determinación (R^2) que representa la bondad de ajuste del modelo, oscilando entre un valor mínimo de 0 y un máximo de 1 (Tabla 5). Estos resultados están en la misma línea que los obtenidos por Lorenzo-Toja et al. (2015) que señalan que existe una gran heterogeneidad en cuanto a la eficiencia de plantas pequeñas debido a que existen múltiples diferencias en su operación.

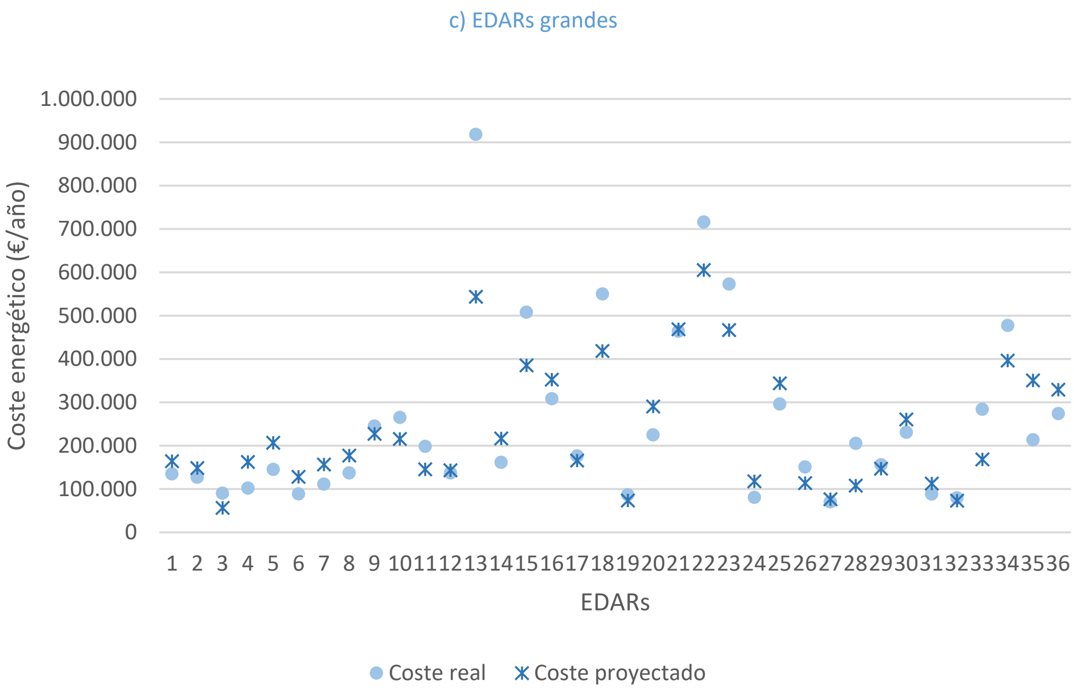
Finalmente, en la Figura 6 se presenta el ajuste de los modelos mediante la representación gráfica del coste energético real de cada una de las EDARs y el estimado mediante los modelos desarrollados y presentados anteriormente en la Tabla 5. Se comprueba que el coste energético de las EDARs puede ser calculado a través de las funciones de coste con una desviación de ±30%.

Figura 6. Comparación de los costes energéticos reales y los estimados mediante las funciones de coste

a) EDARs pequeñas







4.2 Influencia del envejecimiento de las EDARs

El análisis de la influencia del envejecimiento de las instalaciones sobre el consumo energético se lleva a cabo en el ARTÍCULO 3. Mediante el uso de una muestra de 322 EDARs durante tres años consecutivos y se observa que un 51,55% incrementan sus costes energéticos por m^3 de agua residual tratada entre el 2010 y 2012, con un incremento del 34,2% de media. El test de

Kruskal-Wallis (Tabla 7) confirma que las diferencias observadas año tras año son estadísticamente significativas.

Tabla 7. Coste energético por m^3 del conjunto de instalaciones que incrementan los costes energéticos entre el 2010-2012

	Coste energético (€/m^3)			Test de Kruskal-Wallis [a]
	2010	**2011**	**2012**	**p-valor**
Promedio	0,11	0,14	0,15	0,001
Mínimo	0,02	0,03	0,03	
Máximo	0,62	0,81	1,03	

[a] La hipótesis nula es que no existe diferencia entre los grupos

A continuación, se lleva un estudio más específico de las instalaciones que han experimentado un incremento del coste energético a lo largo de los años con el objetivo de detectar distintos patrones dependiendo del tipo de tecnología y del tamaño. En primer lugar, la Tabla 8 permite comparar la evolución del coste energético por m^3 de agua tratada para dos grupos de instalaciones con distinta tecnología: i) tecnología I, las que presentan aporte de oxígeno, grupo constituido por las tecnologías de fangos activos y aireación prolongada; y ii) tecnología II, las que no disponen de sistemas de aporte de oxígeno, formado únicamente por la tecnología de biodiscos.

Tabla 8. Consumo energético agrupados según la tecnología de tratamiento

	Coste energético (€/m^3)			Test de Kruskal-Wallis [a] p-valor
	2010	**2011**	**2012**	
Tecnología I				
Promedio	0,117	0,145	0,150	0,001
Mínimo	0,019	0,028	0,028	
Máximo	0,620	0,807	1,027	
Tecnología II				
Promedio	0,063	0,074	0,089	0,184
Mínimo	0,033	0,046	0,038	
Máximo	0,132	0,154	0,164	

[a] La hipótesis nula es que no existe diferencia entre los grupos

Pese a que el coste energético incrementa a lo largo del tiempo para ambas tecnologías, solamente la Tecnología 1 (fangos activos y aireación prolongada) presenta diferencias estadísticamente significativas de acuerdo con los resultados del test de Kruskal-Wallis. Esto puede ser explicado por el elevado consumo de los equipos de aireación y la degradación a la que estos equipos están sometidos como consecuencia del contacto continuo con el agua residual.

Seguidamente se analiza el comportamiento del coste energético según el volumen de agua tratada para el conjunto de instalaciones. En base a este criterio se ha dividido la muestra en 3 grupos: i) *Tamaño I*, instalaciones que tratan hasta 55.000 m^3/año; ii) *Tamaño II*, plantas que depuran entre 55.000 y 275.000 m^3/año; y iii) *Tamaño III*, instalaciones que procesan más de 275.000 m^3/año.

Tabla 9. Consumo energético (€/m^3) agrupados por tamaño para las plantas con tecnologías que requieren de sistemas de aireación (Tecnología I)

	Coste energético (€/m^3)			Test de Kruskal-Wallis [a]
	2010	**2011**	**2012**	**p-valor**
Tamaño I				
Promedio	0,168	0,216	0,228	
Mínimo	0,036	0,043	0,041	0,003
Máximo	0,620	0,807	1,027	
Tamaño II				
Promedio	0,102	0,128	0,131	
Mínimo	0,019	0,036	0,041	0,003
Máximo	0,215	0,234	0,268	
Tamaño III				
Promedio	0,090	0,102	0,102	
Mínimo	0,025	0,028	0,028	0,287
Máximo	0,270	0,294	0,294	

[a] La hipótesis nula es que no existe diferencia entre los grupos

Tabla 10. Consumo energético (€/m^3) agrupados por tamaño para las plantas con tecnología de biodiscos (Tecnología II)

	Coste energético (€/m^3)			Test de Kruskal-Wallis [a]
	2010	**2011**	**2012**	**p-valor**
Tamaño I				
Promedio	0,076	0,089	0,117	
Mínimo	0,037	0,046	0,057	0,210
Máximo	0,132	0,154	0,164	
Tamaño II				
Promedio	0,048	0,054	0,054	
Mínimo	0,033	0,046	0,038	0,368
Máximo	0,078	0,078	0,080	

[a] La hipótesis nula es que no existe diferencia entre los grupos

Los resultados de la Tabla 9 y la Tabla 10 anteriores muestran que el coste energético (€/m^3) incrementa con el paso del tiempo para cada uno de los tamaños de ambas tecnologías. Por lo que se refiere a las instalaciones que disponen de biodiscos, pese a que existe un incremento en el tiempo, el análisis estadístico muestra que estas diferencias no son estadísticamente significativas (Tabla 10). Sin embargo, para el grupo de plantas de fangos activos y aireación prolongada, esta diferencia es significativa para los tamaños I y II, pero no para el de mayor tamaño (Tabla 9). Los resultados obtenidos pueden ser explicados por las siguientes razones: (1) las instalaciones de mayor tamaño presentan un mejor mantenimiento de los equipos; (2) las instalaciones de menor tamaño tienden a estar sobredimensionadas y se deterioran más rápidamente, con lo cual las diferencias en el consumo energético a lo largo del tiempo son más notables en estos casos; y (3) algunas de las plantas de tamaño III disponen de sistemas de cogeneración, ya que las plantas de mayores dimensiones son técnicamente adecuadas para disponer de estos sistemas, enmascarando de esta forma el efecto del deterioro en este grupo de instalaciones.

Para el grupo de plantas con tecnologías de aireación (Tecnología I) se analiza el incremento promedio del coste energético a lo largo del periodo objeto de estudio. En la Tabla 11 se puede apreciar que el incremento en el coste energético por metro cúbico es mayor cuanto más pequeña es la instalación, y se acentúa cuando este valor se expresa en porcentaje. Las instalaciones de tamaño I y II son las que mayores aumentos porcentuales presentan en promedio, con un 40,74% y 44,81% respectivamente, frente a las de tamaño III, cuyo incremento porcentual en media es de solo un 16,53%. Es decir, que las instalaciones que tratan volúmenes de agua inferiores a 275.000 m^3 al año son las que experimentan aumentos superiores en el consumo energético como consecuencia del deterioro.

Tabla 11. Incremento del coste energético para instalaciones con sistemas de aireación (Tecnología I)

	Número de EDARs con incremento del coste energético	**Aumento del coste energético en promedio**	
	(%)	**(€/m^3)**	**(%)**
Tamaño I	14,60	0,06	40,74
Tamaño II	17,08	0,03	44,81
Tamaño III	17,08	0,01	16,53
Total	48,76	-	-

Tras comprobar la relevancia que tiene el transcurso del tiempo en el grupo de instalaciones que presentan tecnologías con aporte de oxígeno, se modeliza su coste energético teniendo en cuenta el envejecimiento además de otras variables de tipo técnico. La variable envejecimiento se introduce considerando el año 2010, el primer año del cual se tienen datos en la muestra, como el año de referencia, para el cual la variable envejecimiento toma el valor de 1; en el año 2011, estas mismas instalaciones habrán envejecido un año, por lo que la variable envejecimiento tomará el valor de 2; y en el año 2012, las instalaciones habrán sufrido un deterioro equivalente a tres años, por lo que la variable envejecimiento tomará el valor de 3; y así sucesivamente en caso de tener más años de muestra.

Mediante la metodología descrita en el apartado metodología, se desarrolla la ecuación de la Tabla 12, la cual permite proyectar el coste energético de las EDARs considerando el deterioro que padecen los equipos. El modelo que se elabora a partir de la información estadística de 156 instalaciones recogida durante el periodo 2010-2012 muestra que el coste energético (€/año) está directamente relacionado con: V, el volumen de agua tratada (m^3/año); la DQO, cantidad de DQO eliminada (kg/año); y J, el envejecimiento de las instalaciones (años transcurridos desde un año de referencia).

Tabla 12. Función de coste para estimar el coste energético incluyendo la variable envejecimiento.

Funciones de coste	R^2
$CE = 0{,}125 \cdot V^{0{,}791} \cdot e^{5{,}38 \cdot 10^{-8} \cdot DQO + 0{,}103 \cdot J}$	0,890

Nuevamente, para garantizar la viabilidad del modelo no solo se comprueba que las variables explicativas son significativas, sino que se cumplen las cuatro hipótesis básicas de los modelos de regresión (Tabla 13 y Anexo B.2).

Tabla 13. Cumplimiento de las hipótesis básicas del modelo (Anexo B.2)

	cumplimiento de las hipotesis
No colinealidad entre las variables	✓
Normalidad de los residuos	✓
Independencia de los residuos	✓
Homocedasticidad	✓

En los gráficos siguientes (Figura 7, 8 y 9) se presentan el coste energético real y el estimado con la función de coste para cada una de las instalaciones durante los tres años. Pese a que el modelo presenta una bondad de ajuste elevada (R^2) se pueden apreciar que existen algunas diferencias entre los valores reales y los estimados debido fundamentalmente a que la muestra no es del todo homogénea ya que no se distingue entre el tamaño de las instalaciones, variables que influyen en el consumo energético de una EDAR. Sin embargo, es la primera función de coste en la literatura que permite estimar el coste energético de las instalaciones considerando el deterioro de los equipos.

Figura 7. Coste real y proyectado para el año 2010

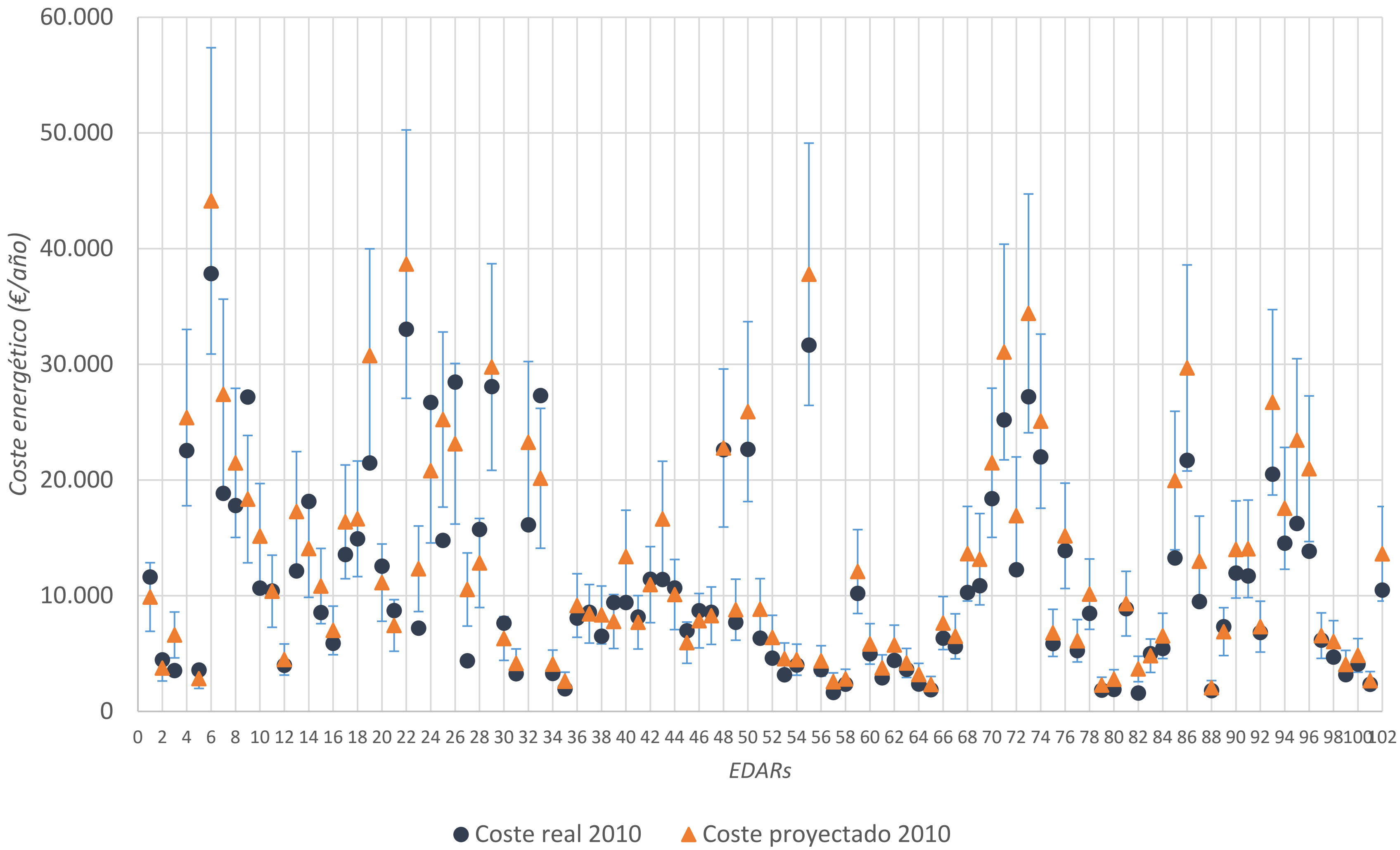


Figura 8. Coste real y proyectado para el año 2011

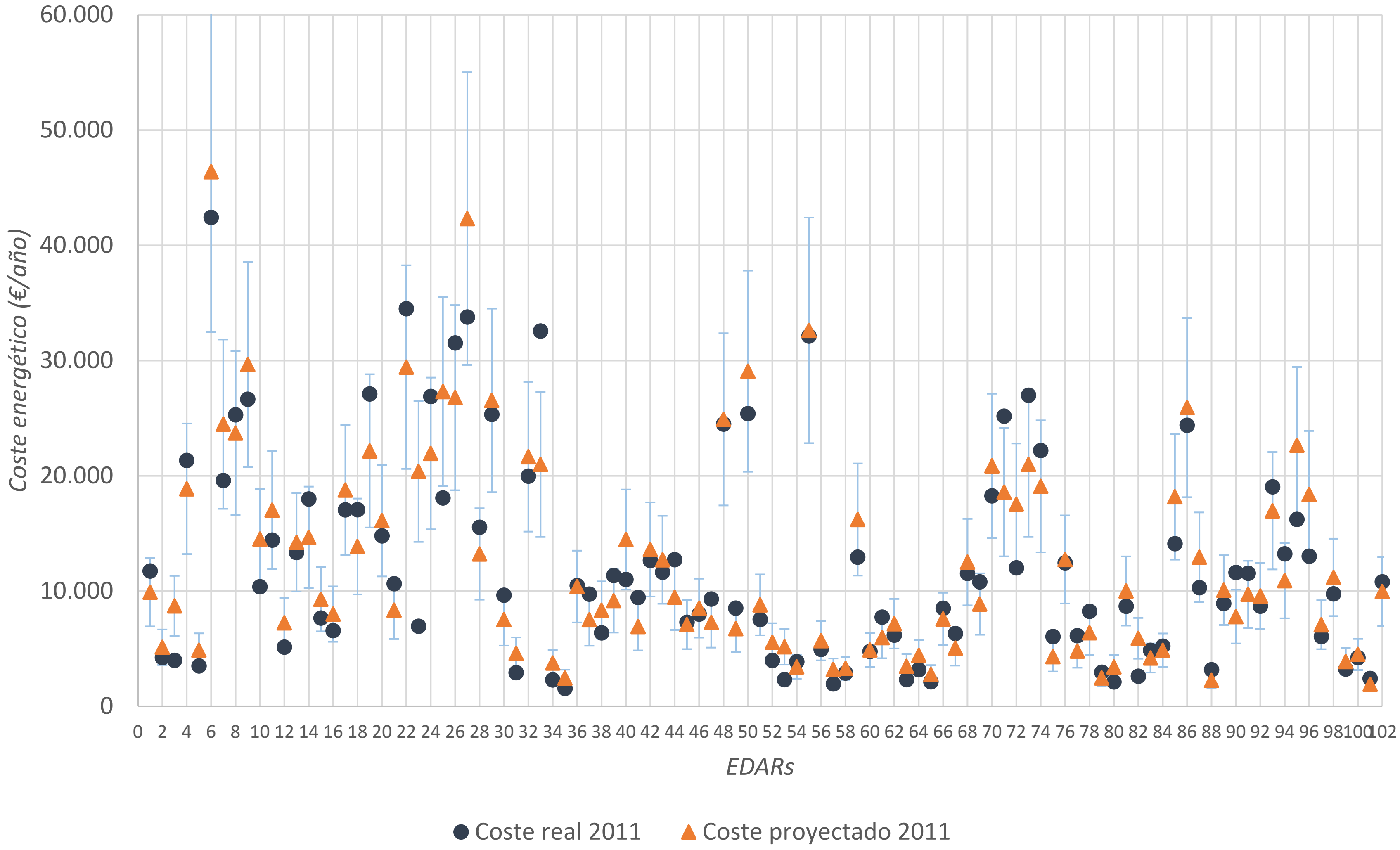
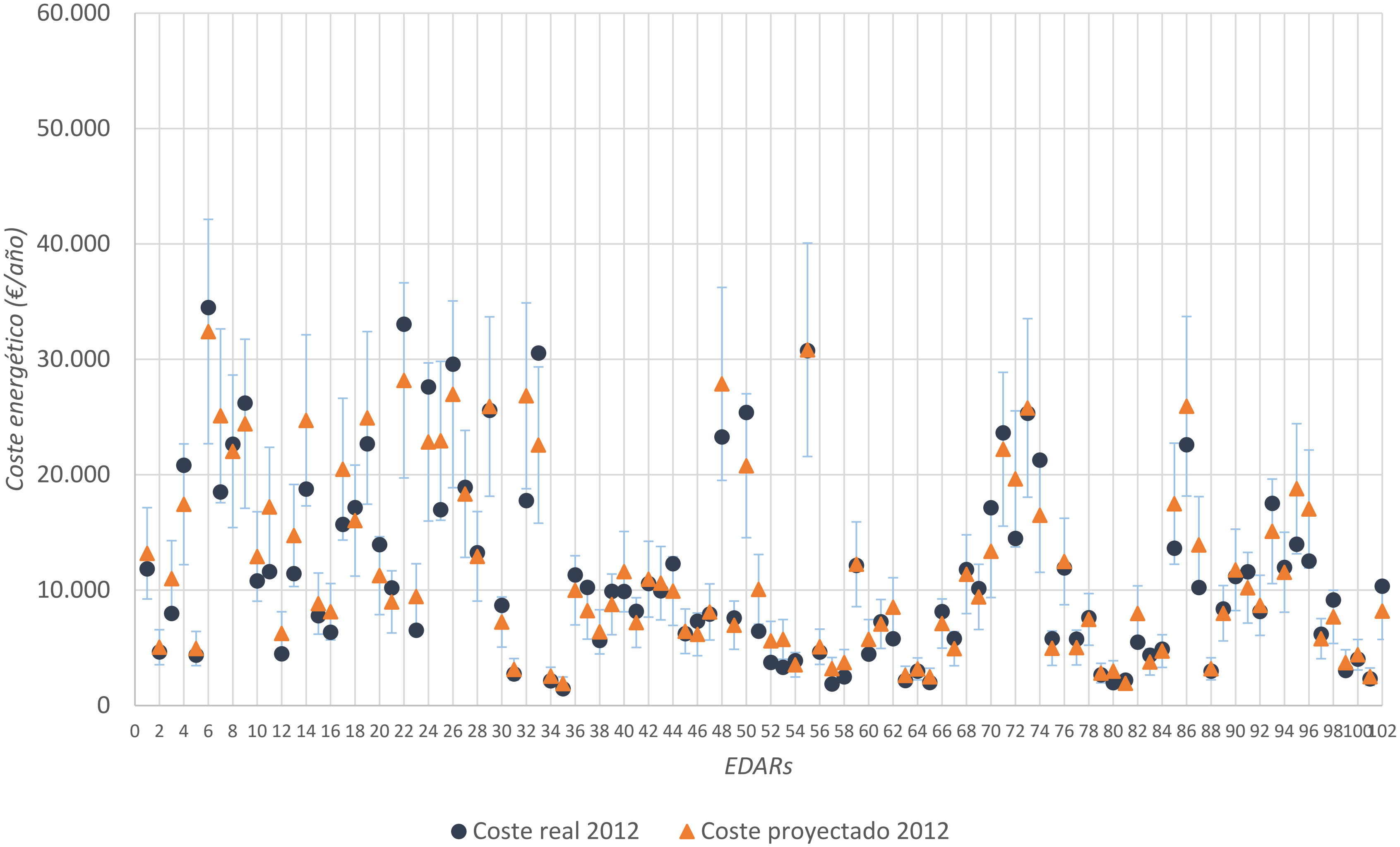


Figura 9. Coste real y proyectado para el año 2012



5. Conclusiones

En las dos últimas décadas el consumo energético ha sido objeto de análisis de muchos estudios relacionados con el ciclo urbano del agua, y en especial del proceso de tratamiento de las aguas residuales, fundamentalmente por la gran cantidad de energía que se consume en el proceso. Optimizar el consumo energético en el tratamiento del agua residual es esencial para reducir los costes operacionales del proceso y el impacto ambiental generado por los gases de efecto invernadero indirectos asociados al consumo eléctrico. Por ello conocer qué factores afectan a este consumo energético y cómo lo hacen es fundamental para la implementación de estrategias de optimización.

En el estudio llevado a cabo se corrobora que existe un elevado potencial de mejora en el sector de la depuración por lo que, a los costes energéticos, y por extensión, al consumo energético se refiere. La necesidad de mejorar o implementar estrategias para reducir el consumo energético se ha abordado en muchos estudios, pero siempre desde un punto de vista técnico. Sin embargo, el presente estudio pretende dar una visión global y centrarse en aspectos más relacionados con su gestión, por ello se ha abordado el tema desde un punto de vista económico, distinto al de la mayor parte de estudios desarrollados en esta materia.

Con este objetivo, se han destacado dos aspectos asociados a la planificación y la gestión de las instalaciones que tienen repercusión en la operación y los costes del proceso, se trata de las diferencias existentes entre el caudal de diseño y el real y el envejecimiento de las instalaciones. A lo largo del estudio se ha demostrado la influencia que tienen estos dos aspectos sobre el coste energético, que es aún más significativo en instalaciones pequeñas, que paradójicamente son las más abundantes en el territorio español.

Generalmente las EDARs tienen una vida útil de 50 años por lo que tanto la obra civil como el equipamiento electromecánico del que se dotan las instalaciones están preparados para tratar un caudal de diseño punta estimado que responde a una simulación de crecimiento poblacional determinada que en muchos casos no acaba coincidiendo con la realidad. Para detectar si el caudal tratado se ajusta al de diseño se ha desarrollado un indicador operacional que no solo cuantifica la diferencia entre ambos, sino que permite diferenciar si es un comportamiento habitual de operación o una situación que se da en determinadas épocas del año por los efectos de la estacionalidad. Del análisis del indicador obtenido y el coste energético se ha podido observar que existe una relación positiva entre ellos, es decir, que cuanto mayor es la diferencia entre el caudal real y el de diseño mayor es el coste energético, siendo esta relación ligeramente más relevante en instalaciones pequeñas.

Por otro lado, el envejecimiento de las instalaciones es una preocupación que ha ido creciendo en los países desarrollados. Existe una primera generación de instalaciones que se construyeron con anterioridad a la publicación de la Directiva 91/271/CE que ya han alcanzado el final de su vida útil y deben ser reemplazadas, pero existe una segunda generación mucho más numerosa, que incluye todas aquellas instalaciones construidas en la primera década del 2000 tras la implementación de la Directiva, cuyo deterioro se ha visto agravado por la adopción de criterios no siempre adecuados. La ausencia de estrategias de mantenimiento planificadas provoca pérdidas de eficiencia de los equipos, incrementa el número de fallos y averías en los sistemas, repercutiendo en mayores costes energéticos y de reparaciones. El deterioro y, especialmente sus efectos, son más notables en las instalaciones de menor dimensión. Esto no significa que las instalaciones de gran tamaño no estén expuestas al paso de los años, sino que disponen de estrategias o planes de mantenimiento capaces de paliar estos efectos.

Además, el estudio ofrece dos funciones de coste que permiten estimar el coste energético de EDARs con tratamiento convencional incluyendo los dos aspectos mencionados anteriormente. Por lo que se ha podido observar las plantas de tamaño pequeño, ya sea en términos de caudal tratado o habitantes equivalentes, presentan mayor vulnerabilidad en cuanto a la influencia de los factores y mayor variabilidad en los costes energéticos por lo que resultan más complejos de predecir para este tipo de instalaciones. Esto remarca la necesidad y el potencial de mejora de las EDARs. Las funciones de coste en combinación con otro tipo de técnicas se presentan como una herramienta de ayuda a la toma de decisión ya que ofrecen al gestor información sobre cómo interactúan distintas variables en el proceso y permite hacer estimaciones ante diferentes escenarios.

Finalmente, optar por estrategias que contemplen planes de ampliación cada 10 años, pudiendo evitar de esta manera grandes variaciones entre el caudal real y el de diseño, y a su vez implementar estrategias de mantenimiento preventivo e incluso predictivo, que ayuden a paliar los efectos del deterioro y garanticen el correcto funcionamiento de los equipos a lo largo de su vida útil podrían ayudar a que el proceso fuese más sostenible económicamente. Ello ayudaría, además, en el cumplimiento del principio de recuperación de costes establecido en el Artículo 9 de la Directiva Marco.

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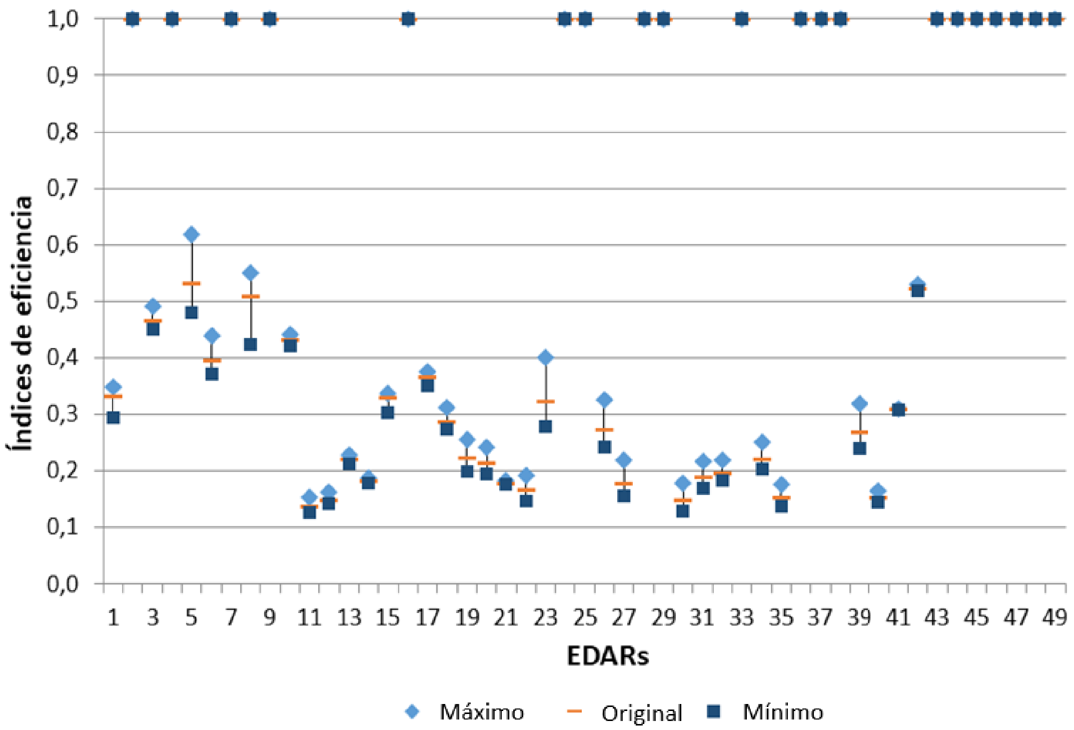
ANEXOS

Anexo A: Análisis de sensibilidad en la evaluación de la eficiencia de las EDARs

Variación en el peso para el input energía

	+100%	+75%	+50%	+25%	+10%	original	-10%	-25%	-50%	-75%	-100%
Ponderaciones	0,5068	0,4434	0,3801	0,3167	0,2787	0,2534	0,2280	0,1900	0,1267	0,0633	0,0000

Variación entre los indices de eficiencia mínimos y máximos respecto al original



Anexo B: Hipótesis básicas de los modelos de regresión

B.1 HIPÓTESIS BÁSICAS DE LOS MODELOS DE REGRESIÓN DE LA TABLA 6

No colinealidad entre las variables

Para comprobar que no existe colinealidad entre las variables explicativas que forman parte del modelo se utiliza el factor de inflación de varianza (FIV). Como los resultados de la prueba no son mayores que 10, se puede afirmar que no existe una relación lineal exacta entre ninguna de las variables que explican Los modelos (Kleinbaum et al., 1988).

FACTOR DE INFLACIÓN DE VARIANZA			
Variables	**EDARs pequeñas**	**EDARs medianas**	**EDARs grandes**
V	1,785	2,438	1,843
BOD	1,087	1,632	1,519
Z	1,898	1,677	1,274

Normalidad de los residuos

El analisis de la normalidad de los residuos se contrasta mediante el test de Kolmogrov-Smirnov (Dodge, 2010).

TEST DE KOLMOGROV SMIROV			
	EDARs pequeñas	**EDARs medianas**	**EDARs grandes**
Significatividad	0,200	0,200	0,200

Independencia de los residuos

Mediante el estadístico de Durbin-Watson se puede confirmar que hay independencia de los residuos cuando éste toma valores entre 1,5 y 2,5 (Baltagi, 2008).

ESTADÍSTICO DE DURBIN-WATSON			
	EDARs pequeñas	**EDARs medianas**	**EDARs grandes**
Estadístico	2,4	1,6	1,9

Homocedasticidad

La varianza de los residuos se contrasta mediante el test Breusch-Pagan (Kleinbaum et al., 1988), el cual confirma que los tres modelos desarrollados presentan homocedasticidad.

TEST ESTADÍSTICO BREUSCH-PAGAN			
	EDARs pequeñas	**EDARs medianas**	**EDARs grandes**
Chi-cuadrado	0,789	0,669	0,295
p-valor [a]	0,374	0,880	0,587

[a] la hipótesis nula del modelo es que la varianza de los residuos es constante

B.2. HIPÓTESIS BÁSICAS DEL MODELO DE REGRESIÓN DE LA TABLA 13

No colinealidad entre las variables

La no colinealidad entre las variables se comprueba mediante el factor de inflación de varianza (FIV). Los resultados obtenidos en este test para la función de costes presentada en la Tabla 12 no superan el valor 10, de modo que no existe una relación lineal exacta entre las variables explicativas (Kleinbaum et al., 1988).

VARIABLES EXPLICATIVAS	FACTOR DE INFLACIÓN DE VARIANZA (FIV)
V	1,843
DQO	1,839
Envejecimiento	1,003

Normalidad de los residuos

Mediante el test de Kolmogrov-Smirnofv (Dodge, 2010) se confirma la normalidad de los residuos ya que el p-valor es superior a 0,05 no se puede rechazar la hipótesis nula de que la variable analizada presenta una distribución normal.

	TEST DE KOLMOGROV SMIROV
Estadístico	0,032
p-valor [a]	0,200

[a] la hipótesis nula del modelo es que la variable presenta una distribución normal

Independencia de los residuos

Puesto que el valor obtenido en el el estadístico de Durbin-Watson se encuentra entre 1,5 y 2,5 se confirma que los residuos son aleatorios e independientes entre sí (Baltagi, 2008), aumentando la robustez del modelo.

	ESTADÍSTICO DE DURBIN-WATSON
Estadístico	1,644

Homocedasticidad

El test Breusch-Pagan (Kleinbaum et al., 1988) con un p-valor superior a 0,05 permite afirmar que los errores de estimación son constantes a lo largo de las observaciones, confirmando nuevamente la fiabilidad del modelo obtenido.

	TEST ESTADÍSTICO BREUSCH-PAGAN
Chi-cuadrado	1,837
p-valor [a]	0,6069

[a] *la hipótesis nula del modelo es que la varianza de los residuos es constante*

Anexo C: publicaciones originales

The relevance of the design characteristics to the optimal operation of wastewater treatment plants: energy cost assessment

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Research article

The relevance of the design characteristics to the optimal operation of wastewater treatment plants: Energy cost assessment

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ABSTRACT

Operational parameters of the wastewater treatment process do not always fit the design ones for several reasons, such as the seasonality or an inaccurate estimation of the population connected. This fact has an effect on the performance of the Wastewater Treatment Plants (WWTPs) and their energy costs. The aim of this paper is to develop a cost function for the energy cost that takes into account the mismatching between the design and the operational inflow. For this purpose, a performance index is constructed in order to represent how far the operational inflow is from the design one, and will be included in the cost model. Moreover, three cost functions, depending on the size of the plants are developed in order to provide the managers of the WWTPs with valuable information that could be used to optimise the wastewater treatment process.

1. Introduction

Wastewater Treatment Plants (WWTPs) are intensive energy consumers (Racoviceanu et al., 2007), which can represent up to the 20% of the total energy consumed by the public utilities in a municipality (Means, 2004). The minimization of the energy consumption has become increasingly important for wastewater policy makers since the electricity tariffs increased (Bodik and Kubaská, 2013; Castellet-Viciano et al., 2018; Gikas, 2016), and the reduction of the greenhouse gases became one of the biggest global challenges (EU, 2010; Shao et al., 2014; Slingerland et al., 2015).

Even if already high, the energy consumption in WWTPs is supposed to increase in the next years for several reasons: new regulations, connected population increase and infrastructure ageing. Several authors (Bolong et al., 2009; Naidu et al., 2016; Noguera-Oviedo and Aga, 2016; Petrie et al., 2015) demonstrated that regulations have to be adapted to improve the standards concerning the discharge of new contaminants; this will require an increase in the energy consumption (Ahmed et al., 2017). Besides this, in different developed countries, the number of WWTPs is likely to rise because of the population growth; for example the urban population in Spain is supposed to rise 10.7% by 2050 (United Nations, Department of Economic and Social Affairs, Population Division, 2015). On the other hand, experts of the wastewater treatment sector in Spain state that wastewater infrastructures are ageing and deteriorating (AEAS, 2014; AEAS, 2016), which will also contribute to enlarge the energy use of the WWTPs (Mo and Zhang, 2013).

The energy consumption of a WWTP is defined by both operational and design parameters, including the technology used in the process, the size of the plant, the volume and the contaminant load of the influent (Tchobanoglous et al., 1991). However, some of the characteristics mentioned above such as the volume of the treated wastewater and its contaminant load present fluctuations in time, depending on the hour of the day, between days or even in different periods of the year (Bragadin and Mancini, 2010; Butler, 1993; Campos and Von Sperling, 1996; Friedler and Pisanty, 2006; Krukowski et al., 2013; Wong and Mui, 2007), having an impact on the operating conditions.

Daily and weekly variations in the quantity and the quality of the wastewater treated are mostly defined by the domestic habits and the use of different appliances. Campos and Von Sperling (1996) found differences in the generation of domestic wastewater throughout socio-economic variables, such as the salary of the population. Moreover, WWTP's performance can also be altered by storm conditions. In fact, a storm event can overflow the sewerage system, bring down the wastewater treatment process (Obaid et al., 2014), increase the energy demand and the sludge production, and negatively affect the contaminant removal efficiency (Stricker et al., 2003). Another important factor in generating variations in the production of wastewater is tourism. In accordance to Muñoz-Aulet and Caus-Pla (2005), the WWTPs of tourist areas only work at their maximum capacity during a short period of the year, being oversized for the most part of time. Accordingly, Sala-Garrido et al. (2012) found that WWTPs subjected to

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0301-4797/

seasonality are less efficient than those that are not.

In order to guarantee the accomplishment of the quality parameters established in the Council Directive 91/271/EEC concerning urban wastewater treatment (EU, 1991), WWTPs are designed to treat those fluctuations in time. Wastewater treatment facilities are designed considering the peak flow and the peak mass loading rate (Mines et al., 2007). In many instances it is assumed a daily wastewater flow per capita using water consumption and socioeconomic information, and then a multiplier factor gives as a result the peak volume and the peak load (Butler et al., 1995).

Differences between the operational volume of the wastewater treated and the design one are responsible for inefficiencies in the process, since those facilities and equipment that are either oversized or undersized are likely to malfunction and fail (Campos and Von Sperling, 1996), decreasing the contaminant removal and increasing the operational costs in terms of energy, reagents, maintenance, and personnel. As far as the energy cost is concerned, Silva and Rosa (2015) report that those WWTPs that are operating at their 80% of their design capacity consume up to 28–53% less energy than those that are operating at half of their maximum capacity.

Due to the relevance of the energy cost in the wastewater treatment process, in the last decades different strategies have been developed to assess and improve the energy efficiency of the process. While most studies have used benchmarking methodologies (Castellet and Molinos-Senante, 2016; Hernández-Sancho et al., 2011; Longo et al., 2016; Panepinto et al., 2016; Torregrossa et al., 2016), the current research aims to contribute to the literature on reducing the energy inefficiencies in the wastewater treatment process from an economical approach based on cost functions.

The use of cost functions is widespread in the literature. In the WWTP field, different authors propose this approach, for example: Hernandez-Sancho et al. (2011) who estimate the costs for different wastewater treatment technologies, Molinos-Senante et al. (2013), to estimate the cost of the sludge and waste management, Plumlee et al. (2014) to analyse the cost of the advanced treatment, and more recently Yumin et al. (2016), for the operational cost estimation of WWTPs in rural areas. Most of the cost functions developed for the wastewater treatment process have been used to estimate the operational and maintenance cost of the process. However, it is very difficult to find studies focused on the energy cost estimation.

The definition of the operational costs of the process can vary among authors. Two approaches can be identified in the existing literature depending on the variables used to explain the costs. Several studies show that it is possible to use operational parameters such as the volume of wastewater treated (Hernandez-Sancho et al., 2011), the load charge expressed as the population equivalent (Sipala et al., 2003; Tsagarakis et al., 2003) or the contaminant removal expressed in Kg of BOD, COD, N or P (Hernandez-Sancho et al., 2011) to explain the costs. In contrast, a second group of authors prefer using design parameters such as the capacity of the plant according to the volume of wastewater they are able to treat (Berbeka et al., 2012; Friedler and Pisanty, 2006; Pannirselvam and Gopalakrishnan, 2015).

The novelty of this paper is to include the effects of the mismatching between the operational and design inflow in the energy cost function since the fact that the equipment does not work at their optimum can have an impact on the energy cost. For instance, Torregrossa et al. (2017) show how the overestimation of inflow can produce avoidable energy costs in pump systems. The use of index has been reported to be very useful in the literature for different purposes since they can provide valuable information (dos Santos Simões et al., 2008; Paruch and Mæhlum, 2012; Shao et al., 2014). In order to achieve our purpose, a performance index is calculated to represent the distance between the operational condition and the design one. Moreover, due to the existence of scale economies in the wastewater treatment process, different energy cost functions depending on the size of the plant have been considered. The equations provided by this paper could be used by the managers of the WWTPs, public authorities and designers in order to estimate and predict the energy cost of the wastewater treatment, obtaining valuable information that would be very useful for the process optimization.

2. Material and methods

Most of the cost functions used to estimate the costs of the wastewater treatment process take the form of an exponential equation (Friedler and Pisanty, 2006). In this paper, the estimation of the energy cost of the wastewater treatment process is based on the model developed by Hernandez-Sancho et al. (2011):

$$EC = AV^b e^{(\sum \alpha_i x_i)} \quad (1)$$

where EC is the energy cost of the plant per year; V is the volume of wastewater treated per year; and x_i are different kinds of variables representative of the treatment processes; A, b and α are parameters.

It seems that treatment costs might be more related to the volume of wastewater treated and the quantity of contaminants removed from the wastewater than the capacity of the plant (Hernandez-Sancho et al., 2011). However, wastewater treatment facilities are designed to treat a specific volume or contaminant load, so all the equipment including technological elements, pumping systems, and other devices will be in accordance to these initial characteristics. It is considered that the closer would be the operational volume to the design one, the more efficient would be the process (Silva and Rosa, 2015). The fact that the equipment does not work at their optimum will have an impact on the energy cost.

To include this phenomenon into the cost function a performance index (Z) is constructed. It represents the difference between the designed capacity of the plant (m^3/day) and the real volume of wastewater treated (m^3/day), as follows:

$$Z = \frac{|q - Q|}{Q} \cdot 100 \quad (3)$$

where Z is the performance index; q is the volume of wastewater treated; and Q is the design flow of the plant.

When the WWTP is treating the same volume of wastewater established in the design condition the value of Z is 0. On the contrary, as the difference between the operational volume of wastewater and the design one increases, the value of Z will rise. Consequently, Z can be used as an indicator of the operational performance of the plants.

According to Eq. (3), a performance index per day will be obtained for each WWTP. However, a representative index per year is needed in order to relate it to the energy cost (€/year) throughout the cost function. Hence, instead of using the average of the daily index, we consider that the use of the median is more appropriated, since it reflects how much time the plant is working at its optimum.

Finally, the parameters of the model are obtained empirically through an ordinary least squares regression analysis, which includes those variables that better explain the energy cost. It should be noted, that the variables in the regression equation are significant at the 95% confidence level. Due to the nature of the process, problems of multicollinearity between the variables could be found, for this reason special attention will be paid to the variance inflation factor (VIF). Moreover, to guarantee the robustness of the model, the behaviour of the residuals will be analysed, throughout different statistical tests that would prove their normality, independence and the homoscedasticity of the model.

The methodology has been applied using empirical data from 156 WWTPs located in the Spanish region of Valencia. This area attracts lots of tourists during the summer, which makes that some cities double the usual population in this season (Rico Amorós, 2007). In order to cope with seasonality, WWTPs are designed to treat the maximum volume of wastewater that they could receive in this period, hence, the volume of wastewater that they usually treat the most part of the year differs from

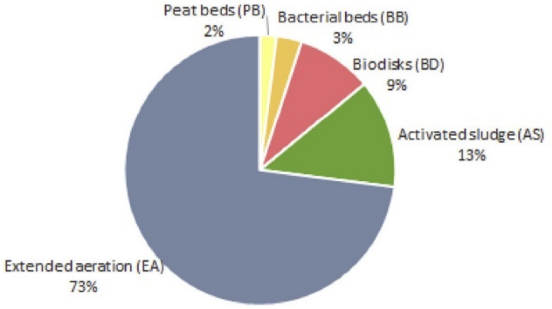

Fig. 1. Technology distribution. Source: own elaboration from data provided by the Regional Wastewater Treatment Authority (Entitat Publica de Sanejament d'Aigües Residuals -EPSAR) of Valencia, Spain.

the design one.

In Fig. 1 illustrates that the most common technologies in Valencia Region are extended aeration (EA) representing the 73%, followed by the activated sludge (AS), with the 13%. The rest consist in those technologies that are less energy demanding such as biodisks (BD), bacterial beds (BB) and peat beds (PB), which represent 9%, 3% and 2%, respectively. The current study has been carried out using a sample of WWTPs apply extended aeration and activated sludge with blowers as oxygen support systems. Moreover, the origin of the wastewater is domestic in all cases, so the characteristics of the influent are similar. Therefore, this might not affect the energy cost.

The size of the WWTPs could affect the energy cost since there exist economies of scale in this sector (Fraquelli and Giandrone, 2003; Guerrini et al., 2017). Hence, taking into account the population equivalent (p.e.) the sample has been divided similarly to Garrido-Baserba et al. (2016) in the following groups: i) small, those WWTPs with less than 2000 p.e.; ii) medium, including a range of p.e. between 2000 and 20,000; and iii) large, those with more than 20,000 p.e.

Table 1 shows the statistical data used to obtain the performance index and the energy cost functions.

3. Results and discussion

3.1. Performance index analysis

Before estimating the energy cost function for each group of WWTPs, it is necessary to calculate the performance index per day for each WWTP considering both operational and design volume. Following the procedure described in section 2, the annual performance index is obtained for each WWTP. In average, the value of Z has been close to 0.5. As we have chosen as a reference the percentile 50, it means that, at least, during half of the year, the plants are treating twice or half the volume of wastewater that they were design to.

When we analyse the index of each WWTP, two different operating patterns can be observed, as it can be seen in Fig. 2. There is a group of WWTPs that are operating far from design inflow, like WWTP A. This plant is designed to treat a peak volume of wastewater of 1140 (m^3/day), but it hardly ever achieves a volume of wastewater similar to this one (Fig. 2). In accordance, the Z value obtained for this facility was 0.82; this means that half of the year the plant is operating up to 82% far from its design volume. In contrast, there is another group of facilities whose operational characteristics are similar to the design ones, such as WWTP B. For instance, WWTP B, whose designed volume is 450 (m^3/day), obtained a Z value of 0.16. It can be understood as this WWTP is working at its optimum the most part of the year (Fig. 2), since the distance between the operational and the design volume is less than the 16% for half of the year.

In Table 2 there is an evidence that generally the design volume of WWTPs differ from the operational ones. It can be observed a great percentage of WWTPs with Z values greater than 0.5 for each group size, up to 41.67% for the large ones, followed by the group of the small facilities with a 46.55%, and 48.19% for the ones that have been identified as medium size. This means that numerous WWTPs are operating far from their design volume, differences up to 50%, during half of the year. Moreover, the Z values obtained show that large wastewater treatment plants seem to work more accurate to their design volume than the medium and the small ones, since they show lesser values of Z. There is a small percentage of large WWTPs (8.33%) with Z values greater than 0.7, and none of them have been found with values of Z greater than 0.8. In contrast, the percentage of small and medium WWTPs with Z values greater than 0.7 rises up to 17.24% and 14.50%, respectively. And there are a few of them, particularly an 8.60% and a 6.45%, respectively, which half of the year their operational inflow differ from the design one in an 80%. This is the case of those WWTPs with Z values greater than 0.8.

3.2. Relation between the Z value and the energy cost

Next step means to prove that the energy cost of a WWTP depends on how close they are working from their design characteristics. As it can be seen in Fig. 3 (a, b and c) there is a moderate growth in the energy cost when the value of Z increases. In order to have more detailed information about the relation between the energy cost and Z, the results are presented independently for the three groups we made previously, accordingly to the size of the WWTPs: small, medium and large.

Moreover, the relation between the energy cost and Z has been measured statistically. For this purpose, and due to the nature of the variables under study it has been used the Spearman's rank correlation coefficient. The results obtained from the correlation test (Table 3) show that there is a positive correlation between the two variables at the 99% confidence level (p-level less than 0.01). It has been noticed that the correlation values are not higher than 0.6 for any of the groups

Table 1
Sample description.

	Small (58 WWTPs)		Medium (62 WWTPs)		Large (36 WWTPs)	
	Average	Standard deviation	Average	Standard deviation	Average	Standard deviation
P.E	1126	486	5676	4665	125,065	20,563
SS influent (mg/l)	191	82	264	103	285	88
SS effluent (mg/l)	6	4	6	4	8	5
COD influent (mg/l)	459	173	635	219	671	211
COD effluent (mg/l)	24	11	28	11	37	13
BOD influent (mg/l)	2542	8682	10,447	41,835	378	168
BOD effluent (mg/l)	6	3	7	2	8	3
Energy cost (€/day)	6756	4440	21,085	17,984	27,665	20,563
Volume of wastewater treated (m^3/day)	182	165	741	735	14,087	13,809
Design volume (m^3/day)	280	125	1166	1213	22,389	18,633

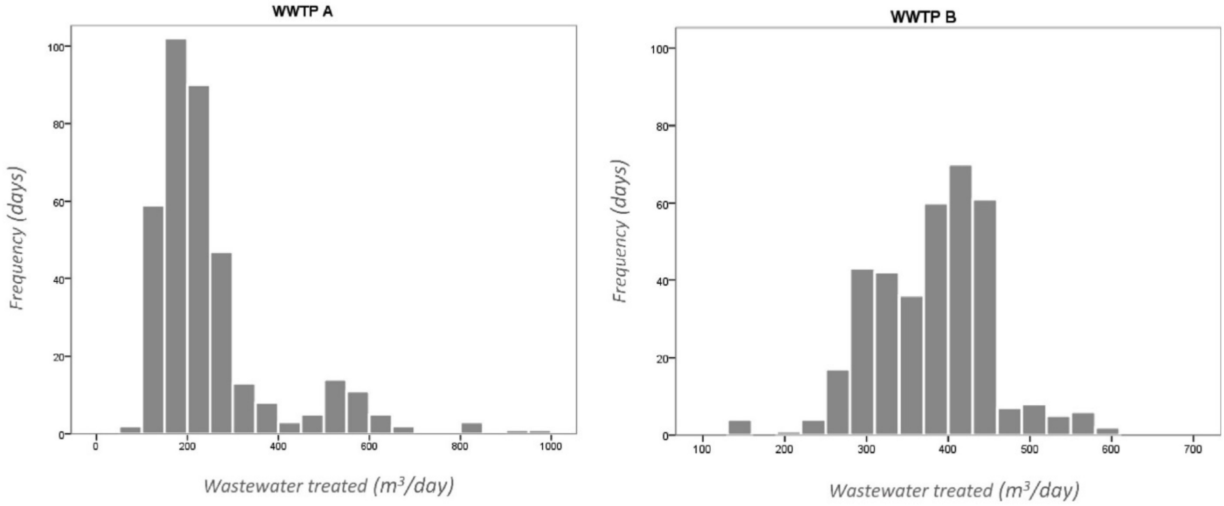

Fig. 2. Volume of wastewater treated during a year for two different WWTPs.

Table 2
Percentage of WWTPs that have obtained a Z value greater than 0.5, 0.6, 0.7 and 0.8.

	Number of WWTP with Z greater than 0.5	Number of WWTP with Z greater than 0.6	Number of WWTP with Z greater than 0.7	Number of WWTP with Z greater than 0.8
Small	46.55%	29.31%	17.24%	8.60%
Medium	48.19%	32.25%	14.50%	6.45%
Large	41.67%	25.00%	8.33%	0.00%

(Table 3), the reason is that the energy cost of the wastewater treatment process not only depends on Z, there are other factors such as the contaminant removal, the age of the plant or the availability of different devices that define the energy cost. However, the relation is strong enough to confirm that the energy cost per m^3 of wastewater treated rises as the Z value increases.

3.3. The index Z as an explicative variable of the energy cost function

Having seen how representative is the Z parameter in the process and its influence in the energy cost, we consider that it should be included in the energy cost estimation. Three energy cost functions have been constructed, one per size, since Kruskal-Wallis test (Kruskal and Wallis, 1952) shows statistical differences in the energy cost between the three groups. Most of the cost functions in the literature use mainly two kinds of variables, the volume of wastewater treated and the contaminant load. In this paper we prove that, besides those variables, the Z parameter, which measures the mismatching between the design volume of the facilities and the volume that they usually treat, explains the energy cost of the WWTPs (Table 4).

In accordance to Brandt et al. (2011), Gikas (2016), Sun and Li (2010) and Zhang et al. (2016), who state that half of the total energy of the process is consumed by the biological treatment, the models include the BOD removal efficiency as a factor to consider when the energy cost of the process is estimated, regardless of the size of the plants. Not only is the volume of wastewater treated relevant for the estimations of the operational and maintenance cost as Hernandez-Sancho et al. (2011) found, but also for the energy cost, particularly. It is also found that the way the WWTPs are operating according to their design characteristics is important for the energy cost of the plant.

The energy cost functions obtained are in accordance to those presented in a recent research about the energy intensity for different WWTPs technologies developed by Molinos-Senante et al. (2018). In this study, exponential functions have also been preferred to represent the energy intensity of the WWTPs rather than linear equations. Moreover, cost functions for extended aeration and activated sludge also include the volume of wastewater treated and the biological oxygen demand removal efficiency in %. Similar results were obtained by Hernandez-Sancho et al. (2011) when the operation and maintenance costs of several technologies were assessed. The relevance of these studies lies in the need of differentiate between technologies when their energy and costs are analysed. Although both studies point out that the wastewater treatment process are affected by scale economies, different sizes of WWTPs are equally assessed. The current study shows that not only should the technology be taken into account to model the energy cost of the wastewater treatment process but also the size of the plant and the mismatching between the design and the real inflow. The adjustment quality of the cost functions measured by the determination coefficient (R^2) can be improved if we compare them with the ones obtained in previous studies, where the values for both technologies range from 0.61 to 0.76.

The accuracy of the energy cost models obtained is measured throughout the coefficient of determination (R^2), which can take values between 0 and 1, being preferred this models with the highest value. Moreover, all variables that take part in the regression equation are significant at the 95% confidence level. As it can be observed in Table 4 the values obtained are quite higher.

Since the Z parameter has been obtained using the volume of wastewater treated, we might prove that the variables in the cost function are not correlated to guarantee the quality of the model. For this purpose it has been used the variance inflation factor (VIF), see Table 5. As the results of the test are not greater than 10, it can be claimed that there is no exact linear relationship between any of the variables that explain the models (Kleinbaum et al., 1988).

Besides the correlation, we have gone further and we have analysed the residuals of the model. As it is expected from an adjustment obtained throughout least squares regression analysis, the residuals of the set of variables that constitute the model are normally distributed with a mean of 0, as Kolmogrov-Smirnof test has confirmed (Dodge, 2010). Moreover, the residuals obtained are independent between them, as Durbin-Watson statistic proves. The range of values around which independence can be assumed is between 1.5 and 2.5 (Baltagi, 2008) (Table 6).

Finally, another feature of the residuals that should be highlighted to prove how good the models obtained are, is the homoscedasticity.

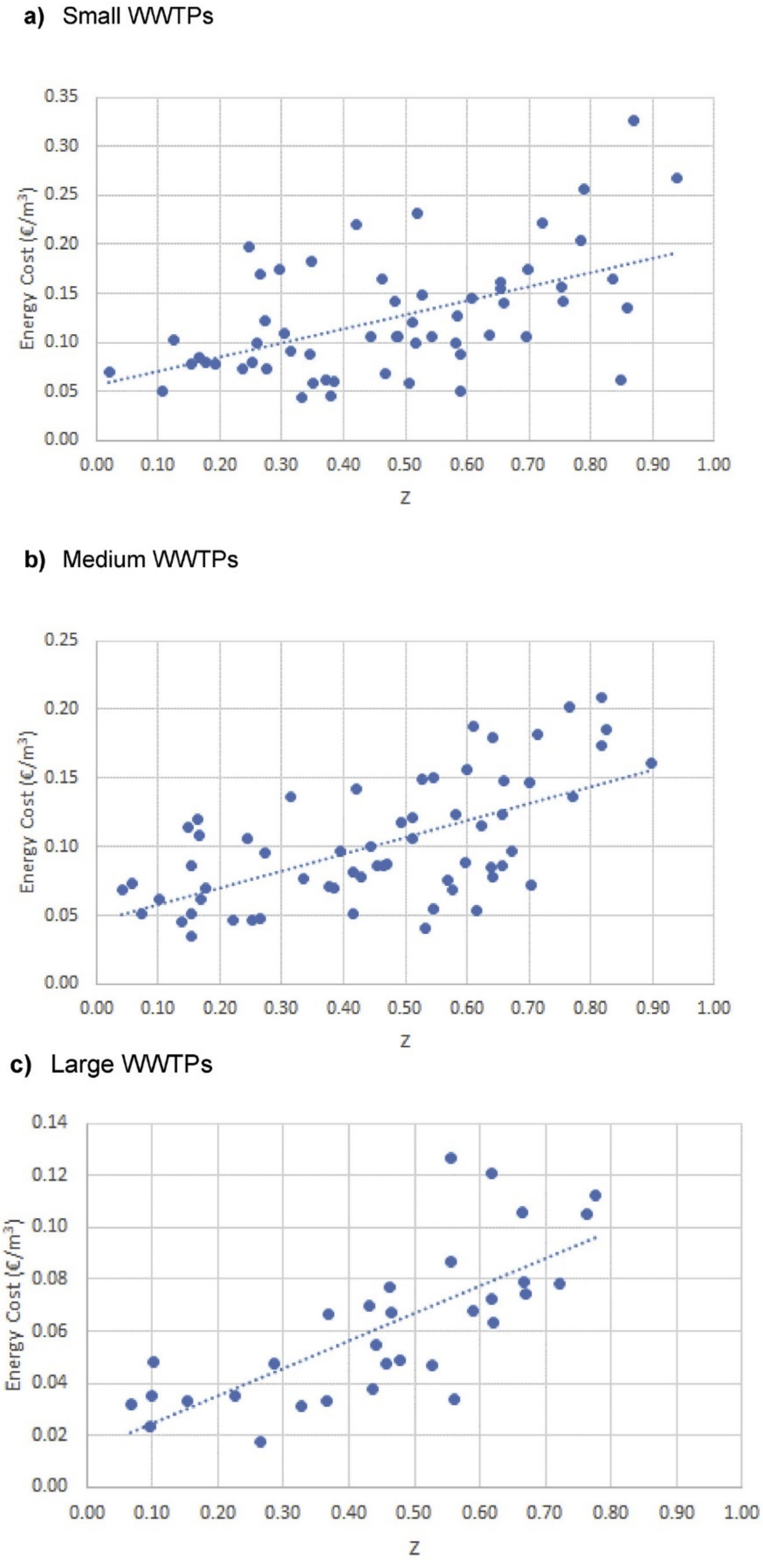

Fig. 3. Relation between the Energy Cost (€/m^3) and Z. a) Small WWTPs. b) Medium WWTPs. c) Large WWTPs.

Table 3
Spearman's rank correlation coefficient.

	Small	Medium	Large
Correlation Coefficient	0.481	0.597	0.552
p-level	0.001	0.001	0.001

Table 4
Cost functions for different sizes of WWTPs and the adjustment.

	Cost Functions	R^2
Small	$EC = 1.983{\cdot}10^{6}{\cdot}V^{0.717}\,e^{(-14.327\,BOD\,+\,0.660\,Z)}$	0.599
Medium	$EC = 1.854{\cdot}10^{-5}{\cdot}V^{0.859}\,e^{(10.152\,BOD\,+\,0.625\,Z)}$	0.851
Large	$EC = 3.949{\cdot}10^{-7}{\cdot}V^{0.746}\,e^{(15.876\,BOD\,+\,0.693\,Z)}$	0.791

Table 5
Non-collinearity test.

Variables	Variance Inflation Factor		
	Small WWTPs Model	Medium WWTPs Model	Large WWTPs Model
V	1.785	2.438	1.843
BOD	1.087	1.632	1.519
Z	1.898	1.677	1.274

Table 6
Durbin-Watson statistic.

	Small WWTPs Model	Medium WWTPs Model	Large WWTPs Model
DW statistic	2.4	1.6	1.9

Table 7
Breusch-Pagan test results.

	Small WWTPs Model	Medium WWTPs Model	Large WWTPs Model
Chi-square	0.789	0.669	0.295
p-value [a]	0.374	0.880	0.587

[a] The null hypothesis is that the variance of the residuals is constant.

Hence, the Breusch-Pagan test (Kleinbaum et al., 1988) has been used, and it confirms that the variance of the residuals is constant within a 95% confidence level (Table 7).

The quality of the model can also be appreciated in Fig. 4 (a, b and c), which show the real energy cost of the plants and the estimated energy costs making use of the cost functions obtained in this paper for the three WWTP sizes (small, medium and large). As it can be observed, most of the projected costs are very close to the real ones, which means that the model obtained offers a good approach to the energy cost, since the real cost of most of the plants can be predicted within a ± 30% of error.

In the event of not considering the index Z in the cost model, it has been proven that differences between real and projected cost increase by 5.5%, 8.5% and 17.11% for small, medium and large WWTPs, respectively. Being large WWTPs more sensitive to the effects of the index Z, as it can also be noticed in Table 8 and Fig. 5.

Furthermore, the energy cost functions developed in this paper could provide the managers of the WWTPs with valuable information in the design phase of the plants, becoming a potential tool to support the decision making process. By using these cost functions, the energy cost of a WWTP can be predicted in advance, reducing the inefficiencies and the uncertainty of the design phase. In order to show the functionality of the cost functions, the energy cost of one WWTP of each group has been estimated and contrasted when different values of Z are given. The criteria used to choose these plants has been the median of the p.e of each group. Particularly, it has been assessed the energy cost when Z is equal to 0.2, 0.4, 0.6 and 0.8, while the other variables remain constant (Table 8).

The energy cost estimation has been made using the cost functions developed previously and shown in Table 4. From the results obtained, it is observed that the energy cost increases as the Z value rises for each WWTP. This effect can be more clearly observed in Fig. 5.

In Fig. 5, it has been represented the energy cost estimated for the WWTPs for different operational situations. Giving different values to the performance index, while the volume of wastewater treated and the BOD removal efficiency remain constant we can predict the energy cost for different situations, and it can be noticed how the energy cost increases with Z values.

As it can be observed in Fig. 5 and Table 8, there is a slight increase in the energy cost (€/m^3) of large WWTPs as the Z parameter rises. In the Spanish region of Valencia, large WWTPs treat the wastewater of big cities, which are affected by the effects of seasonality. These WWTPs were designed with certain flexibility (oversized) in order to be capable of dealing with the peak volume received during the summer months. Oversized WWTPs permit to cope with these variations in the inflow in short term adapting the process to the new operational conditions, however, this has a negative impact on the energy cost, as it has been proven with the operational parameter Z. These results are comparable to those obtained by Silva and Rosa (2015) and Verrecht et al. (2010), who find out an over cost for a plant designed for twice or three times the mean flow.

4. Conclusions

This paper shows that the design volume is not only relevant for the investment cost estimation, but it is also related with the operational costs of the process. Using the daily volume of the WWTPs and the designed volume of the facilities it is proposed to obtain a performance index capable of representing whether the facilities are operating according to their design volume or not for the most part of the year. As it was expected, this index is related to the energy cost of the facilities, since the further the operational inflow is from the design one, the more the energy cost increases.

However, a step forward has been made, and a practical approach is given to this index including it in a cost function that estimates the energy cost of the facilities. This is a novelty contribution to the literature in the field of wastewater treatment. The results of the paper show the high accuracy of the energy cost estimations.

Throughout the cost modelling methodology, it is possible to improve our knowledge about the energy cost involved in the wastewater treatment process. We are aware of the most influencing variables and how they are related, which is relevant for the optimization of the process. This paper shows that the energy cost of large WWTPs is more affected when they operate far from the design conditions.

The cost functions presented in this paper show that the mismatching between the operational and design inflow ought to be taken into account by the managers of the WWTPs when energy costs are estimated. The reason is that they provide the managers with valuable information, very useful for optimizing the process. Moreover, this kind of cost functions are worth using in the decision making process, and when a new facility project is carried out in order to estimate the costs associated with its performance.

EC is the energy cost (€/year); V is the volume of wastewater treated by a plant (m^3/year); BOD is the biological oxygen demand removal efficiency (%); and Z is the performance index.

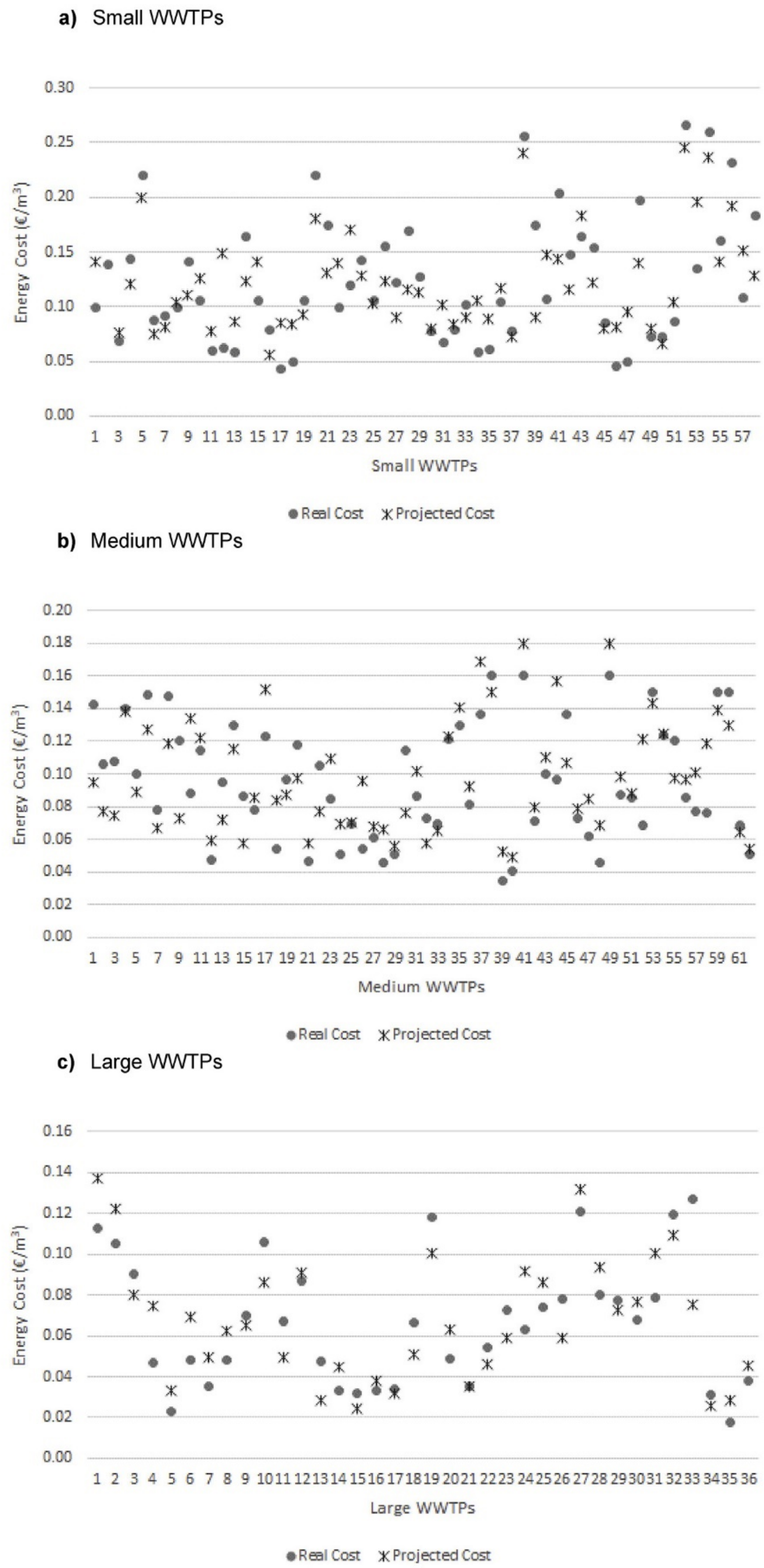

Fig. 4. Representation of real and projected cost (€/m^3). a) Small WWTPs. b) Medium WWTPs. c) Large WWTPs.

Table 8
Information for the energy cost estimation according to different scenarios.

	p.e.	Volume of wastewater treated (m^3/year)	BOD efficiency removal	Z	Energy cost (€/m^3)
Small WWTP	1140	89,131	0.96	0.20	0.09
				0.40	0.10
				0.60	0.11
				0.80	0.13
Medium WWTP	3587	333,154	0.98	0.20	0.07
				0.40	0.08
				0.60	0.09
				0.80	0.10
Large WWTP	87,704	3,499,365	0.98	0.20	0.06
				0.40	0.06
				0.60	0.07
				0.80	0.08

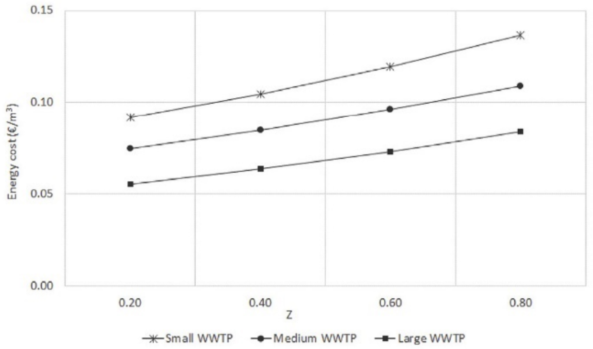

Fig. 5. Energy cost projection for different scenarios.

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Modelling the energy costs of the wastewater treatment process: The influence of the aging factor

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Modelling the energy costs of the wastewater treatment process: The influence of the aging factor

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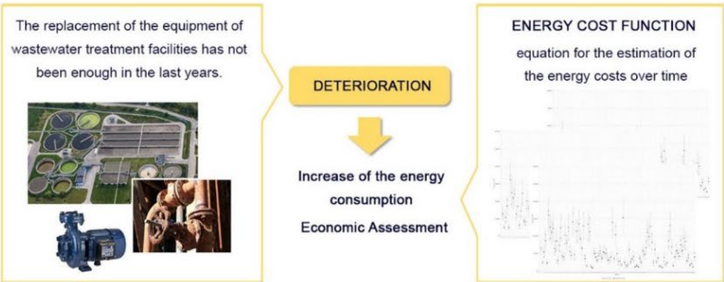
HIGHLIGHTS

- The energy cost of small and medium WWTPs are sensitive to the effects of the deterioration.
- A dynamic energy cost model has been developed.
- The energy cost model could become a useful decision making tool.

GRAPHICAL ABSTRACT



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ABSTRACT

Wastewater treatment plants (WWTPs) are aging and its effects on the process are more evident as time goes by. Due to the deterioration of the facilities, the efficiency of the treatment process decreases gradually. Within this framework, this paper proves the increase in the energy consumption of the WWTPs with time, and finds differences among facilities size. Accordingly, the paper aims to develop a dynamic energy cost function capable of predicting the energy cost of the process in the future. The time variable is used to introduce the aging effects on the energy cost estimation in order to increase the accuracy of the estimation. For this purpose, the evolution of energy costs will be assessed and modelled for a group of WWTPs using the methodology of cost functions. The results will be useful for the managers of the facilities in the decision making process.

1. Introduction

Water and energy are closely interconnected in the urban environment. Not only are they essential for the social and economic development of cities but also the production of one of them depends on the other (Hardy et al., 2012; King et al., 2008; Mo and Zhang, 2013; Perrone et al., 2011; Rio Carrillo and Frei, 2009). Recently the "water-energy nexus" has become more important given the pressure that the population growth has exerted on both resources (Healy et al., 2015; Pate et al., 2007; Siddiqi and Anadon, 2011), together with the high energy requirements of the urban water cycle (Cabrera et al., 2010) and the new energy policies implemented in this sector to reduce the greenhouse gas emissions (Frijns et al., 2012; Svensson et al., 2006). In a more recent study, Spiller (2017) develops a methodology to measure the capability of urban wastewater systems to adapt to what he calls "emerging changes", the reduction of the energy consumption being one of the changes that he mentions.

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Table 1
Sample description.

	2010		2011		2012	
	Mean	Standard deviation	Mean	Standard deviation	Mean	Standard deviation
Energy cost (€/year)	79,867	202,709	78,739	201,226	73,269	188,567
SS Removed (kg/year)	265,154	782,100	236,899	708,380	227,144	671,204
COD Removed (kg/year)	524,012	1,482,234	515,601	1,457,401	500,302	1,401,494
Treated Flow (m^3/year)	954,467	2,640,931	888,163	2,443,864	862,130	2,363,451
Design Flow (m^3/day)	4063	10,168	4063	10,168	4063	10,168
Equivalent inhabitants	13,326	38,395	13,089	37,908	12,876	36,839

Energy is essential in water resources management, as it allows water's exploitation but also maintains and guarantees the sustainability of the resource. The set of supply and sanitation infrastructures that make up the urban water cycle consists of large-scale energy consumers. Moreover, we can find considerable variations by country, generally associated with the availability of water resources, ranging from 1% in Sweden to 10% in Israel (Bodik and Kubaská, 2013).

The energy pattern of the urban water cycle is defined by the energy needs of the four stages that constitute it: 1) water collection and purification, 2) the drinking water supply system, 3) the sewage system, and 4) wastewater treatment and discharge. The energy consumption in the first phase of the cycle depends fundamentally on the nature of the water source: 0.37 kWh/m^3 for surface water and 0.48 kWh/m^3 for groundwater (WWAP, 2014). This difference is mainly due to the pumping system needed to push the groundwater to the surface. When the source is seawater, the energy consumption increases notably to 2.58 and 8.5 kWh/m^3, since the technologies used to treat this kind of water, such as membranes and osmosis, require a large amount of energy (WWAP, 2014). Then, regarding the drinking water system and the sewage network, Venkatesh et al. (2014) find that the energy consumption in the water supply system can range between 0.16 and 0.41 kWh/m^3, while the sewage system consumes much less, 0.03–0.13 kWh/m^3. These variations depend on the characteristics of the area served, the network design, and their management (Bolognesi et al., 2014). As far as the wastewater treatment process is concerned, the energy consumption and the operational cost of the Wastewater Treatment Plants (WWTPs) are influenced by the size of the plant, the quality parameters of the influent and the effluent, the kind of technology used, and the age of the equipment (Bodik and Kubaská, 2013; Corominas et al., 2013). It has been estimated that these technologies, used to implement the secondary treatment, consume 0.62–0.87 kWh/m^3 (WWAP, 2014). On the other hand, Longo et al. (2016) and Hernandez-Sancho et al. (2011b) claim that the implementation of technologies or mechanisms to remove either nutrients or pathogens from the wastewater increases the energy demand of the WWTPs, which could rise to 1.0–2.5 kWh/m^3 (WWAP, 2014).

In spite of the local variations in the energy consumption at the different stages of the urban water cycle, which depend not only on the volume and the quality of the water/wastewater treated but also on the service provided to the population (Venkatesh and Brattebø, 2011), we should be aware of the fact that wastewater treatment is one of the processes of the urban water cycle with higher energy requirements (Racoviceanu et al., 2007).

Table 2
Energy cost of the wastewater treated (€/m^3) for the period 2010–2012 and Kruskal-Wallis test result.\

Energy Cost (€/m^3)				
	2010	2011	2012	Kruskal-Wallis Test
Mean	0.11	0.14	0.15	0.001
Minimum	0.02	0.03	0.03	
Maximum	0.62	0.81	1.03	

There exist numerous technologies for the treatment of wastewater. One of the methods that are getting more attention nowadays on the grounds of the reduction of either operational or maintenance costs are constructed wetlands. However, their use is not widely spread yet, mainly for two reasons: the need of large extensions of land and the fact that they on both environmental and operational conditions, which could put at risk the quality of the effluent, since the characteristics of the wastewater can present large variations in quality and time (Fountoulakis et al., 2009; Vymazal, 2007; Vymazal and Kröpfelová, 2009). For this reason the current study is based on energy-intensive technologies such as extended aeration and activated sludge. According to the literature and the experience of the managers of WWTPs, a high percentage of the operating costs of the process are associated with energy (Guerrini et al., 2017; Hernandez-Sancho et al., 2011b; Torregrossa et al., 2017), which might represent between 25% and 56% of the operation and maintenance costs of the installation (Albaladejo and Trapote, 2013; Panepinto et al., 2016). Generally, more than a half of this energy is consumed by the biological treatment, due to the high energy requirement of the aeration systems of this phase (Brandt et al., 2011; Gikas, 2016; Sun and Li, 2010; Zhang et al., 2016). However, it should be noted that the energy consumption will depend on the characteristics of the plant, including the type of technology used, the size of the facility, and the contaminant load of the influent, among others (Plappally, 2012).

As a result, in recent years the reduction of energy consumption has been the main aim of wastewater treatment plant managers. One of the reasons for this is mainly economic, as a result of the rise in the energy tariffs (Bodik and Kubaská, 2013). There exist different factors that can affect the energy tariffs, such as the use of renewable resources in the production of energy which has increased recently up to 76% in Italy, 65% in Germany, and 17% in France, for instance (Eurostat, 2017); the existence of conflicts in different countries like Iraq; or even due to the interests or conflicts among the countries that are members of the Organization of the Petroleum Exporting Countries. For instance, some authors, including Albaladejo and Trapote (2013), show increases of up to 65.5% and 79.1% in the Spanish electricity tariffs during the period between 2009 and 2012, which had a significant impact on the cost structure of the WWTPs.

Table 3
Energy cost of the wastewater treated (€/m^3) differentiating two groups depending on the technologies applied for the period 2010–2012 and Kruskal-Wallis Test.

Energy Cost (€/m^3)				
	2010	2011	2012	Kruskal-Wallis Test
Group: T1				
Mean	0.117	0.145	0.150	0.001
Minimum	0.019	0.028	0.028	
Maximum	0.620	0.807	1.027	
Group: T2				
Mean	0.063	0.074	0.089	0.184
Minimum	0.033	0.046	0.038	
Maximum	0.132	0.154	0.164	

Table 4
Energy cost of the wastewater treated (€/m^3) by the group of WWTPs with aeration supply systems divided in three groups according to the volume of wastewater treated, for the period 2010–2012, and Kruskal-Wallis Test.

Energy Cost (€/m^3)	2010	2011	2012	Kruskal-Wallis Test
Group: D1				
Mean	0.168	0.216	0.228	0.003
Minimum	0.036	0.043	0.041	
Maximum	0.620	0.807	1.027	
Group: D2				
Mean	0.102	0.128	0.131	0.003
Minimum	0.019	0.036	0.041	
Maximum	0.215	0.234	0.268	
Group: D3				
Mean	0.090	0.102	0.102	0.287
Minimum	0.025	0.028	0.028	
Maximum	0.270	0.294	0.294	

However, the reduction of energy consumption also has an environmental purpose, given the close relation between energy and greenhouse gas (GHG) emissions (Papong et al., 2014; Plósz et al., 2009). Operating an industrial process, the wastewater treatment sector should contribute to accomplishing the latest European energy policies' aim to decrease the industrial energy consumption by 20% by 2020 (Slingerland et al., 2015). The wastewater treatment process, the purpose of which is to avoid an environmental impact by removing the contaminants contained in the wastewater, should be carried out not generating other environmental damages as far as possible. This fact has not passed unnoticed for authors like Zaribaf et al. (2013), whose work quantifies the CO_2 emissions associated with the wastewater treatment process; Molinos-Senante et al. (2015), who estimate the shadow price of the CO_2 emissions produced by the energy consumption in the wastewater treatment process; and Castellet and Molinos-Senante (2016), who carry out a research on the efficiency of a group of WWTPs located on the east coast of Spain, in which the reduction of the energy consumption is prioritised.

In practice, the wastewater treatment sector is facing this challenge through two action lines (Gikas, 2016): i) technological improvements, since more efficient technologies are capable of reducing the energy consumption, which will decrease the operational cost and the CO_2 emissions of the process (Henriques and Catarino, 2015; Zhou et al., 2008); and ii) the implementation of cogeneration systems, through which WWTPs are able to produce their own energy, making use of the biogas generated in the treatment of sludge, providing them with between 39% and 76% of the total electricity consumption (Silvestre et al., 2015), and reducing the CO_2 emissions (Shen et al., 2015) as well as the pressure on water itself, since 44% of the water resources in Europe are used in the energy production processes for cooling (Walsh et al., 2015).

Despite the implementation of these measures, it is estimated that the energy consumption will continue increasing as a result of the population growth, the economic development, the higher quality requirements for the treated water, and the deterioration of the wastewater infrastructures (Mo and Zhang, 2013). This last issue is the one that concerns the present study, which shows the consequences of the deterioration of the WWTPs on the electrical consumption.

Table 5
Collinearity statistics.

Explanatory Variables	VIF
Volume of wastewater treated (m^3/year)	1.843
COD removed (kg/year)	1.839
Aging	1.003

The experts in the wastewater treatment sector are warning about the aging and deterioration of the current wastewater infrastructures, which are causing a loss of efficiency in the process (AEAS, 2014, 2016). From the techno-economic point of view, the efficiency can be understood as the accuracy of the process in terms of the resources used (physical and economic) and the products obtained (contaminant removal and volume of wastewater treated). The deterioration of the water facilities, and particularly the WWTPs, is supposed to increase the resources required to carry out the process, such as the energy, maintenance labour, and reagents, in order to accomplish the quality standards of the treated wastewater. Despite the relevance of the issue, so far no studies quantify this fact. Nevertheless, a few studies exist, such as Hernandez-Sancho et al. (2011a, 2011b), Molinos-Senante et al. (2014), and Molinos et al. (2016), which try to relate the age of the facilities to the efficiency of the process, obtaining non-conclusive results in this regard. The reason for the irrelevance of the year of construction or the age of the facilities to the efficiency of the process in these works could be related to the modifications that many of the WWTPs have undergone over time to adjust to the requirements of the regulations that the administration has imposed since the publication of the first directive on wastewater (Directive 271/91).

Considering the work carried out by these authors, the present study aims to demonstrate the effect of time on WWTPs from another perspective: energy consumption. WWTPs consist of different elements: concrete structures, pipes, pumps, and other electromechanical equipment. The last two are the ones that most concern the managers, mainly for three reasons: i) this equipment has a useful life that is inferior to that of the rest of the elements, approximately ten years; ii) it requires constant maintenance actions; and iii) its success or malfunctioning has relevant implications for the energy consumption. In the end, these issues together affect the operational cost of the facilities.

Given the importance of these elements in the wastewater treatment process and the management of the WWTPs, the present study aims to analyse the energy cost of a set of WWTPs located in the Valencian Community for the period between 2010 and 2012. The evolution of the energy cost is observed throughout this period, and then it is modelled considering the aging of the equipment year after year to predict the future costs. The prediction of the energy costs could become an indicator of the condition of the electrical assets of the facilities, and they will help the managers of the WWTPs to make decisions, such as when the equipment should be replaced or whether maintenance operations should be implemented ultimately to reduce the deterioration of the equipment and costs.

2. Material and methods

2.1. Energy cost model

First, a statistical analysis of the available information on variables representative of the wastewater treatment process is performed. Since our sample does not meet the normality assumption, the Kruskal-Wallis test is used. This is a non-parametric statistical test that allows the comparison of three or more groups, and it is an extension of the Mann-Whitney test, which is used to compare only two populations or groups (Conover, 1999; Kruskal and Wallis, 1952). In order to compare the energy costs of a three-time period, the costs have been deflated using the costs of 2012 as a reference. To achieve this, the authors chose the increase in the electricity tariffs, which depend on the electrical capacity hired for each facility.

As far as the energy cost modelling is concerned, despite the fact that cost functions for estimating the investment and operational costs of WWTPs are widespread in the literature (Chen and Chang, 2002; Friedler and Pisanty, 2006; Gonzalez-Serrano et al., 2005; Guo et al., 2014; Hernandez-Sancho et al., 2011a; Molinos-Senante et al., 2013; Pannirselvam and Gopalakrishnan, 2015), we are not aware of the

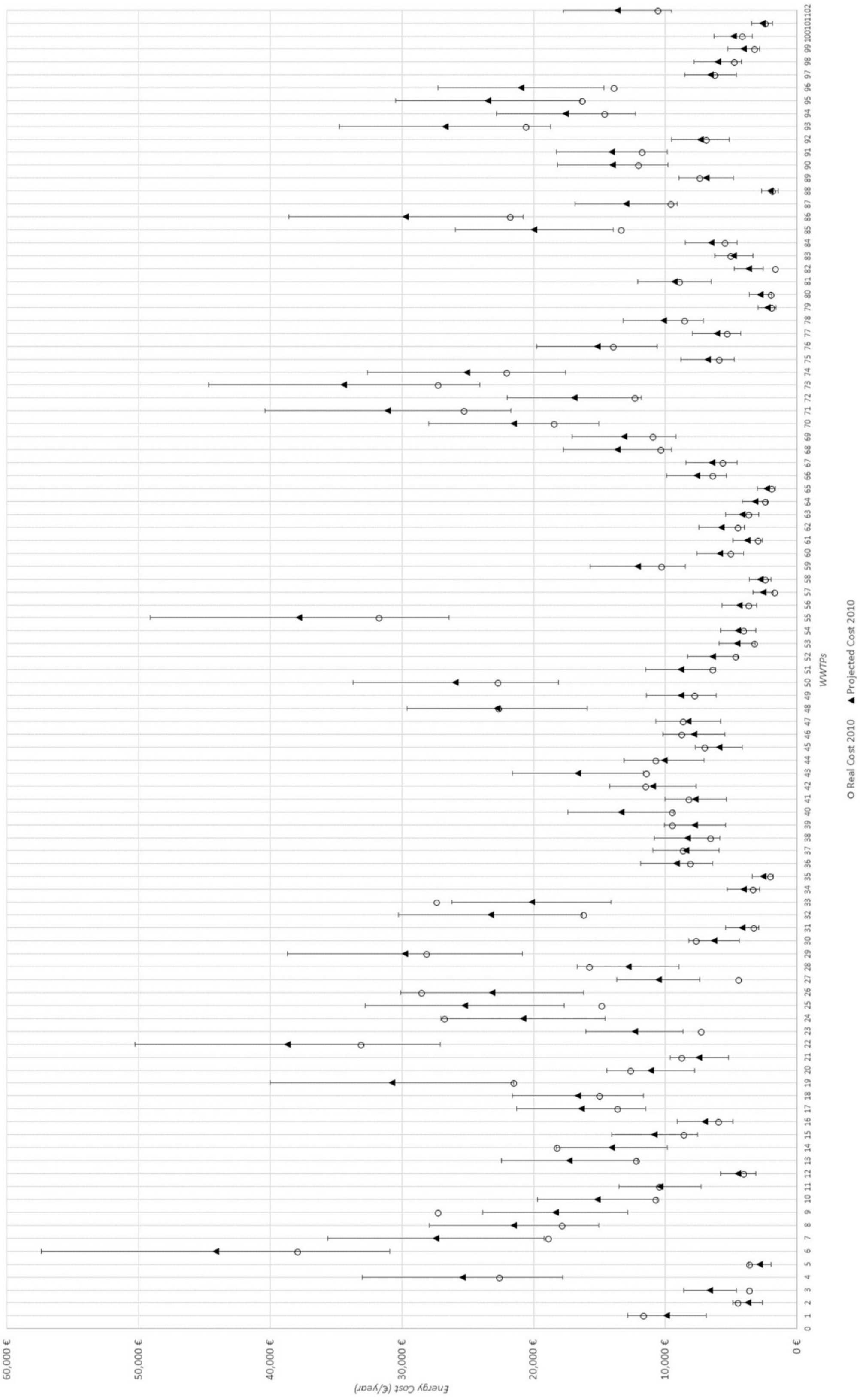

Fig. 1. Real and projected cost representation for 2010.

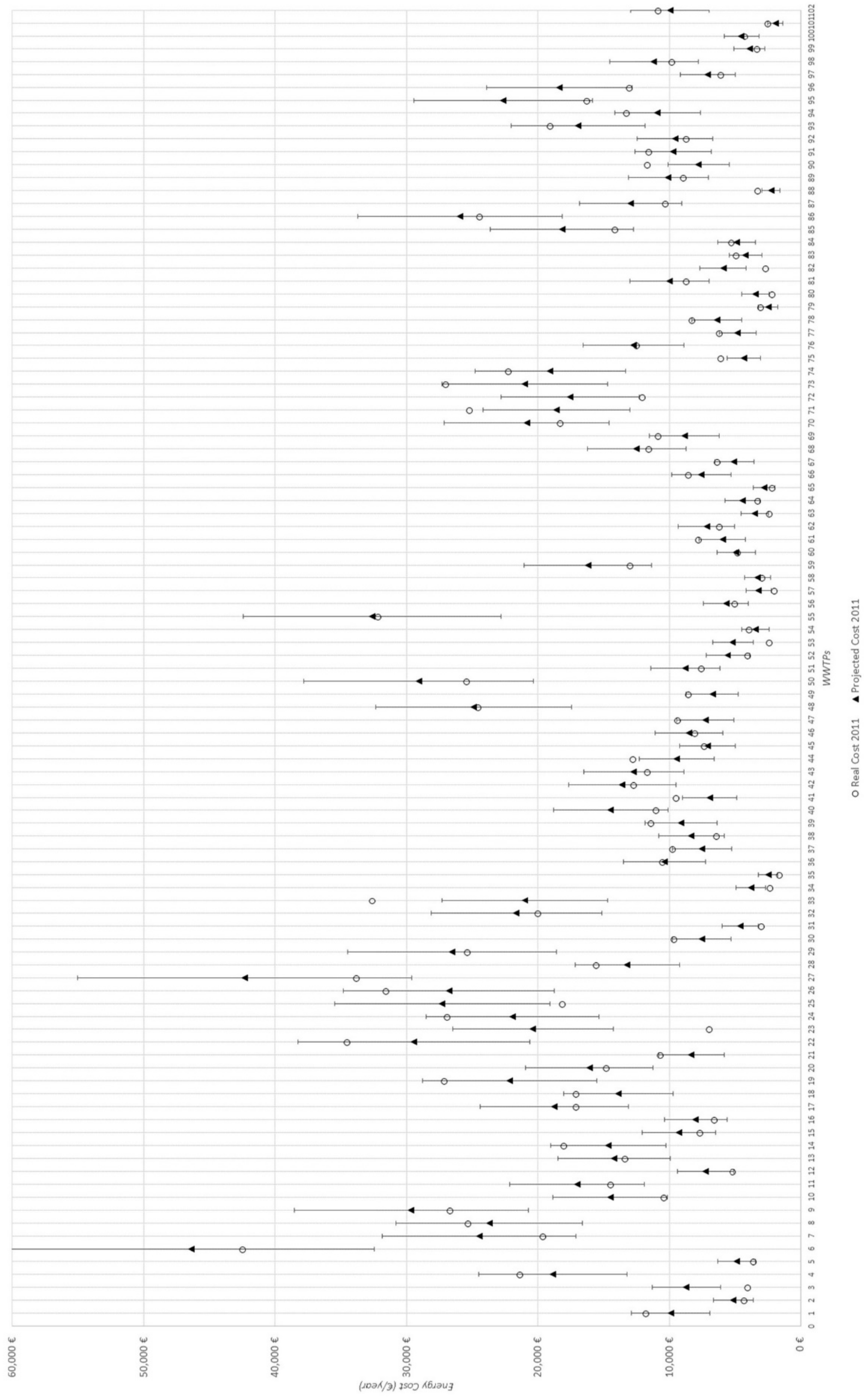

Fig. 2. Real and projected cost representation for 2011.

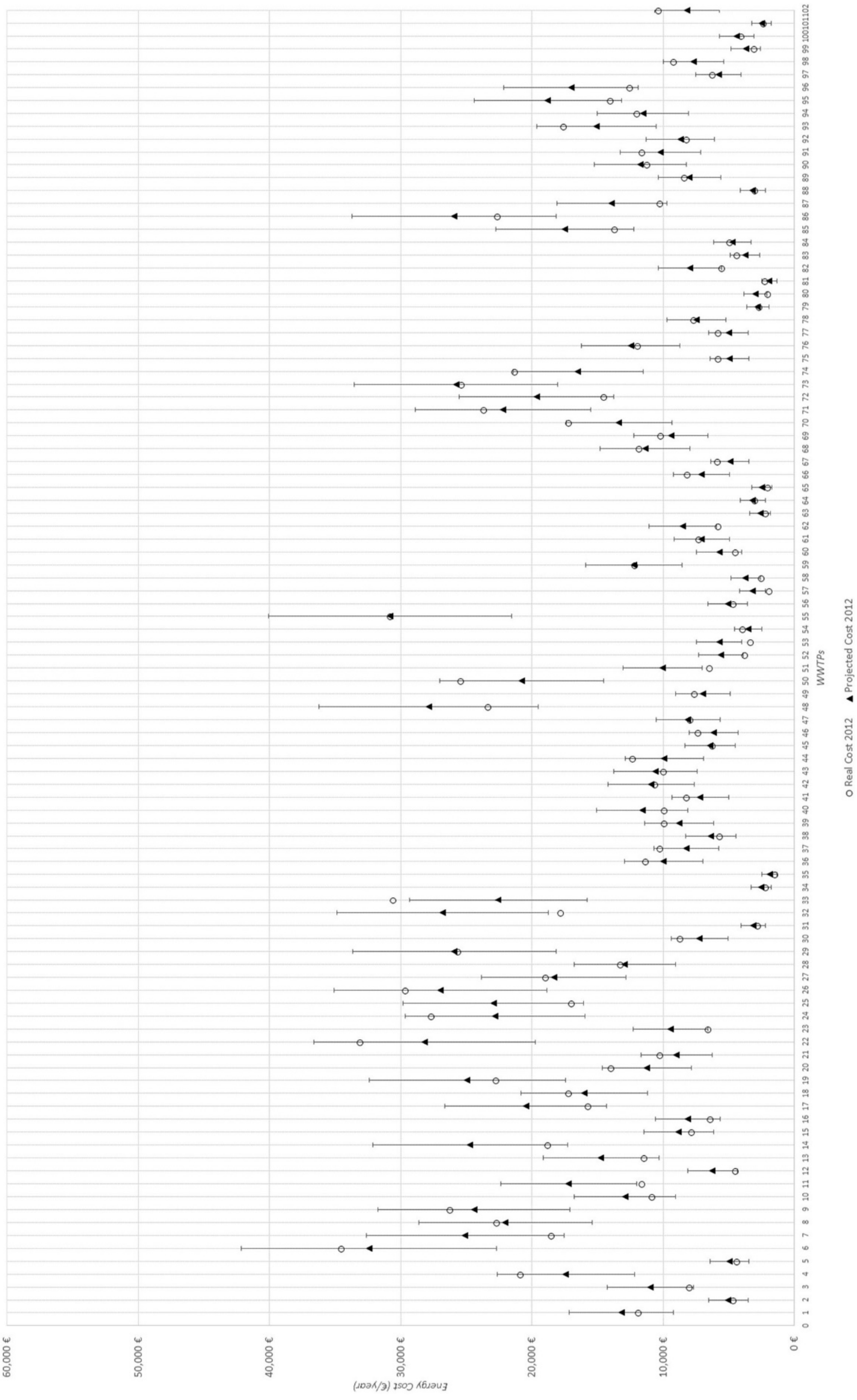

Fig. 3. Real and projected cost representation for 2012.

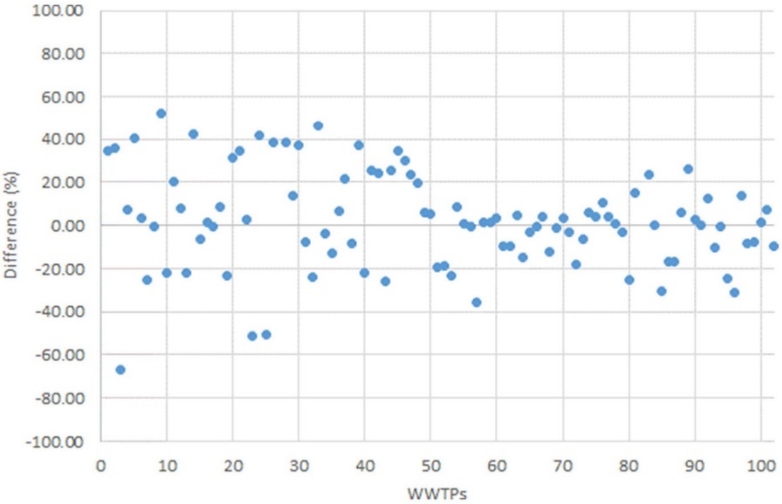

Fig. 4. Differences between real and projected costs for 2010.

existence of any cost function to estimate the energy costs of the process considering the aging of the equipment.

The present study uses a cost function similar to the one previously applied by Hernandez-Sancho et al. (2011a) for modelling the operation and maintenance costs of the WWTPs according to the technology used in the process. Following these authors, since the major part of the operational cost of a WWTP is explained by its energy consumption, the mathematical expression of the model used in the study is the following:

$$EC = A \cdot Z^b \cdot e^{\sum \alpha_i x_i} \tag{1}$$

which can also be expressed in logarithmic terms:

$$\ln EC = \ln A + b \cdot \ln Z + \sum \alpha_i x_i \tag{2}$$

where EC is the energy cost (€/year); A, b, and α are parameters; and Z and x_i are different representative variables of the process, such as the volume of wastewater treated (m^3/year), the amount of contaminants removed from the wastewater (kg/year) and aging (the years that have passed since the year taken as a reference).

In order to determine the variables that explain the energy cost of the WWTPs, we first analyse the correlations between the possible explanatory variables and the dependent variable, as well as, the correlation between the independent variables themselves. The potential variables that explain the model will be those that are highly correlated with the energy cost, and are independent of the others.

Then, through a statistical program, the best combination of variables capable of explaining the model is selected. The final model is a weighted ordinary least squares regression obtained empirically. All the variables in the regression equation are significant at the 95% confidence level.

Due to the complex nature of the wastewater treatment process, it should be proven that the independent variables used in the cost function model are linearly independent of each other to guarantee the feasibility of the model. For this purpose, the variance inflation factor (VIF) is used. According to Kleinbaum et al. (1988), there are problems of collinearity between the variables when the VIF present values higher than 10, while a value of 1 means that the variables are not correlated.

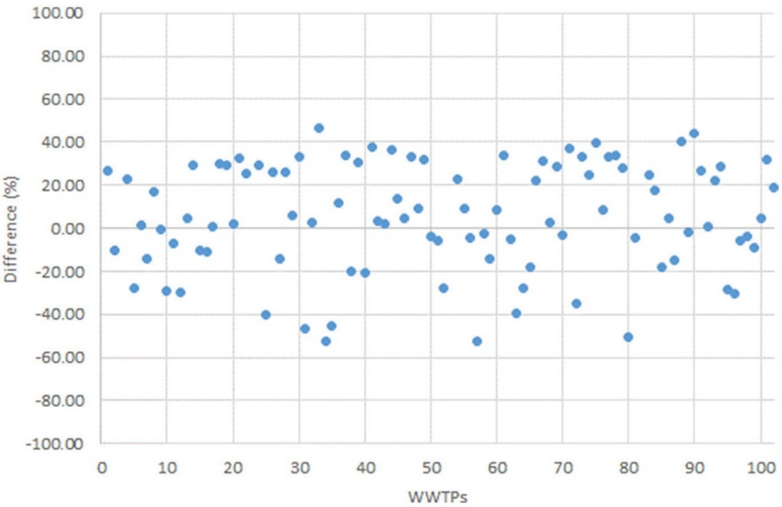

Fig. 5. Differences between real and projected costs for 2011.

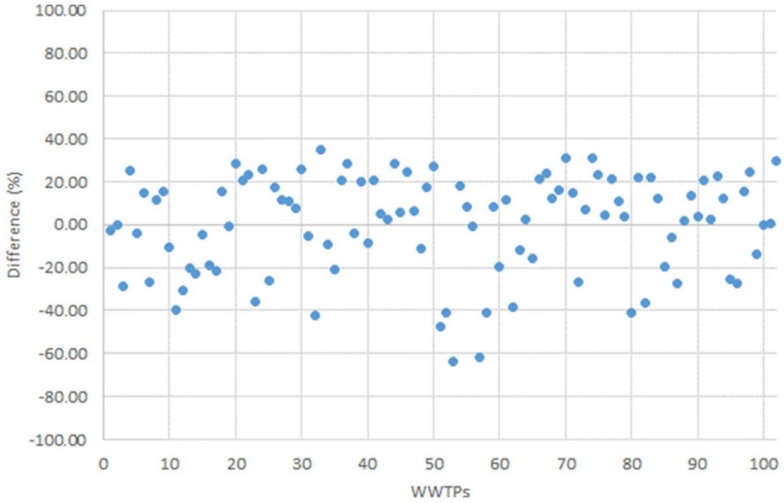

Fig. 6. Differences between real and projected costs for 2012.

Moreover, using temporal data could generate problems of heteroscedasticity in the model. To confirm that this situation does not occur, the Breusch and Pagan (1979) test is applied after proving the normality of the residuals through the Kolmogorov-Smirnov test. Finally, the analysis of the residuals is conducted using the Durbin-Watson statistic (1951) to verify that there is no autocorrelation in the residuals.

2.2. Sample description

The sample used in this empirical research consists of information on 322 WWTPs located in the region of Valencia, in Spain, for the period 2010–2012. We have 966 observations with different technology treatments: activated sludge (82%), extended aeration (12%), and biodisks (6%). The whole sample processes volumes of wastewater that range from 7000 m^3/year to 23,000,000 m^3/year. These WWTPs are managed by private companies but the ownership is public.

Besides the cost associated with the energy consumption of the facilities, which is the object of the study, information related to the process performance is also available, for instance the volume of wastewater treated (m^3/year), the amount of contaminants, such as suspended solids (SS), the chemical oxygen demand (COD) removed from the wastewater (kg/year), the design flow (m^3/day), and the number of equivalent inhabitants.

Table 1 contains a summary of the information used in the empirical application from 2010 to 2012. It can be noted that the energy costs have already been updated to the reference year (2012).

3. Results and discussion

3.1. Energy cost analysis

Analysing the information shown above statistically, and considering the updated energy cost, it is observed that 51.8% of the WWTPs increase their energy costs per m^3 of wastewater treated between 2010 and 2012, as shown in Table 2. Therefore, there is an upward trend over time in the energy cost of the treated wastewater, which is confirmed by the Kruskal-Wallis test.

Next, these facilities that experienced a rise in their energy cost during the period considered are analysed in particular by dividing the sample into different groups according to the technology of the secondary treatment and the size of the installations expressed as the volume of wastewater treated.

The energy consumption of a facility depends to a large extent on the type of secondary treatment due to the different oxygen supply needs of each type of technology. Thus, given the characteristics of the technologies presented in the sample, two technology groups are differentiated: i) T1, which includes those WWTPs of which the technologies have oxygen supply systems (activated sludge and extended aeration); and ii) T2, which is formed by those WWTPs that do not have oxygen supply systems (biodisk technology). The first group is more energy intensive than the second one, since aeration systems are the major consumers of the secondary treatment, while the latter group only requires energy for the rotation of the biodisks (IDAE, 2010).

Table 3 shows how the energy cost increases over time for both groups. However, according to the results of the Kruskal-Wallis test, these differences are only statistically significant for these technologies that present aeration supply systems (T1). One of the most common aeration systems used is diffusers, and prior studies prove that the effects of fouling and scaling lessen their efficiency (Garrido-Baserba et al., 2016; Kaliman et al., 2008; Rosso and Stenstrom, 2006).

In addition to the technology of the facilities, other technical features that should be taken into account when we analyse the operational costs of the wastewater treatment process is the size of the installations in terms of the volume of wastewater treated, due to the existence of scale economies in this kind of process (Fraquelli and Giandrone, 2003; Hernandez-Sancho and Sala-Garrido, 2006). The smaller the volume of wastewater treated is, the greater the energy cost of the process is (Table 4).

Thus, in line with this criterion, the group of WWTPs with aeration supply systems, which presents a significant rise in their energy cost, is now divided into three size groups according to the volume of wastewater treated (m^3/year): i) D1, facilities that treat up to 55,000 m^3/year; (ii) D2, plants treating volumes of wastewater between 55,000 and 275,000 m^3/year; and iii) D3, facilities that process more than 275,000 m^3/year.

As it can be observed in Table 4, the energy cost of the wastewater treated increases in all the groups. However, the variations over time are not statistically different for the largest ones. Thus, it can be said that the facilities that treat less than 275,000 m^3/year of wastewater are those that could experience larger increases in their energy consumption as a result of the deterioration.

The results obtained could be explained by the following: (1) larger facilities present better maintenance of the equipment; (2) smaller facilities tend to be oversized and deteriorate more rapidly, so differences in the energy consumption over time are more notable in these cases;

and (3) some WWTPs of the third group (D3) are provided with cogeneration systems, so they could be masking the effect of greater energy consumption over time in this group of WWTPs.

3.2. Modelling the energy cost

Since the difference in the energy consumption over time is only statistically significant for the small and medium WWTPs that use technologies with oxygen supply systems (activated sludge and extended aeration), modelling the energy costs for these kinds of technologies is considered. Then, the model is elaborated using the statistical information of 102 facilities collected during the period 2010–2012, as reported in the Material and methods section. Previously, the detection of outliers has been carried out using the methods that the statistical software used, the SPSS, offers.

The quality of the energy cost model obtained is measured through the coefficient of determination (R^2), which represents the goodness of fit of the statistical model. The R^2 can take values between 0 and 1, the highest value. Moreover, all variables that take part in the regression equation are significant at the 95% confidence level or better, which means that the *p*-value of the variables should be less than 0.05. And finally, in combination with the above parameters, the standard error ought to be as small as possible. Subsequently, the energy cost model obtained can be expressed as follows:

$$EC = 0.125 \cdot V^{0.791} \cdot e^{5.38 \cdot 10^{-8} \cdot M + 0.103 \cdot J} \quad (3)$$

where:
EC = energy cost (€/year)
V = volume of wastewater treated (m^3/year)
M = COD removed (kg/year)
J = aging (years elapsed)

As it can be observed, the energy cost of the wastewater treatment process of the facilities with activated sludge and extended aeration is explained in part by the volume of wastewater treated (m^3/year). It seems that this variable is essential to explaining the operational cost of the wastewater treatment process, since the model obtained by Hernandez-Sancho et al. (2011a) for the same technologies also includes this variable. In contrast, when the energy cost is modelled separately, the amount of COD removed from the wastewater (kg/year) is more influential than the nutrients removal or the BOD_5, since they were not statistically significant in the model. In order to predict the energy costs, the model includes a variable called aging, which represents the number of years that have passed since the reference year.

The short period of time used in the analysis could be a limitation of the work. However, the results suggest that time has a greater impact on the energy costs of the process than the age of the plants. There is a strong likelihood that a WWTP that is 20 or 35 years old will have replaced some parts of the electromechanical equipment once or twice, which makes it very difficult to link the variable age with the energy consumption. Nevertheless, using time as a variable allows us to include the effects of the deterioration of the equipment. Regardless of the age of the plant, any equipment is subject to the effects of time.

Regarding the adjustment quality, we can say that it is good, since the value of the coefficient of determination is 0.890. It has been proved that the explanatory variables used in the model are significantly correlated with the energy cost, but they do not show any problems of multicollinearity. Table 5 shows the lower values of VIF for each of the independent variables, which confirm that the model does not present multicollinearity.

Besides this, homoscedasticity testing is of importance to the cost model's suitability due to the use of temporal data. Accordingly, the Breusch and Pagan (1979), which assumes normality in the residues, offers a *p*-value of de 0.6069, which means that H_0 cannot be rejected within a 95% confidence level. Moreover, the fact that the residuals are random and independent of each other increases the robustness of the model (Durbin-Watson statistic of 1.644).

The accuracy of the cost function can be observed visually in Fig. 1, Fig. 2, and Fig. 3. These figures show the real energy cost and the energy costs obtained through the cost function for each one of the WWTPs of our sample. As it can be observed, most of the projected costs are very close to the real ones, which means that the model obtained offers a good approach to the energy cost, since the real cost of most of the plants can be predicted within a ± 30% of error (error bars).

Moreover, in order to show the accuracy of the predicted values, the difference between the real and the estimated costs for each one of the WWTPs are represented in Figs. 4, 5 and 6. The lesser is the error, the better is the adjustment.

The accuracy of the energy cost model shows that it could be worthwhile for WWTP managers to use it, since it can provide them with helpful information to manage the process. Not only do they use explanatory variables of the process but also they contemplate the loss of efficiency of their equipment when the energy costs are estimated. Moreover, this kind of tool can become very helpful in making decisions related to when old equipment should be replaced with new equipment. It is supposed that, when the energy costs together with the maintenance costs of the current equipment exceed the costs of replacing it with new equipment, the replacement should be made.

4. Conclusions

Secondary treatments provided with aeration systems, such as active sludge and extended aeration, present significant differences in energy consumption over time. This is mainly due to the fact that the most common aeration systems used consist of diffusers. The blockage of the tiny holes of the diffusers due to fouling and scaling phenomena is responsible for a loss of efficiency of this equipment, which in response increases the energy consumption. The fact that these elements are the main energy consumers of the process results in greater differences in the energy consumption over time for this kind of technology.

Differences in the energy consumption been identified over time not only according to the type of technology but also in consonance with the volume of wastewater treated. The results obtained show that the differences in those facilities that treat less than 275,000 m^3/year of wastewater are more relevant. This result should not be interpreted as indicating that larger ones take longer to deteriorate but that the effects of deterioration are not so noticeable.

Assuming that maintenance operations are similarly performed in any kind of WWTP, independently of their size, we could say that the effect of the deterioration in larger facilities may be masked by the fact that some of them are self-sufficient in energy, thanks to their cogeneration systems. On the other hand, if differences in the maintenance strategies between them really exist, larger installations perform better in maintenance operations, generating consequences for reducing the deterioration of the facilities and the energy consumption.

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Research article

Efficiency assessment of wastewater treatment plants: A data envelopment analysis approach integrating technical, economic, and environmental issues

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ABSTRACT

The assessment of the efficiency of wastewater treatment plants (WWTPs) is essential to compare their performance and consequently to identify the best operational practices that can contribute to the reduction of operational costs. Previous studies have evaluated the efficiency of WWTPs using conventional data envelopment analysis (DEA) models. Most of these studies have considered the operational costs of the WWTPs as inputs, while the pollutants removed from wastewater are treated as outputs. However, they have ignored the fact that each pollutant removed by a WWTP involves a different environmental impact. To overcome this limitation, this paper evaluates for the first time the efficiency of a sample of WWTPs by applying the weighted slacks-based measure model. It is a non-radial DEA model which allows assigning weights to the inputs and outputs according their importance. Thus, the assessment carried out integrates environmental issues with the traditional "techno-economic" efficiency assessment of WWTPs. Moreover, the potential economic savings for each cost item have been quantified at a plant level. It is illustrated that the WWTPs analyzed have significant room to save staff and energy costs. Several managerial implications to help WWTPs' operators make informed decisions were drawn from the methodology and empirical application carried out.

1. Introduction

The adoption of regulations such as European Union (EU) Directive 91/271/ECC concerning urban wastewater or the United States Clean Water Act has involved significant progress in the development and implementation of wastewater treatment technologies. However, water resource issues should not be addressed only from a technical and engineering perspective, but they should have a multidisciplinary nature, as the EU Water Framework Directive (WFD) published in 2000 highlighted. Accordingly, the performance assessment of water facilities should involve economic, environmental, and technical issues.

Within the urban water cycle, special attention has been paid to the efficiency assessment of wastewater treatment plants (WWTPs). In particular, assessing the efficiency of WWTPs allows their performance to be compared and therefore best practices to be identified. In this context, Hernández-Sancho et al. (2011), Sala-Garrido et al. (2012a), Molinos-Senante et al. (2015a), and Guerrini et al. (2015), among others, have assessed the so-called techno-economic efficiency of WWTPs. In doing so, they have considered that the operational and maintenance costs of WWTPs are their inputs, while the pollutants removed from the wastewater are their outputs. This assessment is very useful, as it allows economic and technical variables to be integrated into a single indicator, namely the efficiency index (Molinos-Senante et al., 2014). However, they ignored the fact that the different pollutants removed from wastewater would involve different impacts on the environment if they were dumped.

From a methodological point of view, almost all previous studies have applied the data envelopment analysis (DEA) approach to

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evaluate the efficiency of WWTPs. As Zhu (2015) stated, in DEA models the efficient frontier is obtained empirically from a real database of the consumed resources (inputs) and generated products (outputs). Those units which are located over the frontier mark the minimum number of inputs that a WWTP could operate being efficient (input orientation) or the maximum production achieved given a certain number of resources (output orientation) (Azad and Ancev, 2014). Broadly, two types of DEA models can be distinguished, namely radial and non-radial models. They differ, among other things, in how the distance between the units is analyzed and the production frontier is measured. In radial models, the distance from the units to the production frontier is obtained by projecting on the efficient frontier the line that joins the analyzed decision-making unit (DMU) with the origin (Carvalho and Marques, 2011). Each output and input that constitutes the virtual input and output, respectively, contributes differently in obtaining the virtual input and output. We refer to the input and output contributions as weights. The weights corresponding to each input and output are given by the program itself so that the efficiency of the unit is maximized (Cooper et al., 2011).

A significant shortcoming of radial DEA models is that they assume that the reduction or increase of inputs and outputs are proportional, which is not always the case in real examples. To overcome the problem mentioned before, Tone (2001) proposed the slacks-based model (SBM) which is a non-radial DEA model that aims to individually optimize each resource and/or product that consumes or produces each production unit. This efficiency score is obtained for each input/output, so that we can see in detail the behavior of each input/output.

In most of the empirical applications, the fact that DEA methodology automatically assigns the weights to each input and output is an advantage, as it reduces the subjectivity of the assessment (Murillo-Zamorano, 2004). However, depending on the priorities or managerial preferences given to the outputs or even depending on the own outputs of the DMUs, it is more suitable to assign specific weights to the outputs (Barros et al., 2012). In the case of WWTPs, it is well known that the negative impact that different pollutants would involve in the environment if they were not removed from wastewater is also different. Hence, to integrate the environmental impact in the efficiency assessment of WWTPs, it is necessary to "manually" assign the weight to each output rather than them being assigned through optimization. This can be done by computing the efficiency using the weighted slack-based measure (WSBM) model introduced by Tone (2011). The model is a non-radial DEA model similar to the SBM model, but it allows weights to be assigned "manually" to the set of inputs and outputs.

Against this background, the objectives of this paper are twofold. The first is to assess the efficiency of a sample of WWTPs by integrating technical, economic, and environmental issues. In doing so, the non-radial WSBM model is applied, since it allows us to assign weights to the set of outputs produced by the WWTPs (pollutants removed from wastewater) according their environmental impact. Moreover, since energy use in WWTPs involves not only economic issues but also environmental aspects, this input was also weighted based on the shadow price of CO_2 emissions from WWTPs. Moreover, and as a sensitivity analysis, the impact of different energy weights on the efficiency of the WWTPs was evaluated. The second objective is to quantify the potential economic savings for each cost item at the WWTP level.

This paper contributes to the current strand of literature in the field of WWTP performance measurement by computing the efficiency scores of a sample of WWTPs by introducing weights to the pollutants removed from wastewater which represent its impact on the environment. It should be highlighted that in spite of some studies evaluating the efficiency of WWTPs considering the pollutants removed from wastewater as outputs, none of these previous studies have weighted the outputs based on their environmental impacts. Moreover, no studies were identified that quantify the potential economic savings for each cost item that WWTPs could achieve if they were efficient. In this sense, Molinos-Senante et al. (2014) computed an efficiency score for each input (cost item), but they did not quantify the potential economic savings associated with each one.

From a policy perspective, the results of this study are of great interest for WWTP managers. On the one hand, the evaluation of the efficiency of WWTPs allows managers to compare the performance of the set of facilities assessed. Hence, best operational practices could be identified. The implementation of these practices in inefficient WWTPs would contribute to the improvement of their performance and consequently the reduction of their operational costs. On the other hand, the quantification of potential economic savings for each cost item is essential to support the decision-making process. Thus, WWTP managers could implement the most appropriate measures to further reduce operational costs.

2. Methodology

2.1. Efficiency assessment

To compute the efficiency of WWTPs, the WSBM model introduced by Tone (2011) was applied as it has the advantages of non-radial DEA models and also it allows us to assign weights to the inputs and outputs for all the DMUs according to their importance or relevance from an environmental point of view. In other words, the WSBM model allows the integration of environmental issues in the assessment of the efficiency of WWTPs.

Let the sample of WWTPs to be evaluated as $J=\{1, 2, \ldots, n\}$, each WWTP having m inputs and s outputs. The vector of inputs and outputs for the WWTP$_j$ is denoted by $x_j=(x_{1j}, x_{2j}, \ldots, x_{mj})$ and $y_j=(y_{1j}, y_{2j}, \ldots, y_{sj})$, respectively. The production possibility set is defined as follows (Hoang, 2014):

$$P = \left\{ (x,y) | x_i \geq \sum_{j-1}^{n} x_{ij} \ (\forall i), 0 \leq y_r \leq \sum_{j-1}^{n} y_{rj} (\forall r), e\lambda = 1, \lambda \geq 0 \right\} \tag{1}$$

where e denotes a row vector in which all elements are equal to one and $\lambda=(\lambda_1, \lambda_2, \ldots, \lambda_n)$ is an intensity vector.

The introduction of the slacks allows the inequalities of Eq. (1) to be transformed into the following equalities (Tone, 2010):

$$x = \sum_{j-1}^{n} \lambda_j x_j + s^- \tag{2}$$

$$y = \sum_{j-1}^{n} \lambda_j y_j - s^+ \tag{3}$$

$$s^- \geq 0, \quad s^+ \geq 0 \tag{4}$$

where $s \ = (s_1, s_2, \ldots, s_m) \in R^m$ and $s^+ = (s_1^+, s_2^+, \ldots, s_s^+) \in R^s$ are the input and output slacks, respectively.

According to Tone (2011), the WSBM model is defined as follows:

$$\rho_{IO}^{*} = min_{\lambda,s^{-},\lambda s^{+}} \frac{1-\left(\frac{1}{m}\right)\sum_{i-1}^{m}\frac{w_i s_i^{-}}{x_{io}}}{1+\left(\frac{1}{s}\right)\sum_{r-1}^{s}\frac{w_r^{+}s_r^{+}}{y_{ro}}} \quad (5)$$

s.t.

$$x_{io} = \sum_{j-1}^{n} x_{ij}\lambda_j + s_i^{-} \quad (i = 1, \ldots, m)$$

$$y_{ro} = \sum_{j-1}^{n} y_{rj}\lambda_j - s_r^{+} \quad (r = 1, \ldots, s)$$

$$\sum_{j-1}^{n} \lambda_j = 1$$

$$\lambda_j \geq 0\ (\forall j), s_i^{-} \geq 0\ (\forall i), s_r^{+} \geq 0\ (\forall r)$$

where $\sum_{i=1}^{m} w_i = m$ and $\sum_{r=1}^{s} w_r^{+} = s$. The choice of weights (w_r and w_i) reflects the importance of output r and input i, respectively.

In this case study, as is illustrated in Eq. (5), an input-oriented WSBM model was applied since the objective is to improve WWTP efficiency by reducing costs and keeping the level of purification (contaminant removal) constant. In addition to the orientation of the model, it is also necessary to define under what type of scale returns it operates. Scale returns can be understood as how the DMU production varies if the inputs and outputs involved are altered. Thus, it can be distinguished between constant scale returns, when an input variation produces outputs that vary proportionally, and variable scale returns, where a change in the inputs does not produce proportional changes in the outputs. In this case, the variable scale returns can be increasing if the outputs vary in a greater proportion than the inputs, or decreasing if outputs are generated in less proportion than the inputs. Previous studies (Sala-Garrido et al., 2012a; Molinos-Senante et al., 2014; Guerrini et al., 2015) have evidenced that WWTPs operate under variable returns to scale technology. Hence, this approach was assumed to evaluate the efficiency of WWTPs.

As in all DEA models, the efficiency score obtained for each DMU by applying the WSBM model is between 0 and 1. A DMU (WWTP in our case study) is efficient if and only if its efficiency score is equal to 1 and the slacks are 0. If its efficiency score is less than 1, the DMU is considered inefficient because it could reduce the use of inputs (operational costs) while keeping constant the quantity of outputs (pollutants removed from the wastewater).

2.2. Assignment of weights

The aim of using the WSBM model to evaluate the efficiency of WWTPs is to incorporate the environmental impacts associated with the different pollutants removed from wastewater. The life cycle assessment tool has been widely applied to evaluate the environmental performance of WWTPs (Ontiveros and Campanella, 2013; Wang et al., 2015). However, it provides a synthetic indicator of the environmental impact produced or avoided by WWTPs but not a specific indicator of the environmental impact of each pollutant removed in these facilities. On the contrary, Hernández-Sancho et al. (2010) estimated the shadow price of the four main pollutants removed from wastewater depending on the destination of the treated water. According Molinos-Senante et al. (2011), the shadow prices of the pollutants represent the value, expressed in economic terms, of external effects that could damage the environment if they were not removed from wastewater before its discharge to water bodies. Hence, the assignment of the output weights to be considered in the WSBM was based on the shadow prices of the pollutants estimated by Hernández-Sancho et al. (2010) (see supplemental material).

Since the environmental impact of the pollutants depends on the destination of the treated water, in order to assign the weights of the outputs involved in the WSBM model, it was considered the percentage of treated water that is dumped into the sea, rivers, wetlands, or that which is reused for each WWTP evaluated.

As far as the selection of the input weights is concerned, it should be highlighted that they are expressed in monetary units. Hence, initially all of them should have the same importance (weight). However, it is well known that energy consumption is not only an economic issue but also an environmental issue mainly associated with the emission of greenhouse gases (GHG) (Papong et al., 2014). Following the same methodological approach as Hernández-Sancho et al. (2010), Molinos-Senante et al. (2015b) computed the shadow price of the GHG emissions associated with energy consumption in WWTPs. Using a sample of 25 WWTPs, they estimated that the average shadow price of CO_2 was 17.7% of the market value of the treated water. Hence, according the price of the treated water proposed by Hernández-Sancho et al. (2010), it was computed that the shadow price of the GHGs depended on the destination of the effluent (see Supplemental material).

Knowing the GHG shadow price for each treated water destination, we can estimate the energy weight in the same way as has been done with the outputs using the weighted average. For this, in addition to the GHG shadow prices depending on the final destination of the treated water it was also needed to know the volume of treated water for each WWTP.

3. Sample description

The sample used for this study consisted of the 49 largest WWTPs in the Valencia Region (except Pinedo's WWTP) on the Spanish Mediterranean cost. The statistical information comes from the Valencian wastewater treatment authority—Entitat de Sanejament d'Aigües (EPSAR)—for 2012. A basic premise of applying the DEA methodology is that the units to be evaluated (WWTPs in this case study) should be as homogeneous as possible. In other words, they should perform the same productive process in order to be comparable. Hence, the 49 WWTPs assessed in this study carry out their wastewater treatment through the following processes: pretreatment; primary treatment; secondary treatment, based on an activated sludge system; secondary sedimentation. After passing through the various stages and processes, treated water that meets the quality criteria established by regulations is obtained. As far as the sludge treatment is concerned, the sludge stabilization for all of the 49 facilities takes place through anaerobic digestion.

Following past evidence (Hernández-Sancho et al., 2011; Sala-Garrido et al., 2012a; Molinos-Senante et al., 2014; Molinos-Senante et al., 2015a), it was considered that six cost items constitute the inputs needed to operate the WWTPs: (i) energy costs, defined as the cost of energy required for operation facilities; (ii) staff costs, which involve the salaries of technicians and plant operators; (iii) reagent costs, which are the cost of chemicals needed for the wastewater treatment; (iv) maintenance costs, which involve equipment and infrastructure costs and their maintenance; (v) waste costs, which refer to those costs associated with the management of waste and sludge; and (vi) other costs, which are different types of costs, such as office supplies, administration, or laboratory equipment, among others.

Regarding the selection of the outputs, two approaches have previously been considered, namely the volume of treated water (Gjebrea and Zoto, 2013; Lannier and Porcher, 2014) and the quantity of contaminants removed from the wastewater. As Wu et al. (2015) pointed out, the concentration of pollutants in the influent depends on several environmental and climatic factors, while the effluent of all WWTPs must meet the legal requirements. Hence, the concentration of pollutants to be removed from wastewater is not the same for all WWTPs. Because the operational costs of WWTPs are affected by the efficiency of the pollutant removal (Rodriguez-Garcia et al., 2011), it was considered that four pollutants constitute the outputs obtained from the treatment process: (i) suspended solids (SS); (ii) organic matter measured as chemical oxygen demand (COD); (iii) nitrogen (N); and (iv) phosphorus (P).

Table 1 provides a snapshot of the statistical data used to compute the efficiency scores for each WWTP. It is illustrated that, on average, the most important cost item is staff, representing 36% of total costs. Energy is the next in importance, representing 22% of total costs. Waste management costs contributes 15%. All the other cost items represent a percentage equal to or lower than 10%. In spite of the fact that the size of the WWTPs evaluated in this study is medium-large, their operating cost distribution is consistent with that reported by previous studies (Molinos-Senante et al., 2010; Sala-Garrido et al., 2012b).

4. Results and discussion

4.1. Efficiency scores

Before estimating the efficiency scores for each WWTP, it was necessary to assign the weights for each input and output involved in the WSBM model. Following the procedure described in Section 2.2 and taking into account that the sum of all output and input weights should be 100, Table 2 shows the average value of the input weights and output weights for estimating the efficiency of WWTPs.

Table 2 illustrates significant differences between the weights assigned to the outputs depending on their environmental impact. It is illustrated that both nutrients, nitrogen, and phosphorus have weights considerably greater than the other pollutants. This means that the negative environmental impact associated with the discharge of these pollutants to the environment would lead to one of the main problems of water body contamination: eutrophication.

Once the weights of each input and output were assigned, the efficiency score for each WWTP was computed by applying the WSBM model introduced by Tone (2011). As it is shown in Table 3, the average efficiency score obtained for all facilities is 0.5660, indicating that on average WWTPs could reduce their costs by 43% while obtaining treated water with the same quality as currently produced. However, it should be considered that the efficient WWTPs do not need to improve their performance, as they are identified as the units with the best practices. Improvement efforts should be focused on inefficient WWTP units, which represent 59% of the sample; the results also change dramatically, giving an average efficiency index of 0.2784 for this group of WWTPs. This finding suggests that the saving potential is much greater when only inefficient WWTPs are contemplated, meaning that these inefficient WWTPs could save as much as 72% of their costs while maintaining the quality of the treated water.

Fig. 1 shows the plants (score equal to 1) that comprise the efficient frontier (or benchmark) of best practices in relation to the efficient WWTPs, and Fig. 2 groups the WWTPs in terms of efficiency scores. It is illustrated that 20 out of the 49 WWTPs evaluated are efficient. On the other hand, the remaining plants (29 out of 49) have an efficiency score lower than 0.6. This finding evidences the great potential for performance improvement in inefficient WWTPs. Fig. 2 illustrates that there are no plants with moderate inefficiency, as none of the 49 plants assessed has an efficiency score ranged between 0.60 and 0.99. From a management perspective, WWTP operators are able to broadly be identified in two groups of WWTPs, that is, efficient and inefficient facilities. WWTP managers should identify the characteristics and operational practices of the efficient plants, as they are the best practices. Subsequently, these best operational practices should be implemented in the inefficient WWTPs in order to improve their efficiency. Thus, the operational costs of the WWTPs would be reduced, while maintaining the quality of the treated water.

4.2. Sensitivity analysis

The efficiency score of each WWTP depends on the weights attributed to each input and output and although weights were calculated based on their shadow prices, they are subjected to some uncertainty. In this context, the uncertainty level for energy weight is greater than for outputs weights. This is because although efficiency assessment considered six inputs, only the energy item was weighted according the shadow price of CO_2 emissions associated to energy consumption. Moreover, it should be noted that energy is a resource whose price is highly variable. Therefore, to narrow the uncertainty associated to the weight attributed to energy costs, a sensitivity analysis that considers variations in the weight assigned to energy was made. So that the WSBM model was run with differences that are ±10% ± 25% ± 50% ± 75% and ±100% from the initial energy weight. The energy weights are shown as supplemental material.

Table 4 shows a summary of the efficiency scores related to the 11 different weights attributed to energy input. It is illustrated that changes in energy weights do not affect significantly to the average of the efficiency of the sample of WWTPs evaluated. It is evidenced as well that the number of efficient plants is the same (20 out of 49) in the 11 scenarios evaluated. In order to verify whether these small

Table 1
Sample description.

		Average	Standard deviation
Inputs (€/year)	Energy	269,900	210,368
	Staff	386,374	270,785
	Reagents	86,940	104,663
	Maintenance	106,365	122,175
	Waste	164,321	196,398
	Others	47,755	38,041
Outputs (Kg/year)	SS	1,084,693	1,022,869
	COD	2,306,706	2,255,160
	N	141,911	139,681
	P	24,006	26,557

Table 2
Weights established for inputs and outputs.

Input weights						Output weights			
Energy	Staff	Reagents	Maintenance	Waste	Others	SS	COD	N	P
25.3381	14.9324	14.9324	14.9324	14.9324	14.9324	0.0095	0.1604	32.686	67.1441

Table 3
Summary of the efficiency scores obtained with the WSBM model.

	Number of WWTPs	WWTPs (percentage)	Average of efficiency score	Standard deviation of efficiency	Saving potential (percentage)
Efficient	20	41	1.0000	0.0000	0
No-efficient	29	59	0.2784	0.1227	72
TOTAL	49	100	0.5660	0.3699	43

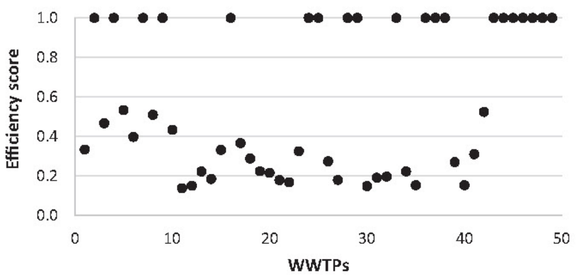

Fig. 1. Efficiency score by WWTP.

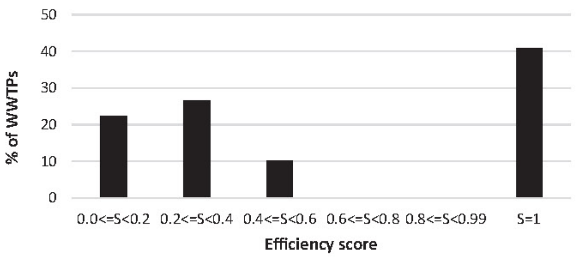

Fig. 2. WWTPs grouped by efficiency score.

Table 4
Summary of efficiency scores considering different weights for energy input.

	Energy weight + 100 percentage	Energy weight + 75 percentage	Energy weight + 50 percentage	Energy weight + 25 percentage	Energy weight + 10 percentage	Energy weight −10 percentage	Energy weight original	Energy weight −25 percentage	Energy weight −50 percentage	Energy weight −75 percentage	Energy weight −100 percentage
Average	0.573	0.564	0.566	0.568	0.571	0.572	0.584	0.574	0.576	0.578	0.581
Standard Deviation	0.364	0.370	0.378	0.376	0.374	0.372	0.371	0.361	0.369	0.368	0.366
Minimum	0.138	0.127	0.130	0.132	0.135	0.137	0.153	0.139	0.141	0.146	0.150
Maximum	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Number efficient WWTPs	20	20	20	20	20	20	20	20	20	20	20

changes in efficiency when energy weights change occur not only in the average scores but also at WWTP level, Fig. 3 shows the variation levels (maximum and minimum values) of the efficiency scores for each WWTPs under the 11 scenarios evaluated. It is verified that at plant level, efficiency scores remain almost constant although the weights attributed to energy item change noticeably. This finding means that efficiency scores of WWTPs do not depend on the weight attributed to energy costs.

4.3. Potential economic saving

Because the WSBM model is a non-radial DEA approach it allows the reduction in each input (cost item) that is necessary for each WWTP to be efficient to be estimated. In other words, the WSBM model allows potential economic savings in each cost item to be quantified. This information is essential for WWTPs manager to support the decision-making process. The quantification of the potential economic savings is fundamental to selecting the priority actions to be implemented in the WWTPs. Tables S4 and S5 in supplemental material section show the potential economic savings that each plant could obtain if they were efficient. According to average values, the items in which WWTPs could save the most costs are staff and energy. Hence, the WWTP operators should focus on implementing operational and managerial measures to optimize energy consumption and the use of human resources.

Within the operational changes that WWTPs should implement to improve its efficiency, special attention should be given to energy consumption because of its importance from an economic, as well as environmental point of view. In this context, Hernández-Sancho et al. (2011) illustrated that WWTPs which use diffusers for aeration are more energy efficient than the plants that use turbines. From a managerial perspective, energy costs of WWTPs are strongly influenced by the energy tariffs (Sala-Garrido et al., 2012a). Hence, it is fundamental that WWTPs' managers optimize the use of blowers, turbines, etc. according time hours.

Moreover, Tables S4 and S5 show a noticeable variability among WWTPs. As was expected, a set of facilities (efficient WWTPs) have no potential to save costs. On the other hand, other plants (inefficient WWTPs) have a large potential saving. It should be highlighted that the maximum potential saving is €0.78/m^3 which

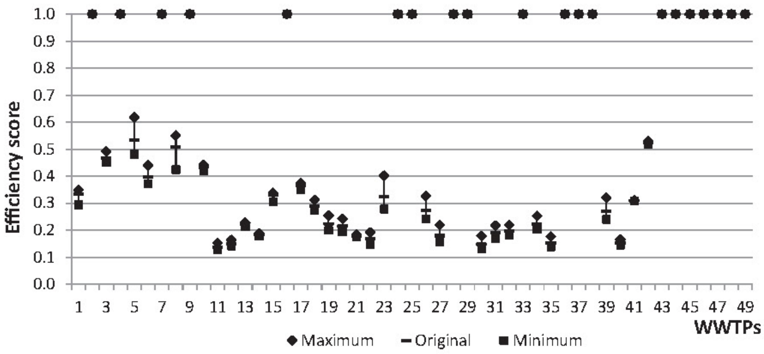

Fig. 3. Maximum, original and minimum efficiency scores of the WWTPs under different energy weights.

corresponds to WWTP11. Taking into account the volume of wastewater treated annually, the potential savings for inefficient WWTPs is not negligible (see supplemental material). If the 29 inefficient WWTPs were to become efficient, they could collectively save more than €22 million annually. As is shown in Fig. 4, inefficient facilities could save around 38% of their personnel costs and 25% of their energy costs. Moreover, they could save 18%, 9%, 8%, and 3% on waste management, maintenance, reagents, and other costs, respectively.

5. Conclusions

The efficiency evaluation of WWTPs is becoming increasingly important as it identifies those plants that make better use of their economic resources without reducing the quality of the water they treat. Thus, companies can identify the best operational practices that could be applied in other WWTPs to contribute to the reduction of operational costs. Ultimately, and taking into account that wastewater treatment services are paid for by citizens through water tariffs, the improvement of the efficiency of WWTPs is also beneficial for society.

From a methodological point of view, previous studies have illustrated that DEA is a suitable technique for evaluating the efficiency of WWTPs. According this approach, the operational costs of the WWTPs are their inputs, while the pollutants removed from the wastewater are the outputs. The so-called techno-economic efficiency of WWTPs is evaluated in this way. However, these previous studies have ignored the different environmental impacts of the pollutants removed from the wastewater if they were dumped into water bodies. To overcome this limitation, this paper evaluates for the first time the efficiency of a sample of WWTPs by introducing technical, economic, and environmental issues. In doing so, the WSBM model was applied, which is a non-radial DEA model which allows weights to be assigned to the inputs and outputs according their importance. Moreover, this model allows the potential economic savings of each cost item to be quantified at the WWTP level.

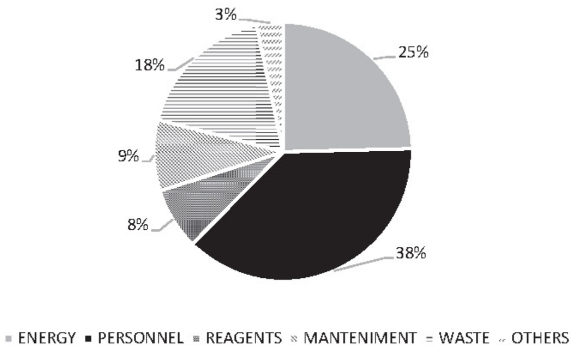

Fig. 4. Distribution of the potential operational costs savings.

The results from a sample of Spanish WWTPs provide the following primary conclusions: (i) shadow prices of pollutants are a good proxy to assign weights to outputs; (ii) there are no facilities with a moderate efficiency score, since WWTPs were identified as either efficient or as inefficient plants (with an efficiency score lower than 0.6); (iii) the efficiency scores of the WWTPs do not depend on the weight attributed to the energy costs; and (iv) the largest potential economic savings are associated with staff and energy costs.

From a policy perspective, the methodology and empirical application carried out in this study are of great interest for (waste) water authorities and company managers. In many countries, wastewater treatment services are provided following a monopoly approach; therefore operators have no incentives towards efficiency and innovation. In this context, benchmarking, assumes strategic importance since through it, (waste)water authorities can promote efficiency in WWTPs which is essential to reduce the wastewater treatment tariffs paid by citizens. From WWTPs' managers perspective, the assignment of weights to the different pollutants allows environmental issues to be integrated in the efficiency assessment of WWTPs. It will create incentives to operators to improve the quality of the effluent of WWTPs. Second, WWTP managers can compare the performance of WWTPs and therefore identify best operational practices. The implementation of these practices in inefficient plants would contribute to improving their efficiency and consequently to reducing operational costs. Third, the quantification of the potential economic savings of each cost item is essential to support the decision-making process. It provides information for the prioritization of the measures that are to be implemented in the WWTPs to further reduce operational costs.

Appendix A. Supplementary data

Supplementary data related to this article can be found at http://dx.doi.org/10.1016/j.jenvman.2015.11.037.

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