Applied Energy 208 (2017) 1430–1440

Contents lists available at ScienceDirect

Applied Energy

journal homepage: www.elsevier.com/locate/apenergy

A data-driven methodology to support pump performance analysis and energy efficiency optimization in Waste Water Treatment Plants

Dario Torregrossa[a,b,*], Joachim Hansen[b], Francesc Hernández-Sancho[c], Alex Cornelissen[d], Georges Schutz[d], Ulrich Leopold[a]

[a] Department of Environmental Research and Innovation (ERIN), Luxembourg Institute of Science and Technology (LIST), Avenue des Hauts-Fourneaux, 4362 Esch-sur-Alzette, Luxembourg, Luxembourg
[b] Université du Luxembourg, 6 rue Richard Coudenhove-Kalergi, L-1359 Luxembourg, Luxembourg
[c] Water Economic Group, Universitat de València, Avda dels Tarongers, s/n, 46022 Valencia, Spain
[d] RTC4Water s.a.r.l, 9, av. des Hauts-Fournaux, 4362 Esch-Sur-Alzette (Belval), Luxembourg

HIGHLIGHTS

- A novel approach for the efficient management of wastewater pumps is presented.
- This approach couples fuzzy logic and data-mining to reduce the pump energy consumption.
- This approach enables to monitor the pumps and provide case-specific suggestions.
- Short-term and long-term phenomena were identified and separately monitored.
- Flow-related issues and early-stage failures were detected.

ARTICLE INFO

Keywords:
Waste Water Treatment Plants (WWTPs)
Energy benchmarking
Time series analysis
Pump system efficiency
Fuzzy logic

ABSTRACT

Studies and publications from the past ten years demonstrate that generally the energy efficiency of Waste Water Treatment Plants (WWTPs) is unsatisfactory. In this domain, efficient pump energy management can generate economic and environmental benefits. Although the availability of on-line sensors can provide high-frequency information about pump systems, at best, energy assessment is carried out a few times a year using aggregated data. Consequently, pump inefficiencies are normally detected late and the comprehension of pump system dynamics is often not satisfactory. In this paper, a data-driven methodology to support the daily energy decision-making is presented. This innovative approach, based on fuzzy logic, supports plant managers with detailed information about pump performance, and provides case-based suggestions to reduce the pump system energy consumption and extend pump life spans. A case study, performed on a WWTP in Germany, shows that it is possible to identify energy inefficiencies and case-based solutions to reduce the pump energy consumption by 18.5%.

1. Introduction

The energy performance of Waste Water Treatment Plants (WWTPs) is generally sub-optimal and an energy saving potential of approximately 25% [1] can be estimated. Moreover, these facilities are energy-intensive and in Europe they consume 27 TWh of electrical energy per year, which corresponds roughly to the global electric energy consumption of a country like Serbia [2]. Various authors have therefore proposed strategies to assess and reduce the energy consumption of these facilities [1–9].

In this introduction, the reader will find a three-part literature review: an assessment of WWTP inefficiency, methodologies for the efficient management of WWTPs and methodologies for pump monitoring and optimization. Subsequently, gaps in literature and the scientific contribution of this paper will be addressed.

1.1. Literature review: assessment of WWTP inefficiency

Many authors have attempted to estimate the potential energy saving in WWTPs, assess inefficiencies and set up realistic targets for

* Corresponding author at: Department of Environmental Research and Innovation (ERIN), Luxembourg Institute of Science and Technology (LIST), Avenue des Hauts-Fourneaux, 4362 Esch-sur-Alzette, Luxembourg, Luxembourg.
E-mail address: dario.torregrossa@list.lu (D. Torregrossa).

http://dx.doi.org/10.1016/j.apenergy.2017.09.012
Received 12 June 2017; Received in revised form 19 August 2017; Accepted 7 September 2017
Available online 18 September 2017

Nomenclature and symbols

Abbreviation	Full name
BEP	best efficient point of the pumps
BUR	wastewater treatment plant in Solingen-Burg, GER
C_{en}	cost of energy
DEA	Data Envelopment Analysis
E_{id}	ideal energy consumption
EOS	Energy Online System
IPS	Intermediate Pumping System
mpeb	maximum potential economic benefit from maintenance
$N_{day-3years}$	number of days in 3 years
pcs	potential cost saving
$\overline{pcs}$	average value of pcs for the period under study
pes	potential energy saving
PLCs	program-logic controllers
SCADA	Supervisory Control And Data Acquisition
WWTPs	wastewater treatment plants
Z	binary value for fluctuation monitoring, Section 2.4
η	efficiency of the pump system
η_t	trend of energy efficiency, calculated with moving median
η_f	fluctuation of energy efficiency

energy performance ([1,3–6]). Castellet and Molinos-Senante [1] analysed a group of WWTPs located in Spain; the authors identified a high economic saving potential (almost 1 million €/year per plant) and showed how energy consumption can play a relevant role in the economic balance. Mizuta and Shimada [3] analysed the specific energy consumption of 983 WWTPs in Japan and showed the impact of economies of scale on energy performance. In [[4], chapter 3, p. 44], the author discussed the potential energy efficiency of WWTPs, and identified energy self-sufficiency as a realistic objective. Hernández-Sancho et al. [5] applied a non-radial DEA approach to analyse WWTPs in Spain and found that only 10% of the plants could be considered energy efficient. Becker and Hansen [6] illustrated the difficulties in reaching a satisfactory energy performance for WWTPs in North-West Europe. In summary, the following conclusions can be made: (I) energy saving in WWTPs is a relevant challenge; (II) the energy consumption of WWTPs is generally high; (III) the energy consumption of WWTPs can be drastically reduced.

1.2. Literature review:methodologies for the efficient management of WWTPs

Various authors (for example [2,7–9]) applied a benchmark based approach to identify inefficiencies and promote the reduction of WWTP energy consumption. Krampe [7] carried out a benchmark analysis of 24 WWTPs located in Australia, identifying global inefficiencies and, more specifically, inefficiencies in pump and aeration systems by using process-based benchmarks. Panepinto et al. [8] monitored the energy consumption of the most important electro-mechanical devices for a WWTP located in Italy, using remote sensors and identifying case-based technical solutions to increase energy efficiency. In [2,9], the authors of this paper developed an Energy On-Line System (EOS) for the collection of high-time resolution (up to many values per second) energy values to allow the comparison of WWTPs regardless of their size. Furthermore, they proposed a methodology for a plant-generic daily benchmarking. In other words, the scientific community is committed to WWTP energy performance assessments, and to the definition of methodologies for the reduction of energy consumption.

1.3. Literature review:methodologies for pump optimization

Various authors have proposed efficiency strategies for pumping systems, including design and calibration, assessment and reporting, maintenance and on-line monitoring [10–20]. In ([10], p. 33), the authors elaborated the most common maintenance strategies for pump efficiency: the simplest approach is a fixed interval scheduled maintenance; a more advanced approach is predictive or conditional maintenance. The latter can be performed using vibration sensors, thermography, or infra-red (IR) scanning [10]; these sensors do not directly provide measures for energy performance but the detection of anomalies can indirectly produce energy savings. In [11], it is proposed a decision-making tool for the efficiency analysis and decision-support based on an economic consideration of WWTP pumps. In [12], it is presented a methodology based on a mathematical optimization to identify the best flow repartition in a parallel-multi-pump system. Zhang et al. [13] obtained positive results developing a methodology, based on a neural network, for the optimal scheduling of operations in multi-pump systems. Chang et al. [14] used fuzzy logic algorithms to find the optimal operating point of multi-pump systems. Olszewski [15] focused his effort on the optimization of multi-pump systems with a genetic algorithm optimization. DeBenedictis et al. [16] proposed a methodology to evaluate the impact of variable speed drives and program-logic controllers (PLCs) on pump system efficiency. Berge et al. [17] focused on the condition monitoring of pump systems using an array of sensors including: pump vibration, motor winding temperature, motor current, motor bearing temperature and pump inflow. Wang et al. [18] proposed an optimization method for the design of a multi-pump system, which analyses the various energy losses in a pump system such as disk friction loss or hydraulic loss. Zhang et al. [19] show that it is possible to save between 6% and 14% on pump energy with data-driven models and optimization approaches. Zhuan and Xia [20] demonstrate the feasibility of reducing maintenance and energy costs of multi-pump systems by using optimization algorithms.

1.4. Pumps efficiency in WWTPs

In WWTPs, pump energy consumption represents a relevant portion of the overall energy consumption (12%,[4,21]). Pump performance can be dramatically decreased by several issues, such as cavitation, over-sizing, wear, leakages and, in extreme cases: blocking. In the WWTP domain pump design is often inaccurate because of significant differences between design and operational flows during the lifetime of the pump [10,11,21]. The costs of inefficiencies can be reduced with proper design and management. This includes the detection of problems related to pump efficiency and an understanding of its implications [10].

Despite the theoretical availability of approaches for enhancing pump energy performance (Section 1.3), in the WWTP domain, pump energy management is generally sub-optimal for a variety of reasons, such as a lack of useful information (for example: vibration measurements) or infrequent assessments (once or twice per year). One of the most widely used analyses relies on the calculation of efficiency indices which are periodically benchmarked [22]. In ([23], p. 64), the author proposes reference values to evaluate the efficiency of a given pump system and some of its most important components: motor, pump and flow controller. According to the experience of the authors, in the WWTP domain, the assessment of energy performance of the pumps is mostly performed just a few times a year using the average values of flow and energy for the period being analysed. This approach is not ideal because it does not take into account seasonal phenomena and pump degradation and does not allow the early detection of failures.

Nowadays, in the WWTP domain, the availability of Supervisory Control And Data Acquisition (SCADA) systems theoretically allows an increased frequency of energy analysis and an improved plant management with a faster response time to inefficiencies found [2]. As for the global energy consumption [2], it is postulated here that a daily pump energy benchmark exercise can improve energy efficiency and reduce pump management costs.

However, the simple scaling of a yearly index to (for instance) a daily resolution is not necessarily beneficial for pump management and can even produce misleading results. The calculation of daily indices can produce time series with a high amplitude and a simple daily efficiency index is therefore difficult to interpret. In practice, pump systems are complex to analyse; some pump system parameters are constant, or change very slowly, over a long period of time (number of pumps, set-up of controller, lift and pump wear) while other parameters change continuously (inflow, temperature, particulates) [10,24]. Many efficiency measures are interdependent and highly dynamic. For example, cavitation depends on temperature, inflow and hydraulic losses ([25], chapter 8, p. 14) while the overall efficiency of the pump system is influenced by the best efficiency point (BEP) and the inflow ([10], p. 37).

Using a daily efficiency index, without thoroughly assessing the effects of operational conditions, could therefore lead to the debatable conclusion that the pump system performance changes day by day. A more precise statement should assert that the pump system performance is, within a sufficiently short interval (typically one day), highly dependant on the operational conditions. Consequently, a detailed daily analysis of pump system performance should be able to effectively separately the effects of system set-up and operational conditions.

1.5. Gaps in literature, objectives and novelty of this paper

A recent review paper on pump efficient control strategy edited by Arun Shankar et al. [26] found that, despite the large number of literature contributions, to date, there seems to be a lack of methodologies for the analysis of pump energy consumption, that (I) can be automatically performed (at least) on a daily basis, (II) that are able to separately assess the effects of system set-up and operational conditions, and (III) rely solely on the parameters commonly available in WWTPs (inflow and energy consumption). Section 1.3 leads to the same conclusion. This is the knowledge-gap that the present paper seeks to address by presenting a data-driven methodology and a tool for pump system energy efficiency which is capable of:

- ✓ automatically carrying out a daily pump efficiency analysis to detect potential inefficiencies at an early stage;
- ✓ identifying and separately addressing long term and short term efficiency patterns;
- ✓ producing an overall index that takes into consideration the pump operational conditions;
- ✓ supporting the plant managers in the early identification of imminent failures;
- ✓ suggesting potential solutions to identify problems;
- ✓ evaluating the solutions according to economic criteria;
- ✓ improving the comprehension of the pump system behaviour examined;
- ✓ relying on information generally available to plant managers (inflow, pump energy consumption, and energy cost).

In [2], we explained how the Energy Online System (EOS) automatically records, collects and processes on-line data from WWTPs and aggregates them in daily KPIs. The tool described in the current paper uses the data automatically aggregated in EOS for pump system analysis. EOS is plant-generic and the pump decision support tool inherited this feature: it functions for many, if not all, WWTPs, despite their differences. For this reason, it was considered essential that it relies solely on information provided by commonly available sensors.

To the best of our knowledge, the methodology proposed in this paper is new and innovative for the following reasons:

- ✓ it combines signal decomposition, fuzzy logic and benchmarking to analyse pump operational conditions;
- ✓ it uses new KPIs as input of fuzzy logic: η_t,η_f,τ,Z (please refer to subsections: 2.2, 2.3 and 2.4)
- ✓ it applies the analysis of truth degree of fuzzy logic rules to provide plant managers with case-based solutions concerning pump efficiency;
- ✓ it estimates a potential energy saving, relying on the trend value of efficiency (η_t), obtained with signal decomposition.

Existing competing methodologies (such as the one proposed by Berge et al. [17]) come to similar conclusions given some of the constraints already discussed (such as the time frequency of the analysis and the early detection of problems). However, they are difficult to reproduce in the WWTP domain, because they rely on information generally unavailable in this area (such as pump vibration, current and motor winding temperature).

2. Material and methods

For this case study we used data from the Solingen-Burg WWTP (BUR) in Germany, which was processed by the EOS system [2]. BUR is equipped with a SCADA system which ultimately provides daily data on the energy consumption of significant devices and operational conditions relating to wastewater inflow, pollution load and wastewater composition. Within BUR, an intermediate pumping station (IPS), comprising 6 pumps (80 kW-power each one) equipped with variable speed drives, lifts the wastewater after primary treatment 10.33 m into the aeration basins. Fig. 1 shows the histograms for the daily flow and the daily energy consumption.

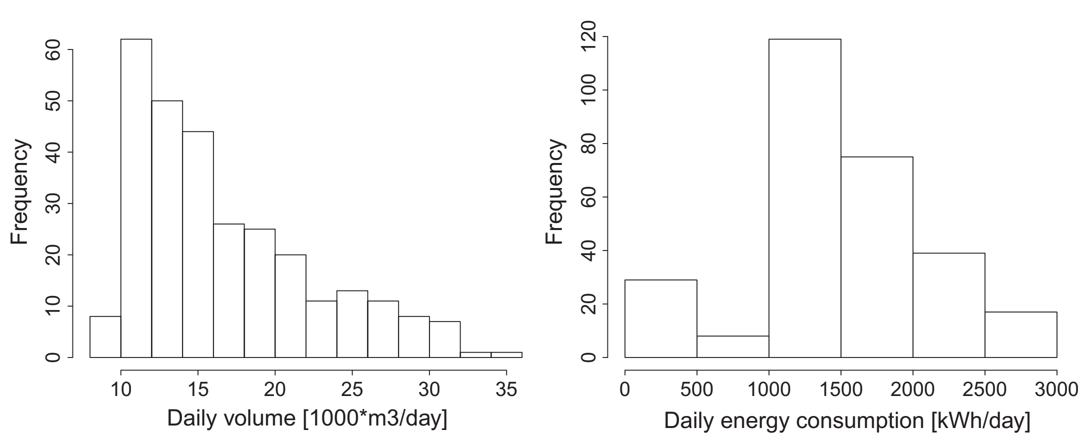

Fig. 1. Histograms for the daily wastewater inflow (left) and daily energy consumption (right) of the intermediate pumping station.

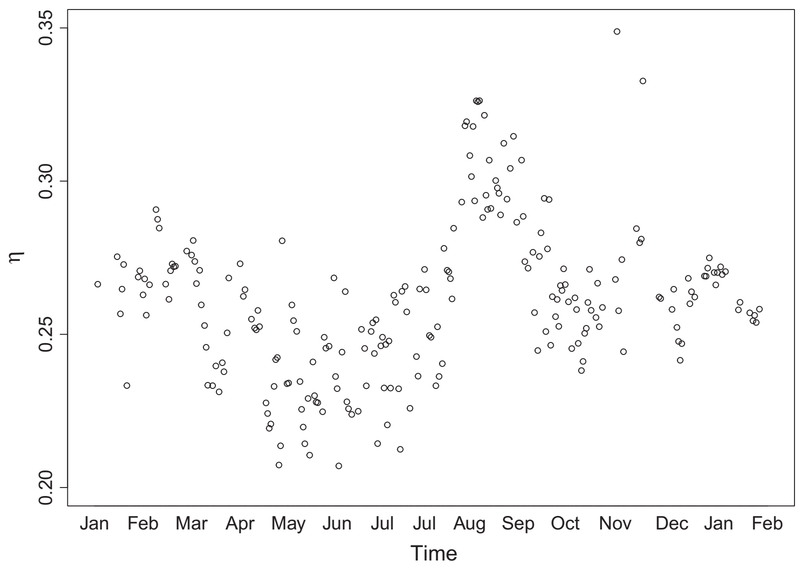

Fig. 2. Subset of time series of η values. This figure shows daily efficiency values for the pump system from January 2015 to March 2016.

2.1. Calculation of the efficiency index

The EOS supplies the daily pumped volume and the daily energy consumption per pump [2]. First, Eq. (1) is used to calculate the IPS efficiency, η. In this formula, m is the mass of wastewater lifted [kg], $h = 10.33\,m$ is the static head, g is the standard gravity [9.81 m/s^2] and E_{obs} is the observed energy [J].

$$\eta = \frac{mgh}{E_{obs}}[dimentionless] \tag{1}$$

When $\eta = 0.32$, the pump system is operating at the minimal acceptable performance, while $\eta = 0.80$ shows highly-performing pump systems [23]. The analysis of the daily time series of η (Fig. 2) shows high fluctuations; as already discussed, a simple comparison of the daily values of η with a reference value is not an optimal strategy.

Consequently, we have attempted to separate the trend value component of the efficiency index from the daily fluctuations in order to individually assess long-term phenomena (such as pump ageing) and short-term phenomena (mainly influenced by operational conditions).[1]

2.2. Trend calculation

The daily trend value is calculated using a rolling window median for the previous 90 days.[2] In a previous work and after extensive testing, we have showed that this is a robust method for this type of data [27]. The number of days included in the rolling median calculation is generally known as the rolling window (W_m). This parameter can be customized as explained in detail in Section 3.6.

If the value of W_m is large enough to be representative of the operational conditions, the trend values represent the performance of the pump system without the effect of short-term phenomena. This fluctuation is calculated as the difference between the daily trend and the daily value. Consequently:

$$\eta = \eta_t + \eta_f \tag{2}$$

In this equation, η_t is the trend value while η_f is the fluctuation.

In the following sections, the values of η_t and η_f are investigated separately and new operative parameters are defined.

2.3. Calculation of the efficiency slope

In order to use the values of η_t to identify changes in the trend, this paper proposes a parameter, τ, representing the average slope of η_t [27]. τ is calculated daily with Eq. (3), in which η_{t_d} is the value of the trend for the reference day and $\eta_{t_{d-I_\tau}}$ is the value of the trend calculated for the I_τ days before the reference day. In our case, $I_\tau = 180$, note: this parameter is customizable as explained in Section 3.6. For the values of τ, which represents the pump system performance degradation, we propose two benchmark values: -0.4%/year for a good degradation rate and -1.6%/year as the threshold degradation rate requiring urgent maintenance [27]. The values of τ are supposed to be negative if no maintenance is performed, otherwise we expect a positive τ (i.e. an increases in performance) after maintenance. Consequently, τ can be used to evaluate both pump ageing and the effect of maintenance.

$$\tau = 365*\frac{\eta_{t_d}-\eta_{t_{d-I_\tau}}}{I_\tau*\eta_{t_{d-I_\tau}}} \tag{3}$$

2.4. Calculation of Z

The values of η_f can be used for the early identification of failures. Normally, the η_f values should fluctuate around the value $\eta_f = 0$. However, if a potential failure (for example a partial-obstruction) occurs in the pump system, the η_f time series will show a series of negative values. Before observing a change in the trend η_t, this effect has to be there long enough to change the 90 day median. Consequently, η_t and τ are not efficient for the early detection of failures. We therefore propose a binary parameter, Z, which is equal to 0 if the system registers 15 consecutive days with $\eta_f < 0$, otherwise Z = 1 (cf. Eq. (4) [3]).

[1] For example, if in the period analysed, η has a normal distribution (let us suppose 0.30 ± 0.1) it is more beneficial to consider the average value 0.30 as the representative value for the efficiency in this period and investigate the relation between the deviations from this representative value and the operational conditions. In any case, since we cannot establish a priori a normal distribution for η values, we used the median instead of the average.

[2] For example, let us consider the first 180 days of a year. The rolling median algorithm calculates the trend value for the 90th day as the median value of days 1 to 90. Then, the algorithm attributes the median value of day 2–91 to the 91st day. This operation is iterated over all the dataset. Please note that the calculation for the first 90 days is made with less data and must be used with caution.

[3] In this equation, $\eta_{f;d=-n}$ corresponds to the value of η_f at the n-day before the reference day

$$\begin{cases} z = 0 \quad \text{if } max(\eta_{f;d=-1};\eta_{f;d=-2};\ldots;\eta_{f;d=-W_Z}) < 0; \\ z = 1 \quad \text{if } max(\eta_{f;d=-1};\eta_{f;d=-2};\ldots;\eta_{f;d=-W_Z}) > 0; \end{cases} \tag{4}$$

The length of the sequence of negative-fluctuation days (W_z) can be customized, as explained in Section 3.6.

2.5. Fuzzy logic and scenario analysis

Fuzzy logic has been shown to be able to store expert knowledge using a human-like language in a series of understandable statements, to deal with uncertainty and to efficiently process multiple parameters; a detailed explanation of fuzzy logic algorithms is provided by Zadeh [28] and Starczewski [29].

At this point, our methodology offers four parameters (η_t,η_f,τ,Z) which represent the efficiency trend, the fluctuation in the trend, the ageing of the pump and the existence of potential new failures respectively; consequently a detailed multi-perspective pump assessment can now be carried out. However, the information contained in our four parameters is still not obvious. In order to deliver clear performance information on the pump system under investigation, for the reasons above explained, we have analysed these parameters with a fuzzy logic engine. Our fuzzy logic approach is based on the set of rules reported in Table 1. Each rule describes a condition of the pump system and the fuzzy logic produces a score for each rule. Table 1 reports the 9 rules of the fuzzy system implemented[4].

The fuzzy logic algorithm requires the mathematical definition of the input variables, obtained by defining the membership functions which associate the input values to their membership degree[5] [29,30]. The membership degrees associated with the functions are shown in Fig. 3.

For each day, the fuzzy logic engine calculates the result of each rule with the Mamdani implication method [31], which produces a truth degree (TD) in the range 0–1 for each scenario.[6] In this paper, the rule with the highest truth degree is defined as the 'winning rule'.

The winning rule is extremely useful for plant managers in a subsequent decision-making process because it effectively describes the current operational condition of the pump system. For example, if rule number 8 has the highest truth degree, there is a decreasing trend over the last two weeks (η_f was negative) and an urgent investigation is required.

However, to fully understand the system behaviour, it is important to simultaneously observe the truth degree of each rule. It is also important to understand that the rules which use the same parameters are complementary and the sum of their membership values is always 1. In this case, there are 3 blocks of complementary rules: 1–4, 5–7, 8–9. The first block reports information about the pump conditions on the day of analysis, the second block analyses long term phenomena affecting pump degradation and the last block monitors potential failures. This rule structure was imposed to avoid illogical results: for example, a pump cannot be fully efficient and fully inefficient at the same time. With the current rule structure, the fuzzy engine will provide 3 fuzzy statements each on:

- pump condition (by analysing the block 1–4);
- pump degradation (by analysing the block 5–7);
- early detection of inefficiencies (by analysing the block 8–9).

The rules for each block are independent, which means that, for example, it is possible that a pump system with a high efficiency is experiencing a high degradation rate, or a normal degradation rate. The analysis of the winning rules provides the correct global view. Table 2 reports a set of remedial suggestions which are related to specific rules.

2.6. Economic considerations

At this point of the methodology, plant managers can effectively assess the condition of the pump system which is described by the rules and evaluate potential options to increase energy efficiency. Clearly, when faced with taking actions, a plant manager should also take into consideration a number of other factors, such as: regulations, management strategy and objectives, budget and economic and environmental issues. Addressing all of these is outside the scope of this paper. However, the proposed methodology additionally attempts to assist the plant manager with answering the following question: *What is the maximum investment that produces positive economic benefits in a reasonable amount of time?*

In order to address this question, a decision maker has to define a 'reasonable time'. In this paper, the default value of 3 years is considered as a reasonable pay-back time, but the tool allows this value to be customized. The tool works under the assumption that maintenance can restore the pump system trend to a normal efficiency of $\eta_t = 0.32$.

The set of Eqs. (5) illustrates the mathematical procedure with the following nomenclature:

- η_t is the value of efficiency trend calculated with the rolling median (cf. Section 2.2);
- η_{id} is the ideal value of efficiency;
- E_t is the value of energy consumption calculated with η_t;
- E_{id} is the ideal value of energy consumption;
- pes is the potential energy saving;
- C_{en} is the cost of energy [€/kWh];
- pcs is the potential cost saving calculated for each day;
- $\overline{pcs}$ is the average value of pcs for the period under study; in our case we calculate the average for the previous 180 days;
- $N_{day-3years}$ is the number of days in 3 years;
- mpeb is the maximum potential economic benefit resulting from maintenance over a period of 3 years. This value corresponds to the maximum investment that the plant manager should accept for extraordinary maintenance.

Table 1
Fuzzy logic rules used[a]

Id	η_t	η_f	τ	Z	Score
1	High	Positive			High
2	High	Negative			Medium
3	Low	Positive			Medium
4	Low	Negative			Low
5			Low		Low
6			Medium		Medium
7			High		High
8				Low	Low
9				High	High

[a] The first 5 columns report the rule Id, and the input parameters. η_t is the trend, η_f is the fluctuation, τ is the average slope of η_t and Z is the binary parameter as described in Eq. (4). The last column expresses the evaluation of the operational condition, depending on the inputs, that will be transformed to a fuzzy output.

[4] For example, the first rule, representing a condition in which the pump system has a high value for the trend and a positive fluctuation, can be read as:

IF η_t IS high AND η_f IS positive THEN Score IS High;

[5] For example, a trend $\eta_t > 0.6$ is considered 'high' with membership value of 1, a trend $\eta_t < 0.2$ is considered 'low' with membership value of 1, while in the region between 0.2 and 0.6 both definitions (high and low) are valid with a different membership degree (for example the trend $\eta_t = 0.4$ is at the same time 'low' and 'high' with a membership value of 0.5). Consequently, the membership values describe a state function.

[6] For example, the statement of the first rule is: 'η_t is high and η_f is positive'. If the output of the first rule is 0, this means that this statement is 'false'; if the output of the first rule is 1, this statement is 'true'. For values of truth degree between 0 and 1, the statement is partially 'true' and partially 'false'.

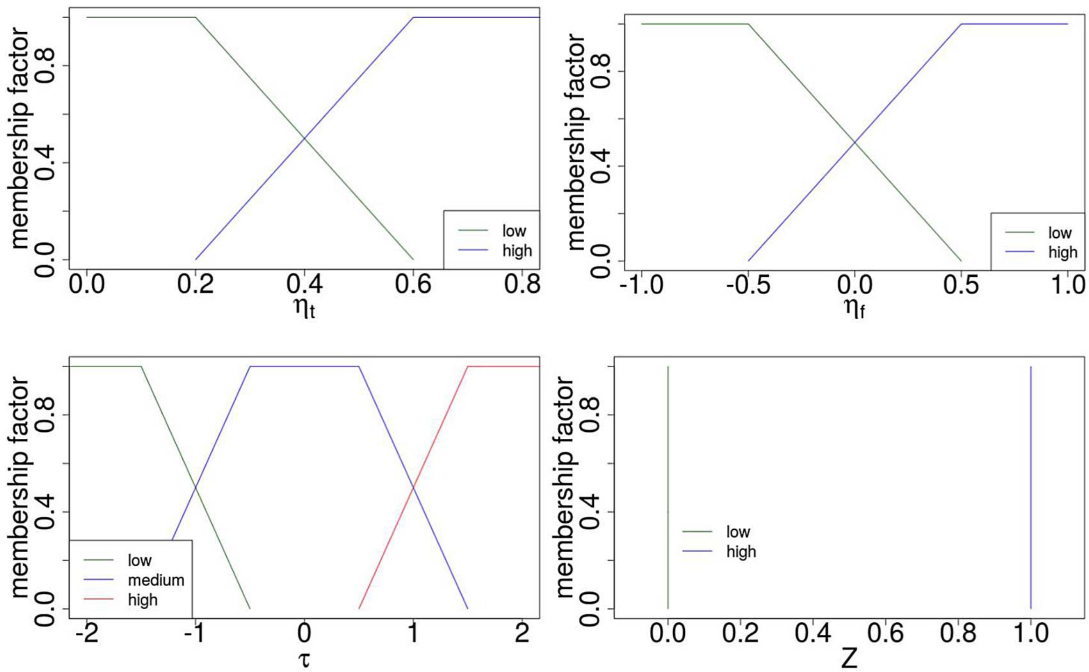

Fig. 3. Membership function for each input.

Table 2
Example (subset) of suggestions related to the rules.

Rule	Suggestion
1	Do nothing
2	If rule 9 has TD = 1, do nothing.
	If rule 8 has TD = 1, plan maintenance urgently
3	The efficiency is not sufficient. Plan maintenance or evaluate pumps replacement
	Are there flow-related patterns? If yes, install a pony pump
4	The efficiency is not sufficient.
	Plan maintenance, urgently if, for rule 8, the TD = 1. Evaluate pump replacement.
	Are there flow-related patterns? If yes, install a pony pump
	If the pump is more than 15 years-old, consider replacing it
5	Pump performance is decreasing fast. Plan maintenance
6	Pump performance slope has a normal value. Do nothing
7	Pump performance is increasing
	Is this the effect of maintenance? If not, check the data consistency
8	In the last 15 days, the fluctuations have been negative
	Are there flow-related patterns? If yes, install a pony pump
9	The fluctuations are regular

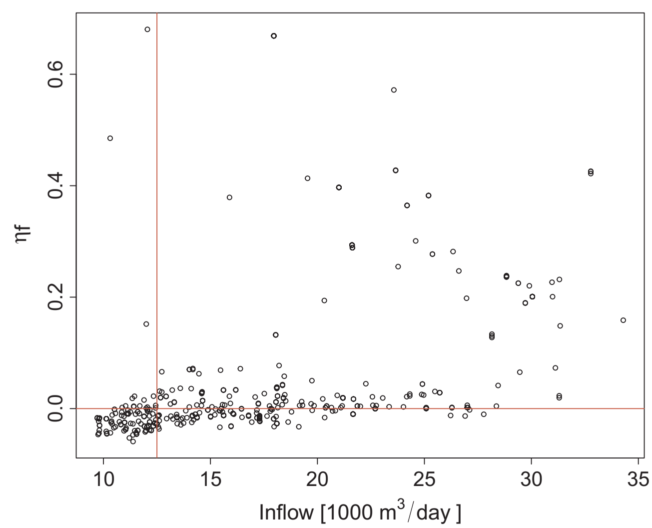

Fig. 4. Effect of fluctuation on volume.

$$\begin{cases} \eta_{id} = 0.32, E_t = \frac{mgh}{\eta_t}\ [\mathrm{J}], \\ E_{id} = \frac{mgh}{\eta_{id}}\ [\mathrm{J}], \\ pes = (E_t - E_{id}) * 2.78 * 10^{-7}\ [\mathrm{kWh}], \\ pcs = pes * C_{en}\ [\mathrm{Euro}], \\ mpeb = \overline{pcs} * N_{day-3years}\ [\mathrm{Euro}] \end{cases} \tag{5}$$

2.7. Data mining for flow-related issues

At this stage of the methodology, plant managers know what the operational conditions and the potential solutions for their pump system are, as well as the maximum cost that they could accept to pay for improvements. A further useful test investigates the relationships between inflow and efficiency. This is particularly useful for discovering any pump system over-sizing. The test is proposed here because pump over-sizing affects 75% of pump systems [32]. Inflow conditions play a relevant role in the determination of the efficiency of pump systems [10]. Each pump has an operational inflow at which the performance is optimal: the best efficient point (BEP), defined by the producer and generally available in the pump manual [11]. When a single pump operates at a flow vastly different from the BEP, performance decreases drastically. The use of variable speed drivers and the use of multi-pump systems can enlarge the range of flow at which the system operate with an acceptable efficiency. Additionally, the definition of the required flow at the design stage is often a complex issue in the WWTP domain because flows are strongly affected by seasonality and rely normally on rough assumptions of future connected populations [21].

Inflow-fluctuation patterns are analysed with a graphical approach (Fig. 4). In this plot, the horizontal line divides the positive and negative fluctuations, while the vertical line divides the dry weather flow and rain weather flow. Consequently, we have four zones:

- top-left for dry period and positive fluctuations;
- top-right for rain period and positive fluctuations;

- bottom-left for dry weather flow and negative fluctuations;
- bottom-right for rain period and negative fluctuations.

If the points are not uniformly distributed, this could mean that there is a pattern between flow conditions and inefficiencies. For example, if the positive values of fluctuations are observed just for high inflow values, it is probable that the pump system is oversized. In this case a potential solution is the installation of pony pumps [10,11], i.e. a pump specifically designed for low inflows (more details in Section 3.5).

2.8. Graphical user interface

The tool developed with this methodology is equipped with a graphical interface (a screen-shot in Fig. 5) and enables plant managers to generate useful information in real time by modifying the customizable parameters. Consequently, this software can be used without programming and enables the end user to analyse pump performance by modifying the customizable inputs.

In conclusion, this methodology takes the pump system time series of inflow and energy as input and produces an assessment that includes: trend analysis, analysis of pump performance deterioration, early failure detection, analysis of operational conditions and an economic analysis.

3. Results

3.1. Index calculation

After the calculation of the daily indices with Eq. (1), the signal is decomposed and the indicators calculated as described in subSections 2.2, 2.3 and 2.4. For each day, we obtain daily values for η_t,η_f,τ and Z. Table 3 shows the summary of the decomposition analysis, i.e. representative statistical values for the key performance indicators calculated.

Table 3 shows that the trend efficiency is below the threshold for the normal efficiency ($\eta_t < 0.32$, [23]). The range of η_f reflects the impact of short term phenomena on pump efficiency. The τ values are in the range of normal pump performance deterioration. The first quartile value of Z shows that for at least 75% of the time, there is no 15-day sequence of negative fluctuations. In other words, Table 3 shows a low-efficiency pump system, which is stable for long periods and with high fluctuations in efficiency in the short term.

3.2. Results of fuzzy logic and scenario analysis

The first output of the fuzzy logic system is an overall performance index in the range 0–100. For BUR, the fuzzy score for each day is below the optimal performance value. This score can provide a direct explanation of pump performance. For example, when Figs. 2 and 6 are compared in the period between July and September, the time series of η values varies greatly due to operational conditions; in the time series of the fuzzy score, the operational conditions have a minor impact on the overall evaluation and the score is stable in the region of 60–70%, corresponding to a sub-optimal condition due to a low η_t. In the plot 6, we can observe that there are points in which the score is under 40: these results occur because of Z (i.e., there was a sequence of negative values).

The analysis of the truth degree of each rule can explain the scenario which mostly influenced the fuzzy score. For example, the fuzzy score of 29 April 2015 was equal to 34. For that day, the rules with the highest truth degree were rule 4, rule 6 and rule 8. This means that, the η_t was low, the fluctuation was negative, the deterioration speed was low and there was no sequence of 15 negative fluctuations. This example highlights the large amount of information obtainable relative to the classical η calculation. With the classical approach, the only information for that day is that $\eta = 0.20$.

Fuzzy logic can also support the analysis of patterns in a period. For example, Fig. 7 reports the average truth degree for each rule in the period between 1 January 2015 and 1 March 2016. The plot shows that rules 3, 6 and 9 have a truth degree higher than 0.5 and consequently they describe the operational conditions dominant in the system.

When these results are related to the set of solutions shown in Table 2, it can be observed that a potential solution for the operational condition described by rule 3 corresponds to a non-urgent maintenance action, while rules 6 and 8 do not require any action. Consequently, the plant manager should schedule a non-urgent maintenance. The analysis of potential cost savings, developed according to the set of Eq. (5), estimates the maximum investment that the plant managers should accept to pay: €60022.

3.3. Data mining to analyse operational conditions

The methodology can also extract useful information for the decision maker by addressing the following question: *Is the pump performance dependent on the inflow?*

This question can be answered by directly observing the impact of flow on fluctuations. Fig. 4 shows that the pump system is not efficient for the dry-weather flow, but produces a better performance for high inflow (the system does not register negative fluctuations for inflows larger than 27,000 m^3/day). We would suggest a specific analysis of the pump controller set-up on pump performance in dry-weather flow during maintenance and integrating this information into the maintenance report.

3.4. Analysis of a potential solution: pump system replacement

With the information available, it is now possible to answer another important question: *Is it beneficial to replace the pump system?*

This is achieved by comparing the cost of under-utilization of the current pump, and the benefits of using a new and more efficient pump system. A new pump system of 480 kW costs €1,045,120 (value estimated with the equations used in [11]). Considering a life span of 20 years, the annual allocated value of the pump is €52,256.02 (1/20 of

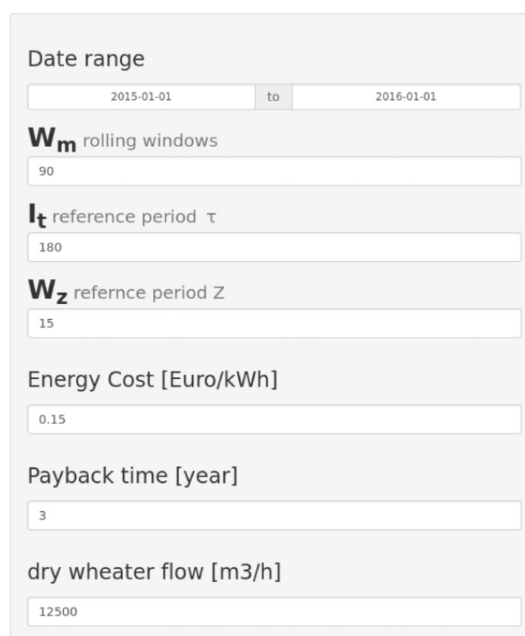

Fig. 5. Screenshot of the graphical interface. The selection of customizable parameters enables the operator to generate Figs. 2, 4, 6, 7 and all the numerical results present in this paper: threshold cost, KPIs, fuzzy output.

Table 3
Summary of decomposition analysis for the WWTP in Burg.

	η_t	η_f	τ	Z
Min	0.23	−0.06	−0.18	0.00
1st Quartile	0.25	−0.02	0.10	1.00
Median	0.27	0.00	0.17	1.00
Mean	0.26	0.05	0.15	0.88
3rd Quartile	0.27	0.03	0.23	1.00
Max	0.29	0.68	0.40	1.00

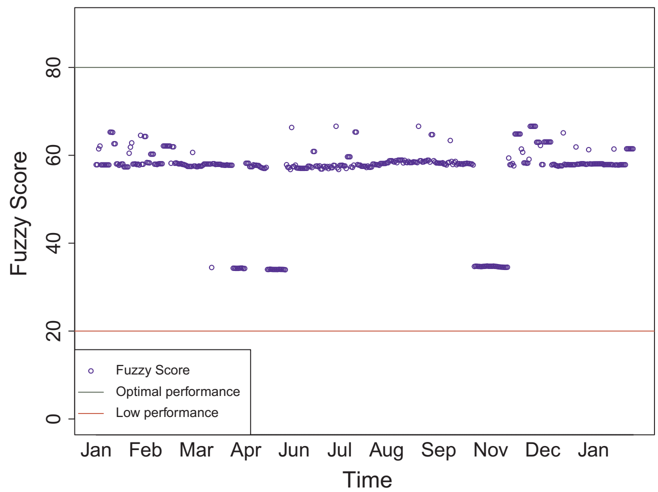

Fig. 6. Fuzzy score time series for BURG from 1 December 2015 to 1 March 2016.

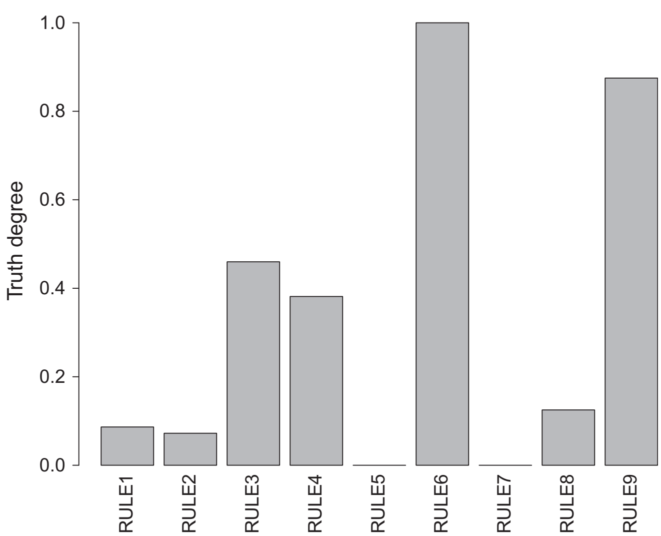

Fig. 7. Strength of the rules.

the total cost). Considering, the age of the pump system, it is expected to have a remaining operational life of 11 years. Replacing this pump system at this stage is equivalent to a cost of 11 years of allocated values (11 × €52,256.02 = €574,816). This cost is significantly higher than the maximum threshold cost (€60,022). Consequently the pump replacement is rejected.

In this subsection, we used a simplified approach to make a decision using the maximum threshold cost. The large difference between this threshold and the cost of under-utilization suggests that a more detailed analysis is not necessary. From the decision support perspective, it is interesting to show how to calculate and use this threshold. A more detailed financial analysis, out of the scope of this manuscript, can be performed, if necessary, including other information such as interest rates.

3.5. Analysis of a potential solution: pony pump installation

The proposed methodology also supports the plant manager in making another important decision: *Is it beneficial to install a pony pump?* We identified a suitable pump able to treat 140 l/s with a static head higher than 12 m and with 36 kW power.

With the equations used in [11], we can estimate an installation cost of €250 k. This value is far higher than the investment threshold (€60 k). Consequently, we suggest rejecting the installation of a pony pump. In this case, the plant manager may identify less expensive alternatives (such as valve regulation or the installation of a variable speed drive) or, regrettably, accept the cost of an inefficiency to avoid the cost of a pump upgrade.

3.6. Sensitivity analysis of the customizable parameters

This algorithm presents some customizable parameters:

- the size of the rolling windows (W_m), that affects the value of η_t. Its default value is 90 days;
- the reference interval for the calculation of τ (I_τ). By default, $I_\tau = 180$;
- the extension of the sequence of negative fluctuations to activate the alarm through the Z parameter (W_Z). By default, $W_Z = 15$.

In order to guarantee the robustness of the methodology and the results, it is important that the end-user has an adequate comprehension of the impact of his choices in the calculation of the KPIs. To this purpose, this sub-section proposes a sensitivity analysis by calculating the KPIs for several values of the respective customizable parameters. In particular, we have analysed:

- the variation of η_t with several values of rolling windows (W_m).
- the variation of τ with several values of I_τ.
- the variation of Z with several values of W_Z.

These analyses were performed using the graphical interface and our script. In these three analyses, the parameters, required by the tool and not used in the calculation of the KPI being analysed, are set up at their respective default values.

The value of W_m should be large enough to be representative of the operational conditions of the plant. Table 4 shows that in a range between 60 days and 360 days the values of η_t are stable enough not to produce changes in the fuzzification process. The selection of values below 30 days produces unstable results (Table 4). The selection of a larger range for the rolling median produces more stable results but it requires a larger database. In the case study, for BUR, $W_m = 90$ is considered a good compromise between stability and data availability.

For the calculation of τ (Eq. (3)), according to the benchmark definition, the easiest solution should be to compare 2 points with an interval of 365 days, but this also requires a large dataset. Table 5 shows how sensitive τ is to this parameter. It is interesting to observe that with $I_\tau > 120, \tau < |0.4|$ and consequently the qualitative assessment of the pump degradation and the results of the parameter fuzzification

Table 4
Sensitivity analysis of W_m.

W_m	Min(η_t)	Mean(η_t)	Max(η_t)
7	0.21	0.31	0.96
30	0.22	0.27	0.55
60	0.23	0.26	0.29
90	0.23	0.26	0.27
120	0.24	0.26	0.28
180	0.25	0.26	0.27
360	0.25	0.26	0.27

Table 5
Sensitivity analysis for I_τ.

I_τ	Min(τ)	Mean(τ)	Max(τ)
7	−2.25	−0.01	3.27
60	−0.60	0.03	1.05
120	−0.39	0.02	0.63
180	−0.26	−0.08	0.23
360	−0.18	−0.0107	−0.0106

Table 6
Sensitivity analysis for W_Z.

W_Z	mean(Z)
3	0.63
7	0.72
15	0.84
20	0.89
30	0.95

do not change. For this analysis, we have imposed $I_\tau = 180$.

The end-user can also set the value of the consecutive fluctuations (W_Z), i.e. the number of negative values of fluctuations that provoke an alert. As expected, Table 6 shows that by increasing the value of W_Z, the Z values move toward 1 (the system needs a larger sequence of negative values to detect a failure). A small W_Z value helps to detect the problem early but also increases the risk of detecting false positives. In this case, $W_Z = 15$ is considered a good balance between a shorter frame that increases the risk of producing false positive alarms and a longer one that requires more time to detect a potential problem.

This simple analysis of the impact of the customizable parameters leads to the following conclusions and suggestions:

- the method is robust because the selection of input values in a reasonable range does not affect the fuzzification process and the operational conclusions;
- set-up $W_m > 60$ days;
- set-up $I_\tau > 120$ days;
- set-up $10 \leqslant W_Z \leqslant 20$ days.

This first simple sensitivity analysis aims to show the robustness of the methodology and to provide meaningful suggestions to end-users. A more detailed sensitivity analysis will be done using different WWTP pump systems in future works.

3.7. Availability of the current methodology for field applications

The methodology is currently suitable for being applied directly to centrifugal pump systems, regardless of their size or the pump system configuration. The methodology relies on data measured on-line and aggregated at a daily resolution, as proposed in the EOS system [2]. This requires an initial set-up of a system able to gather data from remote sensors, process, aggregate and make them available to the decision tool. In the WWTP domain, the required sensors are generally available. After the connection of the WWTPs to the EOS dataset, two options are available to apply this methodology:

- on-line analysis; an automated script processes the data at fixed-time interval and submits the results to the SCADA system;
- on-the-fly analysis; a script, with a graphical interface using customizable parameters, analyses the data and produces the results on-screen.

In the first case, the results are immediately accessible for plant managers, no interaction with the software is required and the analysis is performed over all the records. In the second case, the software requires a parameter set-up but the plant manager can carry out specific tests, for example analysing a specific period. These two approaches can coexist.

4. Discussion

The following discussion section is organized into three parts. Section 4.1 compares the results obtained with current practice and those obtained using the approach in this paper. Section 4.2 explains the results and the solutions proposed for the specific case-study. Section 4.3 deals with the potential development of the methodology, its strengths and limitations.

4.1. Comparison with the state of the art

According to current practice, the assessment of pump systems is performed using an efficiency index η that refers to a period under investigation (generally one year). According to our experience, this index, if not integrated into a more complex analysis, is not sufficient to produce a satisfactory assessment of pump systems; for example it is not able to take into account a wide set of phenomena such as the impact of the operational conditions on the pump performance and the effects of the pump deterioration. The current practice, for the period under investigation, would produce only a little information: $\eta = 0.31$ by using Eq. (1). This value is below the reference ($\eta = 0.32$), it does not explain the pumps behaviour and it is not a satisfactory support for decision-making. We do not consider this approach sufficient for an efficient management of pump systems in the WWTP domain. Consequently, we have presented a methodology to support the decision making process with a more detailed analysis of the pumps based on information generally available in WWTPs: inflow volume and the pump energy consumption. In particular, this paper shows how to analyse the daily values of η and obtain additional information: the condition of the pump system (through η_t and η_f), the deterioration of the pumps (through τ) and potential failures at an early stage (through Z). This information set was used as input for the fuzzy logic engine to produce the analysis of operational conditions and a synthetic pump performance index. This new index explains the pump performance better than η because it is less sensitive to short-term changes in operational conditions. This methodology enables the plant managers to better understand the behaviour of pump systems by performing two additional analyses: the diagnosis of the operational condition and the detection of flow-related patterns. This fills a gap in the literature because, to the best of our knowledge, there are no available methodologies able to investigate flow-related efficiency patterns based on an on-line monitoring of pumps inflow and energy consumption. Moreover, the daily analysis enables plant managers to identify failures at an early stage and can consequently produce operational, economic and environmental benefits.

4.2. Explanation of results

Table 3 shows a median value of $\eta_t = 0.27$, which should be improved by 18.5% to reach the minimal satisfactory level of 0.32. This case study shows that the energy performance of the pumps investigated is quite low but stationary and that the inefficiencies are caused by flow condition. In particular during dry weather flow the pump system efficiency is quite low while peaks of efficiency are observed during rain periods. This information set, coupled with the output of fuzzy logic, supports a better comprehension of the time-series shown in Fig. 2 and is the starting point for the case-base reasoning. Moreover, this approach supports the decision-makers with a list of potential case-based solutions and filters out those that are too expensive. At the current development, for BUR, the installation of a pony pump was rejected because it was too expensive. Alternatively, a check up is proposed for the pump controller, pipe and valves. In further developments, the authors of this paper will enlarge the set of potential solutions.

4.3. Potential development of the methodology, strengths and limitations

In the first stage of the methodology, the decomposition of the η time series has been done with the rolling median. This algorithm was chosen after a comparison with different alternatives [27]: the rolling-median algorithm produces very similar results to the HodrickPrescott filter, the Kalman filter-band, and the Baxter-King filter. Consequently, this methodology is suitable for use with other signal decomposition algorithms such as those mentioned earlier.

This methodology should be seen as an extension of the classical approach and not necessarily as a replacement. Moreover, this methodology could be integrated with the environmental impact assessment of the pump systems and of the proposed alternatives. The test on inflow conditions should be integrated with other tests regarding the water characteristic (such as pH, temperature, and density) or other specific problems (such as cavitation). Moreover, an improvement of this methodology should take into consideration a dynamic calculation of τ benchmarking, because the wear effects are stronger in the final years of the pump systems' time-span.

The methodology is flexible enough to be applied to multiple pump systems because it is based on the use of dimensionless indices (η,η_t,η_f, Z) that can be applied to all centrifugal pump systems regardless of their set-up (for example power, lift, the number of pumps). The methodology also takes into account plant-specific conditions (such as the cost of energy, the cost of new pumps) and performs plant-specific tests.

Moreover, this methodology is extremely sensitive to the cost of energy. In fact, the budget available for efficiency operation is linearly dependant on the cost of energy (cf. system of Eq. (5)). In Europe, the cost of energy for industrial use varies widely[33]: from the maximum price in Germany (0.149 €/kWh) to the lowest price in Sweden (0.059 €/kWh). This means that 2 plants with the same performances in Germany and in Sweden do not have the same economic benefit from an efficient management. In particular, when facing the same inefficiency issue, a plant manager in Germany should be able to invest 2.52 times the budget of his colleague in Sweden. Statistical analyses, which are outside of the scope of this paper, should be performed to investigate the impact of the cost of energy on inefficiency.

5. Conclusion and outlook

Energy efficiency is an important challenge in the WWTP domain and, the energy-saving in pump systems can produce relevant results from an economic and environmental perspective. The availability of on-line sensors can provide support for a better understanding of pump system operational performance and for the decision-making process. Nevertheless, in current practice, plant managers assess their pump system using insufficient information. In this paper, we proposed an innovative and highly-performing data-driven methodology able to produce a detailed pump system assessment and support the plant managers in saving energy. This approach is able to: separately identify and analyse long-term phenomena and short-term phenomena, produce a user-friendly performance index, identify potential failures at an early stage, extract useful information from the database and provide solutions that can be selected according to economic criteria.

This methodology is highly replicable in domains in which the only available information is the energy cost and the inflow.

Acknowledgements

The authors gratefully acknowledge the financial support of the National Research Fund (FNR) in Luxembourg (7871388-EdWARDS) and additional funding from the Luxembourg Institute of Science and Technology. In addition, the plant data was collected in the framework of the INNERS project, financed by the European Union through the INTERREG IVB North West Europe programme (Grant Nr:192G) and the Luxembourg Institute of Science and Technology. The authors are thankful to Lindsey Auguin (LIST) for her support in reviewing the language quality of this manuscript. The methodology, the script and the results presented in this paper are developed in the framework of the PhD project of Dario Torregrossa (EdWARDs).

References

[1] Castellet Lled, Molinos-Senante Mara. Efficiency assessment of wastewater treatment plants: a data envelopment analysis approach integrating technical, economic, and environmental issues. J Environ Manage 2016;167:160–6. http://dx.doi.org/10.1016/j.jenvman.2015.11.037. ISSN 10958630 URL <http://www.sciencedirect.com.proxy.bnl.lu/science/article/pii/S0301479715303911>.

[2] Torregrossa D, Schutz G, Cornelissen A, Hernández-Sancho F, Hansen J. Energy saving in WWTP: daily benchmarking under uncertainty and data availability limitations. Environ Res 2016;148:330–7. http://dx.doi.org/10.1016/j.envres.2016.04.010. ISSN 10960953 URL <http://www.sciencedirect.com/science/article/pii/S0013935116301360>.

[3] Mizuta Kentaro, Shimada Masao. Benchmarking energy consumption in municipal wastewater treatment plants in Japan. Water Sci Technol 2010;62(10):2256–62. http://dx.doi.org/10.2166/wst.2010.510. ISSN 02731223 URL <http://www.ncbi.nlm.nih.gov/pubmed/21076210>.

[4] Shi Cao Ye. Mass flow and energy efficiency of municipal wastewater treatment plants. IWA Publishing; 2011. ISBN 9781843393825.

[5] Hernández-Sancho F, Molinos-Senante M, Sala-Garrido R. Energy efficiency in Spanish wastewater treatment plants: a non-radial DEA approach. Sci Ttotal Environ 2011;409(14):2693–9. http://dx.doi.org/10.1016/j.scitotenv.2011.04.018. 6 ISSN 1879-1026 URL <http://www.ncbi.nlm.nih.gov/pubmed/21549411>.

[6] Becker Markus, Hansen Joachim. Is the energy-independency already state-of-art at NW-European wastewater treatment plants. In: Proceedings of the IWA-conference asset management for enhancing energy efficiency in water and wastewater systems; 2013. p. 19–26. URL < http://orbilu.uni.lu/handle/10993/7857 >.

[7] Krampe J. Energy benchmarking of South Australian WWTPs. Water Sci Technol 2013;67(9):2059–66. http://dx.doi.org/10.2166/wst.2013.090. 1 ISSN 02731223 URL <http://www.ncbi.nlm.nih.gov/pubmed/23656950>.

[8] Panepinto Deborah, Fiore Silvia, Zappone Mariantonia, Genon Giuseppe, Meucci Lorenza. Evaluation of the energy efficiency of a large wastewater treatment plant in Italy. Appl Energy 2016;161(October):404–11. http://dx.doi.org/10.1016/j.apenergy.2015.10.027. ISSN 03062619.

[9] INNERS. Innovative energy recovery strategies in the urban water cycle. Technical report; 2015.

[10] Hydraulic Institute and Department of Energy (US). Improving pumping system performance: a sourcebook for industry. Technical report; 2006.

[11] Torregrossa Dario, Leopold Ulrich, Hernández-Sancho Francesc, Hansen Joachim, Cornelissen Alex, Schutz Georges. A tool for energy management and cost assessment of pumps in waste water treatment plants. Decision support systems VII. Data, information and knowledge visualization in decision support systems, vol. 282. AG: Springer International Publishing; 2017. p. 148–61. http://dx.doi.org/10.1007/978-3-319-57487-5_11. ISBN 978-3-319-57486-8.

[12] Bortoni Edson da Costa, Almeida Roberto Alves, Viana Augusto Nelson Carvalho. Optimization of parallel variable-speed-driven centrifugal pumps operation. Energy Efficiency 2008;1(3):167–73. http://dx.doi.org/10.1007/s12053-008-9010-1. ISSN 1570646X.

[13] Zhang Zijun, Zeng Yaohui, Kusiak Andrew. Minimizing pump energy in a wastewater processing plant. Energy 2012;47(1):505–14. http://dx.doi.org/10.1016/j.energy.2012.08.048. ISSN 03605442.

[14] Chang Wei, Chang Jun-wei, Yin Hsu, Wang Wen-June, Chung Hsin-Yi, Chang Ya-Ching, et al. Energy-saving algorithm for pumping systems based on fuzzy decision making. 2012 IEEE international conference on systems, man, and cybernetics (SMC) IEEE; 2012. p. 2395–400. http://dx.doi.org/10.1109/ICSMC.2012.6378101. 10 ISBN 978-1-4673-1714-6 URL <http://ieeexplore.ieee.org/lpdocs/epic03/wrapper.htm?arnumber=6378101>.

[15] Olszewski Pawel. Genetic optimization and experimental verification of complex parallel pumping station with centrifugal pumps. Appl Energy 2016;178:527–39. http://dx.doi.org/10.1016/j.apenergy.2016.06.084. 9 ISSN 03062619 URL <http://linkinghub.elsevier.com/retrieve/pii/S0306261916308601>.

[16] DeBenedictis A, Haley B, Woo CK, Cutter E. Operational energy-efficiency improvement of municipal water pumping in California. Energy 2013;53:237–43. http://dx.doi.org/10.1016/j.energy.2013.02.012. ISSN 03605442 URL.

[17] Berge SP, Lund BF, Ugarelli R. Condition monitoring for early failure detection. Frognerparken pumping station as case study. Proc Eng 2014;70(1877):162–71. http://dx.doi.org/10.1016/j.proeng.2014.02.019. ISSN 18777058.

[18] Wang Chuan, Shi Weidong, Wang Xikun, Jiang Xiaoping, Yang Yang, Li Wei, et al. Optimal design of multistage centrifugal pump based on the combined energy loss model and computational fluid dynamics. Appl Energy 2017;187:10–26. http://dx.doi.org/10.1016/j.apenergy.2016.11.046. ISSN 03062619.

[19] Zhang Zijun, Kusiak Andrew, Zeng Yaohui, Wei Xiupeng. Modeling and optimization of a wastewater pumping system with data-mining methods. Appl Energy

2016;164:303–11. http://dx.doi.org/10.1016/j.apenergy.2015.11.061. ISSN 03062619.
[20] Zhuan Xiangtao, Xia Xiaohua. Optimal operation scheduling of a pumping station with multiple pumps. Appl Energy 2013;104:250–7. http://dx.doi.org/10.1016/j.apenergy.2012.10.028. ISSN 03062619.
[21] Metcalf E, Eddy H. Wastewater engineering: treatment and reuse. ISBN 0-07-041878-0. doi:10.1016/0309-1708(80)90067-6. URL <http://www.lavoisier.fr/notice/fr097556.html>; 2014.
[22] Hydraulic Institute and U.S. Department of Energy Energy. Energy tips pumping systems. Technical report; September 2005. URL www.eere.energy.gov <http://www.schulzelectric.com/pdf/wp_test_pumping_system__pumping_systemts4.pdf>.
[23] Spellman Frank. Handbook of water and wastewater treatment plant operations. CRC Press; 2003. http://dx.doi.org/10.1016/B978-0-12-369520-8.50043-7. ISBN 9781466553385. < http://books.google.com/books?hl = en & lr = & id = dXxcAgAAQBAJ & oi = fnd & pg = PP1 & dq = Handbook + of + Water + and + Wastewater + Treatment + Plant + Operations & ots = I2ToGvx3v8 & sig = VYDsJINek6Nl4FwUFEE3yO_tf3s%5Cnhttp://books.google.com/books?hl = en & lr = & id = dXxcAgAAQBAJ & oi = fnd & pg = PP1 & dq > .
[24] Gülich Johann Friedrich. Centrifugal pumps; 1998. ISBN 978-3-540-73694-3.
[25] WEF. Operation of municipal wastewater treatment plants, vol. 1542. WEF Press; 2008. ISBN 9788578110796. http://dx.doi.org/10.1017/CBO9781107415324.004.
[26] Shankar Vishnu Kalaiselvan Arun, Umashankar Subramaniam, Paramasivam Shanmugam, Hanigovszki Norbert. A comprehensive review on energy efficiency enhancement initiatives in centrifugal pumping system. Appl Energy 2016;181:495–513. http://dx.doi.org/10.1016/j.apenergy.2016.08.070. ISSN 03062619.
[27] Torregrossa Dario, Hansen Joachim, Hernández-Sancho Francesc, Cornelissen Alex, Schutz Georges, Leopold Ulrich. Pump efficiency analysis of waste water treatment plants: a data mining approach using signal decomposition for decision making. In: Gervasi O, editor. Computational science and its applications ICCSA 2017. ICCSA 2017 Lecture notes in computer science Cham: Springer; 2017. p. 744–52. http://dx.doi.org/10.1007/978-3-319-62407-5_56. 7 URL <http://link.springer.com/10.1007/978-3-319-62407-5_56>.
[28] Zadeh La. Fuzzy sets. Inform Contr 1965;8(3):338–53. http://dx.doi.org/10.1016/S0019-9958(65)90241-X. ISSN 00199958.
[29] Starczewski Janusz T. Advanced concepts in fuzzy logic and systems with membership uncertainty, vol. 284; 2013. ISBN 9783642295195. http://dx.doi.org/10.1007/978-3-642-29520-1.
[30] Zadeh Lofti A. Fuzzy logic. Computer 1988;21(4):83–93. http://dx.doi.org/10.1109/2.53. ISSN 00189162.
[31] Mamdani EH, Assilian S. An experiment in linguistic synthesis with a fuzzy logic controller. Int J Man-Mach Stud 1975;7(1):1–13. http://dx.doi.org/10.1016/S0020-7373(75)80002-2. ISSN 00207373.
[32] Department of Environment (UK). Variable speed pumping a guide to successful applications, executive summary is the result of a collaboration between the Hydraulic Institute, Europump, and the U.S. Department of Energys (DOE) Industrial Technologies Program. A guide to variable speed pumping; 2004. p. 20. doi:DOE/GO-102004-1913.
[33] Eurostat. Simplified energy balances – annual data. Technical report. URL < http://appsso.eurostat.ec.europa.eu/nui/show.do > ; 2015.