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DARIO TORREGROSSA
Luxembourg Institute of Science and Technology, dariotorregrossa@gmail.com

Ulrich Leopold
Luxembourg Institute of Science and Technology, ulrich.leopold@list.lu

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A multi-level decision support system for energy optimization in WWTPs

Dario Torregrossa [a] **and Ulrich Leopold** [a]

[a] *ERIN department, Luxembourg Institute of Science and Technology (LIST), 41 Rue du Brill, 4422 Sanem, Luxembourg*

Abstract: The availability of real-time measurements in Waste Water Treatment Plants (WWTPs) can produce environmental and economic benefits. Since WWTP sensors can generate thousands of records per day, computer support is necessary for efficient decision-making processes. Recently a Shared-Knowledge Decision Support System (SK-DSS) was presented. This tool is based on fuzzy logic and equipped with specific applications for energy saving in pumps and blowers. Each pump and blower can be controlled by SK-DSS in order to produce an assessment of operational conditions and provide case-specific suggestions. With the increasing of number of devices under analysis, a synthetic index become necessary in order to provide a global evaluation of the plants. For this reason, this paper advances the current DSS approach providing a multi-level fuzzy logic engine. In the bottom level, individual assessments of pumps and blowers are performed. The top level produces a score in the range [0-100] by processing the outputs of the individual device assessments without losing the detailed information stored at the bottom level. Moreover, different weights can be attributed to the single devices through the calibration of the top-layer fuzzification process. In the future, the bottom level of the multi-fuzzy engine will be expanded with tools able to monitor other parts of the plants.

Keywords: Waste Water Treatment Plant; Energy Efficiency; Decision Support System

1 INTRODUCTION

In recent years, many authors focussed their efforts on the energy efficiency of Waste Water Treatment Plants (WWTPs) because of the interesting energy savings potential [Castellet and Molinos-Senante, 2016; Torregrossa et al., 2016; Díaz-Madroñero et al., 2018; Castellet-Viciano et al., 2018; Doherty et al., 2017; Panepinto et al., 2016].

Available sensors offer the possibility to monitor on-line WWTPs, improving the comprehension of the plants, automatically identify failures and reduce the response time to inefficiency. This is only possible with a computer assisted tools since the huge amount of data produced (up to 300k values/day, [Torregrossa et al., 2016; Torregrossa and Hansen, 2018]) cannot be efficiently processed by a human operator.

Decision support systems can fill the gap between data availability and the benefit of its intensive use. In WWTP domain, several authors used decision support system for design [Comas et al., 2004;

Gómez-López et al., 2009; Garrido-Baserba et al., 2015; Tomei et al., 2016; Kalbar et al., 2016] and management [Paraskevas et al., 1999; Poch et al., 2004; Guerrero et al., 2011; Gibert et al., 2012; Hakanen et al., 2013; Gisi et al., 2015].

In the framework of the EdWARDS project[1], a cooperative decision support system based on fuzzy logic has been developed [Torregrossa et al., 2017b]. This decision support system, called Shared Knowledge Decision Support System (SK-DSS), produces a fuzzy logic assessment of plant performance, proposes case-specific suggestions and enables the plant managers to cooperate through knowledge exchange. In the framework of SK-DSS, two applications were proposed to monitor blowers [Torregrossa et al., 2017b] and pumps [Torregrossa et al., 2017a]. For example, with the methodology proposed in [Torregrossa et al., 2017b], it is possible to perform a multi-parameters assessment of the blower systems, identify the operational conditions and suggest feasible actions to the operators; for example, if the energy consumption is normal but the amount of air in the tank is insufficient, it is possible that the inefficiency is provoked by holes in the pipes or by an inefficient distribution system. In [Torregrossa et al., 2017a], the SK-DSS methodology was applied to pump systems in order to evaluate the impact of flow-related inefficiencies, detect early failures , identify the operational conditions of the pump system and finally provide suggestions to the operator.

In the perspective of the application of SK-DSS to all the WWTP devices, the amount of information to be analysed increases, and a new plant performance index becomes necessary. For this reason, in this paper, SK-DSS is modified by adding a layer of analysis able to process the information of the fuzzy logic device assessment. This layer takes as input the fuzzy evaluation of pumps and blowers and provides an aggregated index.

SK-DSS was a novelty in the framework of Waste Water Treatment Plants, because, at the time of publication, cooperative decision support systems were not found in literature. Now, in the perspective of a wider application of SK-DSS techniques, in this paper, a multi-layer decision support system is presented to provide the plant managers with a user-friendly global effice index.

2 METHODOLOGY

The input dataset of this methodology is composed by a time-series in which for each day it is recorded the result of the assessment of pump and blower systems obtained with the methodologies available in [Torregrossa et al., 2017a] and [Torregrossa et al., 2017b]). This score is normalized in a range 0-100 and, in this paper, it is the result of a simulation in which the pump performance is stable and the blower performance is rapidly decreasing. Figure 1 shows the diagram flow of the methodology in which

- at the bottom layer, many specific fuzzy systems produce performance scores (for example for pumps, blowers and biogas);
- at the top-layer, a fuzzy-engine takes as input the device assessments and provides a synthetic index in the range 0-100.

The output of the bottom layer consists in the evaluation of single devices and corresponds to the input of the top layer. The global evaluation is performed by aggregating the output of the device assessments. The fuzzification process of the top-layer inputs considers 'high' the condition in which $fuzzy - score > 70$, and 'low' the performance with $fuzzy - score < 30$ (fig. 2). According to fuzzy logic algebra, all the intermediate conditions are at the same time 'low' and 'high' with different degree of truth [Torregrossa et al., 2017b].

Table 1 explains the fuzzy rules applied at the top-layer. In this table, the score associated to each rule reflects the importance of the condition. For example, the system attributes a higher score to the

[1] https://www.list.lu/en/research/project/edwards/

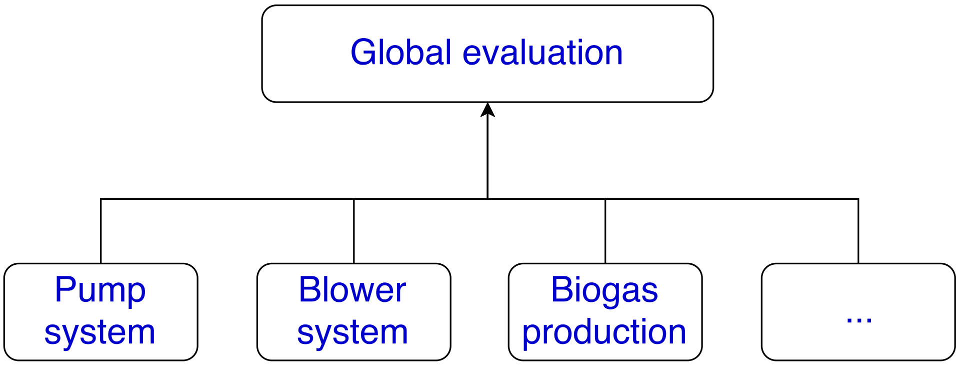

Figure 1. Flowchart of multilevel fuzzy logic

rule 2 (the blower works well, the pump does not) than to the rule 3 (the pump works well, the blower not). This set-up takes into consideration the fact that in the WWTP energy balance the blowers account more than the pumps. The two extreme conditions are expressed by rule 1 (pump and blower performance indices are low) and rule 4 (pump and blower performance indices are high).

Table 1. Rules of multilevel fuzzy system

Rule	Pump Score	Blower Score	Score
1	Low	Low	0
2	Low	High	60
3	High	Low	40
4	High	High	100

3 Results

The input of the top-layer is the fuzzy logic assessment of pumps and blowers previously calculated. The fuzzy output needs to be fuzzified to become an input to the top-layer. The fuzzification input functions for pumps and blowers are reported in figure 2, that provide truth degrees for each device score and each device condition. For example, if the pump score is 80, the pump performance is considered 'high' with truth degree equal to 100%, and 'low' with truth degree equal to 0%. The fuzzified input needs to be coupled with the rules of table 1, in which the scenarios are associated to a Score according to fuzzy logic algebra [Starczewski, 2013]. As previously mentioned, this score is customized according to the importance of the variables. In the example, more importance is attributed to the quality of the blowers because, in WWTPs, they have a bigger impact on energy balance.

For each day, the rules are applied to the database to produce a daily global score in the range 0-100. The time-series of this index is plotted in fig. 3, together with the pump score and the blower score. Fig. 3 enables to perform the following operations:

- it is possible to identify a threshold to alert the plant managers of critical situations;
- it is possible to easily assess each device;
- it is possible to identify the source of efficiency change.

For example fig. 3 shows that inefficiency problems start at the beginning of July, and they are caused

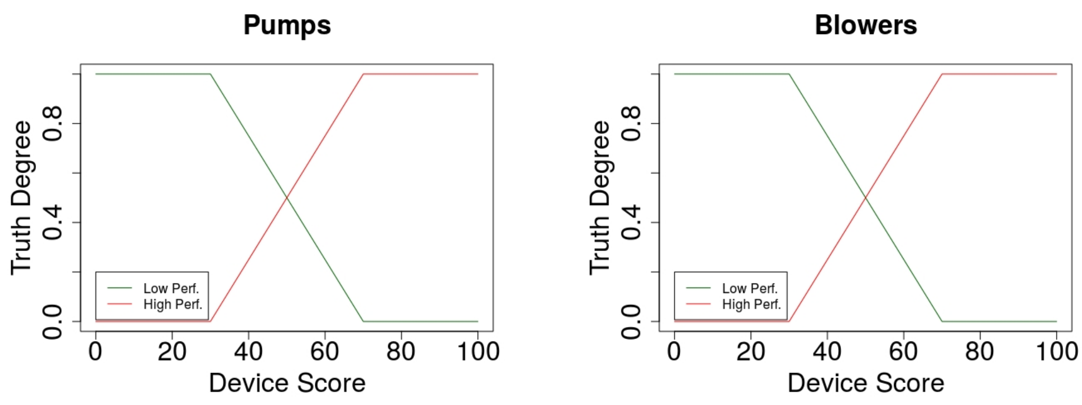

Figure 2. Fuzzification of inputs

by a drop in blower score. The score of the pump does not register any dramatic change during the period under investigation.

The information visualized in fig. 3 can easily lead to identify solutions. In this case, for example, it is necessary to improve the pump score and the blower score and the priority should be given to blower score for two reasons:

- the blower score is decreasing fast, while the pump score even if low appears stable on the long term;
- the blower score is the source of the recent decreasing of the global score.

At this point, if more detailed information are required, it is possible to retrieve the information stored at the bottom layer and calculated with the methodologies presented in [Torregrossa et al., 2017a, b].

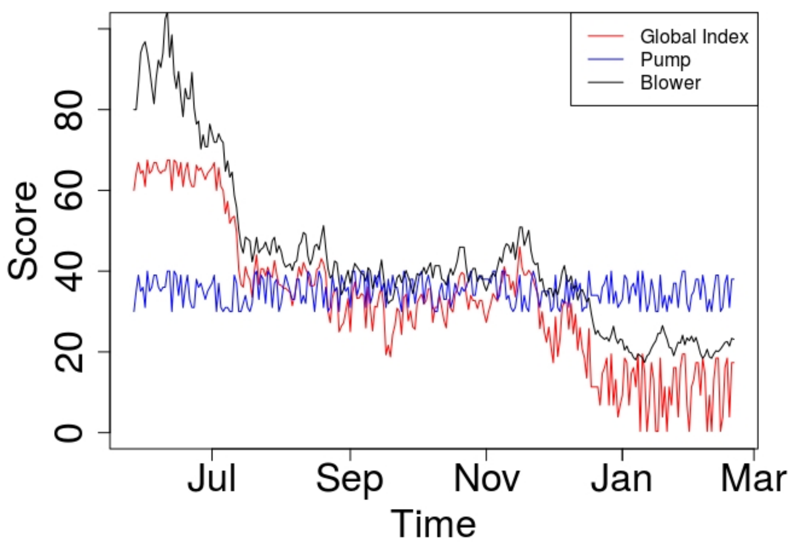

Figure 3. Time Series of Global Index, Pump Score and Blower Score

4 Discussion and conclusion

In previous contributions, SK-DSS proposed methodologies to assess WWTP devices: pump and blowers. In the perspective of an extension of SK-DSS methodology to other plant devices (blowers, stirrer, sludge line...), the increased number of outputs produced by SK-DSS needs to be aggregated in a single user-friendly score. In order to do this, in this paper, a multi-layer decision support system was presented, that processes the outputs of single device assessments, fuzzify them and produce and make an aggregated index. This system is really flexible because it enables to customize the main parameters and, trough the rule score set-up, attribute different weights to the devices at the bottom layer. At this stage of the development, the prototype of multi-level decision support system is based only on analysis of pump and blowers. The results are easy to read and there is no limit to the number of devices to be analysed at the bottom layer. Moreover, in case the number of devices increase too much, it is possible to aggregate them with the present methodology by adding additional bottom-layers. In the future, two improvement will be provided:

- development of tools to monitor new devices;
- a user-friendly graphical interface in order to let the plant managers to customize the main parameters; an example in [Torregrossa et al., 2017a].

The end-user interface can be developed as desktop application and as web-service. Since the fuzzy-logic was developed with R R Core Team [2016], the easier solution will be to provide a development using the Shiny Package [Chang et al., 2017]. A first development can be visualized in `https://dario-torregrossa.shinyapps.io/Ver2/`. Moreover an alert system can be easily associated to the global index using job-scheduler applications (such as Cron from Ubuntu [2018]); at given times, the full analysis can be automatically executed and inform the plant manager about anomalies.

The system and the methodologies behind have been developed and tested for WWTPs. However, since devices such as pump and blowers are commonly used in industry, this set of methodologies can be applied to other fields.

In conclusion, in this paper, a prototype for a multi-device controller, suitable to be applied to WWTPs was presented. This tool is designed for the analysis of a large number of devices and to be used as automatic alert system for inefficiencies.

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