Dynamic reasoning to solve complex problems in activated sludge processes: a step further in decision support systems

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Abstract Decision support systems (DSS) have generated high expectations as a tool to support activated sludge operation because of their ability to represent heuristic reasoning and to handle large amounts of qualitative, uncertain and low-accuracy data. Previous applications have been satisfactory to control simple problems, when static reasoning and literature-based solutions were enough. However, to face complex operational problems with biological origin and slow dynamics (e.g. solids separation problems), it is necessary to use dynamic reasoning and apply long-term control strategies, monitoring the evolution of the process and adjusting the action plan according to the feedback of the process. This paper presents a dynamic reasoning DSS to face solids separation problems in the activated sludge system. The DSS is capable of identifying the complex problem affecting the process, determining if the current situation is new or a continuation from the previous one, assessing what is the specific cause of the situation, and recommending a long-term control strategy, which is daily adjusted according to the evolution of the process.

Keywords Activated; sludge; artificial intelligence; decision support systems; dynamic reasoning; solids separation problems; bulking

Introduction

Decision support systems (DSSs) are intelligent multi-layered information systems capable of integrating classic mathematical or statistical models with artificial intelligence techniques (i.e. knowledge-based systems, soft-computing techniques, data-mining tools, etc.). DSSs have generated high expectations as a tool to tackle environmental systems whose inherent complexity makes their management a difficult task. DSSs reduce the time required to make decisions and improve the consistency and quality of the decisions by offering criteria for the evaluation of alternatives or to justify decisions. In the last fifteen years, different DSS approaches have been developed within the domain of wastewater treatment plants (WWTPs), mainly as a tool to support the activated sludge process operation. DSSs have been chosen as supervisory tools because of their ability to represent heuristic reasoning (ability to mimic human reasoning in situations where there is not a well-defined model of the process) and to handle large amounts of qualitative (e.g. microscopic information), uncertain and low-accuracy data that human operators typically encounter.

However, the first DSSs (e.g. Chan and Koe, 1991; Ladiges and Kayser, 1993; Ozgur and Stenstrom, 1994; Bergh and Olsson, 1996) never really succeeded and were not tested in real facilities because they were too complex and it was difficult to capture all the available knowledge in reliable models and advisory systems (Olsson et al., 1998). More recent applications, which include real-time intelligent data interpretation and
validation, have been implemented and evaluated in real WWTPs (e.g. Puñal et al., 2001; Rodríguez-Roda et al., 2002; Comas et al., 2003; Poch et al., 2004). These latest applications have shown that DSSs can support decision-making, especially to control simple non-biological situations with fast dynamics such as mechanical, physical or electrical problems, organic or hydraulic overloading, etc. In this kind of situations, static reasoning and short-term literature-based solutions are enough to recognize and manage the situation. Nevertheless, DSSs have shown significant limitations when more complex problems arise in a plant. Solids separation problems in the secondary settlers are an example of a complex problem that, due to its microbiological origin, lasts for several days within the process. On such occasions, a static DSS that does not take into account the evolution of the problem would not be a reliable tool to provide an efficient control plan. Therefore, a further step in decision support is required to overcome the limitations found in problems of long duration. In these situations, the DSS must be able to reach a dynamic diagnosis based on the needs of the process at each moment. Dynamic reasoning allows the system to understand how the process evolves (whether the current situation is a new problem or a continuation of a previously detected problem), to react differently according to the process status trend and to propose the most suitable control strategies, based not only on the literature but also on the feedback derived from the evolution of the process.

To prove the necessity for and the usefulness of dynamic reasoning, this paper presents a dynamic knowledge-based DSS capable of dealing with complex problems of long duration within the activated sludge process. First, the proposed DSS architecture is described briefly. Second, the core of the DSS dynamic reasoning is presented. Finally, a case study based on a solids separation problem illustrates the benefits that this type of reasoning can provide.

The dynamic DSS approach

The DSS has been structured into three main levels as shown in Figure 1.

- The first level corresponds to data gathering. Different kinds of data (including both on-line and off-line, numerical and qualitative data) are collected and validated using a data reconciliation system. This stage includes data filtering and fault detection together with a discretization stage (where the numerical values of the different
variables are fuzzy converted into qualitative values, e.g. high, normal or low) in order to feed the system with the most accurate and useful information to reach a diagnosis. Since activated sludge processes are dynamic systems, the optimal monitoring of the process must also include information about the evolution of the main variables. Thus, the proposed DSS computes and analyses the derivatives of some specific variables to detect sudden deviations, trends and periodicities. This feature enables the system to propose suitable actions to prevent significant problems occurring.

- The second level, dynamic reasoning, includes the reasoning module to infer the process status (problem diagnosis and detection of cause) in order to reach a reasonable proposal for a control strategy. This is accomplished through a knowledge-based expert system which, by means of dynamic reasoning and using data gathered at the first level and knowledge structured in heuristic rules, is able to reach a dynamic diagnosis, identify the potential cause, and suggest a long-term control strategy to restore the process to normal operation.

- Finally, at the decision support level, the conclusions of the dynamic reasoning level are provided to the final users (process operators), who refine and apply the control strategy.

In comparison with the conventional DSS based on static reasoning, our dynamic approach includes a counter for any potential solids separation problem in order to identify whether the current problem diagnosis is a new situation or is part of a problem previously initiated and probably already handled. Also, instead of giving a generic solution, a specific long-term control strategy is determined to solve the situation, from beginning to end, and continuously updated according to the feedback and evolution of the process. If a new problem or cause arises in the process, a new control strategy will be established. In contrast, if the problem diagnosis and the possible cause are just like previous ones, then the DSS has to evaluate whether the best option is to maintain the same control strategy (if the process is evolving as expected) or on the contrary to modify it due to inefficient performance or whenever the evolution of the process diverges from the initial prediction. In that sense, once a new problem is identified and a new control strategy is started, dynamic reasoning only checks the required data to be aware of the evolution of the process, avoiding unnecessary reasoning that would lead to repetitive diagnoses (as in static reasoning systems). Also when a control strategy has already been applied to address a specific problem, the DSS considers the results of this application (is the problem already starting to show symptoms of solution or not?) before proposing a new appropriate action plan.

**Decision trees and heuristic rules development**

The decision-making procedures to perform the second level tasks of the proposed DSS have been implemented in the G2-Gensym environment (Gensym, 2000) by means of a knowledge-based expert system. It includes a group of heuristic rules whose objective is to efficiently reach a conclusion about the problem and its potential cause, and finally to suggest the control strategy. As a previous step to their codification, all the knowledge and decision-making procedures have been structured and represented by means of decision trees (DTs) and finally translated into a set of “if-then” rules.

In our approach, the resulting trees have been organized into five different classes comprising meta-diagnosis, problem diagnosis, causes identification, process status and control strategy proposal. Meta-diagnosis DTs have been defined in order to resolve the potential problems that the facility can undergo, according to the main data gathered from the process (for example, meta-diagnosis to start exploring foaming, filamentous bulking, and non-filamentous bulking is only based on the value of one of the two
following variables: V30 and SVI). Then the specific problem diagnosis DTs designed to diagnose the precise problem together with the identification of the potential cause/causes DTs are launched. Finally, previous diagnoses and long-term strategies applied are checked by means of the process status DTs, in order to properly identify in which stage of the problem the process is (a set of specific counters for each solids separation problem are maintained for the DSS).

Figure 2 shows a specific example of the DT developed to diagnose a filamentous bulking problem. The system is able to reach a conclusion by checking the value of only four or less variables (SVI and V30 are previously evaluated in the meta-diagnosis DT). The variables selected in the filamentous bulking example are: sludge settleability (indicative of the sludge sedimentation), floc characteristics and predominant filament (indicative of the microorganisms conditions), and foam presence (used to distinguish between foaming or filamentous bulking situations). All of them are qualitative variables which are determined with a user-friendly qualitative worksheet specifically developed for such application. This worksheet is now routinely filled in by the plant operators. Similar DTs have been developed for each of the following solids separation problems: filamentous bulking, non-filamentous bulking, biological foaming, dispersed growth and pin-point floc.

Figure 3 presents the long-term control strategy developed to face non-filamentous bulking by phosphorus deficiency (NFBPD). Based on the available data and on the evolution of the problem, the dynamic DSS suggests literature solution, computes the P dose, or recommends the application of non-specific control methods such as chlorination and/or polymer addition.

The ambiguity found in the linguistic description of a concept during the decision-making process forces us to incorporate a measure of uncertainty into the DSS conclusions to fully exploit the fallible but valuable judgemental knowledge offered by human experts. The uncertainty associated with the description of heuristic knowledge is a feature common to the problems of any domain involving expert knowledge. There are many approaches to cope with this vagueness. In our approach, uncertainty is tackled using the principles of fuzzy decision theory (Bellmann and Zadeh, 1970). The main idea...
is to represent the uncertainty of a value by the degree to which it is a member of a certain fuzzy set. With fuzzy truth values the system will be able to model, for example, the extent to which a filamentous bulking problem occurs (the degree of membership, also known as possibility, in the set or class filamentous bulking) instead of saying unequivocally whether or not filamentous bulking is occurring.

**Case study**

In order to illustrate the complete performance of our DSS approach, a case study based on real data from an episode of non-filamentous bulking in the Girona WWTP is depicted next.

*Day 1.* During data gathering on the first day, the DSS determines that the process presents a high SVI value. Under these circumstances, the DSS starts its decision-making procedure and by means of the set of meta-rules concludes that filamentous bulking, non-filamentous bulking and biological foaming are potential problems. This possibility then launches the set of problem specific rules: bulking-diagnosis rules, non-filamentous-diagnosis rules and foaming-diagnosis rules. In this example, the floc characteristics variable indicates that the floc presents an important quantity of *Zooglea sp.* or exocellular polymer. In that case, the non-filamentous-diagnosis rules identify a non-filamentous bulking situation. Immediately afterwards the non-filamentous-bulking-causes-identification rules are activated. In that case the rules identify a P deficiency as a possible cause (91% certainty) for the non-filamentous bulking situation (a high COD/P ratio). After that, the process status rules are launched in order to identify whether the
process has just started this problem or whether the problem has been present during the previous days. The system determines that this Day 1 is the first day that the process has suffered from non-filamentous bulking caused by P deficiency (NFBPD counter = 0).

Using both problem diagnosis and cause identification together with the process status results, the system begins the last step of the dynamic reasoning, the control-strategy rules, and identifies a P addition plan as the most suitable control method to resolve the situation (see Figure 3). These rules not only decide about the generic plan but also, using extra data from the process such as the total P concentration in the effluent or general knowledge such as the ideal COD/P ratio, they adapt the knowledge-based suggestion and, calculating the exact P dose that needs to be added into the biological reactor, these rules depict a complete and specific control strategy as shown on the bottom of Figure 4. Once all the diagnoses for other possible problems have been made, all the conclusions are presented to the user by means of a user-friendly interface which compiles and summarizes all this information.

Day 2. The following day the system again identifies a situation of non-filamentous bulking caused by P deficiency (the SVI and the COD/P ratio are still high, 85% certainty). According to this, and by means of the process status rules (NFBPD counter = 1) the system identifies the new situation as being part of the same non-filamentous bulking episode and decides to continue with the same control method suggested before but changing the dose of phosphoric acid to the appropriate one for the current situation (according to the new value of the COD/P ratio = 221 mg O2/mg P). The summary interface will then include in the type of problem diagnosis the message: “today is day 2 of non-filamentous bulking problematic situation” and the control method suggested is an adaptation of the previous one but including the new dose of phosphoric acid required (1.17 ppm H3PO4 in our example), which the plant manager decides to apply.

Figure 4 Example of the interface that the user receives as a summary of the dynamic DSS diagnosis for Day 1 (G2-Gensym environment (Gensym, 2000))
Day 3. The system again identifies a situation of non-filamentous bulking, but concerning the identification of cause, it concludes that it is due to an unidentified cause (at least it is not one of the six possible causes predefined in our system). According to this diagnosis, and again using dynamic reasoning, the system identifies the new situation again as being part of the same non-filamentous bulking episode. Despite not having identified any specific cause, the DSS suggests continuing the application of phosphoric acid (0.90 ppm) within the reactor because it understands that, although the cause of the problem is not currently present (sign of recovery), the problem dynamics may cause the process to last some time before returning to normal operation.

The problematic episode finishes once the DSS identifies that the new process diagnosis is a normal situation or that a different problem is affecting the process (on day 5 according to the real data in our case study). It is necessary to point out that, in the case that the same situation had lasted more than 7 days the control strategy rules would have decided to change the control method due to the low efficiency of the suggested actions. In that case, the information drawn from the process status rules is also used during the control strategy decision in order to optimise the action effectiveness. In our example, the control strategies rules on day 8 would have decided to use non-specific control methods such as chlorination or polymer addition in order to temporarily keep the system under control.

Conclusions

The literature describes successful DSS applications in WWTP, mainly when confronted with non-biological origin and fast dynamics problems. However, DSSs have to evolve incorporating dynamic reasoning to face complex problems, such as solids separation problems in the activated sludge process. These problems, originated by microbiological imbalances, last several days within the process, and thus their early identification and solving requires reasoning able to adapt according to the progress of the anomalous situation. Several decisions, implying processing of uncertain data, qualitative knowledge and analysis of process tendencies must be taken into consideration every time the most adequate control strategies are planned. Reflecting the will to face these problems in the most efficient and fast way, we have proposed a knowledge-based DSS which attempts to reproduce the necessary dynamic reasoning process that a group of experts facing these highly complex situations would follow. The DSS has been designed to know how the process is evolving over time, in which phase of the problem it is whenever its reasoning is required, and which actions have already been carried out. Since this dynamic DSS considers the evolution of the activated sludge process, it is also able to continuously adapt the suggested action plan to the needs, constraints and requirements of the facility. Therefore the suggested DSS becomes a reliable tool that provides practical outputs when faced with real complex problems. Future work implies the validation of the DSS in a real WWTP in Girona where it has recently been implemented.

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