Pergamon

Computers chem. Engng Vol. 21, No. 2, pp. 211–221, 1997

0098-1354(95)00258-8
0098-1354/97 $15.00+0.00

ISCWAP: A KNOWLEDGE-BASED SYSTEM FOR SUPERVISING ACTIVATED SLUDGE PROCESSES

PAU SERRA[a], MIQUEL SÀNCHEZ[b], JAVIER LAFUENTE[c], ULISES CORTÉS[b] and MANEL POCH[d]*

[a] *Grup AGBAR, S.A.P. Sant Joan 45, 08009 Barcelona, Spain*

[b] *Departament de Llenguatges i Sistemes Informàtics (IA) Universitat Politècnica de Catalunya C/ Pau Gargallo 5, 08028 Barcelona, Spain*

[c] *Departament d'Enginyeria Químca, Universitat Autònoma de Barcelona, Campus Bellaterra, 08193 Cerdanyola, Spain*

[d] *Laboratori d'Enginyeria Química i Ambiental (LEQUIA), Universitat de Girona, P Hospital 6, 17071, Girona, Spain*

(Received 28 March 1994; revised 18 September 1994)

Abstract—A Knowledge-Based System for the on-line supervision of activated sludge processes in wastewater treatment is presented. The system performs on-line data acquisition from the sensors installed in the plant, off-line data management of results from analytical determinations in the plant laboratory, and qualitative information supplied by the supervisors of the process. All these elements are integrated in the Intelligent System for Supervision and Control of WAste water treatment Plants (ISCWAP), which includes a set of diagnosis, detection, prediction and operation rules, making the system capable to handle with several usual situations (where mathematical control can be useful) and also with some unusual situations (where quantitative and qualitative information must be considered). Copyright © 1996 Elsevier Science Ltd

1. INTRODUCTION

Wastewater is a combination of the water-carried wastes produced from domestic, commercial and industrial sources. It has a very complex composition, containing many forms of polluting matter, dissolved impurities and a heterogeneous dispersion of organic and inorganic solids, both colloidal and suspended. If wastewater is not effectively treated, several problems can occur: pollutants will be returned to the environment; decomposition of organic components evolves malodorous gases; disease may be spread by microorganisms present in the water or by poisoning due to toxic compounds; the organic nutrients in the wastewater may stimulate growth of aquatic plants.

Activated sludge process is, nowadays, the most used biological treatment for domestic waste water treatment. In this process, a mixture of several microorganisms tansforms the biodegradable pollutants (used as substrate) into new biomass, with dissolved oxygen supplied by aerators. It is of widespread use but, in practice, its operation is still carried out with an important manual operation. Taking into account the objective of these plants, the main objective control is to maintain a prefixed level in the water quality at the output of the plant. These levels are defined by water authorities. The values of Biochemical Oxygen Demand (BOD) and Suspended Solids (SS) are the most usually established, being these the controlled variables. Its control is still not solved due to a set of operational problems, mainly: the complexity and number of factors involved, the strongly nonlinear characteristics of the process, the lack of sensors for on-line measurement of some relevant process variables (such as biomass or organic material); the mathematical models describing the process cannot explain its behaviour as well as required and, frequently, the needed actuations to regulate the manipulated variables (aeration, recycle, and purge flows) are not automated.

Nevertheless, control loops that operate properly have been implemented successfully in real plants, such as the dissolved oxygen (DO) (Ko *et al.*, 1982). Also, waste water plants seem to work well during most of the time, if nothing unusual happens (Beck, 1986). It could be said then, that they can function unattended. This **normal** situation (usually the closest to the design one) can be treated mathematically and analytical control can be achieved. However, some uncontrollable situations may arise, such as **bulking** or **loading of toxic substances**, which compels a management based on the operators experience and background. In these cases, control cannot be performed satisfactorily using analytical control methodologies alone.

In order to overcome these difficulties, the use of Knowledge-Based Systems (KBS) has been proposed recently. KBS are computer applications that solve complicated problems that would otherwise require extensive human expertise or elaborated calculations (Stephanopoulos and Stephanopoulos, 1986). For this purpose, the human reasoning process is simulated by applying specific knowledge and logic inferences. The use of KBS allows for the application of qualitative information into the plant management. As an example,

* Author to whom correspondence should be addressed.

in a wastewater treatment plant, the bad odour in an aeration basin issues an important piece of information for the plant operator, but this information cannot be considered in a mathematical treatment. Also, the suspicion that a pipe is plugged or that a weir is not completely closed, or even that a valve is broken but still sending an electric signal, are situations that can be identified by a KBS, and in this way, the operators can be warned to take appropriate actions.

Among those described in the literature, many KBS are used for off-line consulting, typically in discrete sessions. This feature is useful at the design or diagnosis levels, but it is not applicable for continuous process control purposes. Those KBS do not have the ability for on-line data acquisition and they are not able to work with real-time processes. KBS related to waste water treatment have been developed, for diagnosis (Lapointe et al., 1989, Krichten *et al.*, 1991, Belanche *et al.*, 1992), design (Krovvidy *et al.*, 1991, Krovvidy and Wee, 1993), as a decision aid (Maeda, 1985, 1989, Patry and Chapman, 1989) or for process optimization (Huang et al., 1991). Recently, KBS have been applied for process control of waste water purification processes (Capodaglio *et al.*, 1991, Couillard and Zhu, 1992).

The objective of this paper is to present the development of a knowledge-based system for the supervision and control of the activated sludge process (ISCWAP). The paper is organized as follows: first, the ISCWAP objectives and architecture are described; next, the reasoning strategy (rules) is reported; following, the components of the system (facts, variables and object classes) developed to achieve the proposed goal are presented. Finally, a case study for an actual wastewater treatment plant is presented, showing the advantages of this approach compared against manual operation.

2. ISCWAP SYSTEM

2.1. *Description and architecture.*

The work has been implemented using G2. G2 is a shell for the development of real-time expert systems, produced by Gensym Corp. (Ma. USA). It is able to scan the application, focusing on the relevant areas in the same way as a human expert. It can communicate with the user, many different data sources and other applications with its G2 Standard Interface (GSI).

Although it is expected that ISCWAP will be of generic scope, presented results correspond to the study

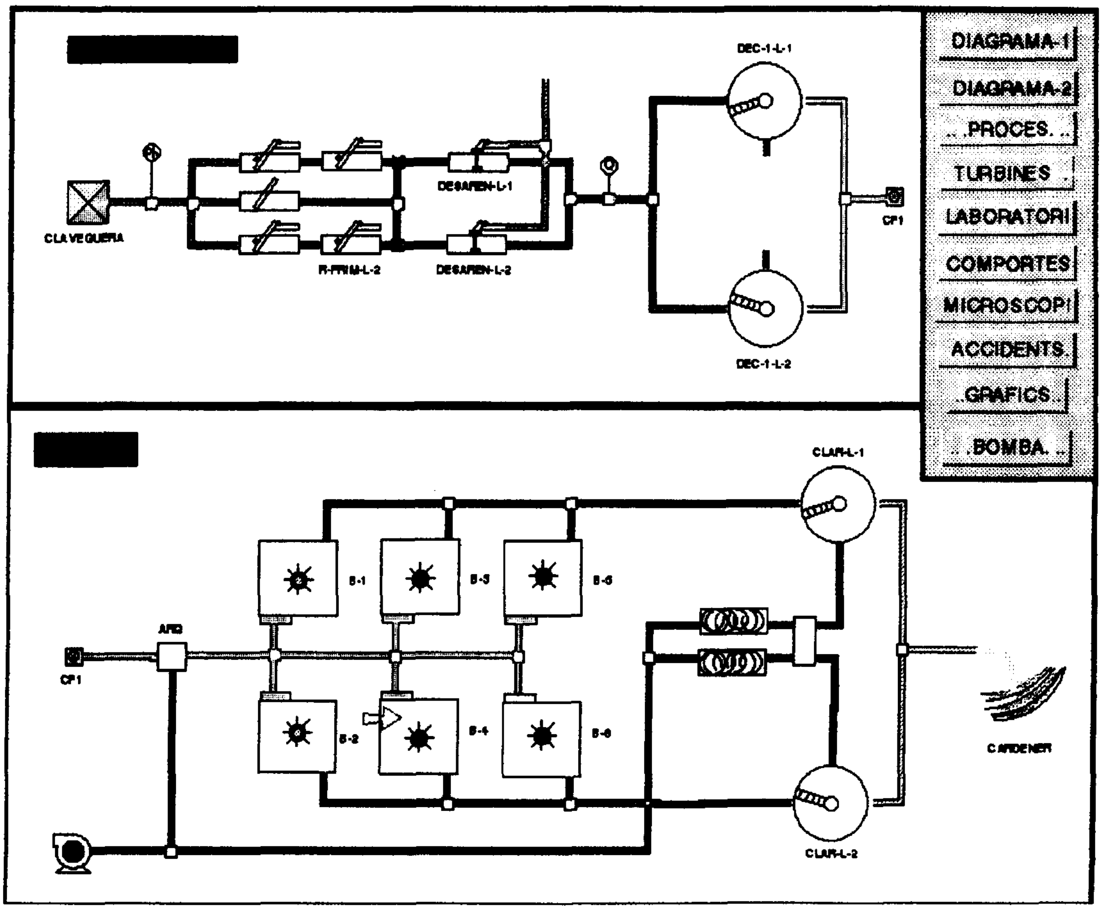

Fig. 1. The graphical interface of the system.

Table 1. Input water characteristics

Parameter	Value
Flow (m^3/day)	37,500
BOD (mg/l)	190
COD (mg/l)	405
pH	7.8
Suspended Solids (mg/l)	225
Volatile Suspended Solids (mg/l)	60
Conductivity	1475

of the water line of wastewater treatment plant (WWTP) in Manresa (close to Barcelona). Figure 1 shows the scheme of the plant, as it is presented by ISCWAP to the user. This plant receives 35,000 m^3/day inflow from a town with 75,000 inhabitants. The process units considered in the KBS are: pretreatment units (screening, grease and sand removers), primary settlers (that are presented on top of the figure), aeration basins and clarifiers (shown on the bottom), and also pumps, pipes, weirs, channels, turbines, valves, sensors and those elements related to the plant operation are included. Table 1 presents a summary of the characteristics of the input water.

The first objective of the KBS is to diagnose at any moment whether the situation is normal or if any unusual case is occurring. It is considered that the normal situation is this one in which the plant is behaving **well** and the depuration goals are obtained, these referred to the plant effluent quality. These two situations might be not equivalent, so they can happen not simultaneously, depending on the input wastewater characteristics. For instance, when the inflow is relatively non polluted, the plant may be achieving the depuration goals, although its function is not appropriate due to operation problems. This situation is identified by some rules that compares the percentage of depuration in the actual situation with the standard values of the plant. It is also the case when the plant is abnormally highly loaded that the depuration goals cannot be achieved, although all the elements may be working properly.

In order to carry out any advanced control, a mathematical description of the process is necessary. In a normal situation, a mathematical model is able to describe the plant evolution. A mathematical model for the studied plant has been developed and validated (Serra, 1993), showing a reasonable fitness with experimental values from the plant. Based on this model, a predictive control algorithm has been developed for this plant (Moreno *et al.*, 1992). This algorithm is defined externally in ACSL (Advanced Continuous Simulation Language from Gauthier and Mitchell. Ma. USA) connected to G2 with GSI. The control module receives the values of dissolved oxygen, substrate and flows and finds the best control action following a predictive control algorithm. The objective function has been established trying to minimize the energy consumption and maintaining the water quality level. Before sending this control action to the actuators, the KBS examines it with some devoted rules in order to ensure that some constraints related to the maintenance of aerators are not violated.

On the other hand, unusual episodes are very difficult to model and simulation results are rather poor. Particularly, **bulking sludge** or **toxic substances loading** effects on plant evolution have not been modelled satisfactorily in spite of different attempts (Van Niekerk *et al.*, 1987, Lau *et al.*, 1984). So, analytical control is not possible for these situations. In the presented work, during any strange (abnormal) situation, ISCWAP will get the control supervision and will carry out an expert control (the control that a human expert would do) based on its reasoning rules, and will deactivate the analytical control if necessary.

Besides the diagnosis of the functioning of the plant, ISCWAP fosters two additional complementary goals. First, it uses the knowledge base for fault detection. It must be considered that the typical environment in the plant is very aggressive, and normally not all of its elements are working properly. The pipes may get clogged eventually, or the sensing elements may be losing efficiency. These disturbances change the normal operation of the plant. The use of numerical state estimation algorithms could be useful for the detection of some of these alterations (Fu and Poch, 1993, 1995). These methods could be complemented with the use of knowledge based systems that permits the use of qualitative information.

The second goal raised is the detection of situations that may lead to a fault state, although they cannot be classified as fault yet. In this case, the system warns the operators that a particular anomaly has occurred in order to correct it.

Figure 2 shows the architecture of the system. In order to get a satisfactory KBS, extensive information of the studied system is needed. This information may be originated in the plant, directly from physical sensors (quantitative information), or through the plant operators (quantitative and qualitative information).

In the first instance, this information is sent to the analytical control module, where the values considered are determined using a predictive control algorithm, as presented previously (Moreno *et al.*, 1992). The information from the sensors is also sent to the knowledge base, in order to actualize the variable values used in the antecedents of the rules.

Once this information is acquired and the rules are evaluated, the system is defined, and the reasoning process can be carried out, as described under Section 3.

The supervising system performs as the core of the process, as it receives and exchanges information

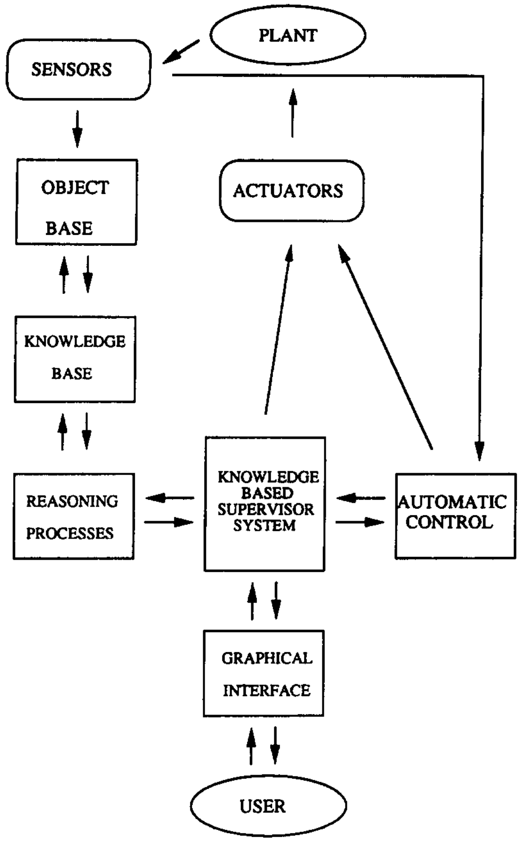

Fig. 2. Architecture of the ISCWAP system.

coming from the reasoning process, the analytical control algorithm and the user interface, and finally it is forwarding a resulting action that will be done through the control actuators, or by a dialogue with the user.

3. REASONING PROCESSES

3.1. Diagnosis

Diagnosis is achieved by reasoning using the methodology known as decisions tree (Rolston, 1988). Using this approach, the knowledge base developer builds a tree's structure, in which the values of the attributes of each node are used to decide which branch to follow. Generally, from the beginning of the tree (in the root), where all situations are possible, until the end of the diagnosis process (that corresponds to a particular situation), the way crosses several nodes where the attributes are evaluated. Each time a branch is selected, this is done following a logical inference from the values and relations of the considered variables. It must be noted that ISCWAP does not ask the operator for values of the variables. For the ISCWAP development, we only considered the information readily available in the plant, both from on-line sensors and from plant laboratory analysis. On-line information is continuously stored at the data base and values are updated when necessary. Values from analysis are entered into the program manually, once they are obtained. Information not available in the plant is not considered in the data base, unless it can be inferred from other parameters.

Table 2. Situations considered at the system

- Normal
- Bulking
- From filamentous bacteria
- other causes
- Rising
- Foaming
- Underaeration
- Overaeration
- Storm
- High plant inflow
- Bad wasting
- Bad clarifiers operation Bad primary settlers operation
- Overloading
- In-plant overloading
- Toxic substances loading
- Surging

The system must assign at any time the exact situation of the process. For its description, the most extended and usual situations in this kind of plants have been considered in this work, being presented in Table 2 and produced by means of a Knowledge Acquisition tool, LINNEO+ (Béjar and Cortés, 1992, Serra *et al.*, 1994)

In Fig. 3, a set of rules that conclude a particular situation is shown as an example of how a diagnosis is carried on. These rules allow to conclude an organic overloading from in-plant sidestreams when it occurs. In the knowledge base this situation is called **sidestreams**. In this case, not only diagnosis is done but also detection of failures because, as COD is measured only at the input of the plant, organic loadings inside the plant (after the input sampling point and before the biological process) are not known. There are no flow sensors nor analyses done in these points to detect the situation. However, if special care were taken, estimation of COD loading would be possible.

Many situations considered in the system are dangerous for the plant and force to perform specific operations to overcome them once they are detected. This is the

```
IF COD-rem-eff-value < 0.8
THEN conclude that
   COD-removing is bad

IF the DO of reactor > 0.3 AND
   the DO of reactor ≤ 4.0
THEN conclude that
   DO-state is normal

IF the biomass of reactor - the simulated value of the biomass of reactor >
   sim-err
THEN conclude that
   biomass-higher-than-normal

IF plant-inflow-state is normal AND
   the COD of input ≤ 450
THEN conclude that
   external-conditions are normal

IF DO-state is normal AND
   external-conditions are normal
THEN conclude that
   environ-conditions are normal

IF COD-removing is bad AND
   biomass-higher-than-normal AND
   environ-conditions are normal
THEN conclude that
   the sidestreams situation is true
```

Fig. 3. A set of diagnosis rules.

case of **bulking** or **toxic substances loading**, where the ISCWAP, after diagnosing them, will suggest starting a set of actions based on previous experience to arrange the situation. At these points, the ISCWAP will deactivate the mathematical control because the mathematical model is not able to describe the process under these conditions. In other situations, the ISCWAP can keep the mathematical control running and carry out either just particular actions taken from experience, or the change of any parameter of the control algorithm. This is the case of **overloading**, where the mathematical model still describes the process correctly. However, control actions could be too long, or insufficient to solve the problem. Consequently a complementary knowledge-based action can be taken.

Finally, some rules will inform the operators to upgrade the in-plant processes involved to avoid new dangerous situations. When rules stop concluding these situations, advanced control will go back to the normal operation. In this case the ISCWAP does not deactivate the mathematical control, it just changes the values of the set points of the controlled variables in order to adequate de control action to the specific situation. Connections and data exchange between the KBS and the advanced control is done through GSI.

3.2. Detection of failures

Sometimes, during the process, the diagnosis rules do not establish the cause of a particular problem. Under these circumstances, the failure detection rules are performed. These rules include the heuristic knowledge corresponding to the particular situation produced when a plant element is malfunctioning. Rules have been defined for the detection of failures in the plant sensors, pipes and weirs. In Figs 4 and 5 two rules are shown as examples of possible disturbances, as well as their solving actions.

In the first example, a pH sensor failure is observed taking advantage of the feature of the fungi to grow in acidic conditions only. This allows to conclude that if fungi are present, and the measured pH value is not low, there must be a fault with the sensing element. In the second case, the rule allows the operators to know if the wasting flow pipe is plugged. For Manresa's plant, due to a mistake in the design, this situation is a rather common failure. If the biomass in the reactors is greater than the normal value, and COD removal efficiency is normal or high, then the cause must be a bad wasting schedule. As the wasting flow is read on-line in the data-base, being the bad wasting operation situation rejected, then the cause inferred is a plugged pipe.

```
IF pH-reactor is not low AND
   presence-fungi is true AND
   the maintenance of pH-sensor is OK
THEN conclude that
   the status of pH-sensor is bad

For any sensor
IF the sensor-status of the sensor is bad
INFORM the operator that
   "The sensor [the name of the sensor] is out of order. You must
    calibrate it"
```

Fig. 4. Rules for fault detection.

```
IF the biomass of reactor - the simulated value of the biomass of reactor >
   sim-error
THEN conclude that
   biomass-higher-than-nbrmal

IF COD-rem-eff-value > 0.8
THEN conclude that
   COD-removing is good

IF biomass-higher-than-normal AND
   COD-removing is good AND
   wasting-flow > 10 m3/h
THEN conclude that
   wasting-pipe-plugged is true AND
INFORM the operator that
   "The wasting pipe is plugged"
```

Fig. 5. Rules for fault detection.

It can happen that the rules can conclude neither a cause nor a failure. Here a message to the operator will show that a new situation, which must be identified, is taking place.

3.3. Prevention

One characteristic of an expert is the ability to predict possible future problems when a specific situation occurs. ISCWAP tries to imitate human experts in this case also. Causes for many waste water plant upsets are known. However, it can take a long time, days or even weeks, for the revealing of the malfunction since the causes are present. So, it can happen that nobody detects that the plant is going to be in a problematic situation. **Bulking** is a typical plant problem where all the above is specially true. There are different causes that can lead to bulking. Most of these causes do not lead to this state immediately, but the effect appears with a long-term delay. Possible causes leading to the bulking situation are low pH at the inflow, extreme low or high F/M values (food/microorganisms ratio), or extreme low or high dissolved oxygen. Moreover the appearance of these values does not lead directly to a bulking situation, as they are not a sufficient condition, but it is necessary to watch their evolution in order to inform that the conditions for bulking are being reached.

A third set of rules in the KB try to avoid these situations; their aim is to detect and to prevent possible trouble. They scan the process looking for any situation that could lead to malfunction. When a possible upset is detected, ISCWAP tries to conclude the variable that must be changed and what must be corrected to avoid it. If the plant is automated enough, a control action is sent to the actuator. If not, a message is sent to the operators telling the actions to be carried out.

Two examples are presented in Figs 6 and 7. A high variability of pH values at the inflow causes **bulking**. The variable pH-in-margin is set according to experi-

```
IF the maximum value of the pH of input during the last 3 houts >
   the minimum value of the pH of input during the last 3 hours +
   2*pH-in-margin
THEN conclude that
   Fear-of bulking is true
```

Fig. 6. Prevention rules.

mental (historical) data. Usually, there are two channels opened at the plant entry, and a third one is closed. If there is an inflow's increase, the third channel needs to be opened to avoid an overflow. In Manresa's case the gate must be opened manually because it is not automated, but this could be done automatically following an ISCWAP order if there was an engine to open it. Care must be taken also to avoid the plugging of the input screens, as the inflow may carry several objects and material (dead animals, vegetables, branches or plastic wastes).

4. COMPONENTS

In order to achieve the proposed objectives the supervisor system contains the following elements:

1. Facts, parameters or variables of the system, ca 250 facts.
2. Object classes to define the system, ca 470 objects.
3. Formulae, tables, equations, simulation formulae (24 items) and descriptive rules (63 rules) to describe the process.
4. Heuristic and expert control rules. They carry on the diagnosis (140 rules), detection of failures (70 rules), prevention (35 rules) and expert control (20 rules).
5. Graphical interface to communicate with the operator.

4.1. Facts, parameters and variables

These correspond to the elements needed to define the system. It is important that the selected facts or attributes must be relevant for the characterization of the domain. The definition of an attribute specifies its type (numeric, boolean or fuzzy). This definition can be accompanied with a short description of the attribute. An example is:

(DISSOLVED-OXYGEN IS

Dissolved oxygen is used by the microorganisms to consume substrate NUMERIC)

where the attribute DISSOLVED-OXYGEN is defined as numeric, that will be used later to characterize the aeration basins. Also, a short description is attached.

```
IF storm is true during the last hour AND
   the flow of input > the flow of input as of 1 hour ago * 1.5
THEN conclude that
   Fear-of overflow is true AND
INFORM the operator that
   "Open the third channel at the input and clear the screens to avoid overflow"
```

Fig. 7. Prevention rules.

The set of facts is like a dictionary that describes the domain features. Facts and objects will be used as components in the rules of the reasoning strategy.

Variables can be: quantitative, such as the dissolved oxygen (DO), biochemical oxygen demand (BOD), chemical oxygen demand (COD), suspended solids (SS), or the sludge volumetric index (SVI); symbolic or qualitative, as water-colour, turbines-state, kind-of-microorganism; or logical, motors switched on or off, weirs open or closed. Certainty values have been assigned to qualitative variables, which allows to operate with approximate reasoning, and also to assign variables such as rather, a lot, quite or correct. The values of the variables can be obtained in three different manners: from formulae, tables and/or functions; from external sources through GSI, such as the variables measured on-line from the plant (i.e. DO, inflow, recirculation flow, wasting flow, turbines on-off, pumps on-off) or data from files; and finally, with end-user control inputs in the screen (buttons and type-in boxes). The latter is the case with the off-line results from the analytical determinations in the plant laboratory (such as biomass, substrate or SS) and also the symbolic variables.

4.2. Object classes

The most common units and objects present in the plant have been stored into the object base. Initially, it is necessary to define the classes of objects that are present in the model, their attributes and icons to represent them. Defining a hierarchy of objects saves time and space, as subclasses can inherit attributes from the superior class. For example, on the Manresa plant, there are two types of aeration turbines, Archimedes screws to convey recycled activated sludge and various pumps. All of these types of equipment are used to impel flow, and so a superior class of liquid impeller could be defined. Many attributes (eg. whether the equipment is running or stopped, a maintenance schedule, power consumption) are common to these objects, so they only need to be defined once in the superior class definition. As it is shown in Fig. 8, the liquid impeller class would have a superior class, for example engine class, which would have as superior class object, that could be the highest level defined. This means that a few powerful rules can be written which apply to a wide range of objects avoiding duplication. Besides, new attributes can be added to any class if more aspects about the class are considered or deleted otherwise. An example of definition is:

```
(AERATION-BASINS
  (Attributes
    INFLOW
    OUTFLOW
    BIOMASS
```

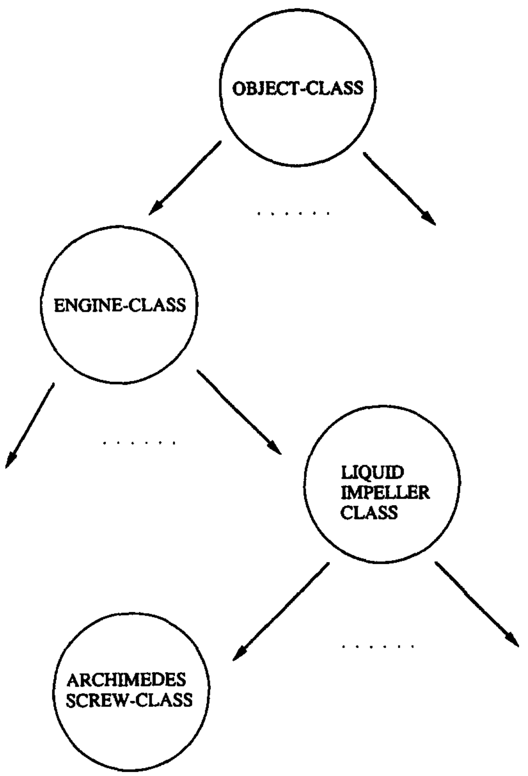

Fig. 8. A scheme of a possible hierarchy of the object classes.

SUBSTRATE(COD)
DISSOLVED OXYGEN
BIOMASS-AT-THE-INPUT
SUBSTRATE-AT-THE-INPUT
DO-AT-THE-INPUT
OXYGEN-UPTAKE-RATE (OUR)
pH
GATE-OPEN-OR-CLOSE
FULL-EMPTY))

Table 3 depicts the classes of objects that have been finally considered in ICSWAP. Once the classes are defined, different instances of them are created and interconnected to build the scheme of the plant.

4.3. *Process description module*

The use of formulae is one available method to get values for the variables. Mass balance in a reactor is defined with a formula; the oxygen saturation concentration (DO) in the mixed liquor is a function of temperature and salinity. Simulation equations are also used to assign values to variables. As it has been noted, a mathematical model giving the evolution of biomass, COD and DO in the reactors and the biomass in the recirculation line has been implemented (Serra, 1993). The model is a modification of a rather known one (Marsili-Libelli, 1989), calibrated with experimental data from Manresa's waste water treatment plant.

Apart from the simulated values, these variables are also experimentally measured. Thus, referring to *the particular variable* its real value is obtained, while referring to the *simulated value of the variable* the value calculated from simulation is obtained. This will allow to compare the actual values against those predicted by the model.

Rules have also been used to describe the process. The use of rules easily explains specific aspects of the plant that are difficult to express quantitatively (for instance the description of the sequence to fill or empty a reactor).

4.4. *Heuristic rules*

Rules containing the qualitative knowledge of the process must be defined into the knowledge base to allow the ISCWAP to reason about what happens in the plant as a human expert would do. Heuristic knowledge is used in diagnosis of plant situation, detection of failures and prevention of possible upsets.

Knowledge stored in the Knowledge Base comes from different sources as books, manuals and papers referred to waste water treatment and, mainly, from experimental work and through interviews with experts, designers and plant operators. A great amount of information has been obtained from the waste water plant of Manresa. Examples of heuristic rules are presented in Figs 3–7, where they are used in the reasoning process.

Table 3. Object base for the Manresa's plant

-Process Equipment
- Bassins
- Settlers
- Primary settlers
- Clarifiers
- Pools
- Sources
- Screens
- Narrow
- Wide
- Manuals
- Sand removers
- Manual valves
- Exterior
- Thickeners
- Flotation units
- Digesters
- Tanks
- Belt filter presses
-Motors
- Turbines
- 1 speed - 2 speed
- Arquimedes screw
- Pumps
- Electrovalves
-Biomass
- Fungi
- Microorganisms
- Protozoa
- Flagellates
- Free-swimming ciliates
- Ciliates
- Vorticella
- Aspidisca
- Rotifers
-Floc
-Microorganism-characteristics
-Situation
-Color-button

4.5. Graphical interface

The operator communicates with ISCWAP through a graphical interface. In the screen a scheme of the plant is shown (see Fig. 1), with readouts of the values of the most important variables (sludge age, plant inflow, recirculation flow, input COD, output COD, etc.). The object Situation with its attributes (**normal**, **bulking**, **foaming** or other) is also present to display at any moment the diagnosis result. Different colours are used to indicate if the engines are stopped or running, if the weirs are open or closed. Alarms or messages appear in one side of the screen. If a fault is detected for any operation unit, a visible sign as a red cross, draws the operator's attention.

The operators enter the off-line information (water colour, odour, and also data obtained in laboratory analysis) with buttons and type-in boxes. These end-user buttons are all in a specific worksheet. This worksheet appears on the screen when called (with an action button).

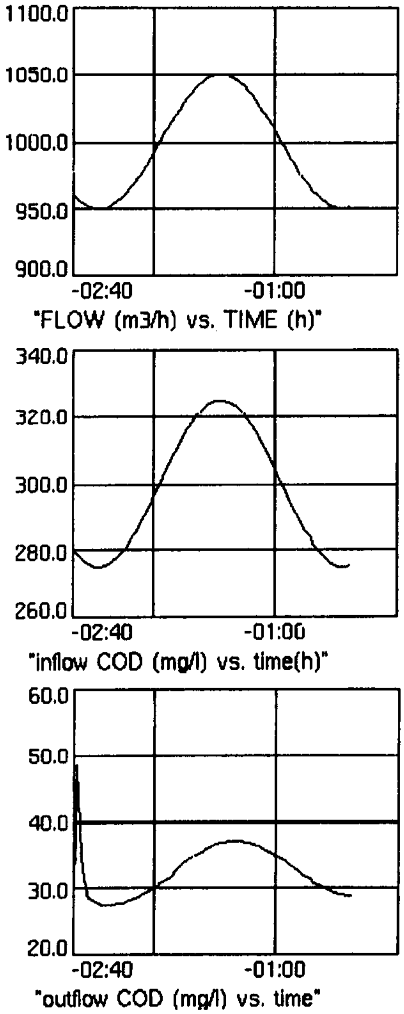

Fig. 9. Sample evolution of the system's variables along time, expressed as a deviation variables.

Access control features have been added to give some protection level to the system, depending on the type of user considered. Operators cannot modify the knowledge base, they just enter the values for the off-line variables. Some parameters evolving with time can be accessed by the manager to update them if necessary (i.e. more reactors were built, input water characteristics changed due to new factories). Although probably, in these cases, also rules ought to be changed. A whole KBS revision should then be done, but its validation can be a laborious task (Meseguer, 1992).

5. A CASE STUDY

As an example of all the elements working together, the supervision of a **sidestreams** situation is described. This example shows how the system works to manage a problem from the diagnosis to the control phase.

The diagnosis process now follows the next steps. First a deficient COD removal is observed by a procedure that evaluates all the efficiency parameters of the plant. Historical data shows that usually, more than 80% of the inflow waste water COD is removed. So the deficiency will be detected if COD uptake scores less than 80%. Just one day of bad efficiency makes this procedure not to activate the specific rules (Fig. 3), as it is considered that important problems last for more than one day. Many possible causes lower the COD depuration efficiency, so more information is necessary.

Next step is to know the DO concentration in the aeration basins. Upsets in the DO level, both overaeration and underaeration, can lead to a bad removal of organic material. If the DO level was different from the desired one, the KBS would focus on DO problems, and arriving to the final conclusion, it will finish the diagnosis process. On the other hand, if DO values are normal the diagnosis must continue.

The following step is to observe the plant inflow. A high plant inflow also lowers the plant efficiency, as the detention time in the basins is reduced. In this situation the KBS uses the variable plant-inflow-state, instead of plant-inflow. Plant-inflow gets numerical values (m^3/h), while plant-inflow-state is a symbolic variable with possible values high, normal or low. These values are assigned by rules depending on the inflow and the particular conditions of Manresa's plant. In general, the normal values of inflow are within 800 and 1600 m^3/h. Occasionally, inflow can suddenly increase during just two or three hours, caused by focused loadings of factories. As they are short in time, they do not affect the plant behaviour, even if they exceed the value of 1600 m^3/h. The KBS realizes that these peaks belong to the tolerated change rate of the plant inflow, which simulates the sudden increase. The rule that gives values to plant-inflow-state takes this fact into account; if plant-inflow is bigger than 1600 m^3/h but factories loading is concluded, plant-inflow-state will still be normal.

If plant inflow is normal, biomass concentration in the aeration basins is checked. The biomass concentration depends on many factors (recirculation and wasting flows, temperature, COD at the input, etc.), making it difficult to ascertain if there is a normal, low or high level of biomass. Our knowledge base considers two aspects for its determination. As the plant usually works within a known range for the values of the variables, normal values of biomass concentration are defined by the plant technicians. They specify as normal for Manresa's plant, biomass levels between 1500 and 3000 mg/l. Because of this, the KBS will conclude that something unusual occurs if biomass is not included in this range of concentrations. However, these values (1500–3000) could be abnormal in specific situations, as during an unexpected very hot weather or an organic overloading. To allow for that, these values are not absolute and they may vary in particular conditions. The knowledge base has an alternate way to decide if the biomass concentration level is correct for the plant performance. It consists on the comparison of the actual values of biomass against the simulated ones, obtained from the mathematical model previously mentioned. The model uses as inputs the real values of all the flows, temperature and aerators schedule, and gives biomass, COD and DO as outputs. If the difference between the real value and the simulated one is larger than a prefixed error, then the KBS concludes a positive difference for the biomass in the reactors (biomass is high), or vice versa, a negative difference (biomass is low).

If the biomass concentration was normal, the COD removal failure would be caused by inhibitors, the presence of toxic substances in waste water (combined with standard DO and inflow values). The effect of toxic substances is the qualitative change of biomass, such as its aspect, motility, cilia's movements and so on. As an assumption, toxic substances do not alter quantitatively the biomass amount. If the biomass concentration level is low, other possible causes must be found, as a bad wasting schedule or the bad operation of clarifiers.

In the presented case, it is considered that the biomass level has a high value. A low wasting flow increases the biomass level in the reactors, but here, the COD uptake efficiency is not low. So, toxic substances loading is not the situation. If overloading is rejected as a possible cause, because COD at the input is not high (COD analyses are carried out daily in the plant), the only cause left for this situation is in-plant **sidestreams**; finally, the situation under which the plant is running is diagnosed.

Continuing with the previous example of **sidestreams**, once the KBS has diagnosed the situation, the following control actions are taken. First, the COD concentration actually coming into the reactors must be known, asking for a laboratory analysis if necessary. Next, this real value replaces the COD value used in the mathematical COD control. Due to the big growth of biomass caused by the increase in organic material, the oxygen consumption in the mixed liquor will be greatly enlarged, leading to a possible shortage of DO. The KBS then modifies the DO control algorithm, providing it with a new biomass value, calculated as the expected from the biomass–COD yield. Finally, some rules will inform the operators to upgrade the in-plant processes involved to avoid a new **sidestreams** situation. When the rules stop concluding the sidestreams situation, the advanced control will be restored to its normal operation. Schematically, the KBS does not deactivate the mathematical control, but it just changes the value of selected variables in order to accommodate the control state to the specific situation.

This case study is a good example for the comparison of the performance of the plant using ISCWAP against manual operation. Schematically, the ISCWAP takes advantage of three intrinsic features of this kind of systems. First, ISCWAP conveys a systematic examination of the variables. Therefore, the system starts detecting possible alterations affecting the evolution of COD just when the values of the laboratory analyses are introduced. With manual operation, the plant's staff cannot be simultaneously evaluating these values and carrying out the calculations on how the plant operation is evolving.

In a second term, the values from the laboratory analyses are continuously compared against the remainder variables in the process (DO in the aeration basins, input flow, etc.). With this procedure, the system is using the heuristic knowledge included in the rules to avoid a systematic comparison of all the variables with all their possible values. The system is acting in an intelligent manner, and searches according to the rules defined for the comparisons that can lead to a more efficient estimate of the situation. Using manual control, when the number of variables increases, it results more difficult for the operator to establish the relationships among the different variables.

Another stated feature is the discrimination among possible situations, by using the results provided by a mathematical model. Here, the differences with the manual control are clear. Though the operator may have a qualitative idea of how the system is going to evolve, he is not able to foresee the exact change of certain variables. The combination of expert information, in the form of rules, with the quantitative information, specified by a mathematical model of the process, makes ISCWAP a more proficient alternative to the control of wastewater treatment plants.

The benefits of the proposed system are increased if the abnormal situation occurs in the absence of the plant's manager. Thus, in plants functioning 24-hours a day, normally with reduced number of operators (and also their qualification) at night, the operator may be in a lack of preparation and/or background to cope with the situation. In this sense, one of the conclusions for the design of KBS is that the number of dialogues present must be kept to a minimum. The number of questions must be reduced, and questions are placed only in the case that the situation cannot be identified using on-line and off-line information. Also, the questions placed must be short and specific. In our case, queries placed by ISCWAP have been agreed with the management of the plant.

6. CONCLUSIONS AND FUTURE WORK

A Knowledge-based system for waste water treatment plants supervision in real-time operation has been developed. In order to obtain the knowledge-base, the experiences from different people with distinct backgrounds (Microbiology, Chemical Engineering and Control Engineering) have been used. Biological, qualitative and quantitative information available from the plant is used to supervise the process. Thanks to this system, the plant can be controlled in both **normal** (mathematical control) and **unusual** (expert control) situations.

The final ISCWAP system is expected to be as generic as possible, applicable to many plants. Those details that can lead Manresa's plant to any problem have been considered because they can be critical for this specific plant (although equivalent episodes can be less relevant for other plants). In order to apply the system to another plant, it will be necessary to integrate specific knowledge from the new plant. Nowadays, our experience is limited, but the application to a second plant, with different characteristics, is under development.

There is much work to be done in the future for the improvement of the proposed system. Two examples are the development of an automated pattern recognition methodology of microbial images to provide this useful qualitative information to the system (Dellepiane et al., 1992), and to apply the data sets and knowledge base as retrofitting information for the optimization of the design of waste water treatment plants (Bañares-Alcántara and Ponton, 1992).

Acknowledgements—This work has been supported by Junta de Sanejament from the regional authorities Generalitat de Catalunya, and the Spanish CICyT projects Bio94-679 and TIC91-1087. The authors wish to acknowledge the cooperation of Aigües de Manresa S.A. and specially Ricard Tomàs, manager of Manresa's waste water treatment plant.

REFERENCES

Bañares-Alcántara R. and J. W. Ponton, Artificial Intelligence techniques in Chemical Engineering Process Design, *Applications in Artificial Intelligence in Engineering* **VII**, pp. 581–607, Computational Mechanics Publications, Bath, UK (1992).

Beck M.B., Identification, Estimation and Control of Biological Wastewater Treatment Processes, IEEE proceedings, **133**, 5 254–264 (1986).

Béjar J. and U. Cortés, LINNEO⁺: Herramienta para la adquisición de conocimiento y generación de reglas de clasificación en dominios poco estructurados, *Actas 3er Congreso Iberoamericano de Inteligencia Artificial*, IBER-AMIA-92, pp. 471481, La Habana, Cuba (1992).

Belanche Ll, M. Sànchez, U. Cortés and P. Serra, A knowledge-based system for the diagnosis of waste water treatment plants, *Proc. of the 5th International Conference on Industrial and Engineering Applications of Artificial Intelligence and Expert Systems (IEA/AIE-92), Springer Verlag, Lecture Notes in Artificial Intelligence*, **604**, pp. 324–336, Paderborn, Germany (1992).

Capodaglio A.G., Jones H.V., Novotny V. and Feng X., Sludge bulking analysis and forecasting: application of system identification and artificial neural computing technologies, Water Research, **25**, 10 1217–1224 (1991).

Couillard D. and Zhu S., Control strategy for the activated sludge process under shock loading, Water Research, **26**, 5 649–655 (1992).

Dellepiane S. G., G. Venturi and G. L. Vernazza, Model generation and model matching of medical images by a fuzzy approach, *Pattern Recognition*, **25**(2) 115–137 (1992).

Fu C.S. and Poch M., Application of a multilayered neural network to system identification, Int. J. Systems Sci., **24**, 1601–1609 (1993).

Fu C.S. and Poch M., System identification and real-time pattern recognition by neural networks for an activated sludge process, Environ. International, **21**, 57–69 (1995).

Huang Y.L., Sundar G. and Fan L.T., Min-Cyanide: an expert system for cyanide waste minimization in electroplating plants, Environmental progress, **10**, 2 89–95 (1991).

Ko K.Y., McInnis B.C. and Goodwin G.C., Adaptive control and identification of the dissolved oxygen process, Automatica, **18**, 6 727–730 (1982).

Krichten D. J., K. D. Wilson and K. D. Tracy, Expert Systems guide biological phosphorus removal, *Water Environmental Technology*, 60–64, October (1991).

Krovvidy S., Wee W.G., Summers R.S. and Coleman J.J., An AI approach for wastewater treatment systems, Journal of Applied Intelligence, **1**, 247–261 (1991).

Krovvidy S. and Wee W.G., Wastewater Treatment Systems from Case-Based Reasoning, Machine Learning, **10**, 341–363 (1993).

Lapointe J., Marcos B., Veillette M., Laflamme G. and Dumontier M., Bioexpert an Expert System for Wastewater Treatment process diagnosis, Computer Chem. Engng, **13**, 6 619–630 (1989).

Lau A.O., Strom P.F. and Jenkins D., The competitive growth of floc-forming and filamentous bacteria: a model for activated sludge bulking, Journal WPCF, **56**, 1 52–61 (1984).

Maeda K., A knowledge-based system for the wastewater treatment plant, *Future Generation Computer Systems* **5**, 29–32, North-Holland, Amsterdam, Holland (1989).

Maeda K., An Intelligent Decision Support System for Activated Sludge Wastewater Treatment Processes, *Instrumentation and control of water and wastewater treatment and transport systems*, Drake editor (IAWPRC), Pergamon Press, Oxford, UK (1985).

Marsili-Libelli S., Modelling, Identification and Control of the Activated Sludge Process, *Advances in Biochemical Engineering/Biotechnology* **38**, 89–148, edited by A. Fiechter, Springer–Verlag, Berlin (1989).

Meseguer P., Towards a Conceptual Framework for Expert System Validation, AI Communications, **5**, 3 119–135 (1992).

Moreno R., C. de Prada, J. Lafuente, M. Poch and G. Montague, Non-linear predictive control of dissolved oxygen in the activated sludge process, *ICCAFT 5 / IFAC-BIO 2 Conference*, Keystone, USA (1992).

Patry G. G. and D. Chapman (Eds.), *Dynamic modelling and expert systems in wastewater engineering*, Lewis Publishers, Chelsea, Michigan (1989).

Rolston D. W., *Principles of Artificial intelligence and Expert Systems development*, McGraw-Hill, New York (1988).

Serra P., Desenvolupament d'un sistema basat en el coneixement per al control i supervisió de plantes depuradores d'aigües residuals urbanes, Ph.D.Thesis, Departament d'Enginyería Química, Universitat Autònoma de Barcelona, 1993.

Serra P., Sánchez M., Lafuente J., Cortés U. and Poch M., DEPUR: a knowledge based tool for wastewater treatment plants, Engineering Applications of Artificial Intelligence, **7**, 1 23–30 (1994).

Stephanopoulos G. and G. Stephanopoulos, Artificial Intelligence in the Development and Design of Biochemical Processes, *Trends in Biotechnology*, pp. 241–249, September (1986).

Van Niekerk A., Jenkins D. and Richard M.G., The competitive growth of Zoogloea ramigera and Type 021N in activated sludge and pure culture A model for low F/M bulking, Journal WPCF, **59**, 5 262–273 (1987).