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A conceptual model to facilitate knowledge sharing for bulking solving in wastewater treatment plants

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Abstract. This paper presents and motivates the use of a given knowledge representation designed to facilitate the knowledge sharing from heterogeneous sources for problem solving in environmental processes using an Agent based technology. In order to test the feasibility of this representation (Domino Model), a common problem occurring in the wastewater treatment process has been selected (filamentous bulking).

Keywords: Knowledge sharing, Multi-Agent Systems, conceptual modelling, wastewater treatment, environmental engineering

1. Introduction

Advances in the use of Internet allow the access to huge amounts of diverse information from very different sources that could be geographically distributed. This possibility has stimulated a demand for understanding how to integrate heterogeneous knowledge sources to provide added value to all that information. Specially, it is even harder when this information has to be processed for problem solving processes. Also, more and more the management of complex installations is supported by telematics infrastructure that provides huge amounts of information about the state and performance of the installation, integrating sensors communication facilities and databases [9]. Despite the efforts made trying to capture complete and useful information, monitoring systems are still a source of uncertainty and incompleteness mainly due to the failures or limitations that some sensors or other measuring systems present. Those facts are creating an increasing demand for systems that are able to operate in environments where uncertainty and incompleteness of information are the norm. Knowledge Engineers are facing this new situation putting together the available tools and metaphors.

In the last decade, most of the application efforts of Artificial Intelligence tools and techniques have been focused in solving the problems of conventional processes by applying one of the different Knowledge-Based Systems (KBS) tools. Specially, related to the wastewater treatment domain, KBS techniques have been developed as off-line decision support tools for: monitoring, diagnosis, design, process optimisation, etc.

In most environmental applications it is assumed that either the available information is as complete as possible so the system can perform its reasoning task or the changes in state of the environment are slow enough [3]. In both cases the reasoning mechanisms need very minor adaptations. Also it is assumed that there will not be any hazards induced by the system performance. But all these systems do not solve only a very specific class of problems and many times neither the knowledge representation nor the reasoning techniques can be reused, as they are too specific.

One knowledge engineering approach that has proved to be useful for dealing with the integration of heterogeneous knowledge sources for problem solving is based on multi-agent architectures (see for example [20]) where software and human agents coop-

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erate to ensure that their goals are met and stays met. As noted by Robertson and Fox, work on agent systems need not involve radically new notations but it does concentrate design efforts on areas of the system, which hitherto might have been taken for granted [15].

Agent-based models see agents as autonomous social entities that exhibit flexible, responsive and proactive behaviour and the interaction among those entities give raise to complex dynamics. Multi-Agent Systems (MAS) are computational systems in which a collection of agents interact to achieve certain goal by performing in a cooperative way a set of tasks. Also, MAS inherit the traditional advantages of distributed problem solving systems [12]. A MAS provides a decomposition of the problem(s) that matches agents to entities, which are realistic actors within the domain, and helps to model the interaction among agents/entities (see for example [14]). This interaction is usually modelled via a message-passing routine and this clarifies who and when an actor has access to a given piece of information, and the decision-making responsibilities it has. To ease this communication and moreover, to enable real sharing and reuse of knowledge and reasoning efforts across a class of related problems and tasks in a given domain, the use of Ontologies and Problem-Solving Methods (PSM) has been proposed ([13] and [7]).

Ontologies are of great theoretical and practical importance, they provide a shared and common understanding of a domain that can be communicated among agents and across applications. Thus, ontologies are becoming a recognized vehicle for knowledge reuse, knowledge sharing, and modelling [8]. They are explicit a conceptualisation which describes the semantics of data.

A common approach is to use ontologies to give a characterization of tasks. Task ontology decomposes tasks into subtasks, in order to identify the required types of knowledge and to serve as the basis in the designing and construction of a problem solver that behaves as an expert.

In MAS agents may be characterized for their own point of view about the world and this means that each one of them has its own ontology that has to be shared with the others or at least a part of it. Also, agents have their own goals that are very influential in defining their position in the world. In the real world agents are associated with knowledge bases (sources) that were created with different meanings and purposes, as for example: perform the diagnosis of the state of a process or monitoring the changes in a standard procedure.

A related approach using the agent technology has been applied in the development of ARTEMIS for environmental emergency management [9]. The ARTEMIS approach integrated both an expertise model of the responsible people (users) and a simulation model of the process. Another example is DAI-DEPUR [16], a system designed, developed and enacted under a centralized control to control a wastewater treatment plant on the basis of the integration of the available AI technology. It was designed also, to allow the change of human end-user role: plant managers or operators. In that system, agents and its infrastructure presented already a great heterogeneity (i.e., developed in different languages, by different parties, with different objectives), also the system incorporated a filtering and validation module designed to cope with incomplete information or failure of some components giving a great reliability.

The aim of the paper is to test the feasibility of the Domino Model as a conceptual approach to facilitate knowledge sharing in a MAS applied to WWTP domain. To illustrate the pros and cons of this approach, an application of the decision making process to deal with a common biological problem in WWTP (filamentous bulking) will be presented.

The organization of this paper is the following. Section 1 provides the rationale of the present study, presenting heterogeneous knowledge sources integration, and potential applications of KBS, MAS and ontologies in decision making to support management of environmental processes. In Section 2, the Domino Model is introduced as the basis to the discussion and the paper presents the authors' own adaptation of it to an Environmental process. This section also discusses the use of decision trees as prototypes to represent knowledge in terms of problem solving methods using a MAS.

Section 3 includes the case study of the paper. Firstly it explains the domain where our approach has been developed. Activated sludge process in WWTP, and filamentous bulking problem are briefly described. Secondly, the knowledge bases and computational functionalities within the Domino model are related to the bulking problem. Finally, some remarks and the future lines of work are presented.

2. The Domino Model

The Domino Model is a framework introduced by Fox and Das [8] to model the interaction among different kind of agents for problem solving in the medical domain. In this model (see Fig. 1), the decision-making process and the plan performance to solve an identified situation are represented in the same diagram, where the knowledge bases (nodes) can be a piece of data that the decision procedure can reason about, a set of possible solutions or an action that can be initiated. On the other hand, the computational functionalities (symbolised by arrows) can be the application of any reasoning system (decision trees, arguments, procedures, rules, etc.) that will be followed until arriving to a conclusion. In the Domino Model temporal issues are treated using branching structures.

Following the model, steps 1 to 4 would correspond to the classical process followed by any Decision Support System to solve general problems. But when it is necessary to diagnose and operate on more specific and complex problems, the actions to be carried out in order to solve that problem must follow a protocol and therefore an specific task program, and this is exactly what Domino Model incorporates in steps 5 and 6.On the other hand, the model will follow different cycles according to the objective that must be attained.

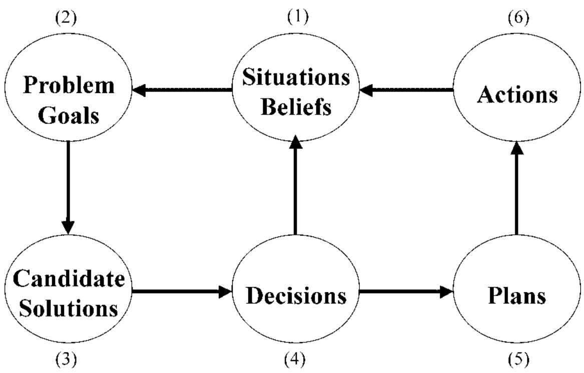

Fig. 1. The Domino Model.

2.1. The Domino Model for an environmental process

An adaptation of this model will be used to environmental problems (see Fig. 2). The decision making-process relies on a cycle including recognition of the parameters that identify a present event (diagnosis) or a future event (prediction), identification of the causes of the event, and plan formation to solve the incidences and execution of the selected actions. Any agent or Agency that performs these activities in a changing world must be capable to model that world internally. A first attempt to test the feasibility of this conceptual model is presented in [11].

2.2. Decision trees as prototypes to support Problem-Solving Methods

As mentioned above, there exist different types of computational functionalities that the system can perform to transform data and information included in knowledge bases and reach a conclusion.

A decision tree could be considered as a prototype for the generic solution of a given class of problems if at each one of its nodes one can find, in a domain-independent way, which reasoning steps and which types of knowledge are needed to identify a situation and to perform a task that helps in the development of a solution by creating a plan for the solution. The trans-

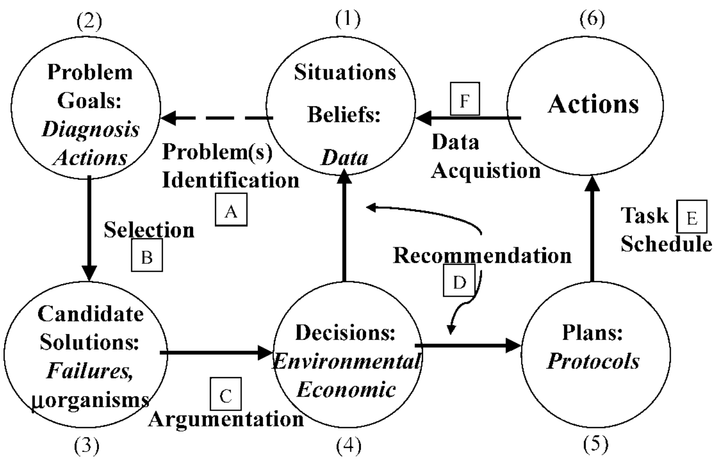

Fig. 2. Domino Model representing knowledge bases (nodes, indicated with numbers) and computational functionalities (arrows, indicated with letters).

formation between two states σ_ζ and σ_δ is ruled by a (computational) function:

$$\alpha_\kappa(\sigma_\zeta) \rightarrow \sigma_\delta,$$

where $\alpha_\kappa \in$ A is one of the possible actions that an agent_i is able to perform. The following notation for this transformation will be used:

$$<\alpha_\text{k}(\sigma_\zeta\})>\sigma_\delta.$$

To denote that there exists an execution of α_k given the conditions σ_ζ that will lead the process to the state σ_δ. A decision tree (T_i) is selected as the basis for the construction of a solution if the system has identified a given state-of-affairs (σ_i) that is considered as possible the cause of a problem. That is there exist an opportunity to apply the methods it contains to bring the process into a state-of-affairs (γ_i), with the intention of keeping (or returning) the system into its *normal* state (γ_i). A decision tree could be considered then as the reasoning system followed to identify a situation and its cause and to apply a generic plan to return the system to a normal or desired situation.

The triplet $(\sigma_\text{i}, \text{T}_\text{i}, \gamma_\text{i})$ is obtained by applying a selection function that matches the actual state σ_ζ with the set of possible (known) states Σ. The identification of σ_i is neither always immediate nor exact but the system could relay on its past experiences using approximate or qualitative reasoning to decide upon. The degree of similarity between two states:

$$\Sigma(\sigma_\zeta, \sigma_\text{i}) \in [0,\ 1]$$

could cause and adaptation of some of the actions α in T_i.

Problem-Solving Methods are nowadays recognized as valuable components for constructing knowledge-based systems [9] but one can trace their identification to the Components of Expertise idea introduced by Steels [18]. PSMs describe the reasoning process performed by a KBS. Problem-Solving Methods are assimilated to those capabilities that an agent_i has and allow him to interact with the world. The existence of a built-in set of plans Π that the agent_i uses to drive a process will be assumed. Each plan $\pi \in \Pi$ could be described as sequence of actions $(\alpha_\kappa)^*$ such that:

$$(<\alpha_\kappa(\sigma_\zeta)>\sigma_\delta)^*$$

and this plan stops when the process arrives to a state that could be identified as the desired goal γ or to an impasse. Problems arise when an agent_i has to set a new goal γ.

Dignum and Conte [5] described the goal formation process dividing goal formation rules into three categories:

- Rules that only work on concrete goals that is rules used to construct plans that will be executed by agen t_i.
- Production Rules, this kind of rules are of the same nature as the rules used in planning but allow the generation of concrete new goals.
- Goal formation Rules allow the creation of new goals on the basis of built-in goals and some beliefs (evidence).

An example of the use of decision trees to support problem solving methods is shown in the work of Comas [2], where the original intention was to represent the space of solutions for the set of known situations in a specific WWTP and to provide the system manager with a recipe to solve an identified problem. The procedural nature of this support for decision-making was implemented as a kind of decision tree (see the tree depicted in Fig. 3). Our claim is that those trees are easy to transform into a task-oriented notation (see for example Fig. 2). This claim is due to the same hierarchical structure both of decision trees and task decomposition problem.

These trees allow for a representation that helps to minimize the effect of potential hazards due to the mismatch between the specification of a problem-solving method and its implementation. This avoids also the possible misunderstandings between the formal definition of the domain and its representation in a knowledge base. Thus, decision trees could be considered as the basis for an incremental construction of Ontologies (see [1]).

However, one has to consider the trade-off between usability and reusability and also to consider the performance of the system as well as the communication and security issues.

3. A practical example

In order to understand the functionality of the Domino Model to facilitate knowledge sharing for bulking solving in the environmental processes domain, the wastewater treatment process and concretely the filamentous bulking problem has been chosen as a practical example.

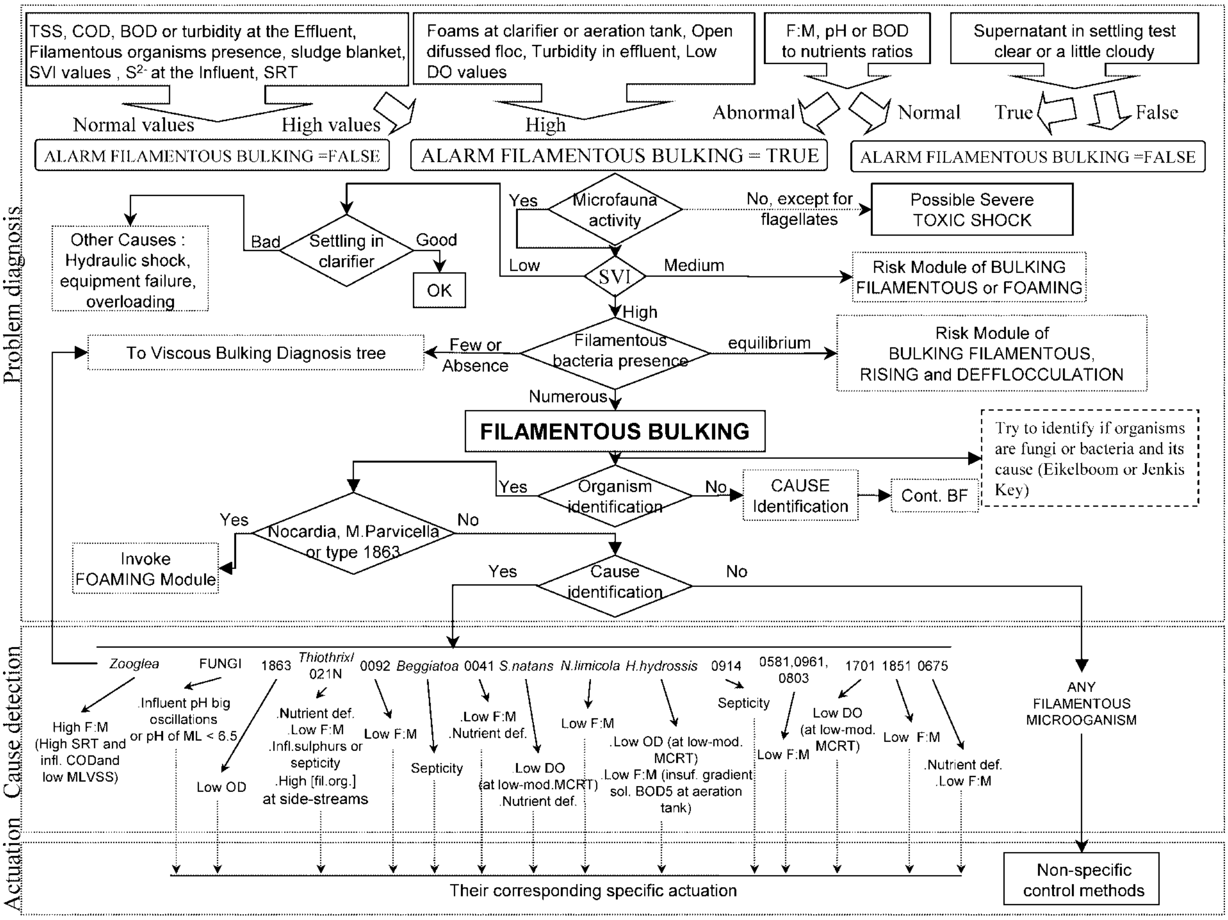

Fig. 3. The filamentous bulking decision tree.

In wastewater treatment plants, the natural process of biological degradation of organic matter and nutrients is used in a controlled way in order to treat the wastewater until obtaining a regulated water effluent with low contaminant load to cause the minimum environmental impact on the quality of the receiving ecosystem. The activated sludge system is the most widely used biological wastewater treatment process in the world. Its successful performance relies on the right operation of two main units, the bioreactor where the organic matter degradation is done, and the secondary settler where biomass is separated from the treated water. Most of the problems of poor activated sludge effluent quality result from the inability of the secondary settler to efficiently remove the biomass from the water, basically due to the proliferation of filamentous microorganisms. This phenomena, called filamentous bulking, occurs when the biomass is strongly colonized by long filamentous bacteria, holding the flocks apart and hindering sludge settlement, which interfere with compactation, settling, thickening and concentration of activated sludge. Although bulking problems are encountered over a high spectrum of systems working at different conditions, the development of systems for the removal of nutrients has resulted in an increase in the presence of filamentous organisms. An enormous amount of research effort has gone trying to understand and eliminate bulking (e.g., [10] and [19]).

Though considerable advances have been made and the frequency of occurrence is slowly reducing, it is still a common and potentially devastating problem in biological wastewater treatment plants.

The filamentous backbone theory of activated sludge [17] assumes that the structure of the flock is formed in two levels. The first level depends on the bioflocculation of flock-forming microbes, with small, spherical and compact flocks, but mechanically rather weak (as shown in case A of Fig. 4). The second level ex-

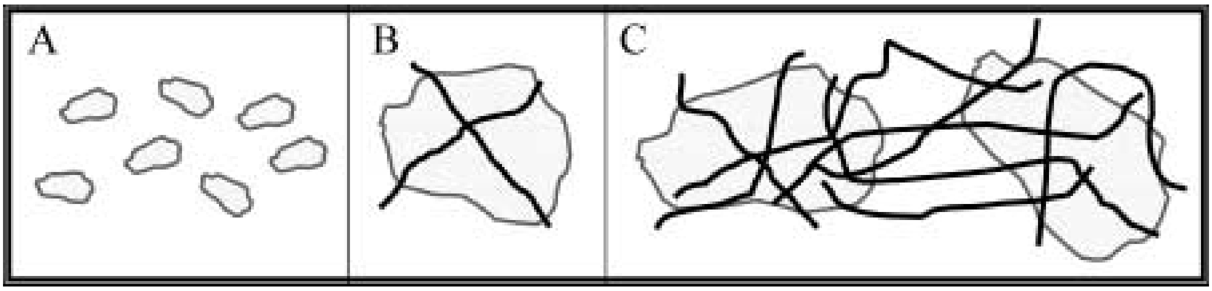

Fig. 4. Balance between flocks () and filamentous bacteria () in activated sludge.

Table 1

Possible causes and control actions

Possible causes	Predominant filamentous	Control actions
Low dissolved Oxygen	Types 1863, 1701, *S. Natans*, *H. Hydrossis*	DO and F/M manipulation
Low food to microorganism ratio (F/M)	*H. Hydrossis*, *Nocardia* sp., types 021N, 0041, 0675, 0092, 1581, 0961, 0803	MLSS decrease and use of biological selectors
Septic wastewater/ sulphide	*Thiothrix sp.*, *Beggiatoa*, type 021N.	Chemical oxidation and wastewater pre-aeration
Nutrient deficiency	*Thiothrix sp.*, *S.Natans*, type 021N	Nutrient addition
Readily Metabolizable Substrate	*Thiothrix sp.*, *N.Limicola*, types 1815, 021N	Use of biological selectors
Low pH	Fungi	Increase alkalinity

hibits large flocks, postulating that filamentous microorganisms form a backbone within the flock, to which the flock-formers are firmly attached by their extra-cellular polymers. The ideal flock is the result of a balanced growth of filamentous and flock-forming organisms (case B of Fig. 4). Thus, when there is an excessive proliferation of filamentous bacteria, these microorganisms grow in profusion inside and outside the flocks, penetrating into the bulk solution, stretching out the flock, making it diffuse, and/or bridging between the flocks, thereby interfering with their close approach (case C of Fig. 4), which gives rise to compactation problems and prevents the flock settling.

Different surveys have demonstrated that the same filamentous organisms types are observed ubiquitously in activated sludge and that approximately 10–12 types account for the great majority of all bulking episodes as shown in second column of Table 1. Thus, microscopic identification of the types, abundance, condition, and growth forms of these filamentous organisms provides the greatest wealth of information about the nature and causes of bulking problems in activated sludge. There are general and specific factors influencing the occurrence of each filamentous type (i.e., biomass retention time, Food to Micro-organism ratio, concentration of Dissolved Oxygen (DO) or nutrients, nature of the substrate, pH, and septic influent), and the identification of the majority filamentous type is a key to discover the operational factor responsible for bulking behaviour.

Since bulking causes basically correspond to the wastewater composition and operating conditions, it seems clear that these causes can be determined following with accuracy all the information provided by the process, e.g., on-line signals, analytical determinations, and microbiological examinations (for this case see Table 1). Once the causes have been identified, a specific solution can be applied to restore the process. When the cause cannot be successfully determined, a non-specific solution (i.e., adding chemicals to increase the weight of the sludge or to kill selectively the filamentous) can be applied to avoid the consequences of bulking.

3.1. *Knowledge Bases and computational functionalities*

In the following tables and figures some pieces of the Knowledge Bases and computational functionalities within the Domino Model related to the Bulking Situation are showed. Among the 10 trees developed by Comas [2], facing up the diagnosis of 7 primary treatment and 17 secondary treatment problems, it is chose, therefore, the one for a specific filamentous bulking problem (see the Bulking tree in Fig. 3). There is an isolation process of some pieces of knowledge

Table 2

Situation beliefs: *Data* (indicated (1) in Fig. 1)

Variable	Current value
:effluent TSS	high
:effluent COD	high
:effluent BOD	high
:effluent turbidity	high
:filamentous presence	high
:sludge blanket	high
:sludge blanket	high
:SVI	high
:SRT	high
:foam	high presence
:flock appearance	open and diffused
:F/M ratio	low
:settling test	supernatant clear

Table 3

Candidate solutions: list of possible diagnosis, causes and control actions List of Diagnosis ((3) in Fig. 2)

Possible diagnosis	Possible causes	Possible actions
Filamentous bulking	Low D.O	Observe
Viscous bulking	Low F/M ratio	Measure
Foaming	Septic wastewater	Diagnose
Toxic shock	Nutrient deficiency	Integrate/Combine
Rising	Readily	Remember
Defflocculation	metabolizable subs.	Simulate
Hydraulic shock	Low pH	Evaluate
Equipment failure		Learn
Overloading		Refuse
		Monitorize
		Avoid

in various Knowledge Bases following the description made in Fig. 2. That is, the information gathered at each node is depicted. In Table 2 the characteristic values of some of the variables compiled from the process that are considered to determine a bulking episode are shown. Their qualitative value (high, normal or low) was set in a previous step of discretization where according to the typical values within the process the value of those variables where classified using these limits. These variables together with their corresponding qualitative value represent thus, the Situation Beliefs within the model. In the following a variable will start with the sign ":".

Following the process within the Domino Model, the next Knowledge Base includes the goal of the decision-making process. Thus, in the bulking example, these goals correspond firstly to the definition of the problem, secondly to the cause identification, and finally to the determination of the best plan to solve the problem.

In the left column of Table 3 the list of the possible diagnosis that the system can offer and that correspond to the Candidate Solutions in Fig. 2 is shown. Table 3 lists also the possible causes and the repertory of general actions that the system is able to perform in order to solve the problems.

More concrete actions are for example: Neutralise the influent or change the operation of the plant (among: to plug-flow, contact-stabilization, add anoxic zone, compartmentalize the aeration tank, work in discontinuous (batch), previous treatment with fixed film), or change or modify a control parameter (SRT: increase/decrease wasting flow rate, DO: increase/decrease aeration flow rate, F/M: wasting or influent loading, a manual actuation: e.g., physical scum or foam removal, other concrete actuations), among those shown in the third row of Table 3. All of them are thus Candidate Solutions, but depending on the goal of the process (represented in different cycles in the model) one or another knowledge base (diagnosis, causes or actions) will be used. Decisions, plans and actions complete the Knowledge Bases of this approach. An example of the entire process for the bulking example is shown in Fig. 5. For a more complete list and description see [11].

On the other hand, and according to the process described in Fig. 2, Figs 6, and 7 show as an example two of the six Computational Functionalities that in our approach the system performs to transform the data and information included in the Knowledge Bases (Selection, Recommendation, Task Schedule and Data Acquisition are the others).

In Fig. 6, the action Check_for::microfauna_activity is identified as the one to be performed to characterise the actual situation. After acquiring the values of the relevant variables and depending on their values a decision has to be made.

In Figs 7 and 8, more examples of computational functionality are shown. In the Argumentation functionality, the value of different variables is checked in order to identify the problem (in Fig. 7). Once the problem has been diagnosed, the cycle starts again to identify the possible cause (computational functionality in Fig. 8). In the decision tree used in our example, the specific variables and the order they are checked, have been represented. Using this kind of representation, then the elaboration of the computational functionality is direct.

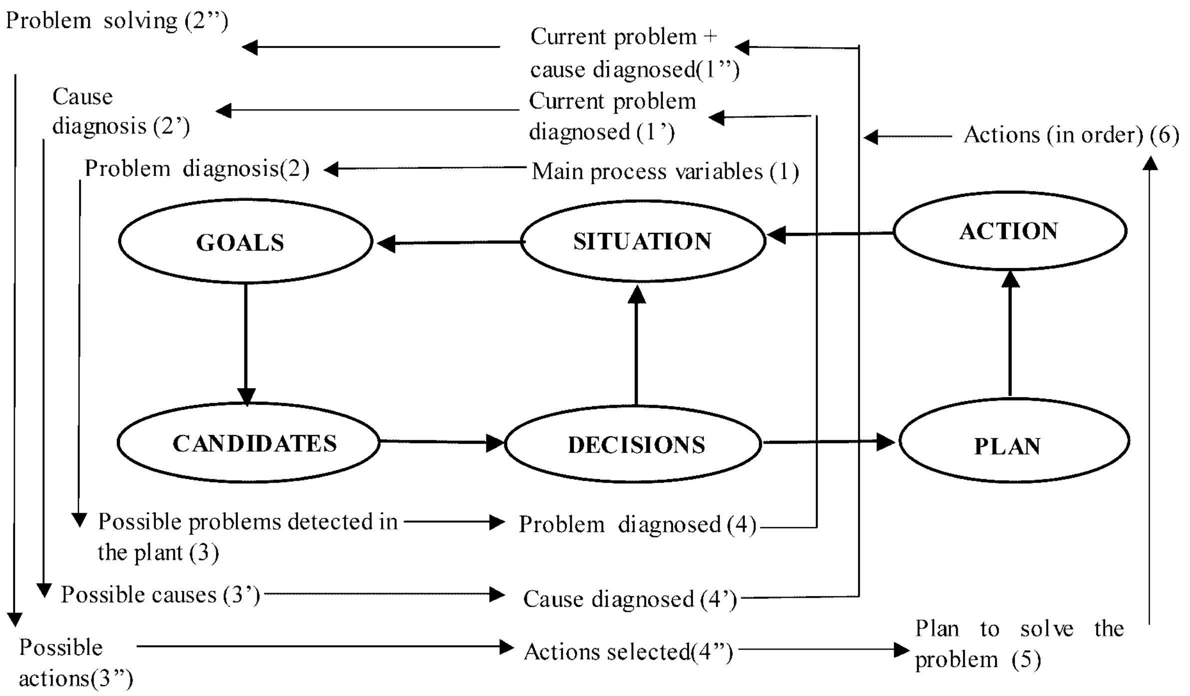

Fig. 5. Adaptation of the Domino Model to the bulking example.

In order, check for:
:microfauna activity
:svi (depending on :svi value)
:setting in clarifier:filamentous bacteria presence

Fig. 6. Problem(s) Identification: *problem diagnosis task* (A in Fig. 2).

Finally, once the problem and its cause are diagnosed, the cycle starts again, and in this case another data is required and another branches of the tree are explored to identify the optimum plan to solve the problem.

Thus, the cycle can be implemented with a multi-agent system integrating several kind of reasoning agents. Most agents are Knowledge-Based agents coping with specific domain areas of the conceptual model. One kind of agents is responsible for the situation identification step. Others are in charge of diagnosing the possible problems. Possible causes are inferred through other kind of KB agents. And finally, decision-making tasks and planning actions are solved by other KB agents. Thus, the conceptual model facilitates the distribution and cooperation among the several agents involved in the final multi-agent system.

4. Conclusions and future work

The feasibility of the Domino Model as a conceptual approach to facilitate knowledge sharing in MAS applied to WWTP domain was presented. The methodology is general enough to ensure reusability to other wastewater treatment plants. In addition the methodology has been applied in more than one plant with good results.

The decision-making process to identify and solve bulking problems in a WWTP was successfully adapted into the Domino Model from a theoretical point of view. Nodes, which symbolize knowledge bases, represent (1) situation beliefs (data that characterize the domain), (2) problem goals, (3) candidate solutions, (4) decisions, (5) plans, and (6) actions. Arrows, which represent computational functionalities, are in charge

:microfauna_activity **yes** &
:svi **high** &
:filamentous_bacteria_presence **numerous/high**
→ **Filamentous_bulking**

:microfauna_activity **no**
→ possible severe Toxic shock (it **requests** for more *situation beliefs* (data))

:microfauna_activity **yes** &
:svi **medium**
→ risk or preventive module of Filamentous bulking or Foaming (request for more data, then launch message alarm of possible bulking and recommend the appropriate specific actuation to carry on to change the current process trend).

:microfauna_activity **yes** &
:svi **low** &
:settling_in _clarifier **bad**
→ request for more situation beliefs (check for hydraulic shock, equipment failure or overloading)

:microfauna_activity **yes** &
:svi **low** &
:settling_in _clarifier **good**
→ OK, no problem at all

:microfauna_activity **yes** &
:svi **high** &
:filamentous_bacteria_presence **equilibrium/normal**
→ risk module of Filamentous bulking, rising and defflocculation

:microfauna_activity **yes** &
:svi **high** &
:filamentous_bacteria_presence **few/absence**
→ request viscous_bulking_diagnosis_tree

Fig. 7. Argumentation: problem diagnosis (C in Fig. 2).

of (a) goal(s) identification, (b) definition, (c) selection, (d) recommendations, (e) task schedule, and (f) data acquisition.

The necessity to provide the *most* appropriate support to decision makers in reasonable time has been a significant focus on our research. The increasing demand for autonomous systems in distributed (via Internet) and real environments leads us to study the price associated to provide safeness and soundness in the ways explored in [14] and [7]. This requires a good theoretical approach, an important effort for knowledge representations and management [4] but also an open eye on the implementation, verification and validation side.

In our view, Domino Model brings new tools for better modelling the environmental processes as for example the temporal nature of the problems. The set of trees defined by Comas [2] could be considered, as an initial seed for the construction of a safe and sound Library of Problem-Solving Methods in the domain of Urban Wastewater Treatment Plant and that has to be expanded and generalized towards a PSMs Library for Environmental Processes. A first successful attempt is shown in [11].

In order, try to:
:Identify the specific filamentous bacteria genera possible,
e.g.,
:S.natans true, :Zooglea false, :type 1863 false , :type 0092 false,
:type 0041 false, :Thiothrix false (. . .)

then the cause will be much more limited:
:S.natans_low DO true, :S.natans_nutrient deficiency false

(if the filamentous bacteria cannot be identified):
:Identify the cause that provokes the excessive growth of the unknown bacteria, check for:
:nutrient deficiency,:high F/M, :low F/M, :high content of sulphurs, :septic conditions, :large quantities of filaments at influent, :large quantities of filaments at sidestreams, :low influent pH, :sudden pH oscillations and :unknown cause

Fig. 8. Argumentation: cause diagnosis (C in Fig. 2).

Future research should pay special attention to handling exceptions and impasses in environmental processes

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