An Application of Heuristic Co-operation to Process Control

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Abstract **This paper shows an application to process control of co-operative approaches. These are solutions to modularise expert knowledge for supervisory and direct control, providing these modules with autonomy and capabilities for asking for information to modules for reasoning. To deal with incoming certainty of knowledge facts an algorithm to reviewing incoming certainties from external sources of knowledge was in [1] presented. Thus, this application uses heuristics for communicating modules. The certainty coefficients, that are associated with communicated information, are reviewed by these heuristics. Since several action models (knowledge, in fact) are usually proposed for solving complex process control problems then to take advantage of them all is intended, These modules have different performances that are measurable by indexes. Better control is then obtained by using reviewed knowledge of each module. The conclusion is that better performance could be obtained by reviewing knowledge versus adding more knowledge to monolithic modules managed by expert systems.**

I. INTRODUCTION

The Artificial Intelligence science (AI) has provided some original tools for dealing with information. Expert Systems (ES) have origin from these techniques and they have greatly performed for many difficult problems using procedural techniques. Multi-Expert Systems approaches try to overpass certain shortcomings of ES.

Over fifteen years after AI began, some classical problems were better solved by this approach of distributed problem solving. In the 70's first models and software of distributed AI were conceived, mainly in the USA, building up solutions by decomposition of tasks into subtasks distributed among several knowledge modules, which were interacting each other.

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From that time the following models appeared: the blackboard approach, the contract net, the agents' approach of Minsky and Papert and so forth.

Some works [2] [3] [4] and others, point to the fact that having more than one expert system to solve complex problems is a good solution.
Attached problems are becoming functionally and spatially more complex, and therefore specialised modules in different fields are required. Moreover they should work together to reach solutions, existing two possible ways: integrating them into a big system or, instead, preserving their independence. In the latter, wonder how could they exchange information and certainty on information each other.

Paper [5] showed some basic points for heuristic communication and a heuristic protocol was exposed. The main worked exposed a function for reviewing certainty that is incoming with information provided by external systems. This function is a two parameters function that is a generalisation of one parameters fusion functions. To show both two parameters are useful the heuristic model is applied to expert process control and better performances will be obtained respect from one parameter algorithm. Then, realise better performance could be achieved by following this methods instead of creating monolithic KB within a only ES.

A. Heuristics for Communication

Referring to the problem of overall consistency, certainty management of transferred information among expert systems is still difficult. Following that investigation line, work [1] tried to find out a solution. Communication behaviour among people was in that way expected to be modelled to create a heuristic communication protocol among expert systems, instead of a deterministic one, where lower level problems of communication were considered properly solved yet.
So far, models and solutions are often inspired by intuition and, thereafter, normalisation in highly procedural methods. From this viewpoint, it could be advisable to use expert systems for coding this heuristic knowledge and trying to experiment a heuristic high-level protocol mainly based on the roughly known human communication procedures.

B. Changing Uncertainty of Information

Let us take into account any communication activity between expert systems. Then, information from source systems is in the heuristic framework reviewed because receiving systems assign new certainty values. Roughly speaking, the reliability on source systems influences to the reviewing functions of the receiving ones. This kind of mind, revision or reviewing, is important when intelligent systems are exchanging information for their inference's work.

Rules for reviewing uncertainty [1] and [7] are based on prestige (reliance) on external systems $\boldsymbol{P}$ and on necessity (reliance) of received information $\boldsymbol{N}$. Receiving information that contain a fuzzy certainty $\boldsymbol{f}$ is then reviewed by those rules. If probabilistic t-norm and co-norm is used for those rules then an almost-procedural function calculates the new certainty, $\boldsymbol{f'}$, that is, $\boldsymbol{f' = f P + N - f P N}$ whenever the incoming certainty is greater than a threshold that depends upon the $\boldsymbol{N}$ parameter.

C. Process Control

In a general overview, many AI techniques are applied in Expert Control (EC), being traditionally ES the widely used systems in control. Fuzzy control, qualitative control, neural networks, genetic algorithms are lastly used too. However, notice it is possible to apply any other techniques to obtain EC. Now, follows to study this ES work-line to know how to improve performance of isolated Knowledge Bases (KB) developed for specific processes. For this purpose developing, maintenance and validation methods are not intended to be studied with extremely relevant results.

Our purpose in process control is generally to drive some physical and chemical properties (mainly inputs of processes) to obtain some results (outputs of processes, performance parameters, etc.) under specifications.

There are in process control many difficult processes to deal with. A large scope of them cannot perfectly be solved using linear methods, thus other approaches are conceived. Predictive control, non linear control, robust control, and so forth are continuously developed and improved.

Expert systems, qualitative reasoning and simulation of systems, neural networks, etc., are nowadays largely used in process control field. They are applied in cases where no complete, exact, updated knowledge of processes to control is useful. In the concrete field of expert systems, co-operative approaches are to be applied. In this last very recent field better performances are tried to be offered using many agents or co-operative systems, expecting to modularise knowledge and methods, and to combine them by means of the reviewing functions.

II. SEVERAL EXPERT SYSTEMS

A. Dealing with Difficult Processes

Some processes are difficult because their models are not very know yet, or they are highly non-linear processes hard to control (even knowing its model), or they have non observable states, etc.

The difficult process to deal with is that one which has not a known model, and in this paper the process is a waste-water treatment plant. There are more than 80 different models for this biological process, and the perfect one does not exist albeit there are models more accurate than others. Therefore, there will be many possible action models or procedures to do expert control on it. Normally look-up tables control sufficiently the plant in normal stationary operating conditions, but results are not brilliant.

B. More than one Expert System as Knowledge Sources

As stated in the previous point, there is not any action model classified as the best one for the class of processes to be controlled. Classical applications of process control and supervision in process control are greatly based on reference models and look-up tables based on experience although they are constrained by the model of the process to control. Better results are expected with good model behaviour and systems dynamics models. Nevertheless, if the process is not enough known its possible action models could be continuously improved.

All action models are not as good as they were conceived to, but not as bad as they are supposed once they are considered obsolete. The proposed framework tries to take advantage of all possible models, managing to ameliorate results of applying just one model out of them for EC and supervisory diagnoses.

III. THE APPLICATION FRAMEWORK

It is a waste water treatment plant. This is a biological process that purifies water. This purification is only for biodegradable products like excrement, biodegradable detergents, etc.

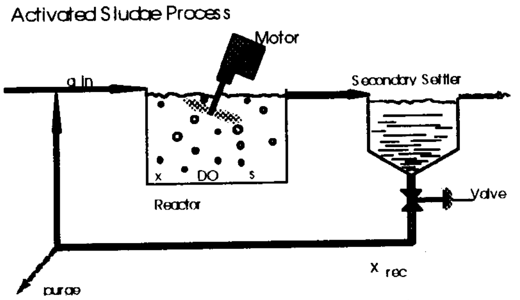

Fig. 1 Waste-water Treatment Plant

Basic components of this plant, based on the biological process of biological matter degradation, are: (1) a reactor that is a basin or tank that contains the mixture of water, organic matter, and living matter that decomposes ("eats") the organic matter producing CO_2 and other products; (2) a secondary settler recycles biomass to the basin and pours the clean water out the plant to rivers.

Regulation of activated sludge processes is essentially based on the observation of six parameters: biological oxygen demand (BOD), volatile suspended solids within the mixture, dissolved oxygen, oxygen uptake rate (OUR), sedimentation features and recycling flow. Another parameter would be the concentration of solids in the incoming flow, that would be great to fix but there is no procedure to control directly. Finally, some physical-chemical parameters are taken into account.

About the nominal values of charge the following table shows the approximate nominal values of the more interesting variables and parameters of the activated sludge process of the waste water treatment plant of city of Manresa (Spain).

Table 1 Nominal Values for the Waste Water Treatment Plant Variables

PARAMETERS	NOMINAL VALUES
s_{in}	280 (mg / l)
s	70 (mg / l)
q_{in}	1400 (m^3 / h)
q_{rec}	800 (m^3 / h)
x	2200 (mg / l)
x_{rec}	5000 (mg / l)
Sludge Residence Time	5 days

s_{in} incoming substrate concentration
s substrate concentration
q_{in} incoming flow, q_{rec} recycling flow
x_{rec} recycling biomass concentration
x biomass concentration

Knowledge about the plant was, as procedure, codified in analytical differential and algebraic equations. Nevertheless, many assumptions were already taken in mind as corresponds to the art of modelling. Further details about the plant are in [8].

A. Evaluation of the Expert Predictive Controller on the Simulated Plant

First the predictive expert control with only one simulator is studied. See how could performance be improved. Then experiences for obtaining deductions from several expert systems are obtained.

The performance index that is used to make comparisons among different issues in co-operation is the following:

$$J = 120\,E + (x-x_{ref}) + 20\,v$$

E: Total wasted *energy* by the aeration motor.
$x - x_{ref}$: Deviation (*error*) from the desired reference of biomass in tanks.
v: *Effort* of valve (the watergate).

Stress the willpower of minimising energy and control effort, maintaining the error of biomass $x - x_{ref}$ as low as possible.

B. Expert Control with Several Expert Systems

After experimentation next step is to be ready to define a complete co-operative framework of ESs. Now, CEES [6] [7], that warrants definition of co-operative ESs, is available.

A little KB that implements a fuzzy controller could control the plant and realise the expert predictive control module enhances the performance of the former KB, and, finally, results of performance of the predictive schema can be a little more improved by means of multiple sources of information that are the various KB coded within the Ess.

All previous knowledge is useful because more evolved co-operative frameworks is now exemplified: An overall EC composed by three co-operative KB that contains three different diagnosers. These diagnosers give advice to the controller module and this one will decide what advised control actions have to be applied to the process.

However, the important point is here to compare performance of co-operative ESs that contain different KBs with the performance co-operative ESs. The expert controller must take advice from the ESs and try to make consensus [1] [7] [9] and [10].

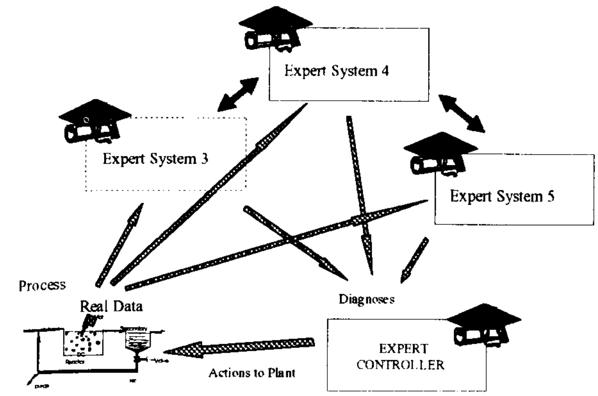

Fig. 2 Application Framework. Co-operative Expert Systems Give Advice to the Expert Controller

The heuristic model has this consensus for an important role because all certainties the expert controller receives are reviewed. At the end, the most promising actions are applied.

This module will only ask for diagnostics (facts of information that will contain the proposed control actions) from the co-operative expert systems ES3, ES4, and ES5. Immediately it receives answer from them and review certainties of incoming facts using any of the CEES reviewing function defined by default, and then deduce the fact into its KB. This framework is quite similar to that of the predictive expert control with several simulators [6] and the difference is that here it receives any diagnostic or knowledge fact: It asks for *diagnoses* without specificating what kind of diagnoses want to receive. Then the KB of this module start to deal with this information in a very simple way: this is only the rule 101 of "Fig. 3" that applies the most certain control actions that are advised by the other modules. In fact, only applies control actions (codified in the diagnostics that the external ESs provided) with at least the minimum certainty of 0.35.

```
///// The Expert Controller Knowledge Base /////
int INF_ENG2::engine ()
{
 RESERVED_VARIABLES;
 DATAFACT *PF;

 retract_all_facts ();

 prestige[ES3.name] = P3; necessity[ES3.name] = N3;
 prestige[ES4.name] = P4; necessity[ES4.name] = N4;
 prestige[ES5.name] = P5; necessity[ES5.name] = N5;

///////// Semantically opposite datafacts /////////////////////////////////
 set_opposites (STARTMOTOR, STOPMOTOR);
 set_opposites (OPENVALVE, CLOSEVALVE);

///////// Asking data to Diagnosers ///////////////////////////////////////
   ask_review_deduce (&ES3, DIAGNOSE); // Asking ES3 for facts.
   ask_review_deduce (&ES4, DIAGNOSE);
   ask_review_deduce (&ES5, DIAGNOSE);
///////// Base of Rules ///////////////////////////////////////////////////

// -----------------------------------------------------------------
 semantic_integrity ();
// -----------------------------------------------------------------
 Rule 101
  Description "Application of Surer Proposed Diagnostics"
  ForAll (PF)
    if (PF->type == DIAGNOSE && PF->cf > 0.35)
        Real_plant.set (PF->result); // Applying here the proposed
                                      // diagnoses to the real plant.
  EndForAll
 EndRule
 return 1;
};
```

Fig. 3 The Expert Controller Implementation

IV. RESULTS AND CONCLUSIONS

The three cases will be compared regarding the optimisation of the consumed energy **E** by the motor, the biomass error $\mathbf{x}\text{-}\mathbf{x}_{ref}$, and the watergate effort **v** all this flocked in the index **J**. Plots show improvements regarding the index: Minimising the biomass error $\mathbf{E_x}$, the biomass setpoint is of 2200 mg/l, and at the same time the watergate effort v and the consume of energy **E** are also wanted to be minimised by the motor, although this energy consumption is continuously growing.

A. The Co-operative Expert Systems

The outline of the three KBs are now codified in three different ESs in CEES. They have got different underlying ideas of the plant to be regulated and the way to do control. Note that ES3 is the worst ES and ES4 is the best one.

B. The Worst Knowledge is Contained in ES3

This diagnoser has bad performance. Its rules are very specific what implies certainty of deduced facts are going to be not much too high. Therefore this ES will find difficulties to control the plant. Behaviour of this ES can be seen at "Fig. 4"

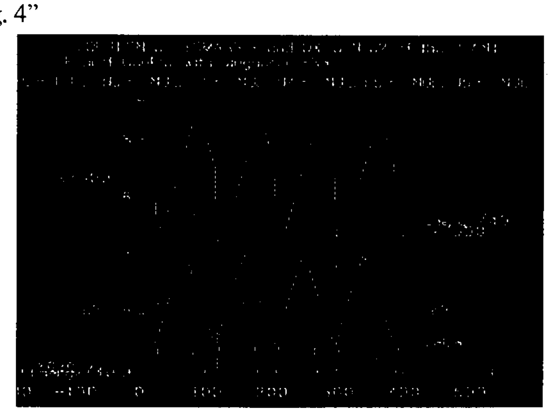

Fig. 4 ES4 Expert System's Performance Index is: 402.1

C. The Best Knowledge is Contained in ES4

This diagnoser has enough knowledge to control the plant with not so bad performance. It is composed only with 5 very general and efficient rules. Behaviour of this ES is the following depicted in "Fig. 5":

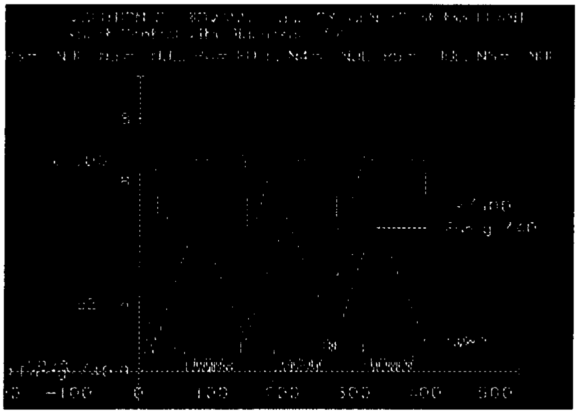

Fig. 5 Expert System ES4's Performance Index is: 176.9

The addition or aggregation of knowledge is expected to improve performance in control because one landmark of ESs is that as much knowledge they have, much better they work. With co-operation it is expected already better performance. This is why ES3 and ES4 are made to co-operate, that is written as "ES3+ES4". Another technique for taking advantage of more information is to aggregate the knowledge into a monolithic ES. Co-operative approach results are in "Fig. 6".

D. Both Co-operative Expert Systems

Following results on "Fig. 6" see that to improve performance is possible (that is, minimise index).

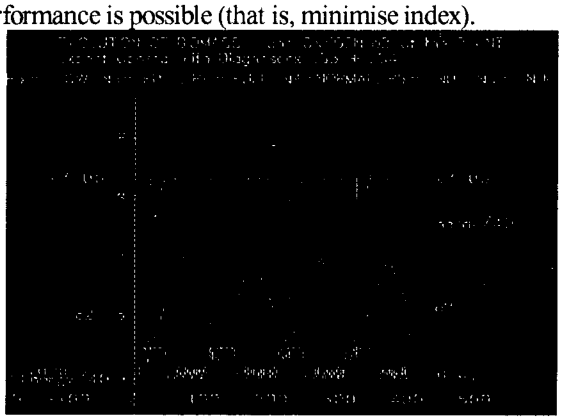

Fig. 6 Making Expert Systems ES3 and ES4 Co-operate, with Performance Index of 98.7

Simulation results are in the following table (Aggr. Means aggregated knowledge and Co-op means the cooperative approach):

	ES3	**ES4**	**Aggr. ES3+ES 4**	**Co-op ES3+ES4**
Energy	0.45	0.44	0.46	0.51
$x - x_{ref}$	346.7	122.7	161.7	36.9
Effort v	0.11	0.11	0.09	0.12
Index J	402.1	176.9	218.0	**98.7**

Table 2. Comparing Performance Indexes of Isolated Expert Systems to Monolithic ones and Co-operative Approaches

The application of this heuristic co-operative framework to isolated ESs shows that to improve performance is possible, as shown in "Fig. 6". See that the energy consumption **E** = 0.51 have not been minimised but the biomass error $\mathbf{x} - \mathbf{x}_{\mathbf{ref}}$ = 36.9 mg/l did get minimised. This ambiguous results must be compared in terms of predefined index performance **J.**

These results were obtained by setting the parameters of the heuristic model to P0 = LOW, N0 = FULL, P1 = FULL, N1 = NORMAL. A possible interpretation of these parameters is to assign higher prestige **P** or necessity **N** to the more reliable systems, in this case ES4, and lower ones to other systems, in this case ES3.

The main difficulty is to assign these values. These values are calculated by optimisation but there already are no analytical method to assigning parameters **N** and **P.** Therefore, heuristics are applied but there are not enough heuristics for this purpose. To find more heuristic but efficient methods to solve this problem is expected.

All results are summarised in "Table 2". Criticising results say that these are not successful but, indeed, they show performance of EC can be often improved within the here proposed heuristic framework.

From the table it could be asserted that the efficiency of predictive control have been improved by adding ESs form different instead of the old intuitive procedure of adding knowledge to the basic KB with better upgraded knowledge. Future work will go on studying several applications of these ideas of co-operation, of influence of adding ESs with worst or good knowledge, of asymptotic performance regarding the number of ESs and simulators, of extensibility of this framework to non-fuzzy mechanisms, and so on and forth.

At the end, this framework could be useful in those applications where modules were able to work with non approximate logic, particularly with fuzzy logic. The background idea about exploiting more than one system, even partially redundant systems, is promising. This framework is being studied to develop these ideas.

Future work is to study further the basic heuristic reviewing functions and co-operative protocol and to study more applications of co-operative approaches to process control. Therefore there is the need to develop open interfaces for this ES generator shell, CEES, so that direct process control and expert supervision could be applied, integrating them in current SCADA (monitoring and supervisory systems).

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