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A NEW METHODOLOGY FOR INTELLIGENT AND DISTRIBUTED PROCESS CONTROL BASED ON NEURAL NETWORKS

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Abstract: As industrial systems grow in complexity, new methodologies for the implementation of their control systems are being developed. Following this line, the application of artificial intelligence (AI) techniques to the implementation of distributed control systems offers several advantages. However, some problems related to the collaboration of both techniques arise, being added to the inherent distributed systems and AI issues. In this article an hierarchical approach has been selected in the implementation of intelligent distributed control systems. A new hierarchical and distributed architecture -based on the combination of neural networks and expert systems- is proposed for the automated greenhouse control providing very interesting results.

Key words: Distributed control systems, artificial intelligence, expert system, neural networks, integral greenhouse automation.

1 Introduction

Nowadays automatic control systems are indispensable in multitude of applications. Two of the most important challenges facing these systems are the geographical distribution of the elements and the difficulty of programming them.

The fact that the elements of a control system are physically distributed might be solved by the application of distributed control systems. In these systems several distant nodes collaborate to each other to carry out the desired function. Since they need to communicate it is indispensable the existence of an interconnection network among them that enables the exchange of information.

Several problems appear in the programming of this type of systems. The necessity to program different nodes, that could be different among themselves. The complexity of using a programming language to the general public, as well as the necessity to know the complex functions that they manage the protocols to control the access to the network, without forgetting the problems of coherence due to the parallelism, etc.

The use of expert systems for the implementation of distributed systems of control offers some interesting advantages, not only offering certain intelligence level to the system, but also being a good solution to solve the problems outlined before.

Continuous and discrete control are not incompatible, but complementary, when dealing with complex systems. Combination of both techniques offers new possibilities, such as the implementation of hierarchical control systems. In this scheme, lower level perform continuous control loops while the upper level, based on discrete control techniques, takes decisions over the system, supervises the system function and diagnoses continuous control failures.

When dealing with the implementation of a continuous control system it was needed to decide the most accurate to the characteristics that the previous protocol had achieved, such as: To be able to control any system with the same benefits that the control systems already existent. Possibility that even non-expert users could design the control system, and even allowing the capacity for the self-learning of the system. Possibility to be executed in a distributed way and easiness when being transmitted through the net for their execution in generic nodes (possibly very different between them).

After an exhaustive study of different techniques of continuous control, Neural Networks [Kung 1993] (NN) have been selected because they meets all the previous conditions. Indeed, NN not only completes the first condition since they can deal successfully with any control system, but, far beyond, they are able to control systems where no other techniques can be applied.

They also fulfill perfectly the second condition due to their learning characteristics [Anthony 1999], making possible that even non-expert users in the design of control systems can be capable, in a centralized way, to define the desired behavior of the system. NN are capable to learn in an automatic way thought the analysis of a group of samples that reflect the answers expected in real situations of execution. Even more, it is possible in the design phase the simulation of the system operation in front of hypothetical situations with the purpose of checking that it fulfills the desired specifications.

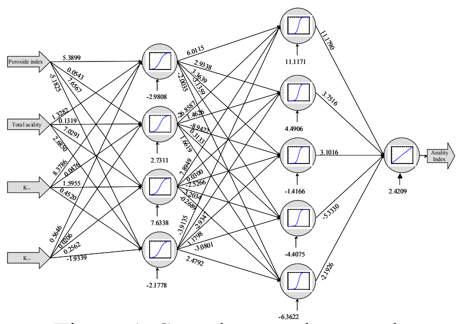

Figure 1. Sample neural network

Since the NN are formed by perfectly detachable units (neurons), the distribution of these neurons in different nodes is not very difficult, so the results obtained by each neuron must be spread thought the interconnection network to be used as an input for any other neuron needing it.

Finally, it is possible to characterize a neural network as a group of neurons. Figure 1 shows a NN where interrelations between neurons are appreciated. All the neurons present a common structure, and they are easily adapted in function of a set of parameters. Therefore, it is possible to locate several generic neurons in the nodes and make a particularization of them in function of the desired control system by means of the transmission of these parameters, and so it is possible to transmit a NN through a distributed system in a simple and efficient way.

NN execution needs some synchronization mechanisms. Several synchronism techniques have been evaluated, and finally the following one has been selected. The system works in a event-oriented way. Any input neuron (those whose inputs correspond to external inputs) can start the operation of the NN. When a Start condition arises, the input neuron send an NN START message, making that all input neurons read all their input values and evaluate their outputs. These outputs must be send through the CAN network, while they are been used as input values of subsequent neurons. Any neuron will calculate and spread its output as soon as it gets all its inputs. Finally, output neurons will not apply its outputs until no remaining value would exist. This is accomplished by means of a fictitious neuron. Fictitious neuron, uses as input values the outputs of the system, and activates the NN for a new operation, allowing output to be applied. Synchronous operation is granted by this procedure.

The fault tolerant characteristics of the system must be highlighted. When being a hierarchical system, the superior level takes charge from the topic of fault tolerance. When a failure in the system is detected, the upper level takes the control of the system, evaluating the failure and deducing from the characteristics of it the correction actions that should be carried out for the reconfiguration of the system (operation in degraded way) or those guided to drive the system into a safe failure state.

CAN network [Bosch 1991] has been selected for the execution of the Distributed Neural Network because of its particular characteristics. First of all, CAN is a diffusion network, providing that all neurons that need a value produced by another neuron get the value with only one message. Even more, these messages are labeled (in the identifier field) with the neuron that produced it, so avoiding any overload. Also, non-destructive contention allows a limited response time. Is it also possible to fix the priority of any messages. Finally, CAN offers several advantages, such as low cost, fault tolerance, great variety of products, etc.

These characteristics make the proposed system easily profitable for users in general, who can start without important computer knowledge to program their own control systems. This is very interesting in applications such as greenhouses automation, etc.

2 Control architecture

A new hierarchical and distributed architecture -based on the combination of neural networks and expert systems- is proposed for the automated greenhouse control, providing interesting characteristics such as:

- Low-cost implementation.
- Possibility that even non-expert users could design the control system, and even allowing the capacity for the self-learning of the system.
- Possibility to be executed in a distributed way.
- Easiness when being transmitted through the net for their execution in generic nodes (possibly very different between them).
- Fault tolerance and real time characteristics.

In this scheme, lower level perform continuous control loops with the information obtained from sensors and other acquisition systems, by means of an continuous control techniques (Neural Networks). In the other hand the upper level, based on discrete control techniques (Rule Nets [Bonastre 2001]), not only controls the discrete variables of the process but also takes decisions over the system and supervises the system function and diagnoses failures (see figure 2).

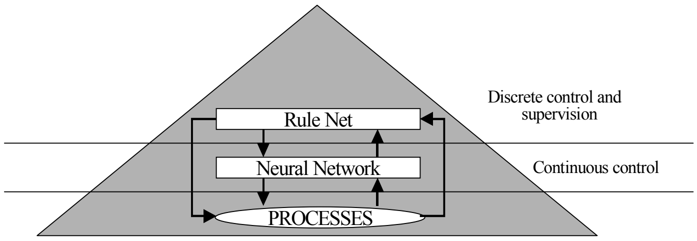

Figure 2. Hierarchical architecture proposed for green house control

By means of combination of both layers, a very powerful control system has been achieved [Bonastre 2000].

Figure 3 shows the physical architecture of the proposed system. The distributed system consists on a group of nodes connected by means of a CAN network (Controller Area Network). Two types of nodes are distinguished. The Programming and Supervision Node (PSN), unique at the network, provide user and designer access. After the validation of the design, the user can order the automatic programming of all the nodes through the network without having to program each one of them individually.

The rest of the nodes are called control nodes (CN). They are connected through their (analog or digital) inputs and outputs to the process to be controlled. Each CN will receive a subset of the whole RN and NN, executing its subset in a concurrent manner with the rest of CN's. They can be implemented by means of low-cost micro-controllers, PC's, PLC's …

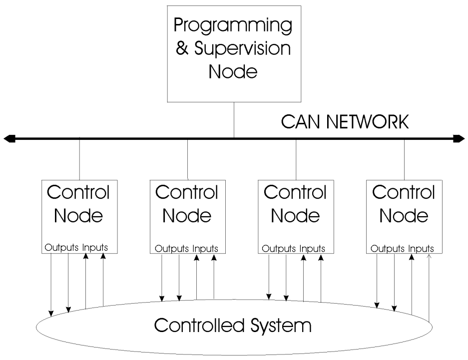

Figure 3. System structure

The developed protocol for this architecture was called ICCAL (Intelligent Control CAN Application Layer) [Bonastre 1999]. It offers several interesting features, such as the capacity to communicate to the user in a completely automatic way, which nodes compose the system as well as the characteristics of each one of them.

3 Test application: Intelligent greenhouse control

As experimental environment for the test of the new architecture capabilities, the integral control of a greenhouse is being implemented in a laboratory scale model, very interesting partial results being obtained at the moment.

A greenhouse is a space with the appropriate microclimate for the optimum development of a specific plantation, therefore, giving the design and the automatic distributed control system should be obtained in him the temperature, relative humidity, adapted ventilation, hatching and carbonic anhydride artificial atmosphere to reach high productivity, at low cost, in less time, with smaller environmental impact, protecting to the rains, the hail, the freezes or the wind excesses that could harm a cultivation.

Nowadays, the supervision and control systems for agricultural applications they are in a world scale development stage. The main inconvenience is the difficult readiness for the high cost. Due to this arises the application of the present methodology and architecture to this field.

The system presents a hierarchical structure where upper level deals with the discrete control, the supervision of lower layers and must perform the adequate actions in case of failure. Middle layer takes into account the continuos control loops, including hardware supervision. Finally, lower layer consists of the system to control and a group of sensors and actuators that carry on the actions defined by upper layers.

Physically, the system consists on at least seven nodes, an PSN (a PC) and six CN, interconnected by means of a CAN network.

There has been built an illumination control loop based on two CNs; first one (N1) is implemented by means of a PC with a USB-CAN communication device, that holds a Neural Network able to recognize simple voice commands. This NN actualizes the value of some variables of the Rule Net, that controls the illumination. N2 is implemented by means of a CANary processor. The collaboration between both networks, NN and RN, has proved to be very effective and successfully resolved.

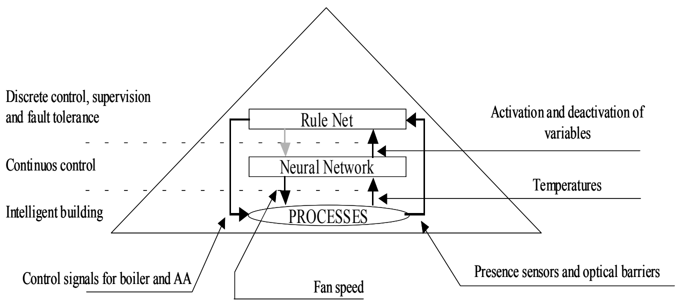

Figure 4. Air Conditioning structure

By the other way, to verify the distributed functioning of the NN, another control loop that controls the ventilation, temperature and humidity conditions of the greenhouse, has been established. This system is composed by four nodes. Node N3 is in charge of the boiler, and it is implemented by means of a CANary processor with a digital output. Node N4 controls the conditioned air, and it is also implemented with a CANary processor, using a digital output (ON/OFF) and an another that, by means of a triack, controls the fan speed. Finally, node N5 is located outside the greehouse and it is the meteorological station. This node provides the windspeed, exterior temperature and pressure, etc. Node N1 is also needed in this subsystem, with a temperature sensor inside. Our NN uses the indoor and outdoor temperatures, humidifies, etc. as inputs, and is able to indicate the RN if the utilization of any control systems (boiler, air conditioner, humidifier etc.) is necessary. If AA is needed, NN controls the analog fan speed, as shown in figure 4.

The irrigation node (N6), implemented by means of a Motorola MPC555, controls the electrovalves that allow the watering, and to pour on the water flow the appropriate nutrients from its deposits. It also have level sensors to manage the deposits.

At last, a gateway PSN-HTML that allows the visualization of the current system variables through the TCP/IP protocol has been implemented. Thanks to this a remote user can know the system state.

After a design process to determine the best topology of the NN and the appropriate training, the distribution of the NN was performed by the user. The system performance was completely successful. Some design and training matters of the NN should need further revision.

Finally, both control systems (RN and NN) work together in a perfect manner, guaranteeing the correct function of the proposed objectives. Nowadays, new specifications are being introduced, such as temperature control by means of voice commands control and self-learning.

4 Conclusions

Given the excellent results obtained, two new approaches are being applied to the system. One of them consists on the implementation of a more powerful PSN software that integrates all options and tools (design, training, distribution, etc.), and could take carry on an automatic distribution of NN. This distribution algorithms should take into account the user restrictions (minimum number of messages on the network, maximize parallelism, fault tolerance by means of redundancy, etc.)

Other interesting question to study is the response time of the proposed system, in order to its application to Real Time control systems, and the impact of fault tolerance in this situations.

Finally, this methodology is being applied to other control systems, such as the integral control of a Diesel engine, substituting current strategies (cartographic methods) with NN based ones. Over them an expert system is responsible of the supervision and control of normal and anomalous operation of the system.

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