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Using Soft Computing Methodologies for Multistage Supervisory Control of Complex Systems*

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Abstract

In this paper, a structure to supervise and control complex systems is presented. The proposed multistage supervisory control system is structured as a hierarchy of three levels - control, supervision and co-ordination levels. While the controllers at control level exercise direct action over the process, the supervision level generates decisions to govern the operations of the control algorithms at the lower level. The co-ordination level governs the supervisory level to assure proper overall system behavior. The system possesses different control and supervisory strategies to accommodate different operating conditions, adaptive behavior to react under uncertain or unfamiliar situations and the capability to coordinate distributed controllers to accomplish the system task. The bottom control level is constituted of conventional controllers or soft control technologies based on Neural Networks, Fuzzy Logic and Genetic Algorithms. The supervisor is modeled as a Fuzzy Cognitive Map. Based on the process status, the set of active control and supervisory algorithm is chosen.

1. Introduction

Many problems in modern engineering practice (as well as in societal, economic and environmental processes) are highly complex, large in dimension and in most cases ill defined and vague. In the area of Large Scale Systems special regard is taken at the problems of structure, decomposition, nonlinearity, complexity and uncertainty. Systems and control theory provides the backbone for solving problems of modern control system design as well as complex systems.

Complexity of the contemporary industrial systems is growing rapidly thus causing severe problems for their smooth operation even for an experienced human operator. Therefore Intelligent methodologies can be successfully involved into solving the various problems of system modeling, control and fault diagnosis.

Although many useful optimality-based controller designs exist, it is sometimes difficult to define and find optimal solutions to highly nonlinear, highly complex problems. This places controller design for such systems in the class of ill-formed problems wherein there is a lack of sufficient information, time, or resources to define or find the optimal solutions. The search for intelligent solutions necessarily addresses (a) the identification of models (whether implicit in expert rules or explicit in differential equations), (b) the definition and computation of acceptable solutions, and (c) the robust

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synthesis of information from multiple sources. To generate intelligent controllers for the overall system, each issue in this non-inclusive list demands a formal and justifiable treatment.

Recent advances and developments of Intelligent technologies in the modeling and control of the complex industrial systems has been owed to the intensive application of fuzzy sets and neural networks methods (Lin and Lee, 1996; Yen *et al*., 1995). The synergism of these methods and general soft computing methodologies can give even more effective performance results (Jang *et al.*, 1997).

To meet the performance specifications for a complex system, different strategies for each individual operating condition, adaptive behavior to react under uncertain or unfamiliar situations and the capability to coordinate distributed controllers to accomplish the system task in a coherent way should be included.

In this research work a concept of multistage supervisory control system in a general manner is presented and analyzed. This system is a dynamic scheme that identifies the current operating status of the complex system, evaluates control performances by dynamically monitoring process behavior, and then selects appropriate supervisory strategy, based on this process observation. The lowest control level includes the usual control actions, which are performed as conventional controllers and/or implementing soft computing control methodologies, using fuzzy logic, neural networks and genetic algorithms. The supervisor is modeled as an Fuzzy Cognitive Map (FCM) (Stylios *et. al*, 1997) a novel methodology, which belong to the soft computing methodologies, combining characteristics from Fuzzy Logic Theory and Neural Network (Kosko, 1997). An augmented Fuzzy Cognitive Map represents existing knowledge for modeling the operation and best describes the behavior of the complex lower level system, FCM is used for planning and supervision the whole system. The coordinator selects the supervisory strategy, it interacts with human and it governs the supervisor and determines appropriate tasks for supervisor according to the specific human requirements.

In this paper, the description of the control level and supervision level will be examined and the use of soft computing methodologies is proposed to modeling these two levels. Modeling methodologies for coordinator will be subject of future research work.

2. General Structure of the Hierarchical Control System

Generally, a supervisory control system should have adaptive behavior to properly react under uncertain or unfamiliar situations, different control techniques available to execute the control policy required for the current operating conditions, and the capability to supervise the operation of control modules to achieve the system wide objectives.

Figure 1 depicts the architecture of the proposed multistage supervisory control system. This hierarchical structure consists of three main levels: control level, supervision level and co-ordination level. The control level refers to the plant dynamics and generates direct control actions over the plant. The complexity of plant requires an ensemble of controllers, which are governed by supervision level. The supervisor assigns control patterns to the controllers to select the control policies to be used on the plant. At the highest layer of the hierarchical structure, the co-ordinator overlooks the operation of the supervisor. The co-ordinator dynamically selects appropriate supervisor tasks and assigns strategy patterns to it, to assure that the process behaves in a desirable manner. Different models describe the process at each level. At the control level, process variables are observed and controlled directly and quantified using numerical values. In general, the dynamics of the process is described by differential or difference equation and control algorithms are usually designed according to continuous or discrete time dynamics models. Symbolic models can also be used to devise controllers that mainly perform symbolic processing of the information. At the supervision level process variables are observed and controlled indirectly. The dynamics of the processes are described by discrete-event equations and supervisory algorithms are usually designed based on discrete-event models or discrete-event systems. At the co-ordination level process information is used for decision making. The resulting decision models define the hypothetical states of the process. Decision systems are modeled in the discrete-event settings and so the coordination level has a discrete-event nature.

Between each level of the multistage structure there is exchange of information, from the lower level to the upper level and vice versa. When information rises, it is filtering, becoming more imprecise, abstractive and qualitative and conversely in his descending towards the plant.

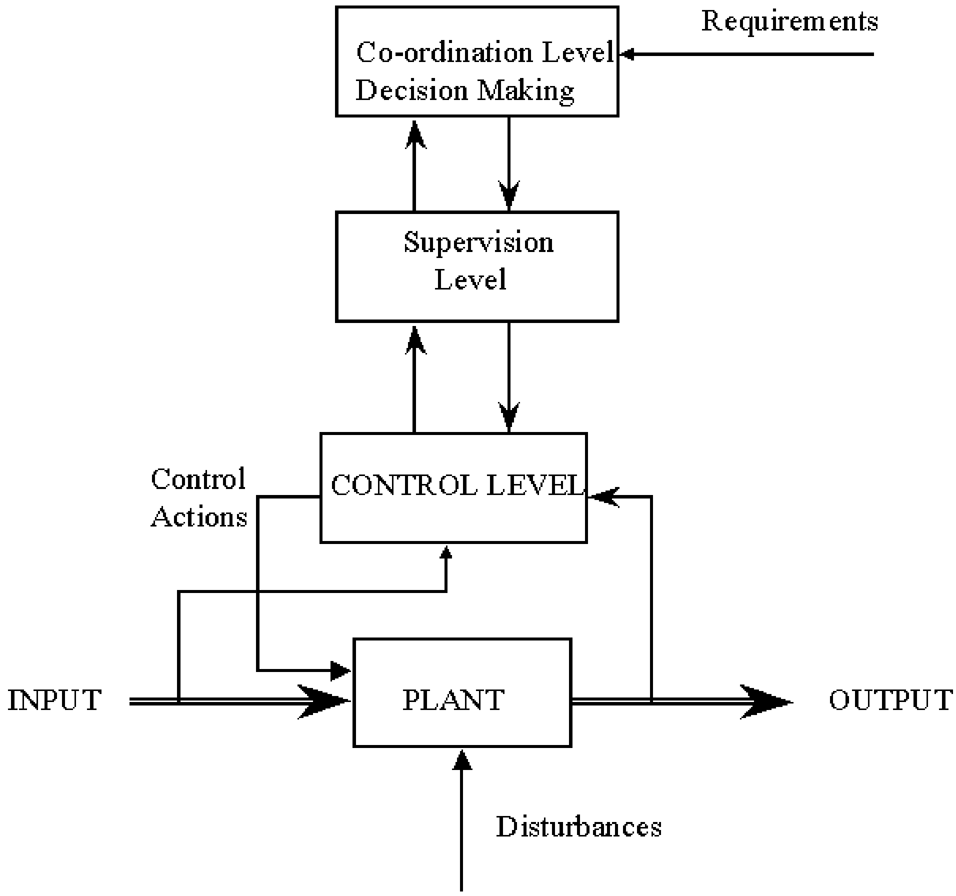

Figure 1. The proposed hierarchical multistage structure

The Control Level acts directly to the process. Controllers take information from sensors and observers of the plant and send the appropriate control actions to the actuators, which influence the plant variables.

To meet highly demanding control specifications in complex systems a number of methods have been developed, which enhance and extend traditional control methods. These methods combine ideas and approaches of control theory, operation research, and artificial intelligence. One of the most popular technologies is fuzzy logic. Employment of fuzzy logic in the field of control systems resulted in the development of fuzzy controllers.

Fuzzy Logic Controllers (FLCs) have been successfully used to complex and non-linear processes (Sugeno, 1985). Fuzzy Logic Controllers have proved to be more robust than conventional controllers in some cases. A comprehensive review of the fuzzy logic controller design and implementation can be found in (Driankov, 1996). Different types of adaptive FLCs such as self-tuning and self-organizing controllers have also been reported (Maeda and Murakami, 1992; King *et. al.*, 1995; Vachkov and Christova, 1996). Recently many researchers are trying to enhance performance and increase robustness of FLCs, using neural networks and genetic algorithms in designing such controllers (Rajapaske *et. al.*, 1998; Lin and Lee, 1996; Jang *et al.*, 1997).

The interest in the identification of fuzzy models is accompanied by a similar surge of interest in the model-based design of fuzzy controllers. Model based fuzzy control uses a given conventional or fuzzy open loop model of the plant under control in order to derive the set of fuzzy if-then rules constituting the corresponding FLC. Much interest there is on centers of stability, performance and robustness analysis of the resulting closed loop system involving both a conventional model and an FLC, or a fuzzy model and an FLC. The major objective of model based fuzzy control is to utilise existing conventional linear and nonlinear design and analysis methods for the design of such FLCs that have better stability, performance and robustness properties than the corresponding non-fuzzy controllers designed by the use of these same techniques.

Neural Networks techniques have been found to be useful for controlling highly uncertain, non-linear and complex systems. In relation to control systems, neural networks are attractive tools for solving problems in which classical analytic methods are difficult to be applied. The application of neural networks in control of complex nonlinear plants is wide: as regulators in the scheme of direct and indirect adaptive control; as controller parameter tuning in the scheme of supervisory control; as hierarchical structures; hybrid and switching control, etc. (Narenda and Mukhopadhyay, 1994; Hunt *et al.*, 1992; Chen and Khalil, 1995).

Supervision Level

The main supervisory task is the monitoring and controlling the whole plant. It supervises the production, allocates the sharing of the resources, it schedules the production, choosing between different production sequences and the right command to the right agent (Jones and Jasek, 1997). Role of supervisor is to extend the range of application of the conventional controllers of the lower level by using a more abstract representation of the process, general control knowledge and adaptation heuristics and to enhance the performance of the whole system. Supervisory control is composed of various types of reasoning in order to relate different aspects of knowledge about process. Model of supervisor is built independently rather than aiming at specific control tasks and it represents both qualitative and quantitative information. Supervisor may replicate some of the knowledge and skills of the control engineer and it is built using a combination of knowledge representation techniques such as causal models, production rules and object hierarchies (Antsaklis and Passino, 1992; Wang and Linkens, 1996).

The supervisor level receives feedback information from the process for each subtask to be executed, evaluate this information and organize the execution of control level according to the global requirements posed by the coordinator.

Co-ordination Level

At the co-ordination level, process information is used for decision making. The co-ordination level is a discrete-event process, because decision systems are modeled in the discrete-event settings. The coordinator assigns strategy patterns to supervisor to assure that the process behaves in a desirable manner. The coordinator selects optimal supervisory strategies using decision-making algorithms.

Coordination level is dedicated for management and organization purposes and it generates general goals. Coordinator selects appropriate supervision tasks, it oversees and directs all the activities at the supervision and control level. It performs high level planning, it can break down or change the control sequence actions.

Generally, two implementation problems mainly exist for the multistage supervisory control of a complex process:

- with respect to the control level, when control algorithm don't work properly or doesn't exist that can satisfy the performance criteria for the complete spectrum of process operating conditions;
- with respect to the co-ordination level – the supervisor can accommodate the overall process requirements.

3. Control methodologies and techniques

In conventional optimal control, explicit models describe possible system consequences, and these possible consequences are examined using a cost function. For well-formed problems, the result of minimizing this cost function is a definition of optimal global performance with respect to the specified cost function and the given explicit model.

Conventional optimal control employs an explicit system model, and assumes an implicit expert who defines a cost function and solves the resulting optimization problem. Though frequently effective for controller design, it appears that some problems are not appropriately addressed by optimality-based methods.

Knowledge-based control is fundamentally different from traditional mathematically intensive control methods, because it is based on system knowledge rather than process models. Intelligent controllers are usually characterized by the way they represent knowledge, but equally important to controller design is the way decisions are made.

Fuzzy logic is one knowledge-based method that has the image of an alternative control method. In contrast to optimal control, conventional fuzzy logic control assumes that there are (a) an explicit expert exists who can (b) construct a rule base which transforms observations into plant controls via an implicit plant model.

During the past few years two principally different approaches to the design of fuzzy logic controllers have emerged: heuristics based design and model based design. The main motivation for the heuristics based design is given by the fact that many industrial processes are still controlled in one of the following two ways:

- the process is controlled manually by an experienced operator
- the process is controlled by an automatic control system, which needs additional manual on-line "trimming" from an experienced operator.

In both cases it is enough to translate the operator's manual control algorithm in terms of a set of fuzzy if-then rules in order to obtain an equally good, or an even better, wholly automatic control system incorporating an FLC. This implies that the design of an FLC can only be done after a "control algorithm" already exists. In the first case, the existing control algorithm may consist of sequential and/or parallel manual control actions performed by the operator upon a process whose mathematical model is either impossible to derive or of negligible utility for cost related reasons. In this case the FLC simply makes explicit the existing manual control knowledge thus becoming a part of the closed loop system. In the second case, the existing control algorithm is a conventional control algorithm in need of additional manual "trimming". An FLC is then again used to automate the manual "trimming" algorithm employed by the operator and thus acts as a supervisor to the conventional closed loop system already in place.

Unlike conventional control, which is based on mathematical model of a plant, a FLC usually embeds the intuition and experience of a human operator and sometimes those of designer and researcher. While controlling a plant, a skilled human operator manipulates the controller output based on the error (e) and change of the error (Δe) of the controlled variable with a view to minimizing the error within the shortest possible time. Fuzzy logic control is a knowledge-based system. In analogy to the human operator the output-scaling factor may be considered a very important parameter of the FLC since its function is similar to that of the controller gain. Moreover it is directly related to the stability of the control system. So the output-scaling factor should be determined very carefully for the successful implementation of a FLC.

Most of the practical processes under automatic control are non-linear higher order systems and may have considerable dead time. Sometimes their parameters may be randomly changed with changes in ambient conditions or with time. Thus, the controller output or process input should be a nonlinear function of e and Δe. In a FLC this non-linearity is incorporated by a limited number of IF-THEN rules which may not always be enough to produce a good approximation to the controller output required for the optimum controller performance. In such a situation only static or fixed valued scaling factors and predefined membership functions may not be sufficient to eliminate this drawback. For the successful design of fuzzy logic controllers proper selection of input and output scaling factors and/or tuning of the other controller parameters are crucial jobs which in many cases are done through trial and error or based on some training data. Relative importance of the input and output scaling factors to the control performance of a fuzzy logic control system is yet to be fully established. A lot of research works on tuning of FLCs have been reported where either the input-output scaling factors or the definitions of fuzzy sets are tuned (on-line or off-line) to match the current plant characteristics (Lin and Lee, 1996; Jang *et al.*, 1997; Driankov *et al.*, 1996; King *et al.*, 1995; Vachkov and Christova, 1996; Rajapakse *et. al.*, 1998; Lin, 1995). Most of them are dealing with the off-line tuning suitable dynamic plants with stable parameters (time-constants, time delay and gain). However in the case of a plant with time-varying parameters another technique including successive plant identification and respective fuzzy controller tuning has to be applied.

Vachkov and Christova (1996) present and analyze a fuzzy rule based method for successive tuning of fuzzy controllers. It is suitable for real time mode and possesses a good flexibility thus improving the performance characteristics of the fuzzy controller. This concept may be implemented in controller design and its main idea is briefly described below:

The investigations of Li and Gathland (1995) have shown that the most sensitive tuning parameter of the fuzzy controller is the scaling factor DU of the singletons of the fuzzy rules (acting directly as a gain factor in normal P and PI controllers). A Fuzzy Tuning Unit (FTU) is proposed and constructed in order to successively update the scaling factor DU as shown in Fig.2. The Fuzzy Tuning Unit (FTU) works as a Fuzzy Rule Based Decision Making Block which output is derived as follows:

$$\mathrm{DU}(k) = \mathrm{DU}(k\text{-}1) + \mathrm{DELTA}(k), \qquad (1)$$

$$\text{where } \mathrm{DELTA}(k) = \boldsymbol{Fuzzy}\,[\,\mathrm{Input1}(k), \mathrm{Input2}(k)] \qquad (2)$$

This is a fuzzy inference procedure for evaluating the most essential time dependent *characteristics* of the transient process of the control system. Since the fuzzy inference is simple to be done by using no more than 2 input parameters named as Input1(k) and Input2(k) in (2), the following two *most representative* characteristics of the transient process have been accepted (Vachkov and Christova, 1996):

- Input1(k) = TE(k) – *tracking_error*, which is a kind of evaluation of the differences between the setpoint value z(k) and the plant's output y(k) during a *past interval* of preliminary given L sampling times;
- Input2(k) = SE(k) – *sign_of_error* which gives information about the *oscillation type* of the transient process during the examined past period of L sampling times.

Once the above two inputs for the fuzzy inference procedure have been selected and calculated then the respective Fuzzy Rule Base for updating DU(k) according to (1) is constructed. For performing the fuzzy inference both inputs TE(k) and SE(k) have been assigned 3 membership functions as follows: *Small*, *Medium* and *Big* for TE(k) and *Negative*, *Zero* and *Positive* for SE(k). The choice of the length L of the past period is sensitive to the final result of quality of the successive tuning. Numerical types of investigations on this influence are shown and discusssed and more details on these procedures are given (Vachkov and Christova, 1996).

The literature on fuzzy control admits that the heuristics based design is very difficult to apply to multiple-input/multiple-output control problems, which represent the largest part of challenging industrial process control applications. The difficulties faced by the heuristics based design explain the recent surge of interest in the derivation of black box fuzzy models of the plant under the control, in terms of the identification of a set of fuzzy IF-THEN rules, by the use of conventional identification techniques, neural networks, genetic algorithms, or a mixture of these techniques.

Another approach for designing controllers at control level of the proposed supervisory control system is by using artificial neural network based controllers. Artificial Neural Networks (ANN) represent an important class of numerical learning tools. They are primarily used for numerical modeling or control of systems for, which very little is known about their dynamics and operating, conditions. The internal architecture of ANN provides powerful computational capabilities, allowing for the simultaneous exploration of different competing hypotheses. Massive parallelism and computationally intensive learning through examples in ANN make them suitable for application in complex and nonlinear processes.

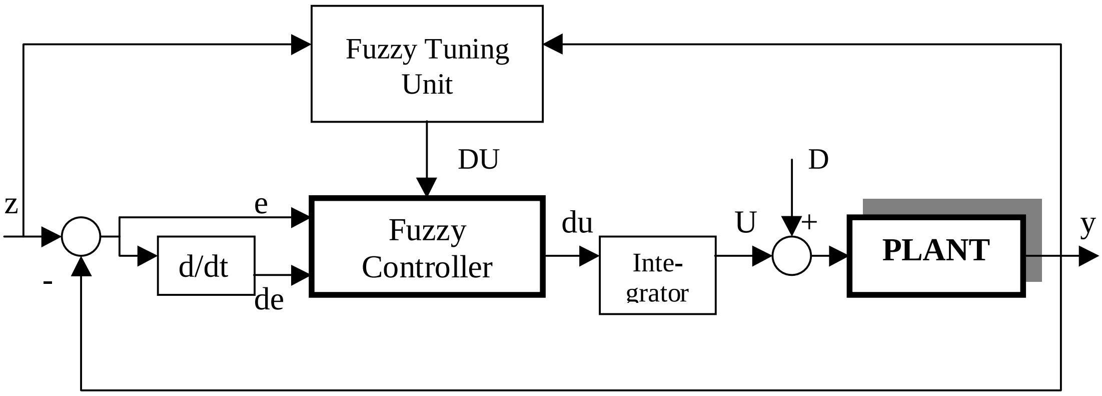

Figure 2. Structure of the Fuzzy Rule Based Successive Tuning of Fuzzy Controller

Model Based Predictive Control (MBPC) is a method for designing controllers that operate in nonlinear, constrained and uncertain environments. Model-based control strategies are characterized by including an explicit Process Model, which is used to predict actual process behavior, identify malfunctions or optimize performances, depending on the specific application. The success of model-based control is due, in large part, to its ability to handle uncertain nonlinear systems with state and input constraints such as those found in complex industrial processes. Model Based Predictive Control has established itself as the most powerful technology able to efficiently control multivariable systems with difficult dynamics, handle feedforward with measured disturbances and assure a graceful degradation when some manipulated variables are lost. The presence of a multivariable dynamic model allows to predict the future values of controlled variables in response both to actions applied by the controller itself and to measured disturbances. The controller will take a decision in real time selecting the moves, which provide the best possible matching between predicted outputs and their desired paths in time. The ultimate goal is to reduce the variance in process variables so to shift the set points as close as possible to the constraints. MBPC is mostly useful when applied to complex processes featuring long lag-times or time-delays, strong interactions between loops and/or multiple process outputs constraints, or where the basic control system may just keep the unit stable because unable to optimize it. Explicit models are used to determine system behavior, which is then used to generate fuzzy controls via conventional fuzzy and classical control methods, respectively (Tso and Fung, 1996) . Several hybrid inference models as combinations of First Principle (FP) and Fuzzy (F) models have examined (Hadjiski and Christova, 1998). A set of relatively simple Fuzzy and FP models is used to fit more precisely the plant behavior at different operation conditions using Rule Based Selector. Because of the lack of direct measurements and large uncertainty hybrid modeling on the base of FP model was implemented as a step in combustion process model based predictive control.

4. Supervision level and Fuzzy Cognitive Maps

Control level is consisted of an ensemble of controllers, which are necessary to control the complex plant, each one of these Fuzzy Logic Controllers is designed to control locally parts of the whole plant. At the lower level among controllers there is no exchange of information. The supervisor at the upper level receive essential information from each controller, such as input, outputs, variables and it sends appropriate signals to the controllers and influence the plant.

Supervisor can intervene to the controller at the lower and set new set points, if some variables of the plant are approaching an undesired control area or in order to achieve the end-user requirements, that are posed by the coordinator. It receives commands to perform predetermined specific control tasks from the coordinator in the upper level and send the appropriate control and identification algorithms to the control level. It can accomplish predetermined control actions and cope with limited uncertainty situations. It may choose among different control models and control, identification and estimation algorithms. Supervisor schedules what models and algorithms will be used in the controller and identifier. It monitors the status of the system at the lower level, what algorithms and models are used and what is the situation of the controlled system. It can perform a kind of maintenance of the system by selecting alternative control methods.

The supervision level is modeled as an Fuzzy Cognitive Map, who serves to monitor the controlled plant, to indicate driven of the plant to undesired or unpermitted states and to intervene taking appropriate actions such as failsafe, reconfiguration schemes. Fuzzy Cognitive Map belong to the neuro-fuzzy systems, which aim at solving real world decision making problems, modeling and control problems (Medsker, 1995). These problems are usually imprecisely defined and require human intervention. Thus, neuro-fuzzy systems with their ability to incorporate human knowledge and to adapt their knowledge base via new optimization techniques, are likely to play an increasingly important roles in the conception and design of hybrid intelligent systems (Jang *et al.*,1997; Parsaei, and Jamshidi, 1995).

Fuzzy Cognitive Map is an expert network, which is built by experts, using an interactive procedure of knowledge acquisition. Experts design a fuzzy graph structure of the system, consisting of concepts-nodes that represent the key principles - functions of the system operation and behavior. Then, they determine the structure and the interconnections of the network using fuzzy conditional statements. Experts use IF-THEN rules in order to describe the relationship among concept, and then to combine all these rules. The fuzzy weighted arcs between concepts that show the fuzzy degree of causation with which each concept influences others depict the interrelationships among these concepts, characteristics of the system. The causal knowledge is stored on the interconnections that summarize the correlation between cause and effect (Kim and Lee, 1998; Kimoto and Hagiwara, 1997).

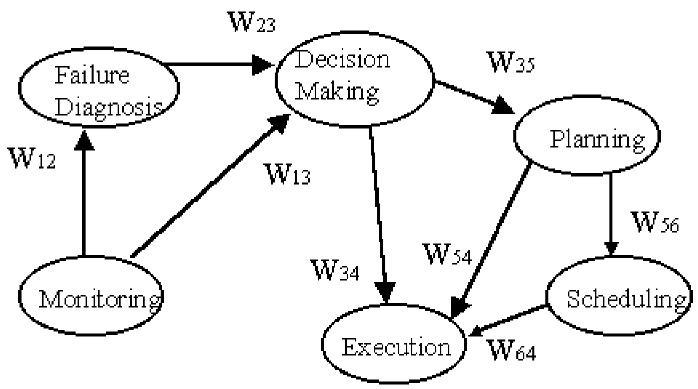

Figure 3. An augmented Fuzzy Cognitive Map modeling the supervisor

An augmented Fuzzy Cognitive Map is used to model the supervisor, which is consisted of individual Fuzzy Cognitive Maps that are interconnected. In Figure 3 this augmented Fuzzy Cognitive Map is depicted, where each one of its concepts represent an individual Fuzzy Cognitive Map. As an example concept 'Failure Diagnosis' stand for an FCM which performs the failure diagnosis task and is consisted of concepts for possible failures, effect and cause analyses (Pelaez, and Bowles, 1996). This Fuzzy Cognitive Map will be consisted of concepts that stand for the irregular operation of some elements of the system, for failure mode variables, for failure effects variables, for failure cause variables, severity of effects and design variables. The construction of a map will be based on the operator's heuristic knowledge about alarms, faults, what are their causes, effects and time of occurrence (Mitchell and Sundstrom, 1997).

Supervisor -Fuzzy Cognitive Map will choose the appropriate controller for the plant and it will decide the set points for the controller at the lower level. If switching between different controllers controls the plant, a Fuzzy Cognitive Map could perform this task. Learning is essential in the development of autonomous system Supervisor uses past experience to increase its efficiency and improve its capability assessment. One of the important advantages of Fuzzy Logic methodologies such as Fuzzy Cognitive Maps is that they are applicable to task-oriented problems (Stylios *et. al.*, 1998).

5. Conclusions

In this paper a new multistage structure for supervisory control of a plant has been proposed. It consists of three hierarchical levels, the control-execution level, the supervisory level and the co-ordination level. For the control level, the use of advanced intelligent techniques, such as Fuzzy Logic Controller and Neural Network, is proposed. Modeling the supervision level of the structure using a Fuzzy Cognitive Map is suggested, which best utilizes existing experience in the operation of the system and is capable in modeling the behavior of complex systems. Fuzzy Cognitive Maps seem to be a useful method in complex system modeling and control, which will help the designer of a system in decision analysis and strategic planning. Fuzzy Cognitive Maps appear to be an appealing tool in the description of the supervisor of hierarchical distributed control systems, which teamed up with other methods will lead to the more sophisticated control systems.

References

Antsaklis, P., and K. Passino (1992). *An Introduction to Intelligent and Autonomous Control,* Kluwer Academic Publishers, Massachusetts.

Chen, F.-C., and H.K. Khalil (1995). "Adaptive Control of Nonlinear Discrete-Time Systems Using Neural Networks," *IEEE Trans. on Automatic Control,* **40**, No. 5, pp. 791-801.

Driankov, D., H. Hellendoorn, and M. Reinfrank (1996). *An introduction to Fuzzy Control,* Springer-Verlag, New York.

Hadjiski, M., and N. Christova (1998). "Hybrid Modelling of Plants with Large Uncertainties," *Advanced Summer Institute ASI'98*, Bremen, Germany, pp. 143-150.

Hunt, K., D. Skarbaro, R. Zbicowski, and P. Gawthrop (1992). "Neural Networks for Control Systems – A Survey," *Automatica*, **28**, No. 6, pp. 1083-1112.

Jang, J., C. Sun, and E.Mizutani (1997). *Neuro-Fuzzy and Soft Computing*, Prentice Hall Publishing, Upper Saddle River, N.J.

Jones, P. M., and C. A. Jasek (1997). "Intelligent support for activity management (ISAM): an architectureto support distributed supervisory control," *IEEE Transactions on Systems, Man, and Cybernetics,* **27**, pp. 274-288.

Kim, H. S., and K. C. Lee (1998). "Fuzzy implications of fuzzy cognitive map with emphasis on fuzzy causal relationship and fuzzy partially causal relationship," *Fuzzy Sets and Systems*, **97**, pp. 303-313.

Kimoto, K., and M. Hagiwara (1997). "AFCM: Automatic fuzzy cognitive maps," *International Conference on Computational Intelligence and Neuroscience*, **2**, No 3, pp. 304-307.

King, P.J., K. Burnham, and D. James (1995). "A Model Reference Self-Organizing Fuzzy Logic Controller," *Control and Computers*, **23**, No. 1.

Kosko, B. (1997). *Fuzzy Engineering*, Prentice-Hall, Upper Saddle River, N. J.

Li, H. X., and H.B. Gathland (1995). "Enhanced Methods of Fuzzy Logic Control," *Proc. of FUZZ-IEEE/IFES'95,* Yokohama, Japan, **1**, pp. 331-336.

Lin, C. T., and C.S.G. Lee (1996). *Neural Fuzzy Systems: A Neuro-Fuzzy Synergism to Intelligent Systems,* Prentice Hall, Upper Saddle River, New Jersey.

Lin, C.-T. (1995). "A Neural Fuzzy Control System with Structure and Parameter Learning," *Fuzzy Sets and Systems*, **70**, pp. 183-212.

Maeda, M., and S. Murakami (1992). "A Self-Tuning Fuzzy Controller," *Fuzzy Sets and Systems*, **51**, pp. 29-40.

Medsker, L.R. (1995). *Hybrid Intelligent Systems,* Kluwer Academic Publishers.

Mitchell, C. M., and G.A. Sundstrom (1997). "Human interaction with complex systems: design issues and research approaches," *IEEE Transactions on Systems, Man, and Cybernetics*, **27**, pp. 265-273.

Narendra, K.S., and S. Mukhopadhyay (1994). "Intelligent Control Using Neural Networks," in *Intelligent Control* (M.M.Gupta and N.K. Sinha, eds.), IEEE, New York.

Parsaei, H., and M. Jamshidi (1995). *Design and Implementation of Intelligent Manufacturing Systems: from ExpertSystems, Neural Networks, to Fuzzy Logic,* Prentice-Hall Inc, Upper Saddle River, N.J.

Pelaez, C. E., and J.B. Bowles (1996). "Using fuzzy Cognitive Maps as a System Model for Failure Models and Effects Analysis," *Information Sciences*, **88**, pp. 177-199.

Rajapakse, A., K. Furuta and S. Kondo (1998). "Adaptive Geno-Fuzzy Control of Process Plants via Perpetual Evolution," *Proceedings of the 1998 IEEE International Conference on Control Applications*, Trieste, Italy, pp. 797-801.

Stylios, C. D. , V.C. Georgopoulos, and P.P. Groumpos (1998). "Fuzzy Cognitive Maps Modeling Supervisory Large Scale Control Systems," *IFAC Large Scale Systems '98*, Patras, Greece, pp. 73-78.

Stylios,C.D., V.C. Georgopoulos, and P.P. Groumpos (1997). "The Use of Fuzzy Cognitive Maps in Modeling Systems," *The 5th IEEE Mediterranean Conference on Control and Systems* Paphos, Cyprus, paper 67 (CD-ROM)

Sugeno, M. (1985). *Industrial Applications of Fuzzy Control*, Elsevier Science, Amsterdam.

Tso, S., and Y. Fung (1996). "Methodological Development of Fuzzy-Logic Controllers from Multivariable Control," *IEEE Trans. on Systems, Man and Cybernetics – Part B: Cybernetics*, **26**, no 5, pp. 677-691.

Vachkov, G., and N. Christova (1996). "Fuzzy Successive Tuning of Fuzzy Controllers," *Proc. of EUFIT'96*, Aachen, Germany.

Wang, H., and D. Linkens (1996). *Intelligent Supervisory Control: a qualitative bond graph reasoning approach* , World Scientific Publishing Co. Pte. Ltd, Singapore.

Yen, J., R. Langari, and L.A. Zadeh (1995). *Industrial Applications of Fuzzy Control and Intelligent Systems*, IEEE Press, New York