A HIERARCHICAL MODELING TECHNIQUE OF INDUSTRIAL PLANTS USING MULTIMODEL APPROACH

C. D. Stylios, N. G. Christova and P. P. Groumpos

Laboratory for Automation and Robotics
Dept. of Electrical and Computer Engineering
University of Patras,
GR-265 00 Rion, GREECE
Phone: +30 610 997 295, Fax: +30 610 997 309
E-mail: {stylios,hristova,groumpos}@ee.upatras.gr

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Abstract

This study investigates the problem of design adequate models for non-linear large and complex plants with high uncertainties. A new hierarchical structure is considered that utilize soft computing methodologies to model the supervisor. The proposed approach is based on the combination of different modelling techniques within a hierarchical supervised structure that has the ability to model system behaviour under different operational circumstances. A Fuzzy Cognitive Map (FCM) is used to aggregate multiple models and to create a hybrid model based on the current operational conditions of the industrial process. The proposed methodology is applied to model and simulate the operation of an industrial plant.

1 Introduction

There is great need to develop reliable process models for the industrial plants within the different fields of computer-integrated manufacturing. The requirements for the higher quality of model design in the process industries have increased significantly in recent years. This leads to the investigation of design systems able to perform intelligent functions such as simultaneous utilization of memory capabilities, learning and high-level decision making procedures.

Development of adequate models for industrial plants and complex systems is usually a complicated task because of the large uncertainties, caused by lack of direct measurements and necessity of inferential approach, high level of non linearity and different types of disturbances. One approach of building models that are accurate enough in a broad range of operational conditions may be successful if different modeling techniques are used that will create a hybrid methodology.

Recent powerful development and use of intelligent technologies for the operation of complex industrial systems have been caused mainly by the intensive application of fuzzy logic and neural network methods [5]. Both fuzzy systems and neural networks have been shown to have the capability of modelling complex non-linear processes to arbitrary degrees of accuracy. Synergistic combinations of these methods can give even more effective performance results [5,6,8,9,10].

Fuzzy logic ideas have influenced relative areas, Kosko enhanced the power of cognitive maps [1] considering fuzzy values for the concepts of the cognitive map and fuzzy degrees of interrelationships between concepts. He introduced the Fuzzy Cognitive Map (FCM) theory as an integration of fuzzy logic and neural networks. Fuzzy Cognitive Maps (FCMs) have already been used to model behavioural systems in many
different scientific areas [7,8]. FCM have great potential and have been used as a tool for aggregation of multiple models.

This research work introduces the idea to develop a hierarchical structure where the supervisor will monitor and intervene to the lower level controllers taking under consideration the conditions of the whole plant environment. This supervisor will create an appropriate hybrid model for the whole system. This hybrid model will be based on the selection and aggregation of multiple models according to the current operational conditions of the industrial process. The supervisor of the system will be based on symbolic abstract modelling methodology and the proposed hierarchical structure follows the principle of "decreasing precision and increasing intelligence" [11]. This multiple models approach incorporates different modelling strategies to accommodate different operating conditions, adaptive behaviour to perform model design under uncertain or unfamiliar situations and the capability to coordinate separate models to accomplish the overall system objectives.

An appropriate modeling technique for the Supervisor of the hierarchical system is Fuzzy Cognitive Maps, which best utilize existing experience in the operation of the system and are capable of modeling the behavior of any complex system. FCM is a useful method for complex system modeling and control, which can perform planning and decision analysis of any system. Fuzzy Cognitive Maps is an appealing tool in the description of modeling techniques, which teamed up with other methods will lead to the more sophisticated model and control design systems.

The main idea of the proposed methodology is to employ multiple models in order to describe the different operation condition and environment. Such modelling methodology performs an efficient model design in dynamical environments possessing a high degree of uncertainty. This approach is well suited for complex processes. Specifically, the operating range of the process is partitioned into a number of mutually exclusive and exhaustive sub ranges and models are designed for each sub range.

For the development of hybrid modelling structure, First Principles (FP) models as well as Fuzzy Logic (FL) based models are implemented. A graphical illustration of the proposed hierarchical structure is
depicted on Figure 1. Fuzzy Cognitive Maps are used to model the supervisor that aggregates the separate models and performs monitoring, supervision and maintenance of the system by integrating alternative modelling techniques. An augmented Fuzzy Cognitive Map can accomplish identification of the process models and cope with limited uncertainty situations. It may comprise different models, identification and estimation algorithms.

First Principles (FP) models are well established and used successfully in various fields of engineering - process industries, metal industry, power generation, manufacturing etc. First Principles models are usually non-linear and could describe adequately the plant behaviour in the full range of operational conditions. FP models transform the space of the input variables into one or multi-dimensional space of the output variables using a set of equations usually derived from material and energy balances, physical and chemical laws, various mathematical relations, constants and parameters. Unfortunately, some FP model parameters are not accurate enough and should be estimated and/or adapted on the base of experimental data, provided by special tests.

Fuzzy Logic (FL) based models belong to the particular case of "black box" models. They require reduced input space of variables, compared with FP models. Both types of models could contain different unmodelled part of the plant behaviour. Thus it is expected that an appropriate combination of them could improve the accuracy of the resulting hybrid model. Every FL based model should be preliminary tuned using off-line optimisation because of the lack of current data for continuous or periodical correction of model parameters. The FL based models are identified most often in off-line mode by using experimental data set of input-output pairs from a real process [15]. Then two different sets of information must be generated, as follows: a set of fuzzy rules describing the structure of the input-output relationship in which the parameters occur and a set of parameters of the rules. The latter can be divided into 2 categories: parameters identifying the membership functions shape and locations and parameters in the consequence of the rules. In this study, the proposed algorithm for optimisation of the fuzzy models in [15] has been used. It is suggested the use of a set of several fuzzy models that are forming a hybrid model for modelling the process behaviour under different operational conditions. Each of the separate models possesses its own input subspace and is tuned to be optimal for corresponding operation conditions.

Figure 1: A hierarchical hybrid modelling structure.

In the case of modelling processes with large uncertainties, it is better to use a set of fuzzy logic based models. Each fuzzy model has been created and tuned off-line to model the process under specific operational conditions. The Fuzzy Rule Based Models that are used in this paper belong to the Takagi-Sugeno type (TS-models) [14]. Generally, a TS fuzzy model with L fuzzy rules \( R_i \) \( i = 1,2,...,L \) is expressed in the following form:

\[
R_i : IF \quad (X_1 \ is \ A_{i1} AND \ ... \ AND \ X_r \ is \ A_{ir}) \ THEN \\
Y_i = P_{io} + P_{i1}.X_1 + ... + P_{ir}.X_r \quad \text{for} \quad i = 1,2,...,L
\]

(1)

where \( r \) is the number of inputs for the process; \( A_{i1}, A_{i2}, ..., A_{ir} \) are the selected \( r \) Fuzzy Sets which define the \( i \)-th Fuzzy Rule and \( P_{io}, P_{i1}, ... \) \( P_{ir} \) are \( r \times 1 \) coefficients of the algebraic consequence part (THEN-part) of this Fuzzy Rule. The fuzzy sets are defined by their membership functions:

\[ A_0(x_j), \quad \text{for} \quad i = 1,2,...,L \quad \text{and} \quad j = 1,2,...,r. \]
The overall (defuzzified) output $Y$ of the Fuzzy Model is calculated as a Weighted Average [14] of the outputs of all the fuzzy rules, as follows:

$$Y = \frac{\sum_{i=1}^{r} f_i Y_i}{\sum_{i=1}^{r} f_i} = \frac{\sum_{i=1}^{r} f_i (P_{io} + P_{i1} X_1 + ... + P_{ir} X_r)}{\sum_{i=1}^{r} f_i}.$$  \hspace{1cm} (2)

where $f_i$ is the so called Activation Degree (Firing Strength) of the $i$-th Fuzzy Rule. It is calculated in the Fuzzy Inference part of the Fuzzy Model by using mainly 2 possible operations:

a) Min-operation:

$$f_i = \min \{A_{i1}(X_1), A_{i2}(X_2), ..., A_{ir}(X_r)\}.$$  \hspace{1cm} (3)

b) Product -operation:

$$f_i = A_{i1}(X_1) \times A_{i2}(X_2) \times ... \times A_{ir}(X_r).$$  \hspace{1cm} (4)

The procedure of creating the Fuzzy Model (Learning of the Fuzzy Model) is an algebraic or iterative calculation process in which all the parameters $P_{io}, P_{i1}, ..., P_{ir}$ ($i = 1,2,..., N$) of the right (THEN) part of the Fuzzy Rules have to be determined in such way, so as to minimise a given performance index (criterion) $Q$. The total number of all the parameters in THEN part of all rules is: $LL = (r+1) \times L$. Here the proposed by Vachkov algorithms [15] for Global and Local learning are used. The Local learning procedure is a kind of decomposition of the overall $LL$ dimensional optimisation task into $L$ optimisation tasks each of them with a smaller $(r+1)$ dimension. As a result a smaller number of consequent parameters of the rules has to be tuned during the learning procedure of each local model. The main advantage of the algorithms for Global and Local learning is their ability to learn from a sparse and/or highly noised data. If this is the case, usually a partial Fuzzy Model is created, that is some of the rules have been identified, but the others are “frozen” at their initial settings.

3 Fuzzy Cognitive Maps representation and development

The synergistic and complementary use of fuzzy logic and neuro-computing has initiated the development of soft computing methodologies. These soft computing methodologies have been investigated and proposed in order to be utilised in the description and modelling of complex systems. Fuzzy Cognitive Maps belong to this category. They originate from a combination of fuzzy logic and neural network theories.

A Fuzzy Cognitive Map (FCM) is consisted of concepts that illustrate different aspects in the behaviour of the system, with each concept representing a characteristic of the system, and these concepts are interconnected with cause and effect relationship that show the dynamics of the system. An FCM integrates the accumulated experience and knowledge on the operation of the system, as a result of the method by which it is constructed, i.e., using human experts that know the operation of system and its behaviour.

The graphical illustration of FCM is a signed directed graph with feedback, consisting of nodes and weighted interconnections. Nodes of the graph stand for the concepts that are used to describe the behaviour of the system and they are connected by signed and weighted arcs representing the causal relationships that exist between concepts (Figure 2). Each concept represents a characteristic of the system; in general it stands for states, variables, events, actions, goals, values, trends of the system which is modelled as an FCM. Each concept is characterised by a number $A_i$, which represents its value and it results from the transformation of the real value of the system’s variable, for which this concept stands, in the interval $[0,1]$. It must be mentioned that all the values in the graph are fuzzy, and so weights of the interconnections belong to the interval $[-1,1]$. With the graphical representation of the behavioural model of the system, it becomes clear which concept of the system influences other concepts and in which degree. This representation permits the ease update.
of the construction of the graph, such as the adding or deleting of an interconnection or a concept.

The most essential part is the development of Fuzzy Cognitive Maps, the determination of the concepts that best describe the system, the direction and the grade of causality between concepts. The selection of the different factors of the system, which must be presented in the FCM, will be the result of a close-up on system’s operation behaviour as been acquired by experts. Causality is another important part in the FCM design; it indicates whether a change in one variable causes change in another, and it can include the hidden causality that it may exist between several concepts. The most important element in describing the system is the determination of which concept influences which other and with which degree. There are three possible types of causal relationships among concepts that express the type of influence from one concept to the others. The weight of the interconnection between concept $C_i$ and concept $C_j$, denoted by $w_{ij}$, could be positive ($w_{ij} > 0$) for positive causality or there is negative causality ($w_{ij} < 0$) or there is no relationship between concept $C_i$ and concept $C_j$, thus $w_{ij} = 0$.

The causal knowledge of the dynamic behaviour of the system is stored in the structure of the map and in the interconnections that summarise the correlation between cause and effect.

The value of each concept is influenced by the values of the connected concepts with the corresponding causal weights and by its previous value. So the value $A_j$ for each concept $C_j$ is calculated by the following rule:

$$A_j^s = f \left( \sum_{i=1 \atop i \neq j}^n w_{ij} A_i^{s-1} + A_j^{s-1} \right)$$

where $A_j^s$ is the value of concept $C_j$ at step $s$, $A_i^{s-1}$ is the value of concept $C_i$ at step $s-1$, $A_j^{s-1}$ is the value of concept $C_j$ at step $s-1$, and $w_{ij}$ is the weight of the interconnection between $C_i$ and $C_j$, and $f$ is a threshold function. Threshold functions squeeze the result of multiplication in the interval [0,1]. Equation (5) includes the old value of each concept, and so the FCM possesses memory capabilities and there is a smooth change after each recalculation. The development and design of the appropriate Fuzzy Cognitive Map for the description of a system require the contribution of human knowledge.

The experts develop Fuzzy Cognitive Maps using an interactive procedure of presenting their knowledge on the operation and behaviour of the system. The procedure for constructing Fuzzy Cognitive Maps is as follows: experts define the main concepts that represent the model of the system, they describe the structure and the interconnections of the network using fuzzy conditional statements. Experts use IF-THEN rules in order to describe the causal relationship among concepts, and based on these rules the FCM structure is developed and the weighted interconnections are determined [13].

![Figure 2: A simple Fuzzy Cognitive Map.](image-url)
In this way, experts describe the causal interrelation between two concepts of the Fuzzy Cognitive Map by an ensemble of linguistic rules, and a set of linguistic rules is created, these rules are combined and create the final overall rule. The overall rule describes the causal relationship between the value of concept $C_i$ and concept $C_j$, thus the weight between concept $C_i$ and concept $C_j$ can be inferred from the rule.

4 Industrial application

The proposed approach has been used to model the pulverising system of boiler fired low rank lignite [4]. Pulverising is crucial process for the steam generators because strong requirement for stability, efficiency and fast reaction of the boiler. A detailed description of the industrial system is given in [4]. First Principles model for estimation of the ventilation rate of the mill fan on the basis of heat and mass balances has been derived. As it is presented in [4] the input vector consists of 11 variables – some of them are directly measurable, but the bigger part must be estimated by particular inference pre-processing. Because of the lack of direct measurements and large uncertainty hybrid modelling on the base of FP model was implemented as a step in combustion process model based predictive control.

A FCM model has been developed for the supervision of the hierarchical system. A Fuzzy fuzzy model.

Five different Fuzzy Logic models have been examined: $(B, Q', \tau)$, $(B, W', t_{fg})$, $(B, t_{am}, t_{fg})$, $(B, W', \tau)$ and $(B, t_{am}, \tau)$. They are presented at Figure 3, where $\tau$ is the number of working hours after the last fan mill repairing. Local and global optimisation of the Fuzzy Logic models was carried out following the approach given in [15]. The Fuzzy Rule Base of each model consists of 125 fuzzy rules. Five linguistic terms for each input variable are defined. Smooth shape type of the membership functions is used. The Membership functions of $(B, Q', \tau)$ model are given at Figure 4.

![Figure 3: Developed Fuzzy Logic Models.](image)

![Figure 4: Input membership functions of $(B, Q', \tau)$ fuzzy model.](image)
Cognitive Map (FCM) has been constructed (Figure 5) in order to aggregate the above mentioned multiple models i.e. the FP model and the five FL models. This FCM models the supervisor of the hierarchical modelling structure (Figure 1) and it processes as a hybrid model of the industrial process according to the current operational conditions.

Figure 5 shows the FCM that is used to model the supervisor of the hierarchical modeling structure, with the initial value of each concept and the interconnections between concepts. There are 2 kinds of concepts the factor-concepts that stand for the main factors of the system that influence and determine the value of the second kind of concepts the model-concepts, which stand for the appropriate models to be used. According to the values of factor-concepts the corresponding model-concepts are influenced with the corresponding weights. Factor-concepts take their initial values that correspond to the real measurements of the plant and model-concepts take initially random values. Then the FCM starts simulate and at each simulation step, the value of each concept is defined by the result of taking all the causal weights pointing into this concept and multiplying each weight by the value of the interconnected concept according to the equation 5.

The simulation results are illustrated on Figure 6 where it can be seen that the Fuzzy Cognitive Map is driven to an equilibrium region after five simulation steps. The analysis of Figure 6 suggests to use FP model, together with FL1 and FL5 models. When the FCM is in this equilibrium region, if a disturbance occurs in the real system and causes a change in the value of one or more factor concepts, the FCM will interact for a limited number of steps and it will reach again another equilibrium region suggesting the hybrid use of some models in the lower level.

The analysis of the obtained results has shown that the integration of FP and Fuzzy Logic (FL) models by usage of FCM improves the accuracy of output variable prediction in average within 6÷10 percents. It could be summarized that the aggregation of multiple models in the hierarchical modeling structure is more efficient than the independent usage of single FP model.

The proposed soft computing based methodology is able to model plant behavior in wide ranges and to perform on-line estimation of directly immeasurable process variables on the basis of the available (usually scarce) on-line process information. Such modeling system performs an efficient model design in dynamical environments possessing a high degree of uncertainty. The integration between different technologies is the actual answer to modern process needs.
5 Conclusions

A new hierarchical structure for modelling complex systems has been presented in this paper. A methodology to aggregating multiple models (FP model and FL based models) using Fuzzy Cognitive Maps has been considered. The introducing of multiple models structure is a prospective way to improve the performance of plant behaviour. For complex plants with immeasurable or hard measurable variables and large uncertainties the scheme using multiple separate models received by aggregation of different modelling techniques is an efficient approach in model design. As it has been described an augmented Fuzzy Cognitive Map can accomplish identification of the process models and cope with limited uncertainty situations. It may comprise different models, identification and estimation algorithms. It can perform a kind of maintenance of the system by integrating alternative modeling methods. The results reveal that the proposed hybrid structure is capable of successfully identifying a highly non-linear pulverising system.

References


