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An Integrated Approach to Intelligent Modeling of Industrial Plants

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Abstract

In this paper an integrated hierarchical soft computing methodology for modeling of industrial plants by aggregating models of different types is presented. The problem of designing adequate and reliable models for non-linear plants with large uncertainties is under consideration here. The proposed approach has the ability to model system behaviour under different circumstances and it is especially efficient for complex industrial systems with immeasurable process variables and large uncertainties. A Fuzzy Cognitive Map (FCM) is used to aggregate multiple models and to create a hybrid model, which makes a selection between the different models, according to the current operational conditions of the industrial process. The proposed methodology is considered as a promising way to cope with the modeling of a real industrial plant.

1 Introduction

Modern systems become more complex and highly sophisticated. They are characterized by highly nonlinear dynamics that couple a variety of physical phenomena in the temporal and spatial domains. For such systems intelligent fuzzy logic based techniques and object modeling are proposed to address uncertainty issues and provide flexible platforms [16]. Capturing and utilizing the expert's knowledge, effectively and efficiently, promises to improve plant operational conditions.

There is a certain need of developing reliable process models in different fields of computer integrated manufacturing. Development of adequate models for real 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. Building of models accurate enough in a broad range of operational conditions may be successful if different hybrid modeling techniques are used.

The synergistic and complementary use of fuzzy logic and neuro-computing has initiated the development of soft computing methodologies [5]. These intelligent technologies have been investigated and proposed in order to be utilised in the description and modeling of complex systems [6, 8, 9, 10].

Fuzzy Cognitive Maps [7] belong to this category. They originate from a combination of fuzzy logic and neural network theories. Fuzzy Cognitive Maps (FCMs) have been applied in a variety of scientific areas [8]. They have been used to describe and model the behavior of a system and its application in the modeling the supervisor of distributed systems [12, 13] for decision analysis, and operation research [2, 3].

This paper introduces the idea of the hierarchical model structure of the system, where a Fuzzy Cognitive Map (FCM) serves as a supervisor that takes into consideration the conditions of the plant environment and creates an appropriate hybrid model of the whole system. This hybrid model is based on the aggregation of multiple models and on the current operational conditions of the industrial process. Using this symbolic abstract methodology to model the supervisor, the principle of "decreasing precision and increasing intelligence" is followed [11].

This multiple models approach incorporates different modeling 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 task.

An appropriate modeling technique is proposed that uses Fuzzy Cognitive Maps (FCM) as a Supervisor of the hierarchical system. The FCM utilize the existing experience about the system operation and are capable of modeling the overall complex systems behavior.

An application of the above proposed approach is shown in the paper for modeling of a pulverisation system that uses a low rank lignite fuel for an industrial boiler.

2 The Integrated Modeling Approach

The major requirements for modeling and control of real plants are to operate in different environmental conditions. Under real operation conditions the plant environment changes, the input-output characteristics of the system change rapidly or even discontinuously. If a single model is identified to model the system, it will have to adapt itself to the new environment. In non-linear systems, a single model may not be adequate to follow the changes in the process behaviour (i.e., a model may not exist in the assumed framework to match the environment). Hence, multiple models could be used to identify the different operation conditions. In some environments different models may be available whose validity (or accuracy) depends upon the region in the state space where the system trajectories lie. All the above considerations suggest that multiple models may be preferable to a single model in many different situations.

2.1. Hierarchical Structure of the Proposed Methodology

The objective of this paper is to develop inferential hybrid models being able to model system behaviour 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. A model integration approach is discussed considering a hierarchical structure, using different kind of modeling techniques. An augmented FCM is used to aggregate the set of different models and to create the appropriate model according to the current operational conditions.

The main idea of the proposed methodology is to employ multiple models in order to describe the different environments. Such modeling system 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.

A methodology for aggregating multiple models of different type by usage of FCMs is proposed in this paper. In the new developed hybrid modeling structure First Principles (FP) model as well as Fuzzy Logic (FL) based models are implemented. A graphical illustration of the proposed hierarchical modeling structure is given in Fig. 1.

A general algorithm of the integrated modeling approach is given in the following:

1. Development of a set of separate models, modeling process behaviour at different operational conditions. Each of the separate models possesses its own input subspace and is tuned in off-line mode to be optimal for corresponding operation conditions.

2. The human experience and knowledge of the operation of the investigated system is used to construct an augmented FCM, where experts determine the concepts that best describe the system and the direction and grade of causality among concepts. Some of the nodes stand for the main factors that are the most important technological parameters, characterizing the current process behavior and the other concepts in the FCM are the various models, created in Step 1. The FCM is trained by Differential Hebbian learning algorithm [8] to adjust the weights of the interconnection between concepts.

3. The FCM starts simulate as concept-factors take their initial values that correspond to the real measurements of the plant and model-concepts take initially random values. When the FCM reaches an equilibrium stage, it suggests the appropriate models that best describe the current process conditions according to the final values of the model-concepts.

The proposed modeling approach is suitable for steady-state but time varying modeling. Details about the determination and the training of the FCM are presented further in Section 3.

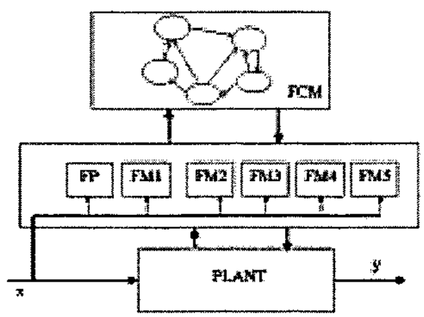

Fig. 1. The Proposed Hierarchical Hybrid Modelling Structure

2.2. Implementation of Different Modeling Techniques

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

It is obviously that high-dimensional FP models for complex industrial systems are difficult to be built and slow to compute. Therefore a hierarchical hybrid platform that uses different modeling techniques aggregated by a FCM on the upper level is proposed.

Fuzzy Logic (FL) based models are a particular case of "black box" models. They require reduced input space of variables, compared to FP models. 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]. In this study, the proposed algorithm for optimisation of the fuzzy models in [15] has been used. It is suggested a set of several fuzzy models to be used forming hybrid models, modeling process behaviour at different operational conditions. The providing of data enough for the multiple fuzzy model tuning is serious problem when the quantity of special experiments must be restricted.

The Fuzzy Rule Based Models used in this paper are from the type of Takagi-Sugeno (TS-models) [14]. As well known, a TS fuzzy model with L fuzzy rules R_i $(i = 1,2,...,L)$ is expressed in the following generalized form:

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

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 $r+1$ coefficients of the algebraic consequence part (***THEN***-part) of this Fuzzy Rule.

The fuzzy sets are defined by their membership functions: $A_{ij}(x_j)$, *for* $i=1,2,\ldots,L$ and $j=1,2,\ldots,r$. 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:

$$Y = \frac{\sum_{i=1}^{L} f_i Y_i}{\sum_{i=1}^{L} f_i} = \frac{\sum_{i=1}^{L} f_i (P_{io} + P_{i1}X_1 + \ldots + P_{ir}X_r)}{\sum_{i=1}^{L} f_i}, \qquad (2)$$

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:

$$f_i = min\ \{A_{i1}(X_1), A_{i2}(X_2), \ldots, A_{ir}(X_r)\} \qquad (3)$$

b) *Product* -operation:

$$f_i = A_{i1}(X_1) \times A_{i2}(X_2) \times \ldots \times A_{ir}(X_r). \qquad (4)$$

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) $\boldsymbol{Q}$. The total number of all the parameters in ***THEN*** part of all rules is: $LL = (r+1) \times L$. Here the proposed algorithms in [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.

FCMs are used to aggregate the separate models and to perform a kind of maintenance of the system by integrating alternative modeling techniques. An augmented FCM can accomplish identification of the process models and cope with limited uncertainty situations. It may comprise different models, identification and estimation algorithms.

3 Fuzzy Cognitive Maps: Representation and Development

Kosko [7] enhanced the power of the 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 the fuzzy logic and neural networks.

The objective of this section is to focus on the construction and the use of FCM in modeling systems. It will be shown that FCMs are useful to exploit the knowledge and experience that human has accumulated for years on the operation of a complex plant. Such methodologies are crude analogs of approaches that exist in human and animal systems and have their origins in behavioral phenomena related to these beings [10]. So, FCM represents knowledge in a symbolic manner and relates states, variables, events and inputs in an analogous to beings manner. This methodology can contribute to engineers' intention to construct more intelligent systems. The FCMs have a potential to be used as a tool for aggregation of multiple models thus creating a plausible model for the overall system behavior.

In a graphical illustration a FCM seems to be a signed weighted graph with feedback, consisting of nodes and weighted arcs. Nodes of the graph stand for the concepts that are used to describe the behavior of the system. Concepts are connected by signed and weighted arcs representing the causal relationships that exist between the concepts. Each concept represents a characteristic of the system; in general it stands for events, actions, goals, values, trends of the system that is modeled as an FCM. Each concept is characterized by a number A_i that represents its value and 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, so weights of the arcs are in the interval [-1,1]. Between concepts, there are three possible types of causal relationships, which express the type of influence of one concept to the others. The weight, denoted by W_{ij}, of the arc between concept C_i and concept C_j, could be positive, $(W_{ij} \succ 0)$ which means that an increase in the value of concept C_i leads to the increase of the value of concept C_j, and a decrease in the value of concept C_i leads to the decrease of the value of concept C_j. Or there is negative causality $(W_{ij} \prec 0)$ which means that an increase in the value of concept C_i leads to the decrease of the value of concept C_j and vice versa. When, there is no relationship between concept C_i and concept C_j, then $W_{ij} = 0$. 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:

$$A_j^s = f\left(\sum_{\substack{i=1 \\ i \neq j}}^{n} W_{ij} A_i^{s-1} + A_j^{s-1}\right) \qquad (5)$$

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 within 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. Experts describe the structure and the interconnections of the network using fuzzy conditional statements. They use ***IF-THEN*** rules in order to describe the causal relationship among concepts, and based on these rules FCM is structured and the weighted interconnections are determined. FCM learning involves updating the strengths of causal links. The FCM is trained by using of Differential Hebbian Learning (DHL) algorithm [8]. Kosko [8] discusses the use of DHL as a form of unsupervised learning for FCMs. DHL can simplify the construction of FCMs by allowing the expert to enter approximate values (even just the signs) for causal link strengths. DHL can then be used to encode some training data to improve the FCM's representation of the problem domain and consequently its performance.

In this paper the above explained FCMs are used as a supervisor for aggregating the set of different models and modeling technologies on the lower level. The further simulations have shown that this hierarchical modeling approach is a very successful tool for system modelling and control that clearly helps the human operator in its real-time decision making for efficient system operation.

4 Industrial Application

The above proposed integrated hierarchical approach has been used to model the pulverising system of a boiler that uses a low-calorie lignite coal fuel as shown in Fig. 2 [4]. Pulverising is crucial process for the steam generators due to the strong requirements about stability, efficiency and fast reaction of the boiler. A detailed description of the industrial system is given in [4]. FP model for estimation of the ventilation rate of the mill fan on the basis of heat and mass balances has been derived. As presented in Fig. 3, 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 based on the FP model was performed as one step in the combustion process model based predictive control.

Five different Fuzzy Logic models have been examined: (B, Q^r, τ), (B, W^r, t_{fg}), (B, t_{am}, t_{fg}), (B, W^r, τ) and (B, t_{am}, τ). They are presented at Fig. 4, where τ 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.

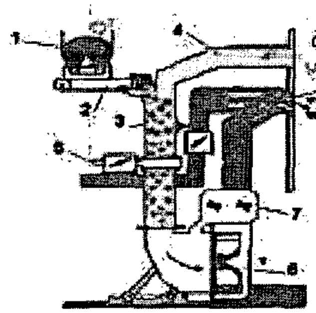

Fig. 2. Scheme of the Pulverizing System

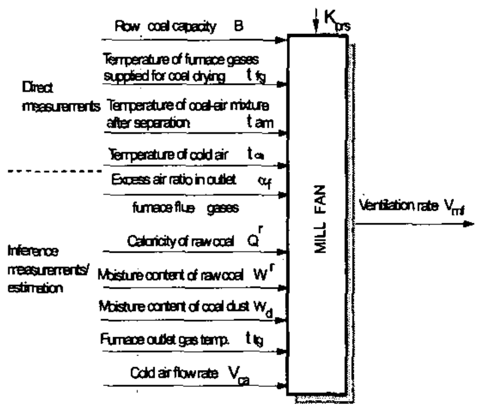

Fig. 3. Block Diagram of the First Principles Model

A FCM model has been developed for the supervision of the hierarchical system. A FCM has been constructed (Fig. 5) in order to aggregate the above mentioned multiple models. This FCM models the higher level of the hierarchical modelling structure (Fig. 1) and it processes as a hybrid model of the industrial process according to the current operational conditions.

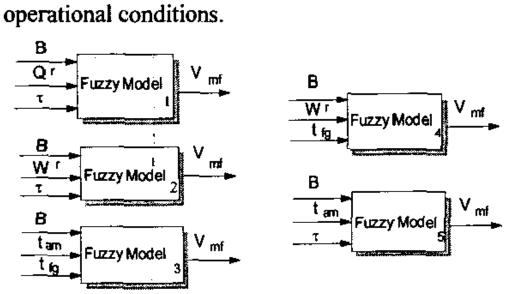

Fig. 4. The Identified Fuzzy Logic Models

Figure 5 shows the FCM that is used to describe the upper level of the hierarchical modeling structure, with the initial value of each concept and the interconnections between concepts. There are 2 kinds of concepts that stand for the main factors of the system that determine the value of the second kind of concepts, which stand for the appropriate models to be used. According to the values of concepts-factors the corresponding concepts-models are influenced with the corresponding weights. Concepts-factors 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 (5).

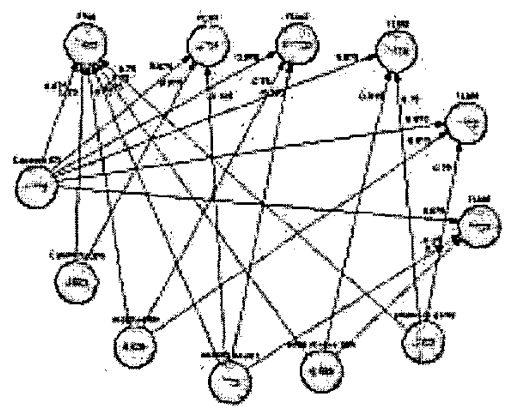

Fig. 5. The FCM model for the Supervisor

The simulation results are illustrated in Fig. 6. It is easy to notice that the FCM is driven to an equilibrium stage (convergence) after a few (five) simulation steps. The FCM suggests that the current system operation is best represented by the 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 will reach again another equilibrium region, suggesting the use of other (or the same) models.

The analysis of the obtained results has shown that the integration of FP and FL models by usage of FCM improves the accuracy of output variable prediction in average with 6÷10 percent.

The developed hierarchical soft computing methodology is able to model the plant behavior in wide ranges and to perform an on-line estimation of the directly immeasurable process variables on the basis of the available (usually scarce) on-line process information. Such modeling system is able to achieve an efficient model design for systems working in dynamical environment with high degree of uncertainty. More detailed research is further needed and is now under way, in order to solve the problems of the overall system model validity, accuracy and generalization ability.

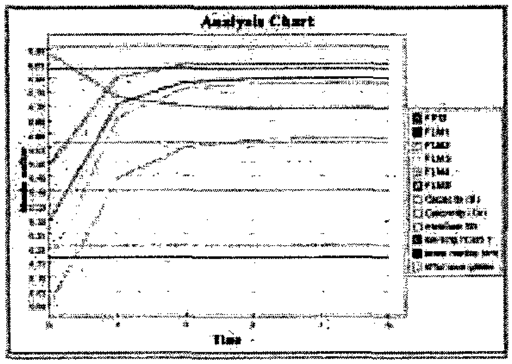

Fig. 6. The simulation procedure of the supervisor FCM

5 Conclusions

An integrated hierarchical approach for aggregating multiple models of different types (FP model and FL based models) using FCMs has been proposed and analysed in this paper. The presented hierarchical multi-model structure is considered as a promising way to improve the flexibility and accuracy of the overall plant model that can be further used for improving the real plant performance and efficiency. The proposed approach is especially efficient for complex industrial systems with immeasurable (or difficult and inefficient to measure) process variables and large uncertainties. As described in the paper, an augmented FCM on the top of the hierarchical structure serves to accomplish the total identification of the process models and is able to cope with limited uncertainty situations.

The described hierarchical structure may consist of different types of models, identification and estimation algorithms. It is able also to perform a kind of "maintenance" of the system by integrating different modeling methods in different operating conditions. The initial results of the practical application show that the proposed hybrid structure is capable of successful identification of the highly non-linear pulverising system that is further used for improving its operation efficiency.

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