Hybrid Modeling and Inference Model Based Control of Complicated Technological Plants

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Abstract: The paper presents some approaches in modeling and control of unmeasurable or hardly measurable technological plants. Hybrid modeling is described using First Principles (FP) models, Fuzzy Logic - based (FL) models and Neural Network (NN) models. Different kinds of aggregations are examined - linear combination, Hammerstein-like models, Gain Scheduling models. The results of comparative analyses of the behaviour of different models are presented, which show higher accuracy of best hybrid models with 6-10 % according to Mean Square Error (MSE). Some problems of advanced Inference Control (IC) implementation using hybrid models, are discussed. Applications of hybrid modeling as well as Inference Control of industrial plants are described - steam boiler mill-fan and dust preparation system, hot strip mill runout table cooling system modeling and control.

1. Introduction

The control of technological plants, in which basic controllable parameters cannot be measured directly, or of which measurement is expensive or/and very incorrect, is a complex problem. Typical examples are final products composition control in mass transfer apparata and chemical reactors; control of a large number of metallurgical aggregates because of the unmeasurable liquid metal temperature, composition of metal pan and slag, temperature along the cross section of thick bodies; control of aggregates in cement, glass, pulp and paper and food industries. In these cases the solution is of the type of Inference Control [1,6,9]. Model based control technologies find ever larger application in continuous technological processes [2,8,13,14,15]. To a large extent this tendency concerns cases in which Inference Control is necessary for output or intermediate controllable parameters. The twenty years development of this method has shown the dominant significance of the creation of precise enough models in order to use them for the formation of indirect feedback [14].

In plants with measurable output parameters the model-based control places moderate requirements on model accuracy, because the system corrects its behaviour at every step of the predictive control. When the controllable variables are unmeasurable, a significant model error would lead to bad control quality or instability. Indirectly measured parameters allow to partially correct the dynamic and static behaviour of the control system, but with a precision limited by the model error.

The requirements for cost- effectiveness, eco-conformity and security impose that in cases of Inference Control better solutions are also sought for. They basically aim at two directions - model precision improvement and development of new control methods. This paper treats some of these recently developed problems [2,3,4,5]. Main attention is paid to hybrid mathematical models. The combination of First Principle (FP) models with Fuzzy Logic (FL) based models as well as with Neural Network based models, is discussed.

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. Some of the model parameters need be estimated on the basis of real experimental data. Fuzzy (F) models are a particular case of "black box" models. If compared with FP models, they require reduced input space of variables. Either type 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.

The standard implementation of NN as a black-box approach could be noticeably improved if hybrid NN models incorporating a priori knowledge of the plant were used. The a priori information is based on the first principle (FP) models of the plant or its parts. Such hybrid models can be structured various ways. In [Psichogios and Ungar, 1992] the FP model is used as a non-parametric estimator of unmeasured process parameters. The standard multi-layer perception (MLP) structure is augmented by direct linear connections between the input and output layers [Haesloop and Holt, 1990]. Johansen and Foss (1992) implemented the FP models through NN with memory to present the unmodelled dynamics during the learning process. In [Su and McAvoy, 1993] NN with a Hammerstein model type structure is suggested that speeds up the learning. A rather different approach is that of applying fuzzy techniques in black-box models [Lindskog and Ljung, 1996] that will not be discussed here due to its diverse nature.

The aim of this paper is to describe some recently obtained results in inferential hybrid models design , being able to perform on-line estimation of directly unmeasurable process variables on the basis of available current indirect information from the plant.

2. First Principle / Fuzzy Logic Based Models

The main element of every hybrid model is First Principle (FP) dynamic model derived according to fundamental physical and chemical laws. FP models are well- established in various fields of engineering - process industries, metal industry, power generation, manufacturing, etc. First Principle models are usually non-linear and could describe adequately the plant behaviour in the full range of operational conditions. Unfortunately some FP model parameters are not accurate enough and should be estimated and/or adapted based on experimental data, provided by special tests. A variety of Fuzzy models could be integrated with FP models to create a hybrid model depending on:

- input variables (type and number);
- output variables (full scale or difference).

Every Fuzzy model should be preliminarily tuned using off-line optimization because of the lack of current data for continuous or periodical correction of model parameters.

2.1 Sequential Hybrid Model

An approach in which the hybridisation is carried out by a fuzzy gain scheduling procedure over a limited number of FP model parameters is presented in Figure 1. A SEL selector is used to considerably reduce the original input space **x** to a respective input space $\mathbf{x_F}$ of the Fuzzy Parameter Estimator (FPE). The tuning of the fuzzy sets parameters is carried out by a non-linear optimization procedure (OPT), which is further described into more detail. Once the model parameters have been tuned, the First Principle model is used only for an on-line estimation of the unmeasurable output variable of the plant **y**. Re-tuning is accepted to be done periodically, but on the basis of another set of inferential information.

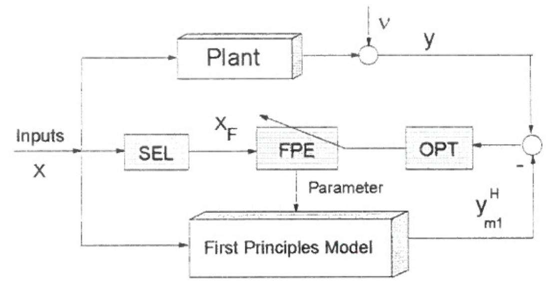


Figure 1. A Fuzzy Gain Scheduling Procedure of FP Model Parameters

The problem here is to restrict as much as possible the number of FP model parameters which will be determined currently by fuzzy gain scheduling.

2.2 Parallel Hybrid Model Using Fuzzy Input-Output Model

The structure of parallel FP model and Fuzzy Input-Output (FIO) model is presented in Figure 2. The inferentially predicted output y^H_{m2} is proposed to be a weighted linear combination of two outputs:

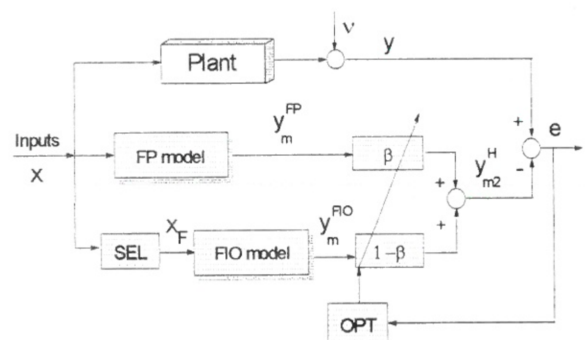


Figure 2. Parallel FP and FIO Model

$$y^H_{m2} = \beta\, y_m^{FP} + (1 - \beta)\, y_m^{FIO} \qquad (1)$$

where y^{FP}_m and y^{FIO}_m are the outputs, predicted by the First Principle model (FP) and the Fuzzy Input-Output model (FIO) respectively, and β is a weight coefficient to be optimized.

The preliminary FIO model is optimized according to the scheme depicted in Figure 3.

After FIO models and weight β are optimized by particularly considering experimental data, both FP and FIO models work on-line in parallel using the current direct measurable input information $\mathbf{x}$.

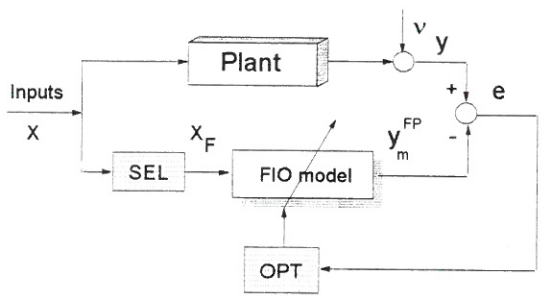


Figure 3. Optimizing Procedure for FIO Model

2.3 Parallel Hybrid Model Using Fuzzy Difference (FD) Model

The structure of this hybrid model is shown in Figure 4. In parallel there is the work gain scheduled according to Figure 1. First Principle model with Fuzzy logic based model, which output estimates the difference $\Delta \mathbf{y}_m^{FD}$ between plant output $\mathbf{y}$ and FP model output $\mathbf{y}^{FP}{}_m$:

$$\Delta y_m^{FD} = y - y_m^{FP} \qquad (2)$$

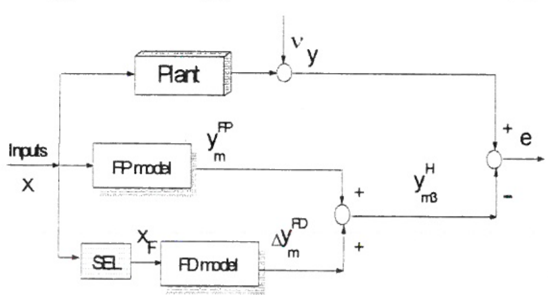


Figure 4. Hybrid FP - FD Model

The tuning of Fuzzy Difference (FD) model is presented in Figure 5. The deviation ε between the plant - FP model mismatch $\mathbf{e}$ and the FD model output $\Delta \mathbf{y}_m^{FD}$

$$\varepsilon = e - \Delta y_m^{FD} \qquad (3)$$

is the driving force for optimizing the OPT procedure, to be discussed in the next Section.

After the off-line FD model tuning based on particular experimental data, the predicted output of hybrid First Principle - Fuzzy Difference model (FPFD) $\mathbf{y}^H{}_{m3}$ is calculated as:

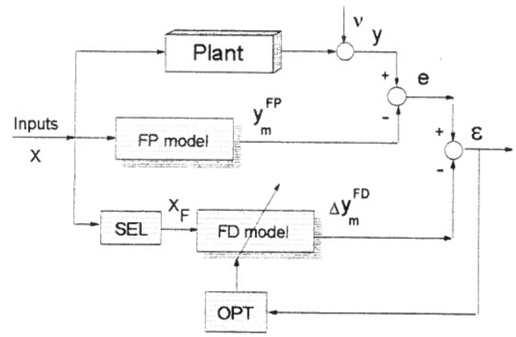


Figure 5. Tuning of Fuzzy Difference (FD) Model

$$\mathbf{y}^H{}_{m3} = \mathbf{y}_m^{FP} + \Delta \mathbf{y}_m^{FD} \qquad (4)$$

The SEL selector has the same function as in Figure 2: to reduce the input space of the FD model.

2.4 Multiple Fuzzy Models Approach

A set of FIO or FD models is proposed for being used in forming the hybrid models described above. As shown in Figure 6 below, a Rule Based Selector (RBS) is incorporated into the scheme which switches on the most appropriate FIO/FD model.

Each of the FIO/FD models possesses its own input subspace $\mathbf{x}_F$ and is tuned according to Figure 3 and Figure 5 in order to become

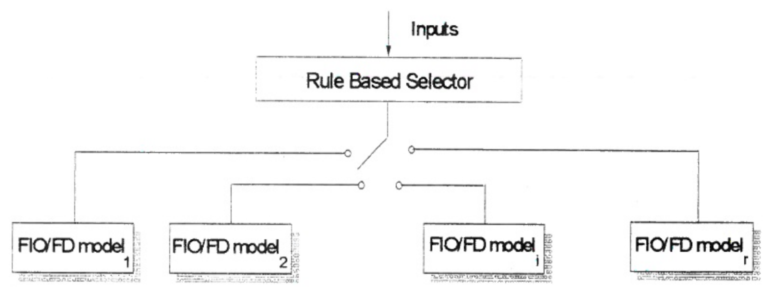


Figure 6. Multiple Fuzzy Models Approach

optimal for corresponding operation conditions. Provision of enough data for the multiple fuzzy model tuning gets a serious problem when the number of special experiments must be restricted.

3. Neural Network Based Modeling of Parameter Dependent Plants

Here a parameter kind of technological plants is under consideration - plants with models depending on internal or external variables. The basic structures for parameter dependent plants modeling are presented in Figure 7, where

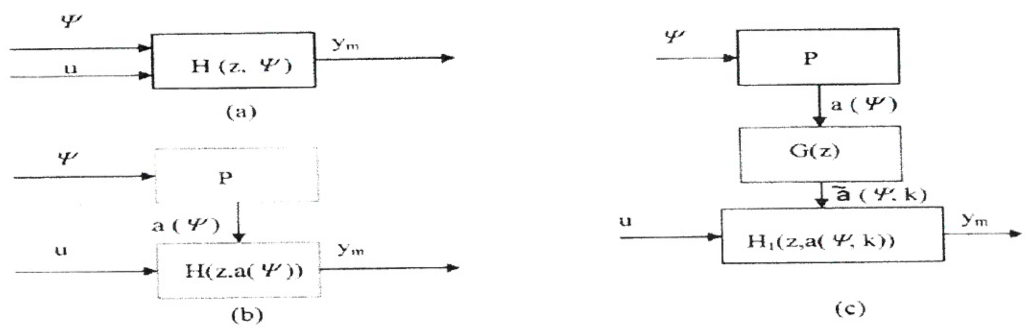


Figure 7. Parameter Dependent Plant Structures: (a) Compact, (b) Gain - Scheduled, (c) GS with Relax

a) Compact model where both control variable u and parametric disturbance Ψ are simply considered as two inputs and are treated identically in the estimation procedure;

b) Gain-scheduled model with static parameter forming part ***P***, and dynamic linear or non -linear signal part ***H***.

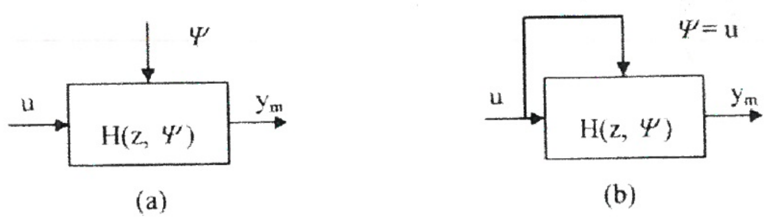


Figure 8. Parametric disturbance characteristics: (a) independent, (b) dependent

c) Gain-scheduled model with parameter relaxing, where model parameters $a_i(\Psi)$, i=1, n and $b_i(\Psi)$, i=0, m are prefiltered via the linear time-invariant block ***G***.

The specific role of parametric disturbance is described in Figure 8, where in corresponding schemes

a) Ψ is an independent parametric disturbance,

b) $u(k) = \Psi$ is at once a control variable and a parametric disturbance.

This contribution takes into account different cases in Figure 7 and Figure 8 in which functional transformations are realised by NNs.

NN Based Modeling of Parameter Dependent Plants

Artificial NNs, mostly with feedforward structure with backpropagation (BP) and recursive NNs, are widely used in non-linear system modeling and identification [Haesloop and Holt, 1990; Su and McAvoy, 1991; Junge and Unbehauen, 1996]. Here the first type of structure has been chosen in the case of static or quasi-static parametric disturbance ($\Psi \approx \Psi_0$) or NN with outer feedback, that could be presented as an extension of the standard MLP-type NN [Su and McAvoy, 1991].

Of course, the two plant inputs u and Ψ have to be sufficiently rich to excite the dynamic properties of the non-linear plant. This can be achieved by generating and putting additive signals during on-line learning, and by keeping the amplitude of these signals within the process limits.

Data Acquisition and NN Structure

Two basic situations could be seen in parametric dependent plants:

The parametric dependence is (or can be) maintained at a constant stepwise changed value $\Psi = \Psi_i$. Model identification for every Ψ_i could be done and further multi-model parameter approximation was possible. In this approach only the "frozen" parameter dependent model could be obtained. If using the received model in operation conditions with fast changes of the parametric disturbance Ψ, the predicted output value y_m will mark significant error [Hadjiski, 1979].

state information under many different operation conditions. This could be an important source for the estimation of static plant characteristics, but for global identification specially dynamic data are recommended. However, in most of non-linear dynamic identification approaches, the abundance of easily accessible steady state data is not considered. Under real conditions a plant can be mildly perturbed from normal operation conditions. Given the above discussed difficulties, a separate procedure of identification of static and dynamic parts of the plant model has been found suitable [Su and McAvoy,1993].

In a Hammerstein model a static non-linear operator φ is placed in series with a dynamic linear operator W (Figure 10a). The following equations can be written:

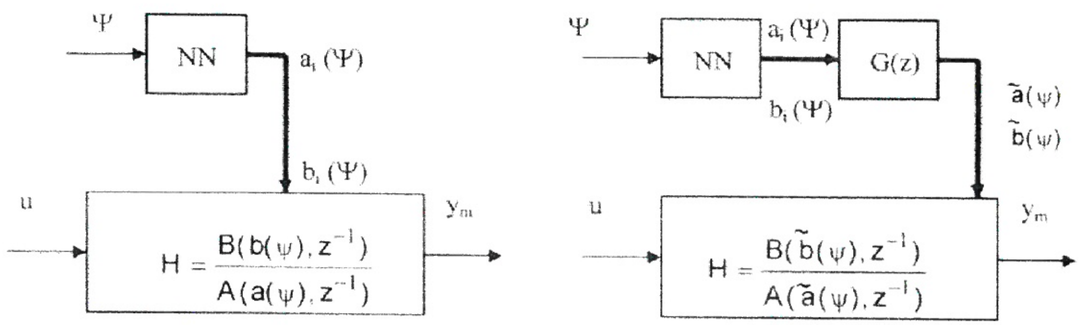


Figure 9. Gain-Scheduled NN-Based Models:

(a) with Static NN, (b) with Static NN and Linear Relaxing Filter G(z)

This type of data is suitable for NN learning in the gain-scheduled models presented in Figure 9. A static NN approximates the dependency between plant parameters $a_i(\Psi)$, $b_i(\Psi)$ and the "frozen" parametric disturbance Ψ (Figure 9a). Control variable u is transformed via input - output or state space linear or non-linear dynamic operator $\boldsymbol{H}$.

Figure 9 presents an additional linear transformation of NN output parameters $a_i(\Psi)$, $b_i(\Psi)$ in order to model a really existing "relaxing period" of plant parameter changing. Linear time invariant filter $\boldsymbol{G(z)}$ will be identified by an additional procedure.

4. Hammerstein like Models

Advanced SCADA and a distributed control system usually store a lot of amount of steady

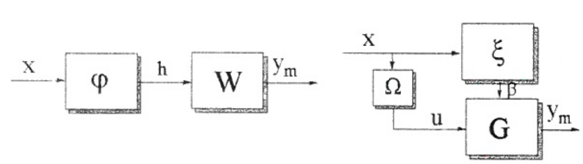
$$h(k) = \varphi(x(k)) \tag{5}$$

$$y(k) = W'(y(k-1),\dots,y(k-n),h(k-1),\dots,h(k-m)) \tag{6'}$$

or

$$y(k) = W''(y_m(k-1),\dots,y_m(k-n),h(k-1),\dots,h(k-m)) \tag{6''}$$

where y, y_m are plant and model outputs.



a b

Figure 10. Hammerstein type Models

a) with Linear Time Invariant Operator W
b) with Parameter Dependent Operator G

Narendra and Parthasarathy (1990) pointed out that a NN could be used as a non-linear operator in Eq(5). Su and McAvoy (1993) proposed a procedure for training φ-operator on the basis of steady state data. The linear operator is usually represented by a discrete dynamic transfer function or an ARMA time invariant model.

For the more complicated case in which operator W is linear but parameter dependent, a model structure of Hammerstein type has been proposed by Hadjiski and Kalaykov (1997)(Figure 10b). The following equations can be written:

$$\beta(k) = \xi(x(k)) \quad \quad (7)$$
$$x_1(k) = \Omega x(k)$$

$$\hat{y}_m(k) = G'(y(k-1),\ldots,y(k-n);u(k-1),\ldots,u(k-m);\beta(k)) \quad (8')$$

or

$$\hat{y}_m(k) = G''(y_m(k-1),\ldots,y_m(k-n);u(k-1),\ldots,u(k-m);\beta(k)) \quad (8'')$$

where

$\beta(k)$ - varying parameter of dynamic operator G', G''

$\Omega(\bullet)$ - selecting vector $\Omega = (1,0,0,\ldots,0)$

$u = x_1$ - control action

For example, dynamic operator G could have the next form:

$$G(z,\beta) = C(x(k)).\frac{\sum_{i=0}^{m} b_i(x(k))\, z^{-i}}{\sum_{i=0}^{n} a_i(x(k))\, z^{-i}}.z^{-d(x(k))} \quad (9)$$

Simulation experiments in [Hadjiski and Kalaykov, 1997] have proved that the structure in Figure 10b separates the static non-linear operator from the dynamic operator, and the training of a Hammerstein-like model is much faster than the training of a fully non-linear neural network dynamic model of parameter dependent plants.

Static operator φ (Figure 10a) and ξ (Figure 10b) could be derived by using several techniques:

- First Principle (FP) models
- Regressions
- Neural Networks
- Fuzzy Logic based models

The Decision will depend on many factors:

- degree of understanding of internal plant mechanisms (chemical, physical)
- complexity
- ability, quantity and quality of measurements
- availability of expert knowledge about the plant
- level of uncertainty

The main idea underlying the approach is the use of a hybrid architecture for Hammerstein type model , taking into account the above mentioned factors as well as the following control system synthesis.

By Hammerstein like models the gain-scheduled control strategy could be generalized and placed within a more rigorous identification and control framework.

5. Applications

5.1 Steam Boiler Pulverizing System Modeling

Due to strong requirements for stability, efficiency and fast reaction of the boiler, pulverizing is a crucial process for steam generators firing low-rank lignites. A simplified scheme of the pulverizing control system is represented in Figure 11.

Raw coal from *bunker 1* through *proportioner 2* falls via *shaft 3* into the *fan mill 4* together with furnace gases supplied for coal drying. Coal dust after *separator 5* is directed to *burner 6* as an air-gas-fuel mixture. The output variable of the pulverizing system (PS) is AGFM temperature θ_{am}.

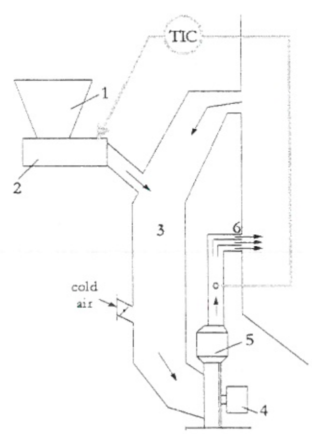


Figure 11. Boiler Pulverizing System

The developed model of PS is given in Figure 12. It has three parts:

1. Inference preprocessing part (IPP)

2. Static neural network (SNN)

3. Linear dynamic part (LDP)

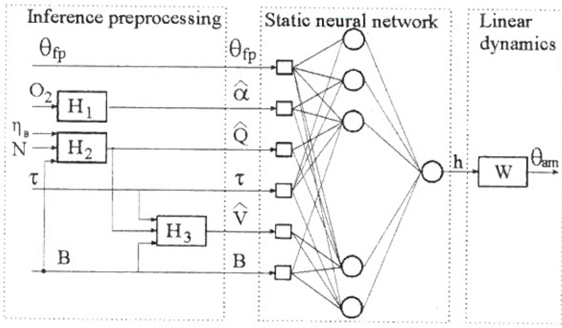


Figure 12. Pulverizing System MISO Hammerstein-type Hybrid Model

The input variables for neural network are:

- θ_{fg} - furnace outlet gas temperature
- $\hat{\alpha}_f$ - excess of air in outlet furnace gases (estimation)
- $\hat{Q}$ - caloricity of the raw coal (estimation)
- τ - working time of beater wheel after current repair
- $\hat{V}$ - total ventilation of fan mill (estimation)
- B - throughput capacity of fan mill

Inference preprocessing part (IPP) contains three IPP blocks trained to estimate the input variables for NN: $\hat{\alpha}_f, \hat{Q}$ and $\hat{V}$. H_1 is a functional block. H_2 infers $\hat{Q}$ on the basis of fan mill capacity B, boiler efficiency and block boiler-turbine power N. H_2 is realized as a non-linear dynamic filter in order to coordinate the signals B and N.

Membership functions of input and output variable fuzzy sets are presented in Figure 13.

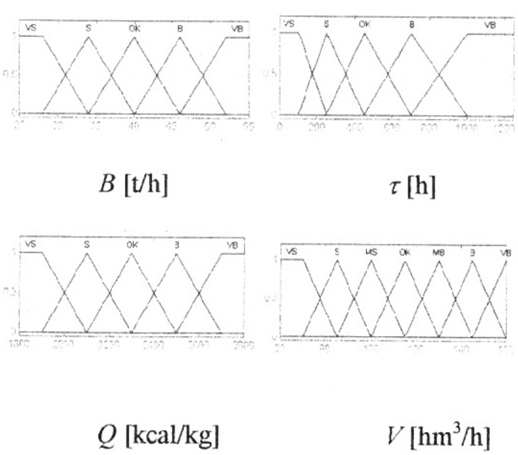


Figure 13. Input and Output Variable Membership Functions

In accordance with these membership functions $M=125$ rules have been extracted from special experimental data received by TPP "Bobov dol", Bulgaria. As NN, a Multi-layer Perceptron (MLP) is used. After reasonable data scaling a *backpropagation* learning method has been implemented. Figure 14 illustrates the neural network structure optimization with one (Figure 14a) and two hidden layers (Figure 14b).

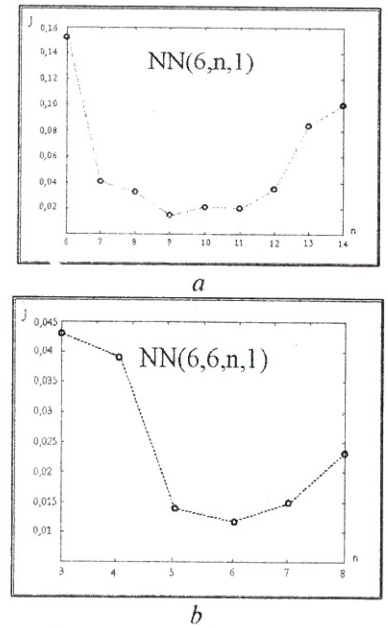


Figure 14. Neural Network Structure Optimization

a) One Hidden Layer

b) Two Hidden Layers

Simulation results show that the second hidden layer does not improve the NN accuracy. This NN, with a single hidden layer with 9 neurons, has been accepted, e.g. the MLP has the final structure (6,9,1). Simulation of the tuned neural network with testing data proves the high accuracy of the hybrid static part of the Hammerstein type model - the RSE is less than 1.5 %.

Dynamic operator W has been derived by using LSM on the input data h and output θ_{am} in the form:

$$W(p) = \frac{1}{(Tp+1)^3} \qquad (10)$$

5.2 Multimodel Based Inference Cooling Control System for Hot Strip Mill Runout Table

The process of cooling a metal strip during its movement on the runout table of a hot strip mill (HSM) is of paramount importance for the whole technological cycle of the mill, because here takes place the final forming of the microstructure of metal, that defines its mechanical and physical properties. It is very important to know at each moment of time the temperature distribution inside the strip, so that, if there are any deviations from a previously given optimal cooling curve, the necessary corrective control actions should be performed. However the technological process does not allow on-line measurements of the temperature on the runout table. Only two temperatures are measured - at the beginning (Θ_0) and at the end (Θ_k) of the table, when it is practically impossible to operate any change in the metal microstructure, therefore in its characteristics and quality. That is why a predictive model should be built, capable of finding the strip temperature distribution and, based on it, appropriate control actions should be taken, so that the error between the optimal cooling curve, used as a setpoint, and the one predicted by the model temperatures, is minimal. The type of this control is determined by the significant time delays between the control action and the temperature change. This leads to a feedforward control along the length of the runout table. At the same time, a local control system is suggested, that considers all the process constraints and disturbances, and provides feedback information about the difference between the predicted by the model and the measured coil temperatures at the end of the table. In this way a new type of hierarchical combined feedforward / feedback control system is designed, to include global determination of the temperature profile along the table's length and local cooling constrained control, based on the Quadratic Dynamic Matrix Control (QDMC) algorithm.

The diagram of the water cooling system is shown in Figure 15. The metal sheet (thickness 2-16 mm, initial temperature Θ_0 = 940° - 980 °C) exits the finishing group and enters the cooling zone. In order to reach a final temperature of 620° - 640 ° C, the cooling process is carried out by means of two types of control actions:

- Water curtains u_1, u_2, ... , u_{r-1} and u_{r+1}, divided into two groups. The water curtains of this type have only two values of the control action: u=0 - the curtain is turned off; u=1 - the curtain is working.

- A water curtain with continuous control action - u_r, placed between the two groups of curtains with two-position control.

The following technological parameters are continuously measured:

- initial temperature of metal Θ_0;
- final strip temperature Θ_k;
- metal sheet thickness h;
- sheet's speed during its movement on the runout table v;
- total cooling water flow rate G;
- cooling water flow rate in the continuous controller G_r.

Control variables are the temperatures at each point of the runout table Θ_i, i=1÷g.

Basic disturbances are:

h - strip's thickness, which varies with the changing working conditions on the hot strip mill;

Θ_0 - initial temperature, which changes due to different rolling conditions and the different heat temperature in the heating furnaces;

v - speed of movement, that changes at the end of each sheet to compensate the metal cooling by the atmosphere;

G - the cooling water flow rate, that changes significantly depending on the pressure in the feeding pipes. Nominal parameters of the model are valid for nominal values of the volume of cooling water in the curtains with two-position control.

Having in mind the gradual importance of precision in the temperature profile's adequacy along the sheet's length, the following weighted integral-quadratic criterion is proposed:

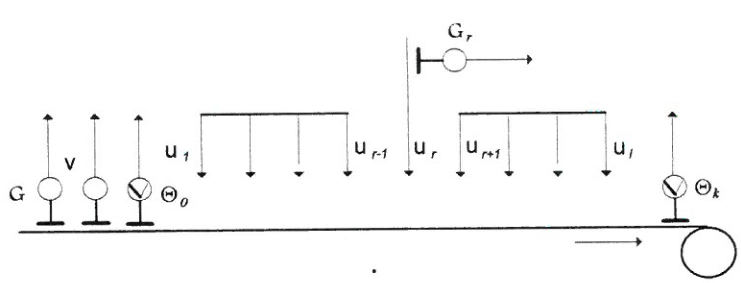


Figure 15. Water Cooling System on the Runout Table

$$J = \sum_{1}^{g} \beta_i (\overline{\Theta}_i^0 - \overline{\hat{\Theta}}_i)^2 \rightarrow \min \qquad (11)$$

where $\overline{\Theta}_i^0$ - mean integral temperature of cross-section i, used as a setpoint; $\overline{\hat{\Theta}}_i$ - computed by the model mean integral temperature of cross-section i along the strip's length (i=1, g); g - number of cross-sections along the strip's length.

The solution of problem (11) is subject to the vector of control actions $u=(u_1,u_2,...,u_l)^T$ at each time step, l is the number of cooling water devices. This is a typical problem of non-linear programming. Given the limited time for strip movement on the runout table, the solution of the optimal problem (11) must be produced under severe time restrictions. To accelerate the calculating procedures, parallel computing might be used [Hadjiski et al, 1994].

Several types of mathematical models can be used for this process:

a) Global mathematical models, that predict the whole metal cooling process along the runout table.

b) Local mathematical models, that describe the temperature field along the strip thickness in one cooling zone, and consider metal's temperature deviation under the influence of technological disturbances - thickness, speed and initial temperature, as well as the cooling water flow rate.

Global mathematical models could be of two types:

1. Analytical - that permit a quick calculation of the temperature along the strip's length. Here the strip is referred to as a thin body with appropriate corrections. This model is appropriate for control in on-line mode.

2. Numerical - that make it possible to compute the temperature profile along the sheet's thickness, and to minutely trace how it changes during the movement along the runout table. This model is precise and detailed, but too heavy and slow in order to be used for control, because the time necessary for calculating the temperature field is longer than the physical time, which the cooling process takes place in.

Local models could also be divided into two groups:

1. Analytical - based on ordinary differential equations. Their disadvantage lies in that they cannot cope with the strong non-linearities of this process. The error, especially within the temperature interval 700° - 800 °C, is enormous. That is why they are not useful here.

2. Numerical - based on partial differential equations, they predict the temperature distribution correctly and cope with all non-linearities and disturbances.

Thus two types of mathematical models remain to be used for control - global analytical models and local numerical models. Both of them are based on the nonlinear transient heat transfer equation :

$$c(\Theta)\rho(\Theta)\frac{\partial\Theta}{\partial\tau} = \frac{\partial}{\partial x}[\lambda(\Theta)\frac{\partial\Theta}{\partial x}] \qquad (12)$$

and the following initial and boundary conditions:

$$\Theta(0,x)=\Theta_0(0,x) \qquad (13)$$

$$-\lambda(\Theta)\frac{\partial\Theta}{\partial x}=\alpha_a(\Theta_s-\Theta_{am}) \qquad (14a)$$

$$-\lambda(\Theta)\frac{\partial\Theta}{\partial x}=\alpha_w(\Theta_s-\Theta_w) \qquad (14b)$$

where α_a, α_w - coefficients of convective heat transfer with air and water [W/m^2 °C]; Θ_s - surface temperature of the strip, °C; Θ_{am} - ambient temperature of air, °C; Θ_w - temperature of water, °C; x - space coordinate; x = y for the global analytical model - it computes temperatures along the strip's length. x = z for local numerical models, because they determine the temperature field along the sheet thickness. One dimensional heat transfer is concerned, because the heat fluxes along the strip length and width are insignificant, compared to the one along its thickness. Heat losses from heat transfer to the rolls are taken into consideration by the heat transfer coefficients. The metal thermophysical properties - thermal conductivity λ, specific heat capacity c and density ρ - are non-linear functions of temperature. The dependencies for the heat transfer coefficients have been determined for several cases – air cooling and water cooling.

Global analytical model

The analytical mathematical model considers metal sheet as a thin body [Hadjiski et al,1996]. In this way a fast cooling process model is developed, capable of determining the temperature distribution along the table length and specifically on its end for a very short time. It is developed by considering two assumptions - that the temperature field along the strip thickness is homogeneous and that it moves with a constant speed. Here the model with larger dimension is approximated by a model with lower dimension, but the precision of calculated temperatures is maintained. With the help of this model the differences between the predicted and set point temperatures are quickly determined and a correction control action is performed in time.

$$\overline{B} = \widetilde{B} + B_v + B_h + B_G \quad (19)$$

L_v, A_v, B_v - matrices, counting the effect of change in strip speed;

L_h, A_h, B_h - matrices, counting the effect of change in strip thickness;

L_G, A_G, B_G - matrices, counting the effect of deviation in the cooling water flow rate.

The interaction between different models - the global and the local ones - is shown in Figure 16. The global model computes the temperature distribution along the table's length. It also determines the optimal heat transfer coefficients α_i for each water curtain. The procedure for model parameter adaptation is described in Hadjiski et al (1996). The so computed temperature is made available to local models as surface temperature Θ_s and together with α_i forms their boundary conditions. Local models work in the following way: the boundary conditions for each of them come from the global model. Initial conditions are given only to the first of them and according to Eq (8) it finds the temperature distribution in metal at each time step in the first cooling zone. The temperature field at the end of the first cooling zone serves as initial conditions for the second one, etc. A sequential computational scheme is followed.

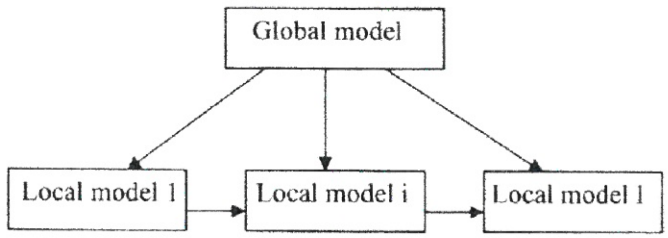


Figure 16. Interaction Between Global and Local Models

Local numerical model

The partial differential equation of heat transfer (12) with the mentioned initial and boundary conditions is solved by means of the finite difference method, using an implicit scheme. Following Hadjiski et al (1996), the solution of the heat transfer model without disturbances ($v = const$, $G = const$, $h = const$) can be expressed by the following matrix equation:

$$\widetilde{L}x(k+1) = \widetilde{A}x(u) + \widetilde{B}u(k) \quad (15)$$

When there are deviations from the nominal cooling conditions caused by some external actions such as change in speed v, thickness h, cooling water flow rate G, the mathematical model (15) is no more adequate. It is necessary to complete it with the external disturbances δv, δh, δG.

In general, the mathematical model of the cooling process can be presented in the state space as follows:

$$\overline{L}x(k+1) = \overline{A}x(k) + \overline{B}u(k) \quad (16)$$

where the corresponding matrices are:

$$\overline{L} = \widetilde{L} + L_v + L_h + L_G \quad (17)$$

$$\overline{A} = \widetilde{A} + A_v + A_h + A_G \quad (18)$$

The scheme is based on continuous running of a mathematical model of the metal strip cooling process, which calculates the criterion (11) for different combinations of control actions. The general cooling control problem is divided into two hierarchical subproblems:

- global control, which gives positions (on/off) of the position control actions;
- local control, which determines the continuous control action u_r.

The whole control system sticks to the idea of a continuous estimation of the local and global models' parameters. The proposed scheme combines the principles of adaptive parameter estimation and of guaranteeing the control system robustness.

The global control problem is solved by an off-line minimization procedure (Eq (11)). Here the optimal reference cooling curve is determined by technological demands on the cooling process, and is previously known for each quality of steel. The difference between this temperature curve and the computed by the global model one is smoothed through the solution of an optimization problem, that finds the best combination of control actions, thereby the desired performance of the control system is attained.

The local feedback system is based on the Predictive Model Based Constrained Control Scheme.

6. Conclusions

Hybrid models allow to gather basic knowledge by means of First Principle models, expert knowledge through Fuzzy Logic models, peculiarities from models' history by means of Neural Networks, as well as results from linear identification procedures. This improves the precision of modeling , which is particularly important for inference control.

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