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by

R. Hampel, W. Kästner, N. Chaker, B. Vandreier

Institute of Process Technique, Process Automation and Measuring Technique
HTWS Zittau/Görlitz (FH)
Department Measurement Techniques and Processautomation
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R. Hampel, W. Kästner, N. Chaker, B. Vandreier

Institute of Process Technique, Process Automation and Measuring Technique, (IPM)
Department Measuring Technique / Process Automation
at the University for Applied Sciences Zittau / Görlitz (FH), (HTWS)
D - 02763 Zittau, Theodor-Körner-Allee 16
Tel: + 49-(0)3583-61-1383, Fax: + 49-(0)3583-61-1288
E-mail: hampel@novell1.ipm.htw-zittau.de

Abstract

The safe operation of nuclear power plants requires the application of modern and intelligent methods of signal processing for the normal operation as well as for the management of accident conditions. Such modern and intelligent methods are model-based and knowledge-based ones being founded on analytical knowledge (mathematical models) as well as experiences (fuzzy information). In addition to the existing hardware redundancies analytical redundancies will be established with the help of these modern methods. These analytical redundancies support the operating staff during the decision-making.

The design of a hybrid model-based and knowledge-based measuring method will be demonstrated by the example of a fuzzy-supported observer. Within the fuzzy-supported observer a classical linear observer is connected with a fuzzy-supported adaptation of the model matrices of the observer model.

This application is realized for the estimation of the non-measurable variables as steam content and mixture level within pressure vessels with water-steam mixture during accidental depressurizations. For this example the existing non-linearities will be classified and the verification of the model will be explained. The advantages of the hybrid method in comparison to the classical model-based measuring methods will be demonstrated by the results of estimation.

The consideration of the parameters which have an important influence on the non-linearities requires the inclusion of high-dimensional structures of fuzzy logic within the model-based measuring methods. Therefore methods will be presented which allow the conversion of these high-dimensional structures to two-dimensional structures of fuzzy logic. As an efficient solution of this problem a method based on cascaded fuzzy controllers will be presented.

1. Application of analytical redundancies

1.1 Introduction

The safe operation of nuclear power plants requires the application of analytical redundancies in addition to the existing hardware redundancies for the normal operation as well as for the management of accident conditions. Analytical redundancies will be established with the help of modern and intelligent methods of signal processing. This modern and intelligent methods will be used for the support of the operating staff during the decision-making.
The spectrum of application of analytical redundancies includes:
- the monitoring of the process state (estimation of non-measurable state variables)
- the diagnosis of the plant operational function (failure detection)
- the control (application as controller)
- the limitation (application within a limitation system).

The knowledge basis is given by:
- knowledge (generated by experiments),
- analytical knowledge and simulation results,
- experiences.

The monitoring of the process state (estimation of non-measurable variables) with the help of model-based and knowledge-based measuring methods will be emphasized in the paper.

1.2 Conventional model-based measuring methods as analytical redundancy

Most applications of analytical redundancies were realized with the help of conventional Model-based Measuring Methods (MMM) like observer or Kalman Estimator.

The Model-based Measuring Method uses measured input and output variables of the process. It consists of the mathematical model of the process and the feedback of the error between the measured and calculated output variable beyond a correction matrix. The estimated and real output variables approach by an appropriate dimensioning of this matrix (Figure 1).

The quality of the estimated state variables depends on the quality of the state space model. The classification of MMM is depending on the mathematical model which is used (linear model, and non-linear model).

![Figure 1: Structure of a linear Model-based Measuring Method (Observer)](image)

<table>
<thead>
<tr>
<th>Variables of Process</th>
<th>Variables of MMM</th>
</tr>
</thead>
<tbody>
<tr>
<td>( u(t) ) - input variables</td>
<td>( \hat{q}(t) ) - estimated state variables</td>
</tr>
<tr>
<td>( x(t) ) - output variables</td>
<td>( \hat{x}(t) ) - estimated output variables</td>
</tr>
</tbody>
</table>
The design methods of linear MMM like Luenberger Observer are well known and are characterized by general validity and simple design algorithms. The disadvantage of the linear MMM are the limited range of validity (exact estimation around the operating point only). An improvement of the quality of estimation can be realized by non-linear MMM based on non-linear model statements. Non-linear observers require special design algorithms (without general validity) and were often applied for special processes only.

For the description of non-linearities a new type of MMM was developed using also algorithms of fuzzy logic.

1.3 Fuzzy-supported Observer

The developed idea of the application of fuzzy logic in connection with model-based measurement methods is the following:

Combination of a linear model-based measurement method (using the advantages of simple design, global ranges of stability and observability) with a fuzzy adaptation in order to expand the range of validity of the linear model statement.

The developed method was realized in form of a fuzzy-supported observer consisting of a linear observer and a fuzzy-supported adaptation of the matrices of the state space model. The observer as well as the fuzzy adaptation is feeded by the input and output variables of the process (Figure 2).

The fuzzy-supported observer was developed with the help of the simulation tool DynStar with Fuzzy Shell which allows the simulation of MMM as well as fuzzy algorithms.

![Figure 2: Structure of the fuzzy-supported observer](image)
2. **Determination of non-measurable variables in pressure vessels**

2.1 **Description of the process**

The application of MMM was realized for the estimation of the non-measurable variable mixture level. The mixture level is a safety-related variable for pressure vessels with water-steam mixture like pressurizer, steam generator and reactor pressure vessels. The monitoring of the mixture level is very important during accidental conditions (depressurizations as a result of a leak). The Figure 3 shows the different levels within a pressure vessel.

The following levels within the pressure vessel can be classified:

- \( h_c \) - collapsed level of the pressure vessel
- \( h_{c_{bf}} \) - collapsed level between the fittings of the narrow range measuring system
- \( h_{c_i} \) - collapsed level indicated by the measuring system
- \( h_m \) - mixture level of the pressure vessel
- \( h_{c_{lf}} \) - collapsed level below the lower fitting

(characterizes the steam content in the volume below the lower fitting)

![Figure 3: Pressure vessel in connection with a hydrostatic level measuring system](image)

The global aim is the estimation of the non-measurable mixture level \( h_m \) during negative pressure gradients \( h_m = f \left( p, \frac{dp}{dt}, h_{c_{bf}}, h_{c_{lf}} \right) \). In the first step it was necessary to estimate
the collapsed level below the lower fitting $hc_{IF}$ which is an input variable for the calculation of the mixture level. For the realization of the estimation of the non-measurable collapsed level below the lower fitting $hc_{IF}$ the measurable process parameters
- pressure $p$ (as a result the pressure gradient $dp/dt$)
- collapsed level between the fittings of the narrow range measuring system $hc_{SF}$
are used.

2.2 Non-linearities and fuzziness of the process

If only the influence of the depressurization is considered the non-linear model statement for the description of the collapsed level below and between the fittings is characterized by the following dependences:

$$hc_{IF} = f(p, dp/dt)$$  \hspace{1cm} (1)

$$hc_{SF} = f(p, dp/dt, hc_{IF})$$  \hspace{1cm} (2)

The non-linearities of the presented process can be classified as follows:

$\Rightarrow$ **algorithmic non-linearity**
- non-linear terms of the state equations in form of products of state variables and input variables: $\mathbf{q}(t) \cdot \mathbf{u}(t) = \mathbf{hc} \cdot \frac{dp}{dt}$

$\Rightarrow$ **non-linearity depending on thermodynamic properties**
- density and enthalpy depending on pressure: $\rho(p), h(p)$

$\Rightarrow$ **non-linearity depending on process state**
- steam temperature above the saturation temperature: $T_{st} > T_{sa}$
- disturbances: feed, bleed, spray

The fuzziness of the described process can be characterized by:

$\Rightarrow$ **description of phase separation:** velocity of the steam and water phase

$\Rightarrow$ **description of heat transfer conditions:** heat transfer coefficient

2.3 Linear MMM for the estimation of the collapsed level $\Delta hc_{IF}$

For the estimation of the non-measurable state variable collapsed level below the lower fitting $hc_{IF}$ a state space model for a linear observer was developed. The model is based on a nodalization of the volume of water-steam mixture. The simpliest nodalization is the subdivision in two nodes:
- the zone below the lower fitting of the measuring system
- the zone of water-steam mixture between the fittings of the measuring system.
As a result of this simplified nodalization a state space model of second order was generated which is characterized by the following variables:

- **input variable:** pressure gradient \( \frac{dp}{dt} \)
- **state variables:**
  - deviation of collapsed level below the lower fitting of the narrow range measuring system \( \Delta h_{c_{IF}} \)
  - deviation of collapsed level between the fittings of the narrow range measuring system \( \Delta h_{c_{bF}} \)
- **output variable:** deviation of collapsed level between the fittings of the narrow range measuring system \( \Delta h_{c_{bF}} \)

The state equations are:

\[
\begin{bmatrix}
\frac{d \Delta h_{c_{IF}}}{dt} \\
\frac{d \Delta h_{c_{bF}}}{dt}
\end{bmatrix} =
\begin{bmatrix}
a_{11} & a_{12} \\
a_{21} & a_{22}
\end{bmatrix}
\begin{bmatrix}
\Delta h_{c_{IF}} \\
\Delta h_{c_{bF}}
\end{bmatrix} +
\begin{bmatrix}
b_1 \\
b_2
\end{bmatrix}
\begin{bmatrix}
dp/dt
\end{bmatrix}
\]

(3)

\[
\Delta h_{c_{bF}} = \begin{bmatrix} 0 & 1 \end{bmatrix}
\begin{bmatrix}
\Delta h_{c_{IF}} \\
\Delta h_{c_{bF}}
\end{bmatrix}
\]

(4)

**Figure 4:** Non-linear characteristic field of the matrix element \( a_{11} \) of the system matrix depending on the pressure \( p \) and the pressure gradient \( \frac{dp}{dt} \)
The model matrices are characterized by the following dependences:

- Elements $a_{11}, ..., a_{22}$ of the system matrix depending on pressure $p$ and pressure gradient $dp/dt$.
- Elements $b_1, b_2$ of the input matrix depending on pressure $p$.

Figure 4 demonstrates the influence of the pressure and the pressure gradient on the matrix element $a_{11}$ of the system matrix.

The non-linear character of the elements of the model matrices requires an adaptation of this model matrices depending on the changing of the process state. The adaptation was realized on the basis of knowledge which was generated by experiments and simulations.

3. **Generation of the knowledge basis**

For the investigations it was necessary to generate a data basis with the following aims:

- Analysis of the non-linearities which must be considered in the analytical redundancy
- Verification of the state space model
- Verification of the designed model-based measurement method
- Generation of the knowledge for the knowledge-based algorithm.

The realization was carried out with the help of test facilities as well as the simulation code ATHLET, which is a complex simulation code for thermofluid-dynamic processes.

![Diagram of process flow](image)
Blow down experiments were carried out on the pressurizer test facility of the IPM equipped with additional measuring systems. The experiments were post calculated with the help of the simulation code ATHLET. The identity between the measured experimental datas and the calculated parameters by ATHLET resulted in the conclusion that the ATHLET-data set describes the real process in the right way. In the next stage the simulation code serves as a compensation of the real process with the advantage that all parameters (measurable and non-measurable) were provided by ATHLET. So the possibility was given to verify the model as well as the Model-based Measuring Method (Figure 5).

4. **Design of the fuzzy-supported observer**

Within the developed fuzzy-supported observer each element of model matrices which must be adapted was calculated by a fuzzy controller. On the basis of the chosen example the aim is the adaptation of the elements $a_{11}$, $a_{12}$, $a_{21}$, $a_{22}$ of the system matrix $A_b$ and $b_1$, $b_2$ of the input matrix $B_b$ depending on the change of pressure and pressure gradient.

The design of the fuzzy-supported observer can be simplified if the amplification gain is designed for the complete range of parameter changing (range of changing of the elements of the matrix $A_b$). In this case the adaptation of the elements of the proportional feedback $K$ is not necessary.

The practical applications often require more than two input parameters for the fuzzy controller which resulted in high-dimensional structures of fuzzy logic. In this case a reduction of these high-dimensional structures to two-dimensional structures is advantageous.

**Fuzzy Sets**

The range of parameter changing was subdivided into representative parts. As a criterion of the choice of the partial ranges the changing rate of the pressure was used. For the above mentioned example the range of pressure was described by seven characteristic points. Each point of pressure was represented by a value of the linguistic variable (Table 1).

<table>
<thead>
<tr>
<th>Representative</th>
<th>value of the linguistic variable</th>
</tr>
</thead>
<tbody>
<tr>
<td>$p_{\lambda}^{0.6}$ MPa</td>
<td>Very Small (VS)</td>
</tr>
<tr>
<td>$p_{\lambda}^{1.0}$ MPa</td>
<td>Small (S)</td>
</tr>
<tr>
<td>$p_{\lambda}^{1.2}$ MPa</td>
<td>Medium Small (MS)</td>
</tr>
<tr>
<td>$p_{\lambda}^{1.5}$ MPa</td>
<td>Medium (M)</td>
</tr>
<tr>
<td>$p_{\lambda}^{1.6}$ MPa</td>
<td>Medium Great (MG)</td>
</tr>
<tr>
<td>$p_{\lambda}^{1.8}$ MPa</td>
<td>Great (G)</td>
</tr>
<tr>
<td>$p_{\lambda}^{2.0}$ MPa</td>
<td>Very Great (VG)</td>
</tr>
</tbody>
</table>

**Table 1:** Values of the linguistic variable pressure

In Figure 6 the distribution of the fuzzy sets characterized by triangle-type membership functions is represented for the linguistic variable pressure.
For the pressure gradient and the elements of the model matrices values of linguistic variables were defined in the same way.

![Graph showing fuzzy sets of pressure](image)

**Figure 6:** Fuzzy sets of pressure

**Rules**

The relationships between the linguistic values are described in form of IF - THEN - rules. For the matrix element $a_{11}$, the following rule can be generated:

IF 'pressure' = 'Very Small' AND 'pressure gradient' = 'Very Great Negative'

THEN 'matrix element $a_{11}$' = 'Very Great'

(5)

Table 2 presents the matrix of rules generated for the matrix element $a_{11}$ depending on the linguistic variables pressure and pressure gradient.

<table>
<thead>
<tr>
<th>dp/dt</th>
<th>VGN</th>
<th>GN</th>
<th>MGN</th>
<th>MN</th>
<th>MSN</th>
<th>SN</th>
<th>VSN</th>
</tr>
</thead>
<tbody>
<tr>
<td>P</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>VS</td>
<td>VG</td>
<td>VG</td>
<td>VG</td>
<td>VG</td>
<td>VG</td>
<td>VG</td>
<td>G</td>
</tr>
<tr>
<td>S</td>
<td>VG</td>
<td>VG</td>
<td>VG</td>
<td>VG</td>
<td>G</td>
<td>S</td>
<td>S</td>
</tr>
<tr>
<td>MS</td>
<td>VG</td>
<td>VG</td>
<td>VG</td>
<td>G</td>
<td>S</td>
<td>S</td>
<td>S</td>
</tr>
<tr>
<td>M</td>
<td>VG</td>
<td>G</td>
<td>S</td>
<td>S</td>
<td>S</td>
<td>S</td>
<td>S</td>
</tr>
<tr>
<td>MG</td>
<td>G</td>
<td>S</td>
<td>S</td>
<td>S</td>
<td>S</td>
<td>S</td>
<td>S</td>
</tr>
<tr>
<td>G</td>
<td>S</td>
<td>S</td>
<td>S</td>
<td>S</td>
<td>S</td>
<td>S</td>
<td>S</td>
</tr>
<tr>
<td>VG</td>
<td>VS</td>
<td>VS</td>
<td>VS</td>
<td>VS</td>
<td>VS</td>
<td>VS</td>
<td>VS</td>
</tr>
</tbody>
</table>

**Table 2:** Rules of the matrix element $a_{11}$ of the system matrix

In the same way the rules of the other elements of the matrices were generated. With the help of these algorithms of fuzzy logic the description of the non-linear behaviour of the matrix elements was realizable.
5. **Results of the state estimation**

The results of the state estimation were demonstrated on a blow down experiment which was realized at the pressurizer test facility at the IPM and postcalculated with the help of the ATHLET-Code. The pressure reduction was realized from 1.8 MPa to 0.9 MPa in the period \( t = 70 \ldots 250 \text{s} \).

**Input variables for the model-based and knowledge-based methods**

The Figures 7 and 8 show the response characteristics of the pressure and the pressure gradient during the experiment.

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**Figure 7:** Response characteristic of the pressure during a blow down experiment

**Figure 8:** Response characteristic of the pressure gradient during a blow down experiment
The following kinds of analytical redundancy were compared with the process:
- linearized parallel model (linear state space model)
- conventional observer (based on the linear state space model)
- fuzzy-supported observer (based on the linear model in connection with adaptation of model matrices).

**Results of state estimation of the measurable state variable**

The measurable state variable deviation of collapsed level between the fittings $\Delta h_{cb}^F$ was exactly estimated by all kinds of observers. The produced identity between the measurable output variable of the process (ATHLET) and the calculated output variable of the observer is the result of the feedback of the estimation error beyond the correction gain (Figure 9).

![Graph showing deviation of collapsed level](image)

**Figure 9:** Response characteristic of the measurable state variable $\Delta h_{cb}^F$ of Process, linear Parallel Model and the Observers (conventional Observer, fuzzy-supported Observer)

The calculated state variable of the linear parallel model is characterized by great differences during the depressurization in comparison to the process as a result of the influence of the non-linearities. A good reconstruction was realized only around the operating point of the linear model characterized by the initial pressure before the depressurization ($t \approx 70$ s).

**Results of state estimation of the non-measurable state variable**

The non-measurable state variable deviation of collapsed level below the lower fitting $\Delta h_{cq}^F$ was estimated with different quality by the different kinds of observers (Figure 10). The quality of reconstruction can be improved by the application of the conventional observer in comparison to the parallel model. As a result of the influence of the non-linearities the estimation is characterized by a non-negligible estimation error at the end of the blow down ($t \approx 250$ s).
The best estimation of the non-measurable state variable was realized by the fuzzy-supported observer.

![Graph](image)

**Figure 10:** Response characteristic of the non-measurable state variable $\Delta h_{cP}$ of Process, linear Parallel Model, conventional Observer and Fuzzy-supported Observer

The mixture level will be calculated on the basis of the estimated state variables.

6. **Cascading high-dimensional fuzzy controllers**

The implementation of fuzzy logic in Model-based Measuring Methods for the description of strong non-linear and complex processes often requires the consideration of many input variables for the fuzzy controller. Generally that leads to a multi-dimensional structure of the controller.

The amount of the individual rules increases with the number of the input variables and the corresponding linguistic values complicating a real time processing. The formulation of the rules for more than two input variables is complicated and their representation not clear. In this case, it is difficult to set up the rules from the experience knowledge about the dynamic behaviour of the system. The parameterization and optimization of the fuzzy controller is hardly possible because of the many degrees of freedom of the fuzzy controller.

A possibility of the simple implementation of the experience knowledge despite the high amount of the input variables and the real time capability is the structure optimization.

In [2] was already pointed out that a fundamental problem of the parameterization and optimization of the fuzzy controller is the amount of the individual rules.

To reduce the number of these rules it was proposed to use cascaded controller structures.
In addition, it is to prove that the associative law is valid for the basis-rule:

\[ X_1 \cap X_2 \cap X_3 = (X_1 \cap X_2) \cap X_3 \]  

(6)

With \( n \) input variables result \( n-1 \) two-dimensional fuzzy controllers and \( n-2 \) virtual linguistic variables which do not have to have an absolutely physical meaning.

The cascaded controller structure has fewer rules than a multi-dimensional controller. For example, with 3 linguistic values (Fuzzy - Sets) per input variable result 81 rules for a controller with 4 input variables, while the cascaded structure with 3 (=4-1) two-dimensional fuzzy controllers and 2 (=4-2) virtual linguistic variables contains only just 27 rules.

The equation (6) is described by the following signal flow diagrams (Figure 11).

**Figure 11:** Cascading of a 3-dimensional fuzzy controller

First, it is assumed for the further investigations that equation (6) is fulfilled if, for a given definition of the number of the sets for \( X \) and \( Y \), the linguistic values for \( Y_1 \) and \( Y_{\Pi} \) agree (Figure 11).

To carry out this proof, the following consideration must be placed before:

*For high dimensional fuzzy controllers it is expedient to define* dominating input variables \( (X_1, X_2) \)

*and*

non-dominating input variables \( (X_3) \).

*With the dominating input variables the base shape of the characteristic field is formed and with the non-dominating input variable results a deformation of the base characteristic field (Figure 12).*

\[ \begin{align*}
  a) & \quad \text{Characteristic curve from the base characteristic field (} X_2 = \text{Const.}) \\
  b), c) & \quad \text{by } X_3 \text{ caused deformation of the characteristic field}
\end{align*} \]

**Figure 12:** Examples for possible deformations of the base characteristic field
For example, the deformation in Table 3 is thereby realized that for
\( X3 = L \) a displacement in L - direction
\( X3 = H \) a displacement in H - direction
follows in the result matrix \( Y \).

One can denote such an establishment also as an adaptation rule. The adaptation rule applied for Table 3 is implemented in the cascaded structure in the FC2-matrix (Table 4). The rule matrix FC1 corresponds to the matrix in Table 3 for \( X3 = N \).

The marked errors in Table 3 of the rule matrix show which individual rules are different. With an increasing number of the input variables and fuzzy sets, the number of the mismatches increases.

By introducing a larger number of sets (5) for the virtual variable \( Y1 \), this lack can be removed. With the given rule matrix in Table 5 for the cascaded controller, the complete correspondence with the complete rule matrix in Table 3 is obtained.

For monotonous symmetrical characteristic fields it could be shown that the mismatches do not or only slightly have an effect on the numerical values for \( Y \). Further investigations are necessary for asymmetrical characteristic fields. As a result, rules should be derived for the structure optimization of multidimensional fuzzy controllers.

\[
\begin{array}{c|ccc}
Y1 & X1 &  \\
\hline
L & L & L & L \\
N & L & L & N \\
H & L & N & H \\
\hline
L & L & L & N \\
N & L & N & H \\
H & N & H & H \\
\hline
L & N & H \\
N & N & H & H \\
H & H & H & H \\
\end{array}
\]

**Table 3:** Complete rule matrix for the three-dimensional fuzzy controller FC (Figure 11)

\[
\begin{array}{c|ccc}
Y1 & X1 &  \\
\hline
L & L & L & N \\
N & L & N & H \\
H & N & H & H \\
\hline
L & L & L & N \\
N & L & N & H \\
H & H & H & H \\
\end{array}
\]

**Table 4:** Complete rule matrix for the cascaded fuzzy controller (FC1 and FC2 in Figure 11)
<table>
<thead>
<tr>
<th>$Y_1$</th>
<th>$X_1$</th>
</tr>
</thead>
<tbody>
<tr>
<td>L</td>
<td>N</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>$X_2$</th>
<th>$Y_1$</th>
</tr>
</thead>
<tbody>
<tr>
<td>N</td>
<td>L</td>
</tr>
<tr>
<td>H</td>
<td>N</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>$Y_{II}$</th>
<th>$X_3$</th>
</tr>
</thead>
<tbody>
<tr>
<td>VL</td>
<td>L</td>
</tr>
<tr>
<td>L</td>
<td>L</td>
</tr>
<tr>
<td>N</td>
<td>L</td>
</tr>
<tr>
<td>H</td>
<td>N</td>
</tr>
</tbody>
</table>

a) FC1

Table 5: Rule matrix for the 3-dimensional cascaded fuzzy controller with 5 sets for $Y_i$

- very low
- low
- normal
- high
- very high

7. Conclusions

The monitoring and diagnosis of the actual process state especially in the case of arising accidental conditions as well as during accidents require the application of intelligent methods and high performance algorithms of signal processing (e.g. Model-based Measuring Methods).

The advantages of such methods of signal processing are:
- more information about the actual process state,
- realizable in existing control systems,
- real time application.

The determination of non-measurable process parameters is realizable by the application of Model-based Measuring Methods (MMM). The combination of conventional MMM with knowledge-based algorithms (fuzzy logic) improves the quality of the state estimation.

The advantages of such hybrid methods are:
- description of complex multi-variable systems,
- description of complex non-linearities,
- description of the fuzziness of systems.

The generation of the knowledge requires specific investigations of the process (experiences, experiments, complex simulations).

A fundamental problem of parameterization and optimization of fuzzy controllers is the high number of the rules. To reduce the number of these rules, a controller structure was proposed. As the associative law is valid for monotonous symmetrical characteristic fields, the multi-dimensional fuzzy controller structure can be transformed in a cascaded one. The dominating input variables determine the base shape of the characteristic field, while the non-dominating input variables generate the necessary deformation of the base characteristic field.

References
