The evaluation of disturbed control systems by means of fuzzy supervision

Ralf Mikut, Georg Bretthauer
Forschungszentrum Karlsruhe GmbH, Institute of Applied Informatics (IAI),
P.O. Box 3640, D-76021 Karlsruhe, Germany
Phone: ++49-7247-82-5731, Fax: ++49-7247-82-5785, E-Mail: mikut@iai.fzk.de

ABSTRACT: A new data-based approach to supervise the stability of complex control systems is given. It integrates elements of human operator's multi-level strategy and classical control strategies to process stabilization. The method uses a qualitative stability definition based on the technological tolerability of process states. A model is not strongly required but improves the supervision quality. Here, different types of models including fuzzy models with and without defuzzification, Artificial Neural Nets, mathematical models and multi-model approaches with fuzzy degrees of plausibility are considered. The main focus is concentrated on the behaviour under real process conditions characterized by disturbances and changed reference values. As a result, a fuzzy-based supervisor classifies on-line the stability by means of a fuzzy degree of stability between zero and one.

KEYWORDS: fuzzy control, stability, supervision, adaptation, Fuzzy Lyapunov function

1 INTRODUCTION

In the last few years, fuzzy controllers became an accepted approach for many industrial control problems. They provide a sufficient control performance also in case of some nonlinear and time-variant processes. A main motivation to use fuzzy control is a simplified intuitive design and a reduction of modelling and analysing effort of the process and the resulting control loop. However, fuzzy controllers are characterized by a nonlinear behaviour and the resulting behaviour of the control loop is difficult to analyse. Small design errors can cause significant trouble in practical use up to safety problems.

In classical control theory, a stability analysis is normally performed in order to guarantee the normal operation behaviour. For it, the process and the controller are mathematically described. Then, a stability test allows a crisp decision "stable" or "unstable". This decision can be obtained by means of algebraic and geometrical criterions. For their sophisticated theoretical level they are not in common use. A successful proof guarantees only certain requirements for the performance of the control loop, e.g. bounded outputs in case of bounded inputs (BIBO stability) or a region of attraction nearby an equilibrium point or a trajectory (Lyapunov stability), see e.g. Krstič et al. (1995).

At the moment, different positions for handling these stability problems in fuzzy systems exist (Bretthauer et al., 1994):

1. The stability problems will be ignored. A practical or simulative test shows if in the tested situations stability problems occur.
2. The fuzzy controller and the process will be mathematically described. The resulting control loop will be analysed by use of slightly modified methods of the nonlinear control theory as Lyapunov theory, Harmonic Balance, Hyperstability theory. The papers of Opitz (1993), Bretthauer et al. (1994), Titli et al. (1994) and Strietzel (1996) resume known approaches for this way. In addition, some modifications are introduced to tune these methods to typical structures of fuzzy controllers, see e.g. Böhm (1994), Jäkel (1999), Kiendl et al. (1995), Rüger (1994), Schäfers et al. (1997), Tanaka et al. (1992) and Wang (1993).

Unfortunately, the theoretical stability decision of the latter case differs substantially from the decision of a human operator if the system is "stable" or not. The human operator often uses compromises between complete stability and complete instability. The stability decision depends crucially on the technological state of the process and it includes all known information (measured values, reference values). Model knowledge about a process enables the estimation of reasons for an unsatisfactory behaviour, e.g. caused by external disturbances or a wrong control strategy. The flexibility of the human operator bases on changes of control strategies if non-tolerable system behaviour is detected and on special strategies to stabilize the process after unexpected errors. Some principles of this multi-level strategy including different types of cognitive tasks can be found in Rasmussen (1983). Skill-based and unconscious actions dominate on the base level of operation. In higher levels, rule-based schemes use saved knowledge about previously successful actions. On top, knowledge-based strategies search for acceptable ways in unknown or dangerous situations.

Fuzzy logic promises to implement human strategies. The state-of-the-art is less impressive - only the skill-based and some simplified rule-base strategies of the operator are implemented in technical systems. Actually, the most rule-based actions of fuzzy controllers map only the skill-based human behaviour. More sophisticated control strategies to detect and handle dangerous situations are normally not part of fuzzy systems.

Some differences between human and theoretical stability interpretation will be explained by means of an example. The control task is to drive a car in the middle of the track. Deviations of some millimetres are not critical also in case of small oscillations about the optimal trajectory. If the controller causes these deviations in the undisturbed case (e.g. by discretizations of the actuating values), a classical stability analysis detects instability. In contrast to it, bounded deviations of some meters are critical for the car but stable in the sense of the BIBO (bounded input bounded output) stability. To overcome these contradictions, modified stability definitions and criterions for fuzzy systems were proposed in Bandemer et al. (1997), Mikut et al. (1995, 1996 a, 1997 and 1999) and Marin et al. (1997).

The following concept integrates different approaches: the principal strategy of the human operator for a rule-base on-line supervision and adaptation of the system and mathematical methods of the classical control theory. The main purpose is to design a supervision concept applicable for practical conditions including model uncertainties, disturbances and changing operating points (Mikut et al. 1995, 1997 and 1999). The aims of this paper are

- to derive a concept for the on-line stability supervision of complex systems on the base of so-called Fuzzy-Lyapunov functions,
- to describe its characteristics to define a tolerable system behaviour and
- to outline practical implementations.

2 CONCEPT OF FUZZY SUPERVISION

2.1 FUZZY LYAPUNOV FUNCTIONS

The main problem for an on-line supervision is the statement whether an actual situation is tolerable or not. The human operator includes in this decision information about

- the control aims (reference values),
- the actual situation (all measured values including derived values as time derivatives, filtered values) and
- the expected system behaviour as reaction to the actions of the operator.

The control aims and the actual situation include only measured or known data. The expected behaviour refers to a process model. This model is normally very roughly known and gives only qualitative information about the process.

As a base of the supervision, the main idea of classical Lyapunov functions $L(\underline{x})$ is chosen. Here, $\underline{x}$ notes the states of the system. A Lyapunov function of a system guarantees asymptotic stability of the equilibrium point $\underline{x} = \underline{0}$, if the function L fulfils the following conditions:

- The first partial derivatives with respect to $\underline{x}$ are continuously.
- The function L has only in the equilibrium point the value of zero and positive values else:

$$L(\underline{x}(t)) \begin{cases} = 0 & \text{if} \quad \underline{x}(t) = \underline{0} \\ > 0 & \text{if} \quad \underline{x}(t) \neq \underline{0}. \end{cases} \tag{1}$$

- The first derivative with respect to t has negative values outside the equilibrium point in the whole investigation zone $\mathscr{H}$

$$\dot{L}(\underline{x}(t)) \begin{cases} < 0 \text{ if } \underline{x} \in \mathscr{H}; \underline{x}(t) \neq \underline{0} \\ = 0 \text{ if } \underline{x}(t) = \underline{0}. \end{cases} \tag{2}$$

This mathematical description L allows a linguistic interpretation as a fitness function (evaluation function). This fitness function maps deviations of the desired reference state into a scalar value. As a consequence, it is the first step for an on-line supervision to decide if a process situation is tolerable or not.
The formulas can be interpreted as rules:

IF Value of L is zero THEN System is stable
IF Time derivative of L is negative THEN System is stable.

For the practical use, different problems occurs:

1. The complete state vector is often not available on-line. An observer structure to estimate the state vector would increase unacceptably the design effort of the control structure.
2. Disturbances and changes of the reference value $\underline{w}$ lead to an increasing value of L. As a consequence, the system seems to be unstable.
3. As discussed above, the human operator includes additional information and does not conclude on the base of one function and its time derivative. In contrast, operators use qualitative descriptions and trends of process values for its decision.

The first problem will be solved by the exclusive use of output values $\underline{y}$ of the process.

The human operator handles the process also from the available measured data. In addition, different modified output values can be added as further outputs (e.g. time derivatives of process values). From the control theory point of view, the observability of the process is necessary where all effects in the states can be reconstructed from known output values. In the following, only time-discrete values will be used according to the requirements of a practical realization in the control system.
Now, the supervision bases on a so-called evaluation function

$$L_k = \underline{e}_k^T \cdot \mathbf{P} \cdot \underline{e}_k = (\underline{w}_k - \underline{y}_k)^T \cdot \mathbf{P} \cdot (\underline{w}_k - \underline{y}_k), \quad \underline{e}_k - \text{control error} . \tag{3}$$

It is similar to a Lyapunov function and it fulfils a condition similar to Eq. (1), if **P** is a positive definite matrix. The stability decision for an observable system changes to

$$L_{k+1} \begin{cases} < L_k & \text{für } L_k > 0 \\ = L_k & \text{für } L_k = 0 \end{cases} \quad \text{with} \quad L_k(\underline{y}_k, \underline{w}_k) \begin{cases} = \underline{0} & \text{für } \underline{y}_k = \underline{w}_k \\ > \underline{0} & \text{für } \underline{y}_k \neq \underline{w}_k \end{cases} . \tag{4}$$

The evaluation function codes a so-called tolerable behaviour: All output values will be classified as stable if they cause a decreasing value of Eq. (3) in the undisturbed case with constant reference value. The evaluation function reduces the vector-valued information of the original or extended output values into a scalar-valued variable.
The second and the third problem (role of disturbances and reference values, necessary qualitative reasoning) remain and will be discussed in the sections 2.2 and 2.3.

2.2 HANDLING OF DISTURBANCES AND CHANGED REFERENCE VALUES

The stability decision in Eq. (4) only investigates undisturbed trajectories correctly. If a disturbance at the system output occurs, the value of L may increase. The same effect could be caused by changes in reference values. The problem is demonstrated for an example in Fig. 1. The evaluation function L is marked by "x" and increases between k = 0 and k = 1 caused by a modified reference value and at k = 10 caused by a disturbances change $\Delta\underline{z}_k$. As a consequence, the system seems to be unstable in the sense of Eq. (4).

The idea of a correction bases on a decomposition of L into dependent and independent terms of these changes $\Delta\underline{w}_k = \underline{w}_{k+1} - \underline{w}_k$ and $\Delta\underline{z}_k = \underline{z}_{k+1} - \underline{z}_k$:

$$\begin{aligned} L_{k+1} = {} & \underbrace{(\underline{w}_k - \underline{\bar{y}}_{k+1} - \underline{z}_k)^T \cdot \mathbf{P} \cdot (\underline{w}_k - \underline{\bar{y}}_{k+1} - \underline{z}_k)}_{\text{dependent on changes of reference and disturbance values}} \\ & + \underbrace{\left((\Delta\underline{w}_k - \Delta\underline{z}_k)^T \cdot \mathbf{P} \cdot (\underline{w}_k + \Delta\underline{w}_k - \underline{\bar{y}}_{k+1} - \underline{z}_k - \Delta\underline{z}_k) + (\underline{w}_k - \underline{\bar{y}}_{k+1} - \underline{z}_k)^T \cdot \mathbf{P} \cdot (\Delta\underline{w}_k - \Delta\underline{z}_k)\right)}_{\text{independent on changes of reference and disturbance values}} . \end{aligned} \tag{5}$$

The term $\underline{\bar{y}}_{k+1} = \underline{y}_{k+1} - \underline{z}_{k+1}$ denotes the undisturbed system output.

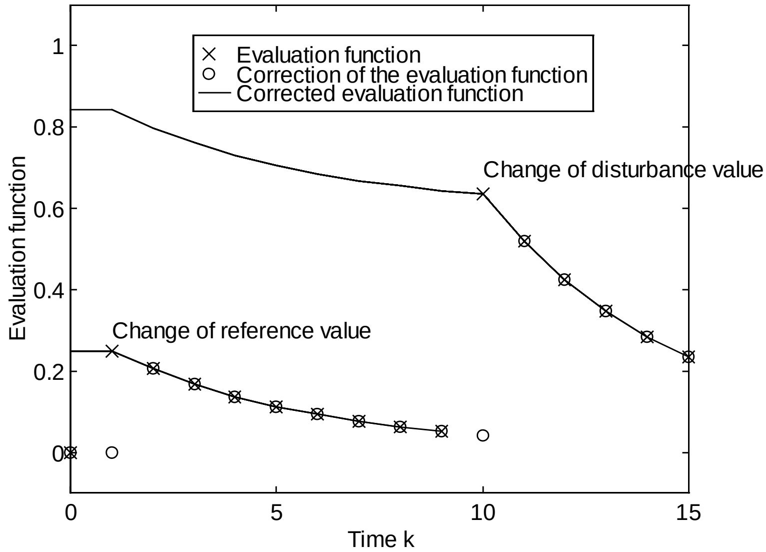

Figure 1: Evaluation function Eq. (3), correction of evaluation function Eq. (8) and corrected evaluation function Eq. (10) as function of time after a change of the reference value (k = 1) and a change of the disturbance value (k = 10)

This decomposition enables a reconstruction of the reasons for an increasing value of L. The aim is to derive a correction function $\overline{L}$ satisfying the following two restrictions:

1. If the reference and disturbance values are constant, the correction function should be equal to the evaluation function itself:

$$\overline{L}_{k+1}(\underline{y}_{k+1}, \underline{w}_{k+1}, \underline{0}, \underline{0}) = L_{k+1}(\underline{y}_{k+1}, \underline{w}_{k+1}) . \tag{6}$$

2. If the reference values or the disturbances change, the correction should be equal to the evaluation function in the hypothetical case that no change of these values occurs:

$$\overline{L}_{k+1}(\underline{y}_{k+1}, \underline{w}_{k+1}, \Delta\underline{w}_k, \Delta\underline{z}_k) = L_{k+1}(\underline{y}_{k+1} - \Delta\underline{z}_k, \underline{w}_{k+1} - \Delta\underline{w}_k) . \tag{7}$$

This leads to

$$\overline{L}_{k+1} = L_{k+1} - (2\underline{w}_{k+1} - 2\underline{y}_{k+1} - \Delta\underline{w}_k + \Delta\underline{z}_k)^T \cdot \mathbf{P} \cdot (\Delta\underline{w}_k - \Delta\underline{z}_k). \tag{8}$$

The correction function is also displayed in Fig. 1 and signed by 'o'. The stability decision now bases on

$$\overline{L}_{k+1} \begin{cases} < L_k \text{ if } L_k > 0 \\ = L_k \text{ if } L_k = 0 \end{cases} . \tag{9}$$

As a consequence, all pair-wise comparisons in Fig. 1 between 'x' and 'o' fulfil Eq. (9). But Eq. (9) enables only this pair-wise comparison. In contrast to it, the human operator investigates the whole function for a longer time period to come to a decision. In addition, the disturbance change $\Delta\underline{z}_k$ is unknown.

The comparability over a longer time period will be reached by a permanent backward correction demonstrated by the lines in Fig. 1. To any past value of the evaluation function L_{k-q}, all future correction terms using Eqn. (3) and (8) from k-q+1 up to k will be added to build the new introduced corrected evaluation function $\tilde{L}_{k-q}^{(k)}$:

$$\tilde{L}_{k-q}^{(k)} = \begin{cases} L_k \quad \text{if } q = 0 \\ L_{k-q} + \sum_{i=0}^{q-1} (L_{k-i} - \overline{L}_{k-i}) \text{ if } q > 0. \end{cases} \tag{10}$$

Resulting from different correction terms, this function has to be computed for each k in an iterative way because it does not hold $\tilde{L}_{k-q}^{(k)} = \tilde{L}_{k+1-q}^{(k+1)}$ in each case. This function enables a human-like analysis of the whole function by using qualitative terms and trends.

The unknown disturbance change $\Delta \underline{z}_k$ can be estimated by using an input-output-model of the process. With the measured controlled variable $\underline{y}$ and its estimation of its undisturbed value $\hat{\underline{y}}$ follows

$$\Delta \hat{\underline{z}}_k = \underline{y}_{k+1} - \underline{y}_k - \hat{\underline{y}}_{k+1} + \hat{\underline{y}}_k . \tag{11}$$

In the case that no mathematical model is known one possibility to get information about the system is to describe it by a fuzzy model characterized by uncertainties of the conclusions. This uncertainty should not be destroyed by a defuzzification in the classical sense. Schäfers et al. (1997) shows a possible way with a modified inference method for fuzzy systems.

An alternative way is to assume a set of different models with fuzzy memberships or degrees of validity (fixed or on-line estimated as a function of the model errors, Fig. 2). All partial models (i = 1,...,q) can be mathematical models, fuzzy models with defuzzification or Artificial Neural Nets (ANN). It is similar to human tolerance for possible and not possible system reactions.

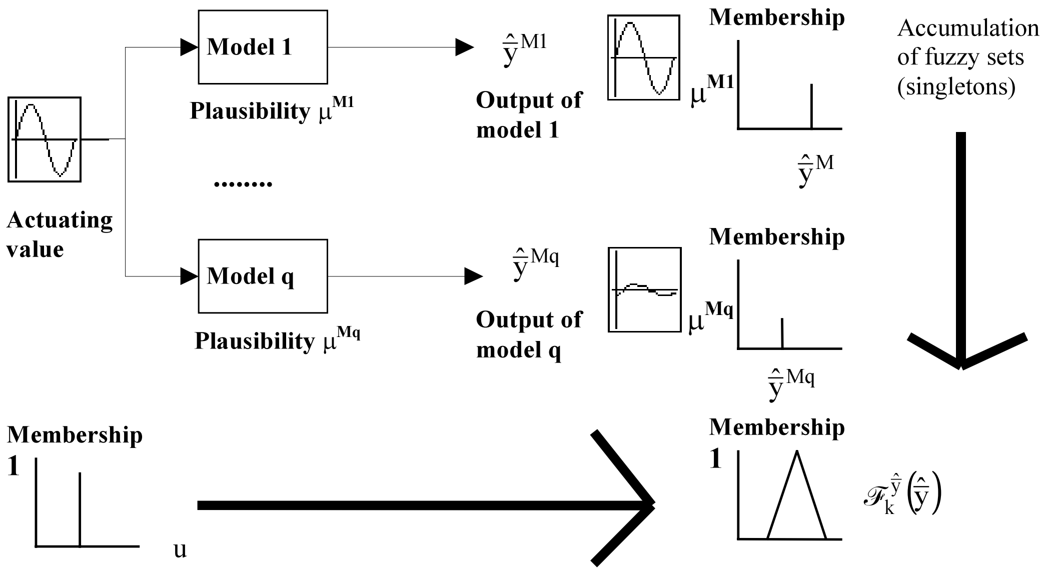

Figure 2: Multi model approach to describe model uncertainties

An uncertain model leads to uncertainties of the estimations in the undisturbed output values $\hat{\underline{y}}$ in Eq. (11). The estimations of the disturbance change will be uncertain. As a consequence, all computations in Eqn. (8), (10) and in the equations in the following chapters require now the use of the extension principle introduced of Zadeh (1978). Here, all possible solutions $\underline{y}$ of an equation $\underline{f}(\underline{x})$ with an input vector $\underline{x}$ will be computed and characterized by a fuzzy degree of membership.

This degree of membership μ (y) of a fuzzy set $\mathscr{F}_k^y$ depends on the degrees of membership of the input values μ ($\underline{x}$) leading to the output result:

$$\mathscr{F}_k^y = \sup_{\substack{x_1,..,x_n \in \mathcal{X} \\ y = f(x_1,..,x_n)}} \min\left(\mu_k^{X_1}(x_1),..,\mu_k^{X_n}(x_n)\right). \tag{12}$$

With the extension principle, the fuzzy sets of the undisturbed model output $\hat{\underline{y}}$ in Eq. (11) raise to fuzzy sets of the disturbance changes and of the correction function in Eq. (8). In the latter step, the quadratic parts in Eq. (8) lead to more complicated fuzzy sets described in Mikut (1999). To avoid further computing with these complicated sets, only the support of the corrected evaluation functions with upper and lower bounds of Eq. (10)

$$\widetilde{L}_{k-q}^{(k),UP} = L_{k-q} + \sum_{i=0}^{q-1}\left(L_{k-i} - \min_{\overline{L}}\left(\operatorname{supp}\mathcal{F}_{k-i}^{\overline{L}}\right)\right) \text{ if } q > 0 \tag{13}$$

$$\widetilde{L}_{k-q}^{(k),LO} = L_{k-q} + \sum_{i=0}^{q-1}\left(L_{k-i} - \max_{\overline{L}}\left(\operatorname{supp}\mathcal{F}_{k-i}^{\overline{L}}\right)\right) \text{ if } q > 0 \tag{14}$$

will be considered. The operator supp characterizes the support of the resulting fuzzy sets of the correction evaluation function $\mathcal{F}_{k-i}^{\overline{L}}$. All values of L itself are non-fuzzy because they only depend on measured values.
In Fig. 3, an illustrative example for a model with large uncertainties is given. A more detailed description of this example for an undisturbed and unstable process with extreme model uncertainties can be found in (Mikut 1999).
The evaluation function is marked by a bold line and the support of the corrected evaluation function in the Eqn. (13) and (14) is displayed by smaller solid lines. The sectors of the corrected evaluation functions are only displayed for a short time (up to q = 20) to improve the interpretability of the figure.
The fuzziness in the Eqn. (13) and (14) is influenced on the uncertainties of the model parameters and on the input values in the real process. Uncertain models cause also large uncertainties in upper and lower bounds.
In the rectangular-marked area, the lower and the upper bounds decrease and fulfil Eq. (9). At this time, the decision leads for all considered model uncertainties to the result that the system is stable.
In contrast to it, a decision whether the values of the corrected evaluation increase or decrease is not possible in the case marked by an ellipsoid in the lower part of the figure and in the increasing part from k = 60. Here, the upper bounds are easy to detect and the lower bounds in Eq. (14) are equal to the evaluation function. A wrong model without analysis of uncertainties could lead to a too optimistic stability decision. The consideration of the uncertainties detects that an instability of the system is possible.

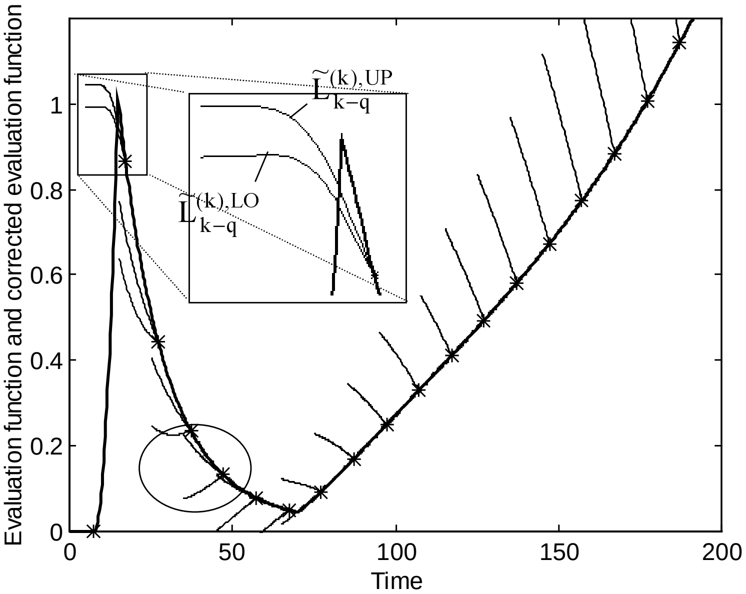

Figure 3: Consequences of fuzzy models for the corrected evaluation function

2.3 FILTER FUNCTIONS

The human operator observes a process for a longer time period to assess its stability. Advantages of this long-time evaluation are the damping of disturbances, short-time effects and small deviations of the desired behaviour (e.g. small overshooting).
The introduced corrected evaluation function provides a unified base for this decision but does not allow this long-time reasoning. To improve the stability decision, the qualitative reasoning of the human will be simulated by filtering the corrected evaluation function with two time windows M and N.

The original concept introduced by Gertler (1986) uses finite input response rectangular filters of different lengths. The mean value $\widehat{L}_k^M$ of the longer time window M and the mean value $\widehat{L}_k^N$ of the shorter time window N will be compared. If the mean value in M is higher, the resulting trend is negative.
In a generalized form, a trend D is computed by

$$D_k = \frac{\widehat{L}_k^N - \widehat{L}_k^M}{T_N - T_M} \tag{15}$$

with

$$\widehat{L}_k^N = \frac{\sum_{j=0}^{\infty} h_j^N \widetilde{L}_{k-j}^{(k)}}{\sum_{j=0}^{\infty} h_j^N} \quad \text{and} \quad \widehat{L}_k^M = \frac{\sum_{i=0}^{\infty} h_i^M \widetilde{L}_{k-i}^{(k)}}{\sum_{i=0}^{\infty} h_i^M}. \tag{16}$$

The functions h_i^M and h_j^N describe so-called form functions in the time windows M and N. These functions can build finite or infinite response filters (FIR or IIR). The terms in the denominator of Eq. (15) compute the mean time of the filtered function values of M and N:

$$T_N = \frac{\sum_{j=0}^{\infty} (k-j) \cdot T_A \cdot h_j^N}{\sum_{j=0}^{\infty} h_j^N} \quad \text{and} \quad T_M = \frac{\sum_{i=0}^{\infty} (k-i) \cdot T_A \cdot h_i^M}{\sum_{i=0}^{\infty} h_i^M}. \tag{17}$$

The different terms are explained in Fig. 4. In this example, a human classifies a qualitatively decreasing function unless the short-time effects (e.g. k = -15, k = -5). The trend with the filters M and N lead to the same result.

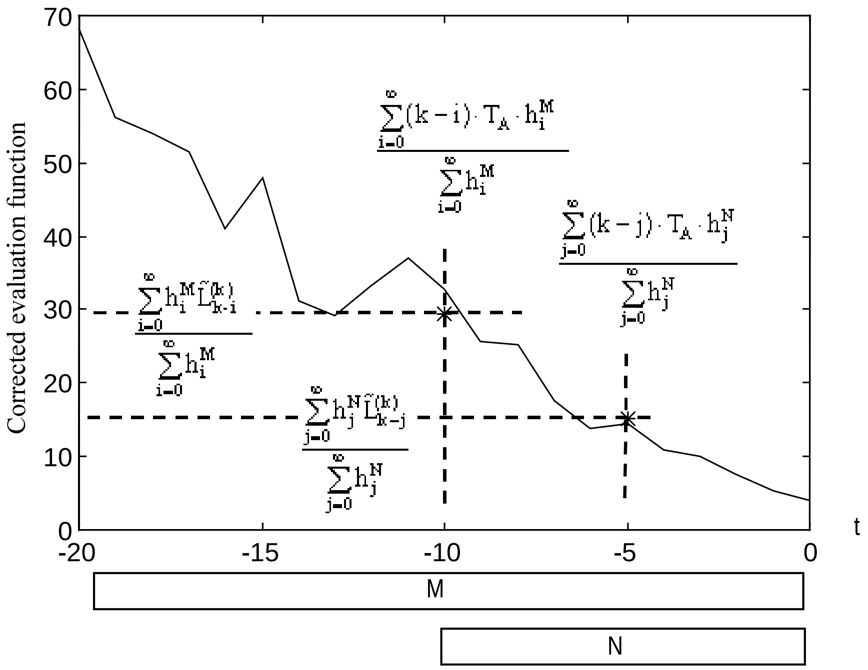

Figure 4: Trend computation by means of filters M and N
(here: rectangular filter, filter lengths m = 20 and n = 10)

Uncertainties in the system model create also uncertainties in the trend. With a further use of the extension principle for the trend in Eq. (15), it follows as a result of the Eqn. (13) and (14)

$$\frac{\hat{L}_k^{N,LO} - \hat{L}_k^{M,UP}}{T_N - T_M} \le D_k \le \frac{\hat{L}_k^{N,UP} - \hat{L}_k^{M,LO}}{T_N - T_M} \tag{18}$$

with

$$\hat{L}_k^{M,LO} = \frac{\sum_{i=0}^{\infty} h_i^M \tilde{L}_{k-i}^{(k),LO}}{\sum_{i=0}^{\infty} h_i^M} \quad \text{and} \quad \hat{L}_k^{M,UP} = \frac{\sum_{i=0}^{\infty} h_i^M \tilde{L}_{k-i}^{(k),UP}}{\sum_{i=0}^{\infty} h_i^M}. \tag{19}$$

One disadvantage of the trend is the absolute description of changes in the corrected evaluation function. It is independently from the absolute value of the corrected evaluation function. The human operator includes more relative information as trends weighted by absolute values or time periods to reach the desired values (e.g. increasing 10% per seconds *from the actual value*). To uses this idea, a weighted trend

$$\hat{D}_k = \frac{D_k}{\hat{L}_k^M} \tag{20}$$

is introduced. Model uncertainties cause uncertainties in the weighted trend by using Eq. (18) and Eq. (19). An alternative way is to use the filtered value of the evaluation function itself in the denominator of Eq. (20) and as input of the fuzzy components described in the next section.

2.4 FUZZY-RULES

The filtered values introduced in section 2.3 will be used as input values of a rule-based processing of the process situation. The linguistic meaning of Lyapunov functions discussed in section 2.1 is implemented as fuzzy rules in Table I. It copies the rule-based human reasoning with qualitative process descriptions and trends.

LJAP TREND	ZE	PS	PB
NEG	ST	ST	ST
ZE	ST	STL	STL
PS	ST	STL	STL
PB	ST	UST	UST

Table I: Rule base for the degree of stability (linguistic variable STAB)

The filtered corrected evaluation function forms the linguistic variable LJAP resulting from a fuzzification of the value $\hat{L}_k$. It describes the corrected deviations from the desired process situation.

The weighted trend (linguistic variable TREND) results from the fuzzified value of $\hat{D}_k$.

The terms of the linguistic variables *Negative* (NEG), *Zero* (ZE), *Positive Small* (PS), and *Positive Big* (PB) are used to describe the qualitative characteristics of the values.

Typical membership functions are given in Fig. 5.

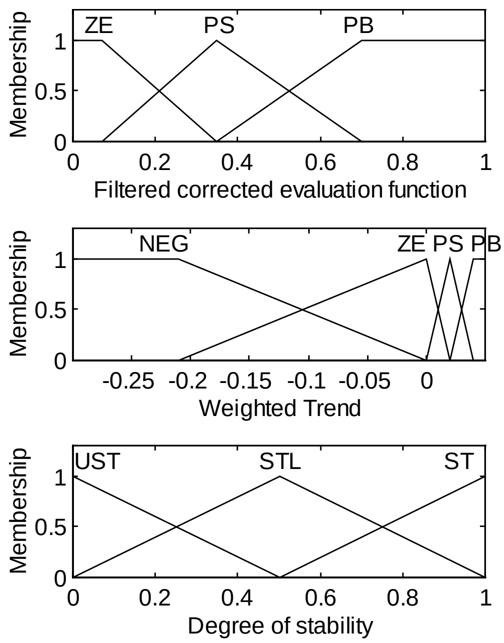

Figure 5: Membership functions of the supervision component
(top: LJAP, middle: TREND, bottom: STAB)

The terms *Stable* (ST) and *Unstable* (UST) define the situations "stable" behaviour and "unstable" behaviour of the closed loop. Some situations are difficult to classify. E.g., a slow increasing function with small values (TREND = PS and LJAP = PS) leads to the classification as system on the stability limit. The term *Stability Limit* (STL) means this limit between stable and unstable behaviour. A defuzzification gives values between 0 (unstable) and 1 (stable).

In Fig. 5, the fuzzy set ZE of the linguistic variable LJAP (filtered corrected evaluation function) has the value of one up to values of 0.05. With this definition, all controlled values near the reference value are classified as stable.

An analytical description of uncertainties is possible in case of a sum-prod inference. Here, a piece-wise multi-linear characteristic field describes the input-output behaviour of the fuzzy component (see e.g. Kiendl et al. 1995). The analytical search for minimal and maximal values of the possible values in Eqn. (18) and (19) estimates upper and lower bounds of the degree of stability. An additional "degree of disturbances" and a "degree of actuation" improve the recognition quality. They give the possibility to estimate why the controlled variable deviates of the expected behaviour and to integrate actuating values explicitly (Mikut 1999).

2.5 EXAMPLE

An example for the practical use shows Fig. 6. At the start, the reference value was changed from zero to one. The tolerated values for the controlled value at the sampling period time k + 1 are displayed as vertical lines. On the left-hand side, an evaluation function with the original output of the system and **P** = 1 is used. Here, only PT1-like behaviour of systems is tolerated (upper part of the figure). An overshooting will be classified as not stable (bottom). The small tolerated zone around the reference value is a result of the fuzzy term ZE of LJAP (see section 2.4).

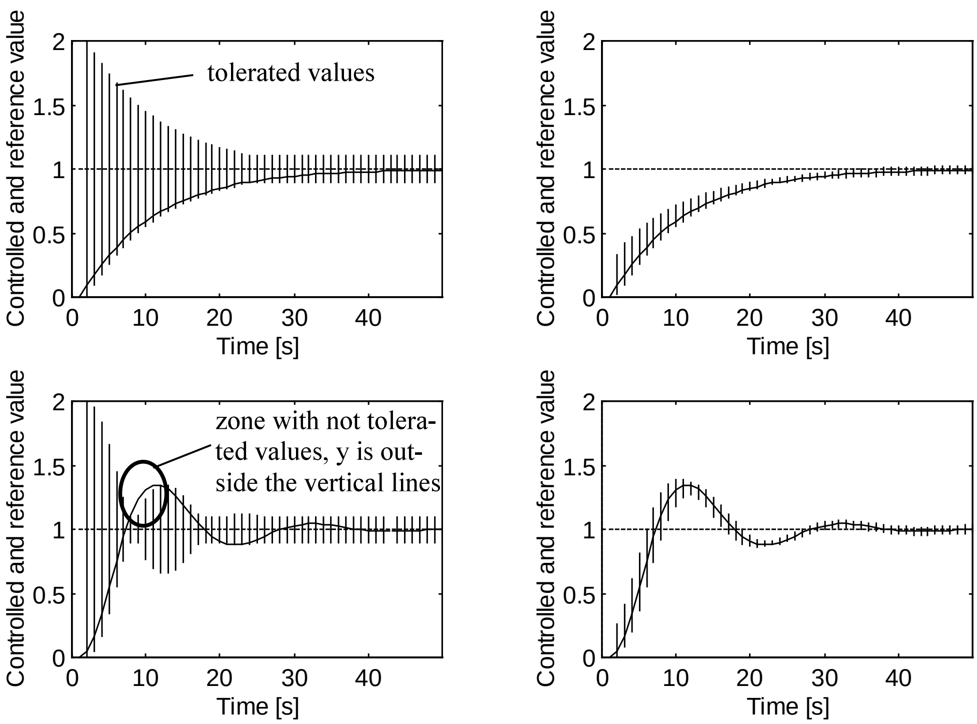

Figure 6: Tolerable situations at the next sampling period as function of controlled and reference values, fuzzy sets and different evaluation functions
(top: PT1-like closed-loop behaviour, bottom: PT2-like closed-loop behaviour, left: simple evaluation function with P = 1, right: advanced evaluation function using Eq. (21))

A modified evaluation function with the change of control error as additional output and

$$\mathbf{P} = \begin{pmatrix} \alpha & 0 \\ 0 & \beta \end{pmatrix}, \quad \alpha > 0, \text{ß} > 0, \alpha = \text{const}, \beta = \text{const}., \tag{21}$$

is demonstrated on the right-hand side of Fig. 6. This latter function tolerates overshooting as demonstrated in the right picture at the bottom. One disadvantage is the use of time derivatives that can be critically for disturbed processes.

3 PRACTICAL REALIZATION

In order to realize the operator's strategy for on-line stability supervision, a closed-loop structure consisting of supervisor, process model, adaptation component and the base control loop was proposed in Mikut (1995). The adaptation tunes the controller and switches to a more conservative controller if the supervisor recognizes a situation as unstable. The process model (e.g. a fuzzy model or an Artificial Neural Network) is necessary to separate the influence of the disturbance signal $\underline{z}$ to the output $\underline{y}$ of the system.

The supervisor contains all components that have been discussed in chapter 2. The resulting functions (the fuzzy representation of the corrected evaluation function and its trend) have been called Fuzzy-Lyapunov functions to characterize the similarities of the stability analysis between both concepts.
The resulting structure of the supervisor is displayed in Fig. 7. The concept has been used for the stability supervision of a flow control system, a coupled pressure-level system and the mould level control in the continuous casting of steel. More detailed results are outlined in Mikut et al. (1996b), Mikut (1999) and Dumitriu et. al. (1999).

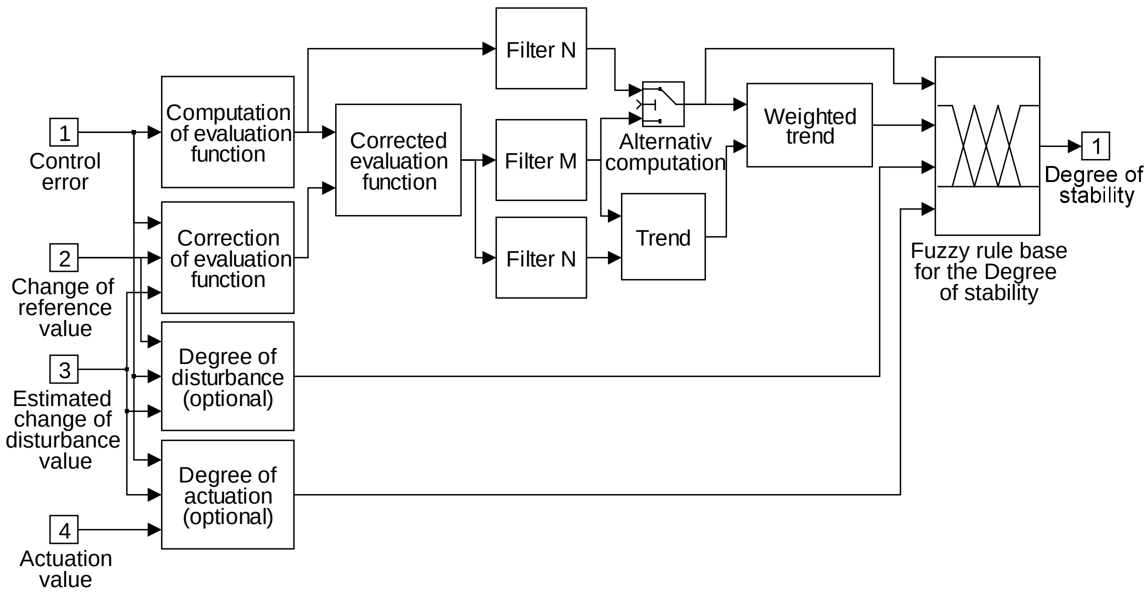

Figure 7: Structure of the on-line supervision component to compute the degree of stability

4 CONCLUSIONS

A method for the stability supervision of multi-level systems using a higher control level on the base of so-called Fuzzy-Lyapunov functions was presented. This method overcomes the contradiction between the philosophy of fuzzy controller design and an analytical stability test. It bases on a simplified interpretation of human strategies on the supervision of processes. The concept analyses the stability mainly data-based but it includes also model information. This model information can contain uncertainties modelled as fuzzy components without defuzzification or multi-model approaches with fuzzy degrees of plausibility. The supervisor classifies the system with a fuzzy degree of stability.

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