Multivariable fuzzy predictive functional control of a MIMO nonlinear system

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***Abstract*— A novel approach of multivariable fuzzy predictive functional control is presented. The control law is derived in the state-space domain, and given in an analytical form. The method was tested on a model of a 2-by-2 MIMO nonlinear plant, and compared to the control system using gain-scheduling of a linear dynamic compensator. The process was linearized in 63 operating points, and the compensator parameters were optimized using Edmunds' frequency-response-based technique. The results show that the proposed approach exhibits better reference-model tracking in a wider operating range, even without the use of optimization.**

I. INTRODUCTION

In recent years model based predictive control has received a lot of attention in the control theory and applications. A model of the controlled process provides the forecast of the process output signal, and the control signal is calculated in every step in a way that the difference between the reference and the output signal is minimized. The fundamental methods are essentially based on the principle of predictive control by Clarke (generalized predictive control [3]), Richalet (predictive functional control [14]), Cutler (dynamic matrix control [4]), De Keyser (extended prediction self-adaptive control [5]) and Ydstie (extended horizon adaptive control [21]).

The majority of industrial plants is multivariable in nature, i.e., there are many output variables to be controlled, and more than one input variable is coupled with the outputs. When the interactions are not negligible, some type of multivariable control has to be applied to achieve satisfactory performance of the closed-loop system. Process control of the truly multivariable systems has been extensively studied in the literature [15], [12], [11]. Leithead and O'Reilly presented an approach where by designing decoupling compensators the interactions are diminished and common univariable controllers are sufficient to provide quality control [9]. Edmunds proposed a frequency-based method of the multivariable-compensator tuning [7]. Some robust multivariable methods are presented in [13]. However, if the process to be controlled exhibits nonlinear behaviour several of the above mentioned methods will not provide satisfactory results. To tackle nonlinear process control, a fair number of methods including fuzzy models [6], [1], neural networks [16], fuzzy-adaptive sliding-mode approach [18], and gain-scheduling-based linear compensators [10] have been proposed. Furthermore, over the last few decades a substantial amount of work has been dedicated to various linearizing feedback approaches, see e.g. [8]. Nevertheless, a lot of problems when providing the analytical control schemes are still open.

This paper presents a novel control method for MIMO nonlinear systems. The predictive functional control method, presented in [19], was extended to nonlinear systems. In [20] a similar approach was used to tackle univariable-system control problems. The basis of the multivariable fuzzy predictive functional control approach (MFPFC) is to build a fuzzy model of a process, formulate it in the state-space domain, and connect it in parallel to the process. Reformulation in the state-space domain will lead to a simple control-law solution. The fuzzy input-output relations provide instant linearization of the model parameters, and the model states and outputs are directly used in an analytically-derived predictive control law. This way, satisfactory control can be extended to a wider operating range without the help of optimization.

The paper is organized in the following way. In Section 2 the derivation of the MFPFC control law is given. In the following section the proposed method is tested on a simulation experiment, and compared to Edmunds' control approach with gain-scheduling. Section 4 gives the conclusions and some future directions.

II. DERIVATION OF MULTIVARIABLE FUZZY PREDICTIVE FUNCTIONAL CONTROL LAW

A nonlinear system with multiple inputs and outputs is given by

$$\begin{aligned} \dot{\mathbf{x}}(t) &= \xi(\mathbf{x}, \mathbf{u}, t) \\ \mathbf{y}(t) &= f(\mathbf{x}, t), \end{aligned} \tag{1}$$

where $\mathbf{x} \in \mathbb{R}^n$ is the vector of states, $\mathbf{u} \in \mathbb{R}^m$ is the input vector, $\mathbf{y} \in \mathbb{R}^l$ denotes the output vector, $\xi : \mathbb{R}^n \times \mathbb{R}^m \times \mathbb{R}^+ \to \mathbb{R}^n$ is a smooth vector field representing a nonlinear function of the states and the inputs, and $f : \mathbb{R}^n \times \mathbb{R}^+ \to \mathbb{R}^l$ is the output function. To be able to derive a fuzzy model of the system, the following assumption will be considered throughout the paper:

Assumption 1: *The system states are bounded for any combination of the system inputs from some compact domain of interest, i.e.,* $\mathbf{x}(t) \in L_\infty,\ \forall t \geq 0,\ \forall \mathbf{u} \in \mathcal{U}$

The fuzzy model of the system is described by rules [17] which locally describe linear input-output relations of the

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system in the state-space domain:

$$\begin{aligned}&\mathbf{R}_j:\ \textbf{if}\ x_{p1}(k)\ \textbf{is}\ \mathbf{P}_{j,1}\ \textbf{and}\ \ldots\ \textbf{and}\ x_{pq}(k)\ \textbf{is}\ \mathbf{P}_{j,q}\\ &\textbf{then}\ \mathbf{x}_m(k+1)=\mathbf{A}_{m,j}\mathbf{x}_m(k)+\mathbf{B}_{m,j}\mathbf{u}(k)+\mathbf{r}_j(k)\end{aligned} \tag{2}$$

The q-element vector $\mathbf{x}_p^T(k)=[x_{p1}(k),...,x_{pq}(k)]$ denotes the input or variables in premise, and $j=1,\ldots,n$ is the number of rules. With each variable in premise $x_{pi}(k)$ j fuzzy sets $(\mathbf{P}_{i,1},\ldots,\mathbf{P}_{i,j})$ are connected, and each fuzzy set $\mathbf{P}_{i,k_i}$ $(k_i=1,\ldots,j)$ is associated with a real-valued function $\mu_{P_{i,k_i}}(x_{pi}):\mathbb{R}\rightarrow[0,1]$ that produces membership grade of the variable x_{pi} with respect to the fuzzy set $\mathbf{P}_{i,k_i}$. $\mathbf{A}_{m,j}$ and $\mathbf{B}_{m,j}$ are the system model state-space matrices, and $\mathbf{r}_j(k)$ are the associated residual vectors. The variables x_{pi} are not the only inputs of the fuzzy system. Implicitly, the r-element vector $\mathbf{x}_m(k)^T=[x_{m,1}(k),...,x_{m,r}(k)]$ also represents the input to the system. It is usually referred to as the consequence vector.

The whole output of the system is given by the following equation:

$$\begin{aligned}\mathbf{x}_m(k+1)&=\frac{\sum\limits_{j=1}^{n}\prod\limits_{i=1}^{q}\mu_{P_{i,j}}(\mathbf{x}_{pi})\boldsymbol{\phi}(\mathbf{x},\mathbf{u},\mathbf{r},k)}{\sum\limits_{j=1}^{n}\prod\limits_{i=1}^{q}\mu_{P_{i,j}}(\mathbf{x}_{pi})},\\ \boldsymbol{\phi}(\mathbf{x},\mathbf{u},\mathbf{r},k)&=\mathbf{A}_{m,j}\mathbf{x}(k)+\mathbf{B}_{m,j}\mathbf{u}(k)+\mathbf{r}(k).\end{aligned} \tag{3}$$

To simplify (3), a partition of unity is considered where functions $\beta_j(\mathbf{x}_p)$ defined by

$$\beta_j(\mathbf{x}_p)=\frac{\prod\limits_{i=1}^{q}\mu_{P_{i,j}}(\mathbf{x}_{pi})}{\sum\limits_{j=1}^{n}\prod\limits_{i=1}^{q}\mu_{P_{i,j}}(\mathbf{x}_{pi})} \tag{4}$$

give information about the fulfilment of the respective fuzzy rule in the normalized form. It is obvious that $\sum_{j=1}^{m}\beta_j(\mathbf{x}_p)=1$ irrespective of $\mathbf{x}_p$ as long as the denominator of $\beta_j(\mathbf{x}_p)$ is not equal to zero (that can be easily prevented by stretching the membership functions over the whole potential area of $\mathbf{x}_p$).

Combining (3) and (4), the fuzzy model in the state-space domain can be described as a response to the system input vector $\mathbf{u}(k)$

$$\begin{aligned}\mathbf{x}_{m1}(k+1)&=\sum_{j=1}^{m}\beta_j(\mathbf{x}_p)\left[\mathbf{A}_{m,j}\mathbf{x}_{m1}(k)+\mathbf{B}_{m,j}\mathbf{u}(k)\right]\\ \mathbf{y}_{m1}(k)&=\sum_{j=1}^{m}\beta_j(\mathbf{x}_p)\mathbf{C}_{m1,j}\mathbf{x}_{m1}(k)\end{aligned} \tag{5}$$

and to the system residual vector $\mathbf{r}(k)$

$$\begin{aligned}\mathbf{x}_{m2}(k+1)&=\sum_{j=1}^{m}\beta_j(\mathbf{x}_p)\left[\mathbf{A}_{m,j}\mathbf{x}_{m2}(k)+\mathbf{B}_{mr}\mathbf{r}(k)\right]\\ \mathbf{y}_{m2}(k)&=\sum_{j=1}^{m}\beta_j(\mathbf{x}_p)\mathbf{C}_{m2,j}\mathbf{x}_{m2}(k),\ \mathbf{B}_{mr}=\mathbf{I}.\end{aligned} \tag{6}$$

The system output is then given as a sum of the responses

$$\mathbf{y}_m(k)=\mathbf{y}_{m1}(k)+\mathbf{y}_{m2}(k). \tag{7}$$

The control goal is to determine the future control action so that the predicted output values coincide with the reference trajectories. The point where the reference and output signal coincide is called a coincidence horizon, and is denoted by H. The reference model trajectory in the state space domain is given by

$$\begin{aligned}\mathbf{x}_r(k+1)&=\mathbf{A}_r\mathbf{x}_r(k)+\mathbf{B}_r(k)\mathbf{w}(k)\\ \mathbf{y}_r(k)&=\mathbf{C}_r\mathbf{x}_r(k).\end{aligned} \tag{8}$$

The reference model parameters should be chosen to fulfil the condition $\mathbf{C}_r(\mathbf{I}-\mathbf{A}_r)^{-1}\mathbf{B}_r=\mathbf{I}$ to enable the reference trajectory tracking, i.e., the steady-state gain of the reference model should be equal to one. One way to accomplish this is to define

$$\begin{aligned}\mathbf{B}_r&=\mathbf{I}-\mathbf{A}_r\\ \mathbf{C}_r&=\mathbf{I}.\end{aligned} \tag{9}$$

The prediction is calculated under the assumption of constant future manipulated variables ($u(k)=u(k+1)=\ldots=u(k+H-1)$), i.e., the mean level control, and under the assumption of constant $\beta_j,\ j=1,...,m$ through the whole prediction horizon. Under those assumptions, the H-step ahead prediction of the system and reference model output, respectively, at time instant k is obtained as:

$$\begin{aligned}\mathbf{y}_{m1}(k+H|k)&=\tilde{\mathbf{C}}_{m1}\left(\tilde{\mathbf{A}}_m^H\mathbf{x}_{m1}(k)+\tilde{\mathbf{K}}_{m1}\mathbf{u}(k)\right)\\ \mathbf{y}_{m2}(k+H|k)&=\tilde{\mathbf{C}}_{m2}\left(\tilde{\mathbf{A}}_m^H\mathbf{x}_{m2}(k)+\tilde{\mathbf{K}}_{m2}\tilde{\mathbf{r}}(k)\right)\end{aligned} \tag{10}$$

$$\mathbf{y}_r(k+H|k)=\mathbf{C}_r\left(\mathbf{A}_r^H\mathbf{x}_r(k)+\tilde{\mathbf{K}}_r\mathbf{w}(k)\right), \tag{11}$$

where

$$\begin{aligned}\tilde{\mathbf{K}}_{m1}&=\left(\tilde{\mathbf{A}}_m^H-\mathbf{I}\right)\left(\tilde{\mathbf{A}}_m-\mathbf{I}\right)^{-1}\tilde{\mathbf{B}}_{m1}\\ \tilde{\mathbf{K}}_{m2}&=\left(\tilde{\mathbf{A}}_m^H-\mathbf{I}\right)\left(\tilde{\mathbf{A}}_m-\mathbf{I}\right)^{-1}\tilde{\mathbf{B}}_{mr}\\ \tilde{\mathbf{K}}_r&=\left(\mathbf{A}_r^H-\mathbf{I}\right)\left(\mathbf{A}_r-\mathbf{I}\right)^{-1}\tilde{\mathbf{B}}_r\end{aligned}$$

$$\begin{aligned}&\tilde{\mathbf{A}}_m=\sum_{j=1}^{m}\beta_j(\mathbf{x}_p(k))\mathbf{A}_{m,j},\ \tilde{\mathbf{B}}_m=\sum_{j=1}^{m}\beta_j(\mathbf{x}_p(k))\mathbf{B}_{m,j}\\ &\tilde{\mathbf{C}}_{m1}=\sum_{j=1}^{m}\beta_j(\mathbf{x}_p(k))\mathbf{C}_{m1},\ \tilde{\mathbf{C}}_{m2}=\sum_{j=1}^{m}\beta_j(\mathbf{x}_p(k))\mathbf{C}_{m2}\\ &\tilde{\mathbf{r}}=\sum_{j=1}^{m}\beta_j(\mathbf{x}_p(k))\mathbf{r}_j\end{aligned}$$

The main idea of the MFPFC is the equivalence of the process objective increment and the process model output increment at a certain horizon. The process objective increment $\boldsymbol{\Delta}_p$ is defined as the difference between the predicted reference trajectory $\mathbf{y}_r(k+H|k)$ and the actual process output signal $\mathbf{y}_p(k)$

$$\begin{aligned}\mathbf{\Delta}_p &= \mathbf{y}_r(k+H|k) - \mathbf{y}_p(k) \\ \mathbf{\Delta}_p &= \mathbf{C}_r\left(\mathbf{A}_r^H \mathbf{x}_r(k) + \tilde{\mathbf{K}}_r \mathbf{w}(k)\right) - \mathbf{y}_p(k),\end{aligned} \tag{12}$$

and the model output increment can be written analogously using (7)

$$\begin{aligned}\mathbf{\Delta}_m &= \mathbf{y}_m(k+H|k) - \mathbf{y}_m(k) \\ \mathbf{\Delta}_m &= \mathbf{y}_{m1}(k+H|k) + \mathbf{y}_{m2}(k+H|k) - \mathbf{y}_m.\end{aligned} \tag{13}$$

The control law of the MFPFC in explicit analytical form is obtained by assuming the equivalence of the increments

$$\mathbf{\Delta}_p = \mathbf{\Delta}_m, \tag{14}$$

and using (10), (11), (12), and (13):

$$\begin{aligned}\mathbf{u}(k) = \tilde{\mathbf{K}}_{m1}^{-1}\big(&\mathbf{y}_r(k+H|k) - \tilde{\mathbf{C}}_{m1}\tilde{\mathbf{A}}_m^H \mathbf{x}_{m1}(k) \\ &- \mathbf{y}_{m2}(k+H|k) + \mathbf{y}_m(k) - \mathbf{y}_p(k)\big)\end{aligned} \tag{15}$$

Note that the control law (15) is realizable if the matrix $\mathbf{K}_{m1}$ is non-singular.

III. Simulation example

A. Tuning of the MFPFC

The proposed method was tested on a two-input two-output nonlinear system given by (16).

$$\begin{aligned}\dot{y}_1 &= -2y_1 + 0.3\frac{y_1}{y_2} + 0.7y_2 + 5\sqrt{u_1} \\ \dot{y}_2 &= -0.8y_1 + 3y_1 \cdot 0.5y_2 - 0.8y_2 + 7\sqrt{u_2}\end{aligned} \tag{16}$$

Firstly, a fuzzy model was built from the input-output identification data. Fig. 1 and Fig. 2 show the input and the associated output signals. Sampling time was $T_s = 0.02$ s, and the number of the input-output data pairs for each process output was 10000. Using Gustafson-Kessel clustering method [2], the fuzzy parameters of the local linear models in 5 fuzzy subsets were established. Antecedent vector consisted of four elements, the process outputs and inputs in k-th step, $\mathbf{x}_p^T(k) = [y_1(k),\ y_2(k),\ u_1(k),\ u_2(k)]$. Tables I and II give the obtained model parameters that multiply the associated elements of the consequent vector $\mathbf{x}_m^T(k) = [y_{m1}(k),\ y_{m2}(k),\ u_1(k),\ u_2(k),\ r(k)]$. In Fig. 3 the results of the model verification are presented. The variances for the first and second model outputs were 0.0114 and 0.0030, respectively.

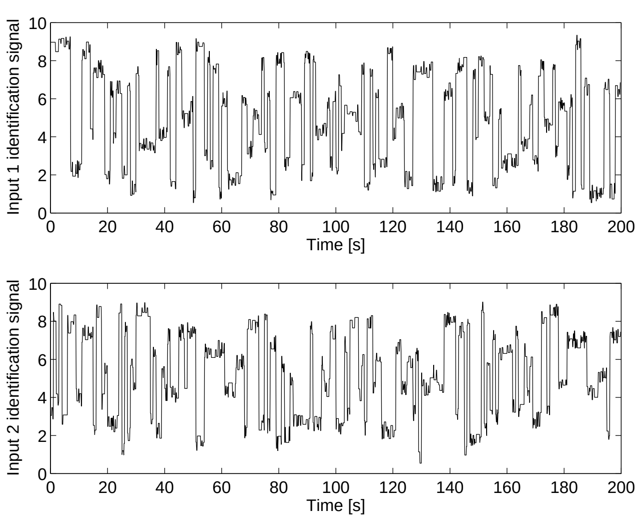

Fig. 1. Input identification data

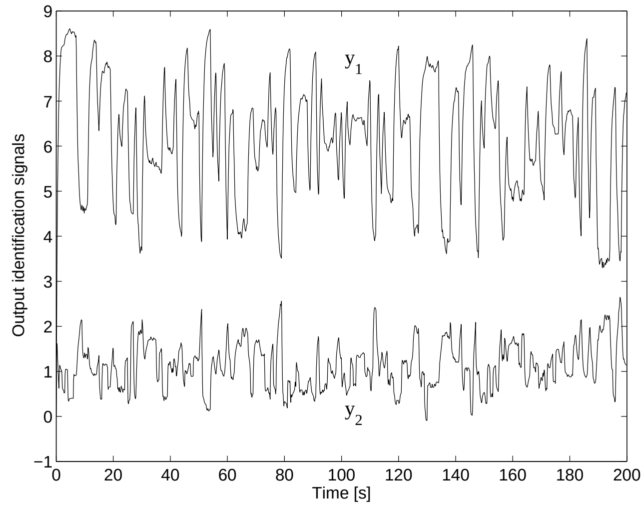

Fig. 2. Output identification data

TABLE I

Model parameters of the first fuzzy-model output

	$y_1(k)$	$y_2(k)$	$u_1(k)$	$u_2(k)$	$r(k)$
$\mathbf{P}_{1,i}$	0.9369	0.0227	0.0730	0.0024	0.0924
$\mathbf{P}_{2,i}$	0.9711	0.0166	0.0222	-0.0014	0.0465
$\mathbf{P}_{3,i}$	0.9638	-0.0044	0.0222	0.0001	0.1461
$\mathbf{P}_{4,i}$	0.9814	0.0947	0.0211	-0.0076	-0.0502
$\mathbf{P}_{5,i}$	0.9628	-0.0464	0.0139	0.0013	0.2014

B. PI compensator method using the Edmunds' tuning technique and gain-scheduling

The proposed method will be compared to a combination of a classical multivariable PI-controller-tuning technique and gain-scheduling, as presented in [10]. The system, given by (16), was first linearized at 63 selected operating points throughout the complete operating range. The operating

TABLE II

Model parameters of the second fuzzy-model output

	$y_1(k)$	$y_2(k)$	$u_1(k)$	$u_2(k)$	$r(k)$
$\mathbf{P}_{1,i}$	-0.0513	0.9228	0.0054	0.0159	0.2626
$\mathbf{P}_{2,i}$	-0.0423	0.8697	-0.0053	0.0246	0.3194
$\mathbf{P}_{3,i}$	-0.0167	0.7905	-0.0050	0.0480	0.1422
$\mathbf{P}_{4,i}$	-0.0575	0.7769	-0.0039	0.0247	0.4954
$\mathbf{P}_{5,i}$	-0.0197	0.8904	0.0053	0.0187	0.0971

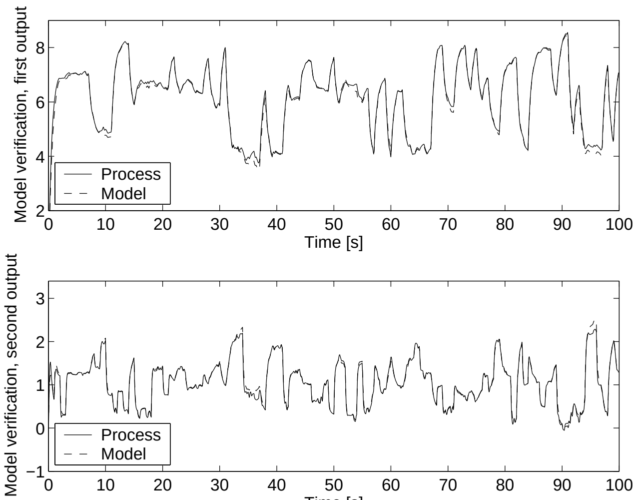

Fig. 3. Verification of the model outputs

points were selected based on the system outputs. Edmunds' method [7] was then used to design a linear multivariable PI compensator for each operating point. The compensator parameters were obtained by optimization based on the model and desired process frequency responses. The objective of this method is to design a simple robust controller, which achieves a desired performance criteria. The drawback is in the time-consuming procedure of defining the operating points, linearization and optimization of parameters.

The tuning parameters were a first-order reference model time constant of $T_{ref} = 0.25$ s and a closed-loop frequency band of $\omega = [10^{-2}\ ,\ 10^{4}]$. The scheduling variables were the process outputs y_1 and y_2. The obtained compensator parameters k_{Pij} and $k_{Iij},\ \ i,j \in \{1,2\}$ are presented in Fig. 4 and Fig. 5.

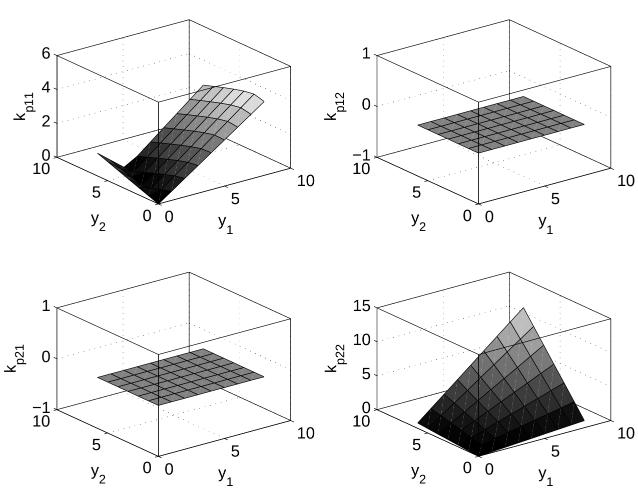

Fig. 4. Parameters of the proportional part of the Edmunds' compensator

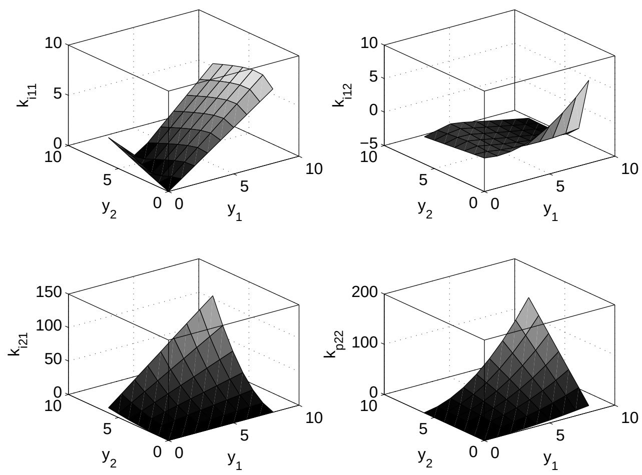

Fig. 5. Parameters of the integral part of the Edmunds' compensator

C. Comparison of the results

The parameters for the MFPFC controller are the reference model matrix

$$\mathbf{A}_r = \begin{bmatrix} 0.92 & 0 \\ 0 & 0.92 \end{bmatrix}, \tag{17}$$

and horizon $H = 10$. The parameters of the reference model were chosen according to the reference-model time constant of the Edmunds' controller. In Fig. 6 to Fig. 9 the results of the comparison of reference tracking experiment and the associated input signals are given. It can be seen

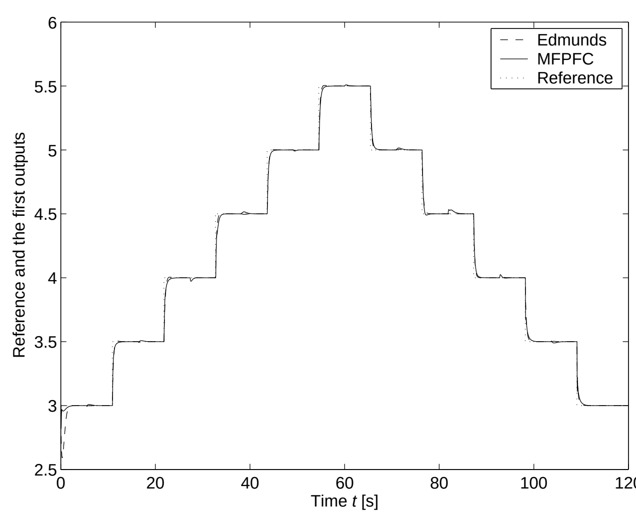

Fig. 6. Comparison of reference tracking for the first output

that both approaches gave satisfactory results in reference tracking. To consider the differences, let us take a closer look to the transients of the second output when reference is descending (Fig. 10) and ascending (Fig. 11). It can be seen that the MFPFC exhibits fairly equal transient responses in different operating points, while the transients of the gain-scheduling Edmunds' controller "suffer" slightly

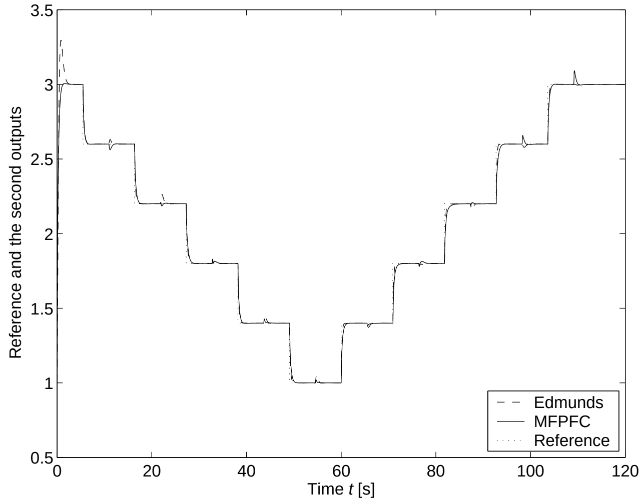

Fig. 7. Comparison of reference tracking for the second output

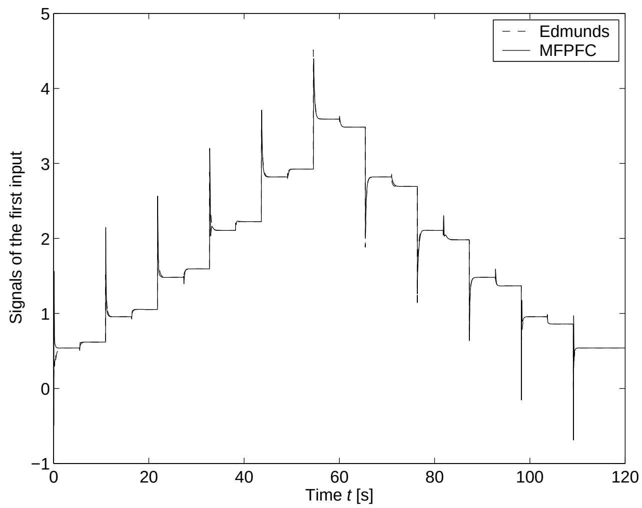

Fig. 8. Comparison of the associated input signals, first input

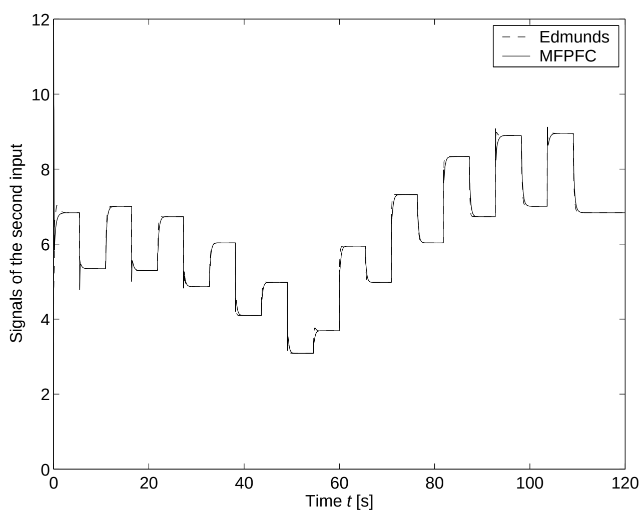

Fig. 9. Comparison of the associated input signals, second input

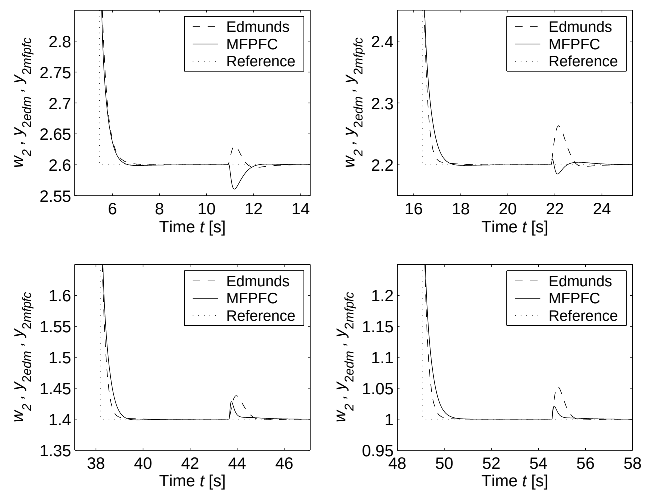

Fig. 10. Transients in tracking of the descending reference

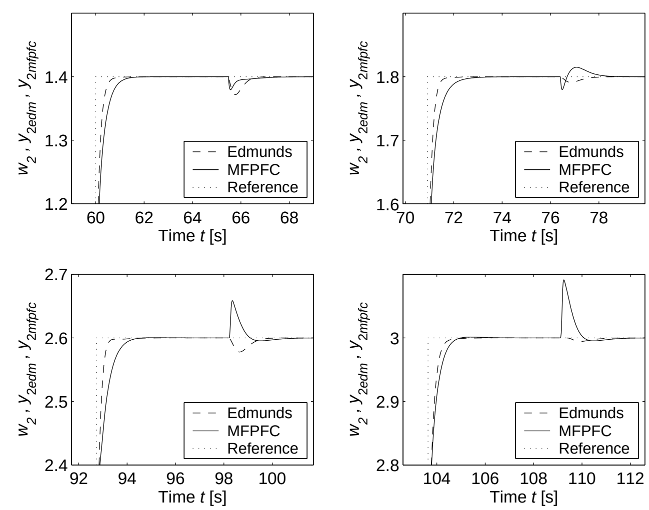

Fig. 11. Transients in tracking of the ascending reference

from operating condition change. In the case of the output-disturbance rejection, following the reference changes in the opposite process input, the proposed method provided better results for the second output while the Edmunds' method gave better results for the first one. In general, the advantage of the MFPFC is a quality control in a wide operating range without the explicit use of optimization because the control law is given analytically.

IV. Conclusions and future works

A. Conclusions

A novel approach of nonlinear multivariable control was presented. For a MIMO nonlinear system a fuzzy model was built and used in a multivariable fuzzy predictive functional control scheme. The control law was derived in the state space domain and given in an analytical form. The method was tested on a model of a 2-by-2 multivariable nonlinear plant, and compared to the gain-scheduling-based linear dynamic compensator using Edmunds' optimization technique. The results show that the proposed approach exhibits better reference-model tracking in a wider operating range, even without the explicit use of optimization, and provides a simple and effective method of tackling the control of nonlinear multivariable systems.

B. Future Works

Based upon the results, studying the effects of the MF-PFC design-parameter choice, parallel distribution of the control law, and stability issues deserve further attention.

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