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"Nonlinear Internal Model Control for MISO Systems Based on Local Linear Neuro-Fuzzy Models"
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Internal Model Control Based on Locally Linear Model Tree (LOLIMOT) Model with Application to a PH neutralization Process*

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Abstract *- The internal model control (IMC) scheme has been widely applied in the field of process control. So far, IMC has been mainly applied to linear processes. This paper discusses the extension of the IMC scheme to nonlinear processes based on local linear models where the properties of linear design procedures can be exploited. The IMC scheme results in controllers that are comparable to conventional multi layer perceptron (MLP) networks. In practice, the tuning of conventional MLP based controllers can be very time-consuming whereas the IMC design procedure is very simple and reliable. In this paper, the design effort of the IMC based on locally linear model tree (LOLIMOT) algorithm will be discussed and control results will be compared by application to nonlinear control of an industrial-scale PH neutralization process. Simulation studies of a PH neutralization process confirm the excellent nonlinear modeling properties of the proposed locally linear network and illustrate the potential for set point tracking and disturbance rejection within an IMC framework.*

Keywords: Internal model control, neural network, nonlinear control, locally linear model tree model, PH neutralization process.

1 Introduction

In process control, internal model control (IMC) [2,3,4,10,11] has gained high popularity due to the good disturbance rejection capabilities and robustness properties of the IMC structure. This structure provides a practical tool to influence dynamic performance and robustness to modeling errors transparently in the design. Furthermore, the controller design is simple and straightforward such that the controller can easily be tuned by the process engineer. It is particularly appropriate for the design and implementation of controllers for linear open-loop stable systems [2,3]. The IMC controller design is theoretically well explored for linear processes. In practice, however, almost every process displays nonlinear behavior especially if it is driven in a wide operating range. Hence, the need emerges to extend the linear design procedure to nonlinear systems [3]. Development of a nonlinear extension of the IMC scheme presents serious difficulties duo to the inherent complexity of nonlinear systems. In spite of potential for closed-loop performance improvement, nonlinear control strategies should be applied with some caution duo to commensurate increase in computational load.

Neural networks as well as fuzzy systems have been widely employed for the representation of nonlinear systems and the idea of internal model control can be combined with these types of models [5,14]. In this paper, a LOLIMOT model will be used [7,8,12,13], see figure 1. Here, the output of the model is calculated as an interpolation of locally valid linear models. Local model architectures have several advantages over conventional black-box approaches. On the one hand, their transparent architecture allows the combination of prior knowledge about the process with measured identification data. On the other hand, classical linear control design methods can be utilized for nonlinear controller design. For the IMC approach, this local linearity can be exploited directly and a nonlinear gain-scheduled controller can be obtained.

It can be shown that for simple linear models, the IMC loop can be transferred to classical feedback structures resulting in e.g. PI or PID controllers [10,11]. In practice, the tuning of conventional PI or PID controllers can be very time-consuming compared to the straightforward IMC design. Here, the IMC scheme can be exploited to evaluate parameters for classical controllers. In this paper, the proposed IMC based on LOLIMOT model is applied to a PH neutralization process, which simulation results exhibit excellent performance of that in comparison IMC with conventional MLP neural networks.

The paper is organized as follows. First, local model networks are briefly introduced in Section 2. Then, the extension of linear design techniques to local model systems is discussed in Section 3. Here, the internal model control scheme will be described and compared to conventional IMC with MLP networks. The reliability and effectiveness of the presented IMC method is shown by application to a PH neutralization process, which is a highly nonlinear process, in Section 4. A summary and conclusions are given in Section 5.

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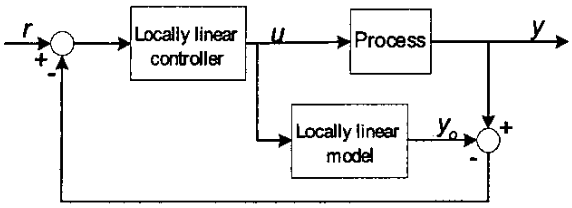

Figure 1. Scheme of the proposed IMC based on LOLIMOT model.

2 Locally linear model tree algorithm for system identification

In the following, the modeling of nonlinear dynamic processes using LOLIMOT models is described. The network structure of a local linear neuro-fuzzy model [4,5] is depicted in Fig. 2. Each neuron realizes a local linear model (LLM) and an associated validity function that determines the region of validity of the LLM. The validity functions form a partition of unity, i.e., they are normalized such that

$$\sum_{i=1}^{M} \varphi_i(\underline{z}) = 1 \tag{1}$$

for any model input $\underline{z}$.

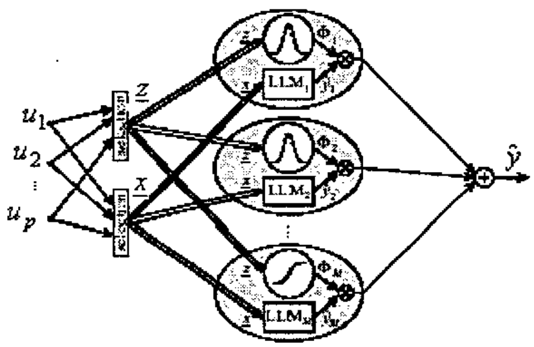

Figure 2. Network structure of a local linear neurofuzzy model with M neurons for nx LLM inputs x and nz validity function inputs z.

The output of the model is calculated as

$$\hat{y} = \sum_{i=1}^{M} (w_{i,o} + w_{i,1}x_1 + \ldots + w_{i,n_x}x_{n_x})\varphi_i(\underline{z}) \tag{2}$$

where the local linear models depend on $\underline{x} = [x_1, \ldots, x_{n_x}]^T$ and the validity functions depend on $\underline{z} = [z_1, \ldots, z_{n_z}]^T$. Thus, the network output is calculated as a weighted sum of the outputs of the local linear models where the $\varphi_i(.)$ are interpreted as the operating point dependent weighting factors. The network interpolates between different Locally Linear Models (LLMs) with the validity functions. The weights w_{ij} are linear network parameters.

The validity functions are typically chosen as normalized Gaussians. If these Gaussians are furthermore axis-orthogonal the validity functions are

$$\varphi_i(\underline{z}) = \frac{\mu_i(\underline{z})}{\sum_{j=1}^{M} \mu_j(\underline{z})} \tag{3}$$

with

$$\mu_i(\underline{z}) = \exp\left(-\frac{1}{2}\left(\frac{(z_1 - c_{i,1})^2}{\sigma_{i,1}^2} + \ldots + \frac{(z_1 - c_{i,n_z})^2}{\sigma_{i,n_z}^2}\right)\right) \tag{4}$$

The centers and standard deviations are *nonlinear* network parameters.

In the fuzzy system interpretation each neuron represents one rule. The validity functions represent the rule premise and the LLMs represent the rule consequents. One-dimensional Gaussian membership functions

$$\mu_{i,j}(z_j) = \exp\left(-\frac{1}{2}\left(\frac{(z_j - c_{i,j})^2}{\sigma_{i,j}^2}\right)\right) \tag{5}$$

can be combined by a t-norm (conjunction) realized with the product operator to form the multidimensional membership functions in (3). One of the major strengths of local linear neuro-fuzzy models is that premises and consequents do not have to depend on identical variables, i.e. $\underline{z}$ and $\underline{x}$ can be chosen independently.

The LOLIMOT algorithm consists of an outer loop in which the rule premise structure is determined and a nested inner loop in which the rule consequent parameters are optimized by local estimation.

1. *Start with an initial model:* Construct the validity functions for the initially given input space partitioning and estimate the LLM parameters by the local weighted least squares algorithm. Set M to the initial number of LLMs. If no input space partitioning is available a-priori then set $M = 1$ and start with a single LLM which in fact is a global linear model since its validity function covers the whole input space with $\varphi_i(\underline{z}) = 1$.

2. *Find worst LLM:* Calculate a local loss function for each of the $i=1,\ldots,M$ LLMs. The local loss functions can be computed by weighting the squared model errors with the degree of validity of the corresponding local model. Find the worst performing LLM.

3. *Check all divisions:* The LLM l is considered for further refinement. The hyperrectangle of this LLM is split into two halves with an axis-orthogonal split. Divisions in each dimension are tried. For each division $\dim = 1, \ldots, n_z$ the following steps are carried out:

   (a) Construction of the multi-dimensional MSFs for both hyperrectangles.

   (b) Construction of all validity functions.

   (c) Local estimation of the rule consequent parameters for both newly generated LLMs.

(d) Calculation of the loss function for the current overall model.

4. *Find best division:* The best of the n_z alternatives checked in Step 3 is selected. The validity functions constructed in Step 3(a) and the LLMs optimized in Step 3(c) are adopted for the model. The number of LLMs is incremented $M \to M+1$.

5. *Test for convergence:* If the termination criterion is met then stop, else go to Step 2.

For the termination criterion various options exist, e.g., a maximal model complexity, that is a maximal number of LLMs, statistical validation tests, or information criteria. Note that the *effective* number of parameters must be inserted in these termination criteria.

Fig. 3 illustrates the operation of the LOLIMOT algorithm in the first four iterations for a two-dimensional input space and clarifies the reason for the term "tree" in the acronym LOLIMOT. Especially two features make LOLIMOT extremely fast. First, at each iteration not all possible LLMs are considered for division. Rather, Step 2 selects only the worst LLM whose division most likely yields the highest performance gain. For example, in iteration 3 in Fig. 3 only LLM 3-2 is considered for further refinement. All other LLMs are kept fixed. Second, in Step 3c the local estimation approach allows to estimate only the parameters of those two LLMs which are newly generated by the division. For example, when in iteration 3 in Fig. 3 the LLM 3-2 is divided into LLM 4-2 and 4-3 the LLMs 3-1 and 3-3 can be directly passed to the LLMs 4-1 and 4-3 in the next iteration without any estimation.

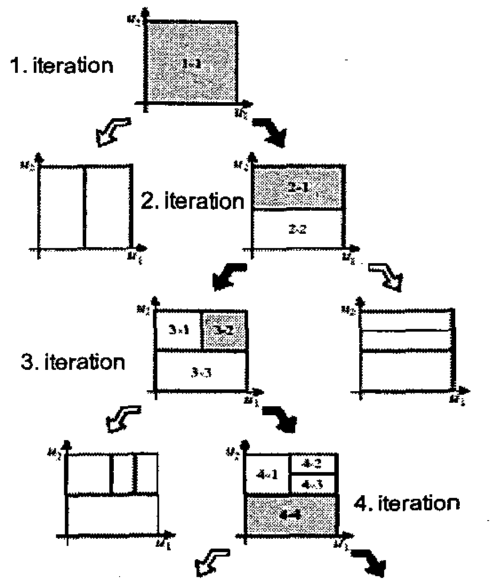

Figure 3. Operation of the LOLIMOT structure search algorithm in the first four iterations for a two-dimensional input space ($p = 2$).

3 IMC based on LOLIMOT model

In this section, the IMC design procedure based on locally linear models will be described. There are generally two control design approaches for local model networks that can be pursued, the linearization and the local model based controller design [5]. The linearization based design is a general approach and can be utilized for any nonlinear model. Here, the model is linearized for each sampling instant at the current, dynamic operating point and subsequently a linear controller is designed online based on that linearized model. For the local model based approach, linear controllers are designed offline for each local model separately and later merged to one operating point dependent controller by weighting the local linear controllers according to the actual operating point. This approach is pursued in this paper. The local model based concept is also called parallel distributed compensation (PDC). For this approach, powerful methods for proving closed-loop stability via solving linear matrix inequalities (LMIs) are available for local model control design [15]. The interpolation of the controller parameters closely follows the idea of model based adaptive control or the gain-scheduling control approach [6].

For nonlinear systems, the IMC approach can be extended to nonlinear models [3,6]. In general however, the inversion of nonlinear models is more involved and analytical solutions may not exist such that solutions have to be found numerically. In the case of local linear networks, the linearity can be exploited directly and an analytical solution can be obtained [3,5]. Following the local model approach, a separate inversion of each local linear model is performed. The control output is then calculated as a weighted sum of locally valid linear controllers yielding a globally nonlinear gain-scheduled controller. Clearly, the weighted average of the local inverse is generally not equal to the global inverse. For this application, however, the difference is negligible and the computation effort of the local model approach is smaller than calculating the global inverse [5].

The IMC design procedure can be utilized to design and tune conventional controllers. In practical applications, the controller tuning process should be as simple and straightforward as possible. However, manual tuning of conventional controllers can be very time-consuming since the dependence of the control performance on the controller parameters is not intuitive. On the other hand, the IMC design procedure is very simple and reliable since only one parameter has to be tuned. Additionally, this parameter is the time constant of the low-pass filter and has a physical meaning. It describes the desired closed-loop dynamics of the system.

For a good control performance, one has to adjust the two controller parameters in order to reach the minimum of the cost function. In comparison to that, only one parameter has to be tuned for the IMC design. The manual tuning effort can be considerably reduced by using the IMC design procedure. It should be noted that the minimum that can be reached with the IMC procedure depends on the quality of the model. Hence, some effort should be put into finding a good model. In case of systems with measurable disturbances and operating point dependent offsets, these influences have to be compensated in the control loop. In particular for the IMC scheme, this compensation has to be implemented in the inversion procedure. For the global nonlinear process, the compensators for the local models have to be blended similar to the local controllers.

4 Application to PH neutralization Process

The neutralization of PH represents a highly nonlinear process, and hence offers a suitable case study for the demonstration and evaluation of locally linear model network techniques. A schematic of a PH neutralization plant is shown in figure 4. This is effectively a continuous stirred tank reactor (CSTR) into which acid, base and buffer streams are added and mixed. The input – output data for the system identification is available at [16]. The acid and base flowrates q_1 and q_3, respectively, are controlled using PI controllers. The nominal operating conditions of the PH neutralization plant are shown in table 1.

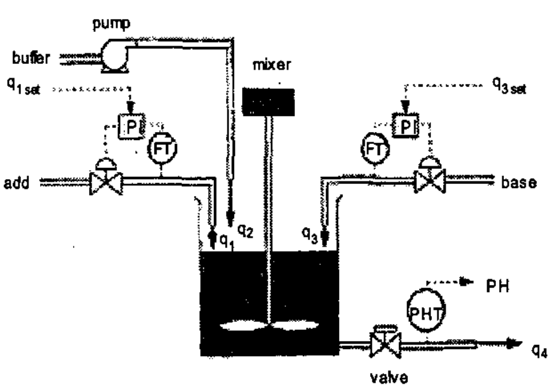

Figure 4. PH neutralization plant.

Table 1. Nominal operating conditions of the PH neutralization plant

Acid stream	0.003 $MHNO_3$
Buffer stream	0.03 $MNaHCO_3$
Base stream	0.003 MNaOH 0.00005 $MNaHCO_3$
Acid flowrate q_1	16.5ml/sec
Buffer flowrate q_2	0.55ml/sec
Base flowrate q_3	15.7ml/sec
Time delay T_d	30 sec
Liquid level in tank h	12 cm
Tank c.s.a.	207 cm^2

The proposed IMC based on LOLIMOT model is applied to the control of the PH neutralization plant. Figure 5 compares the set point tracking behavior of the proposed controller with that of IMC based on MLP neural networks. The results demonstrate the superior performance of the proposed controller. Figure 6 shows the disturbance rejection capabilities of the LOLIMOT model based control action for an unmeasured disturbance for the buffer flowrate from 0.55ml/sec to 0ml/sec. This reduction significantly increases the process gain and causes the oscillatory behavior of the controllers based on MLP network. The LOLIMOT model based controller, on the other hand, has a significantly better response with minimal control effort. Despite its much simpler formulation, the LOLIMOT based controller performs better than the MLP neural controller during the same disturbance and set point tests.

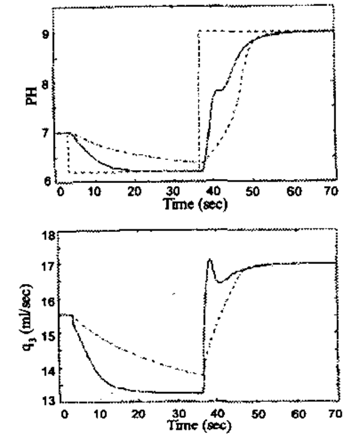

Figure 5. Set point tracking, IMC based on LOLIMOT/IMC based on MLP:
------ set point, -.-.-.- IMC based on MLP network
—— IMC based on LOLIMOT model

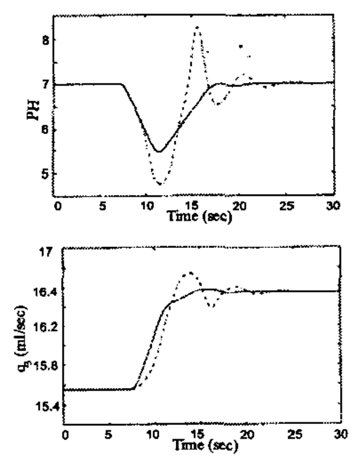

Figure 5. Disturbance rejection, IMC based on LOLIMOT/IMC based on MLP:
------ IMC based on MLP network
—— IMC based on LOLIMOT model

5 Conclusion

In this paper, the design of internal mode control strategy based on locally linear models was presented. The proposed control strategy was applied to the control of PH neutralization process and the results were compared with those of internal model control based on multi layer perceptron neural networks. Simulation results showed the superiority of the proposed controller.

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