An Approach to Observability and Controllability Analysis of Nonlinear Plants on the Basis of TSK Models

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Key Words: *Nonlinear plant; observability and controllability analysis; TSK plant model; two-tank system.*

Abstract. *Most industrial plants are nonlinear, multivariable, inertial and with model uncertainty. They are difficult to model using classical approaches and thus their observability and controllability necessary for the design of the controller are hard to analyze. The aim of the present research is to derive conditions for the analysis of the observability and the controllability of nonlinear plants, represented by state space Takagi-Sugeno-Kang (TSK) models. The main results are a simple and general approach to observability and controllability study of nonlinear plants, which is based on equivalent linear systems and illustrated on a two-variable nonlinear plant – a laboratory two-tank system. The TSK plant model needed can be derived from an existing nonlinear plant model or applying a suggested procedure for development of modified transfer-functions-based TSK models from expert and experimentation data.*

1. Introduction

The plant observability and controllability are necessary conditions for the existence of a controller that can ensure the closed loop system stability and desired performance. The observability is a measure for how well all n internal states $x(t)$ of a system can be inferred by knowledge of its external outputs $y(t)$. The controllability defines the possibility the control $u(t)$ to affect all state space variables of a system, so that the system state can be successfully transferred from initial to any desired final state in finite time.

For linear plants the study of plant observability and controllability is based on the plant state space representation ($\mathbf{A}_{nxn}$, $\mathbf{B}_{nxm}$, $\mathbf{C}_{rxn}$), where $\mathbf{A}_{nxn}\in\mathbf{R}^{nxn}$, $\mathbf{B}_{nxm}\in\mathbf{R}^{nxm}$, $\mathbf{C}_{rxn}\in\mathbf{R}^{rxn}$ are the state, the control and the output matrices related respectively to the vectors of n state space variables $x(t)\in\mathbf{R}^{n}$, m plant inputs (control actions) $u(t)\in\mathbf{R}^{m}$ and r plant outputs $y(t)\in\mathbf{R}^{r}$.

The plant is observable if and only if the rank of the defined observability matrix Ob=[$\mathbf{C}$ $\mathbf{CA}$ $\mathbf{CA}^2\ldots\mathbf{CA}^{n-1}]^T$ is n - rank(Ob)=n, and controllable if and only if the rank of the defined controllability matrix Cb=[$\mathbf{BABA}^2\mathbf{BA}^{n-1}\mathbf{B}$] is n - rank(Cb)=n. Then it is stated that the couple ($\mathbf{A}_{nxn}$, $\mathbf{C}_{rxn}$) is observable and the couple ($\mathbf{A}_{nxn}$, $\mathbf{B}_{nxm}$) is controllable [1-3].

If the system (plant) is either uncontrollable or unobservable or both uncontrollable and unobservable in the used state space representation ($\mathbf{A}_{nxn}$, $\mathbf{B}_{nxm}$, $\mathbf{C}_{rxn}$) among the many possible, a zero-pole cancellation problem is present in the transfer function of the system $T(s)=\mathbf{C}(s\mathrm{I}-\mathbf{A})^{-1}\mathbf{B}$. Therefore the system is transformed to a lower order both controllable and observable minimal realization by removing the stable uncontrollable and/or unobservable modes.

The observability and the controllability analysis for the case of nonlinear plants is even more important for their successful control than for the case of linear plants, but it is rather difficult and often neglected. Various approaches have been developed for specific types of nonlinear systems (Hamiltonian, polynomial, etc.) and their canonical and minimal presentations, all based on existing nonlinear plant model [4-6]. In [7] necessary and sufficient conditions for observability are derived in function of the time instant as extension of the classical observability rank conditions for continuous-time and discrete-time systems.The observability and controllability analysis of nonlinear dynamic systems in [8] starts from checking of the observability (controllability) of the initial nonlinear system linear part and if unobservable (uncontrollable), examining whether the nonlinear terms are responsible for this.

Most of the industrial processes are nonlinear inertial multivariable plants with time delay which makes their modelling difficult or unsatisfactory using classical approaches [9-12]. The design of the controller is still often model-based and can be successful only for fully observable and controllable plants. The fuzzy logic Takagi-Sugeno-Kang (TSK) modelling offers a suitable technique for deriving of simple and accurate state space models also from experimental and expert data that can enable the formulation of rank conditions for the analysis of the nonlinear plants observability and controllability based on the well-developed linear control theory. TSK models can approximate any nonlinear plant by fuzzy switching among local linear state space plant models, defined for a few overlapping operation zones in the "if-then" fuzzy rules conclusions [13-15]. The premise in the TSK plant model assesses of the degrees of belonging of the system (plant) current state to the operation zones for which the linear plant models are derived. The fuzzy rules are small in number and correspond to the number of the linearization zones. For a standard TSK plant model the rule in the k-th linearization zone, k=1чr, is the following:

(1) $\mathbf{R}_k$: **IF**$z_1(t)$ is Lz_{k1}**AND…AND**$z_p(t)$ is Lz_{kp}

$$\textbf{THEN.}\begin{cases}\dot{x}(t)=\mathbf{A}_k x(t)+\mathbf{B}_k u(t)\\ y(t)=\mathbf{C}_k x(t)\end{cases}$$

where $z(t)=[z_j(t)]$, j=1чp is the vector of the premise variables z_j that measure or estimate the system current state, z_j takes linguistic values Lz_{kj}, represented by fuzzy sets,

$x(t)\in \mathbf{R}^n$ is the vector of n state space variables, $u(t)\in \mathbf{R}^m$ is the vector of m plant inputs (control actions), $y(t)\in \mathbf{R}^m$ is the vector of m plant outputs and $\mathbf{A}_i\in \mathbf{R}^{nxn}$, $\mathbf{B}_i\in \mathbf{R}^{nxm}$, $\mathbf{C}_i\in \mathbf{R}^{mxn}$ are the corresponding state, control and output matrices.

Each current measured or estimated plant state matches the defined overlapping linearization zones to different degrees, i.e. the rules conditions are fulfilled to different degrees which scale the computed plant outputs in the rules conclusions. The scaled outputs in all rules are united and a weighted average of them yields the final plant output. So, as a result of the fuzzy inference mechanism and the weighted average defuzzyfication the model output is obtained as soft blending of the individual rules conclusions in the form

$$\text{(2)}\quad \begin{aligned} \dot{x}(t) &= \frac{\sum_{\mathrm{k=1}}^{\mathrm{r}} w_{\mathrm{k}}(z(t))[\mathbf{A}_{\mathrm{k}}x(t)+\mathbf{B}_{\mathrm{k}}u(t)]}{\sum_{\mathrm{k=1}}^{\mathrm{r}} w_{\mathrm{k}}(z(t))} = \sum_{\mathrm{k=1}}^{\mathrm{r}} h_{\mathrm{k}}(z(t))[\mathbf{A}_{\mathrm{k}}x(t)+\mathbf{B}_{\mathrm{k}}u(t)],\\ y(t) &= \frac{\sum_{\mathrm{k=1}}^{\mathrm{r}} w_{\mathrm{k}}(z(t))\mathbf{C}_{\mathrm{k}}x(t)}{\sum_{\mathrm{k=1}}^{\mathrm{r}} w_{\mathrm{k}}(z(t))} = \sum_{\mathrm{k=1}}^{\mathrm{r}} h_{\mathrm{k}}(z(t))\mathbf{C}_{\mathrm{k}}x(t) \end{aligned}$$

where $w_{\mathrm{k}}(z(t)) = \prod_{\mathrm{j=1}}^{\mathrm{p}} \mathrm{Lz}_{\mathrm{kj}}(z_{\mathrm{j}}(t)), \left| \begin{array}{l} \sum_{\mathrm{k=1}}^{\mathrm{r}} w_{\mathrm{k}}(z(t)) > 0 \\ w_{\mathrm{k}}(z(t)) \geq 0 \end{array} \right.$ is the degree of fulfillment of the compound condition in the fuzzy rule premise and $\mathrm{Lz}_{\mathrm{kj}}(z_{\mathrm{j}}(t))$ the degree of matching of $z_{\mathrm{j}}(t)$ with $\mathrm{Lz}_{\mathrm{kj}}$, $h_{\mathrm{k}}(z(t)) = \frac{w_{\mathrm{k}}(z(t))}{\sum_{\mathrm{k=1}}^{\mathrm{r}} w_{\mathrm{k}}(z(t))}, \left| \begin{array}{l} \sum_{\mathrm{k=1}}^{\mathrm{r}} h_{\mathrm{k}}(z(t)) = 1 \\ h_{\mathrm{k}}(z(t)) \geq 0 \end{array} \right.$ is the normalized rule activation degree.

TSK models are developed via linearization of existing nonlinear models in [14]. In [12,16,17] neuro-fuzzy structures that present first order Sugeno models (TSK models) are trained on available experimental and expert data using MATLAB™ toolbox Adaptive Neuro-Fuzzy Inference System (ANFIS) [18,19]. First the number of the membership functions (MFs) is computed by partitioning of the input-output space via fuzzy clustering, then the fuzzy rules are automatically generated and finally the parameters of the MFs and the gains in the conclusions are optimized. The obtained TSK model conclusions $\begin{cases} \dot{x}(t) = \mathbf{A}_{\mathrm{k}}x(t) + \mathbf{B}_{\mathrm{k}}u(t) + \mathbf{D}_{\mathrm{k}} \\ y(t) = \mathbf{C}_{\mathrm{k}}x(t) \end{cases}$ contain free gains $\mathbf{D}_{\mathrm{k}}$ which express the nonlinear terms in the state space linearization. The training sample should be representative and pre-processed by normalization or standardization, noise filtering, correlation elimination, etc. The training, however, can be slow and validation may turn unsuccessful.

The validated standard TSK model can be used to study and ensure plant observability and controllability. The fully observable and controllable plant model is employed for the design of a controller that can ensure system stability and desired performance. In case the plant observability and/or controllability is not proven, the plant model has to be modified to minimal realization thus avoiding the zero-pole cancellation, correlation or redundancy problems.

For each TSK model a parallel distributed compensator (PDC) can be built of local linear controllers each developed for the corresponding local linear plant applying the linear control theory approaches [14,15]. The standard PDC consists of the same small number of fuzzy rules with the same premises and local state feedbacks via the control matrices $\mathbf{F}_{\mathrm{k}}$

(3) $\mathbf{R}_{\mathrm{k}}$**:** **IF**$z_1(t)$ is $\mathrm{Lz}_{\mathrm{k1}}$**AND…AND**$z_{\mathrm{p}}(t)$ is $\mathrm{Lz}_{\mathrm{kp}}$

THEN $u(t) = -\mathbf{F}_{\mathrm{k}}x(t).$

The PDC design till now does not consider the requirement the plant model used to be fully observable and controllable. The observability and controllability of the local linear plants required for the local linear controllers design can easily be established by the ranks of the defined observability and controllability matrices according to the linear control theory. The global nonlinear plant has also to be observable and controllable.

PDCs are also designed using dynamic linear controllers such as PID-based, Smith predictors, internal model controllers (IMCs), etc. [12,20-25]. They are appealing because can be developed and applied to any nonlinear plant in a unified manner, using the well mastered linear control techniques both for the design and the nonlinear system stability analysis. Standard TSK-PDC description enables global nonlinear system stability analysis based on the adopted from the classical control systems theory Lyapunov methods and the linear matrix inequalities (LMIs) numerical techniques [14,26].

In the engineering practice often the dynamic state space presentation of the local linear plants in the standard TSK model (1) is difficult to directly derive from available expert and experimental data especially for multivariable processes and processes with time delay or without self-regulation. Besides, the design of the PDC in the form (3) is also complicated for standard local linear controllers such as PID based, Smith predictors, IMCs, etc., which are developed on the basis of simple transfer functions representation of the local linear plant models. This motivates to develop modified TSK plant models with local linear plants represented by transfer functions or matrices thus facilitating its derivation out of expert and experimental data, the design of the frequently spread in the engineering practice local linear dynamic controllers and also the PDC completion in industrial programmable logic controllers (PLCs) [27-29]. For the purpose of the nonlinear plant observability and controllability analysis prior the PDC design and the final nonlinear closed loop system stability the modified TSK plant model has to be transformed to state space form (1)-(3).

So, the aim of the present paper is to derive conditions for the analysis of the observability and the controllability of nonlinear plants, based on their state space TSK models description and to suggest an engineering procedure for development of modified TSK models. Further the paper is organized as follows. In Section 2 a more general approach to TSK modelling is developed for nonlinear plants that may be multivariable and with time delay based on available for most cases expert and experimentation data. The modified TSK plant model suggested is built of a Sugeno fuzzy unit (FU) for distinguishing the degrees of belonging of the current plant state to different overlapping linearization zones and local for each zone linear dynamic models described compactly by simple transfer functions or matrices of clear physical nature that correspond to the conclusions in (1). The parameters of the FU MFs and of the linear local plant models are determined via optimization on the basis of experimentation data. Then the easily obtained local plant transfer function models are transformed into state space leading to the standard TSK model (1). In Section 3 nonlinear plant observability and controllability conditions are derived and an approach for their computational analysis suggested. The application of the developed approach is illustrated for a two-variable nonlinear plant – a laboratory-scale coupled-tank system in Section 4 where a modified TSK model is derived and the plant observability and controllability is studied. Section 5 summarizes the main contributions and outlines the future research.

2. TSK Modelling from Expert and Experimentation Data

A modified TSK structure is suggested based on separating of the fuzzy part from the local linear dynamic models. The FU is designed as a zero order Sugeno model with several outputs that give the degrees of belonging of the current state, described by the predicate variables, to each of the linearization zones. In *figure 1* such a modified TSK model is illustrated for three linearization zones – S (small), M (medium or norm) and B (big), represented by Gaussian MFs with parameters mean value and standard deviation "sigma", plant output as a single predicate variable $-z(t)=y(t)$ and local plants dynamics described by time lags. It is possible to easily extend the model for the case of more predicate variables and rules. Then the Sugeno model outputs will correspond to the level of activation of the corresponding rule. The dynamic models for each zone can also vary in type and may contain time delays and integrators as well. Often Ziegler-Nichols (ZN) linear plant models are accepted with transfer functions $P(s) = Ke^{-\tau s}(Ts+1)^{-1}$, where the parameters – plant gain K, time constant T and time delay τ vary in the different linearization zones. The local ZN models are well known in the engineering practice for their physical meaning and easy derivation via experimentation and approximation or estimation from expert knowledge. They are the basic models used for the empiric design of the most widely spread industrial controllers such as standard PID based, Smith predictor, IMC, etc. designed here as local controllers.

In each linearization zone in *figure 1* the local plant dynamic is expressed by a series connection of an individual (Transfer Fcn k) and a common for all zones (Common Transfer Fcn) time lags. The Sugeno model in *figure 1* is in open structure to enable tuning of the accepted Gaussian MFs. It can be fixed in a fuzzy logic controller (FLC) block in a Simulink model after being designed and optimized or simply can be designed from expert knowledge as a FLC. The optimized Sugeno model in *figure 1* is shown as a fixed FLC block in *figure 2.* The rules are in the form:

Rule 1. IF y is S **THEN** Output 1 is 1
AND Output 2 is 0 **AND** Output 3 is 0
Rule 2. IF y is M **THEN** Output 1 is 0
AND Output 2 is 1 **AND** Output 3 is 0
Rule 3. IF y is B **THEN** Output 1 is 0
AND Output 2 is 0 **AND** Output 3 is 1.

Experts can easily suggest the number of the linearization zones and the types of the linear dynamic models of the local plants. In case of available experimentally obtained plant step responses to input changes in different operation points the linearization zones can be outlined by grouping of similar adjacent step responses [12,20,21]. If there is plant input-output data collected the linearization zones can be estimated by cluster analysis, e.g. using ANFIS. For complex and multivariable plants and plants with no self-regulation where identification is difficult or complex, the structure can be expert based on a minimal number of three linearization zones – operation at the Norm (desired operation point), below the Norm and above the Norm. The zones can be recognized by plant state variables or most often by the plant outputs $y(t)$ since when under closed loop control, the plant outputs follow their reference y_r and smoothly pass through all sub-domains from the initial to the final. Then in each zone a simple type of the average local linear model is assumed – mainly of time lags, integrators and time-delays.

In *figure 3* a TSK model structure is shown for the first output y_1 of a two-variable nonlinear plant with local linear plants described by a transfer matrix $\mathbf{P}(s) = \begin{bmatrix} P_{11}(s) & P_{12}(s) \\ P_{21}(s) & P_{22}(s) \end{bmatrix}$, where each output $y_i(t)$ is the sum of main channel $y_{ii}(t)$ and cross channel $y_{ij}(t)$ (i, j=1,2 and $i \neq j$) outputs, which expressed in Laplace yields $y_i(s)=y_{ii}(s)+y_{ij}(s)=P_{ii}(s)u_i+P_{ij}(s)u_j$ with $y_{ij}(s) = P_{ij}(s)\, u_j(s)$. The main and the cross channel have the structure in *figure 1.*

The TSK model for the second output y_2 has an identical structure only the FLC block is different as seen in *figure 4* (FLC1≠FLC2) since the second output variable is different and the linearization zones can be defined in a different way with different MFs and ranges. A general two-variable modified TSK model is illustrated in *figure 5*, where the subscript k denotes the linearization zone, k=1ч3 for this example. Each TSK plant output y_{iTSK}, i=1, 2, is computed as a weighted average of the local models outputs $y_i^k(t)$ for all zones

$$y_{\mathrm{iTSK}}(t)=\frac{\sum_{k=1}^{3}\mu_{\mathrm{FLCi}}^{k}(y_i(t))\,y_i^{k}(t)}{\sum_{k=1}^{3}\mu_{\mathrm{FLCi}}^{k}(y_i(t))},\quad \sum_{k=1}^{3}\mu_{\mathrm{FLCi}}^{k}(y_i(t))=1. \tag{4}$$

In a similar manner structures of modified TSK models can be built for arbitrary multivariable plants and linearization zones.

In order to compute the modified TSK model parameters experimental data should be supplied accounting for the range of control actions, operation conditions and modes covering the whole plant operation range in order to collect rich in magnitudes and frequencies experimental data for the plant input u_{ex} and output y_{ex}. The collected experimental data (u_{ex}, y_{ex}) are normalized or standardized and processed to filter noise and reduce correlation and redundant and non-informative data. Then the data are divided into two – a set for modeling (u_{ex}^{m}, y_{ex}^{m}) and a set for model validation (u_{ex}^{v}, y_{ex}^{v}).

The TSK model parameters are computed from minimization of an accepted cost function of the error between the outputs of the TSK model y_{TSK} and the experimentally recorded real plant outputs y_{ex}^{m} – mean squared error, integral squared or absolute error, relative integral squared or absolute error, etc. The TSK model inputs are the data set $(u_{ex}=u_{ex}^{m}, y_{ex}=y_{ex}^{m})$, recorded from the experiments on the real plant.

In the present approach genetic algorithms (GAs) are employed to compute the optimal parameters of the modified TSK plant model. The fitness function to be minimized

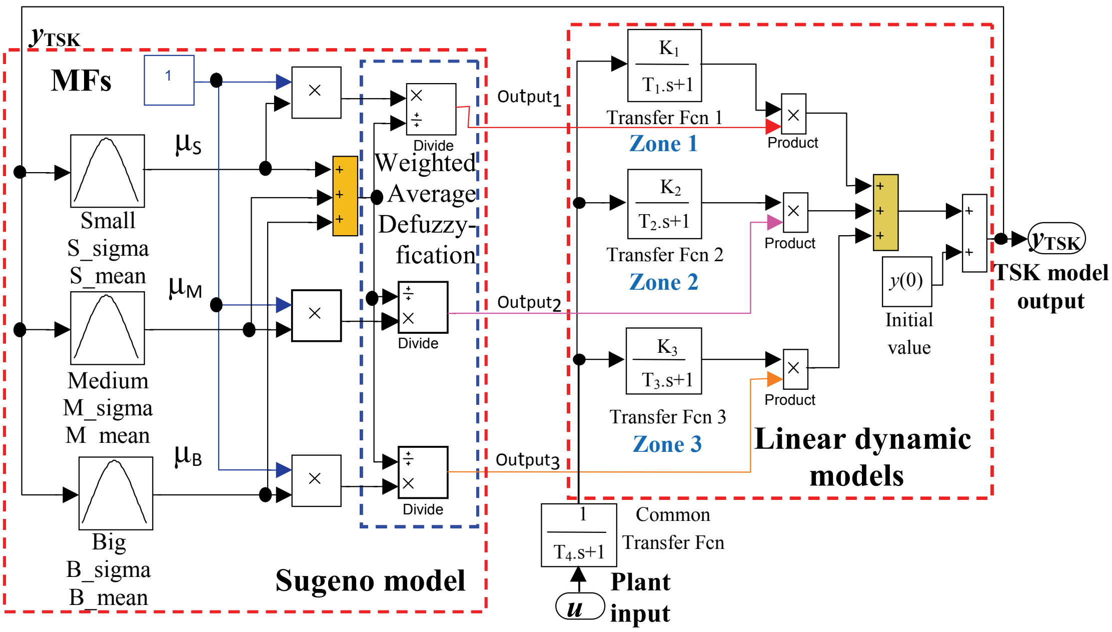


Figure 1. Modified TSK model

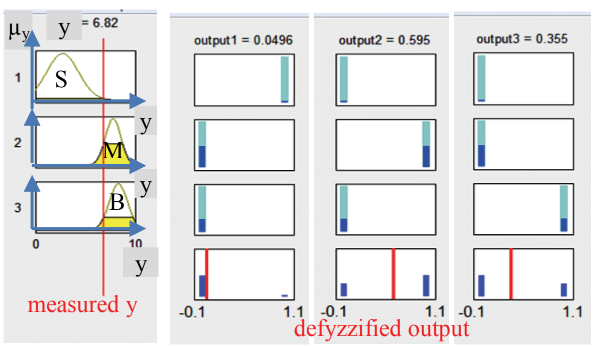


Figure 2. Sugeno model in aSimulink FLCblock – single input y, three Gaussian MFs, outputs and fuzzy rules

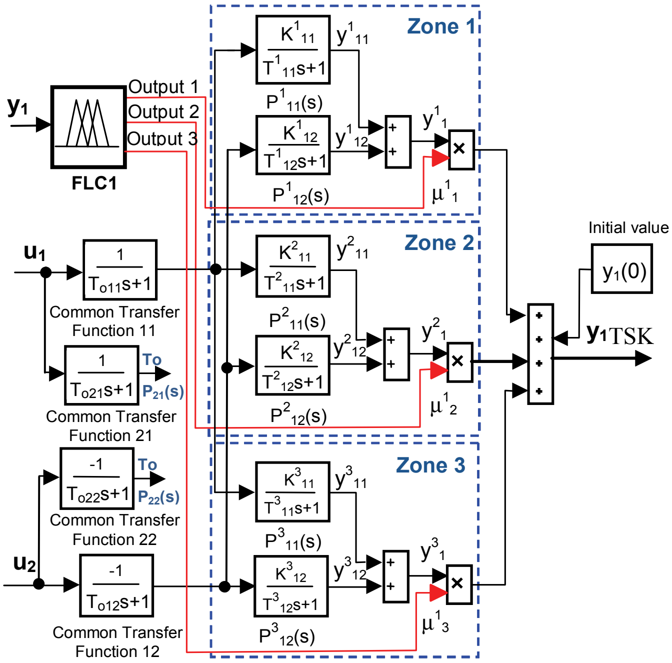


Figure 3. FLC-based TSK two-variable plant model for three linearization zones – output 1

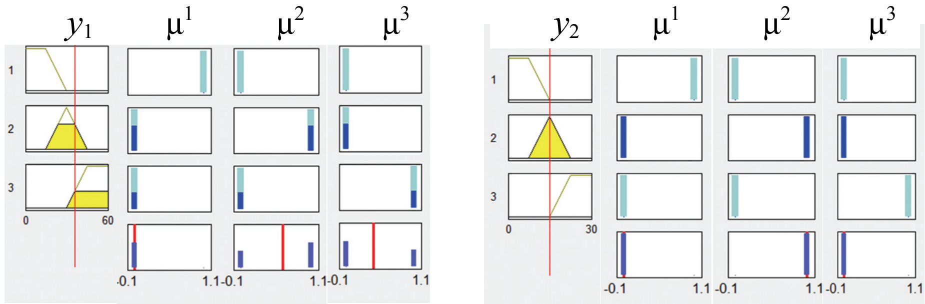


Figure 4. FLC1 and FLC2 in the TSK two-variable plant model for three linearization zones

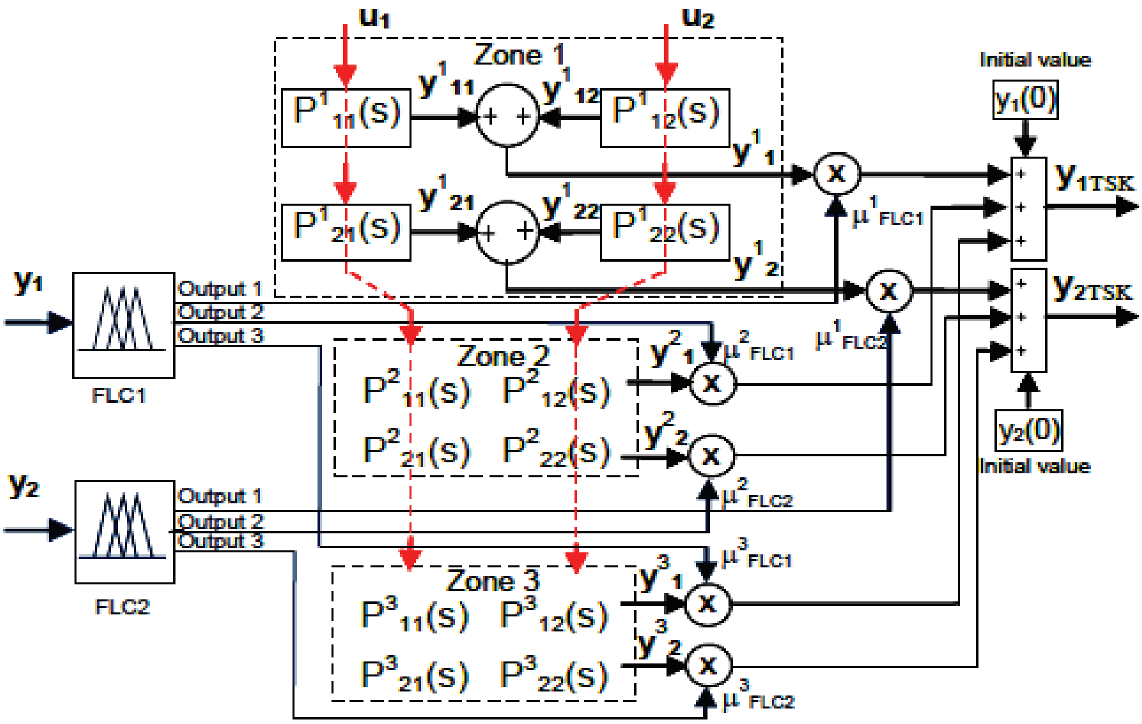


Figure 5. Two-variable TSK plant model for three linearization zones

is the following:

$$(5)\quad \mathbf{F}_{\mathrm{TSK}}=\int\Sigma_{\mathrm{i}}\{[y_{\mathrm{iTSK}}(t)-y_{\mathrm{iex}}(t)]/y_{\mathrm{iex}}(t)\}^2.dt \rightarrow \underbrace{\mathrm{q}_{\mathrm{TSK}}}_{}^{\min}.$$

The TSK plant model parameters to be computed that minimize (4) are respectively:

in *figure 1*

$\mathbf{q}_{\mathbf{TSK}}=[K_1K_2K_3T_1T_2T_3T_4y(0)\mathrm{S\_sigmaS\_meanM\_sigmaM\_meanB\_sigmaB\_mean}]$

in *figure 3*

$\mathbf{q}_{\mathbf{TSK}}=[K^1{}_{11}T^1{}_{11}K^1{}_{12}T^1{}_{12}K^1{}_{21}T^1{}_{21}K^1{}_{22}T^1{}_{22};K^2{}_{11}T^2{}_{11}K^2{}_{12}T^2{}_{12}K^2{}_{21}T^2{}_{21}K^2{}_{22}T^2{}_{22};K^3{}_{11}T^3{}_{11}K^3{}_{12}T^3{}_{12}K^3{}_{21}T^3{}_{21}K^3{}_{22}T^3{}_{22};\ T_{\mathrm{o}1}\ \ T_{\mathrm{o}2};y_1(0)\ y_2(0)].$

The GAs applied here for approximation is a derivative-free stochastic method for multi-criteria optimization with respect to a great number of parameters that comprise the chromosomes. A global minimum of multimodal and nonlinear cost functions under different restrictions defined via data from simulation or experiments is searched in parallel for all chromosomes in a generation via random mating, cross-over and mutation techniques for evolving of the new generation. The on-line GAs optimization is avoided as it influences the plant operation, is slow for the many experiments required, is inaccurate because of the many disturbances from the industrial environment, and is restricted by the system stability, parameters and signals constraints. The off-line GAs optimization is based on evaluation of the accepted fitness function using plant model simulations and a representative sample of experimentation data.

If the accuracy reached is not enough for a great number of generations and runs of the GAs optimization at different random initial chromosomes and bounds of the parameters, the structure of the modified TSK model is changed by increasing the linearization zones symmetrically on both sides of the term Norm and/or by varying the local plant dynamics representation (using different transfer functions, etc.).

The TSK plant model is validated for a different set of experimental data ($u_{\mathrm{ex}}{}^{\mathrm{v}}$, $y_{\mathrm{ex}}{}^{\mathrm{v}}$). The TSK model response y_{TSK} allows evaluation of (5). If $\mathbf{F}_{\mathrm{TSK}}$ is acceptably small the TSK plant model has captured correctly the real plant peculiarities and nonlinearity and it is independent of the specific experimental data. So, the investigations with it provide new reliable knowledge about the real plant.

The validated modified TSK plant model is transformed in the standard description (1) of a first order Sugeno fuzzy model with local state space dynamic models in the rules conclusions. For the modified TSK two-variable plant model in *figure 3* the channels transfer functions are $P^{\mathrm{k}}{}_{\mathrm{ij}}(s)=K^{\mathrm{k}}{}_{\mathrm{ij}}[(T^{\mathrm{k}}{}_{\mathrm{ij}}s+1)(T_{\mathrm{oij}}s+1)]^{-1}$ $(i,j=1,2)$ with T_{oij} common for all linearization zones for the corresponding main and cross channel. The control plant input vector is $u(t)=[u_1(t)\ \ u_2(t)]^{\mathrm{T}}$ and the plant output vector is $y(t)=[y_1(t)\ y_2(t)]^{\mathrm{T}}$, $y_{\mathrm{i}}(t)=y_{\mathrm{i}1}(t)+y_{\mathrm{i}2}(t)+y_{\mathrm{i}}(0)$. Following the plant transfer matrix the state space models of the local plants in (1) have the following possible n state space variables, n=8, and corresponding matrices for the k-th linearization zone:

$$x(t)=[x^1(t)\ \ x^2(t)]^{\mathrm{T}},\ x^1(t)=[x_1(t)=y_{11}(t)\ \ x_2(t)=\dot{x}_1(t)\ \ x_3(t)=y_{12}(t)\ \ x_4(t)=\dot{x}_3(t)]^{\mathrm{T}},$$

$$x^2(t)=[x_5(t)=y_{21}(t)\ \ x_6(t)=\dot{x}_6(t)\ \ x_7(t)=y_{22}(t)\ \ x_8(t)=\dot{x}_8(t)]^{\mathrm{T}},$$

$$(6)\qquad \mathbf{A}_{\mathrm{k}}=\begin{bmatrix}\mathbf{A}^1_{\mathrm{k}} & \mathbf{O}\\ \mathbf{O} & \mathbf{A}^2_{\mathrm{k}}\end{bmatrix}_{8\mathrm{x}8},\ \mathbf{B}_{\mathrm{k}}=\begin{bmatrix}\mathbf{B}^1_{\mathrm{k}}\\ \mathbf{B}^2_{\mathrm{k}}\end{bmatrix}_{8\mathrm{x}2},\ \mathbf{C}=\begin{bmatrix}\mathbf{C}^1 & \mathbf{C}^2\end{bmatrix}_{2\mathrm{x}8},\ \ \mathbf{C}^1=\begin{bmatrix}1&0&1&0\\0&0&0&0\end{bmatrix}_{2\mathrm{x}4},\ \ \mathbf{C}^2=\begin{bmatrix}0&0&0&0\\1&0&1&0\end{bmatrix}_{2\mathrm{x}4},\ \mathbf{O}=\begin{bmatrix}0&0\\0&0\end{bmatrix}_{4\mathrm{x}4}$$

where

$$\mathbf{A}^1_{\mathrm{k}}=\begin{bmatrix}0&1&0&0\\ -\dfrac{1}{T_{\mathrm{o}11}T^{\mathrm{k}}_{11}} & -\dfrac{T_{\mathrm{o}11}+T^{\mathrm{k}}_{11}}{T_{\mathrm{o}11}T^{\mathrm{k}}_{11}} & 0 & 0\\ 0&0&0&1\\ 0&0&-\dfrac{1}{T_{\mathrm{o}12}T^{\mathrm{k}}_{12}} & -\dfrac{T_{\mathrm{o}12}+T^{\mathrm{k}}_{12}}{T_{\mathrm{o}12}T^{\mathrm{k}}_{12}}\end{bmatrix}_{4\mathrm{x}4},\quad \mathbf{A}^2_{\mathrm{k}}=\begin{bmatrix}0&1&0&0\\ -\dfrac{1}{T_{\mathrm{o}21}T^{\mathrm{k}}_{21}} & -\dfrac{T_{\mathrm{o}21}+T^{\mathrm{k}}_{21}}{T_{\mathrm{o}21}T^{\mathrm{k}}_{21}} & 0 & 0\\ 0&0&0&1\\ 0&0&-\dfrac{1}{T_{\mathrm{o}22}T^{\mathrm{k}}_{22}} & -\dfrac{T_{\mathrm{o}22}+T^{\mathrm{k}}_{22}}{T_{\mathrm{o}22}T^{\mathrm{k}}_{22}}\end{bmatrix}_{4\mathrm{x}4}$$

$$\mathbf{B}^1_{\mathrm{k}}=\begin{bmatrix}0&0\\ \dfrac{K^{\mathrm{k}}_{11}}{T_{\mathrm{o}11}T^{\mathrm{k}}_{11}} & 0\\ 0&0\\ 0 & \dfrac{-K^{\mathrm{k}}_{12}}{T_{\mathrm{o}12}T^{\mathrm{k}}_{12}}\end{bmatrix}_{4\mathrm{x}2},\quad \mathbf{B}^2_{\mathrm{k}}=\begin{bmatrix}0&0\\ \dfrac{K^{\mathrm{k}}_{21}}{T_{\mathrm{o}21}T^{\mathrm{k}}_{21}} & 0\\ 0&0\\ 0 & \dfrac{-K^{\mathrm{k}}_{22}}{T_{\mathrm{o}22}T^{\mathrm{k}}_{22}}\end{bmatrix}_{4\mathrm{x}2}$$

The matrix **C** is the same for all linearization zones.

MATLAB™ Control toolbox supports transfer functions to state space models transforms, linear systems (plants) observability and controllability study and systems minimal realizations computation [30]. Thus fully observable and controllable final plant models are computed with no redundancy and pole-zero cancellation problems which can be applied for the controller design.

3. Conditions for Observability and Controllability of Nonlinear Plants

Here a general methodology for nonlinear plants observability and controllability analysis is suggested on the basis of standard TSK plant models derived from existing nonlinear models or from experimental data and modified TSK models. If the modified TSK plant model contains time delays in the local plant models the delay elements are first approximated, usually by the first term of the Taylor's series expansion – $e^{-\tau s} \approx \dfrac{1}{\tau s + 1}$, before transforming into a standard TSK model.

The TSK plant model via the fuzzy inference mechanism and the weighted average defuzzyfication yields a nonlinear plant output as soft blending of the local plants outputs (2), which for a single premise variable become:

$$(7)\quad \left|\begin{array}{l} \dot{x}(t) = \sum\limits_{k=1}^{r} h_k(z(t))[\mathbf{A}_k x(t) + \mathbf{B}_k u(t)], h_k(z(t)) = \dfrac{\prod\limits_{j=1}^{p} \mu_j^k(z_j(t))}{\sum\limits_{k=1}^{r}\prod\limits_{j=1}^{p} \mu_j^k(z_j(t))}, \sum\limits_{k=1}^{r} h_k(z(t)) = 1 \\ y(t) = \sum\limits_{k=1}^{r} h_k(z(t)) y_k(t),\ y_k(t) = \mathbf{C}_k x(t). \end{array}\right.$$

Thus for r linearization zones (7) can be rewritten as

$$(8)\quad \left|\begin{array}{l} \dot{x}(t) = h_1[\mathbf{A}_1 x(t) + \mathbf{B}_1 u(t)] + h_2[\mathbf{A}_2 x(t) + \mathbf{B}_2 u(t)] + \ldots + h_r[\mathbf{A}_r x(t) + \mathbf{B}_r u(t)] \\ y(t) = h_1\mathbf{C}_1 x(t) + h_2\mathbf{C}_2 x(t) + \ldots + h_r\mathbf{C}_r x(t), \end{array}\right.$$

which after simplification yields

$$(9)\quad \left|\begin{array}{l} \dot{x}(t) = \mathbf{A}^e(h)x(t) + \mathbf{B}^e(h)u(t) \\ y(t) = \mathbf{C}^e(h)x(t), \end{array}\right.$$

where $h=[h_1\ h_2\ \ldots\ h_r]^T$, $\mathbf{A}^e(h) = \sum\limits_{k=1}^{r} h_k\mathbf{A}_k$, $\mathbf{B}^e(h) = \sum\limits_{k=1}^{r} h_k\mathbf{B}_k$, $\mathbf{C}^e(h) = \sum\limits_{k=1}^{r} h_k\mathbf{C}_k$ are equivalent matrices computed as a sum of scaled by h_k, $h_k \in [0, 1]$, local plants matrices.

The nonlinear plant according to (9) is represented by an infinite number of linear plant models ($\mathbf{A}^e(h)$, $\mathbf{B}^e(h)$, $\mathbf{C}^e(h)$), derived for various combinations of values for $[h_1 \ldots h_r]$. So, an infinite number of nonlinear plant observability and controllability matrices can be defined with respect to the equivalent matrices ($\mathbf{A}^e(h)$, $\mathbf{B}^e(h)$, $\mathbf{C}^e(h)$) as a function of h

$$(10)\quad O^e(h)=[\mathbf{C}^e(h) \,|\, \mathbf{C}^e(h).\mathbf{A}^e(h) \,|\, \mathbf{C}^e(h).\mathbf{A}^e(h)^2 \,|\, \ldots \,|\, \mathbf{C}^e(h).\mathbf{A}^e(h)^{n-1}]^T,$$

$$(11)\quad C^e(h)=[\mathbf{B}^e(h) \,|\, \mathbf{A}^e(h).\mathbf{B}^e(h) \,|\, \mathbf{A}^e(h)^2.\mathbf{B}^e(h) \,|\, \ldots \,|\, \mathbf{A}^e(h)^{n-1}.\mathbf{B}^e(h)].$$

Thus a plant represented by a TSK model is observable if and only if the ranks of all observability matrices for the possible combinations of h_k, $k=1\div r$, are n - rank$[O^e(h)]=n$ for all h. Then all couples [$\mathbf{A}^e(h)$, $\mathbf{C}^e(h)$] are observable. The plant is controllable if and only if the ranks of all controllability matrices for the possible combinations of h_k, $k=1\div r$, are n – rank $[C^e(h)]=n$ for all h. Then all couples [$\mathbf{A}^e(h)$, $\mathbf{B}^e(h)$] are controllable. The TSK plant model observability and controllability can be studied computationally.

In case the nonlinear plant observability and controllability is not proven, a minimal realization for each h is computed which ensures full observability and controllability. So, the minimal realization is the final plant model used to design the controller.

If no minimal realization is required, the modified TSK plant of transfer-functions-based local plant models or the derived from it standard TSK model is used for the design of the local either industrial or state or feedback controllers respectively. If necessary for the PDC design a ZN approximation of the local transfer functions representation is carried out in case the modified TSK plant is not derived with ZN local plant models. If a minimal realization is required, first a state space to transfer functions transformation is carried out and the corresponding modified TSK model updated.

The study of the global nonlinear system stability is possible for standard TSK plant and PDC descriptions with and without time delay using different Lyapunov-LMIs conditions [12,14,21].

4. A Coupled-tank System Observability and Controllability Analysis

A Laboratory-scale Two-variable Plant

The plant which observability and controllability is studied employing the developed approach is a laboratory-scale coupled-tank system. It consists of two identical tanks with connected via a pipe outflows at the tanks bottoms and a collective tank. Each tank is equipped with an industrial level sensor and transmitter. The levels H_1 and H_2 are the plant outputs - $y_1=H_1$ and $y_2=H_2$. The plant inputs that control the levels are the DC voltages U_i to two pumps $u_1=U_1$ and $u_2=U_2$. Pump 1, located at the bottom of the collective tank, pumps up liquid in Tank 1 from the top while Pump 2, located at the bottom of Tank 2, pumps out liquid of Tank 2 from the top into the collective tank. No identification of the plant is possible as a step change of U_1 leads to incessant increase of H_1 and respectively of H_2 till the liquid overflows the tanks, or a step change of U_2 finally empties both tanks. The plant is two-variable nonlinear with linear models of transfer matrices $\mathbf{P}^k(s)$ in each linearization zone. The gains in $P_{11}(s)$ and $P_{21}(s)$ are positive – an increase in U_1 leads to an increase in H_1 and H_2, while the gains in $P_{22}(s)$ and $P_{12}(s)$ are negative – an increase in U_2 causes a decrease in H_2 and H_1.

Experiments using a Simulink model in MATLAB™ real time and a plant-computer interface with Analog-To-Digital (ADC) and Digital-To-Analog Converters (DAC) [31] are carried out manually changing of plant inputs in the range of the control actions and recording the responses of the two levels H_{iex}. Plant input-output data (U_{iex}, H_{iex}), shown in *figure 6*, is collected, processed and divided into two – for use in computing of the parameters of a suggested modified TSK plant model ($U_{iex}^{\ m}$, $H_{iex}^{\ m}$), and for model validation ($U_{iex}^{\ v}$, $H_{iex}^{\ v}$).

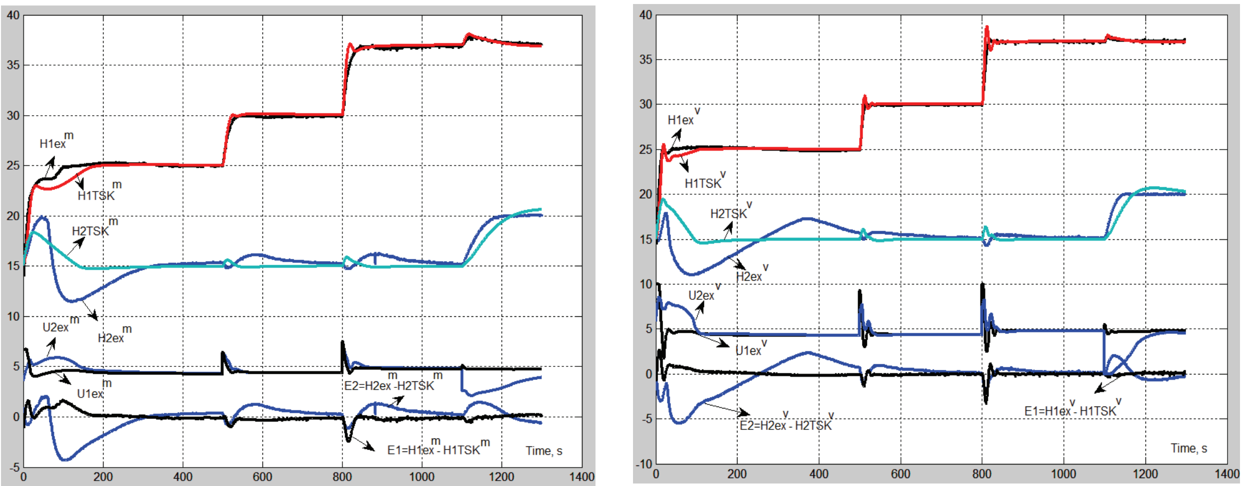
A TSK Plant Modelling and Validation

The modified TSK plant model structure suggested is the shown in *figure 3* and *figure 5*. It is based on the expert assumptions for three linearization operation zones for each plant output, presented in *figure 4*, and approximation of zones dynamics by time lags. The FLC1 and FLC2 have single inputs H_1 and H_2 respectively, three rules and three outputs each, yielding the MFs μ^k_{FLCi} of belonging of the current level H_i to the three linearization zones k=1ч3. The MFs of FLC1 and FLC2 in *figure 4* are orthogonal and every two adjacent MFs are overlapping. So, $w_k(H_i) = \mu^k(H_i)$,

$$\sum_{k=1}^{3} \mu^k(H_i) = 1 \text{ and } h_k = \frac{\mu^k(H_i)}{\sum_{k=1}^{3} \mu^k(H_i)} = \mu^k(H_i).$$

The optimal parameters of the local plant models are computed in GAs minimization of the integral sum of squared relative errors (4) using the processed data for modelling from the real time experimentation

$$\begin{aligned}\mathbf{q}^o_{TSK}=[&K^1_{11}=1,\ T^1_{11}=5.4,\ K^1_{12}=0.85,\ T^1_{12}=0.95, K^1_{21}=0.15, T^1_{21}=0.5,\ K^1_{22}=0.3,\ T^1_{22}=48;\\ &K^2_{11}=3.6,\ T^2_{11}=4.6,\ K^2_{12}=0.2,\ T^2_{12}=1.86, K^2_{21}=0.6,\ T^2_{21}=1, K^2_{22}=0.6,\ T^2_{22}=5;\\ &K^3_{11}=6,\ T^3_{11}=6.3,\ K^3_{12}=0.08,\ T^3_{12}=0.95,\ K^3_{21}=1.7, T^3_{21}=14,\ K^3_{22}=0.2,\ T^3_{22}=1.3;\\ &T_{o11}=10,\ T_{o12}=40,\ T_{o21}=9,\ T_{o22}=39,\ y_1(0)=y_2(0)=15 \text{ cm}].\end{aligned}$$



a b

Figure 6. Real plant and TSK plant model input and output from: a) modelling data; b) validation data

The TSK plant model with the optimal parameters is simulated for model inputs ($u_i=U_{iex}^{\ m}$, $y_i=H_{iex}^{\ m}$) and the outputs $H_{iTSK}^{\ m}(t)$ are overlaid in *figure 6*. The modeling errors $E_i=H_{iex}^{\ m} - H_{iTSK}^{\ m}$ as seen from *figure 6* are small and prove a good model accuracy. The errors remain small for the validation data ($U_{iex}^{\ v}$, $H_{iex}^{\ v}$) from the real time experimentation with different plant input which validates the TSK plant model making it independent of signals within the operation range and hence reliable for further use in different investigations that lead to new knowledge about the real plant.

The standard TSK plant model is of the type (1), (6) with 8 state space variables, grouped in two blocks $x(t) = [x^1(t)\ \ x_2(t)]^T$ each associated to the corresponding plant output as seen from matrix **C.**

TSK Plant Model Observability and Controllability

The observability and controllability of the nonlinear plant can be established by the ranks of the corresponding observability and controllability matrices (10) and (11) for all possible combinations of measured plant outputs (H_1, H_2) which fall with μ_1^k and μ_2^k respectively to the three linearization zones, k=1ч3 for each output. Since independent linearization zones are defined for H_1 and H_2, each combination of measured (H_1, H_2) corresponds to a combination of MFs from the vectors $\mu_1=[\mu_1^1\mu_1^2\mu_1^3]$ and $\mu_2=[\mu_2^1\mu_2^2\mu_2^3]$. The description (6) of the local plants with block diagonal state space matrices $\mathbf{A}^i_k$ and output matrix **C,** associating the first four state space variables to output $y_1(t)$ and the next four – to $y_2(t)$, allows decomposing the model into two independent in the state space and coupled via the two inputs two-input-single-output subsystems, each of order n_i=4:

$$\begin{cases} \dot{x}^1(t) = \mathbf{A}_k^1 x^1(t) + \mathbf{B}_k^1 u(t) \\ y_1(t) = \mathbf{C}^1 x^1(t) \\ \dot{x}^2(t) = \mathbf{A}_k^2 x^2(t) + \mathbf{B}_k^2 u(t) \\ y_2(t) = \mathbf{C}^2 x^2(t) \end{cases}.$$

The defuzzyfied outputs of the TSK plant model can be separately expressed as

$$(12)\quad \begin{cases} \dot{x}^1(t) = \mu^1_1[\mathbf{A^1}_1 \,.\, x^1(t) + \mathbf{B^1}_1 \,.\, u(t)] + \mu^2_1[\mathbf{A^1}_2 \,.\, x^1(t) + \mathbf{B^1}_2 \,.\, u(t)] + \mu^3_1[\mathbf{A^1}_3 \,.\, x^1(t) + \mathbf{B^1}_3 \,.\, u(t)] \\ y_1(t) = (\mu^1_1 + \mu^2_1 + \mu^3_1)\mathbf{C}^e \,.\, x^1(t) = \mathbf{C}^e \,.\, x^1(t) \end{cases}$$

$$(13)\quad \begin{cases} \dot{x}^2(t) = \mu^1_2[\mathbf{A^2}_1 \,.\, x^2(t) + \mathbf{B^2}_1 \,.\, u(t)] + \mu^2_2[\mathbf{A^2}_2 \,.\, x^2(t) + \mathbf{B^2}_2 \,.\, u(t)] + \mu^3_2[\mathbf{A^2}_3 \,.\, x^2(t) + \mathbf{B^2}_3 \,.\, u(t)] \\ y_2(t) = (\mu^1_2 + \mu^2_2 + \mu^3_2)\mathbf{C}^e \,.\, x^2(t) = \mathbf{C}^e \,.\, x^2(t) \end{cases}$$

where $\mathbf{A}^i_k$ and $\mathbf{B}^i_k$ are the computed for the optimal plant parameters $\mathbf{q^o}_{\mathbf{TSK}}$ matrices from (6) and $\mathbf{C}^e_{1x4}$=[1 0 1 0] represents the first line from $\mathbf{C}^1$ or the identical to it second line of $\mathbf{C}^2$.

Equations (12), (13) show that from the initial two-variable TSK model with local linear plants originate two independent two-input-single-output subsystems, and for each of them an infinite number of equivalent linear subsystems can be derived ($\mathbf{A}^{e1}$, $\mathbf{B}^{e1}$, $\mathbf{C}^{e1}$) and ($\mathbf{A}^{e2}$, $\mathbf{B}^{e2}$, $\mathbf{C}^{e2}$) of the type:

$$(14)\quad \begin{gathered} \mathbf{A}^{e1}(\mu_1,\mu_2) = \sum_{k=1}^{r} \mu_1^k \mathbf{A^1}_k,\ \mathbf{A}^{e2}(\mu_1,\mu_2) = \sum_{k=1}^{r} \mu_2^k \mathbf{A^2}_k \\ \mathbf{B}^{e1}(\mu_1,\mu_2) = \sum_{k=1}^{r} \mu_1^k \mathbf{B^1}_k,\ \mathbf{B}^{e2}(\mu_1,\mu_2) = \sum_{k=1}^{r} \mu_2^k \mathbf{B^2}_k,\ \mathbf{C}^{e1} = \mathbf{C}^{e2} = \mathbf{C}^e. \end{gathered}$$

Thus from (14) the observability (10) and controllability (11) matrices of these equivalent systems can be computed. So, the TSK plant model is observable if both couples ($\mathbf{A}^{e1}(\mu_1,\mu_2)$, $\mathbf{C}^e$) and ($\mathbf{A}^{e2}(\mu_1,\mu_2)$, $\mathbf{C}^e$) related with the two subsystems are observable for all combinations (μ_1,μ_2), and the TSK plant model is controllable if both couples ($\mathbf{A}^{e1}$, $\mathbf{B}^{e1}$) and ($\mathbf{A}^{e2}$, $\mathbf{B}^{e2}$) are controllable for all combinations (μ_1,μ_2).

The plant observability and controllability is analyzed computationally for discrete values μ_i. Considering the expert accepted orthogonal MFs, shown in *figure 4,* in $\mu_i=[\mu_i^1\mu_i^2\mu_i^3]$ always at least one μ_i^k is zero, while the other two complement to 1.The *i*-th local plant model is described for μ_i^k= 1. For equal steps $\Delta\mu$=0.2 eleven combinations in each μ_i are computed, separated by semicolon:

μ_i=[1 0 0;0.8 0.2 0;0.6 0.4 0;0.4 0.6 0;0.2 0.8 0;0 1 0;0 0.8 0.2;0 0.6 0.4; 0 0.4 0.6; 0 0.2 0.8;0 0 1].

The row-vectors in (μ_1,μ_2) are formed by taking different combinations from μ_1 and from μ_2. Thus 121 linear systems are defined and their observability and controllability investigated. For all of them rank[$O^{e1}(\mu_1, \mu_2)$]=n=4, rank[$O^{e2}(\mu_1, \mu_2)$]=4, rank[$C^{e1}(\mu_1, \mu_2)$]=4, rank[$C^{e2}(\mu_1, \mu_2)$]= 4. This proves that the nonlinear two-variable plant is fully observable and controllable. As a result the TSK model in *figure 3* and *figure 4* with the optimal parameters $\mathbf{q^o}_{\mathbf{TSK}}$ can be used for the engineering design of a modified PDC, similar in structure to the TSK plant model in *figure 3* and *figure 4* with standard local linear controllers. For the example of the two-variable hydraulic plant in each linearizing zone a two-variable decoupling controller of standard PID channels controllers can be designed on the basis of the local plant transfer matrix description to ensure local linear system stability and desired performance. Then the controllers are presented in state space in a similar way to (6) to enable global nonlinear system stability analysis using derived Lyapunov stability conditions for various types of standard TSK-PDC systems, which solution is searched by the LMIs approach []. The modified PDC that ensures system stability is easily and efficiently with respect to the computational resources programmed for the existing functional blocks (FB) – PID controllers and fuzzy FBs, of industrial PLCs for wide real time applications in process control [27-29].

5. Conclusion and Future Work

The main results in the present paper conclude in the following.

Conditions for observability and controllability of nonlinear plants are derived based on TSK models which can describe in state space any nonlinear plant and also enable the application of the well developed and mastered classical control theory approach to linear plant observability and controllability analysis. The observability and controllability conditions are formulated on the basis of defined weighted average equivalent matrices.

An engineering procedure for development of the needed TSK plant model is suggested in the more general case when only expert and experimental data is available and the local linear plants are represented by transfer functions of clear physical meaning. First, a structure of the modified TSK plant model is accepted and its parameters optimized my minimization of the model error based cost function. Then the easy to derive modified TSK plant model is transformed to standard state space description.

The engineering procedure and the derived observability and controllability conditions are illustrated for the TSK modelling and observability and the controllability analysis of a laboratory-scale nonlinear two-tank plant.

The future research will focus on the design of a two-variable transfer-functions-based PDC for the two-tank plant, study of the closed loop stability and a PLC completion of the PDC.

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