A Decision Support System for Safe Switching Control - Design and Implementation

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Abstract: - In the present work a Decision Support System (DSS) is described, that supports decision making with regard to the selection of the appropriate control design approach for nonlinear plants. More specifically, this DSS supports decision making concerning several aspects of designing safe switching controllers. Decisions are based on specific available information about the plant's description and characteristics, as well as the available experimental data. The implementation of this DSS using MATLAB is also presented.

Key-Words: -Decision Support System, Safe Switching, Nonlinear Control Systems

1 Introduction

Decision making regarding the selection of the control design approach which is appropriate to be applied for each industrial plant is a complex task, since it has to consider a number of factors, as for example the known characteristics of the plant, the desired design goal, the prerequisites for the application of each control approach, as well as its performance characteristics, the required data, etc. The decision should be based on any available theoretical or experimental information about the plant, taking into account the degree of assurance and/or accuracy of the available information, as well as the potential presence of erroneous data. In other cases the available data may appear to be inconsistent to each other, which implies that part of the available information should be discarded. These, in conjunction with the fact that industrial plants are usually characterized by complex behavior, nonlinearities, lack of analytical models and parameter uncertainty, complicate significantly decision making regarding the design and development of efficient industrial automation systems. In practice such problems are solved by experts who reckon together the available data to propose a suitable control approach.

Decision support systems (DSS) are software tools aiming to support or even replace human expert decision making [1]-[8]. Three main approaches to develop DSSs are [4]: a) the data driven approaches, as for example the principal component analysis and the partial least square, which are dimensionality reduction techniques, b) the analytical approaches, as for example parameter estimation and observer based methods and c) the knowledge based approaches ([9]-[18]), as for example expert systems, machine learning, etc. As referred in [4], "an expert system is a software system that captures human expertise for supporting decision making". Thus, expert systems are particularly suited for cases where the available information is uncertain or incomplete, as well as for cases where complex decisions are required, which may depend on several factors.

Switching control is a supervisory control scheme that may be used to control nonlinear plants, whose range of operation is large enough to make inadequate control by a single linear field controller ([19]-[27]). Switching control schemes consists in general, of a set of field controllers, each designed to achieve specific performance requirements for a limited range of operation of the nonlinear plant, as well as a supervisory controller that performs switching between field controllers, as the plant's input/output trajectories move between corresponding areas of operation. Switching control together with gain scheduling and Takagi-Sugeno fuzzy control, constitute a wide family of control approaches that incorporate robust linear control techniques in designing controllers for nonlinear plants.

Safe switching is a switching control scheme that aims to achieve safe transitions between different operating ranges of a given plant ([22]-[27]). This may be achieved using several control approaches, which share a common characteristic: they use "common" controllers for transitions between neighboring operating areas, that is controllers that achieve desired performance requirements simultaneously for two or more neighboring operating areas. A main representative of the aforementioned safe switching approaches is the Step-Wise Safe Switching (SWSS) for nonlinear plants, that was first introduced in [22] for the case of single input single output (SISO) systems with unknown description. However, there are a number of approaches that have been developed to contribute towards safe switching [23]-[34]. These approaches differ with respect to the required characteristics of the plant's model, the required a priori information about the plant, the design goal, etc. The selection of the appropriate safe switching control approach is a complex task, that requires expert evaluation of the available theoretical and/or experimental data.

In the present work a DSS is described, that supports decision making regarding the design and application of safe switching controllers. The proposed DSS is designed as a rule-based expert system (see [1]). The designed DSS emphasizes on the case of SISO systems. However, its design may be extended for the case of multivariable systems. It is also important to note that the DSS presented in the following sections is a generic tool, that may be easily applied for a variety of industrial control plants. The DSS has been implemented using MATLAB of MathWorks, and it has been embedded as an independent software unit within a supervisory scheme for Safe Switching Controllers ([25]), also implemented in MATLAB. A short version of the present results has been presented in [35].

As already mentioned, nonlinearities, lack of analytical models and parameter uncertainty, may be also faced using other control approaches, such as gain scheduling (see for example [36]-[39]) or fuzzy control (see for example [40]-[43]). Hence, a DSS system could be designed to incorporate also these or other similar approaches. In the present work, it has been chosen to focus on safe switching control approaches, since this work emphasizes on industrial control plants with high safety requirements. Safe switching control approaches are developed to achieve specific safety prerequisites. This is one of their main advantages when compared with other similar control approaches, such as fuzzy control, which, in some cases, may be designed to achieve satisfactory performance but not necessarily satisfy safety requirements. Note that more details on comparison of safe switching control with other approaches, are given in [22], where possible advantages of safe switching have been illustrated through simulation results. For similar reasons a deterministic rule based approach has been used to develop the DSS system.

Section 2 presents the required background material regarding the safe switching control approaches, incorporated as potential suggested control approaches within decision making of the presented DSS. Section 3 presents the design of the DSS, organized in the form of a rule based expert system. Section 4 presents the implementation of the DSS, emphasizing on the graphical user interface (GUI) used to communicate with the operator.

2 Background Material: Safe Switching Control Approaches

2.1 Step-Wise Safe Switching

As already mentioned, the Step-Wise Safe Switching (SWSS) algorithm was first introduced for SISO nonlinear plants with unknown description case in [22]. In the following the main guidelines of this algorithm are presented [22]-[26].

Consider a SISO plant with nonlinear dynamics. Let y and u denote the plant's output and input, respectively. Let $\ell = [Y, U]$ denote a point on the (y, u) plane, at which the plant's input/output trajectories may settle at steady state, which implies that if $u(t) = U$, $\forall t \geq t_0$ and $y(t_0) = Y$, then $y(t) = Y$ for all $t \geq t_0$. The set of operating points of the nonlinear plant usually form a curve, which is called operating curve. When the plant's model is unknown, the operating points may be derived by performing sequential experiments where small step variations of the input signal are applied to the plant and the corresponding steady state output values are recorded. Let now $L = \{\ell_i = [Y_i, U_i], i = 1, \ldots, \mu\}$ denote a set of plant's nominal operating points, which are usually selected to denote specific operating conditions, which are important for the plant's performance.

It is well known, that when the nonlinear plant's model is known, then the dynamics of the nonlinear system may be locally approximated, in neighborhoods of the operating points $\ell_i = [Y_i, U_i]$, by linear models determined as linearizations of the nonlinear model. When the plant's nonlinear model is unknown, these linearized models may be approximated by linear models determined through identification around the nominal operating points. Let $S_i, i = 1, \ldots, \mu$ denote a set of linear models, derived either through linearization or identification, that approximate the plant's dynamics within neighborhoods of the corresponding operating points $\ell_i = [Y_i, U_i]$, $i = 1,\ldots,\mu$. The ranges of these neighborhoods depend significantly on the plant's nonlinear dynamics. Even when the plant's model is known, these areas may be difficult to determine.

In [22], an experimental approximation of these areas is suggested, which exploits experimentally derived step responses of the nonlinear plant. Namely, for each ℓ_i, the so called *target* (O_i) and *tolerance* ($\bar{O}_i$) operating areas are determined. The target operating area is determined as a rectangle in the (y,u)-space, according to the following rule: For each step transition between an initial operating point $\rho_s = [Y_s, U_s]$ within O_i to a final operating point $\rho_f = [Y_f, U_f]$ also within O_i, the percentage of deviation ([22]) between the responses of the nonlinear system and the corresponding linearized system S_i remain smaller than a threshold value $\varepsilon_{\text{target}}$. The tolerance operating area is determined in a similar way using a threshold value $\varepsilon_{\text{tol}} > \varepsilon_{\text{target}}$.

The nominal operating points are selected dense enough to satisfy the following requirements [22]: $O_i \cap O_{i+1} \neq \varnothing$, $O_1 \cup O_2 \subset \bar{O}_1$, $O_{\mu-1} \cup O_\mu \subset \bar{O}_\mu$, $O_{i-1} \cup O_i \subset \bar{O}_i$, $O_i \cup O_{i+1} \subset \bar{O}_i$, $i = 2,\ldots, \mu-1$. The above conditions constitute an experimental formulation of the *dense web principle* [22], according to which the set of linear models S_i, $i = 1,\ldots,\mu$ describes satisfactorily the plant's behavior.

The determination of the target and tolerance operating areas in [22] is performed using exclusively experimental data and rules. However, it has been proved in [24], that experimental data which are usually available in industrial applications, as for example the operating curve of the plant and small amplitude step or pulse responses, may be used to establish local Input-to-State Stability (ISS) properties, and then determine regions of the nominal operating points within which safe transitions may be designed using the SWSS control approach. In [23] and [26] similar results have been derived for the case when the nonlinear model is known.

Finally, consider that for each pair (ℓ_i, ℓ_{i+1}) of adjacent operating points, there exists a "common" controller $C_{i,i+1}$, that satisfies a set of desired design requirements simultaneously for both linear models S_i and S_{i+1}. Then, the following SWSS, algorithm introduced in [22], orchestrates appropriate switching between the set of "common" controllers $C_{i,i+1}$, $i = 1,\ldots,\mu-1$, as the plant's trajectories move between adjacent target operating areas.

Stepwise Safe Switching Algorithm [22]

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Step 1: Apply a safe controller until the output variable is relaxed (i.e. reaches a steady state).
Step 2: Set $j = 1$
Step 3: Read the present operating point, let $\rho_j$.
Step 4: Read the desired operating point $\rho_{j+1}$.
Step 5: Choose a pair of adjacent target operating areas $(O_{\eta_j}, O_{\eta_{j+1}})$, such that $\rho_j$ lies within $O_{\eta_j}$ and $\rho_{j+1}$ lies within $O_{\eta_{j+1}}$, else return to Step 1.
Step 6: Switch to controller $C_{\eta_j,\eta_{j+1}}$ and force the closed loop system from $\rho_j$ to $\rho_{j+1}$.
Step 7: While the I/O values of the plant remain within the areas $\bar{O}_{\eta_j} \cup \bar{O}_{\eta_{j+1}}$ wait for a time period $t \le t_{\max}$ or till the system approaches a steady state namely an operating point $\rho^*_{j+1}$, else return to Step 1.
Step 8: Set $j = j + 1$ and return to Step 3
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According to this algorithm, transitions always take place between operating points lying in the same or within adjacent operating areas. During transition from any operating point in O_{i-1} to any operating point in O_i, the controller $C_{i-1,i}$ is applied. Before initiating transition to a third operating point in O_{i+1}, switching to controller $C_{i,i+1}$ takes place. Controller switching is allowed to take place only when the I/O trajectories are close to an operating point. This requirement is strict but avoids undesirable effects that may come from switching while moving e.g. instability. Thus, the motion between any two different operating points is performed by moving in a step-wise manner between operating areas of an appropriately selected sequence of adjacent nominal operating points.

As already mentioned, when the nonlinear plant's model is unknown, SWSS requires identification of the linear models $S_i, i = 1,\ldots,\mu$ that approximate the nonlinear plant's behavior. This is achieved by small range off-line identification experiments which are performed within neighborhoods of the corresponding operating points. The implementation of the supervisory control logic provides the possibility to extend the plant's operating range that can be treated by SWSS in comparison with adaptive control, which also exploits identification results. This is due to the fact, that on-line identification, which is used in adaptive control, may lead to erroneous results when the parameters of the identified linear model change rapidly as the plant's trajectories move between areas of operation corresponding to different operating points. Moreover, eliminating the need for on-line identification reduces the computational burden for the controller implementation.

The SWSS algorithm of [22] was oriented towards the case when the plant's nonlinear model is unknown. However, in several industrial applications, a nonlinear model is derived based on known physical laws. Then, as already mentioned, SWSS may be also applied by deriving the linear models $S_i, i=1,\ldots,\mu$ through linearization and determining the corresponding areas of operation analytically using the local stability properties of the nonlinear plant (see [23], [26]).

2.2 "Common" Controller Design

The main characteristic of SWSS is the application of "common" controllers, which achieve desired closed-loop performance for two or more neighboring linearizations of the plant. "Common" controllers may also be used to achieve safe switching for another class of industrial plants, whose description has the form of a multi-linear model [28]. A multi-linear model is constituted by a set of models and a set of switching conditions that governs the plant's transition from one linear description to another. Switching can be activated by environmental factors, by control commands or by changes in the mode of operation of the plant.

The application of a "common" controller $C_{i,i+1}$ to the multilinear model $S_i, i=1,\ldots,\mu$ should achieve [28]: a) satisfactory closed-loop performance within the range of validity of each linear model S_i and S_{i+1} and b) safe and satisfactory closed-loop performance for all transitions between the two models S_i and S_{i+1}.

A generic heuristic algorithm has been introduced in [28] for the derivation of "common" PI controllers for multi-linear plants. This algorithm, which may be easily extended for other classes of controllers, is also suitable for the design of "common" controllers for nonlinear plants whose description is approximated by a multi-linear model.

"Common" controller design may also be treated as a robust control problem. In [29]-[34] a number of robust control methods have been proposed, that may be used to design "common" controllers (see also [25]). All these works present robust control techniques for linear systems with nonlinear uncertain structure, without requiring any limitation or specification (continuity, boundness, smoothness, etc.) on the structure of the uncertainty. Moreover, these robust control approaches may cover the case of slowly varying uncertain parameters, fact that makes them particularly suited for the design of "common" controllers to be applied within a SWSS framework. The proposed robust control approaches serve the following design requirements: a) Robust command following with PI ([30]) or PID ([32]) controllers. b) Robust pole assignment with dynamic controllers ([31]). c) Robust exact model matching with dynamic controllers ([29]). d) Robust input-output decoupling for generalized state space systems with static controllers ([33]). e) Robust disturbance rejection for generalized state space systems with static controllers [34]. The selection of the approach to be used should be performed based on the characteristics of the plant, the desired requirements for the closed-loop system, as well as the structure of the controller to be applied.

Fuzzy control approaches could also be used to design "common" controllers. However, robust control techniques, which provide analytic criteria to guarantee satisfactory performance within a specific range of uncertainty, may benefit with respect to safety of the controlled plant.

As it follows from the previous discussion, selection of the appropriate safe switching control approach, as well as selection of the appropriate "common" controller design approach requires expert knowledge, in order to identify the plant characteristics which are critical for the controller selection, based on any available theoretical and/or experimental information about the plant. Moreover, the DSS should identify potential inconsistencies between the available information, as for example when the known model plant is inconsistent with the experimental data, which implies that the available experimental data cannot be reproduced by simulations of the known plant's model.

3 Decision Support System

The designed DSS is a rule-based decision support system constituted by three typical components [1]: the rule base, the inference engine and the user interface. The rule-base comprises a set of rules in the form of a generic "IF *condition* THEN *action*" structure. Each rule requires specific data about the plant and is activated whenever these data are available. Activating the appropriate rule based on the available data is performed by the inference engine. The DSS operator uses a graphical user interface (GUI) to answer an appropriate questionnaire and provide any available theoretical and experimental information about the plant. The following subsections present the main characteristics of the DSS. Subsection 3.1 presents the rules of the DSS in a data-condition-action form, while Subsection 3.2 provides clarifications on these rules. Subsection 3.3 comments on the determination of uncertainties, which is required at several actions activated by the DSS rules.

3.1 DSS Rules

In the following the rules that determine the functionality of the DSS are presented in a data-condition-action structure. The "data" field is the distinguishing characteristic of each rule. The inference engine activates the rule whose data field coincides with the available to the DSS information about the plant. The "condition" field denotes the set of conditions which are tested by the rule. Whenever a condition is found to be true, the DSS proceeds with the execution of the action described in the corresponding "action" field.

The DSS comprises the following seven rules.

RULE 1

Data:
1.1 Model of the plant

Condition 1.1: The plant is described by a multi-linear model.

Action 1.1: Apply the heuristic "common" controller design technique for multi-linear models [28]. Design "common" controllers for groups of two or more adjacent linear systems.

Condition 1.2: The plant is described by a nonlinear model.

Action 1.2: Apply SWSS for known nonlinear models [23], [26].

RULE 2

Data:
2.1 Nonlinear model of the plant
2.2 Operating curve of the plant, derived from experimental data.

Condition 2.1: The experimental operating curve coincides with the operating curve derived from the plant's model.

Action 2.1: Apply SWSS for known nonlinear models [23], [26].

Condition 2.2: The experimental operating curve deviates moderately from the operating curve derived from the plant's model.

Action 2.2: Determine parametric uncertainties on the plant's model, so as to derive an uncertain description of the plant, which is consistent with the experimental operating curve. Apply SWSS for known nonlinear models. Determine the corresponding linearizations as uncertain linear systems. Apply robust control techniques to design "common" controllers for neighboring uncertain linearizations.

Condition 2.3: The experimental operating curve deviates significantly from the operating curve corresponding to the known plant's model.

Action 2.3: Ignore the whole plant's model or those parts of the model that are responsible for the inconsistency between the experimental and the theoretically derived operating curve. Perform identification to derive linearized models for the plant or the discarded parts of the plant's model. Apply SWSS for nonlinear systems with unknown description [22], [24].

RULE 3

Data:
3.1 Nonlinear model of the plant
3.2 Operating curve of the plant, derived from experimental data.
3.3 Experimental measurements of the plant's variables.

Condition 3.1: The experimental operating curve coincides with the operating curve derived from the plant's model.

Action 3.1: Ignore the available measurements of the plant's variables and apply SWSS for known nonlinear models [23], [26].

Condition 3.2: The available measurements of the plant's variables are consistent with the available plant's model. However, the experimental operating curve deviates from the operating curve corresponding to the known plant's model.

Action 3.2: Perform additional experiments to determine the operating curve and use the results to determine uncertainties on the plant's model.

Condition 3.2.1: The additional experiments succeed to determine a plant's uncertain description, which is consistent with the experimental operating curve.

Action 3.2.1: Proceed as in Action 2.2

Condition 3.2.2: The additional experiments fail to determine a plant's uncertain description, which is consistent with the experimental operating curve.

Action 3.2.2: Proceed as in Action 2.3.

Condition 3.3: The available measurements and the experimental operating curve are inconsistent with the plant's model.

Action 3.3: Proceed as in Action 2.3.

RULE 4

Data:

4.1 Part of the plant's model available through modeling based on known physical laws.

4.2 Part of the plant's model available through identification.

Action 4.1: Consider the plant's model as known and apply Rule 1.

RULE 5

Data:

5.1 Linearized models of the plant are available through identification around specific operating points.

Action 5.1: Apply SWSS for plants with unknown nonlinear models [22], [24].

RULE 6

Data:

6.1 A set $S_i, i=1,\ldots,\mu$ of uncertain linear models for which "common" controllers should be designed

Condition 6.1: The field controllers are PI controllers.

Action 6.1: Check if conditions for robust command following with PI controllers, given in Theorem 2 of [30], are satisfied. If no select a different type of controller.

Condition 6.2: The field controllers are PID controllers.

Action 6.2: Check if conditions for robust command following with PID controllers, given in Theorem 2 of [32], are satisfied. If no select a different type of controller.

Condition 6.3: The field controllers are dynamic and the design goal is exact model matching.

Action 6.3: Check if conditions of Theorem 1 in [29] are satisfied. If yes determine the controller parameters based on Theorem 2 of [29]. If no select a different type of controller and design goal.

Condition 6.4: The field controllers are dynamic and the design goal is pole assignment.

Action 6.4: Check if conditions of Theorem 3 in [31] are satisfied. If yes determine the controller parameters based on Theorem 4 of [31]. If no select a different type of controller and design goal.

Condition 6.5: The models S_i are multivariable and the design goal is I/O decoupling.

Action 6.5: Check if conditions of Theorem 3.1 in [33] are satisfied. If yes determine the controller parameters based on Theorem 3.2 of [33]. If no select a different type of controller and design goal.

Condition 6.6: The models S_i are multivariable and the design goal is disturbance rejection.

Action 6.6: Check if conditions of Theorem 3.1 in [34] are satisfied. If yes determine the controller parameters based on Corollary 3.1 of [34]. If no select a different type of controller and design goal.

RULE 7

Data:

7.1 A set $S_i, i=1,\ldots,\mu$ of linear models (not uncertain) for which "common" controllers should be designed

Action 7.1: Design "common" controllers using a heuristic search algorithm (see [28]). If this algorithm fails, then proceed with robust control approaches as in Rule 6.

3.2 Clarifications on the DSS Rules

In the following several clarifications are presented, regarding the functionality and the implementation of the DSS rules.

Rule 1: Rule 1 is applied when the plant's model is known, while there are not available any experimental data. Then the control design approach is selected based exclusively on the characteristics of the known model. More specifically, if the plant is described by a multi-linear model $S=\{S_j, j=1, \ldots,m\}$, then "common" controllers are designed for each pair of adjacent linear models belonging to S, using the heuristic "common" controller tuning technique proposed in [28]. Two linear models S_i and S_k of S are adjacent, if there exists potential switching events that drive the plant from description S_i to description S_k. Consider now two pairs (S_i,S_k) and (S_k,S_l) of adjacent linear models in S and the corresponding "common" controllers $C_{i,k}$ and $C_{k,l}$. To guarantee safe transitions, controller $C_{i,k}$ is applied before any switching event between S_i and S_k, while controller $C_{k,l}$ is applied before any switching event between S_k and S_l.

If the plant is described by a known nonlinear model, then SWSS for known linear models is applied ([23], [26]). The set of linear models that approximate the plant's behavior are determined using linearization. "Common" controllers may be designed using the aforementioned heuristic technique, or even robust control techniques. Finally, this approach exploits the knowledge of the plant's model to establish local ISS properties and determine analytically the operating areas around each nominal operating point, inside which safe transitions may be guaranteed by SWSS algorithm.

Rule 2: Rule 2 is applied when besides the plant's model, there is available an experimental operating curve. Then, before selecting the control approach, the DSS checks the consistency between the plant's model and the experimental operating curve. More specifically, the DSS compares the operating curve, derived theoretically using the known plant's model, with the experimentally derived operating curve. The comparison may be performed using an appropriate measure function. Without loss of generality, let assume that the theoretically derived operating curve is given by a function $y = o(u)$. The measure that determines the deviation between the theoretical and the experimental operating curve is defined as $M_o = \|E_o\|_2 \Big/ \sqrt{o^2(u_1) + \cdots + o^2(u_{N_o})}$, where

$$E_o = \left[o(u_1) - \overline{y}_{u_1} \quad o(u_2) - \overline{y}_{u_2} \quad \cdots \quad o(u_{N_o}) - \overline{y}_{u_{N_o}} \right],$$

$\|\cdot\|_2$ denotes the Euclidean norm, $u_1,\ldots,u_{N_o}$ is an appropriate sampling of the control variable and $\overline{y}_{u_i}$ denotes the output value of the corresponding operating point $(u_i, \overline{y}_{u_i})$ on the experimental operating curve. The measure of deviation M_o is compared with two threshold values h_1 and h_2, that determine insignificant, moderate and significant deviation, respectively.

When the two curves coincide, which implies that the deviation measure M_o is smaller than the threshold value h_1, the control design proceeds as in Rule 1, considering the plant's model to be known.

In case the range of deviation between the theoretical and the experimental curve is moderate, which implies that $h_1 \le M_o \le h_2$, the DSS determines parametric uncertainties on the plant's model, so as to derive an uncertain description of the plant, which is consistent with the experimental operating curve (see Subsection 3.3). Then, SWSS for known nonlinear models, is applied, with the "common" controllers being designed applying robust control techniques, since the plant's linearizations are uncertain linear systems.

In case the range of deviation between the theoretical and the experimental curve is significant, that is $M_o > h_2$, then the DSS discards the plant's model and suggests to proceed with identification, to derive a set of linearized identified models for the plant, based on experimental data. In this case the control design is performed using the SWSS algorithm for unknown models [22], [24]. In some cases, the deviations may be due to a specific part of the known model. Then, the DSS may discard only the specific part, while keeping the rest equations of the known plant's model.

Rule 3: This rule is applied when the available data comprise a plant's model, an experimental operating curve, as well as measurements of all or some of the plant's input, output and state variables. Before selecting the control approach, the DSS checks consistency between the plant's model and the experimental operating curve, following the steps previously described for Rule 2. When consistency is established, the DSS discards the measurements of the plant's variables and the control design proceeds as in Rule 1, considering the plant's model to be known.

If the experimental operating curve is inconsistent with the available plant's model (moderate or significant deviations), then the DSS proceeds with checking consistency of the plant's model with the available measurements of the plant's variables. This is achieved by performing simulation of the plant's model using as input, the values of the control variable which are available from experimentation. Then experimental state and output values are compared with those derived through simulation. More specifically, let x denote a state or output variable of the plant and let $\overline{x}$ denote the corresponding measurements. Then, the measure of deviation between the simulated and the experimental values is determined by $M_x = \|E_x\|_2 \Big/ \sqrt{x^2(k_1) + \cdots + x^2(k_{N_x})}$, where

$$E_x = \left[x(k_1) - \overline{x}(k_1) \quad \cdots \quad x(k_{N_x}) - \overline{x}(k_{N_x}) \right]$$

and $k_1,\ldots,k_{N_x}$ appropriate instants of time. The measure of deviation M_x is compared with an appropriate threshold value h_x. If $M_x \le h_x$ for all measured variables, the model is consistent with the experimental measurements, while the DSS suggests execution of additional experiments to determine the operating curve, as well as uncertainties on the plant's model (see Subsection 3.3). In case this fails to succeed, the DSS discards the plant's model and proceeds as in Action 2.3, with identification and application of the step-wise safe switching algorithm for plants with unknown description. Otherwise the DSS proceeds as in Action 2.2.

If $M_x > h_x$ for at least one measured variable, then the model is inconsistent with both the experimental operating curve and the measurement data. Then the DSS discards the plant's model and proceeds as in Action 2.3, with identification and application of the SWSS algorithm for plants with unknown description.

Rule 4: This rule is valid for the case where some parts of the plant's model are available through implementation of known physical laws, the rest parts are determined through identification, while no experimental data are available. Then the DSS considers the plant's model to be known, and proceeds as in Rule 1.

Rule 5: This rule is valid for the case where the whole model of the plant is derived through identification. In this case the DSS proposes the application of the SWSS algorithm for plants with unknown models.

Rules 6 and 7: These rules concern the selection of the appropriate design approach for "common" controllers. Whenever the linearized models of the plant are subject to uncertainty (see for example Actions 2.2 and 3.2.1), robust control approaches are applied, according to Rule 6, which selects the appropriate approach based on the desired design goal, the structure of the field controllers and the structure of the linear models. If the linearized models are not subject to uncertainty, heuristic control design techniques are preferred. In case the heuristic algorithm fails to determine "common" controllers, the DSS activates Rule 6 to propose a robust control approach.

3.3 Determination of Uncertainties

As already mentioned, when the plant's model is not consistent with the experimentally derived operating curve, while the deviation between the experimental and the theoretical operating curve is found to be moderate, the DSS proceeds with the determination of parametric uncertainties on the plant's model. This implies that the DSS determines ranges of uncertainty for specific parameters of the model, so that the derived uncertain model is consistent with the experimental operating curve. More specifically, consider, without loss of generality, that the theoretically derived operating curve is expressed by an equation of the form $y = o(u;\lambda)$, where $\lambda = [\lambda_1, \ldots, \ \lambda_p]$ a vector of plant parameters. For each parameter λ_i there are available information concerning its physical interpretation. Moreover, there may be available information concerning physical constraints that may be imposed on its value, as well as a nominal value $\lambda_{i,n}$.

The range of uncertainty for each parameter λ_i is determined by solving the problem of minimizing the measure of deviation M_o, with respect to λ. In case constraints are known for the values of the parameters λ_i, the corresponding problem is expressed as a minimization under constraints problem. Let $\tilde{\lambda} = [\tilde{\lambda}_1 \ \cdots \ \tilde{\lambda}_p]$ denote the value of λ, that minimizes M_o. Then, the range of uncertainty of each parameter λ_i is determined as $[\lambda_{i,n}, \tilde{\lambda}_i]$. In case there is not available a nominal value for the parameter λ_i, the range of uncertainty is determined as $[0, \tilde{\lambda}_i]$. The derived uncertain model is considered to be consistent with the experimental operating curve provided that the value of M_o corresponding to $\tilde{\lambda}$ is smaller than h_1.

4 Implementation

In the present section, the implementation of the DSS is described, using the programming environment MATLAB of MathWorks, emphasizing on the graphical user interface (GUI) used for the data interchange, between the operator and the DSS. Figure 1, illustrates the main window, through which the operator feeds the DSS with all the available information about the plant. Namely, through the main window the operator clarifies the available data (model, experimental operating curve, experimental measurement of the plant's variables), specifies the type of model (nonlinear, multi-linear, etc.), the type of field controllers and design goal to be used for the "common" controllers design, as well as the names of the files where the corresponding data are stored.

As it is shown in Figure 1, the operator provides the filename of a m-file, that includes all the available information about the plant's model, which has the generic form $\dot{x} = f(x,u), \ \ y = c(x)$, where $x \in \mathbb{R}^n$ the state vector. Figure 2 presents an indicative form of this m-file. The fields that should be modified by the operator, depending on the plant's model, are presented in Figure 2 within frames. All the rest commands should be kept in their present form. More specifically, frame 1 is used to provide all the nominal values of the plant's parameters. Frame 2 builds a MATLAB row vector that includes the variables of the plant's parameters. Frame 3 includes the strings used as names for the program variables that represent the plant's parameters. Frame 4 is used to determine the number n of state variables. Frame 5 inserts in symbolic form the equation that relates the plant's output with the state vector. Frame 6 is used to provide the function $y = o(u)$ of the operating curve. This is used to determine the theoretically derived operating curve of the plant. Finally, Frame 7 inserts the state equations of the plant.

Moreover, the operator may provide, if available, to the DSS a text file, where there are stored experimental input and output values, that denote the operating points forming the experimental plant's operating curve, as well as text files where there are stored experimental measurements of certain plant's input, state and/or output variables.

Figure 3 illustrates the execution of the algorithm in the case when the available data result to the activation of Action 2.2 of Rule 2. More specifically, the operator has provided a plant's nonlinear model and an experimental operating curve. After appropriate computations, the DSS determined that the experimental operating curve is not consistent with the theoretical one (see Subsection 3.2). Then the window (a) in Figure 3 informs the operator that uncertainties on the plant's parameters should be determined. Window (b) is used for the operator to determine the threshold values h_1 and h_2, that characterize the deviation between the experimental and the theoretical operating curve. Window (c) is used to provide the parameters' nominal values, while window (d) is used to provide minimum and maximum values for these parameters. Then, the DSS determines within these intervals, values of the plant's parameters that minimize M_o (see Subsection 3.3) and consequently determine intervals of uncertainty for these parameters. These intervals are made known to the operator with window (e) in Figure 3.

In a similar form, the DSS program implements the rest rules, using pop-up windows a) to ask for additional data, as for example text files including measurements, b) to ask for threshold values, c) to inform the operator about the derived results, d) to suggest additional actions, as for example more experiments and d) to make known the final DSS suggestion to the operator.

The implementation of the DSS is user friendly and generic, since it may cover a large class of industrial applications. The DSS has been included as an independent unit within an implementation, also in MATLAB programming environment, of a supervisory system for SWSS, whose basic design guidelines have been presented in [25].

5 Conclusions

A DSS that supports decision making regarding the design and application of safe switching controllers for industrial plants, has been designed. The proposed DSS is designed as a rule-based expert system, which may be implemented in a variety of high level programming software tools. Implementation issues of the DSS in MATLAB environment have been presented, emphasizing on the GUI of the DSS. The designed DSS concerns mainly the case of SISO systems. However, its design may be extended for the case of multivariable systems. This DSS is a generic tool, that may be easily applied for a variety of industrial control plants.

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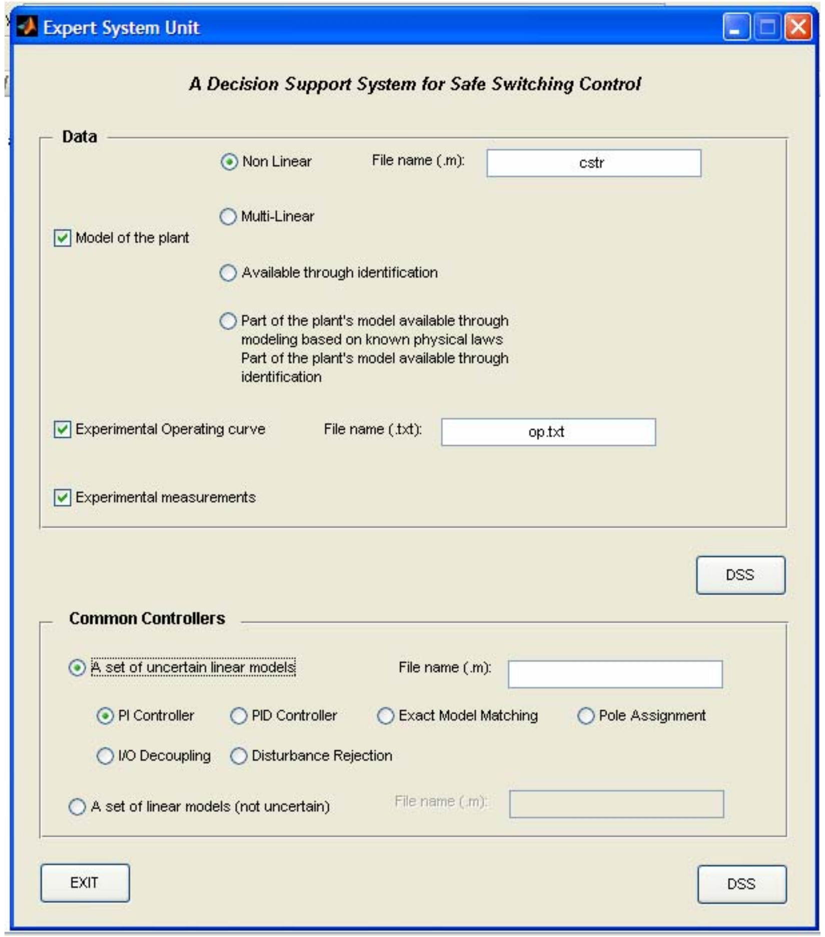


Expert System Unit

A Decision Support System for Safe Switching Control

Data

☑ Model of the plant

● Non Linear   File name (.m): cstr

○ Multi-Linear

○ Available through identification

○ Part of the plant's model available through modeling based on known physical laws
Part of the plant's model available through identification

☑ Experimental Operating curve   File name (.txt): op.txt

☑ Experimental measurements

Common Controllers

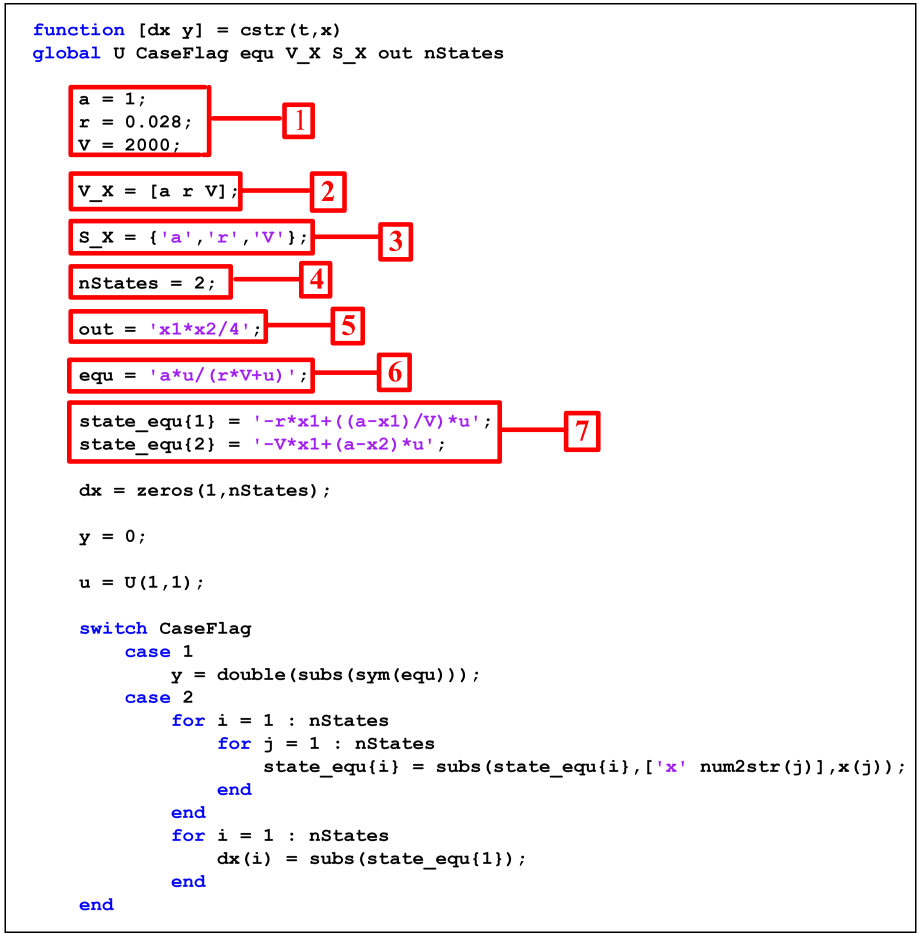
● A set of uncertain linear models   File name (.m):

● PI Controller   ○ PID Controller   ○ Exact Model Matching   ○ Pole Assignment

○ I/O Decoupling   ○ Disturbance Rejection

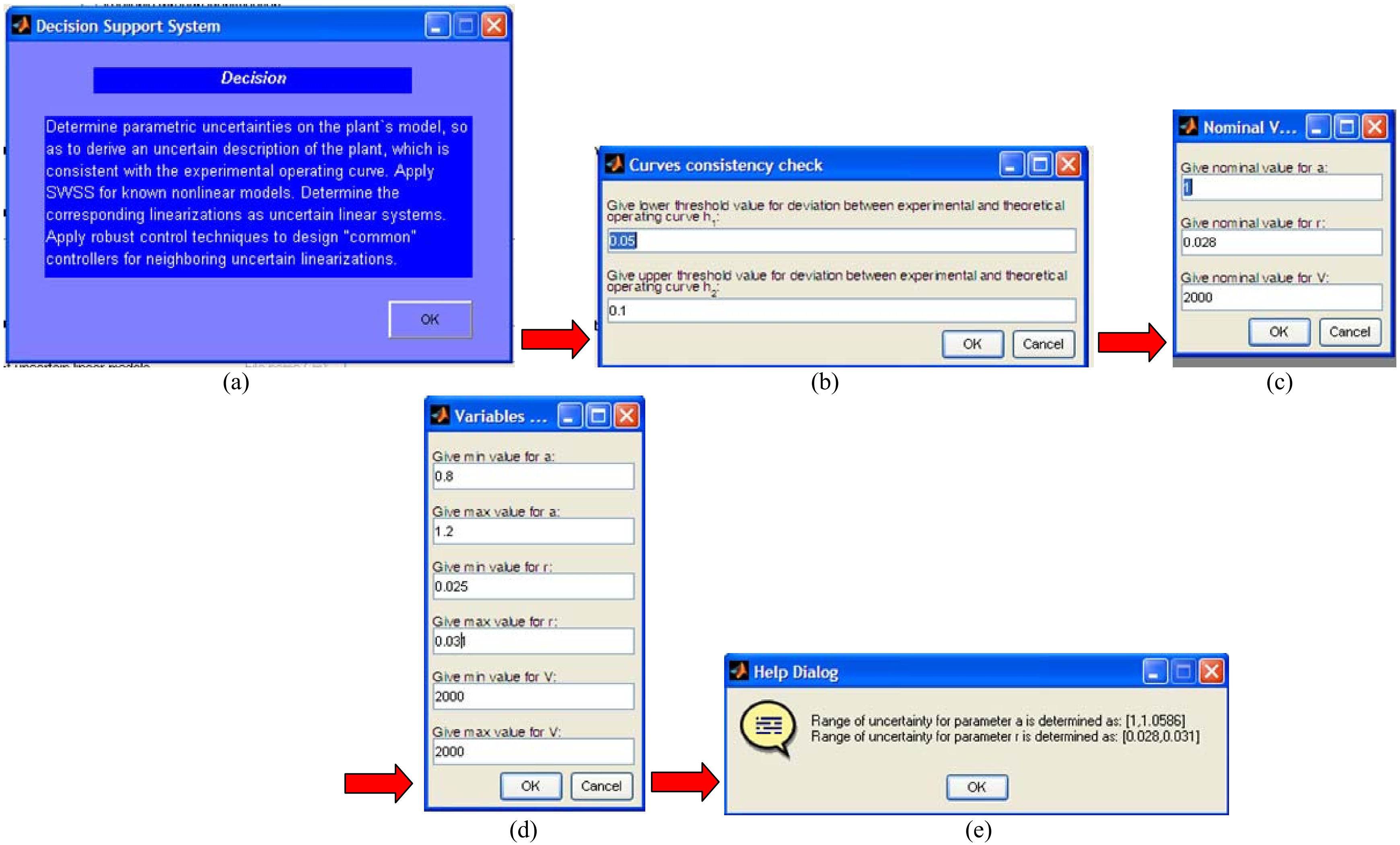
○ A set of linear models (not uncertain)   File name (.m):

Figure 1: Main window of the GUI



```
function [dx y] = cstr(t,x)
global U CaseFlag equ V_X S_X out nStates

    a = 1;
    r = 0.028;
    V = 2000;

    V_X = [a r V];

    S_X = {'a','r','V'};

    nStates = 2;

    out = 'x1*x2/4';

    equ = 'a*u/(r*V+u)';

    state_equ{1} = '-r*x1+((a-x1)/V)*u';
    state_equ{2} = '-V*x1+(a-x2)*u';

    dx = zeros(1,nStates);

    y = 0;

    u = U(1,1);

    switch CaseFlag
        case 1
            y = double(subs(sym(equ)));
        case 2
            for i = 1 : nStates
                for j = 1 : nStates
                    state_equ{i} = subs(state_equ{i},['x' num2str(j)],x(j));
                end
            end
            for i = 1 : nStates
                dx(i) = subs(state_equ{1});
            end
    end
```

Figure 2: M-file for the specification of the plant’s model



(a) Determine parametric uncertainties on the plant`s model, so as to derive an uncertain description of the plant, which is consistent with the experimental operating curve. Apply SWSS for known nonlinear models. Determine the corresponding linearizations as uncertain linear systems. Apply robust control techniques to design "common" controllers for neighboring uncertain linearizations.

(b) Give lower threshold value for deviation between experimental and theoretical operating curve h_1: 0.05

Give upper threshold value for deviation between experimental and theoretical operating curve h_2: 0.1

(c) Give nominal value for a: 1

Give nominal value for r: 0.028

Give nominal value for V: 2000

(d) Give min value for a: 0.8

Give max value for a: 1.2

Give min value for r: 0.025

Give max value for r: 0.031

Give min value for V: 2000

Give max value for V: 2000

(e) Range of uncertainty for parameter a is determined as: [1,1.0586]
Range of uncertainty for parameter r is determined as: [0.028,0.031]

Figure 3: Activation of Rule 2, Action 2.2