A Decision Support System for Safe Switching Control

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

Key-Words: -Decision Support System, Safe Switching, Control Design

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 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 each 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 processes are 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 which aim to support or even replace human expert decision making [1]-[8]. The three main approaches to develop decision support systems 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 used to control nonlinear plants, whose range of operation s large enough to make inadequate control by a single field controller ([19]-[22]). A switching control scheme 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 implements the switching logic, that is it performs switching between the field controllers, as the plant's input/output trajectories move between different areas of operation.

Safe switching is a switching control scheme that aims to achieve safe transitions between different operating ranges of a given plant ([22]-[25]). 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 characteristics simultaneously for two or more neighboring operating areas. The main representative of the aforementioned safe switching approaches is the Step-Wise Safe Switching (SWSS) for nonlinear plants with unknown description, that was first introduced in [22]. However, there is a number of approaches that have been developed to contribute towards safe switching [22]-[31]. 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 designed, 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]), which may be implemented in a variety of high level programming software tools, as for example Matlab. The designed DSS emphasizes on the case of single input single output (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. Moreover, it can be embedded as an independent software unit within a supervisory scheme for Safe Switching Controllers ([25]).

2 Safe Switching Control Approaches

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

Consider a single input-single output process, where y and u denote the output and the input of the process, respectively. Let $L=\{\ell_i=[Y_i,U_i], i=1,\ldots,\mu\}$ denote a set of plant's nominal operating points (points of the input-output space where the process may settle at steady state), where Y_i, U_i are the nominal output and input values, respectively. Let also the plant's description be approximated by a set $S_i, i=1,\ldots,\mu$ of linear models, determined through identification about the nominal operating points. For each ℓ_i we determine, using exclusively experimental data, the so called *target* (O_i) and *tolerance* ($\bar{O}_i$) operating areas [22], which are experimental approximations of the neighbourhood of validity of each local linear model S_i. The nominal operating points are selected dense enough to satisfy the following requirements [22]: $O_i \cap O_{i+1} \neq \emptyset$, $O_1 \cup O_2 \subset \bar{O}_1$, $O_{\mu-1} \cup O_\mu \subset \bar{O}_\mu$, $O_{i-1} \cup O_i \subset \bar{O}_i$, $O_i \cup O_{i+1} \subset \bar{O}_i$, $i=2,\ldots, \mu-1$. 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 process behaviour. 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 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 process trajectories move between adjacent target operating areas.

The main characteristics of this algorithm are summarized as follows: a) The SWSS approach is based on the application of controllers that commonly achieve the required performance simultaneously for adjacent nominal operating points. b) Controller switching is allowed to take place only when the process has reached 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. c) The plant's linearizations and the corresponding operating areas are determined using exclusively experimental data. In [22] the target and tolerance operating areas of each operating point are determined using empirical rules. However, it has been proven in [24], that for the case of first order nonlinear plants, the range of these areas can be determined using experimental plant data and Input to State Stability Lyapunov theory, so as to guarantee safe transitions during SWSS. The extension of these results for higher order systems is currently under investigation.

The SWSS algorithm of [22] is applied for the case when the plant's nonlinear model is unknown. However, in several industrial applications, a nonlinear model may be derived based on known physical laws. In this case SWSS may be also applied. However, in this case the linear models $S_i, i=1,\ldots,\mu$ may be derived using linearization, instead of identification. Moreover, the corresponding areas of operation may be determined analytically using the local stability properties of the nonlinear plant. The application of SWSS for known first-order nonlinear plants has been studied in [23].

Its extension for higher order plants is currently under investigation.

As already mentioned, one of the main characteristics of SWSS is the application of "common" controllers, which achieve desired closed-loop performance characteristics for two or more neighbouring 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. 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 process. For example, in the case of a wheeled mobile robot, switching between different dynamic models occurs when the motion of the wheels changes from rolling to sliding. Typical examples of such systems include batch processes, power systems, relay systems, transmission and stepper motors, internal combustion engine control, constrained robotics, etc.

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

A generic heuristic algorithm has been introduced in [26] 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 the field of robust control, a variety of control design problems have been solved. A case of special interest for the control of industrial processes is that of robust dynamic controllers, as for example PI or PID controllers, which may be designed to serve a variety of design requirements. Other interesting cases for control problems in industrial environment are robust controllers designed to achieve input/output decoupling and/or disturbance rejection for uncertain systems subject to constraints, as the case of uncertain singular systems.

To treat the problem of designing "common" controllers as a robust control problem, a number of robust control methods may be proposed (see [27]-[31]). 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 ([28]) or PID ([30]) controllers. b) Robust pole assignment with dynamic controllers ([29]). c) Robust exact model matching with dynamic controllers ([27]). d) Robust disturbance rejection for generalized state space systems with static controllers. e) Robust input-output decoupling for generalized state space systems with static controllers ([31]). The selection of the approach to be used should be performed based on the characteristics of the process, the desired requirements for the closed-loop system, as well as the structure of the controller to be applied.

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 the case when the known model plant is inconsistent with the experimental data, which implies that the available experimental data cannot be reproduced by the known model plant.

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. The activation of the appropriate rule based on the available data is performed by the inference engine. The user interface provides a graphical interface through which the operator of the DSS answers a questionnaire and provides any available theoretical and experimental information about the plant. The following subsections present the main characteristics of the DSS. Subsection III.A presents the rules of the DSS in a data-condition-action form, while Subsection III.B provides clarifications on these rules. Subsection III.C 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. Each rule in a data-condition-action structure. The "data" field is the distinguishing characteristic of its rule. The inference engine activates the rule whose data field coincides with the available to the DSS information about the plant. The "condition" fields of each denote the set of condition which are tested by the rule. Whenever a condition is found to be true, the DSS proceeds with the execution of 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. 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.

RULE 2

Data:

2.1 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.

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 the plant's model or the aforementioned missing parts. Apply SWSS for nonlinear systems with unknown description.

RULE 3

Data:

3.1 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.

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. Use these experiments to determine uncertainties on the plant's model.

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

Action 3.2.1: Proceed as in Action 2.2

Condition 3.2.1: The additional experiments fail to determine an uncertain description of the plant, which is consistent with the experimental operating curve.

Action 3.2.1: 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 The plant's model is available through identification

Action 5.1: Apply SWSS for plants with unknown nonlinear models.

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: Apply the robust control approach of [28]

Condition 6.2: The field controllers are PID controllers.

Action 6.2: Apply the robust control approach of [30]

Condition 6.3: The field controllers are dynamic and the design goal is pole assignment.

Action 6.3: Apply the robust control approach of [29]

Condition 6.4: The field controllers are dynamic and the design goal is exact model matching.

Action 6.4: Apply the robust control approach of [27]

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

Action 6.5: Apply the robust control approach of [31]

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

Action 6.6: Apply the robust control approach of robust disturbance rejection for multivariable systems.

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

Condition 7.1: The linear models $S_i, i = 1, \ldots, \mu$ are not uncertain models.

Action 7.2: Design common controllers using a heuristic search algorithm (see [26]). 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 [26]. Two linear models S_i and S_k of S are considered to be 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 $C_{k,l}$. 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, in order to guarantee safe transitions.

If the plant is described by a known nonlinear model, then SWSS for known linear models is applied [23]. 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 determine analytically the operating areas around each nominal operating point, inside which safe transitions may be guaranteed by the step-wise safe switching 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

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

$\|\cdot\|_2$ 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 three threshold values h_1, h_2 and h_3, that correspond to 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 $h_1 < M_o < h_2$, 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 III.C). 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 $M_o \geq h_2$, then the DSS discards the plant's model and proceeds with identification, to derive a new model for the plant, based on experimental data. In this case the control design is performed using the SWSS algorithm for unknown models. 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

$$E_x = \left[x(k_1) - \overline{x}(k_1) \quad x(k_2) - \overline{x}(k_2) \quad \cdots \right.$$
$$\left. x(k_N) - \overline{x}(k_{N_x}) \right]$$

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 $M_x \leq h_x$ for all measured output and state variables, then the model is consistent with the experimental measurements, while the DSS suggests the execution of additional experiments in order to determine the operating curve, as well as uncertainties on the plant's model (see Subsection III.C). In case this fails to succeed, the DSS discards the plant's model and proceeds, as in Rule 2 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 the both the experimental operating curve and the measurement data. Then the DSS discards the plant's model and proceeds, as in Rule 2, with identification and application of the step-wise safe switching algorithm for plants with unknown description.

Rule 4: This rule is valid for the case where some part of the plant's model is available through the implementation of known physical laws, while the rest part is determined through identification, while no experimental data are available. In this case, 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 step-wise safe switching 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 it was referred in the previous subsection, 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 operating curve is expressed by an equation of the form $y = o(u;\lambda)$, where $\lambda = [\lambda_1,\ldots,\lambda_p]$ a vector of physical 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 $\lambda_m = \begin{bmatrix} \lambda_{1,m} & \cdots & \lambda_{p,m} \end{bmatrix}$ denote the value of λ, that minimizes M_o. Then, the range of uncertainty of each parameter λ_i is determined as $[\lambda_{i,n},\lambda_{i,m}]$. In case there is not available a nominal value for the parameter λ_i, the range of uncertainty is determined as $[0,\lambda_{i,m}]$. The derived uncertain model is considered to be consistent with the experimental operating curve provided that the value of M_o corresponding to λ_m is smaller than h_1.

4 Conclusion

A DSS, that supports decision making regarding the design and application of safe switching controllers for nonlinear 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, as for example Matlab. The designed DSS emphasizes on 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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