IEE Seminar on Model Validation for Plant Control and Condition Monitoring, London, March 2000, pp. 5/1-5/3

IDENTIFICATION AND VALIDATION FOR ROBUST CONTROL: DESIGN ISSUES

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Model validation is the scientific exercise that consists of assessing whether a model of some underlying system is {\it good enough.} Good enough for what? Well, that is precisely the point. The assessment of the quality of a model cannot be decoupled from the purpose for which the model is to be used. And just as the research on system identification has, in the last 10 years, focused on issues of {\it design} in order to obtain a nominal model that suited the objective, so must the validation experiment similarly be designed in such a way that the model is guaranteed to deliver what the model is supposed to deliver. Thus, one must think in terms of "goal-oriented validation". This presentation focuses on model validation for robust control.

The validation step is the ultimate quality control station that allows the model builder to provide the user with certified guarantees about the quality of his/her model. Without such certification the user cannot confidently use the model for his particular application, since he has no guarantees about whether the model is able to achieve its purpose.

The subject of model validation is almost as old as the subject of system identification: a reputable engineer should indeed never deliver a product without a statement about its precision. Nevertheless, much less attention has been paid to the derivation of model validation and quality assessment tools than to the design of model estimation tools. This is because until the early 1980's most of the research in system identification focused on questions of convergence and efficiency, with the underlying assumption that the system was in the model set. In the 1980's system identification began to be seen as an approximation theory, and it then became essential to be able to quantify the error between the model and the underlying system: the estimation of bias error and variance error of identified transfer functions became a coveted topic of research.

Spurred by the strong reliance of robust control design theory on uncertainty descriptions, the research on model uncertainty estimation and on model validation gathered momentum in the 1990's. Several directions were being pursued.The first consists of using data sets to estimate uncertainty regions around estimated models, i.e. attempting to assess the size of the model error from data.

In the approach, developed by Goodwin and collaborators, estimates of the total mean square transfer function error at each frequency were obtained by adopting, for the bias error, a parametrized probability distribution, and by estimating the parameters of this distribution from the data, just as is done for the noise error. An alternative approach, taken by Ljung and Guo, essentially consists of declaring a model validated if its bias error is dominated by its variance error, which is much easier to compute. \item In the hard bound (or bounded error) framework, uncertainty models have been derived under a variety of hard bound assumptions on the measurement errors and on the error model. \item A third direction consists of starting with an a priori model set resulting from prior assumptions on the system and on the noise, and of then using observed input-output data to (and thus delete from this prior set) those models that are found to be inconsistent with these prior assumptions.

A revival of interest in model validation was spurred by the model error model (MEM) approach proposed by Ljung in his plenary lecture at CDC 97. In this approach, which belongs to the first direction mentioned above, the idea is to identify an unbiased model of the model error from validation data using classical prediction error (PE) identification techniques. Since the model error model is assumed unbiased, its variance directly defines the total mean square error of the initial model.

The key ingredient of the MEM approach to model validation is the use of an unbiased model structure for the identification of the MEM. This eliminates the difficult step of estimating the bias error, as is done in the stochastic embedding approach, since the total error on the initial model is directly computed from the variance error on the MEM, for which standard formulae exist in PE identification. As a matter of fact, an obvious alternative to validation by identification of a model error model is validation by identification of an unbiased model for the full underlying system. Indeed, the only purpose of the validation step is to define an uncertainty set to which the true system belongs with some prescribed probability. Thus, PE validation is in fact set membership PE identification.

Our initial work on model validation for control in 1998 was inspired by Ljung's MEM approach. However, a drawback of Ljung's approach is the error introduced by the first order approximation that was used to map covariance ellipsoids in parameter space to corresponding ellipsoids in the Nyquist plots of transfer functions. We have since been able to develop robust stability and performance analysis tools that are based on the exact transfer function uncertainty sets resulting from PE validation, thus avoiding the errors produced by the first order approximation. These transfer function uncertainty sets are directly defined by the ellipsoidal regions in parameter space. We call them Prediction Error (PE) model uncertainty sets, because they correspond to the model sets obtained by PE validation, without any approximation error or conservatism.

Our robust analysis tools take the form of necessary and sufficient conditions for a given controller $C(z)$ to stabilize all models in such PE uncertainty set, or to achieve a specified level of performance with all models in such PE uncertainty set.

Thus, we have developed a robust control analysis theory for uncertainty sets produced by PE validation. Earlier attempts at connecting PE identification and validation with robust control theory aimed at producing one of the standard frequency domain uncertainty sets that are at the root of most of robust control results, namely additive, multiplicative, coprime factor uncertainty sets, etc. To arrive at such uncertainty sets required either the use of a fixed denominator model for the model error model, such as in the stochastic embedding approach, or else the approximation or overbounding of the uncertainty regions delivered by the prediction error method such as in Ljung's Model Error Model approach.

The development of robust control analysis tools for model uncertainty sets delivered by PE identification and validation is important because it contributes significantly to bridging the huge gap that existed in the early nineties between PE identification theory and robust control theory, as was evidenced in the 1992 Santa Barbara Workshop; it paves the way for the development of a robust control design theory based on such transfer function uncertainty sets defined by parameter vectors in ellipsoids.

In addition to these new robust analysis tools, we have established a connection between a measure of size of the validated PE uncertainty sets and the size of the model-based controller sets that are guaranteed to stabilize all models in the corresponding validated PE uncertainty sets. This measure of size of a validated set is an extension of the ν-gap, a distance measure between two transfer functions introduced by Vinnicombe in 1993. The interesting aspect of this "measure of size" of a validated set, which we have called the worst-case ν-gap between the model and the validated set, is that it is directly related to the size of the set of model-based stabilizing controllers. Indeed, we show that the smaller the worst-case gap between a model G_{mod} and a validated PE uncertainty set ${\cal D}$, the larger is the set of G_{mod}-based controllers that are guaranteed to stabilize all models in ${\cal D}$. This worst-case ν-gap is therefore an indicator of how well a validated PE uncertainty set is tuned for robust control design. Our results therefore give a meaning to the concept of model validation for control: a validation experiment is "tuned for robust control design" if the worst case ν-gap between the validated model and the validated set is small, because it implies that, for that validated set, the set of robustly stabilizing controllers is large.

The abundant research on identification for control in the nineties has made it obvious to theoreticians and practicioners alike that, when a model is to be used for control design or controller retuning, the identification criterion for the nominal model must be a function of the control performance criterion. Numerous methods have been proposed to achieve this goal - often in an iterative way - and successful applications have been reported. However, just as the design of the identification of the nominal model must be controller dependent, so must the design of the validated set be controller dependent. The establishment of a link, all the way from PE model validation design to controller robustness, is a much harder nut to crack. Our model validation for control results, are a first important step in this direction.

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