The Role of Experimental Conditions in Model Validation for Control*

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Abstract. Within a stochastic noise framework, the validation of a model yields an ellipsoidal parameter uncertainty set, from which a corresponding uncertainty set can be constructed in the space of transfer functions. We display the role of the experimental conditions used for validation on the shape of this validated set, and we connect a measure of the size of this set to the stability margin of a controller designed from the nominal model. This allows one to check stability robustness for the validated model set and to propose guidelines for validation design.

1 Introduction

Model validation is the exercise that consists in assessing whether a model of some underlying system is good enough. Such quality control step 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 design in order to obtain a 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”.

In this chapter we focus on the situation where a model is to be validated with the purpose of designing a controller for the underlying system. This is called model validation for control.

The assessment of the quality of a model can take a variety of forms, such as a frequency-domain bound on the error between the system and the model transfer functions, or a worst-case bound on such error over all

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frequencies, or the certification of a region in the complex plane in which
the system and the model are guaranteed to lie (set membership validation).
Depending on the application some of these quality statements can be more
useful than others.

Spurred by the strong reliance of robust control theory on specific un-
certainty descriptions, the research on model uncertainty estimation and on
model validation gathered momentum in the 1990s. Two directions have
been pursued.

1. The first consists in estimating uncertainty regions around estimated
    models. In the stochastic framework, estimates of the total mean square
    transfer function error 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 [4].
    In the "hard-bound" framework, uncertainty models have been derived
    under a variety of hard-bound assumptions on the error model and on
    the noise: see e.g. [3], [5].

2. The second direction consists in reducing a prior set of admissible mo-
    dels by invalidating models on the basis of observed data and prior
    hard-bound assumptions: see e.g. [11], [9]. The concept of model inval-
    idation, on the basis of an observed incompatibility between a model,
    prior assumptions and data, was extended to controller invalidation in
    [10].

The validation theory presented in this chapter is inspired by recent vali-
dation results of Ljung and collaborators [6], [8], [7] that are based on signal
statistics, with essentially no prior assumptions other than some unavoid-
able invariance assumption. To paraphrase Swedish literature [7], one would
like to approach the model validation problem 'as naked as possible' and
strip off common covers such as prior assumptions, probabilistic framework,
worst case model properties. What we are then left with are experimental
data that we can collect on the true system and compare with simulated
data generated by the model, statistics that we can compute from these
data, and some invariance assumption that states that the future statistics
will not be different from those observed so far.

The key idea of the method proposed by Ljung for the validation of a
model \( \hat{G} \) is that the residuals \( \epsilon \), obtained by substracting simulated outputs
from measured outputs, contain information about the model error \( G_0 - \hat{G} \).
The identification of an unbiased model for the dynamics connecting the
input signal \( u \) to the residuals \( \epsilon \) delivers an estimate of the model error
\( G_0 - \hat{G} \) and a covariance for this estimate.

Our departure from the validation results of Ljung and collaborators,
and the new contributions of this chapter, are contained in the following
sequence of new ideas and observations whose presentation will form the
essence of this chapter.