ASSESSMENT OF A BAYESIAN MODEL AND TEST VALIDATION METHOD

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ABSTRACT

Probabilistic Principal Component Analysis (PPCA) is a promising tool for validating tests and computational models by means of comparing the multivariate time histories they generate to available field data. Following PPCA by interval-based Bayesian hypothesis testing enables acceptance or rejection of the tests and models given the available field data. In this work, we investigate the robustness of this methodology and present sensitivity studies of validating hybrid powertrain models of a military vehicle simulated over different proving ground courses.

INTRODUCTION

Computer modeling and simulation are the cornerstones of product design and development in the ground vehicle industry. Computer-aided engineering tools have improved to the extent that virtual testing may lead to significant reduction in prototype building and testing of vehicle designs. In order to make this a reality, the need exists to assess confidence in the predictive capabilities of simulation models. Therefore, validation of both experimental and simulation results is critical.

Verification, validation and accreditation are very active areas of study in industry, academia, government, and professional societies [1-6]. Particular challenges arise with data associated with dynamic systems; such data are typically available in the form of multivariate time histories. One promising method for validating computational models, by means of comparing the multivariate time histories the models generate to available field or test data, is the application of Probabilistic Principal Component Analysis (PPCA) [7] for dealing with dimensionality, uncertainty and correlation issues, followed by interval-based Bayesian hypothesis testing (IBHT) [8] for accepting or rejecting the model based on a computed Bayes factor given the available test data. The attractiveness of this approach is that it potentially can be used to identify the amount of necessary test data to validate a computer model.

In this work, we investigate the robustness of this method and present sensitivity studies of validating hybrid powertrain models of a military vehicle simulated over different proving ground courses.

VALIDATION FRAMEWORK

For the purposes of exposition, we restrict attention to considering validation of a computational model, denoted as the CAE model, with the understanding that the framework presented is equally applicable to validating lab tests with respect to field data. Figure 1 presents a schematic of the model validation framework for dynamic systems. A brief outline of the framework is provided herein, for complete details, refer to [9].

Field or test data, denoted as physical test, consists of time histories of one or more data channels. Each data channel time history is scaled (normalized), so that the maximum absolute values of the different data are similar in magnitude. This procedure avoids biasing the validation framework based upon the magnitude of the data responses. The scale factors used to scale each test data channel are used to scale each of the corresponding CAE model data sets.

Probabilistic Principal Component Analysis [7] is applied to the normalized test data. PPCA produces a rank-ordered decomposition of the test data, based upon the percent of variability in the data. The user of the method can then choose the number of principal components to retain in the test data reduction, based upon the amount of variability, or percent of information, desired to be retained in the validation process. The transformation matrix obtained by

PPCA is applied to the CAE model data to obtain a reduced set of CAE data.

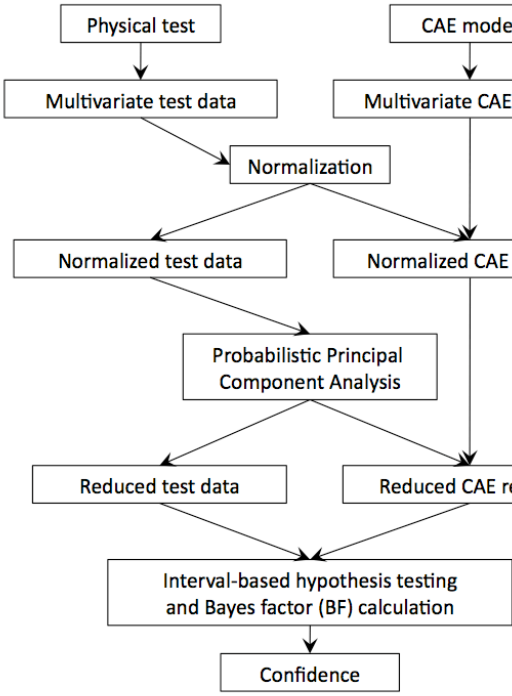

Figure 1: Model validation framework for dynamic systems.

With both the reduced test and CAE data sets, interval-based Bayesian hypothesis testing is applied and the Bayes factor is calculated. Interval-based testing is employed as it enables a more robust validation test than more typical set-point based Bayesian testing; see [8] for details.

The choice of the interval does impact the Bayes factor value. In this study, we employed a calibration procedure that equates the confidence value computed with the percent of variability captured by the included principal components from the field test data. The calibration factor that produces this equivalence is then used for the model validation assessment. More details of the procedure can be found in [9].

APPLICATION

The example application consists of a hybrid vehicle that was driven over two proving ground courses. For this vehicle, two different computational models were developed. Figure 2 depicts a comparison of four data channels of measured field data compared to the normalized CAE data channels computed using model 1, while Figure 3 depicts the results from CAE model 2 compared to the course 1 test data. Figures 4-6 show the field test data reconstruction using one, two and three principal components obtained from the PPCA process applied to the field data. As the number of principal components increases, the percent of information captured by the principal components increases (62%, 86%, 99.9% respectively for one, two and three principal components).

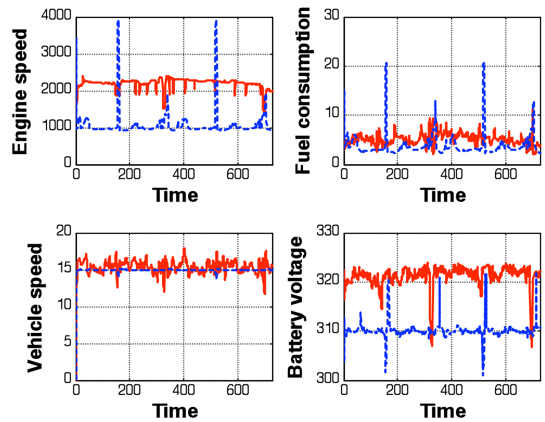

Figure 2: Comparison of field test and CAE model 1 time histories for course 1 (red=test, blue=CAE).

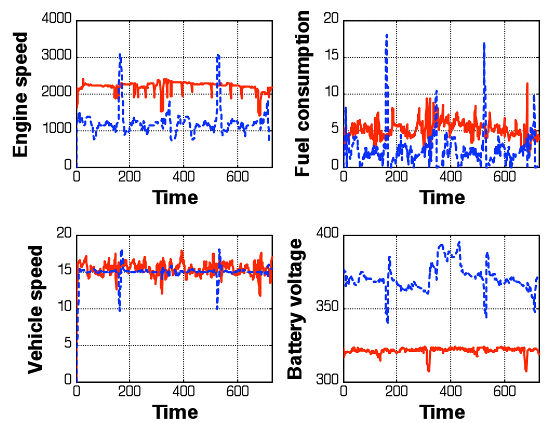

Figure 3: Comparison of field test and CAE model 2 time histories for course 1 (red=test, blue=CAE).

Figure 7 presents the parametric study of determining the appropriate value of the interval calibration parameter, *b*, following the procedure outlined above. Note that the calibration parameter does vary depending on the number of principal components employed. Using these calibration parameter values, Figure 8 provides the confidence values computed for both models, for one, two and three principal components. Note that the largest confidence value for the CAE models is obtained for 86% of information, that is, for two principal components. When three principal components were considered, the noise associated with the third component resulted in a reduction in model confidence. It is important to note that in all cases the confidence value is below 50%, which suggests that the models should be rejected. In other words, the models need more refinement and adjustment to provide acceptable comparisons with the test data.

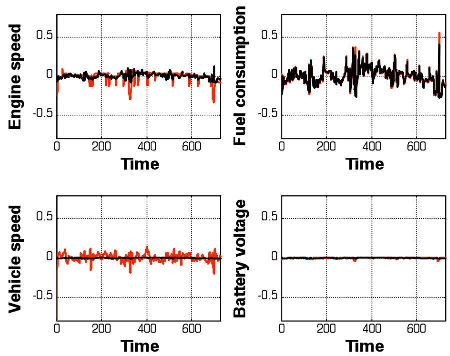

Figure 4: Comparison of field test (red) and reconstructed test data from 1 principal component (black).

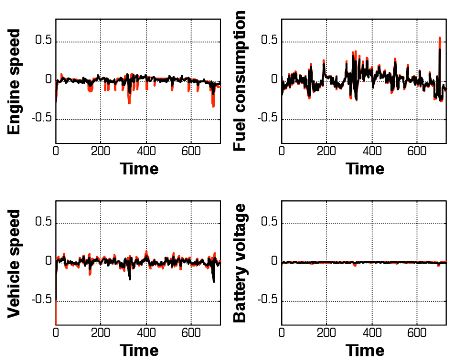

Figure 5: Comparison of field test (red) and reconstructed test data from 2 principal components (black).

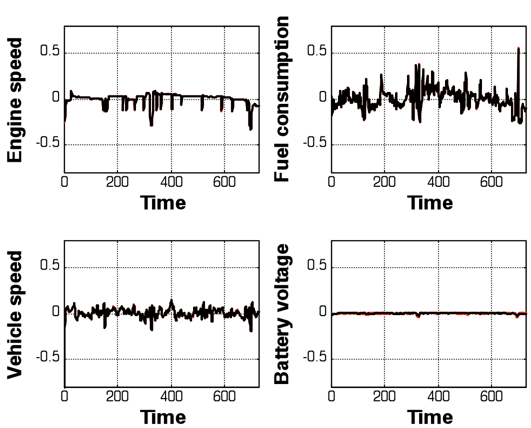

Figure 6: Comparison of field test (red) and reconstructed test data from 3 principal components (black).

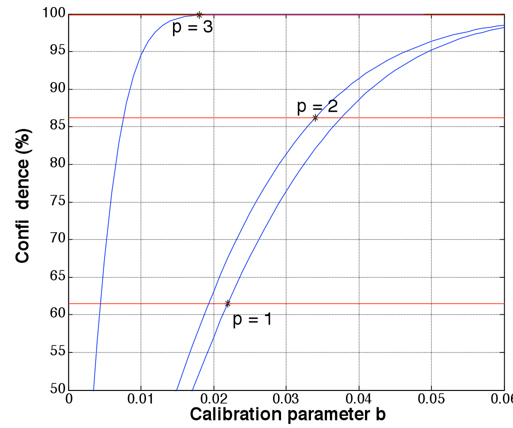

Figure 7: Choosing calibration parameter, *b*, based upon setting percent of information equal to confidence value for number of principal components, *p*.

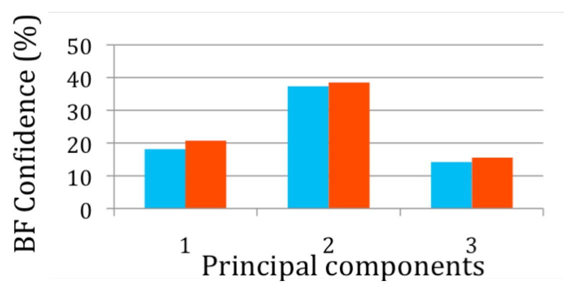

Figure 8: Confidence measure, in percent, for course 1, model 1 (blue), model 2 (red), and number of principal components.

The PPCA process and Bayesian interval-based testing were repeated for the course 2 test and computer simulations. The confidence values are summarized in Figure 9. As with course 1, the confidence values are less than 50%, which indicates the models should be rejected. In this case, however, the variation in confidence with number of principal components is much smaller.

DISCUSSION

The application presented in the previous section demonstrates that the confidence measure is dependent on the choice of the number of principal components and upon the selection of the interval calibration parameter. Further research is ongoing to provide engineers with guidelines on determining application-relevant calibration parameters and on assessing the information contained in the principal component analysis. The usefulness of the confidence metric can be seen as it provides a quantitative measure of model validity. Equally important, it can help guide the modeler towards better models by capturing differences in models that are below the acceptance threshold. In conclusion, this work represents a first step towards providing a VV&A toolkit for Army engineers to assess not only M&S results, but also laboratory tests.

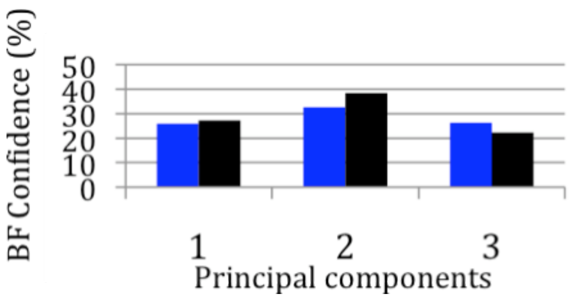

Figure 9: Confidence measure, in percent, for course 2, model 1 (blue), model 2 (black), and number of principal components.

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