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GROUND TEST DATA VALIDATION USING A SUBSCALE F/A-22 ENGINE INLET EMPIRICAL MODEL±

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ABSTRACT

The US Air Force's two main aeropropulsion test centers, Arnold Engineering Development Center and the Air Force Flight Test Center, are developing a common suite of modeling and simulation tools employing advanced predictive modeling technologies. These modeling and simulation tools incorporate real-time data validation, system identification, parameter estimation, model calibration, and automated model updating as new test results or operational data become available. The expected benefit is improved efficiency and accuracy for online diagnostic monitoring of Air Force assets. This paper describes the integrated approach to real-time data validation. Implementation of a software package to enable efficient model handoff between test groups and centers and extension of the capability to aeropropulsion models is discussed. An F/A-22 inlet model is used to demonstrate the approach. Compact polynomial function models of the distortion and recovery flow descriptors and 40-probe pressure values are derived from quasi-steady and instantaneous subscale wind tunnel data. The total-pressure inlet distortion and recovery models are integrated in a real-time equipment health monitoring system designed to support test operations, and preliminary results are given. A companion paper describes the integrated approach to system identification, parameter estimation, and model updating.

INTRODUCTION

The United States Air Force has a long history of using modeling and simulation (M&S) in the test and evaluation (T&E) process [Ref. 1, 2, 3]. While most M&S usage to date has been in the aircraft performance and flying quality areas, advancing technology and complex integration requirements are resulting in increased M&S use across a broader spectrum of technical disciplines, including aircraft inlet/engine integration. Modeling and simulation cannot replace testing the actual article; however, it can be used to significantly improve test capabilities across the three sub-processes of test planning, test execution, and data analysis and evaluation.

Generally, M&S is used during T&E as a predictive tool. Most predictive model generation techniques have some level of uncertainty. In most cases, the level of uncertainty in predictive models requires that the models be updated based on tests of the actual article within its intended environment. Arnold Engineering Development Center and the Air Force Flight Test Center, are developing a common suite of modeling and simulation tools employing advanced predictive modeling technologies to reduce the time and complexity of validating and updating component and system level models. Two foundational technologies for this advanced M&S suite are the Algorithms to Update Simulation Parameters with Experimental Data (AUSPEX™)

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MATLAB® modeling environment, developed by Barron Associates, and the Real-time Turbine Engine Diagnostic System™ (RTEDS) on-line monitoring framework, developed by Expert Microsystems. This common set of tools will permit model handoff from ground test to flight test (or flight test to ground test) phases and ultimately to operational phases.

AUSPEX provides a flexible suite of tools to assist the user in applying simulation, test, or operational data to create and update high fidelity models of systems and equipment. The RTEDS tools provide a model-based diagnostics framework for real-time data validation and equipment health monitoring based on various model types, including AUSPEX models. The capabilities and interactions of these tools are summarized in Fig. 1. RTEDS capabilities are the subject of this paper while AUSPEX capabilities are the subject of a companion paper [Ref. 4].

The AUSPEX modeling environment is used for the development of on-line capable system and equipment models, as shown in the model calibration and updating step of Fig. 1. The models are derived from simulation or operating data using advanced orthogonal function modeling techniques [Ref. 4]. The modeling is currently performed off-line prior to use for on-line monitoring of the system and equipment. An important aspect of the AUSPEX technique is its model updating capability. As operational data are acquired, the AUSPEX tools provide a high fidelity automated means to improve the model representation of the system and equipment by learning an improved model from the data.

The RTEDS on-line monitoring tool uses the AUSPEX models as the predictive element of its fault detection and isolation (FDI) methodology. The AUSPEX models are used to provide signal estimates (expected values) given each observation of the actual signal values. Next, a fault detection model is used to evaluate for excessive residual error (difference) between the analytical signal estimates and the observed signal values. Then, a probabilistic decision model is used to perform automated high-level fault and event classification for reporting to the engine or test operator.

This paper describes an integrated approach to system identification, parameter estimation, and model updating using an F/A-22 inlet model. Implementation of a software package to enable efficient model handoff between test groups and centers is discussed. Compact polynomial function models of the inlet total-pressure distortion and recovery flow descriptors, and the 40-probe pressure values, are derived from quasi-steady subscale wind tunnel data. The inlet distortion and recovery models are integrated into a real-time equipment health monitoring system to aid test execution, and performance analysis results are given. One expected benefit is the development of models and analysis capabilities that allow an improved comparison of results from wind tunnel and flight test, including their use to predict results at flight conditions that haven't been tested. These resultant models could also be used for flight manual development, determining SPEC compliance, or to aid in real-time equipment monitoring.

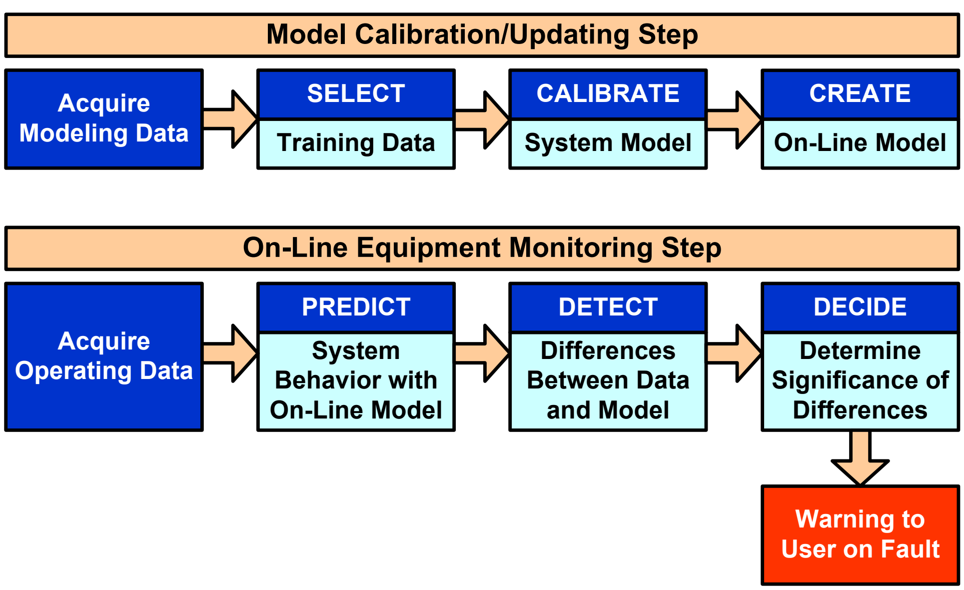

Fig. 1. Test Operations Support Using AUSPEX and RTEDS Tools

SUBSCALE F/A-22 INLET TEST CONFIGURATION

The sub-scale F/A-22 model test configuration, shown in Fig. 2, is a subscale representation of the aircraft external duct and inlet duct geometry from the nose to the Aerodynamic Interface Plane (AIP). Duct lines reflect the production aircraft configuration with fully modeled inlet with bleed and bypass systems. Flow blockage associated with the F119 fan and fan nose spinner was not simulated. Configuration variables included a simulated flight test nose boom assembly, nose landing gear assembly, inlet ramp bleed porosity, inlet ramp bleed exit area, weapons bay doors, bypass exit area, air data probes, and secondary air system. Additional details of the F/A-22 inlet testing are given in Ref. 5.

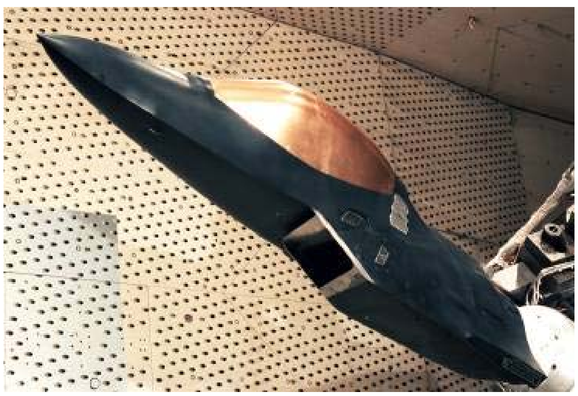

Fig. 2. Sub-scale F/A-22 Inlet Model

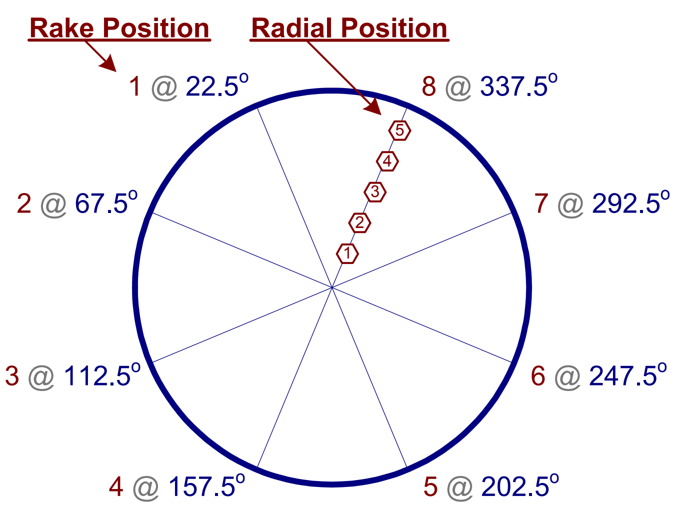

Fig. 3. Wind Tunnel Engine Inlet Rake Configuration Forward Looking Aft

A typical wind tunnel inlet instrumentation array for measuring inlet recovery and distortion is composed of eight equiangular-spaced rakes with five probes per rake located at the centroids of equal areas (Fig. 3). The number 1 rake for the inlet model was located 22.5 deg counterclockwise from top dead center (forward looking aft). The inlet rake geometry used for the current analysis is consistent with the Society of Automotive Engineers (SAE) recommended practice for turbine engine inlet testing. The steady-state pressures were measured with model-mounted Electronically Scanned Pressure (ESP) modules. More than 300 additional steady-state and high-response total and static pressure probes provided data to aid inlet development, for better understanding of the distortion patterns, and to determine off-schedule geometry effect, bleed effect, inlet stable range, and definition of control system/inlet destabilizing effects.

SUMMARY OF THE MODELING APPROACH

To aid in flight inlet performance analysis, AUSPEX M&S tools have been developed to predict flight inlet performance from the subscale wind tunnel database thereby facilitating a comparison of flight data with the performance expected based on sub-scale wind tunnel tests. The AUSPEX tool suite includes system identification and parameter estimation algorithms. The system identification algorithms enable the development of empirical models from simulation, test, or in-service data, and address the complete model selection problem, that is, they empirically determine the terms and parameters of the model. The parameter estimation algorithms provide functionality to calibrate either the models created by the companion system identification software or an arbitrary user provided model including analytic, statistical, or black box model types. A database updating capability permits the results to be merged to appropriate regions of existing simulations.

For the current analysis, separate subsonic and supersonic models were developed for each flow descriptor because the inlet characteristics can change substantially as a function of Mach number. This division of the data is also consistent with potential flight test program uses, where subsonic and supersonic conditions are evaluated in separate flight tests and the data can be analyzed between tests. This modeling is discussed in detail in Ref. 4.

The F/A-22 subsonic and supersonic wind tunnel data respectively contain up to 8,851 and 13,123 data points for a chosen screening parameter. This application of the modeling algorithm to a typical estimation problem for the F/A-22 wind tunnel data demonstrates that compact models characterized by four to six candidate input variables and quadratic to fourth order polynomials can be used to represent this large body of empirical data. In the current application, 84 steady-state flow descriptors are modeled for portions of the subsonic and supersonic envelopes. Less than four hours are required to run the model selection and calibration algorithms demonstrating that it is feasible to use the algorithm for post-flight data analysis on a daily basis and without adversely impacting a typical testing schedule.

MODEL-BASED FAULT DETECTION AND ISOLATION

Integration of the AUSPEX models with the Real-time Turbine Engine Diagnostic System (RTEDS) as well as integration of RTEDS with AEDC's Data Validation Manager (DVM) is illustrated in Fig. 4. AEDC's Data Validation Manager (DVM) is described in Ref. 6. RTEDS provides the capability to monitor for, distinguish between, and classify the source and type of sensor, engine, and facility faults based on the AUSPEX model results. This on-line diagnostic monitoring system will ultimately enable faster and more accurate decisions to certify or maintain an engine system in both test and operational environments.

An RTEDS on-line diagnostic system is comprised of a combination of *Predict*, *Detect*, and *Decide* model elements working together to accomplish real-time data validation and fault detection and isolation (FDI) objectives. In monitoring mode, the calibrated AUSPEX models provide expected values for each set of observed values from the test article. The difference between an observed value and an expected value is termed a "residual." The software fault detection procedures determine whether the observed residual values are uncharacteristic of the learned diagnostic model and thereby indicative of a sensor or equipment fault. Instead of using simple thresholds to detect fault indications (i.e., declaring a fault when a signal's residual value exceeds a preset threshold), the software's fault detection procedure provides more definitive information about signal validity using a patented statistical analysis technique known as adaptive sequential probability testing. This procedure provides a superior surveillance tool because it is sensitive not only to disturbances in the signal mean, but also to very subtle changes in the statistical quality (variance, skewness, bias) of the signals. For sudden, gross failures of a sensor or item of equipment, the procedure will annunciate the disturbance as fast as a conventional threshold limit check. However, for slow degradation, the procedure can detect the incipience or onset of the disturbance long before it would be apparent with conventional threshold limits.

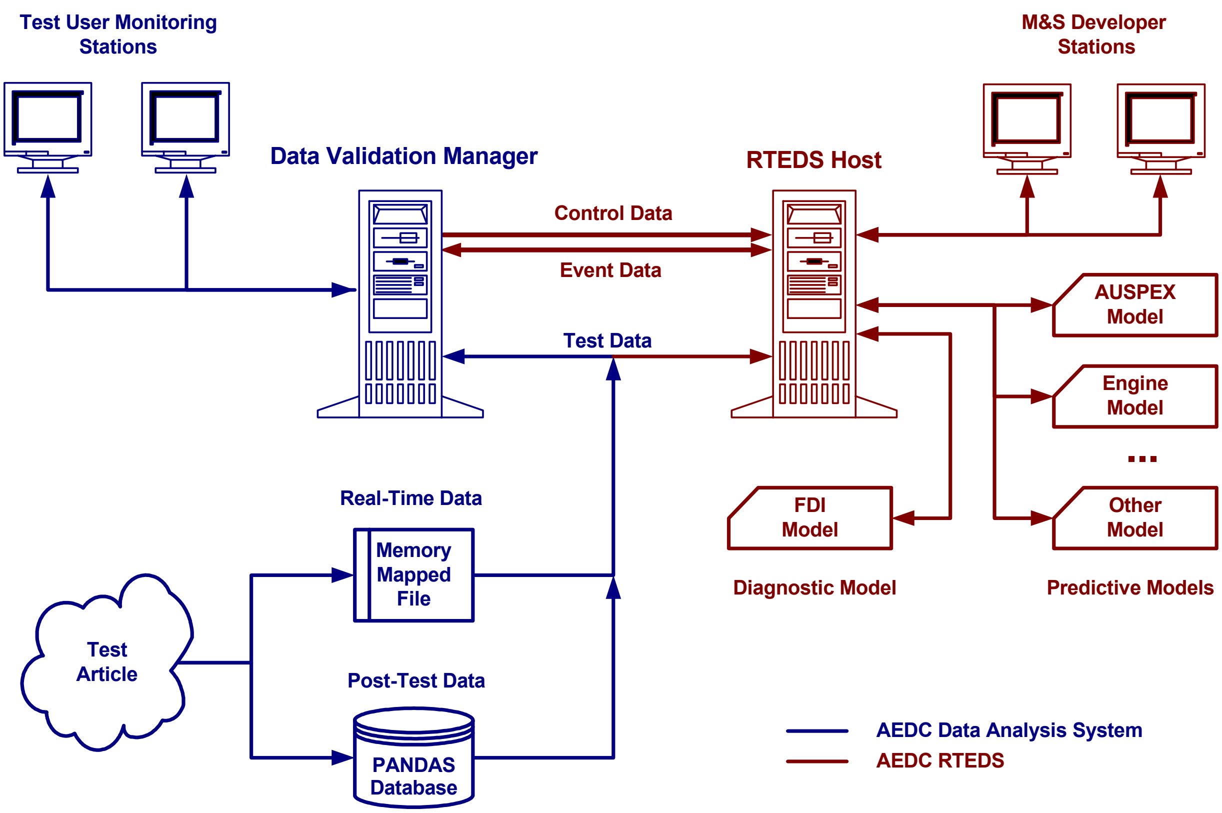

Fig. 4. Integration of RTEDS and AUSPEX for Test Operations Support

The presence of fault alarms related to the various signals can indicate several non-exclusive possibilities about the state of the monitored test article. These include the failure of one or more signals to provide true readings of the monitored variables, the degradation or failure of an article of equipment, or the operation of the test article in a mode different from those modes learned from the calibration data. An analysis regarding which of these states are most probable given the current state of the monitored system is made using a probabilistic decision manager. The decision manager weighs all possible diagnoses against one another to determine which has the most evidence for its substantiation. On completion, the software returns its diagnostic results to the user or to a host software process and waits for the next input observation from the test article.

Taken together, these model elements are used to implement an advanced fault detection and isolation (FDI) methodology. The FDI models will, in general, be used initially for their data validation function. As operating experience is acquired, the equipment fault detection signatures will be incorporated into the FDI model to capture the expertise of the designers and test engineers for the future benefit of Air Force operations users of the system. Additionally, the FDI models provide direct feedback to the predictive model designer as to the effectiveness of the model for equipment monitoring applications.

As shown in Fig. 1, the methodology includes a model calibration or updating step prior to the on-line monitoring step. In this work, the initial calibration step is performed using the AUSPEX tools. The calibrated AUSPEX models are readily integrated with RTEDS by virtue of its open, standardized Predictive Model Interface (see discussion below). Various other model types are also readily implemented.

INTEGRATION OF THE WIND TUNNEL INLET FLOW DESCRIPTOR MODELS

The RTEDS Predictive Model Interface allows one or more user-selected predictive models to operate simultaneously in the *Predict* step of the diagnostic decision method. The Predictive Model Interface defines the object-oriented methods and attributes that must be implemented by a user-defined predictive model in order to enable interoperability with the other complementary elements of the RTEDS tool suite. The interface allows for all data and control flows necessary to:

– Provide a dedicated graphical user interface for on-line configuration of the predictive model.

– Save predictive model configuration attributes within an RTEDS project file.

– Specify RTEDS signal data streams for use as predictive model input and output variables.

– Train or calibrate a predictive model in-situ using RTEDS provided data and data management.

– Operate a predictive model as a parameter estimator to return a set of estimated signal values given each new set of observed signal values from a monitored system.

– Operate a predictive model on-line at data rates consistent with the predictive model real-time capabilities.

Two AUSPEX-calibrated inlet flow descriptor model sets were integrated with RTEDS using the Predictive Model Interface. The first model set includes 84 individual models of the inlet flow descriptors for low Mach number subsonic conditions, valid over the Mach number range from 0 to 0.5. The second set includes 84 additional models of the inlet flow descriptors for high Mach number subsonic conditions, valid over the Mach number range from 0.5 to 1.0. Each model set is combined for convenience into separate low and high Mach range predictive models with each configured as an RTEDS plug-in module. The two predictive models are then combined into a single RTEDS project using RTEDS' patented automated mode partitioning capability [Ref. 7] to transparently switch between the two predictive models on-line as the actual inlet conditions vary over the test envelope. For brevity, models and results for supersonic conditions are not presented herein. The nomenclature used in these models and in the following figures is summarized in Table 1.

The RTEDS on-line monitoring user interface for surveillance of these 168 individual models (2 model sets) is illustrated in Fig. 5. The screen image shown also illustrates the software detection of a simulated bias error for signal PREFPT31, the steady-state pressure ratio at the ring 3, rake 1 location. The software fault simulator – which can be used to overlay shift, drift, and noise errors on top of the actual signals – was used to produce this simulated bias error for fault detection performance testing.

REPRESENTATIVE RESULTS

The AUSPEX inlet flow descriptor models were evaluated in RTEDS over the wind tunnel training data set to determine their baseline performance metrics. One model quality metric computed by RTEDS is the root mean square (RMS) residual error value (formed as the difference between the observed and predicted values) normalized by the RMS observed signal value, expressed as a percentage. The RMS Error metric for the steady-state pressure ratio signals is plotted as a function of circumferential position for each radial ring number (identified by colored legend) at the low subsonic Mach number conditions in Fig. 6 and at the high subsonic Mach number conditions in Fig. 7. Corresponding plots for the high response RMS pressure ratio signals are presented in Fig. 8 and Fig. 9. The RMS Error metric is less than 1% for the steady-state pressure ratio signals and generally less than 10% for the high response RMS pressure ratio signals.

The RMS Error metric results reported in Fig. 6 - 10 provide a measure of the agreement between the AUSPEX models and the observed data for the nominal signal values. Out of range data was removed from the data set prior to computing these results. However, the inclusion of some inlet operating points exhibiting a buzz instability (discussed below) results in higher RMS error values than might otherwise be obtained had these unstable points been excluded during AUSPEX model development. Because the flight vehicle control system is designed to prevent operation at inlet buzz conditions, it is recommended that future versions of the AUSPEX models be trained with buzz conditions excluded.

Table 1. Signal Nomenclature for Inlet Flow Descriptor Monitoring

Signal Description	Signal Name
Input Signals	
Mach Number	M
Angle of Attack	ALPHA
Angle of Sideslip	BETA
Corrected Airflow	WC2
Predicted Signals	
Average Engine-Face Total-Pressure Recovery	REC
Average Engine-Face RMS Turbulence	PTRMSPT2
Circumferential Distortion Intensity	DPCAVG
Tip Radial Distortion Intensity	DPRTIP
Ratio of Individual Steady-State Total-Pressure to Pt_0, Free Stream Total-Pressure (i=Ring, j=Rake)	PREFPTij
Ratio of RMS of High Response Pressure to Pt_2, Engine-Face Total-Pressure (i=Ring, j=Rake)	RMSPT2ij

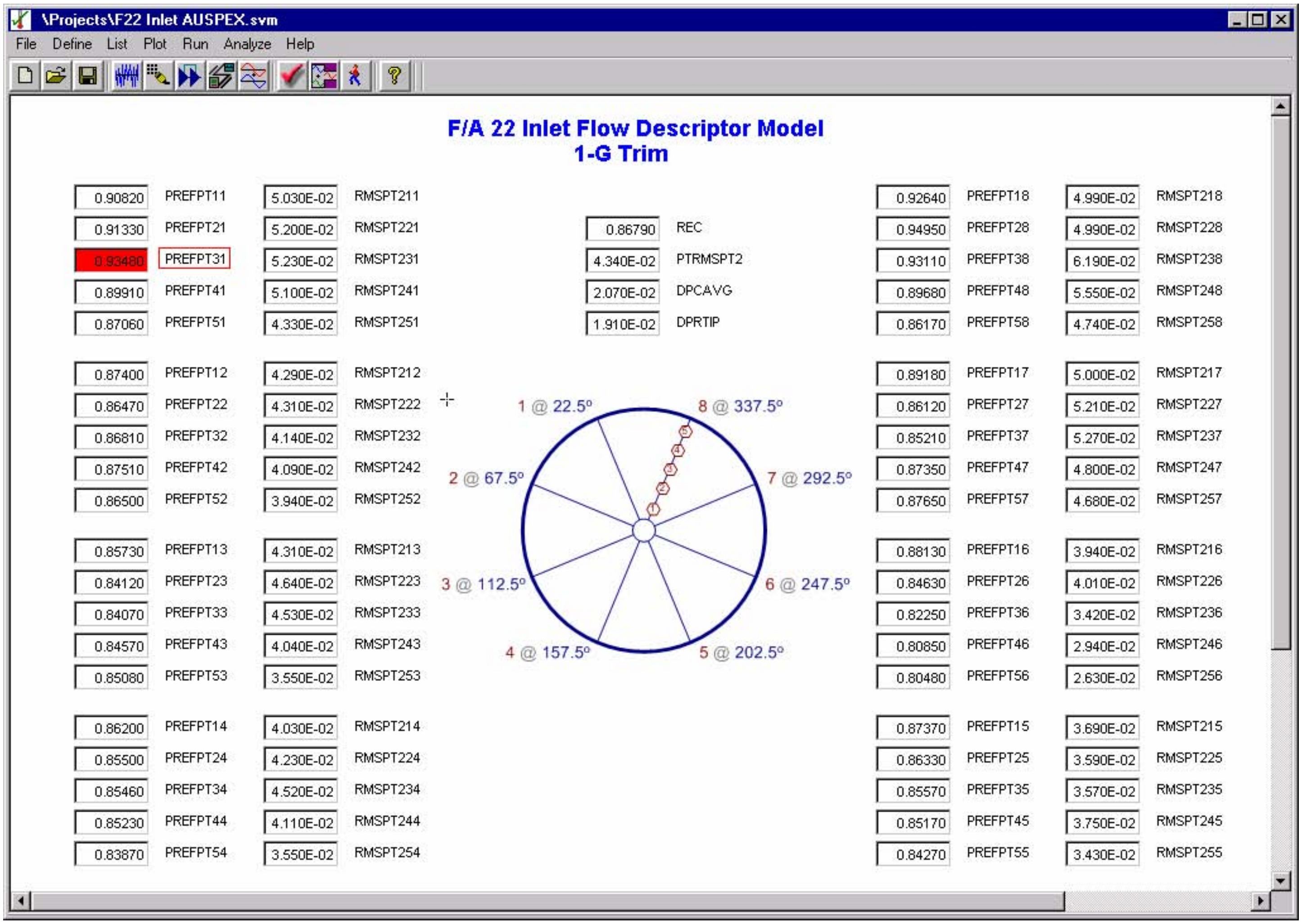

Fig. 5. RTEDS User Interface for On-line Inlet Flow Descriptor Monitoring with Detection of a Simulated Bias Error for Signal PREFPT13

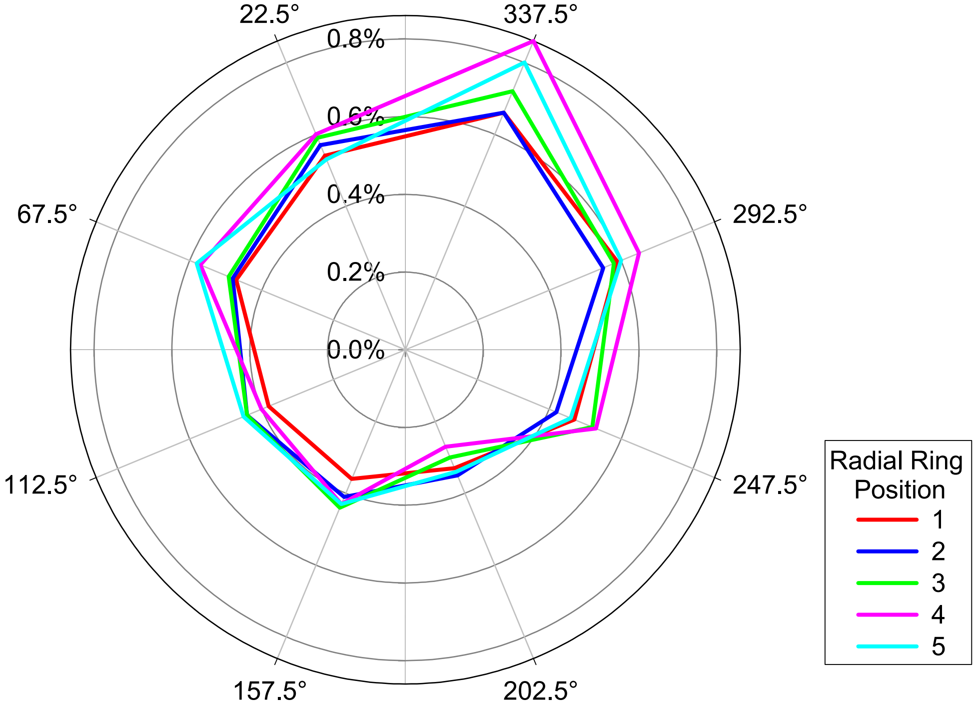

Fig. 6. Prediction RMS Error, %, for Steady-State Pressure Ratio at Low Subsonic Mach Condition

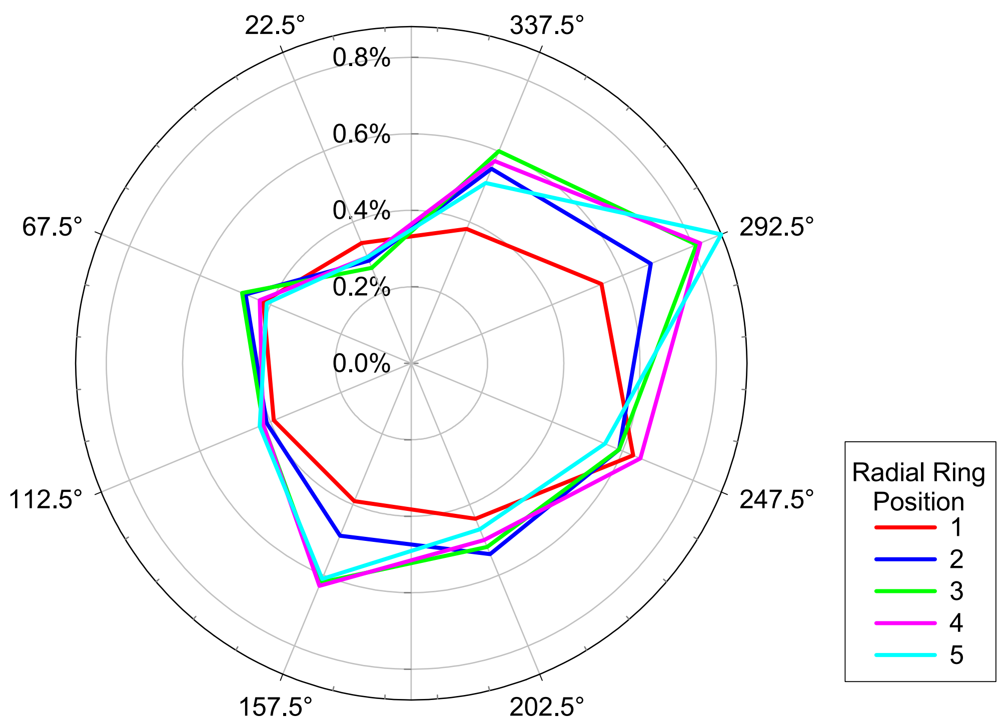

Fig. 7. Prediction RMS Error, %, for Steady-State Pressure Ratio at High Subsonic Mach Condition

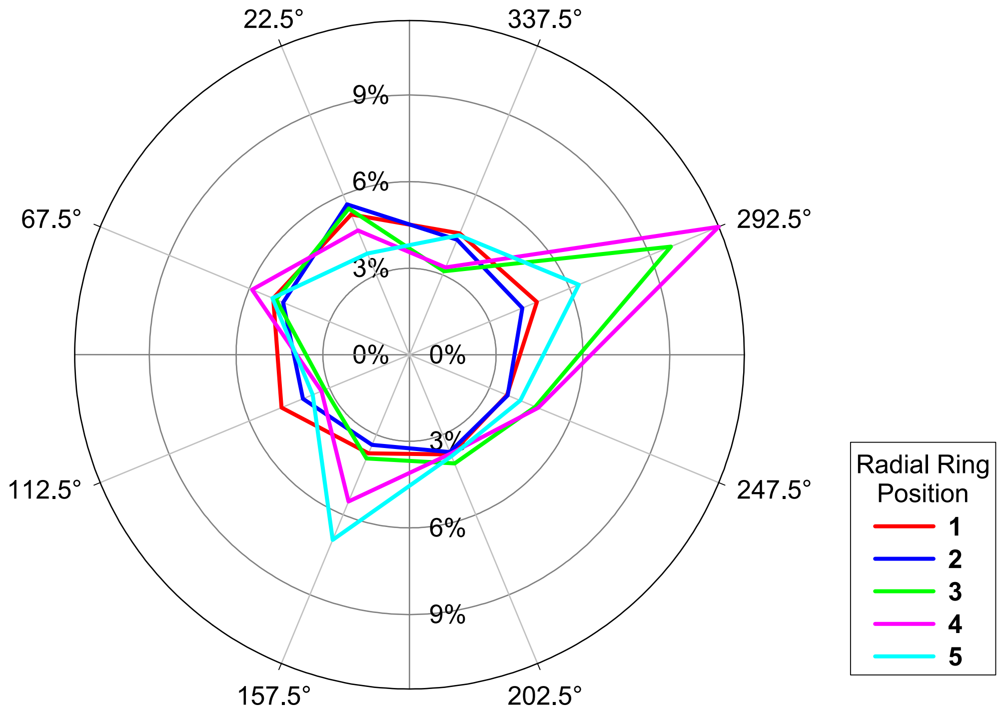

Fig. 8. Prediction RMS Error, %, for High Response RMS Pressure Ratio at Low Subsonic Mach Condition

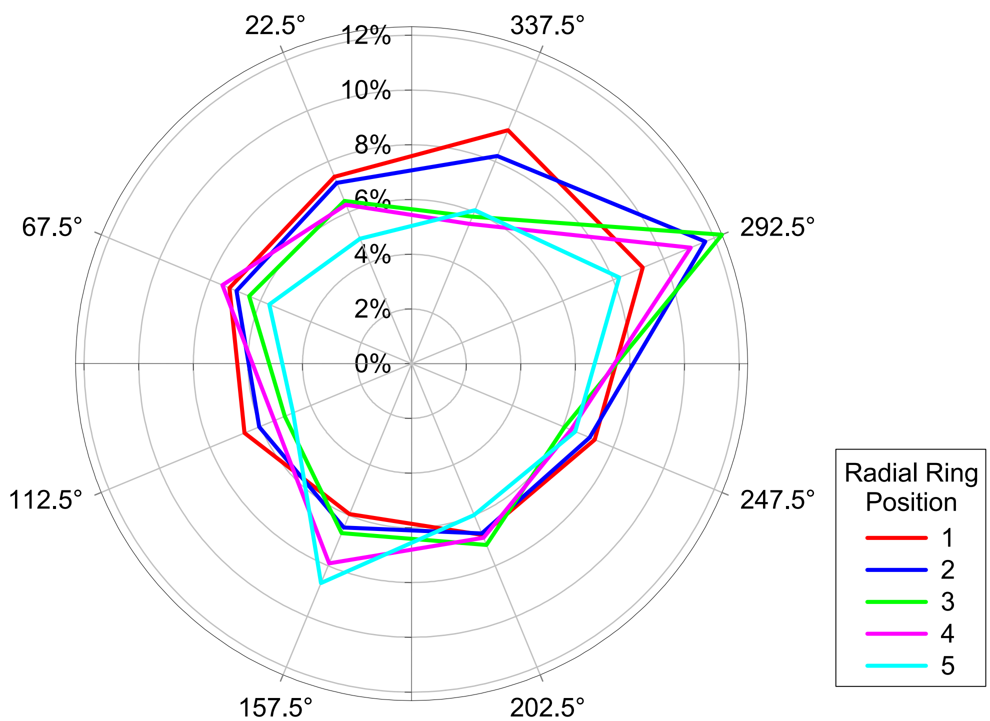

Fig. 9. Prediction RMS Error, %, for High Response RMS Pressure Ratio at High Subsonic Mach Condition

The ability of RTEDS to automatically detect bad data and anomalous operating conditions greatly facilitated the data assessment process. The F/A-22 wind tunnel database aptly illustrates the need for automated data validation and equipment diagnostic tools such as RTEDS. The original database contained 17,354 test data points, each consisting of 147 individual parameter values. This represents over 2.5-million data items in the database. The inlet distortion descriptor data had been previously screened for outlier data items and the database was considered to be "clean" of bad data. However, RTEDS used in combination with the AUSPEX models easily identifies a number of data items that might be considered bad, missing, or inconsistent with "normal" operation. Several of these are illustrated herein.

Several of the parameter values were recorded as 0.0 during some of the tests. This is a common signature of data values that are known to be missing or incorrect at the time of data acquisition or data recording. In comparing the recorded data with the expected data from the AUSPEX models, it may be seen in Fig. 10 that the models provide reasonable values for these parameters. The recorded values are considered invalid when they are not representative of the expected values of the parameters. In this figure, the blue "**x**" symbols are the recorded values of the high response RMS pressure ratio and the red "**Δ**" symbols are the model predicted high response RMS pressure ratio values for each observed value. RTEDS automatically generates an alert when an inconsistency between the observed and expected values is detected. Subsequent inspection of the F/A-22 wind tunnel database confirms that the parameter values noted as invalid in Fig. 10 are missing and have been replaced with values of 0.0. There were multiple instances of this type of bad or missing data identified by RTEDS in the "clean" F/A-22 wind tunnel database.

In another example, RTEDS detected the presence of "buzz" at the engine inlet for several operating points within the database. Buzz is a low frequency oscillation that is the result of harmonic separation and reattachment of flow in the duct that may occur at low inlet mass flow ratio [Ref. 8]. If buzz occurs at transonic or supersonic conditions when a shock is present, the magnitude of the buzz can be significantly exacerbated, which may result in engine stall or flameout. The signature of buzz is a sudden in-phase increase in high response RMS pressure as airflow is decreased, as shown in Fig. 11, which is usually accompanied by a drop in the total-pressure recovery value. Confirmation of the inlet buzz is seen in the variation of high response RMS pressure ratio, Fig. 12, and total-pressure recovery, Fig. 13, with respect to corrected airflow.

The buzz condition data is within the normal operating range for wind tunnel testing and was not considered anomalous by the model development team. Because the AUSPEX models were trained prior to recognition that the buzz events in the wind tunnel test database were unique to the wind tunnel test environment, the AUSPEX models are observed to follow the high response RMS pressure ratio characteristic of buzz at some, but not all of the low inlet mass flow conditions. As a result, the models overall effectiveness for discriminating a buzz condition from a no-buzz condition is reduced. Since the occurrence of buzz conditions is sporadic at the low inlet mass flow conditions in this database, it is unlikely that effective AUSPEX models could be designed to accurately predict this behavior. Moreover, because the buzz conditions occurred in the sub-scale wind-tunnel test, and the flight vehicle control system is designed to keep the inlet out of buzz, it is recommended that the models be retrained with buzz conditions excluded. Then, the RTEDS system could be used to detect and identify buzz automatically by using the inconsistent high response RMS pressure ratio measurements as a high probability indicator of an anomalous or buzz condition.

The buzz detection example demonstrates the expected benefit of improved efficiency and accuracy for online diagnostic monitoring of Air Force assets that result from the evolving suite of modeling and simulation tools. By combining the AUSPEX system identification, model calibration, and model updating tools with the RTEDS real-time data validation and equipment health monitoring tools, large data sets can be quickly and automatically processed to ensure that only high quality data is used for model development and for real-time test operations support.

The RMS Error metric results (presented in Fig. 6 - 10) would be improved by retraining the AUSPEX models with buzz conditions excluded. The highest RMS errors occur when the models are presented with normal no-buzz data at low airflow conditions and erroneously predict buzz behavior. This result is apparent in Fig. 14 at the 4404 and 4431 test index points. At these points, there is a small increase in the mean turbulence as the inlet approaches the buzz condition. However, the AUSPEX models are trained to expect more buzz in the vicinity of these airflow points and the model agreement with the data is degraded. Excellent agreement between the model and the data at higher inlet airflow values is evident in Fig. 14.

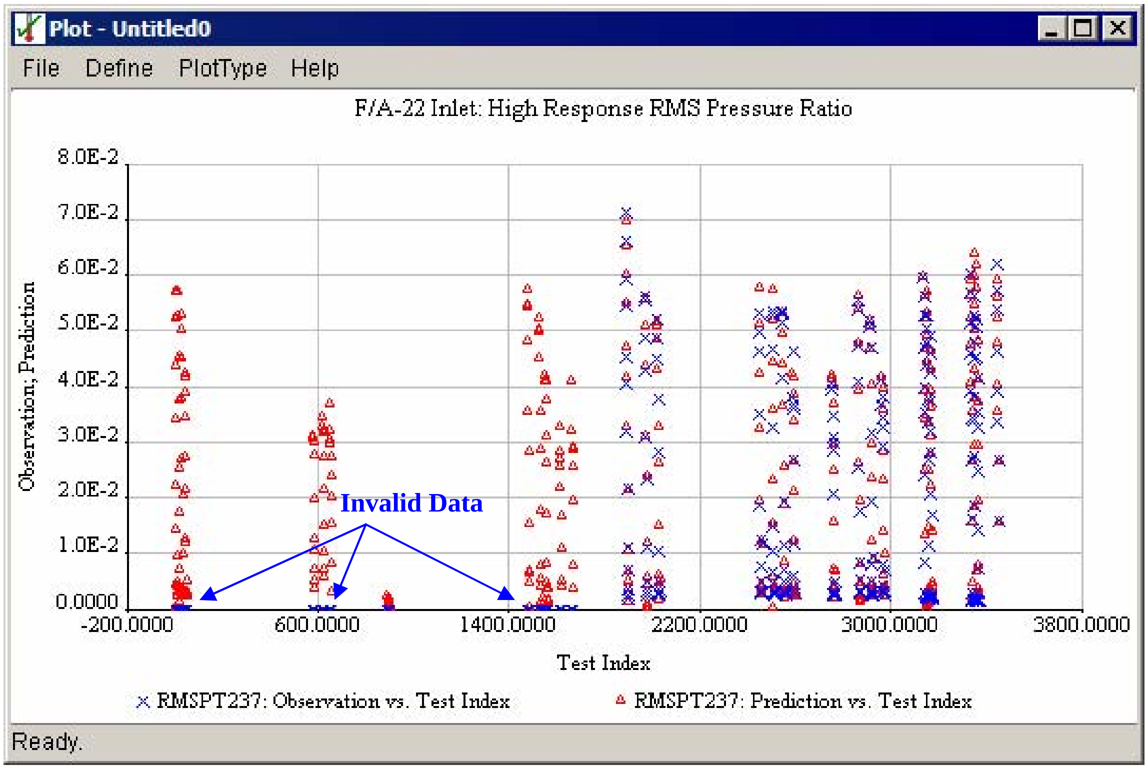

Fig. 10. RTEDS Detection of Invalid Parameter Data (Multiple Tests Shown)
Model Predicted and Observed High Response RMS Pressure Ratio versus Test Index

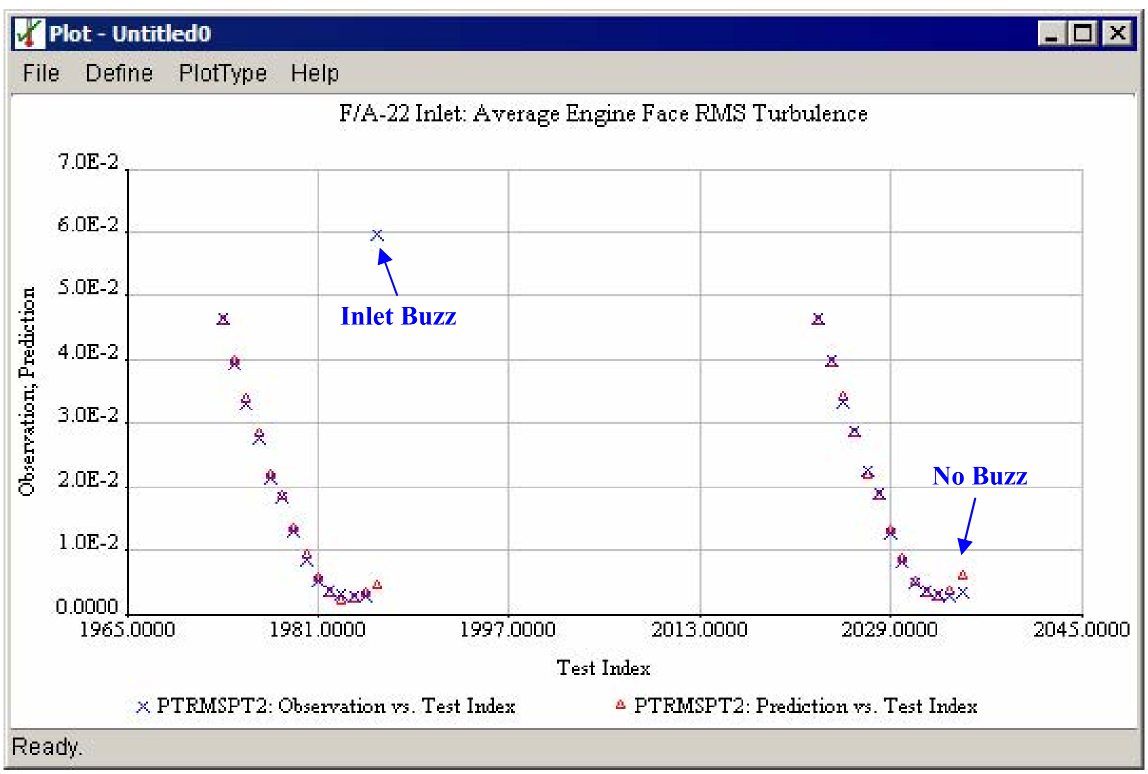

Fig. 11. RTEDS Detection of Inlet Buzz Condition (Left Side)
Model Predicted and Observed Average RMS Turbulence versus Test Index

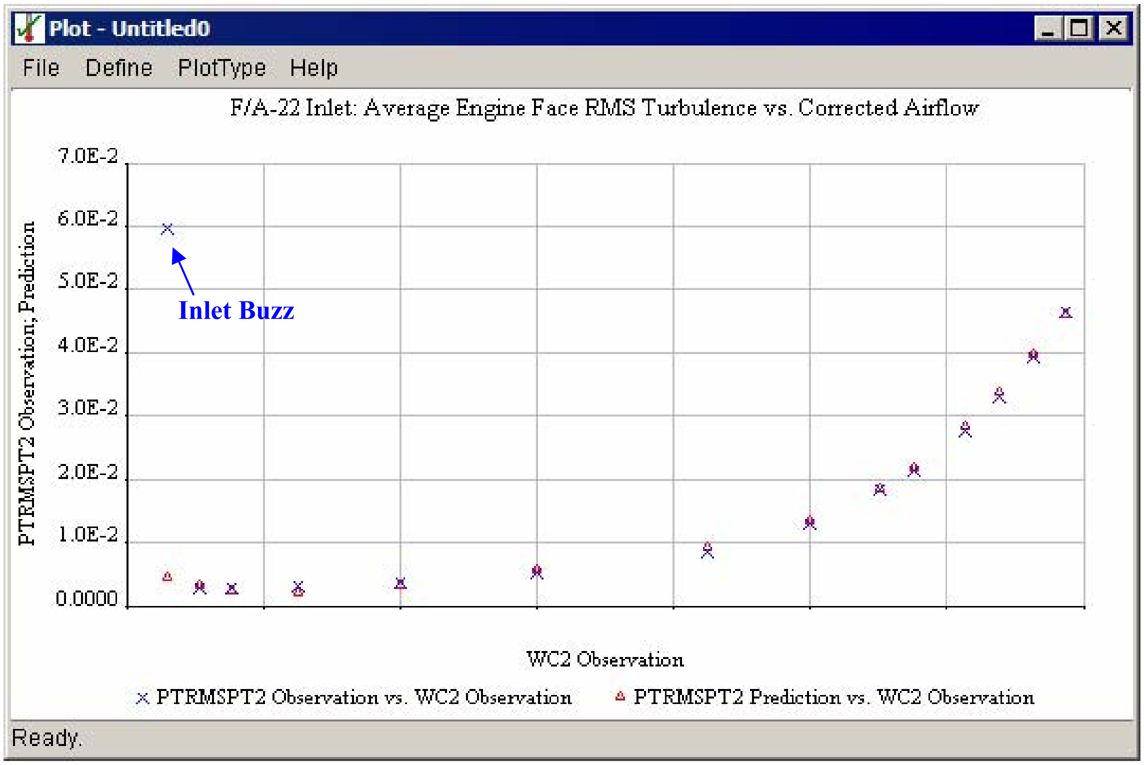

Fig. 12. Confirmation of Inlet Buzz Condition
Model Predicted and Observed Average RMS Turbulence versus Airflow

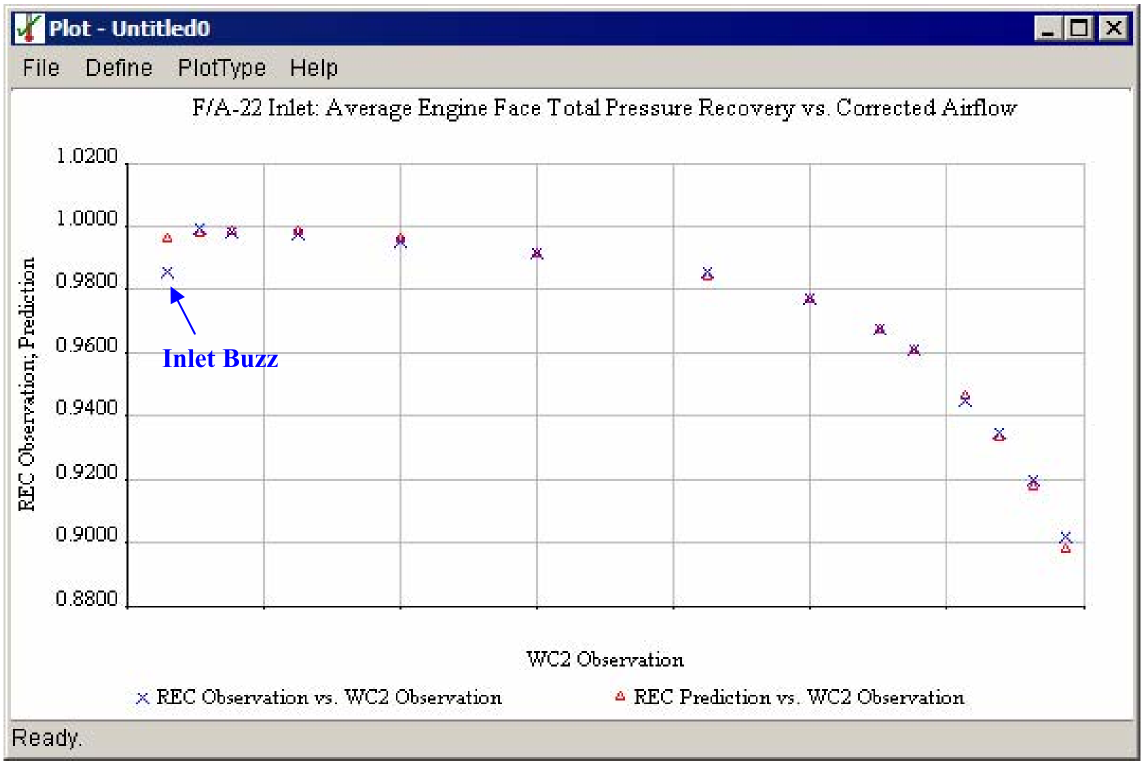

Fig. 13. Confirmation of Inlet Buzz Condition
Model Predicted and Observed Average Total-Pressure Recovery versus Airflow

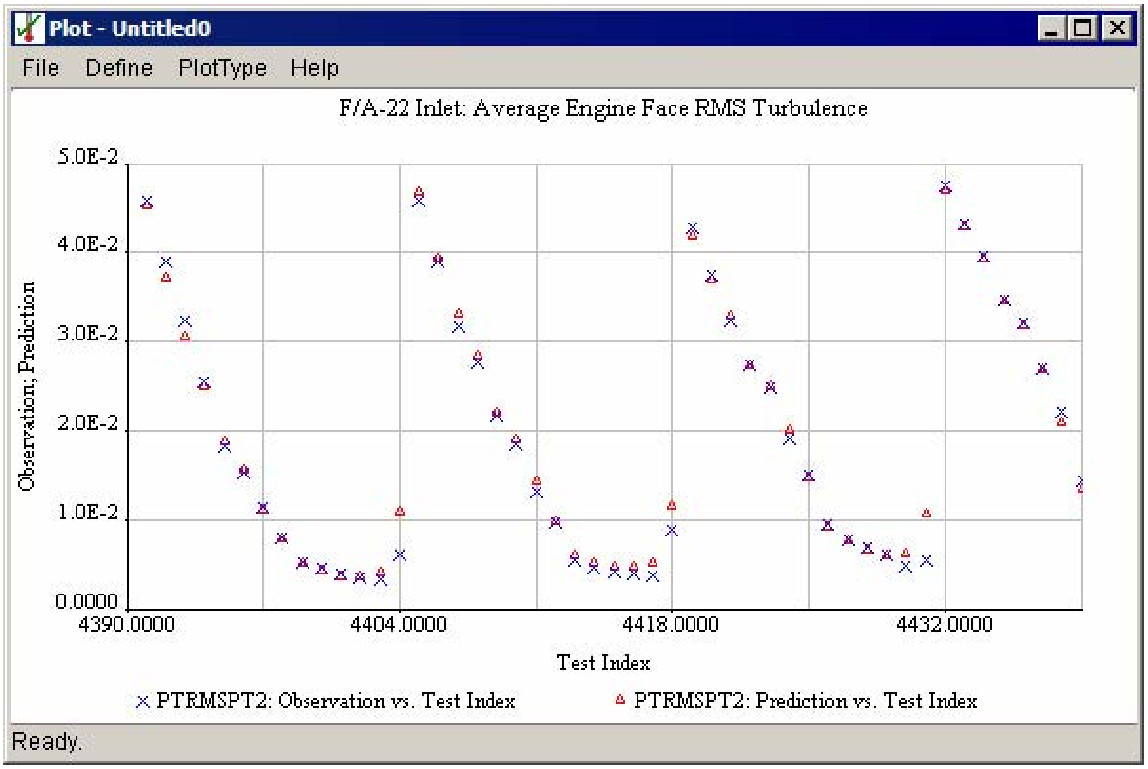

Fig. 14. AUSPEX Model Error Increases at Low Airflow Condition (Multiple Tests Shown) Model Predicted and Observed Average RMS Turbulence versus Test Index

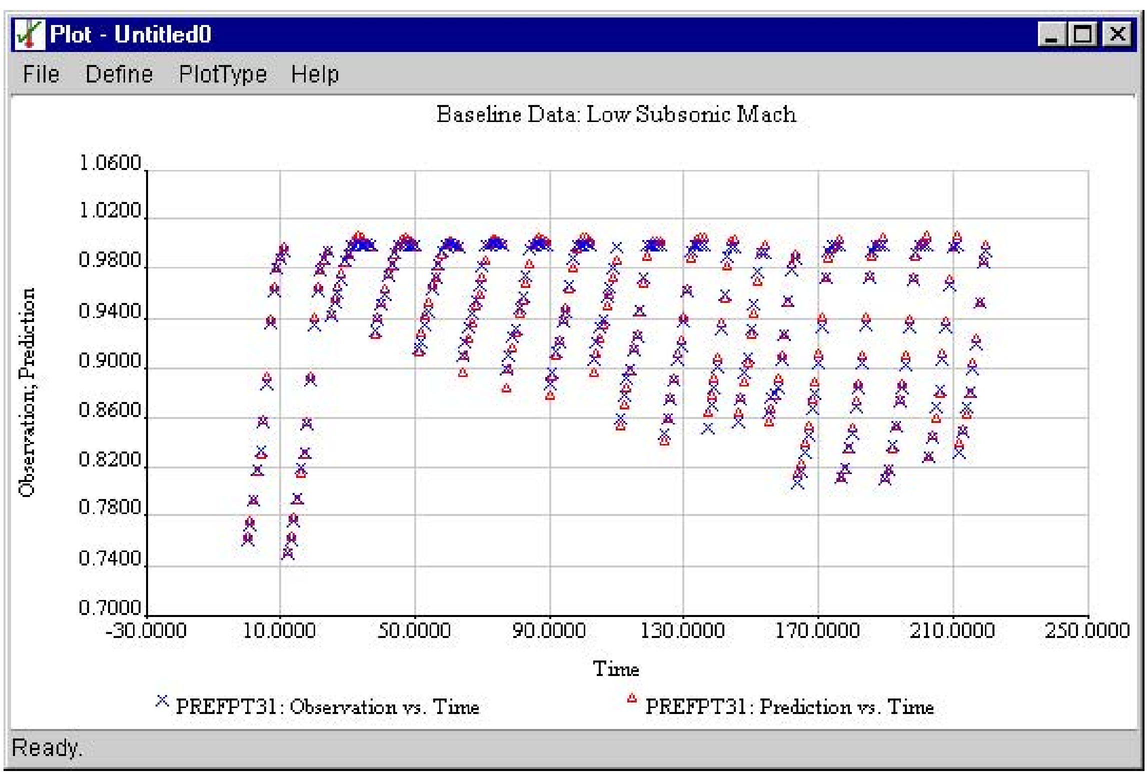

Fig. 15: Model Predicted and Observed Steady-State Pressure Ratio vs. Test Index without a Simulated Negative Bias Error

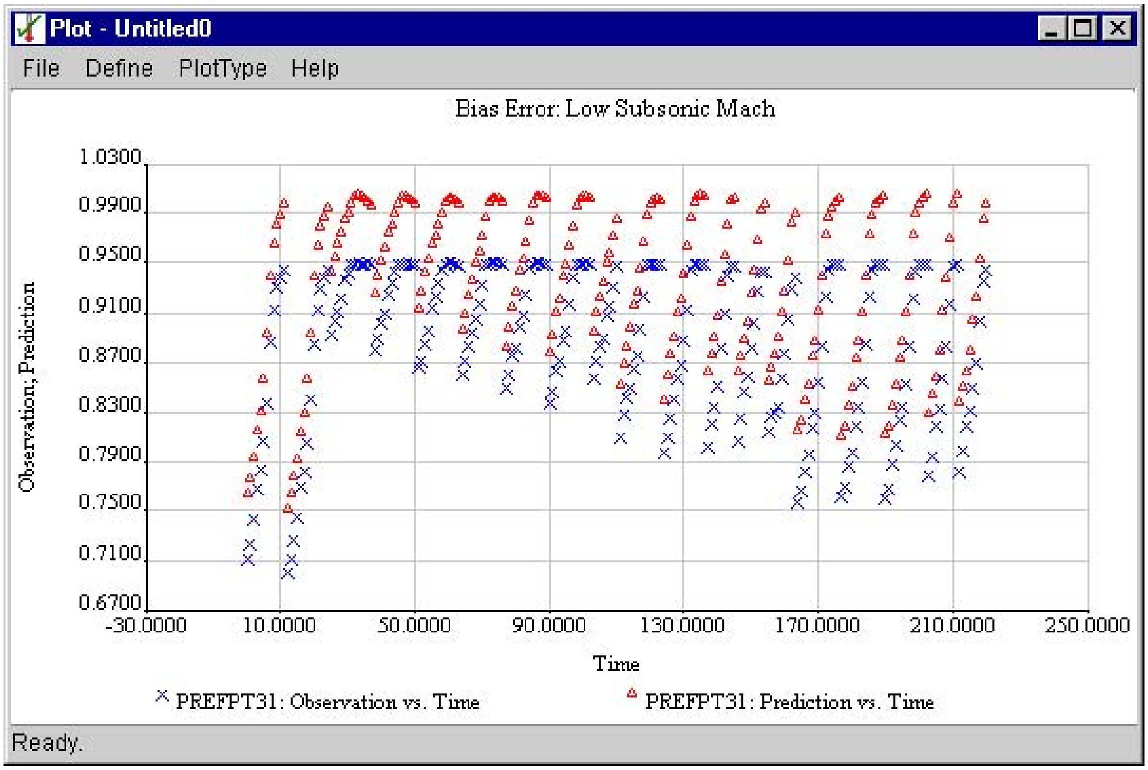

Fig. 16. Model Predicted and Observed Steady-State Pressure Ratio vs. Test Index with a Simulated Negative Bias Error

The ability of the model to reproduce the observed steady-state pressure ratio data is further illustrated in Fig. 15. As before, the blue "**x**" symbols are the measured values of the steady-state pressure ratio and the red "**Δ**" symbols are the model predicted steady-state pressure ratio values for each observed value.

The RTEDS user interface warning of a sensor bias error is illustrated in Fig. 5. The screen image shown was taken with a constant bias error of +0.025 simulated on the steady-state pressure ratio at circumferential rake position 1 (22.5°) and radial position 3. The bias error causes the observed steady-state pressure ratio to deviate from the predicted steady-state pressure ratio thereby generating a diagnostic system alarm and a red visual indication on the RTEDS user interface.

The effect of the simulated bias error on the predicted and observed steady-state pressure ratio is illustrated in Fig. 16. Using the same symbol conventions, this figure shows the model behavior when the same data is modified for testing with a simulated bias error imposed on the steady-state pressure ratio. The figure demonstrates that the model predictions are insensitive to the bias error and continue to accurately predict the expected value of the measured pressure. The deviation in the observed value is manifested as a negative mean shift in the residual error formed as the difference between the observed and predicted values and is readily detected as a data quality error condition by the RTEDS fault detection and decision management algorithms.

LESSONS LEARNED

Several important lessons were learned from applying these modeling and simulation capabilities to on-line data validation and diagnostics for the F/A-22 inlet test data. First, the effort underscored that the modeling algorithms are most effective when used as aids to an experienced analyst. Second, the importance of carefully selecting training data when developing empirically derived models was shown and the utility of using automated data validation techniques to streamline the training data selection process was demonstrated. It is important to highlight that the training data must not contain any "abnormal" features or else the empirical models will learn these as "normal", as we have seen with the buzz anomaly above.

Training data selection can be a time consuming process since very large data sets are often required to capture the full range of normal system behaviors. When presented with a very large data set, it is impractical to expect the analyst to manually derive the most desirable subset of training data for empirical model development. A more practical solution is to use a “bootstrapping” technique as follows: (1) carefully examine and clean up a subset of the data; (2) generate models of expected parameter behavior using automated tools such as AUSPEX; (3) use these models of expected parameter behavior in an automated data validation and diagnostic application such as RTEDS to further screen the data; and (4) iterate steps 2 and 3 to converge on a high-fidelity model. The bootstrapping method takes maximal advantage of the RTEDS software ability to discriminate normal data from abnormal data and the AUSPEX software ability to perform efficient model updating.

CONCLUSIONS

The utility of a common suite of modeling and simulation tools employing advanced predictive modeling and on-line diagnostic technologies was demonstrated. This common set of modeling and simulation tools incorporates real-time data validation, system identification, parameter estimation, model calibration, and enables automated model updating as new test results or operational data become available. The expected benefit is improved efficiency and accuracy for online diagnostic monitoring of Air Force assets. The foundational technologies for this modeling and simulation suite are the Algorithms to Update Simulation Parameters with Experimental Data (AUSPEX) MATLAB modeling environment, developed by Barron Associates, and the Real-time Turbine Engine Diagnostic System (RTEDS) on-line monitoring framework, developed by Expert Microsystems. AUSPEX provides a flexible suite of tools to assist the user in applying simulation, test, or operational data to create and update high fidelity models of systems and equipment. The RTEDS tools provide a model-based diagnostics framework for real-time data validation and equipment health monitoring based on various model types, including AUSPEX models.

Excellent agreement between the AUSPEX models and the data was demonstrated at higher inlet airflow values. At lowest airflow values, the agreement between the models and the data was degraded by the sporadic occurrence of inlet buzz conditions. The ability of RTEDS to automatically detect bad data and anomalous operating conditions greatly facilitated the data assessment process. It was concluded that the AUSPEX models should be retrained excluding the buzz condition data and that RTEDS should be used to automatically detect the occurrence of buzz conditions as well as other anomalies.

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