



# Descriptor sensitivity analysis shows local dependencies of missile aerodynamic coefficients in artificial neural network models

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## Descriptor sensitivity analysis shows local dependencies of missile aerodynamic coefficients in artificial neural network models

“DSA identifies the key parameters driving the model...”

“Excellent correlation was achieved between predicted and observed coefficients...”

“Q<sup>2</sup> values for different flow regimes

were 0.993 or higher with RMSEs of 0.297 or lower”

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### ABSTRACT

A variety of machine-learning methods has been applied to problems for which physics-based solutions are either nonexistent or computationally expensive. Based on such methods, surrogate models, i.e., empirical models that are trained on outputs of the more computationally intensive methods, can provide acceptable accuracy while dramatically reducing execution time, storage space, and expense. This work describes the application of an artificial neural network ensemble (ANNE) approach to train surrogate models that predict missile aerodynamic coefficients. The surrogate models developed to predict aerodynamic coefficients for arbitrarily shaped missiles at arbitrary Mach numbers and angles of attack have resulted in highly accurate predictions that execute in milliseconds on a modern laptop computer. The ability for rapid predictions can be integral to the design process for missiles and other aerodynamic bodies, as well as to estimate flight capabilities for observed missiles developed by others.

Building on previous work, we show how descriptor sensitivity analysis identifies the key parameters driving the model performance independently for any point within the parameter space, and relates inputs to outputs to help meet critical design/mission objectives.

### DATA

Data used to train these proof-of-concept models was generated by AERODSN using a range of missile geometries at various Mach numbers and angles of attack. Inputs are normalized to missile diameter or length, as is typical.

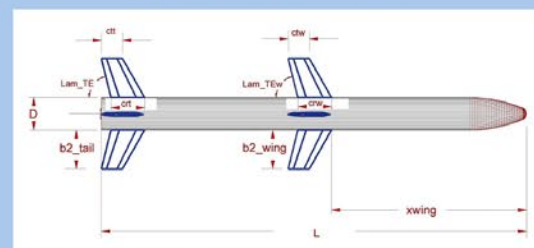


Figure 1: Missile geometry.

Training/Prediction Inputs	Configurations Explored
Mach number	0.20, 0.50, 0.70, 0.90, 0.95, 1.05, 1.10, 1.15, 1.20, 1.30, 1.40, 1.60, 2.00, 2.50, 3.00, 3.50, 4.00, 5.00
Finesness ratio	10
alpha (angle of attack, degrees)	-2, 2, 5, 8, 12, 18
b2_tail (tail semispan)	0.01, 0.5, 1, 2, 3.5
crt (tail root chord)	0.01, 0.5, 1, 2, 3.5
trt (tail taper ratio, ct/crt)	0, 0.00001, 0.2, 0.5, 0.7, 0.9
Lam_TE (tail trailing edge sweep angle)	0, 5, 10
b2_wing (wing semispan)	0.01, 0.5, 1, 2.5
crw (wing root chord)	0.01, 0.5, 1, 2.5
trw (wing taper ratio, ctw/crw)	0, 0.00001, 0.2, 0.5, 0.7
Lam_Tew (wing trailing edge sweep angle)	-10, 0, 10
xwing (wing location)	1.5, 2, 3.5

Table 1: Training data included combinations of these flight conditions and geometric parameters.

Aerodynamic force coefficients were calculated in AERODSN for model training and model testing for each geometric combination, resulting in approximately 500K data points for each Mach number.

Dependent Variables/Outputs	Description
CN	Normal force coefficient
CMcg	Moment coefficient about the nose
CA	Axial force coefficient

Table 2: Calculated values of these parameters were used as dependent variables for training. Resulting models predict these outputs for novel missile designs.

### Descriptor Sensitivity

The prototype AEROModeler's new Descriptor Sensitivity Analysis (DSA) tool enables point interpretation of model predictions in structural terms. DSA allows a user to explore the relationship between each specific descriptor and the model output in detail, for one data record (observation) at a time. This “local sensitivity” is significantly different from “global” sensitivities often reported for models, which try to average sensitivity across the entire data set. The sensitivity of a coefficient to a particular input is “local” – dependent on the missile configuration and flight conditions at each point. A coefficient may have very high sensitivity to angle-of-attack when at high angle-of-attack for one missile geometry and Mach number, but angle-of-attack may be less sensitive than another input for another missile geometry at different flight conditions. Thus, this tool may provide useful guidance on how to optimize a missile's properties.

After a model is built, it can generate predictions not only for the original training points, but for any hypothetical point within the parameter space used to train the model (as well as extrapolation for a limited range beyond the training space). The user can then select any point of interest, and each descriptor's influence on the modeled output can be examined. Such analysis can identify the key geometric parameters affecting flight at a critical point, for instance, to guide design or to avoid certain flight conditions by limiting flight dynamics via control algorithms.

$$s_i(x) = \left( \frac{\partial y}{\partial x_i} \right)_x$$

Equation 1: Definition of local descriptor sensitivity

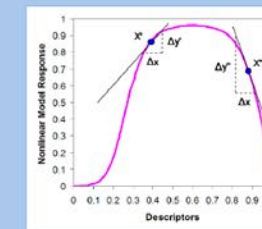


Figure 2: Local descriptor sensitivity for a non-linear model

### RESULTS

Excellent correlation was achieved between predicted and observed coefficients for subsonic, transonic, and supersonic models. An overall model encompassing all Mach numbers also shows high correlation between predicted and observed coefficients.

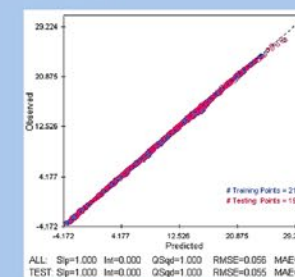


Figure 3: Subsonic. Correlation plot for predictions of CN at M=0.20, 0.50, 0.70 and 0.90, modeled with 11 inputs and 50 neurons.

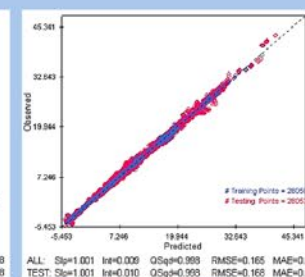


Figure 4: Transonic. Correlation plot for predictions of CN at M=0.90, 0.95, 0.70 and 0.90, modeled with 11 inputs and 100 neurons.

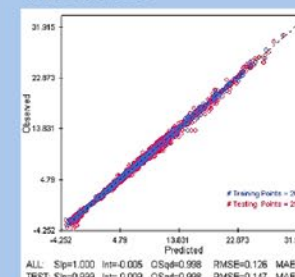


Figure 5: Supersonic. Correlation plot for predictions of CN at M=1.2, 1.3, 1.4, 1.6, 2.0, 2.5, 3.0, 3.5, 4.0, 5.0, modeled with 11 inputs and 100 neurons.

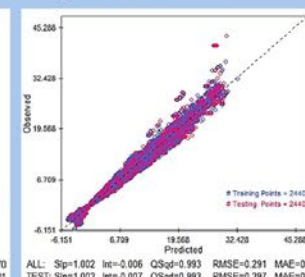


Figure 6: Full Mach range. Correlation plot for predictions of CN at M=0.2 to 5.0, modeled with 11 inputs and 50 neurons.

Figures 7 and 8 show that in this sample observation, consisting of a selected missile configuration and flight condition, the model for CN is most sensitive to alpha, b2\_tail, and b2\_wing (tail and wing semispans), in that order. [Mach=0.95, Fine=10, alpha=[-2,5], b2\_tail=1, crt=1, trt=0.5, Lam\_TE=5, b2\_wing=1, crw=1, trw=0.5, Lam\_Tew=0, xwing=2]

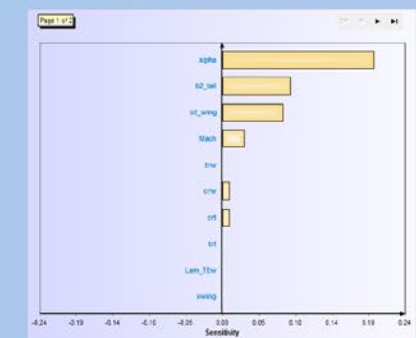


Figure 7: Selected example depicting descriptor sensitivity for a transonic model for a given missile configuration (alpha= 5 degrees)

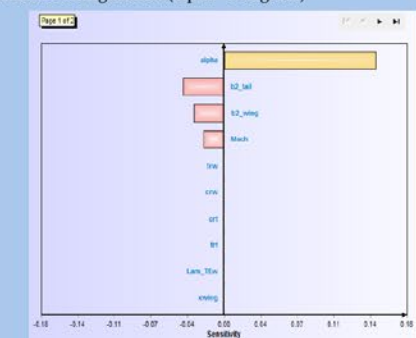


Figure 8: Selected example depicting descriptor sensitivity for a transonic model for a given missile configuration (alpha= -2 degrees)

### CONCLUSIONS

Existing techniques using wind tunnel data, flight data, and CFD data achieve good results, but are time-, CPU-, and capital-intensive. In this prototype effort, we have demonstrated an advanced machine-learning method that could be applied to wind tunnel, flight test sensor data, and CFD results for aircraft of similar geometries and flight conditions to provide rapid and accurate predictions of aerodynamic coefficients.

Further, we've shown how Descriptor Sensitivity Analysis (DSA) can be used to explore which features are most critical to the design, not just globally, but at any given point in the model space (geometry, attitude, and flight conditions).

To further the development of this tool, real wind tunnel and flight test data, as well as high-fidelity CFD data, are needed to build extensive models for selected scenarios. Working with real-world data would demonstrate the robustness of the modeling capabilities in an environment of experimental error and real-world physics instead of idealized conditions, and allow us to move forward with modeling complex aircraft shapes such as those contained in the 'Digital Twin' Initiative.

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