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"...3,000 unique missiles distributed throughout a wide range of feasible designs."

"A Q[2] of 0.963 and overall RMSE of 0.066"

"AEROModeler...was used to characterize missile diameters from simulated telemetry data."

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Characterization of missiles in flight from post-burnout critical points using artificial neural network ensembles

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ABSTRACT

This study demonstrates the use of an advanced machine-learning methodology to characterize the diameter of a missile in flight in near-real time. In missile defense scenarios, accurate characterization of an incoming missile facilitates selecting the best possible countermeasures. High-fidelity modeling techniques generally have the ability to produce good results; however, the computational cost of such applications makes them impractical in a real-time scenario where results are needed quickly. Solvers that use approximations to compute analytical solutions are faster than physics-based models, but come at the cost of accuracy. Properly-trained artificial neural network ensembles (ANNEs) can provide accurate results in times on the order of milliseconds. This is achieved by training the ANNEs on high-fidelity data prior to running the application during a launch.

The goal of this proof-of-concept study was to predict the diameters of missiles in flight using simulated radar data from the trajectories of single-stage missiles. A large, representative set of missile scenarios was generated using the AERODSN software by varying missile geometric parameters and launch configurations. This method employed the missiles' velocity and altitude at rocket motor burnout and at apogee as the independent variables; the prediction of diameter is then made within milliseconds of apogee.

DATA

A simulated radar data set was created using a six-degree-of-freedom solid rocket motor (SRM) fly-out code and was seeded using a Latin hypercube uniform distribution. This resulted in over 3000 unique missiles distributed throughout a wide range of feasible designs. Each of the unique missiles had a single simulated trajectory, with a launch angle of 65 to 85 degrees. A total of 35 geometric parameters (as seen in Table 1).

Parameter	Max	Min	Parameter	Max	Min
r_{nose}/r_{body}	0.43	0.37	b^2_t/D_{body}	1.6	1.2
l_{nose}/d_{body}	2.3	1.7	cr_{tail}/D_{body}	1.332	0.932
fuel type	3.15	3.05	tr_{tail}	0.81	0.51
R_p	0.637	0.477	$t_{LEsweep}$	17.5	2.5
R_i	0.19667	0.11667	x_{TEtail}	0.9925	0.9915
# of star points	7.25	4.15	Auto-$pilot_{delay}$	2	0.5
$fillet_{radius}$	0.099	0.069	launch angle	85	65
$epsilon_{grain}$	0.96138	0.80138	x_{k1}	4.4	3.6
$point_{angle}$	10.53149	9.53149	x_{k2}	3.5	1
fractional nozzle length ratio	0.92686	0.60686	nozzle exit diameter ratio	0.6	0.3
d_{throat}/D_{body}	0.3693	0.2193	Dumy	2	1
L_{body}/D_{body}	14.73367	10.93367	δe_0	5	1
d_{body}	1.5	0.2	δr_0	0.025	-0.005
b^2_w/D_{body}	0.0015	0.0005	dt_{check}	0.5	0.1
cr_{wing}/D_{body}	0.0015	0.0005	psicor	0.00721	-0.00778
tr_{wing}	0.935	0.925	δx-z	40000	40000
$w_{LEsweep}$	1.84921	0.84921	δx-y	40000	40000
x_{LEw}	0.35643	0.34643			

Table 1: Geometric missile parameters used to generate data set.

The candidate independent variables used to train the ANNs were based on the state at motor burnout (in this case defined as the point at which the acceleration along the flight vector is no longer positive) and at apogee (maximum altitude). At each of these two critical points, four parameters were used to define the missile state: time from launch, altitude measured from launch, the ground vector of range from the launch point, and the velocity along the flight vector.

This meant that eight potential state descriptors (independent variables) were used in training each ANNE. During training, the ANNE software (a prototype we call AEROModeler™) includes filtering steps to select the descriptors that are most informative and to eliminate descriptors that do not add statistically significant information.

MODEL BUILDING

The eight potential state descriptors at the critical points of each simulated trajectory were used as potential independent variables, and the missile diameters used to generate the simulated trajectories were the dependent variables. The prototype AEROModeler software automates each of the following steps necessary to build high-quality predictive models:

- Filtering to remove descriptors that are redundant and/or highly correlated, have relatively small variance, or are underrepresented in the data set;
- Clustering of data points to ensure intelligent selection of training, verification, and external test sets;
- Ranking descriptors by their effects on the predicted property (in this case, missile diameter) for each ANNE architecture (numbers of inputs and neurons);
- Training multiple ANNEs to allow selection of the most appropriate neural network architecture (numbers of descriptors and neurons);
- Selecting the best ANNE to use as the final predictive model.

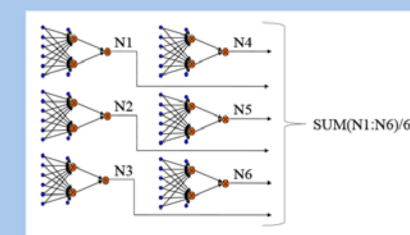

Figure 2: Simple ensemble of artificial neural networks. Multiple networks are trained separately, then averaged to produce the output value. This ensemble uses 6 inputs, 2 neurons, and 6 networks. (The best model in this proof-of-concept study used 50 ANNs, each with 5 inputs and 14 neurons.)

RESULTS

From eight potential descriptors, five were selected by the modeling process to best represent the encoded trajectory. The descriptors selected are shown in Table 2 with their sensitivities. The other three descriptors were filtered out by the training process due to high correlation with other active descriptors.

Descriptor	Sensitivity	Relative Sensitivity
Velocity at burnout	0.661	1.000
Time at burnout	0.610	0.924
Range at burnout	0.484	0.732
Velocity at apogee	0.378	0.572
Range at apogee	0.261	0.395

Table 2: Selected descriptors for best performing ANNE.

Due to our novel encoding of the trajectory, we examined the correlation plots of the descriptors versus the diameter of the missile for qualitative confirmation that the descriptors would be modeled well. Below are samples of these plots. The divergence in some of the plots that occurs around a 0.9 meter diameter is likely due to the amplified effects of multiple combinations of star points and star point radius in the solid propellant rocket motor designs used to generate the trajectories.

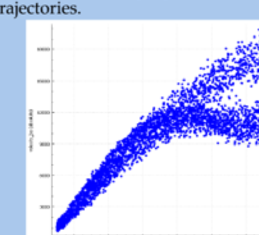

Figure 3: Velocity at burnout vs. body diameter.

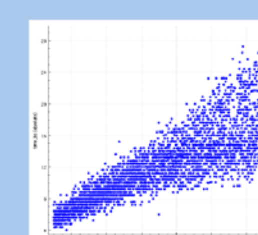

Figure 4: Time at burnout vs. body diameter.

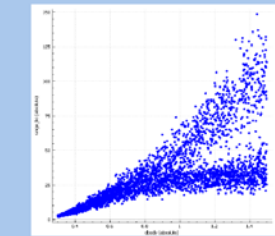

Figure 5: Range at burnout vs. body diameter.

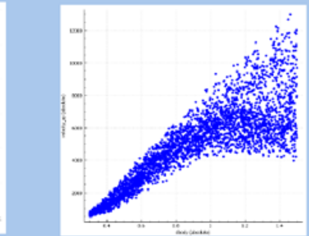

Figure 6: Velocity at apogee vs. body diameter.

Models were built using a variety of ANNE architectures. The best performance was found with an ensemble of 50 ANNs, each using the five inputs in Table 2 and 14 neurons in the hidden layer. Figure 7 shows the correlation between the predicted and observed diameters across the entire data set, with 15% of the data points in the external, held-out test set (shown in red). The final ANNE performance for more than 3,000 missiles is very dense along the diagonal—the outliers that fan out as diameter increases above 0.9 meters are actually relatively few in number. The overall RMSE is 0.066 for the test set (0.067 for all data), indicating very accurate prediction performance.

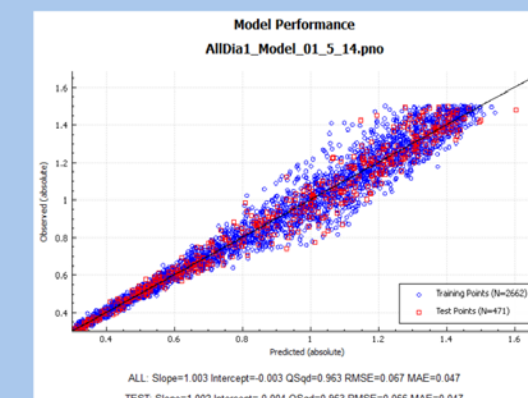

Figure 7: Plot showing correlation between predicted and observed diameters in meters.

CONCLUSIONS

The prototype AEROModeler software program was used to characterize missile diameters from simulated telemetry data at burnout and apogee. This method of modeling could have applications as an aid to current and future missile defense systems whose effectiveness could be enhanced with a better and more accurate characterization of the target vehicle while in flight.

In future studies, other missile characteristics can be modeled across a wider range of missile geometries and trajectories to provide greater discrimination across various missile types. This study held certain parameters constant to demonstrate proof-of-concept for a single geometric parameter (diameter). Varying other parameters such as fuel type and various material densities, more complex data sets could be generated and might accommodate coupling other computational intelligence methods or other trajectory diagnostic tools such as infrared analysis of the plume signature. Such multimodal analysis could also allow models to address and overcome sandbagging (early termination of rocket thrust). Additional information about the trajectory and the missile, such as observed G-forces, images, or other intelligence, might unlock the ability to fully characterize a missile in flight, and to do so earlier in the flight.

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