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MODELING OF STORE SEPARATION BEHAVIOR BASED ON A NEURAL NETWORK AND UNSTEADY FLOW SOLUTIONS

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ABSTRACT

In this study a neural network based method is developed for the prediction of separation characteristics of external store weapons carried under aircraft wings. The method is based on an artificial neural network trained by high fidelity unsteady flow solutions. The unsteady flow solutions as the store separates from the carriage and the resulting six degrees of freedom motion of the store are computed conditions by a commercial flow solver for various flight conditions. The trajectory of the store and the unsteady aerodynamic loads acting on it are used to train a neural network. A simulation is used for evaluating the 6 degrees of freedom motion of a store based on the aerodynamic loads predicted by the neural network as a function of the flight conditions and the instantaneous position of the store. The efficiency and the accuracy of the method developed are determined by comparing the predicted and computed trajectories of the store for flight conditions not used in the training set. It is shown that the method developed can successfully predict the store separation characteristics.

INTRODUCTION

Store separation study is a complex and expensive study both in time and cost wise. High fidelity analyses prior to ground and flight testing may aggressively decrease the time and money spent on store separation tests. The grid method is widely employed for the prediction of store trajectories. It is based on building an aerodynamic load database with the store's possible projected positions and attitudes w.r.t. wing and the instantaneous aerodynamic loads acting on the store. The aerodynamic data needed to form the database may be obtained from wind tunnel tests or from CFD simulations. The database is then used together with a 6DOF ODE solver to evaluate the position and the attitude of the store after its separation from the carriage. A store separation can be simulated efficiently by the use of the grid method provided that aerodynamic loads can be interpolated for a given position and attitude, which requires a properly populated database. It may not be always possible to find an interpolation grid for all positions and attitudes within the database, and extrapolations are usually avoided for accuracy considerations.

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In this study, instead of a grid based interpolation, an artificial neural network based, continuous “interpolation” methodology is employed. An artificial neural network (ANN) algorithm is a computational model inspired by an animal’s central nervous system, especially the brain. Artificial neural networks can be defined as systems of interconnected neurons (outputs) which can compute values from inputs. They are widely used to solve a variety of tasks that are either time consuming or difficult or both to solve using ordinary, rule-based algorithms [Rojas,1996].

METHODOLOGY

Neural networks are typically organized in layers. Layers are made up of a number of interconnected 'nodes' which contain an 'activation function'. Patterns are presented to the network via the 'input layer', which communicates to one or more 'hidden layers' where the actual processing is done via a system of weighted 'connections' (pages.cs.wisc.edu/~bolo/shipyard/neural/local.html). Neural networks are trained with training inputs and well-known outputs so that the activation function and respective weights can be determined within the desired error band. There are various approaches in training a neural network. In this study the back propagation training algorithm is employed.

An artificial neural network may be trained for the prediction aerodynamic loads acting on the store as it separates from its carriage under an aircraft wing and falls freely as a function of its position. Studies in order to estimate aerodynamic load coefficients are already conducted by [Rajkumar and Bardina, 2003] & [Norgaard, Jorgensen, Ross, 1997]. In the current study, an open source neural network software developed by [Lonnblad, Peterson, Pi and Rognvaldsson, 1997] is employed for the estimation of aerodynamic forces as a function of position and attitude of a store separated from its carriage. The training data for the neural network are extracted from the unsteady flow solutions under different flight conditions.

For testing the ANN code, the variation of a side force coefficient as a function of angle of attack, aileron and rudder deflections is predicted by a trained neural network. An experimental data set with 300 rows including 8 inputs and six outputs in each row is used in the training and the testing stage. The back propagation algorithm is employed in the training process with 275 data items and with a relative error tolerance of 0.01 or less. Remaining 25 rows are used for testing of ANN algorithm.

The neural network is trained with the data sampled in order to provide the aerodynamic loads and moments (6 variables) for a given position and attitude of the store (six parameters). The performance of the neural network based trajectory reconstruction algorithm to be developed is assessed by simulating store separations for various angle of attack and sideslip angles of the aircraft and comparing them with the corresponding Fluent solutions. For ANN algorithm, the best combination of the number of hidden layers, the training tolerances, the ratio of the datasets employed for training and testing and the optimum frequency of the data items extracted from an unsteady solution required for an accurate reconstruction is determined by trial&error. Trial & error field is narrowed by using hidden layer recommendations from literature (**www.heatonresearch.com/node/707**). Number of hidden layers, number of nodes per each layer and epoch (iteration) number is given below for each force/moment coefficient.

Table 1 ANN algorithm parameters

Coefficient	# of training epochs	# of hidden layers	Number of nodes per layer
Cx	3000	1	8
Cy	5000	1	8
Cz	3000	1	8
Cmx	3000	2	7
Cmy	3000	1	7
Cmz	3000	1	7

The unsteady flow solutions and the aerodynamic loads are obtained using Fluent®. The dynamic mesh creation feature of Fluent® handles the store separation process. The Spalart-Allmaras turbulence model is used in unsteady flow solutions. The position and the attitude of the store and the corresponding aerodyamic loads acting on it are extracted at various frequencies as the store separates from the carriage and falls. The discrete data extracted are then used to train the neural network for the prediction of aerodynamic loads as a function of the angle of attack, the side slip angle and the instantaneous position and attitude of the store.

The neural network trained with unsteady flow solutions is then employed for the simulation of the store separation and its trajectory at various flight conditions. The six degrees of freedom motion is evaluated by means of a Matlab® function exported in C language and coupled to the ANN solver in executable format. The flowchart of the simulation process is given below in Figure 1.

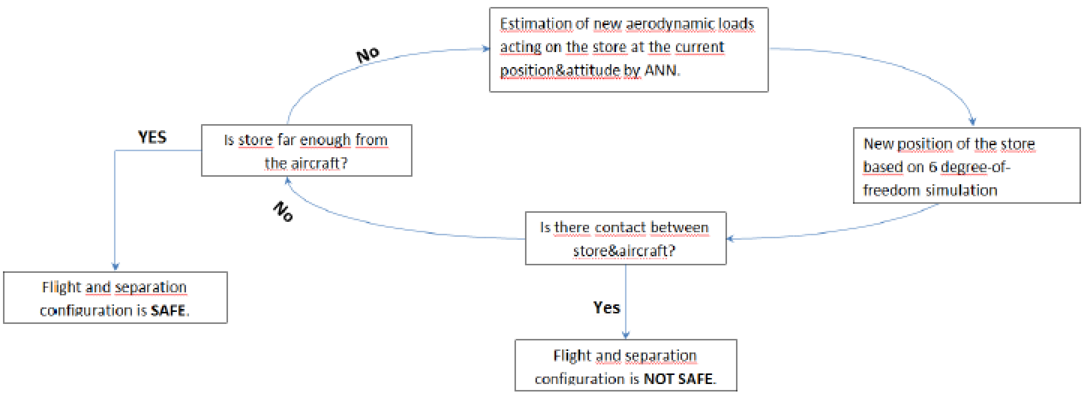

Figure 1. Flowchart for the modeling of the store separation behavior

RESULTS

The separation of a Mk-82 store from its rack mounted on a generic wing (Figure 2) is aimed to be investigated by using ANN based training and prediction of aerodynamic loads and the integration of store path based on a six-degree-of-freedom solver coupled loosely.

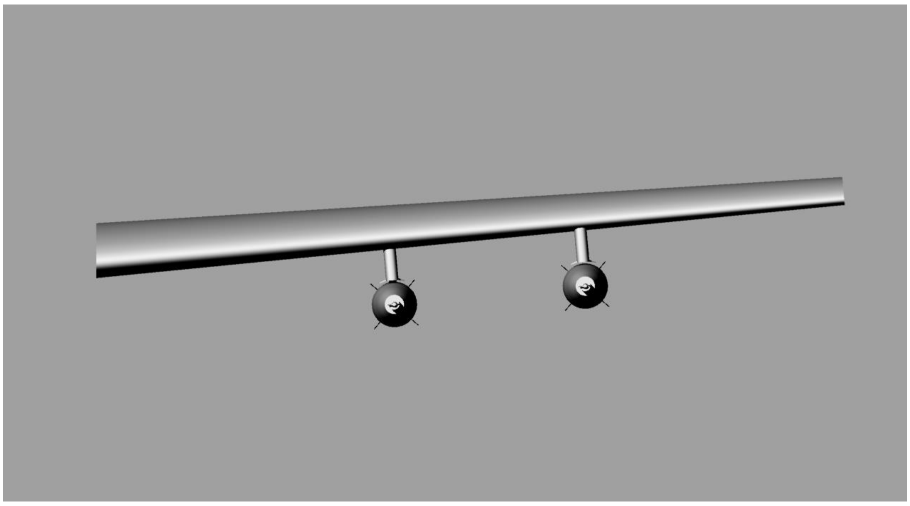

Figure 2 A generic rack and Mk-82 stores under a generic wing geometry

The training data set for the ANN is obtained by a set of CFD analyses. A total of 12 unsteady flow solutions given in Table 2 are obtained with Fluent 6.3.26® to generate the training data set for the neural network. Freestream velocity is set to 0.3 Mach @ 10,000ft standard atmosphere conditions.

Table 2 Flight conditions for unsteady flow solutions

AoA (^{o})	Sideslip Angle (Beta) (^{o})
-1.5	-10
-1.5	0
-1.5	+10
1.5	-10
1.5	0
1.5	+10
5	-10
5	0
5	+10
10	-10
10	0
10	+10

For all cases, the same time dependent piston force variation (Figure 3) taken from the static ejection tests is applied for releasing the store from the rack. The forces applied by two pistons are transferred to the CG of the store and a single force and a moment variation is obtained. The time dependent force and moment variations are curve fitted by 7th order polynomials, which are then used as an input function in Fluent in order to apply the piston forces acting on the store. The unsteady flow solutions are performed for about 0.5sec following the store separation, in which the store drops down about 5m.The instantaneous aerodynamic loads acting on the store, and the position and attitude of the store with respect to the wing are sampled at 50 Hz along its 6 degrees of freedom falling motion. . For each unsteady flow case, about 20 data points are sampled. The position and attitude of the store, and the instantaneous aerodynamic loads acting on it, a total of 12 data items, are stored for each data point.

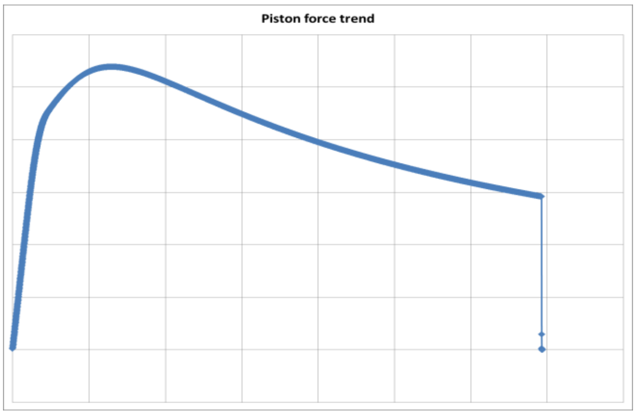

Figure 3 Piston force variation with time

21 million unstructured elements have been used for the CFD analysis. The mesh is generated using Gridgen v15®. An O grid is employed ın the spanwise direction and the half grid is used for numerical efficiency. Sideslip conditions have been used up to 10 degrees such that symmetry condition is usable at the mid-plane. (Figure 4)

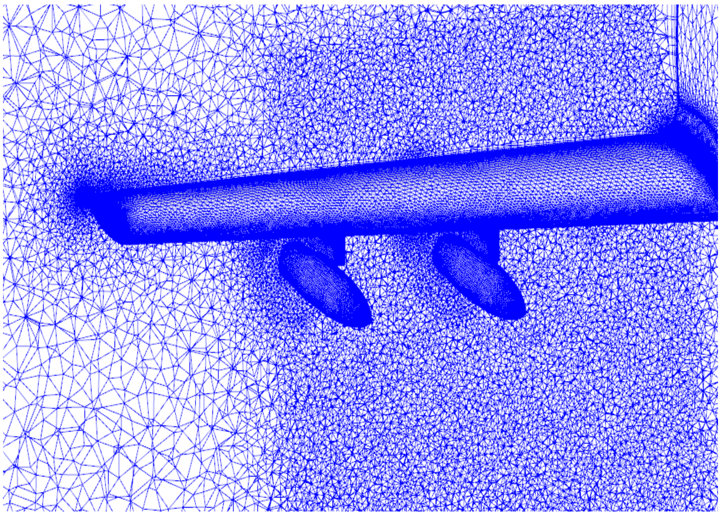

Figure 4 Grid used for wing&store

A sample Fluent solution is given in Figure 5, which shows the position of store and the surface pressure distribution after 0.5 seconds from the release of the store.

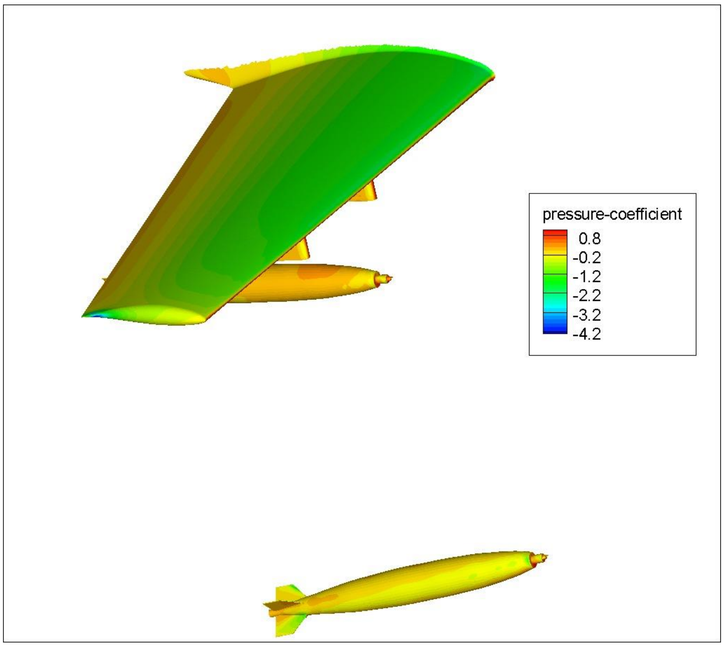

Figure 5 General pressure distribution of unsteady result after 0.5 seconds

Along each unsteady solution for the conditions given in Table 2 the position of the store and the aerodynamic loads acting on it are sampled to form a database to be used in training the neural network. The back propagation learning algorithm [Riedmiller & Braun, 1993] is employed in the training process. The database formed by the unsteady flow solutions is randomly broken into 275 data points for training and remaining 25 data points for validation. The performance of the ANN on the validation data set is given Figure 6. As seen, the prediction of the aerodynamic loads and moments at arbitrary data points, which are excluded from the training data set, are in good agreement with the actual values computed by Fluent .Yet, the error in the moment coefficients are slightly greater than those of the load coefficients.

Next, a store separation is simulated by using the ANN predicted aerodynamic loads and moments for a given flight condition. For the given flight condition, which is excluded from the ANN training, the ANN predicts the time dependent aerodynamics loads and moments at any given position starting from the fixed initial location of the store attached to the carriage. The new position of the store after a discrete time step (0.004 s) is obtained by a 6-DOF solver developed in Matlab. The trajectory and attitude of the store is obtained by repeating the one time-step process described above. The discrete time integration continues for 0.5 seconds, in which the store drops more than 3 meters.

In the first validation case, the flight condition is taken as AoA 5^o and the side-slip angle, Beta, 0^o, which is excluded from the ANN training process. The store separation trajectory and the attitude of the store evaluated by the ANN based method developed is compared to the Fluent solution in Figures 7 and 8. As shown the predicted positions and attitudes of the store agree quite well with the Fluent solution.

Another validation case is taken at AoA 1.5^o and Beta 0^o, which is again excluded from the ANN training data set. The predicted store trajectory and the attitudes are

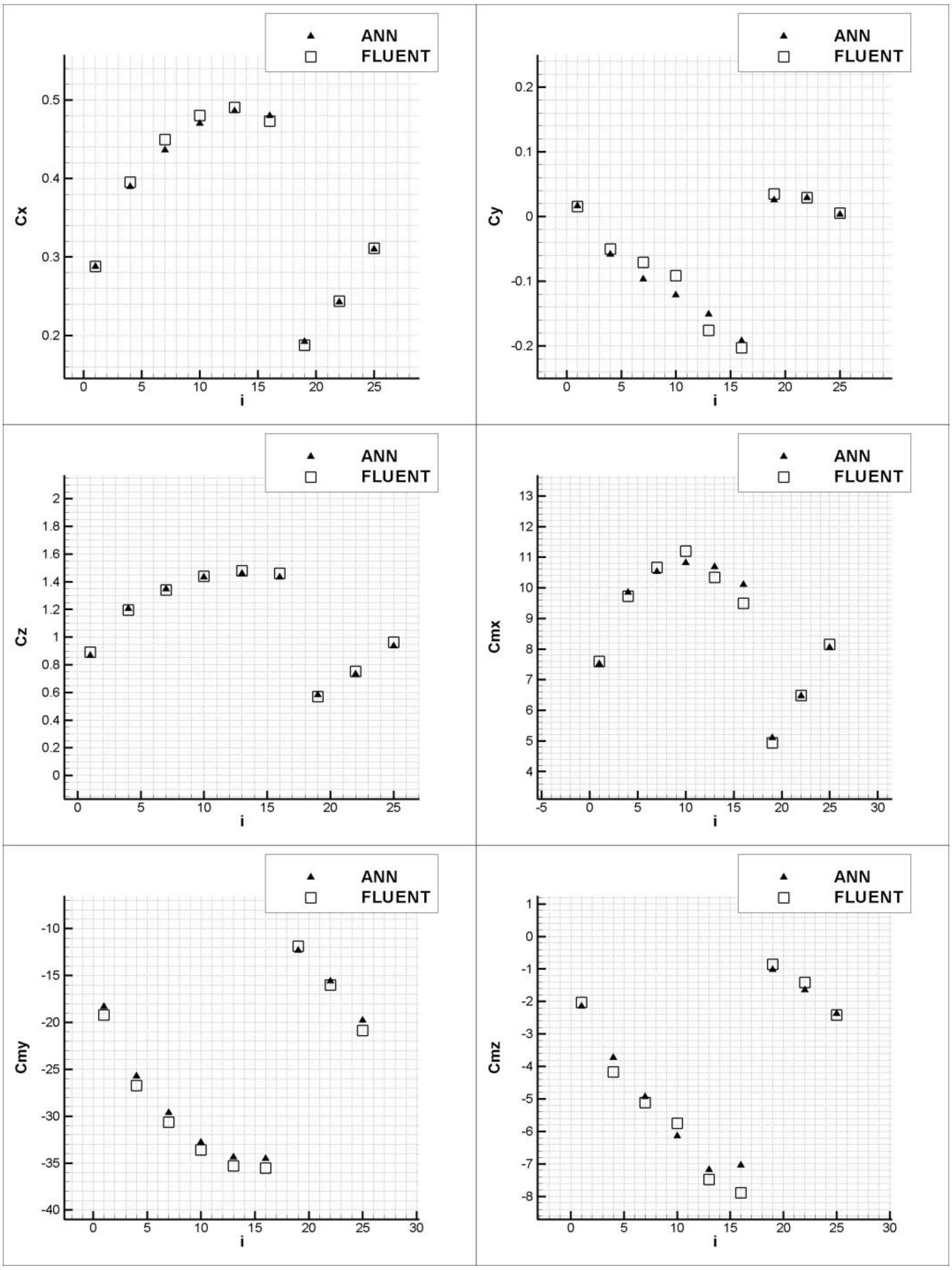

Figure 6 Force and moment coefficients comparison for ANN code performance

similarly compared with Fluent predictions in Figures 9 and 10. The vertical trajectory of the store again agrees well with the Fluent solution. But there is some deviation in attitudes. The pitch angle, ϴ, deviates the most by more than 3 degrees. Such a deviation may, in general, be attributed to the underpopulated training data set. It suggests that the variation of the pitch angle in the vicinity of the current data set must be high, and the resolution of the training data set should be increased.

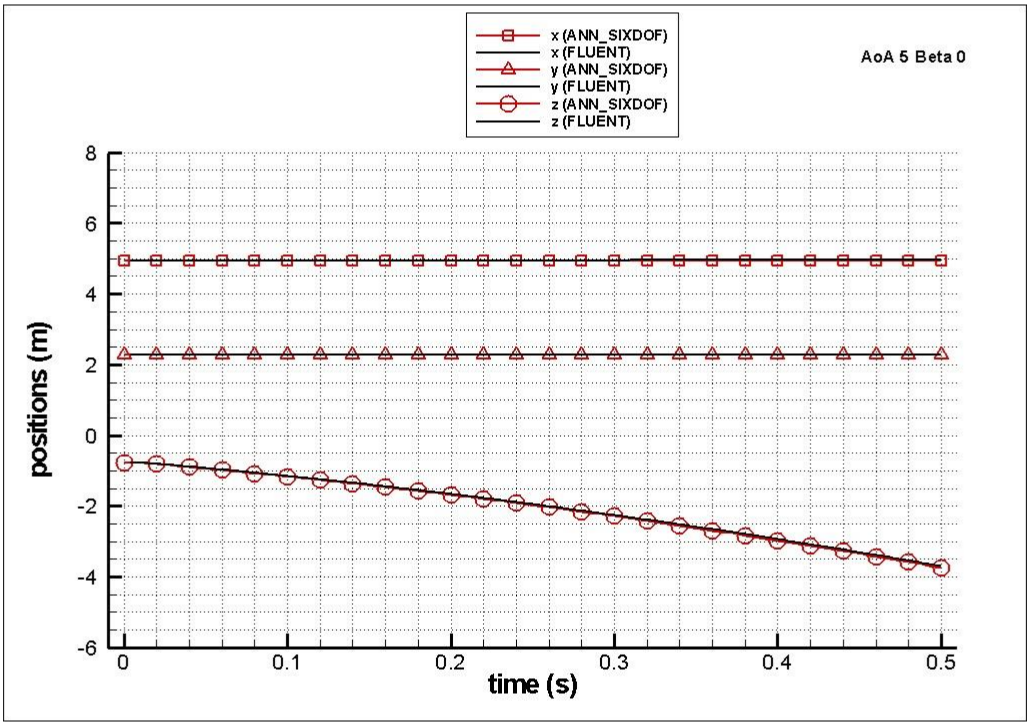

Figure 7 Position comparisons of store for AoA 5^o Beta 0^o case

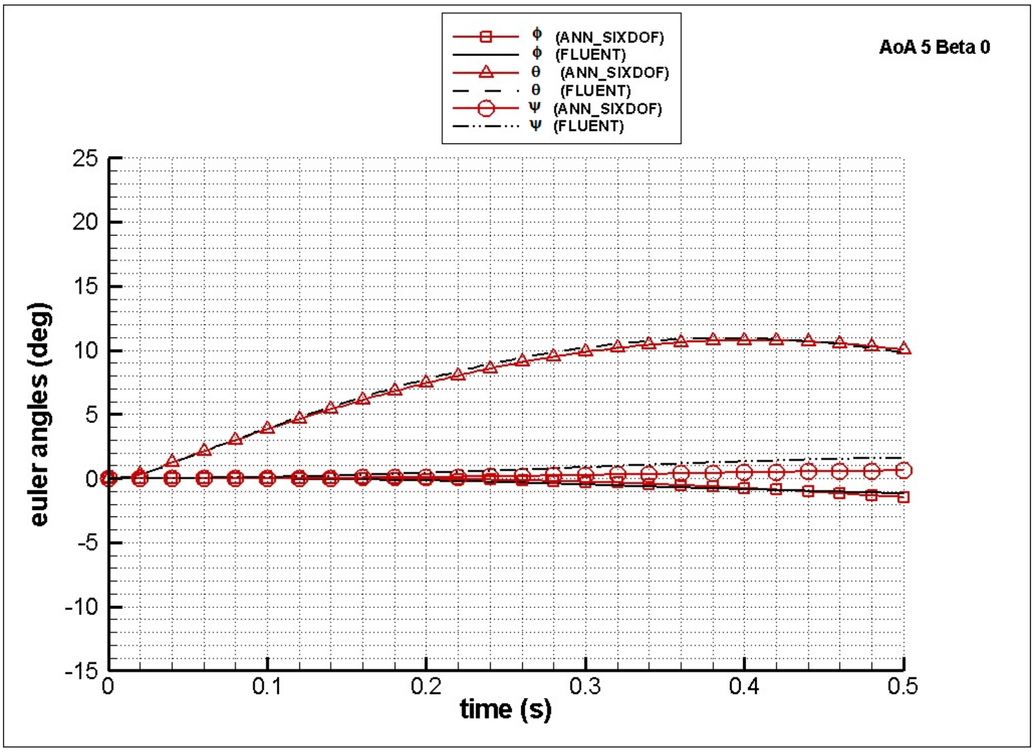

Figure 8 Euler angle comparisons of store for AoA 5^o Beta 0^o case

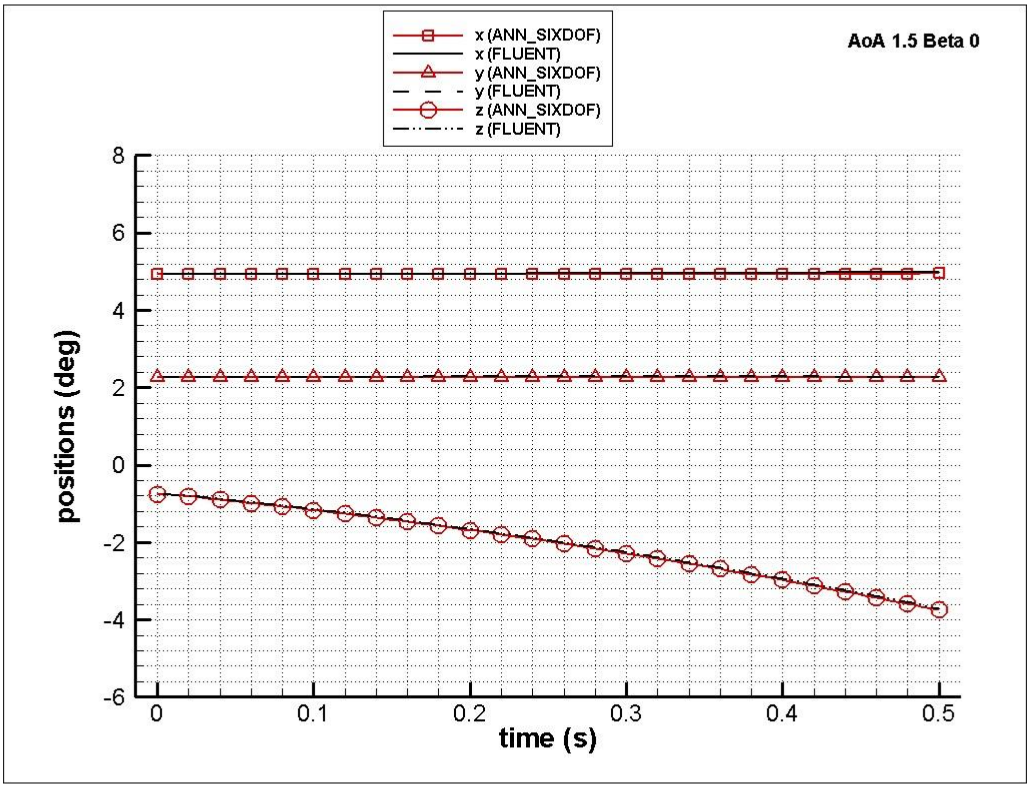

Figure 9 Position comparisons of store for AoA 1.5^o Beta 0^o case

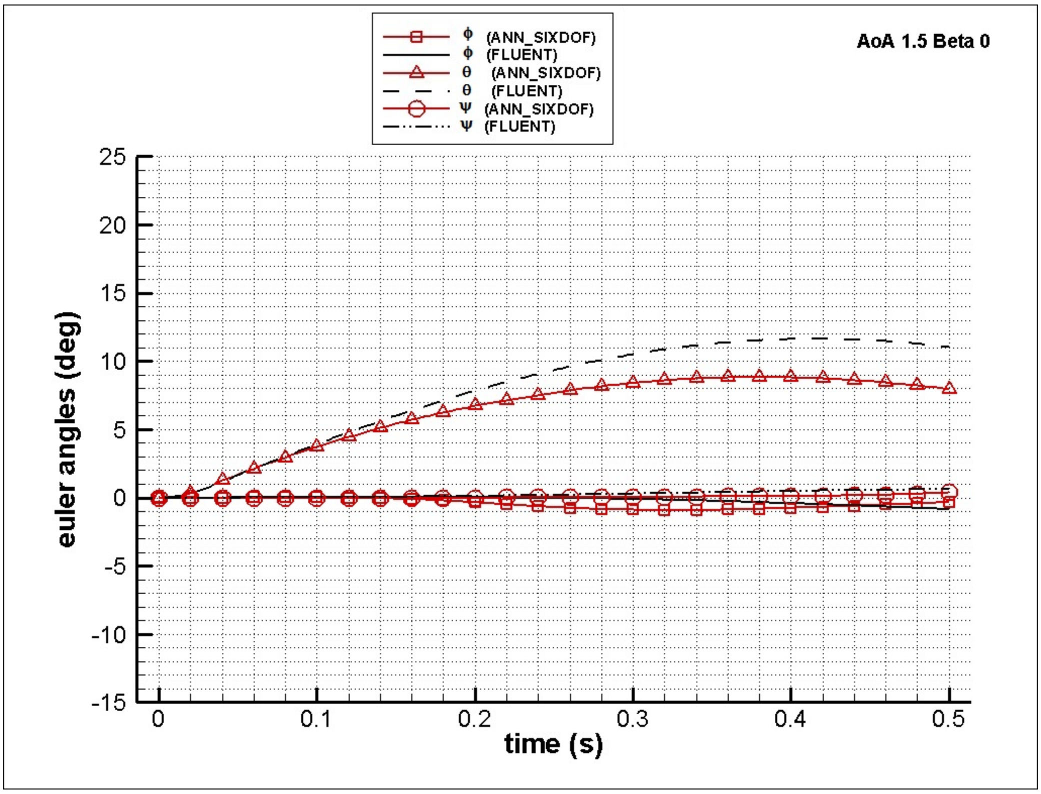

Figure 10 Euler angle comparisons of store for AoA 1.5^o Beta 0^o case

CONCLUSION

A fast prediction tool for the simulation of store separation in the conceptual design process is developed. This tool is based on a neural network which is trained by numerical solutions in order to predict the aerodynamics loads and moments as a function of flight conditions and the current location and attitude of the store. The validation results with a limited number of training data set show that the neural network, in general, performs quite well in predicting the store trajectory. Such a prediction tool can be used for predicting the critical cases of store separation prior to wind tunnel or flight testing. The current study will next try to quantify the effect of the size of the training data set on the prediction accuracy.

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