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DETERMINATION OF SHAPED CHARGE JET CHARACTERISTICS USING A NEURAL NETWORKS MODEL BASED ON HYDROCODE SIMULATIONS

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ABSTRACT

Shaped charges are widely used in military and civil applications for their ability to penetrate deep into even the hardest targets like armor steel and granite rocks by creating a hypervelocity-moving jet, typically with a velocity more than 6 km/s, called shaped charge jet. Penetration performance of a shaped charge jet is characterized by jet particles' diameter, length, and velocities. The most widely used method to determine shaped charge jet characteristics is numerically solving continuum equations consisting of the conservation laws and the constitutive relations. The solvers which can handle these special shock physics are called Hydrocodes. In this study, an alternative approach is proposed. First, a Neural Networks model is trained based on the solutions of hydrocode simulations for a little number of different shaped charges. Then, the model is used to determine the jet characteristics of new shaped charges. The advantage of the proposed method is on speeding up the evaluation processes during the conceptual design by reducing the number of hydrocode simulations.

INTRODUCTION

A cylinder of explosive with a hollow cavity, which may be of any axisymmetric shape such as a cone, is known as hollow charge; and, if the hollow cavity is covered with a thin liner, such as thin metal sheet in the form of the cavity, the device is called as shaped charge [Ayisit, 2008]. Upon the initiation of the explosive charge at the end of the cylinder, opposite the hollow cavity and liner, gaseous products are formed due to the detonation reaction and the cavity causes these reaction products to focus their energy towards the axis of the cylinder. The focusing of the detonation products creates an intense force on the liner and the liner forms a hypervelocity-moving jet along the axis, typically with a velocity more than 5 km/s, called shaped charge jet. An illustrative example of a shaped charge device is shown in Figure 1.

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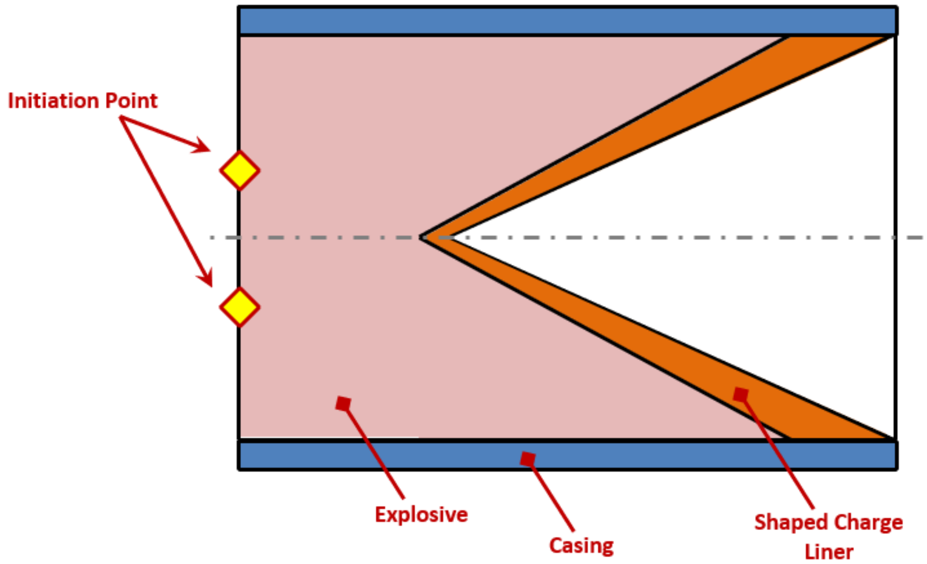

Figure 1*:* An Illustrative Shaped Charge Warhead Layout

The hypervelocity-moving metal jet is mostly utilized in anti-tank weapons due to its capability of penetrating into hard targets like armor steel, or reinforced concrete, etc. Oil industry also uses shaped charges where it is necessary to drill deep into geological materials. Performance of a shaped charge is therefore defined by its penetration capability against a specific target.

The depth of penetration of a shaped charge jet increases with increasing distance from the shaped charge base to the target (called standoff distance) up to a certain optimal distance, then starts to decrease again when the distance is increased further [Held, 1990]. A typical standoff behavior is shown in Figure 2.

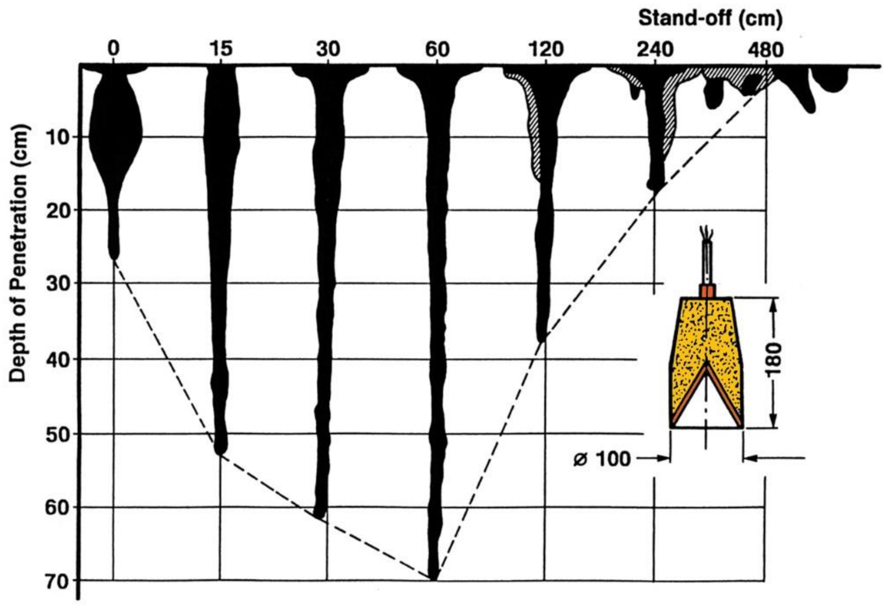

Figure 2: Typical Stand-Off Curve of a Shaped Charge [Held, 1990]

This specific behavior of shaped charge is due to the fact that the shaped charge jet does not have a constant velocity throughout its length, in fact there is a velocity gradient along the jet. After formation, shaped charge jet starts to elongate due to this velocity gradient. However, the metal jet does not lengthen indefinitely, but will break up into particles after a certain time (Figure 3).

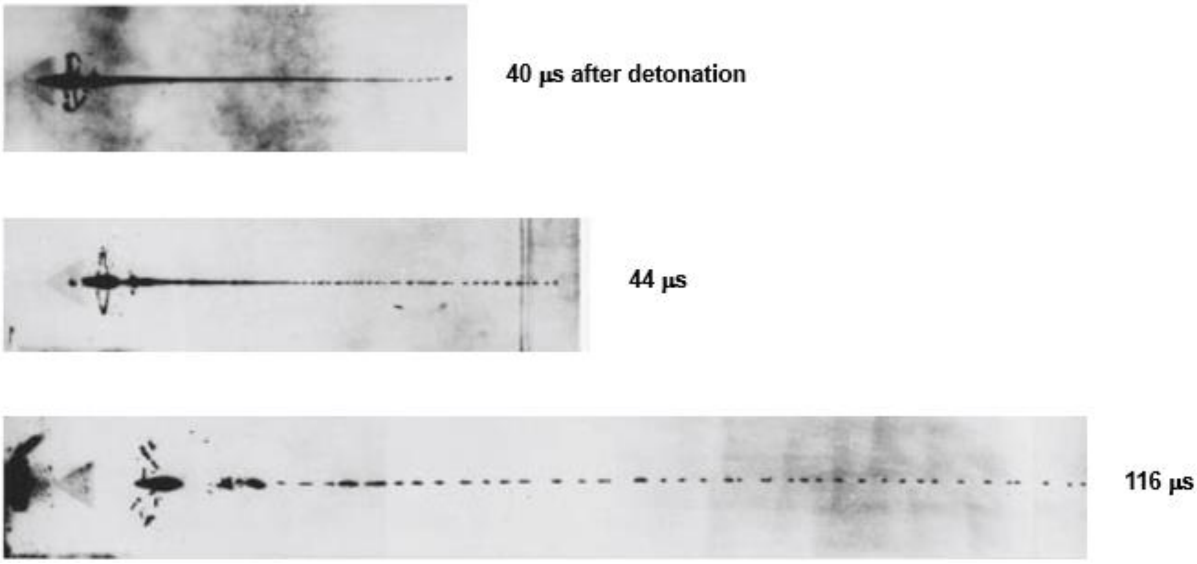

Figure 3: Shaped Charge Jet Elongation and Breakup into Particles [Held, 1990]

Performance of a shaped charge can be determined either by experiments, hydrocode simulations or analytical/empirical calculations. Although experiments provide the actual behavior of the shaped charge, they are very expensive compared to computational methods.

The most widely used method to determine shaped charge performance is solving continuum equations numerically by hydrocodes, which are special shock physics solvers. Hydrocode simulations are more accurate compared to analytical/empirical method for determining jet characteristics and its penetration capability, yet it is also more demanding in terms of time, computational source and cost. Also, for lower standoff distances, where the jet is still continuous, hydrocode simulations might be a good option to determine the depth of penetration. However, at higher standoffs, where the jet breaks up into particles before or during the penetration, even the quite sophisticated hydrocodes mostly fail to deliver reliable results as stated in [Hartmann et.al., 2017].

Since they are fast, computationally less demanding and provide reasonable accuracy, analytical/empirical solution methods are preferred when there is a need for performing a large number of analysis. Examples include but not limited to shaped charge design optimization and vulnerability/survivability analysis of armored platforms against shaped charge threats.

In most of these methods, shaped charge jet is assumed to be a collection of individual particles, which are initially intact and stretching until breakup, and penetration of stretching jet and the individual particles are computed using an appropriate model such as Walker-Anderson model, which describes the penetration and erosion process of a rod-like projectile penetrating a semi-infinite target [Walker and Anderson, 1995] . A good example is given in [Hartmann et.al., 2017], where they utilize a slightly modified version of Walker-Anderson model to calculate penetration of jet particles.

As stated earlier, to determine the properties of individual jet particles (diameter, length, velocity), one can use experiments, hydrocode simulations or analytical solution methods, where the hyrdrocode simulations. In this study, an alternative approach is proposed where a Neural Networks based model is trained for shaped charge jet characteristics calculated using a hydrocode simulations.

METHOD

Hydrocode Simulations

In this study, shaped charge jet formation simulations are performed in SPEED (**S**hock **P**hysics **E**xplicit **E**ulerian **D**ynamics) software by Numerics GmbH [NUMERICS, 2012]. A sample SPEED hydrocode model setup is given in Figure 4.

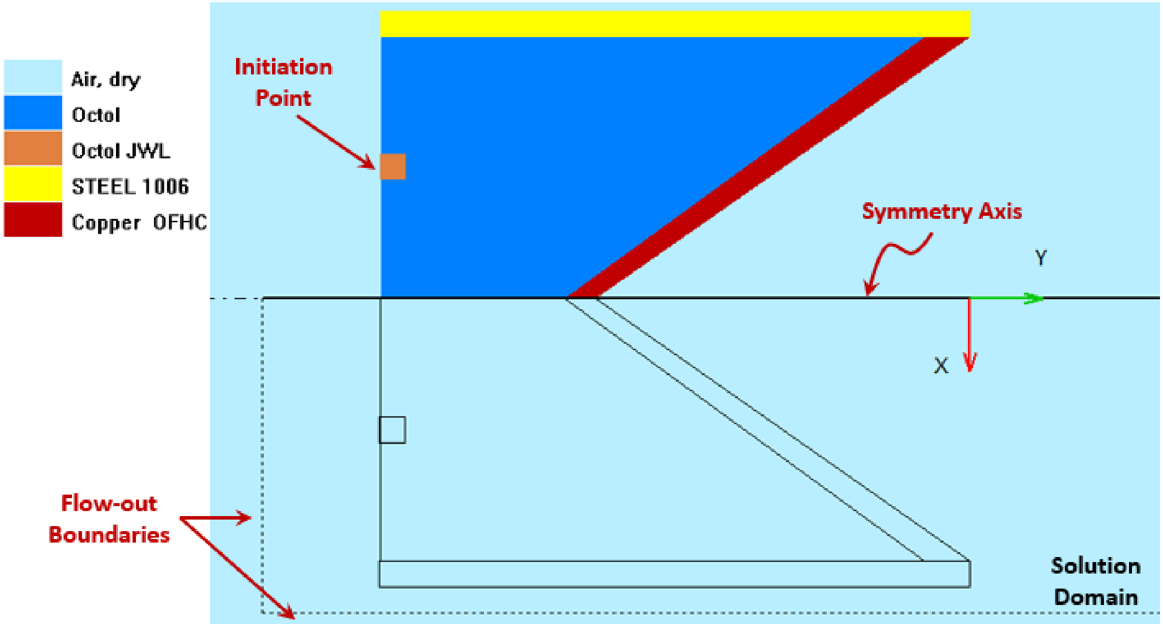

Figure 4: A Sample SPEED Hydrocode Simulation Model Setup

The progress of simulation can be seen in Figure 5 and Figure 6, former showing the detonation of explosive charge, collapse of the metal liner and the initial phase of jet formation, latter showing jet formation and elongation along the axis.

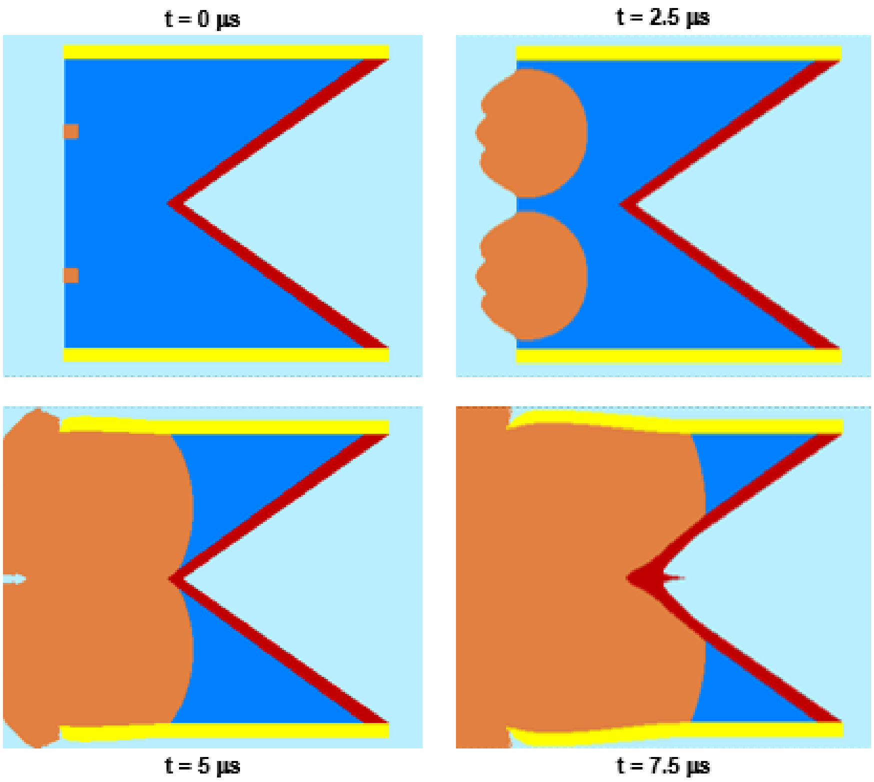

Figure 5: Explosive Detonation, Liner Collapse and Initial Phase of Jet Formation

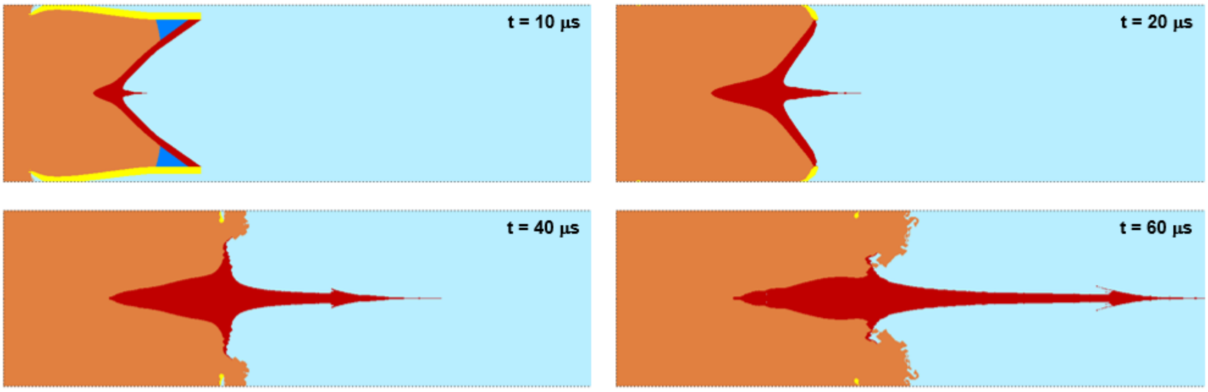

Figure 6: Shaped Charge Jet Formation and Elongation

In each simulation, shaped charge jet is stretched until its tip is reached 3 charge-diameter distance from the base of the shaped charge liner cone. At this point, the liner material is extracted from the state file of the simulation and then the extracted jet is discretized to constant-width individual particles as shown in Figure 7.

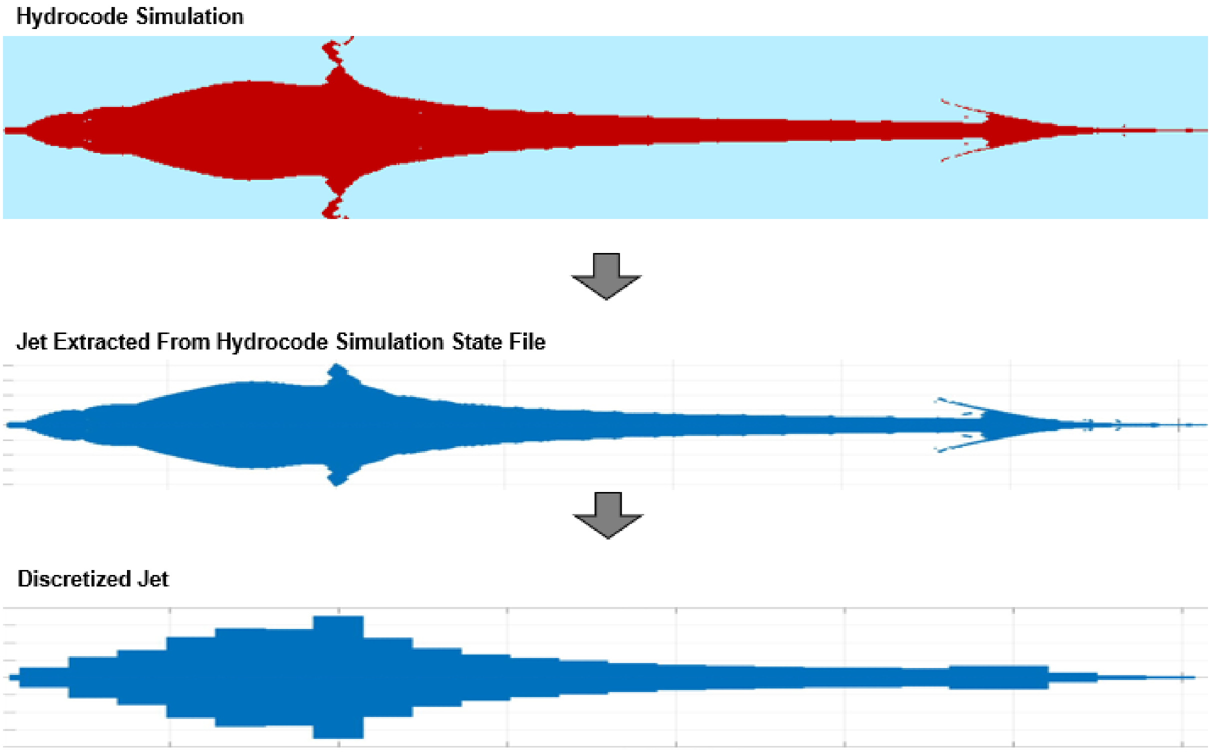

Figure 7: Jet Discretized to Constant-Width Individual Particles

Width, diameter, tail velocity and tip velocity of each particle in discretized jet is used in the neural network study.

Design of Experiment

Table 1 lists the shaped charge parameters used for generating samples in design of experiment. Figure 8 and Figure 8 illustrates these parameters on a sample shaped charge design. The six parameters which do not have fixed values are the input to the neural networks model: α, t_{apex}, t_{base}, $D_{initiation}$, $dX_{initiation}$ and t_{casing}.

For the neural network study, a six-parameter Box–Behnken design of experiment is set up, where each independent variable, called factor, takes values at three equally spaced levels usually indicated as -1, 0, +1 [Box and Behnken, 1960]. Actual values of each independent parameter used in hydrocode simulations are listed in Appendix A.

Table 1: Shaped Charge Parameters for Design of Experiment

Related Shaped Charge Section	Symbol	Parameter	Value
Shaped Charge Liner	CD	Charge Diameter	Constant
	α	Cone angle	40° - 90°
	t_{apex}	Thickness at the apex region	0.02 – 0.05 * CD
	t_{base}	Thickness at the base region	0.02 – 0.05 * CD
	-	Material	OFHC Copper
Initiation Point	$D_{initiation}$	Initiation diameter (2*offset from center)	0.0 – 0.5 * CD
	$dX_{initiation}$	Offset from shaped charge liner apex	0.2 – 0.5 * CD
Confinement (Casing)	t_{casing}	Thickness	0.02 – 0.05 * CD
	-	Material	Mild Steel
Explosive	-	Material	Octol

CD : Charge Diameter, i.e. diameter of the explosive

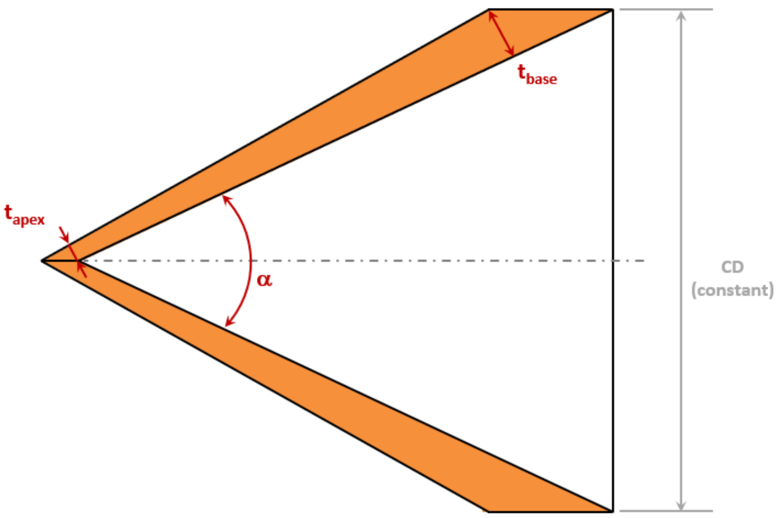

Figure 8: Shaped Charge Liner Parameters

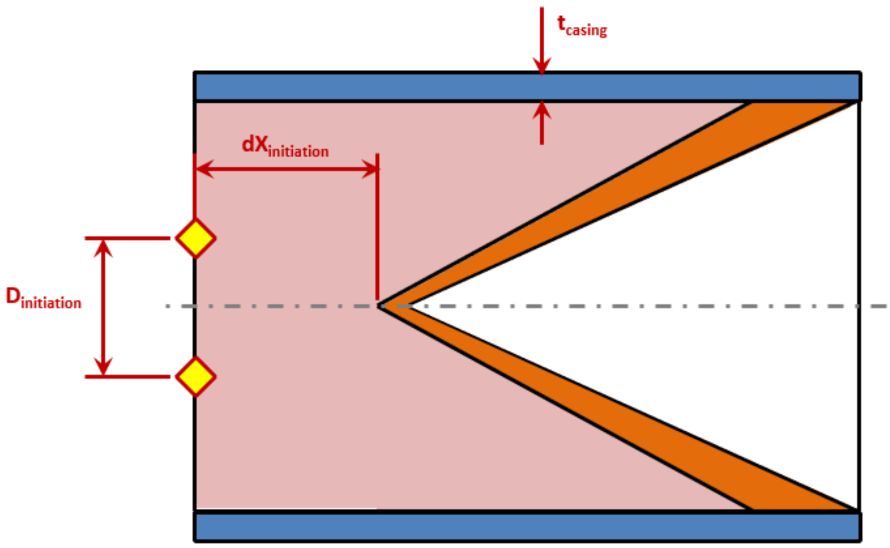

Figure 9: Shaped Charge Warhead Parameters

Neural Networks Model

Neural networks as a machine learning method has been widely used in the last decades for the simplification of complex engineering designs like CFD problems [Kaya and Elfarra, 2019; Kurtuluş, 2009]

The type of the artificial neural networks system used in this study is a feedforward backpropagation network. A feedforward network is composed of a series of layers. The first layer takes the network input. The network output is given by the last layer, which is called the output layer. The other layers are named as hidden layers. Each hidden layer is connected to the next layer by a transfer function. A transfer function may also be used in the output layer before producing the output. The independent parameters of the transfer function may be considered as data transported by neurons as in a biological neural systems. Data entering a layer are linearly weighted and combined according to the number of neurons in this layer. Some bias may also be added to this combination. The aim is to determine the weight matrices and bias vectors, which is called the network training.

Feedforward networks are employed for mapping from any kind of input to any kind of output. In this study, a feedforward network with one hidden layer and 5 neurons in this layer, is constructed to fit the jet characteristics values as functions of the parameters which define the geometry of the shaped charge liner. The transfer function of the hidden layer is selected as the hyperbolic tangent function.

A schematic for the neural networks model used in this study is shown in Figure 10. There is only one hidden layer in the model with 6 inputs and 76 outputs. w^h and w^o are the weights in the linear combination of data entering the hidden and the output layers, respectively. Similarly, b^h and b^o are the bias in the layers.

The neural network model used in this study has 6 inputs while the number of the outputs is 76. The first element in the output vector is the total jet length while the remaining 75 elements are the characteristics of the jet divided into 25 constant-width particles. Each particle is characterized by 3 parameters: particle diameter, tip velocity and tail velocity of the particle.

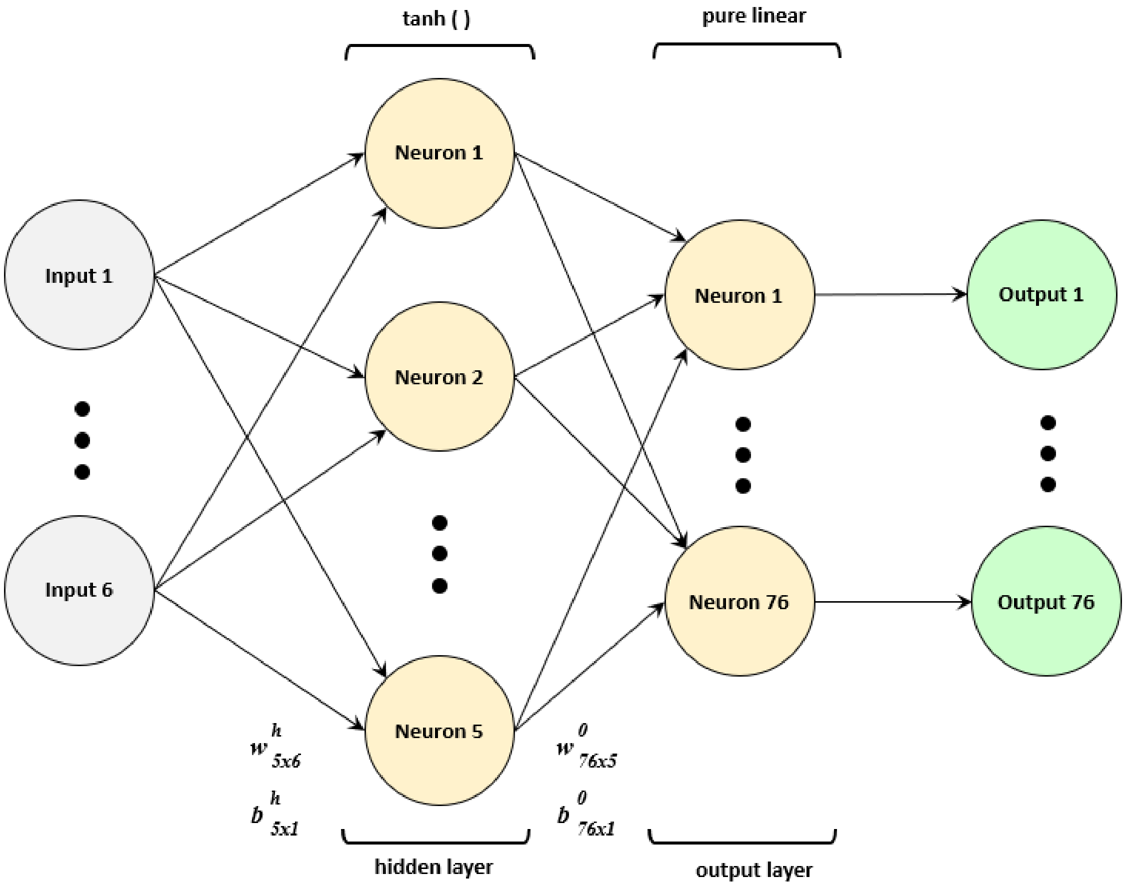

Figure 10: Schematic for Neural Network Model

The neural network model was trained using a single hidden layer containing 5 neurons. This design of the model was decided according to a validation study. 6 samples out of 49 samples in the design of experiment was used for the validation. The following designs are considered in the validation study, and tried for the calibration of the model:

1) Single hidden layer with 4 neurons
2) Single hidden layer with 5 neurons
3) Single hidden layer with 6 neurons
4) Double hidden layers with 2 and 2 neurons
5) Double hidden layers with 3 and 3 neurons
6) Double hidden layers with 3 and 3 neurons
7) Triple hidden layers with 3, 3 and 3 neurons

The model having a single hidden layer with 5 neurons provided the highest performance, and therefore was chosen as the running model. The performance is calculated in terms of the minimum square error between the output of the model and the actual target (jet characteristics).

After the calibration according to the validation study, the model was trained using 38 samples randomly chosen from the design of experiment. A relatively fast method, the Levenberg-Marquardt algorithm was used for training. The performance of this algorithm may be measured by two indicators:

1) The minimum square error between the output of the model and the actual target
2) Minimum gradient attained during the optimization iterations

RESULTS AND DISCUSSION

The Levenberg-Marquardt algorithm converged in 25 iterations, leading to a minimum square error of 0.15 and a gradient value of 0.033 for the final accepted training. Before each trial of training, the input and the output are scaled using the mean and the standard deviation of 49 samples in the design of experiment.

For testing, 5 samples are used. The neural network training was initialized several times until the test performance is compatible with the training performance. The test performance of the final training is 0.18. The change in training performance, validation performance, testing performance and gradient of the neural network model with iteration number is plotted in Figure 11.

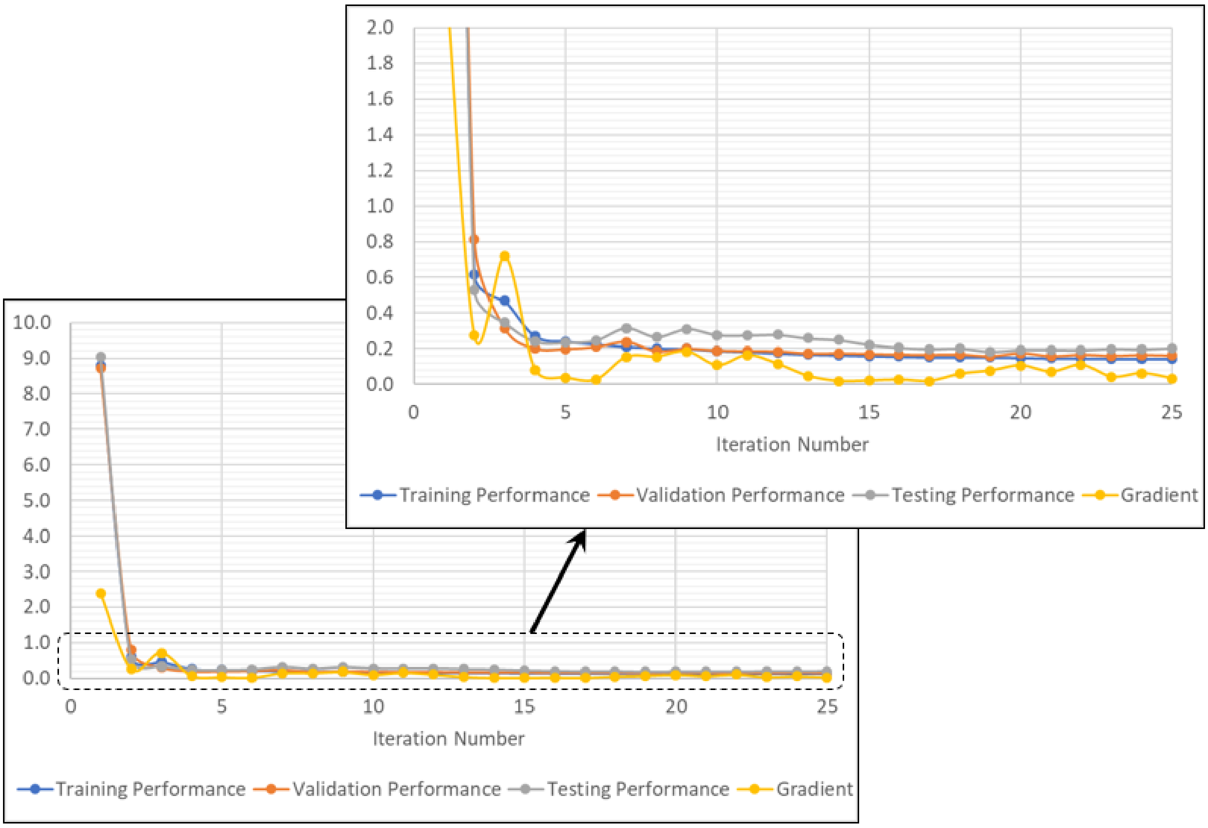

Figure 11: Performance of Neural Network Model

To illustrate the neural network model performance, discretized shaped charge jets from actual hydrocode simulations and the ones estimated by the neural network model for samples #4, #15, #26 and #37 are given in Figure 12. In Figure 13, Cumulative Jet Length vs Jet Velocity graphs are presented for the same samples.

It can be seen from Figure 11, together with Figure 12 and 13, that the neural network model estimations are in agreement with the hydrocode simulation results.

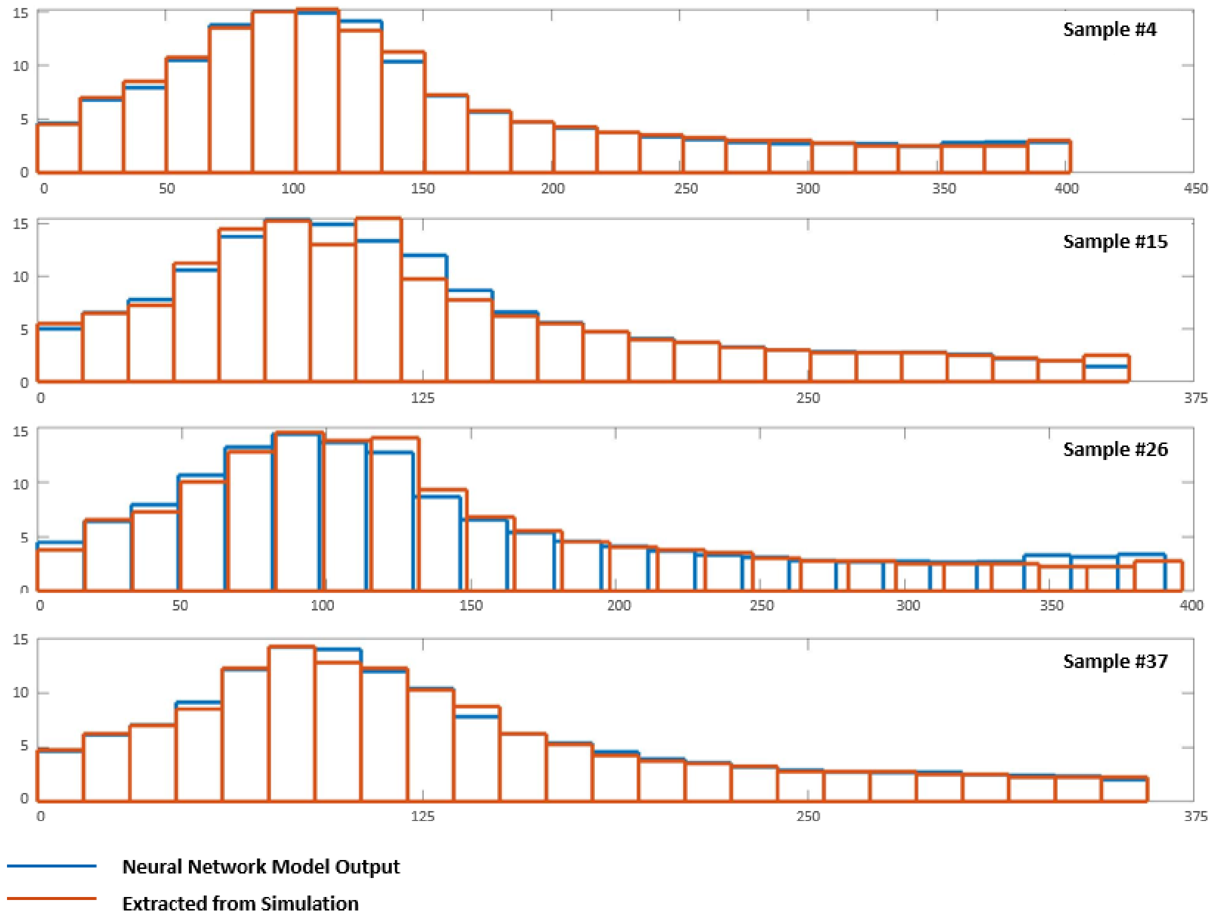

Figure 12: Comparison of Discretized Jet (Hydrocode Simulation vs Neural Networks Model)

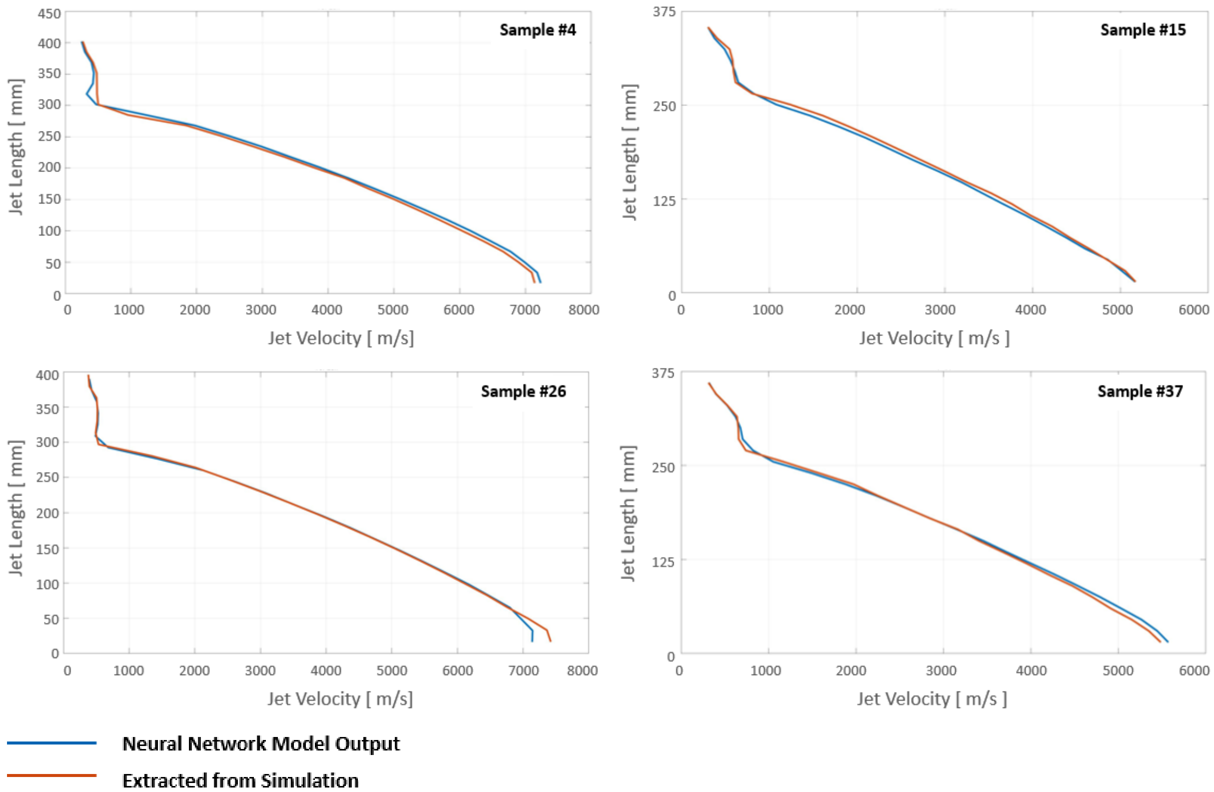

Figure 13: Comparison of Jet Length vs Velocity (Simulation vs Neural Networks Model)

Performance of the neural network model is further tested with some random shaped charge designs which are not in the design of experiment setup. Geometric parameters of these shaped charge designs are listed in Table 2.

Table 2: Shaped Charge Parameters for Neural Network Model Test

	$\alpha/2$ [°]	t_{apex} [*CD]	t_{base} [*CD]	$D_{initiation}$ [*CD]	$dX_{initiation}$ [*CD]	t_{casing} [*CD]
#1	36.38	0.0487	0.0306	0.3922	0.3530	0.0422
#2	30.01	0.0461	0.0312	0.4228	0.3085	0.0317
#3	30.37	0.0363	0.0385	0.0835	0.5115	0.0278
#4	32.84	0.0389	0.0393	0.6073	0.2474	0.0402

Discretized shaped charge jets and Cumulative Jet Length vs Jet Velocity graphs from neural network model estimations and hydrocode simulations are compared in Figure 14 and Figure 15.

It can be seen from Figure 14 and Figure 15 that the neural network model makes estimations that are fairly accurate compared to hydrocode simulations. Maximum deviation from hydrocode simulations are observed with the shaped charge #4. The most prominent difference of shaped charge #4 compared to other three designs is the diameter of initiation (**$D_{initiation}$**), which is more than 0.6*CD, beyond the limits of neural network sample designs.

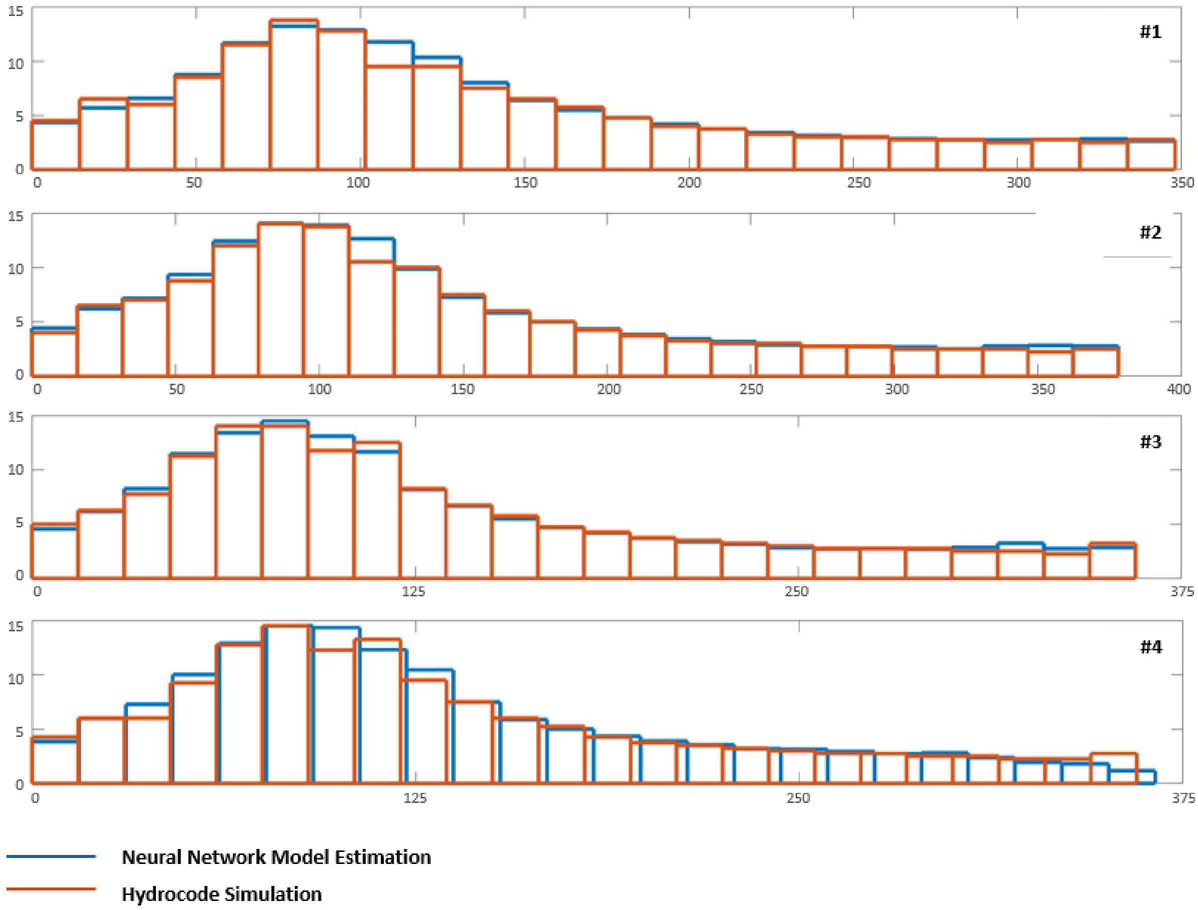

Figure 14: Comparison of Discretized Jet (Model Estimation and Simulation)

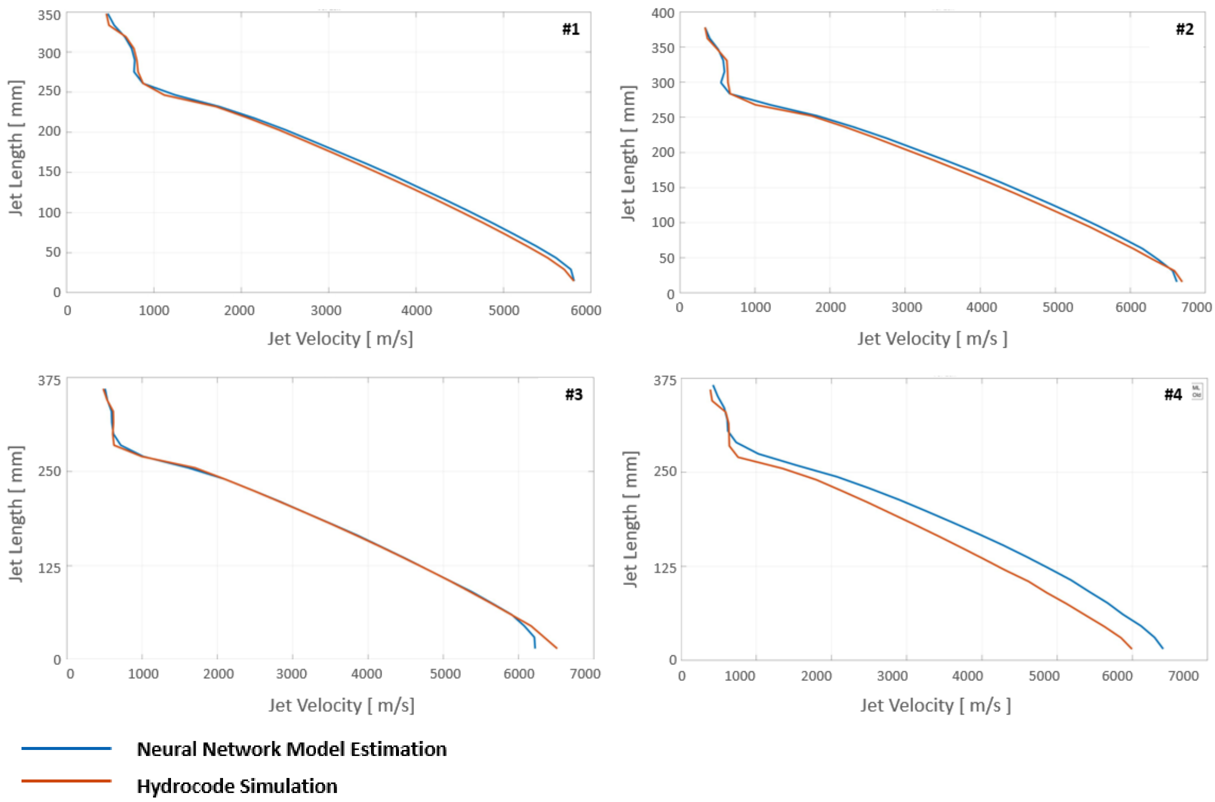

Figure 15: Comparison of Jet Length vs Velocity (Model Estimation and Simulation)

CONCLUSIONS

Properties of individual particles of a shaped charge jet can be determined by experiments, hydrocode simulations or analytical solution methods. In this study, an alternative approach is proposed where a Neural Networks based model is trained for shaped charge jet characteristics calculated using a hydrocode simulations.

First, a Neural Networks model is trained based on the jet properties obtained by hydrocode simulations for 49 shaped charge designs. The geometric parameters of these shaped charges are determined by design of experiment based on Box-Behnken design. Shaped charge jets determined from hydrocode simulations are discretized into 25 constant-width particles, where each particle is characterized by 3 parameters: particle diameter, tip velocity and tail velocity of the particle.

Then, the neural network model is trained using the jet properties of these 49 shaped charge samples obtained from hydrocode simulations. This model is then used to determine the jet characteristics of new shaped charge designs.

Estimation of neural network model is in good agreement with hydrocode simulations, especially if the new designs are constructed such that the design parameters are within the original neural network sample space.

This method can be used when there is a need for performing a large number of analysis, such as shaped charge optimization during preliminary stages of a shaped charge design. The advantage of the proposed method is on speeding up the evaluation processes during the conceptual design by reducing the number of hydrocode simulations.

Acknowledgement

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APPENDIX : Shaped Charge Parameters for Design of Experiment

	Para#1	Para#2	Para#3	Para#4	Para#5	Para#6
	$\alpha/2$	t_{apex}	t_{base}	$D_{initiation}$	$dX_{initiation}$	t_{casing}
	[°]	[*CD]	[*CD]	[*CD]	[*CD]	[*CD]
Analysis #1	25	0.020	0.035	0.000	0.350	0.035
Analysis #2	25	0.020	0.035	0.500	0.350	0.035
Analysis #3	25	0.050	0.035	0.000	0.350	0.035
Analysis #4	25	0.050	0.035	0.500	0.350	0.035
Analysis #5	45	0.020	0.035	0.000	0.350	0.035
Analysis #6	45	0.020	0.035	0.500	0.350	0.035
Analysis #7	45	0.050	0.035	0.000	0.350	0.035
Analysis #8	45	0.050	0.035	0.500	0.350	0.035
Analysis #9	35	0.020	0.020	0.250	0.200	0.035
Analysis #10	35	0.020	0.020	0.250	0.500	0.035
Analysis #11	35	0.020	0.050	0.250	0.200	0.035
Analysis #12	35	0.020	0.050	0.250	0.500	0.035
Analysis #13	35	0.050	0.020	0.250	0.200	0.035
Analysis #14	35	0.050	0.020	0.250	0.500	0.035
Analysis #15	35	0.050	0.050	0.250	0.200	0.035
Analysis #16	35	0.050	0.050	0.250	0.500	0.035
Analysis #17	35	0.035	0.020	0.000	0.350	0.020
Analysis #18	35	0.035	0.020	0.000	0.350	0.050
Analysis #19	35	0.035	0.020	0.500	0.350	0.020
Analysis #20	35	0.035	0.020	0.500	0.350	0.050
Analysis #21	35	0.035	0.050	0.000	0.350	0.020
Analysis #22	35	0.035	0.050	0.000	0.350	0.050
Analysis #23	35	0.035	0.050	0.500	0.350	0.020
Analysis #24	35	0.035	0.050	0.500	0.350	0.050
Analysis #25	25	0.035	0.035	0.000	0.200	0.035
Analysis #26	25	0.035	0.035	0.000	0.500	0.035
Analysis #27	25	0.035	0.035	0.500	0.200	0.035
Analysis #28	25	0.035	0.035	0.500	0.500	0.035
Analysis #29	45	0.035	0.035	0.000	0.200	0.035
Analysis #30	45	0.035	0.035	0.000	0.500	0.035
Analysis #31	45	0.035	0.035	0.500	0.200	0.035
Analysis #32	45	0.035	0.035	0.500	0.500	0.035
Analysis #33	35	0.020	0.035	0.250	0.200	0.020
Analysis #34	35	0.020	0.035	0.250	0.200	0.050
Analysis #35	35	0.020	0.035	0.250	0.500	0.020
Analysis #36	35	0.020	0.035	0.250	0.500	0.050

APPENDIX A (Continued)

	Para#1	**Para#2**	**Para#3**	**Para#4**	**Para#5**	**Para#6**
	$\alpha/2$	**t_{apex}**	**t_{base}**	**$D_{initiation}$**	**$dX_{initiation}$**	**t_{casing}**
	[°]	**[*CD]**	**[*CD]**	**[*CD]**	**[*CD]**	**[*CD]**
Analysis #37	35	0.050	0.035	0.250	0.200	0.020
Analysis #38	35	0.050	0.035	0.250	0.200	0.050
Analysis #39	35	0.050	0.035	0.250	0.500	0.020
Analysis #40	35	0.050	0.035	0.250	0.500	0.050
Analysis #41	25	0.035	0.020	0.250	0.350	0.020
Analysis #42	25	0.035	0.020	0.250	0.350	0.050
Analysis #43	25	0.035	0.050	0.250	0.350	0.020
Analysis #44	25	0.035	0.050	0.250	0.350	0.050
Analysis #45	45	0.035	0.020	0.250	0.350	0.020
Analysis #46	45	0.035	0.020	0.250	0.350	0.050
Analysis #47	45	0.035	0.050	0.250	0.350	0.020
Analysis #48	45	0.035	0.050	0.250	0.350	0.050
Analysis #49	35	0.035	0.035	0.250	0.350	0.035

References

Ayisit, O. (2008) *Numerical Determination of Wave Shaper Effects in Shaped Charge Jet Performance*, METU.

Box, G. and Behnken, D. (1960) *Some New Three Level Designs for the Study of Quantitative Variables*, Technometrics, Volume 2, pages 455–475.

Hartmann, T., Rottenkolber, E. and Arnold, W. (2017) *Ballistic Performance Prediction for SC Jets*, 30th International Symposium On Ballistics.

Held, M. (1990) *Shaped Charge Jet Section in Hazard Studies for Rocket Propellant Motors*, NATO AGARD.

Kaya, M. and Elfarra, M. (2019) *Optimization of the Taper/Twist Stacking Axis Location of NREL VI Wind Turbine Rotor Blade Using Neural Networks Based on Computational Fluid Dynamics Analyses*, J. Sol. Energy Eng. Feb, 141(1): 011011.

Kurtuluş D. F., (2009) *Ability to Forecast Unsteady Aerodynamic Forces of Flapping Airfoils by Artificial Neural Network*, Neural Computing and Applications, Vol. 18, No.4, p.359.

NUMERICS GmbH (2012) SPEED (Shock Physics Explicit Eulerian Dynamics) - Theory Manual,

Walker, J. D. and Anderson, C.E. (1995) *A Time-Dependent Model for Long-Rod Penetration*, Int. J. Impact Engng., Vol 16, p: 19-48.