INTERNATIONAL RESEARCH JOURNAL OF HUMANITIES AND INTERDISCIPLINARY STUDIES
(Peer-reviewed, Refereed, Indexed & Open Access Journal)
DOI : 03.2021-11278686 ISSN : 2582-8568 IMPACT FACTOR : 6.865 (SJIF 2023)

Development of a Predictive Model for Calculating Damage Potential of Cylindrical Projectile on Bumper Plate at Hypervelocity using Artificial Intelligence

Gauri Bedekar
Dr. D.Y. Patil Institute of Technology,
Pune (Maharashtra, India)
E-mail:gaurinaik23@gmail.com

Rashmi Kolhatkar
V. P. Institute of Management Studies and Research,
Sangli (Maharashtra, India)
E-mail:rashmikolhatkar04@gmail.com

Om Ban
Dr. D.Y. Patil Institute of Technology,
Pune (Maharashtra, India)

DOI No. 03.2021-11278686 **DOI Link ::** https://doi-ds.org/doilink/03.2023-16622146/IRJHISIC2302038

Abstract:

Hypervelocity is a very complex phenomenon which shows changing damage trends for various impact conditions. For finding out damage caused to bumper plate different techniques like simulations and experimentation are used conventionally. However, the techniques are observed to be time consuming and costly. Eventually developed empirical models overcame these limitations but couldn't capture the changing trends of hyper velocity phenomenon.

In the work presented in the paper, an attempt is made to develop a python script artificial neural network (ANN) model for prediction of damage potential at different hyper velocity impact conditions of varying incidence angle, yaw angle and velocity vector. The developed python script ANN predictions were compared with results obtained by simulations. It is observed that predictions done by ANN are in good agreement with the simulation results.

1. Introduction:

An in-depth understanding of the variation of parameters that control the damage generated by projectiles travelling at hyper velocity is of significant importance for aerospace and military applications. In real impact scenario, the shape, mass, velocity, incident angle vary considerably. When shape and geometry are combined with relatively complicated targets, it is often difficult to determine which impact conditions is the most damaging, variation of cylindrical projectile impact conditions affect the damage cause to plate [1].

2. Overview of past penetration mechanics work:

A comprehensive comparative analysis of the damage potential of different shapes of projectiles for a wide range of impact configurations is not available in the literature. There has been study of the penetration characteristics of spherical projectiles for different impact velocities, obliquity velocity angles and for different types of materials. Also studies of the penetration mechanics of cylindrical projectiles of different materials, different L/D ratios, V_A, θ and for a range of α are extensively available in literature. Nonetheless, there has been very little work done to compare and analyse the damage potential of wide range of impact angle parameters, lethal than one another for cylindrical projectiles other than spherical projectiles.

It is widely recognized that the L/D, V_A, θ and α have a large effect on the penetration level of cylindrical projectiles. Since 1940s, cylindrical projectile penetration has been studied. Yield stress play a significant role in penetration mechanisms, derived from work done by Anderson et al[6] and Rosenberg et al [7]. The work was based on experimental data and numerical simulations. Empirical predictive mathematical model was derived in by Dhote and Verma[4] The constants and radicals of the model were derived using multi-variable regression technique[4]. Predictive model of Artificial neural network using MATLAB toolbox was developed considering same impact conditions for spherical projectile but it predicted results of residual projectile for a limited combinations of impact configurations by Gauri Naik and Satish Chinchanikar [2]. Since the simulation and predicted results of the MATLAB developed network were in good agreement. Reference data for this paper was taken from [1,2]. It should be observed that most of the models for penetration mechanics studied by the above-mentioned authors are for normal impacts on semi-infinite targets. As previously mentioned, the predictive ANN models focus primarily on normal impacts on semi-infinite targets and limited variations of impact conditions. Although their work proved the feasibility of relying on numerical simulations, it covered only a very limited range of θ, α and V_A configurations. The effort to include non-normal impacts for cylindrical projectile at hypervelocity into ANN models has not been strong and this reflects in a lack of references in the literature. Furthermore, efforts towards the development of similar generalized analytical ANN models for the penetration of thin plates and cylindrical projectile with vast combination of impact configuration have been very limited. However, studies of non-normal impacts on semi-infinite and spaced plate targets through numerical simulations and experimental work have been widely published.

3. Comparative study:

The rational selection of adequate projectile impact condition of cylindrical projectile for different applications requires an in-depth understanding of the damage potential of projectile impact angles. Although the work done since the 1940s in the area of penetration mechanics is extensive, a detailed comparative study of the damage potential of cylindrical projectile is still lacking. Specifically, the work done on cylindrical projectile has only covered a very limited range of θ and α and this limited information is not in a format suitable for damage comparisons to calculate maximum lethal damage. Proven and derived damage potential comparison data [1] is used in this paper which is based on a set of single impact numerical simulations of tungsten cylindrical projectile impacting at hypervelocity on bumper plate at different impact configurations.

The artificial neural network has large applications in the prediction of data in various fields. ANN helps in predicting complex trends by learning the variations available in input data. Training and processing of ANN is comparatively easy and faster less time consuming process, and it does not require any in depth knowledge of problem background. The applications of ANN were found in literature for high velocity impact analysis and projectile embedment and damage analysis Fernandez-Fdz et al [15, 16] and Artero-Guerrero[17].

In this present work ANN is developed using python script to prediction the damage quantification and yaw angle parameter for infinite number of input parameter combinations. For training of network simulation data from [1] is considered. Predicted values of ANN are comparable with simulation data which was validated with experimental results and found more than 90% data has error around 10%.The programming language Python was selected to develop a script for Artificial Neural Network, which resembles a good agreement of predictions with the output data referred from [1,2]. This PSANNM has advantage of predict and calculate fast results within seconds for accurate damage potential, than the numerical simulation method that takes hours and days to calculate same results. The predictive model of PSANNM eliminates the problem of simulation setup conditions and time required to achieve results. This program clearly maintains the boundary conditions specified in simulations. It has been shown that PSANNM produces very accurate results of full penetration problem at any infinite variation and combination of impact conditions, which is main interest of our study.

One steel plate of mention dimensions in Table 1 was selected as idealized complex target. The maximum impact velocity of 2.15 km/s and a tungsten projectile with a mass of 15g were selected for the predictive result study reference data [1].

Table: 1 Bumper plate dimensions (cm).

Plate	Length	Width	Thickness
1	18	8	0.5

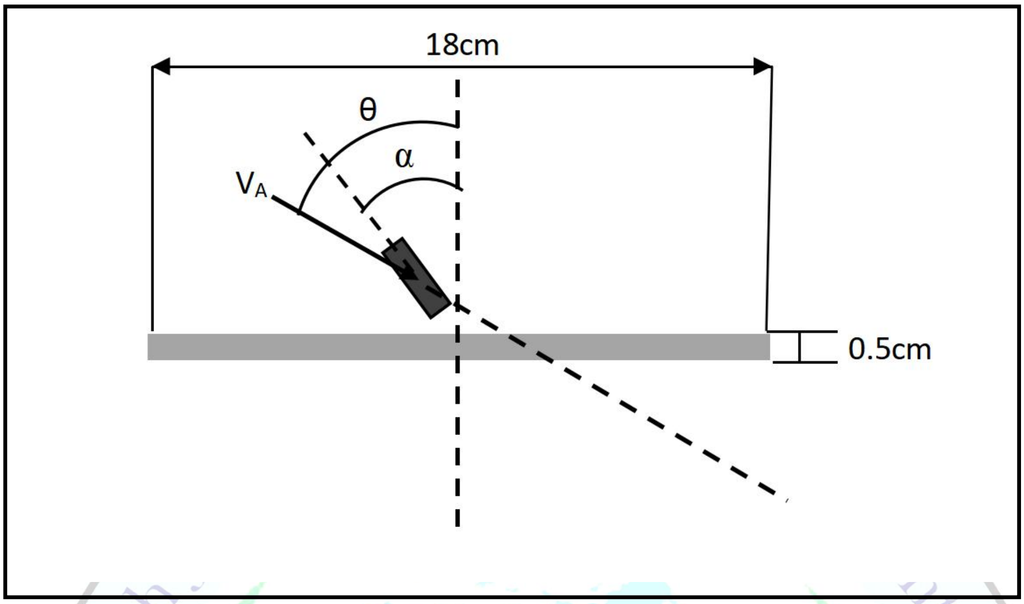


Figure 1: Setup model for predictive model input data with one plate and cylindrical projectile

This physical model and projectile mass and velocity were defined based on preliminary numerical simulations of the most lethal configuration of projectile θ, αand V_A. This guaranties meaningful damage comparisons where, in all predictions, the kinetic energy of the projectile is depleted and its ''damage potential'' has been completely spent.

For the cylindrical projectiles with single impact plate [Figure 1] predictive trial runs in PSANNM were conducted with projectile velocities of 0.5, 1.25 and 2.15 km/s and obliquity angles θ from 0° to 75° with 15° increments. In addition, α was varied from -75° to 90° with 15° increments and with L/D of 1, 2, 3 and 4. For all simulations reference data the mass of the projectile was kept constant [1].

4. Artificial Neural Network (ANN):

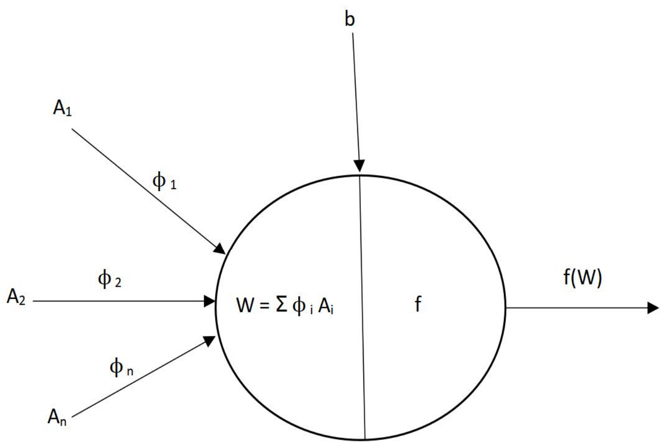


Figure 2: Artificial Neuron

Artificial Neural Network is a tool to predict the output by processing the information provided. Working of ANN is explained by behaviour of a single artificial neuron. Inputs and Outputs for a neuron are shown in figure2. Neuron receives input signals as (A_1,A_2…A_n). These signals are multiplied by weights to get a summation (w) of inputs. An activation function takes the (w) as input and gives the f (w) to as output of neuron. An activation function can be either logistic, hyperbolic tangent or linear function. Choice of activation function depends on problem to be solved. There are several types of artificial neural networks however, multi-layer perception architecture (MLP) is most commonly used. MLP is characterized by multiple layers of neurons which include one input, one output layer and multiple hidden layers. In general, each neuron is connected to all the neurons in adjoining layers. The number of hidden layers and neurons in those layers needs to be determined at time of designing the network [10].

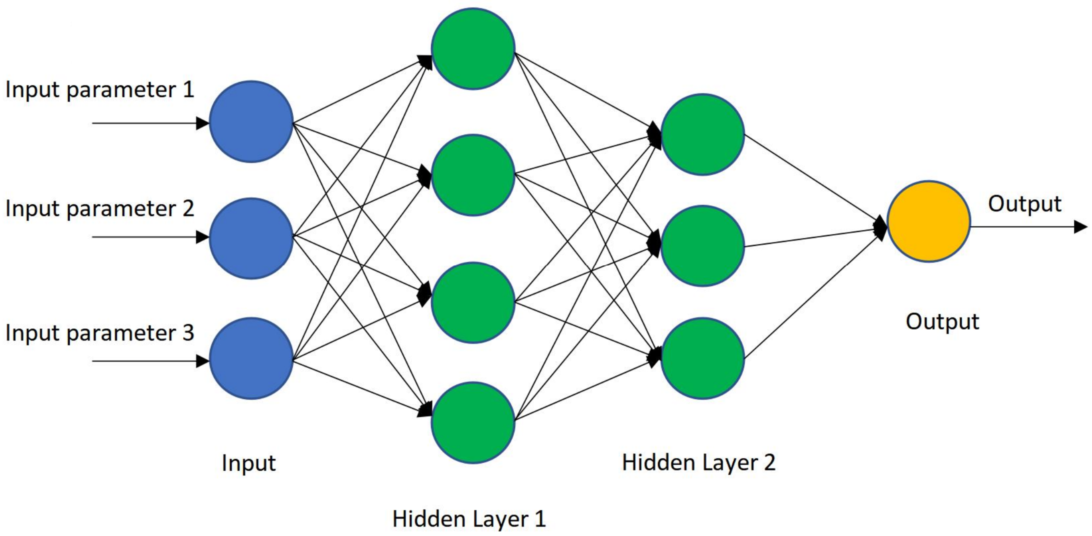


Figure 3: Typical Neural Network Architecture

Training a neural network means adjusting the weights φ_i. There are various algorithms to train a neural network. One of the most preferred training algorithms is error back propagation algorithm. Following are the key steps in the algorithm.

- Initialize weights and thresholds.
- Let (I_1,I_2…I_3) be an input data/pattern and let (y_n) be desired output.
- Let (o_1,o_2…o_k) be the output obtained from the output layer of the network when (I_1,I_2…I_3) is presented at input layer.
- Output of each neuron f (w_i) is calculated from the input data and initialised weights which lead to final output prediction of the network.
- The error at i^{th} output node is o_i-y_i.

- The weights between hidden layer and output layer are modified based on error at each output node.
- Weights in the previous layers are modified by back propagating errors calculated at output layer nodes.

This process is repeated for a set of input and output of training data. The training stops when output of neural network is sufficiently close to the desired output for each set [14]. ANN is evolved using error back propagation algorithm for hypervelocity impact of cylindrical projectile on plate.

5. Development of ANN:

Simulation data for hypervelocity impact presented in reference [1] is taken to develop a network. The impact conditions considered for the simulations were for a range of V_A, L/D,θ,α. The projectile was of tungsten in cylindrical shape having L/D of 1,2,3 an 4. Steel plate was of thickness 5mm. V_A was considered as 0.5, 1.25 and 2.15 km/s with θ of 0°, 15°, 30°,45°, 60° and 75°. In this predictive simulations SIDI and α were recorded as output.

The network was developed using Python script AI tool. V_A, L/D, θare inputs to the network. The outputs to the network are SIDI andα. The network was trained by varying the number of hidden neurons to find the optimum architecture. Network which resulted minimum errors was selected for further predictions. The model also suggests a selective choice of α to result into even more lethal damage, for provided impact parameters of hypervelocity.

6. Damage prediction:

Based on the comparative data inspections, it was observed that the damage generated on the bumper plate could be characterized in terms of the depth of penetration of the projectile and the size of the penetration holes generated on plate.[1] . It is evident, from a simple visual inspection of the figures, that for these two specific cases the cylindrical projectile is more lethal tat higher impact speeds than other impact parameters. To be able to correctly quantify the level of damage produced by a projectile, it is important to define the level of damage as a combination of both effects; the depth of penetration and the size of the penetration holes. The size of the penetration holes is defined in terms of the volume of particles that exceed a threshold plastic strain. This damage quantity is called ''displaced volume''.These two damage quantities are aggregated to obtain as follows:

[Total Damage] (SIDI) Reference [1].

SIDI = Volume displaced + Volume penetrated

7. Results and Discussions:

A total of 936 computer simulations with cylindrical projectiles were conducted with varied impact parameters as described above reference data [1]. Traditionally, the normal impact or the α=0°impact configurations are assumed to be the most lethal, but in this case that assumption was proved to be incorrect [1]. It should be noted that in general the SIDI values decrease as αincreases.

The trained network was implemented for predicting the damage potential (penetrating hole diameter) SIDI, and α for varied impact conditions. Below is the result table of α and SIDI values for different combinations of impact condition parameters predicted by PSANNM.

V_A, L/D, θand α these four parameters are sufficient to predict the damage intensity.

Table 2: Results of Python ANN model

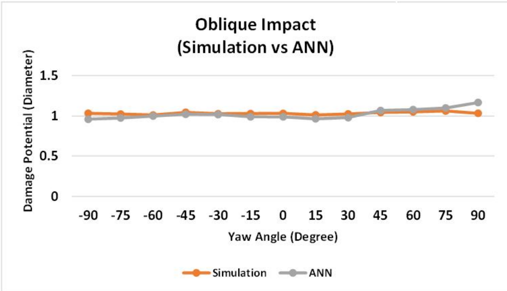
L/D	(V_A)	(θ)	(α)	Simulation (SIDI)	ANN (SIDI)	Error %
1	0.5	0	60	1.04	0.909725487	12.53
1	0.5	0	45	1.047	0.911589026	12.93
1	0.5	0	-15	1.021	0.966103733	5.38
1	0.5	0	-30	1.043	1.027398348	1.5
1	0.5	0	-45	1.032	1.046355367	1.39
1	0.5	0	-60	1.033	1.056901813	2.31
1	0.5	0	-75	1.017	1.055575728	3.79
1	0.5	0	-90	1.022	1.043395638	2.09
1	0.5	15	90	1.033	1.020002007	1.26
1	1.25	0	90	0.961	0.926623225	3.58
1	1.25	0	75	0.963	0.923032224	4.15
1	1.25	0	60	0.966	0.913699985	5.41
1	1.25	0	45	0.977	0.912066817	6.65
1	1.25	0	30	0.954	0.969264209	1.6
1	1.25	0	15	0.938	0.963395	2.71
1	1.25	0	0	0.955	0.937427223	1.84
1	1.25	0	-15	0.952	0.973159194	2.22
1	1.25	0	-30	0.949	1.024379015	7.94
1	1.25	0	-45	0.967	1.014114618	4.87
1	1.25	0	-60	0.964	1.014826536	5.27
1	1.25	0	-75	0.967	1.014482737	4.91
1	1.25	0	-90	0.961	1.008230686	4.91
1	1.25	15	90	1.106	1.006188512	9.02
1	1.25	15	75	1.007	0.992562234	1.43
1	1.25	15	60	1.001	1.020678997	1.97

1	1.25	15	45	1.004	1.005115271	0.11
1	1.25	15	30	0.989	0.981948435	0.71
1	1.25	15	15	0.99	0.987389565	0.26
1	2.15	15	30	1.029	0.99409312	3.39
1	2.15	15	15	1.022	1.001851201	1.97
1	2.15	15	0	1.021	0.969659984	5.03
1	2.15	15	-15	1.029	1.014648199	1.39
1	2.15	15	-30	1	1.043151975	4.32
1	2.15	15	-45	1.003	1.042763948	3.96
1	2.15	15	-60	1.03	1.041007042	1.07
1	2.15	15	-75	1.01	1.040792108	3.05
1	2.15	15	-90	1.018	1.047275782	2.88
1	2.15	30	90	0.995	1.041782379	4.7
1	2.15	30	75	1.015	1.034483671	1.92
1	2.15	30	60	1.038	1.00359726	3.31
1	2.15	30	45	1.025	0.978909552	4.5
1	2.15	30	30	1.034	1.017147064	1.63
1	2.15	30	15	1.031	1.0095402	2.08
1	2.15	30	0	1.004	0.997653663	0.63
2	0.5	15	-30	1.051	1.051043272	0
2	0.5	15	-45	1.082	1.077193737	0.44
2	0.5	15	-60	1.09	1.100598574	0.97
2	0.5	15	-75	1.119	1.136108398	1.53
2	0.5	15	-90	1.156	1.237673283	7.07
2	0.5	30	90	1.192	1.223432541	2.64
2	0.5	30	75	1.122	1.148926497	2.4
2	2.15	30	75	1.04	1.054608941	1.4
2	2.15	30	60	1.019	1.006111383	1.26
2	2.15	30	45	1.012	0.980299115	3.13
2	2.15	30	30	1.013	0.979239941	3.33
2	2.15	30	15	1.004	1.012438297	0.84
2	2.15	30	0	0.977	0.999017358	2.25
2	2.15	30	-15	1.014	1.041798472	2.74
2	2.15	30	-30	1.075	1.056565523	1.71

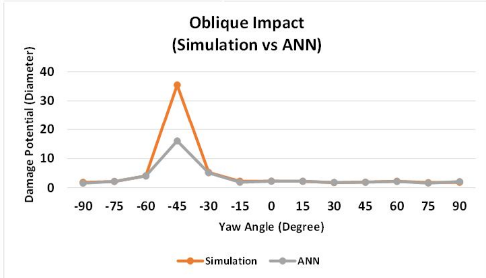
2	2.15	30	-45	1.072	1.064179659	0.73
3	1.25	15	15	0.855	0.958022177	12.05
3	1.25	15	0	0.869	0.952914834	9.66
3	1.25	15	-15	1.018	1.030136108	1.19
3	1.25	15	-30	1.086	1.032665491	4.91
3	1.25	15	-45	1.171	1.040212274	11.17
3	1.25	15	-60	1.187	1.047327518	11.77
3	1.25	15	-75	1.186	1.056756258	10.9
3	1.25	15	-90	1.17	1.10537827	5.52
3	1.25	30	90	1.145	1.096319675	4.25
3	1.25	30	75	1.125	1.070910692	4.81
3	1.25	30	60	1.04	1.021275401	1.8
4	0.5	75	45	2.1969	2.127502441	3.16
4	0.5	75	30	3.6187	3.767508984	4.11
4	0.5	75	15	5.5919	5.971271992	6.78
4	0.5	75	0	5.8559	6.186156273	5.64
4	0.5	75	-15	11.166	10.69966698	4.18
4	0.5	75	-30	6.1437	5.546171665	9.73
4	0.5	75	-45	5.1222	4.503412724	12.08
4	0.5	75	-60	3.7272	3.614416599	3.03
4	0.5	75	-75	4.7308	4.894571781	3.46
4	0.5	75	-90	6.8357	7.377656937	7.93
4	1.25	0	90	1.0672	1.028984427	3.58
4	1.25	0	75	0.9784	1.010852814	3.32
4	1.25	0	60	1.0024	0.978261948	2.41
4	1.25	0	45	1.0119	1.012570381	0.07
4	1.25	0	30	0.9825	0.976766706	0.58
4	2.15	60	90	1.1038	1.053035378	4.6
4	2.15	60	75	1.0383	0.993341804	4.33
4	2.15	60	60	1.0114	0.976063251	3.49
4	2.15	60	45	1.0362	0.962522507	7.11
4	2.15	60	30	0.9607	0.933220387	2.86
4	2.15	60	15	0.994	0.978697956	1.54
4	2.15	60	0	1.0526	1.074080706	2.04

4	2.15	60	-15	1.07	1.126398683	5.27
4	2.15	60	-30	1.0883	1.133628845	4.17
4	2.15	60	-45	1.0646	1.083877087	1.81
4	2.15	60	-60	1.1345	1.133806348	0.06
4	2.15	60	-75	1.1239	1.118051767	0.52
4	2.15	60	-90	1.1038	1.049974203	4.88
4	2.15	75	90	1.0885	0.933939338	14.2
4	2.15	75	75	0.884	1.036758542	17.28
4	2.15	75	60	0.958	1.047468424	9.34
4	2.15	75	45	0.9793	0.912585974	6.81
4	2.15	75	30	1.2516	1.176283598	6.02
4	2.15	75	15	1.5481	1.499622464	3.13
4	0.5	15	30	1.3942	1.303353071	6.52
4	0.5	15	15	1.325	1.241942883	6.27
4	0.5	15	0	1.3591	1.316878557	3.11
4	0.5	15	-15	1.1787	1.159826756	1.6
4	0.5	15	-30	1.0608	1.132802963	6.79
4	0.5	15	-45	1.0681	1.250833035	17.11
4	0.5	15	-60	1.1619	1.449528337	24.75
4	0.5	15	-75	1.531	1.837339163	20.01
4	0.5	15	-90	2.0423	2.079298019	1.81
4	0.5	30	90	2.0934	1.76739943	15.57
4	0.5	30	75	1.4481	1.554734349	7.36
4	0.5	30	60	1.2799	1.376147032	7.52
4	0.5	30	45	1.5163	1.342331529	11.47
4	0.5	30	30	1.6491	1.45047164	12.04

1) L/D = 1

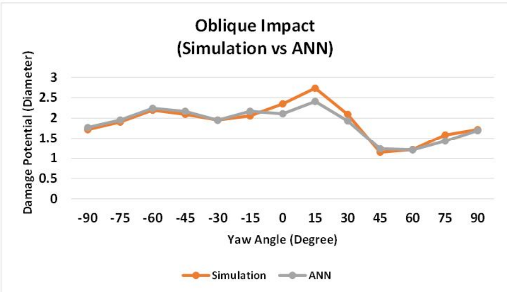


V_A= 0.5km/s θ = 15°

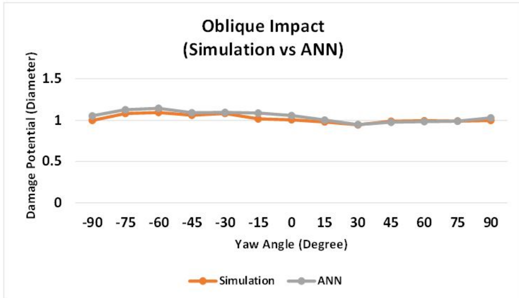


V_A= 0.5km/s θ = 75 °

2) L/D = 2



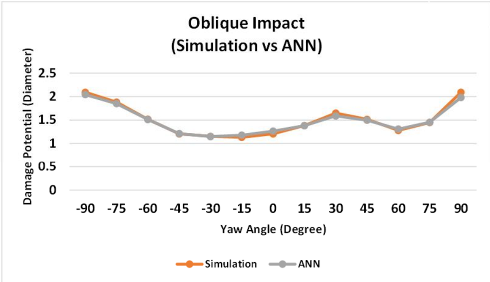
V_A = 0.5km/s θ = 30°



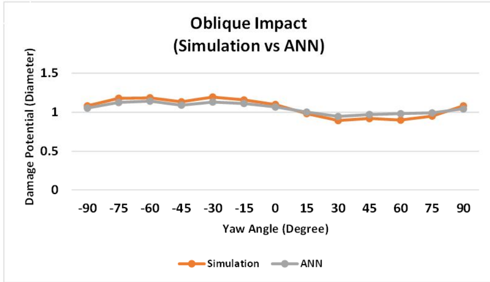
V_A = 2.15km/s θ = 60°

Figure 4: Trend comparison of predictive results of ANN and Simulation results

3) L/D = 3

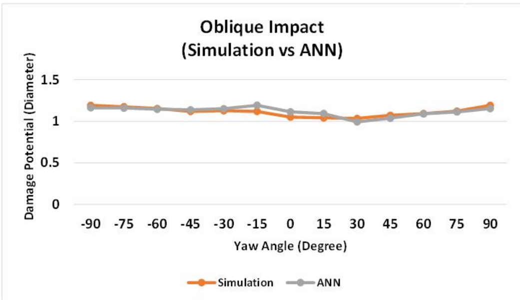


V_A = 0.5km/s θ = 60°

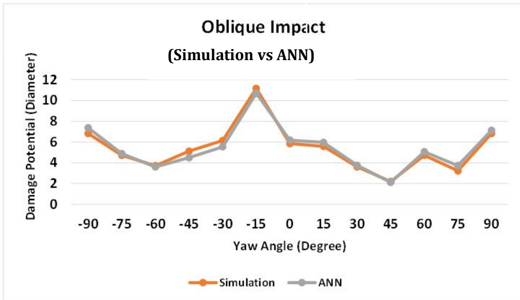


V_A = 2.15km/s θ = 60°

4) L/D = 4

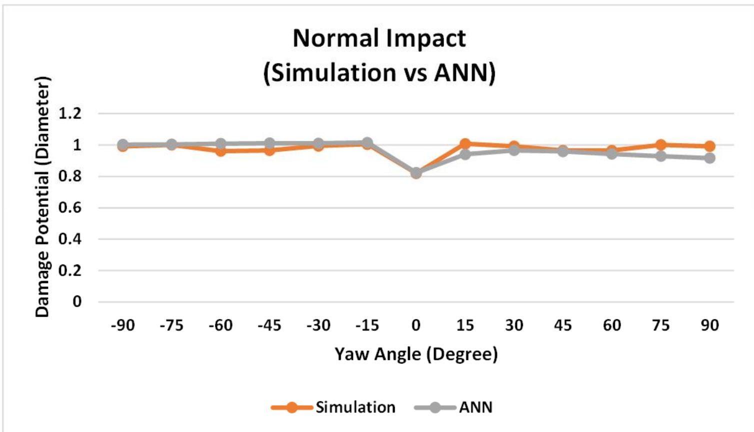


V_A = 0.5km/s θ = 30°



V_A = 0.5km/s θ = 75°

NORMAL IMPACT



V_A = 2.15km/s θ = 30°

Figure 5

From figure 5It is observed that simulation results and the artificial neural network results tend to follow similar trends. As we receive the α and SIDI as results in actual experimentation therefore the graphs are plotted with SIDI on the Y-axis and α on the X-axis hence giving us a thorough comparison on the simulation and artificial neural network results.

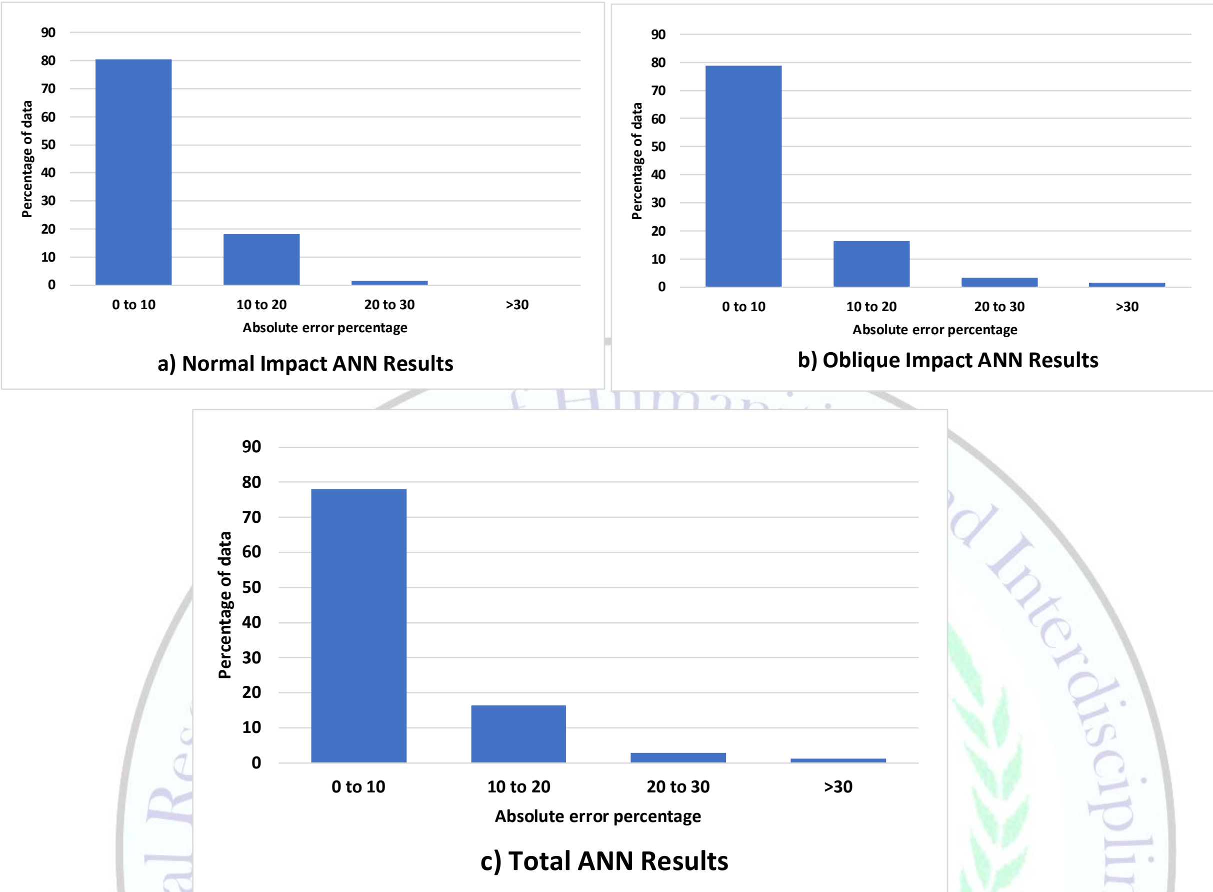


Figure 6.1. Comparison between simulation and artificial neural network results for different L/D, V_A and θ.

For the case of cylindrical projectiles results from PSANNM with an L/D = 2, as the V_A increases, a clear pattern emerges indicating that the cylindrical projectile causes more damage for only a narrow band of θ and α pairs. For the cases of the cylindrical projectiles with L/D = 4, the relative damage potential pattern is the same as for an L/D = 2. In this case the narrow band where the cylindrical projectile is more damaging is better defined and at the highest impact speed (2.15 km/s) it has a α that falls between ±30°. This means that for cylindrical projectiles with an L/D = 4 and α outside of 30° their damage potential decreases. It is evident that as the angle θ increases, the depth of penetration decreases, but also the size of the penetration holes increases. Values of the SIDI are also printed in the plots below and they range from 0.14 to 1.06.For this case the SIDI ranges from 0.24 to 1.04. It is interesting to note that the maximum SIDI does not occur for a θ = 0° (normal impact) or θ= 30° (α=0°) Traditionally, the normal impact or the zero α impact configurations are assumed to be the most lethal, but in this case that assumption was proved to be incorrect. It should be noted that in general the SIDI values decrease as a increases. One interesting feature of the results shown for a θ= 0° (normal impact) and for increasing values of α is that even though the depth of penetration decreases significantly, the SIDI value is not significantly different. The reason for this is that as the depth of penetration decreases, the size of the penetration holes increases, resulting in SIDI values that are not that very different. but due to the large number of simulations only a subset of the plots is included in this paper [1] and Table 1. However, as the impact speed increases, a narrow band appears where the cylinder is more damaging than other speeds and θ and α. It is interesting to note that this maximum relative damage potential tends to decrease as the impact speed increases, indicating a decreased geometric effect for high impact speeds. Of course this can only be concluded for cases within the range of geometric configurations and impact speeds studied. For the relative damage potential tables corresponding to cylindrical projectiles with an L/D = 4, the tendency is the same.

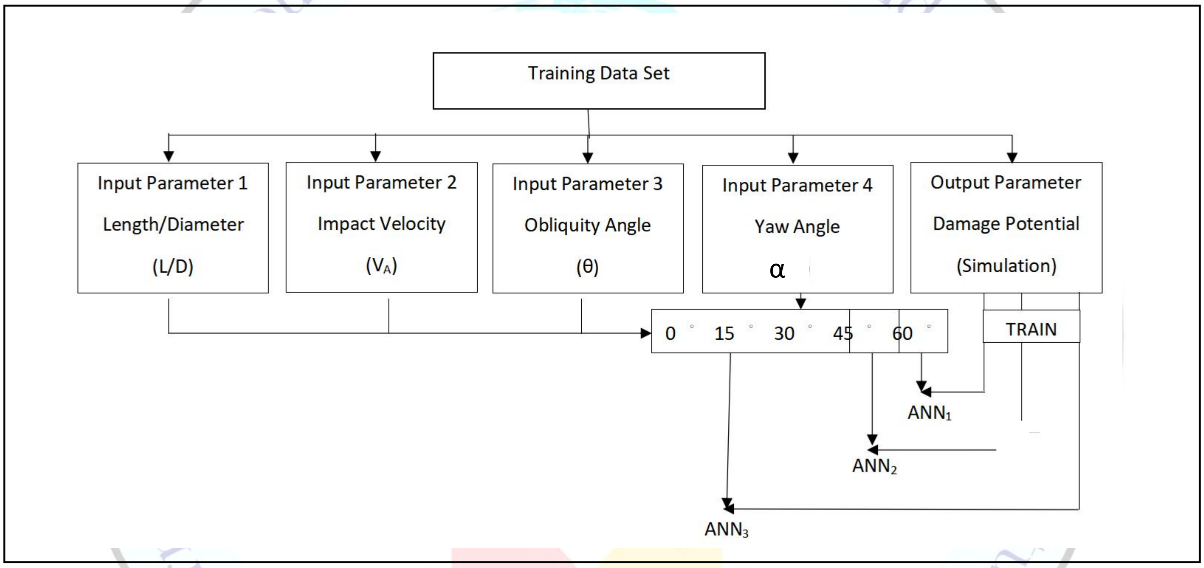


Figure 7.1: Schematic of working of PSANNM

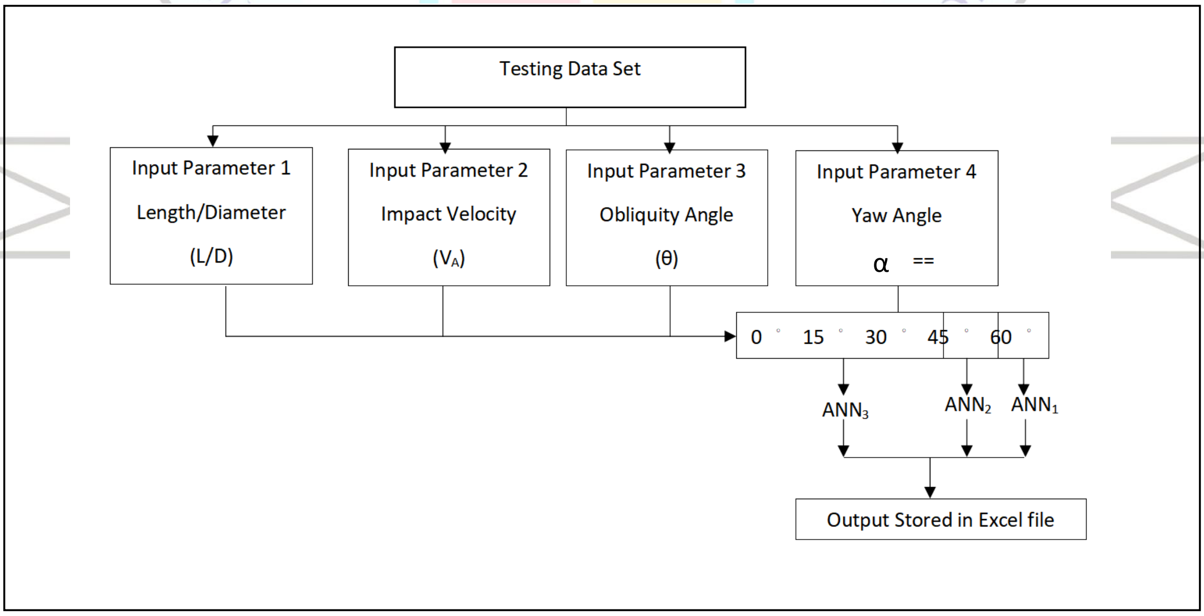


Figure 7.2: Schematic of working of PSANNM

8. Conclusions:

In this paper, a methodology is proposed for predicting the maximum lethal damage potential (penetrating hole diameter) characteristics in case of hypervelocity impact. Artificial Neural Network is developed for prediction of SIDI (total damage potential) and yaw angle. The data published in literature is used for development of network. The trained network predictions were compared with the simulation results of literature reference. It is observed that the proposed methodology can be easily applied for the hypervelocity phenomenon. Maximum percentage of data is having error around 27%. The change in trends are observed when the graphs of velocity angle, SIDI, obliquity angle, L/D ratio are plotted for impact velocity of 0.5, 1.25 and 2.15 km/s .The trends followed by simulation results and ANN predictions are similar. cylindrical projectile is more damaging is better defined and at the highest impact speed (2.15 km/s) it has a yaw angle that falls between ±30°. This means that for cylindrical projectiles with an L/D = 4 and α outside of 30° their damage potential decreases. It is evident that as the angle θ increases, the depth of penetration decreases, but also the size of the penetration holes increases. The simulation SIDI and PSANN-SIDI are in accurate agreement, which proves selected prediction architecture for various impact conditions to be right.

The proposed methodology is helpful in predicting maximum lethal damage potential and yaw angle for infinite combinations of input parameter after hypervelocity impact on a single bumper plate. The variations in damage can also be predicted accurately by the network within short span of time ranging from seconds to few minutes compared to simulation time of hours to many days or even months. Hence, developed PSANNM (Python Script Artificial Neural Network Model) is successful at predicting the damage potential of a plate at hypervelocity accurately at any provided impact conditions relatively faster than simulation method. The model also suggests a selective choice of yaw angles to result into even more lethal damage, for provided impact parameters of hypervelocity.

Nomenclature	
V_A	Impact Velocity
α	Yaw or Orientation angle of cylindrical projectile
θ	Obliquity angle
L/D	Length to diameter ratio
SIDI	Single Impact Damage Index
PSANNM	Python Script Artificial Neural Network Model

Acknowlegements:

The authors are grateful to Dr. R. S. Deodhar, Sc 'F', and Dr. K.D. Dhote, Sc 'F', ARDE for addressing the problem and guidance.

References:

[1] C. Carrasco et al. Damage potential comparison of spherical and cylindrical projectiles impacting on a system of bumper plates. Int J of Impact Eng.33 (2006) 143-157.

[2] Gauri Naik, Satish Chinchainikar. Estimating primary fragment characteristics during hypervelocity impact of spherical fragment on thin plate using artificial neural network. Int J Symposium on ballistics. 4-8(2019).

[3] Verma P. N., Dhote KD. Characterising primary fragment in debris cloud formed by hypervelocity impact of spherical stainless steel projectile on thin steel plate. Int J Impact Eng 2018; 120: 118-125. https://doi.org/10.1016/j.ijimpeng. 2018.05.003.

[4] Dhote K. D., Verma P. N. Investigation of hole formation by steel sphere impacting on thin plate at hypervelocity. Thin Wall Struct 2018; 126: 38-47. https://doi.org/10.1016/j.tws.2017.05.012.

[5] Tate A. Further results are the theory of long rod penetration. J Mech Phys Solids 1969;17:141-50.

[6] Anderson CE, Orphal DL, Franzen RR, Walker JD. On the hydrodynamic approximation for long-rod penetration. Int J Impact Eng 1999; 22:23 43.

[7] Rosenberg Z, Dekel E. Further examination of long rod penetration: the role penetrator strength at hypervelocity impacts. Int J Impact Eng 2000; 24:85-102.

[8] Anderson CE, Walker JD, Bless SJ, Partom Y. On the L/D effect for long-rod penetrators. Int J Impact Eng 1996;18:247-64. [9] Walker JD, Anderson CE. A time-dependent model for long-rod penetration. Int J Impact Eng 1995;16:19-48.

[9] Rosenberg Z, Dekel E. The relation between the penetration capability of long rods and their length to diameter ratio. Int J Impact Eng 1995;15:125-9.

[10] Christiansen EL, Kerr JH. Projectile shape effects on shielding performance. Int J Impact Eng 1997;20:165-72.

[11] Johnson GR, Cook WH. Lagrangian EPIC code computations for oblique, yawed-rod impacts onto thin-plates and spaced-plate targets at various velocities. Int J Impact Eng 1993;14:373-83.

[12] Whipple F. L. Meteorites and space travel. Astronomical J 1947; 5: 131-8. http://adsbit.harvard.edu/full/1947AJ.....52Q.131 W.

[13] Schonberg W. P., Taylor R. A. Penetration and ricochet phenomena in oblique hypervelocity impact. AIAA J 1989; 27: 639-46. https://doi.org/10.2514/3.10155.

[14] Haykin S. Neural Networks and Learning Machines. 3rd ed. Pearson; 2009.

[15] Fernandez-Fdz D., Lopez-Puente J., Zaera R. Prediction of the behaviour of CFRPs against high velocity impact of solids employing an artificial neural network methodology. Compos Part A-Appl S 2008: 39: 989-96. https://doi.org/10.1016/tws.2017.05.012.

[16] Fernandez-Fdz D., Zaera R. A new tool based on artificial neural network for the design of lightweight ceramic-metal armour against high velocity impacts of solids. Int j Solids Struct 2008; 45: 6369-83. https://doi.org/10.1016/j.ijsolstr.2008.08.009.

[17] Artero-Guerrero J. A., Pernas- Sanchez J., Matin-Montal J., Varas D., Lopez-Puente J. The influence of laminate stacking sequence on ballistic limit using a combined Experimental/FEM/Artificial Neural Networks (ANN) methodology. Compos Struct 2018: 183: 299-308. https://doi.org/10.1016/j.compstruct.2017.03.068.