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Neural Models for Predicting Trajectory Performance of an Artillery Rocket

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This paper presents a feed forward neural network model for predicting the trajectory performance of an artillery rocket. Three problems of artillery rocket performance are addressed under known ambient conditions to predict 1) the range for the specified firing angle, 2) the firing angle for the specified range, and 3) the range obtainable under standard (specified) conditions. The neural model bypass the need for any mathematical modeling or their solutions as hitherto resorted to for predicting the trajectory performance. For the purpose of present study, data from the range table of G-rocket, supplied by the user agency, are used. An appropriate set of input/output variables from the given data is selected to train, validate, and predict via the proposed neural models. A comparison of the neural model estimate with the values from the range table shows close agreement for all the proposed neural models.

I. Introduction

Artillery forms an important wing of an army in providing firepower, during both war and cross-border skirmishes with the enemy. Artillery rockets are a class of projectiles around which much of the aeroballistic theory was originally developed, and it continues to form a significant part of the aero ballistician's interest. The effectiveness of artillery rocket is largely judged by the accuracy in hitting the targets. Various error sources inherent in the rocket system, together with the external conditions such as wind, cause dispersion of the rocket from its intended path. The actual path traversed by the rocket is compared to the predicted trajectory in order to calculate its accuracy.

Beginning with the simplest, but relatively inaccurate, in-vacuo trajectory mathematical model, more and more sophisticated models of increasing accuracy, such as the point mass model, the modified point mass model, and the six-degree of freedom model,[1] have been developed. However, even the best of these models have their limitations because of 1) an inability to model all of the problem variables (e.g., the initial conditions at the time of rocket leaving the launcher, the tip-off effect, the aerodynamic jump, the variable atmospheric conditions, etc.) and 2) the non-availability of accurate and reliable aerodynamic coefficients (e.g. drag coefficient, damping in roll derivatives, etc.) required as inputs by the mathematical models. The recent interest in evolving applications of artificial neural networks (ANN) to diverse fields such as signal processing, pattern recognition, robotics, medical diagnosis, system identification, and control have led many researchers to explore their capability for aerospace engineering problems. The neural modeling has been employed in solving aerospace problems such as aerodynamic modeling,[2] buffet,[3] fatigue crack growth,[4] design of civil aircraft,[5] aircraft parameter estimation from flight data,[6,7] etc. In the present work, an attempt is made to develop a neural model for predicting the performance of an artillery rocket under known ambient atmospheric conditions. Because the field data on the performance of an artillery rockets have a number of noisy parameters that interact in a nonlinear manner, the neural modeling is an attractive alternative to the traditional mathematical modeling and regression techniques. The neural modeling has the ability to accommodate nonlinearties and to generalize from the data shown during the training sessions. The later property is especially useful when one has to model sparse real data from field trials of artillery rockets

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II. Artillery Rocket Data And Modeling

The performance data for artillery rockets are generally available in the form of range tables. Range tables are prepared using actual fired data. Typically, range table might list the Range R obtainable for various firing (elevation) angles □ under standard calm conditions for a rocket having nominal mass m and fired with nominal thrust F. Also listed are the time of flight T_f and the lateral drift in terms of correction to bearing angle □ that would be required to hit the target. Information is provided for correcting R,T and □ for 1) variations in the ambient atmospheric conditions (air temperature $\Delta T°$, ground air pressure Δp mm being different from these corresponding to standard atmosphere, and the propellant/charge temperature $\Delta T_c°$ being different from the standard temperature), 2) the presence of head/tail wind W_x and cross wind W_z. Generally, range tables are prepared based on a chosen mathematical model that is adjusted and validated for a few measured data. This may require introduction of a few fudge factors to achieve reasonable matching; a fudge factor used to modify the aerodynamic coefficients might be a constant or a function of problem variables, for example, □. Although T, p, W_x, and W_z vary along the path of the projectile, the corrections provided for these in the range tables are based on some equivalent constant (average) values. Note that it is possible to account for the varying wind and atmospheric conditions in some of the proposed mathematical models.[8] However, the inverse problem of finding the firing angle for a specified range and existing ambient conditions cannot be directly solved via mathematical models, and one has to rely on the range table for an answer. It is in this context that the proposed neural approach is shown to yield an answer as easily to the inverse problem as it does to the direct problem.

The performance data for an artillery rocket (G-rocket) were supplied by Armament Research and Development Establishment, Pune, India. The data supplied in the form of range table have 95 data points, listing R, T_f, and □ as a function of □ under standard atmospheric conditions (T=288.0°K, p=760 mm, T_c=288.0°K) and calm conditions ($W_x = W_z = 0$) for a rocket of nominal thrust (2240 newtons) and the time of all burnt (1.87 s). A procedure is also provided to correct the R, □ and for T, p and T_c being different from the standard (nominal) values and for equivalent head/tail/cross wind. By the use of the basic 95 points, and applying correction for any arbitrarily chosen set of atmospheric conditions as many additional data points can be generated as desired. The data set so generated is used to select appropriate Input/Output (I/O) pairs for the neural model. It may be mentioned that due to non-availability of fired data, the performance data (in terms of impact point) as given in the range table, are used for the neural training.

III. Neural Model

From the point of view of field application, a solider would want to know the required firing angle and bearing correction to achieve the required range. The information available before firing in terms of R, T, p, T_c, W_x, and W_z is used to form the input vector, whereas the required information in terms of □ and □ forms the output variables of the neural model. In the network input file, any deviations from the standard temperature, pressure, and charge temperature are given as the differential change (ΔT, Δp, ΔT_c) from the nominal values. The neural model does not require either the postulation of a mathematical/numerical model, or an estimate of initial conditions at the time of rocket leaving the launcher. Whereas functional mapping of the I/O pairs creates a black box type of neural model, the initial conditions are taken care of implicitly by the mapping. Measured data (fired data) can be directly used to train the network. As stated earlier, due to the non-availability of measured data; the data from the range table are taken as the measured data for the purpose of training, validation and prediction via the proposed neural model.

For modeling, a set of I/O pairs selected randomly is used for training sessions. Sets of varying number of I/O pairs were used to arrive at a minimum number of I/O pairs required for adequate training of the network. It is acknowledged that in the real life, the number of measured I/O pairs available might be limited due to the cost involved in collecting such fired data, hence the search for the minimum number of data samples to achieve an acceptable neural model. The numbers of I/O pairs used were varied to have 95, 48, 30, and 15 samples. Obviously, the higher the number of samples, the better the training, but even as few as 15 samples gave satisfactory levels of training. The suitability of the models is tested by a validation (test) data set, typically consisting of 15 or 30 I/O pairs, but other than those used for training. The rule of thumb used is that if, for the validation data, the mean square error (MSE) is only of the order of two times or less than the MSE prescribed for the training phase, the neural model is acceptable and its architecture is fixed for the next step of the prediction phase. If not, the tuning parameters of the network, such as the learning rate, the number of neurons in the hidden layer, the momentum rate, the number of iteration etc. are varied until the network meets the given conditions for MSE for the training as well as the validation phase.

For prediction, a set of randomly selected input data is taken from the range table and presented to the validated network. The predicted output is compared with the corresponding values from the range table. Typically, for prediction, 10 samples were randomly selected from the range table. Because the neural model is required to predict more than one output, that is, θ and ψ, the following study was undertaken to answer the following question: For the same set of inputs, is it better to train the network separately for one output at a time, or to train it on all outputs at once? The former approach always yielded relatively more accurate predictions and, therefore, all of the results presented herein are based on the single output option.

A mathematical model could be solved to yield range for the chosen firing angle, but it would not directly calculate the firing angle required for a specific range. This indirect problem is of practical use in the field application of artillery ammunition.[9] A soldier would want to know the firing angle and bearing correction to be used to achieve the required range for engaging a target. The information available prior to firing in terms of R, ΔT, ΔT_c, Δ_p, W_x, W_z is used to form the input vector of the neural model while the required information in terms of θ and ψ form the output variable separately.

Table 1 presents the predicted q and y required for engaging a target at range R under given ambient conditions. Column 1 of Table 1 lists the values of required target range while columns 2-6 list the variation in ambient atmospheric conditions. Columns 7-9 present a comparison between firing angle θ and bearing angle ψ respectively obtained through range table and proposed neural model. A close look at the numerical values of θ, and ψ showed that relatively accurate values of θ, and ψ are predicted for the smaller values of these. The trend was observed repeatedly for many sets of input variables selected for study. At the lower end of θ values, the range obtainable is more sensitive to variations in θ. Typically, increase of 1 mil in θ results in range increasing by 90m for a nominal value of θ = 84 mil, but at nominal value of θ = 737 mil, a 1 mil increase in θ results in range increasing by only 2.8 m. Notwithstanding this observation, the predicted values by neural model are satisfactory for the whole range of θ. Based on the results presented in these columns, it can be observed that the proposed neural model is a viable way of modeling many input variables that affect the relationship between the range and the firing angle.

Table 1 Comparison of actual and predicted elevation (firing) angle and bearing angle under known ambient atmospheric conditions

			Differential Change in Parameter w.r.t. Standard Atmosphere			Firing Elevation (θ)mils[1]		Bearing (ψ)mils	
Required target range in m (R)	Range wind in m/s (W_x)	Crosswind in m/s (W_z)	Ambient Temperature in C (ΔT)	Ambient Pressure in mm (ΔP)	Charge Temperature in ^oC (ΔT_c)	Range Table	Neural Model	Range Table	Neural model
2577.94	-5.07	8.62	1.01	0.52	-2.44	86.00	85.94	-41.031	-43.685
3863.33	6.55	-7.56	-0.99	-0.28	-0.93	117.00	117.40	37.59	34.764
6547.42	-9.32	-3.63	-2.04	-3.36	3.12	159.00	160.37	14.634	14.878
8983.99	5.53	-8.33	1.34	1.24	-11.53	203.00	203.64	40.813	41.068
11000.24	-7.53	-6.59	2.55	-1.18	-6.73	265.00	266.70	27.284	29.005
15659.24	-2.84	-9.59	0.00	-1.38	-4.80	435.00	434.01	42.114	39.482
18708.11	2.36	9.72	-2.04	3.27	3.26	561.00	561.20	-56.172	-48.716
19766.98	6.78	-7.35	-0.49	-1.14	-2.64	640.00	636.26	53.104	51.647
19637.83	-9.31	3.65	0.63	4.75	2.92	737.00	727.94	-36.017	-29.706

[1]6400 mils = 360 degrees

IV. Conclusion

The study presents an alternative approach to mathematical modeling used hitherto for predicting rocket performance in terms of the firing angle needed for the required range. The neural model is shown to be a viable way of modeling many input variables that affect the relationship between the range and the firing angle. It is envisaged that the measured data for rocket could be used for developing neural models that would be useful in field applications, including finding the firing angle and the drift angle for the specified range.

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