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Hybrid Genetic Learning of Radial Basis Function Networks (RBFNs) for the Modeling of the Explosive Cutting Process of Plates

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In this paper, a genetic algorithm is used as a learning method of the radial basis function networks for the modeling of the explosive cutting process of plates by shaped charges. The explosive cutting process of plates is one of the high rate energy processes used in different applications of mechanical and industrial engineering. The aim of such modeling is to show how the depth of penetration varies with the variation of important parameters involved in the explosive cutting process, namely, the apex angle, standoff liner thickness and mass of charge. It is also demonstrated that hybrid genetic algorithms, in which the result of the genetic algorithm's search is refined by Powell's method, provide more effective means of designing the RBFNs to precisely map such input-output relationships.

INTRODUCTION

During the last few decades, the use of explosives as a source of energy has found many applications in engineering. Explosives, magnetomotive forces and impact make a very large amount of energy available to do work in a very short period of time compared to any other source of energy. Explosives are now used in such diverse fields as welding, bulk cladding of plates, forming, sizing, powder compaction, hardening, and cutting. The advantage of using explosives is not solely their speed but, also, that there may sometimes be no other way of achieving the same results, as in the explosive welding of dissimilar metals.

There are three main methods by which metals may be cut using explosives. Firstly, by using contact demolition charges, the explosive is placed in direct contact with the part to be cut. The cutting action is usually a shearing effect, due to the large contact pressure generated at the interface between the explosive and the metal. Secondly, in the stress wave cutting of metals, a relatively small amount of explosive is placed in contact with the part to be cut. When the explosive is detonated, stress waves are generated which follow theoretically predictable paths. The cutting effect is the consequence of interaction and superposition of the stress waves at certain predetermined locations within the part. Thirdly, in cutting metals using a linear shaped charge, an explosive charge with a metallic liner is placed at a certain distance from the metal part. The cutting action is the consequence of the development of a very high-speed jet of molten metal produced by the collapse of the liner. A linear shaped charge consists of a long metal liner backed with an explosive charge, as shown in Figure 1. The explosive is usually detonated from one end. As the detonation proceeds down the length of the charge, the metallic liner collapses inwards and is projected as a high velocity linear jet of metallic particles. A standoff between the cutter and the target is essential to the proper formation of the jet and problems occur in the use of linear shaped charges underwater as the standoff must be filled with air.

The normal parameters of interest that may affect the performance of any shaped charge, are linear material, liner thickness, type of explosive, explosive weight, liner shape, and standoff distance [1,2].

The modeling of processes and systems identification using input-output data, have always attracted much research. In fact, system identification techniques are applied in many fields, in order to model and predict the behavior of unknown and/or very complex systems based on given input-output data [3]. Theoretically, in order to model a system, it is required to understand the explicit mathematical input-output relationship precisely. Such explicit

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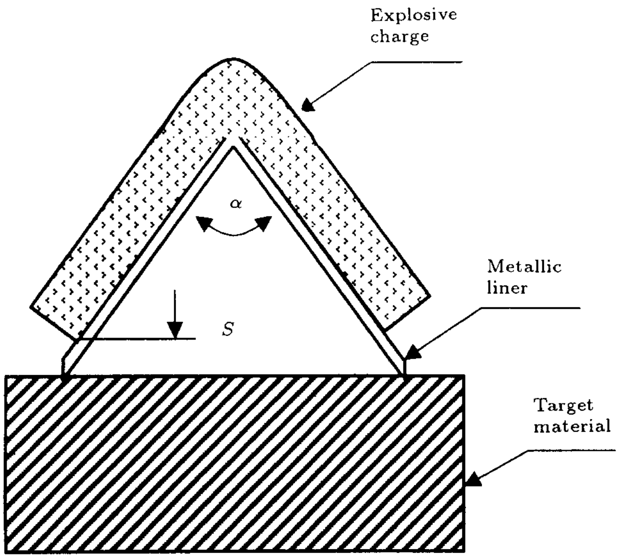

Figure 1. A linear shape charge: S = stand-off distance; α = apex angle.

mathematical modeling is, however, very difficult and is not readily tractable in poorly understood systems. Alternatively, soft-computing methods [4], which concern computation in imprecise environments, have gained significant attention. The main components of soft computing, namely, fuzzy-logic, neural networks, and genetic algorithms have shown great capability in the solving of complex non-linear systems identification and control problems. Much research effort has been expended to use evolutionary methods as effective tools for system identification [5-8]. Among these methodologies, fuzzy systems as universal approximators [9-11] and GMDH-type neural networks have recently been effectively employed to perform input-output mapping in the modeling of such explosive cutting processes of plates [12,13]. Moreover, neural networks and, in particular, Radial Basis Function Networks (RBFNs) [14,15] can be employed to perform input-output mapping. RBFNs such as these are trained by examples $(\mathbf{X}_i, y_i)(i = 1, 2, \cdots, M)$. However, the tuning of such RBFNs (or, equivalently, receptive fields) for complex models like an explosive cutting process, can frequently be difficult, particularly when the number of such receptive fields is large. Several learning algorithms have been proposed to identify the parameters involved in the Gaussian activation function of RBFNs [16]. The basic part of such learning methods is a pure back-propagation rule which, in turn, needs derivative information, in addition to a good initial guess. It is believed, however, that such derivative-based search techniques tend to locate the local rather than global optimum. However, genetic algorithms [17] provide an effective means of optimally solving various complex engineering problems with a high capability in finding global solutions. It has been shown [18] that such adaptive learning algorithms can easily automate the design of intelligent controllers for highly non-linear and complex plants. Thus, such intelligent techniques can be integrated to effectively model the depth of penetration as a function of important input parameters in an explosive cutting process.

In this paper, it is shown that genetically-designed RBFNs can effectively model the depth of penetration as a function of important input parameters in an explosive cutting process, namely, the apex angle, the standoff, the liner thickness and the mass of charge. Besides, it is shown that a hybrid genetic algorithm, in which the results of a simple GA are refined by the multi-dimensional Powell method, outperforms the results of a simple GA alone. It is also shown, in each case, that the models obtained using a training set can be effectively used to predict the output for an unforeseen test set in the training process.

MECHANISM OF JET FORMATION

The mechanism of a liner collapse is illustrated in Figure 2a. A detonation wave has travelled to the right and is in the process of collapsing the liner, as shown in the figure. This wave has produced pressures so great that the strength of the liner may be neglected and the material may be treated as a non-viscous fluid. When the walls collide, very high pressures are generated,

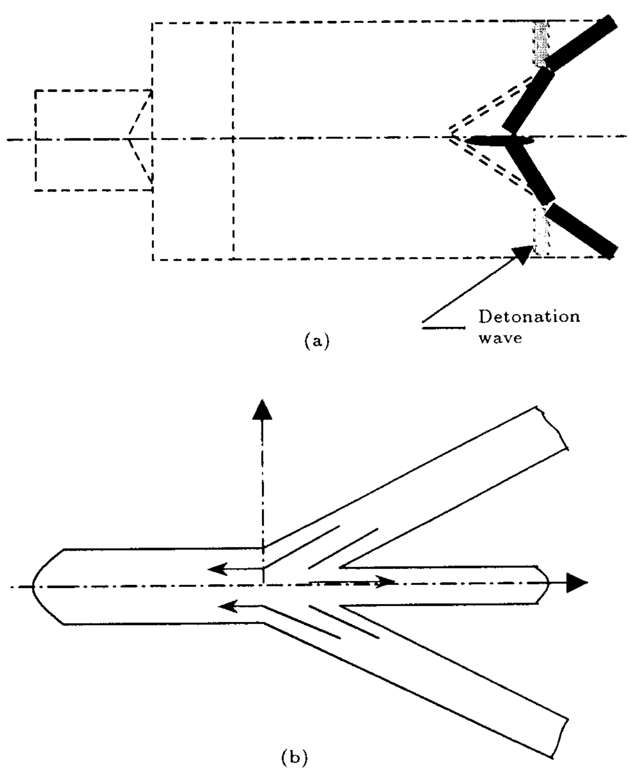

Figure 2. (a) The mechanism of liner collapse; (b) Formation of jet and slug by a cone or wedge shaped liner.

which are well in excess of the dynamic yield strength of the liner material, thus, causing the material in the collision zone to behave as a fluid. Behind the advancing collision point, a low velocity slug is formed from the outer layers of the liner while the inner layers form a high velocity re-entrant jet which travels ahead of the collision point, as shown in Figure 2b. By virtue of its very high energy, such a jet is capable of penetrating a thick metal target. The process of penetration of a target material by a charge-shaped jet is much like that of a high speed jet of water from a fire hose nozzle penetrating a bank of soft mud.

It has been shown that, under certain conditions, the rate of and depth of penetration into some target materials is independent of the strength of the target material, due to the fact that the high velocity jets produce pressure in the order of 0.25 million atmospheres at their point of impact, which is far above the yield point of most materials. Hence, the strengths and viscosities of target materials can be neglected and the problem can be treated by hydrodynamics [1].

EXPERIMENTAL PROCEDURE AND RESULTS

Most of the parameters were studied using mild steel plates as targets. The first operation was to form the liner. This was achieved by cutting rectangles from the metal sheets and bending them on the bending machine to the required angles. Then, the thickness, length and weight of the liner were recorded. The sheets of explosive were then rolled to the final thickness. Afterwards, the explosive charge was shaped into strips of a length equal to that of the liner. Finally, thickness measurements along the length of the liner were taken on both sides and the total weight of explosive per unit length was determined. The assembly was placed on a steel plate as a target. The detonator was accommodated in the charge and the leads connected to the shot-firing cable.

For the first set of tests, the standoff distance was varied whilst the liner thickness, the apex angle (defined as the perpendicular distance from the end of the charge to the target) and the weight of the charge were maintained at a constant. In the second set of data, the standoff distance was varied whilst the apex angle, the liner thickness and the weight of the charge were maintained at a constant. In the third set of data, the liner thickness was varied whilst the apex angle, the standoff and the liner thickness were kept at a constant. It should be noted that this experiment was repeated for three different values of charge weight. Finally, in the fourth set of data, the charge weight, together with the liner thickness, was varied whilst the apex angle and the standoff were kept at a constant.

Throughout the experimental work, a special measuring arrangement was employed to measure the depth of penetration. Several measurements were taken along the length of the cut and the average value of penetration was determined.

Experimental results obtained [2,19] indicate that the standoff distance has an appreciable effect on penetration. Increasing the standoff allows the jet to elongate before it runs into the target. An optimum standoff is found to exist, after which the penetration is shallower. The depth of penetration was also found to be affected by the apex angle.

RADIAL BASIS FUNCTION NETWORKS (RBFNS)

Artificial Neural Networks (ANNs), which mimic the nervous systems of biological organisms, have been widely used in various fields of engineering, particularly in control, modeling and prediction. The nervous systems of biological organisms are the most complex systems in the world and the ANN is an abstract simulation of a real nervous system, that involves a collection of neuron units connected to each other via weighting factors. Such ANNs have many characteristics such as non-linear mapping, learning and parallel processing [20]. A typical neuron unit is shown in Figure 3.

The input signal $\mathbf{X}(x_1, x_2, \cdots, x_p)$, in association with adjustable values called weights, has an excitatory influence in the activation function $f(.)$, which provides the output value. Several activation functions have been reported, namely, linear, ramp, step and sigmoid functions, together with several ANN architectures. RBFNs are two-layer networks that have universal approximation capabilities. The Gaussian activation function is more often used in RBFNs. A single-output RBFN is shown in Figure 4. Such activation functions are described in the following forms:

$$R_i(X) = R_i\Big(||X - U_i||/\sigma_i\Big), \quad i = 1, 2, \cdots, n, \tag{1}$$

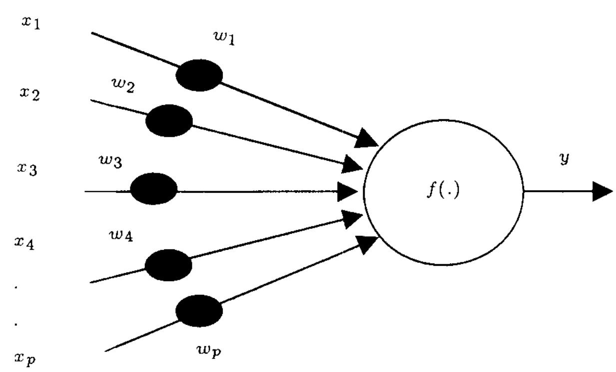

Figure 3. Schematic diagram of an artificial neuron unit.

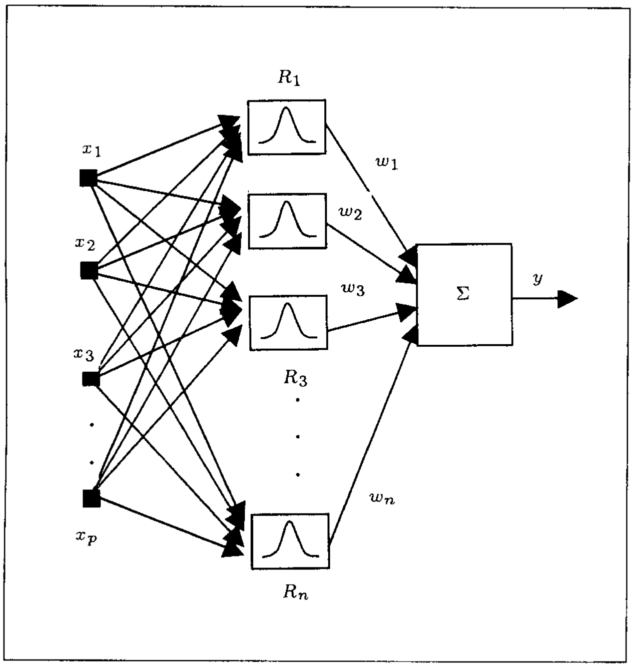

Figure 4. A single-output RBFN.

and:

$$R_i(X) = \exp\left(-\frac{||X - U_i||}{2\sigma_i^2}\right), \quad i = 1, 2, \cdots, n, \tag{2}$$

where X is a multi-dimensional input vector, $U_i (i = 1, 2, \cdots, n)$ is a vector with the same dimension as that of the input vector for each RBF and n is the number of RBFs. It is, therefore, very convenient to compute the output of such RBFNs as:

$$y = \text{RBF}(X) = \sum_{i=1}^{n} w_i R_i(X), \tag{3}$$

or:

$$y = \text{RBF}(X) = \sum_{i=1}^{n} w_i \exp\left(-\frac{||X - U_i||}{2\sigma_i^2}\right), \tag{4}$$

where w_i, σ_i and $U_i = (u_i^1, u_i^2, \cdots, u_i^p)$ are adjustable parameters. It is evident that the number of such parameters involved in the design of radial basis function networks can be readily calculated as $(p+2)n$, where p is the dimension of the input vector and n is the number of RBFs. In order to optimally train such network, it is required to define an appropriate objective function. If the learning sample consists of M input-output pairs, such as $(\mathbf{X}_i, t_i)(i = 1, 2, \cdots, M)$, the objective function can be readily defined by:

$$E = \sum_{j=1}^{M} \left(t_j - \text{RBF}(\mathbf{X}_j)\right)^2, \tag{5}$$

where RBF () is the radial basis function network's output of a particular input vector. Accordingly, an optimization method is needed to search for appropriate RBFN parameters so that the objective function defined in Equation 5 is minimized.

GENETIC LEARNING OF RBFNS FOR MODELING OF AN EXPLOSIVE CUTTING PROCESS

There have been several learning algorithms proposed to identify the parameters $\left(w_i, \sigma_i \text{ and } U_i = (u_i^1, u_i^2 \cdots, u_i^p)\right)$ of an RBFN. The most commonly used learning algorithm for RBFNs is the gradient descent algorithm, similar to back-propagation for the MLP nets. It is believed, however, that such learning algorithms are often hindered by the local minimum problem. Besides, it is also evident from the nature of such optimization algorithms, that the initial guess of RBFNs' parameters can have a significant influence on the performance of such optimization schemes [15,21]. In addition to these derivative based techniques, a variety of sequential training algorithms for RBFNs have been reported [15]. However, genetic algorithms [17], as stochastic population-based search techniques, have been extensively applied in recent works to train different aspects of computation intelligence, including fuzzy-logic and neural networks [22-29]. Such evolutionary schemes proved to be more efficient in problems that may have many local optima and are unlikely to be trapped [28]. Thus, the main advantage of using GAs to train neural networks is that the global optimum is more likely to be found, compared with gradient descent search techniques.

The incorporation of a genetic algorithm into such radial basis function networks starts by representing the real-value parameters $\left(w_i, \sigma_i \text{ and } U_i = (u_i^1, u_i^2, \cdots, u_i^p)\right)$ as a string of concatenated sub-strings of binary digits. Thus, each such sub-string represents RBFNs' parameters $\left(w_i, \sigma_i \text{ and } U_i = (u_i^1, u_i^2, \cdots, u_i^p)\right)$ in a binary coded form. In each entire string of $(2+p)n$ encoded parameters in binary digits, the first 2n sub-strings represent, in encoded form, the weighting factor and the variance of Gaussian functions, whilst the remaining *pn* sub-strings represent, in encoded form, the centres (mean) of the Gaussian functions. Thus, the concatenated sub-strings of binary digits involve the weighting factor, variance and centres of such Gaussian activation functions. The fitness, Φ, of each entire string of binary digits, which represents an RBF network, to model the explosive cutting process with an input vector of dimension p, is readily evaluated in the form of:

$$\phi = 1/E, \tag{6}$$

where E is the objective function given by Equation 5 and is minimized through an evolutionary process by maximization of the fitness, Φ. The evolutionary process starts by randomly generating an initial population of binary strings, each as a candidate solution. Then, using the standard genetic operations of tournament selection, crossover and mutation [17], entire populations of binary string are caused to improve gradually. In this way, RBFN models of an explosive cutting process with progressively increasing fitness, Φ, are produced until no further significant improvement is achievable. However, hybrid genetic algorithms, in which the exploration scheme of simple GAs is crossed with the exploitation of another (derivative-based or non-derivative-based) search technique, can successfully refine the solution obtained by a global search like GA. Therefore, the multi-dimensional Powell method [30], as a non-derivative-based method, has been used to climb the best hill found by a simple GA. In this work, the hybrid GA stands for the method in which the best solution found by a simple GA is used as a suitable initial guess for further refinement by the Powell method. This means that the hybrid genetic algorithm in this work employs a simple GA plus the multi-dimensional, non-derivative based Powell method. It should be noted that there are many different ways of hybridisation [31]; but most of them incorporate a local optimizer to the simple GA main loop.

MODELING OF THE EXPLOSIVE CUTTING PROCESS OF PLATES BY SHAPED CHARGES

The hybrid genetic algorithm mentioned in the previous section is used to train RBFNs for a set of given experimental input-output data in a series of explosive cutting tests of plates using shaped charges. The parameters of interest in this multi-input single-output system that affect both the performance of the shaped charge and the depth of penetration, are liner material, explosive material, liner shape, apex angle, liner thickness, explosive weight and distribution and standoff distance. Among these parameters, the liner and explosive material, together with the liner shape, have been kept fixed. The liner material, explosive material and liner shape have been selected as Copper/Polymer, SX2, and 'V' shape, respectively. Accordingly, there has been a total number of 43 input-output experimental data considering 4 input parameters, namely, apex angle, standoff, liner thickness and explosive weight, in four different groups. Therefore, the input vector, $\mathbf{X}$, is represented as $\mathbf{X} = \{AA, S, LT, EW\}$, where AA, S, LT and EW stand for apex angle, standoff, liner thickness and explosive weight, respectively, as illustrated in Figure 1. In this work, the output parameter is the Depth of Penetration (DP) and its 43 different experimentally obtained values are given in Table 1, together with the four corresponding values of the input parameters. In the first set of data, the apex angle varied from 45 to 135 degrees whilst other parameters were fixed as $S = 0$, $EW = 50$ g, and $LT = 0.9$ mm. In the second set of data, the standoff varied from -0.4 to 1(or, equivalently, non-effective standoff from 4.3 mm to 14.5 mm), whilst other parameters were fixed as $AA = 100$ degrees, $EW = 50$ g and $LT = 0.9$ mm. In the third set of data, the liner thickness varied, whilst other parameters were fixed as $AA = 100$ degrees, $S = 0$, for three different values of EW: 50 g, 150 g, and 250 g. Finally, in the fourth set of data, the explosive weight and liner thickness varied simultaneously, whilst other parameters were fixed as the $AA = 100$ degrees and $S = 0$. In order to model the 4-input-single-output set of data, 10 RBF have been considered. It is then evident that the number of parameters involved in the optimal design of such RBFN parameters is $(4+2)\times 10 = 60$. The complete binary string of these 60 parameters consists of $60 \times 5 = 300$ digits, representing 32 different states of each parameter, which leaves the search space with $2^{300} \approx 2. \times 10^{90}$ alternatives. A population size of npopsize = 200 was employed, together with a crossover probability of pcross = 0.7 and a mutation probability of pmutate = 0.02 in a generation number of 10,000, after which no further improvement has been achieved for such population size. Such genetic design procedure was repeated six times and the best result obtained for the best-of-generation is shown in Figure 5.

The influence of apex angle on the depth of penetration is shown in Figure 6, using the computed values of a genetically-designed RBFN, hybrid genetically-designed RBFN, and the actual values obtained experimentally. It is evident that the performance of such RBFN model obtained using hybrid method has been highly improved. The influence of standoff on the depth of penetration is shown in Figure 7, using the computed values of a genetically-designed RBFN, hybrid genetically-designed RBFN, and the actual values obtained experimentally. Again,

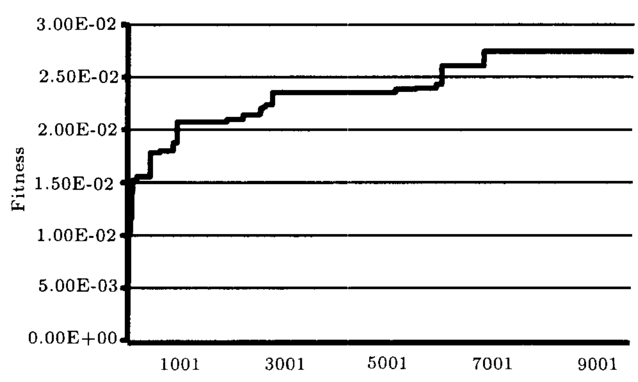

Figure 5. Evolution of the best-of-generation of fitness.

Table 1. Inputs-output data of explosive cutting process.

	Inputs				Outpus
Number	**Apex Angle**	**Standoff**	**Charge Mass**	**Liner Thickness**	**Depth of Penetration**
1	45	0	50	0.9	2.4
2	60	0	50	0.9	3.1
3	75	0	50	0.9	4.7
4	90	0	50	0.9	6.1
5	95	0	50	0.9	8
6	100	0	50	0.9	8.2
7	105	0	50	0.9	7.1
8	120	0	50	0.9	5.4
9	135	0	50	0.9	4.7
10	100	-0.4	50	0.9	7.0
11	100	-0.2	50	0.9	8.2
12	100	0.0	50	0.9	9.05
13	100	0.2	50	0.9	8.25
14	100	0.4	50	0.9	8.25
15	100	1.0	50	0.9	7.8
16	100	0	12.25	0.4	2.0
17	100	0	50	0.9	9.0
18	100	0	50	1.38	8.3
19	100	0	50	1.26	8.3
20	100	0	50	1.13	9.3
21	100	0	50	1	9.3
22	100	0	50	0.74	6.9
23	100	0	50	0.61	7.1
24	100	0	50	0.48	5.9
25	100	0	50	0.35	6.0
26	100	0	150	2.4	16.3
27	100	0	150	1.95	17.1
28	100	0	150	1.5	16.0
29	100	0	150	1.05	13.1
30	100	0	150	0.83	11.1
31	100	0	150	0.6	10.3
32	100	0	250	3.0	21.9
33	100	0	250	2.81	22.2
34	100	0	250	2.52	21.1
35	100	0	250	2.23	21.9
36	100	0	250	1.9	22.4
37	100	0	250	1.65	22.4
38	100	0	250	1.36	21.5
39	100	0	100	1.2	12.1
40	100	0	150	1.5	16.1
41	100	0	200	1.7	19.6
42	100	0	250	1.9	22.4
43	100	0	300	2.0	25.0

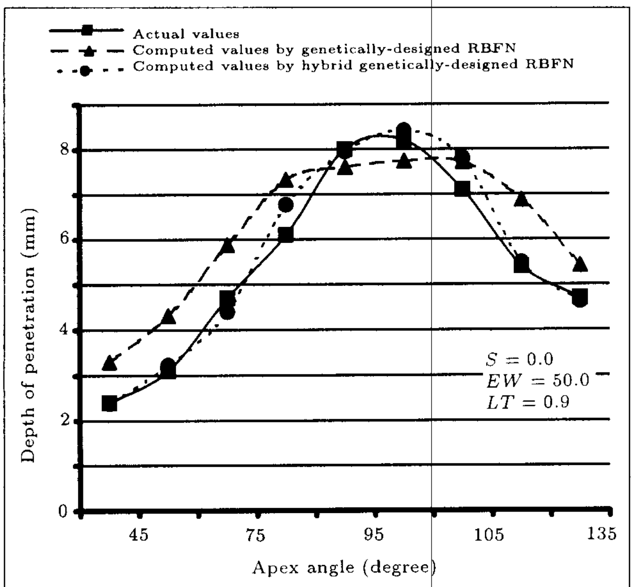

Figure 6. Effect of apex angle on penetration: Comparison of experimental and trained RBFN computation results.

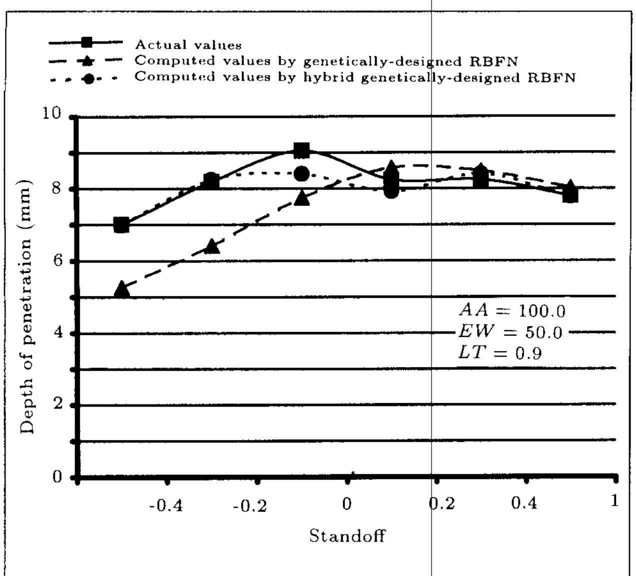

Figure 7. Effect of standoff on penetration: Comparison of experimental and trained RBFN computation results.

it is evident that the performance of such an RBFN model, obtained using the hybrid method, has been highly improved. These two different trained models (genetically-designed RBFNs and hybrid, genetically-designed RBFNs) have also been used for the computation of the depth of penetration versus liner thickness for different explosive charges. The results obtained for explosive charges of 50 g, 150 g, and 250 are shown in Figures 8 to 10, respectively.

Similarly, it is clearly evident that the performance of the hybrid genetically-designed RBFN is superior to that of the genetically-designed RBFN.

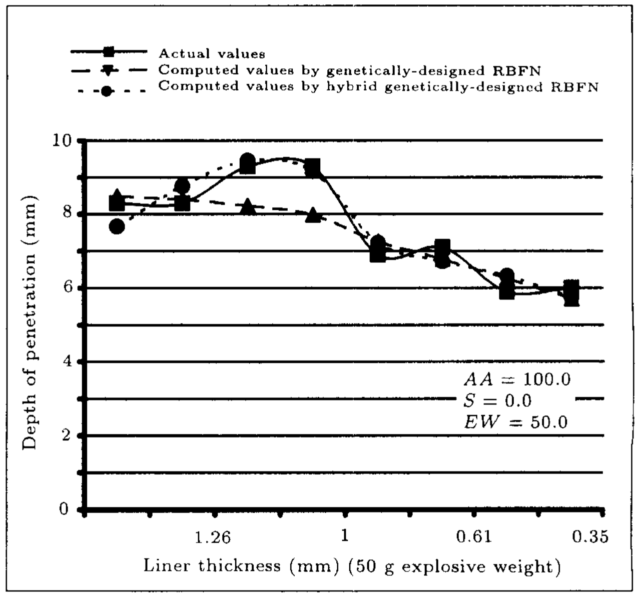

Figure 8. Effect of liner thickness on penetration (50 g explosive weight): Comparison of experimental and trained RBFN computation results.

Finally, the influence of charge mass on the depth of penetration is shown in Figure 11 using both methods.

It should be noted that such behavior, with respect to different input, is obtained using 43 4-input-single-output data employing two genetic and hybrid genetic optimization methods. Thus, it should be considered that there is only one model in each case, obtained using either a genetic algorithm or a hybrid genetic algorithm, which can be utilized to compute the output (DP) subjected to the different values of input $(AA, S, LT$ and $EW)$. In summary, Figures 12 and 13,

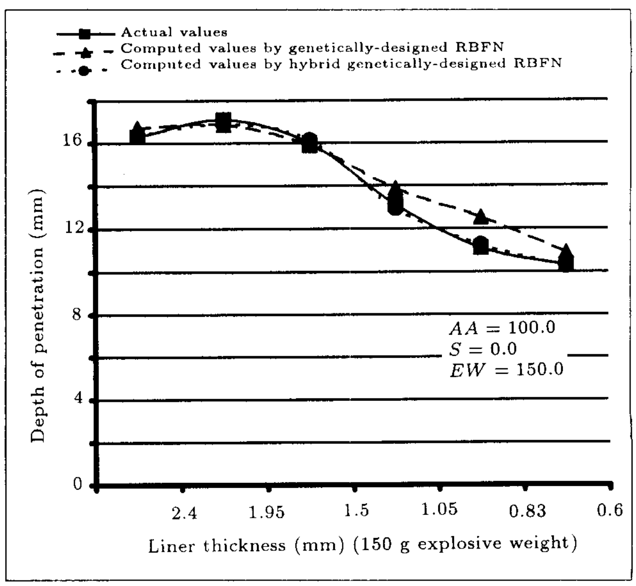

Figure 9. Effect of liner thickness on penetration (150 g explosive weight): Comparison of experimental and trained RBFN computation results.

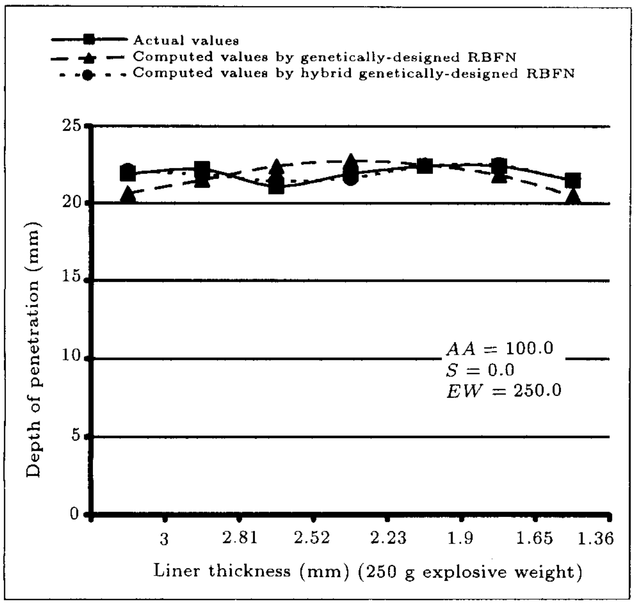

Figure 10. Effect of liner thickness on penetration (250 g explosive weight): Comparison of experimental and trained RBFN computation results.

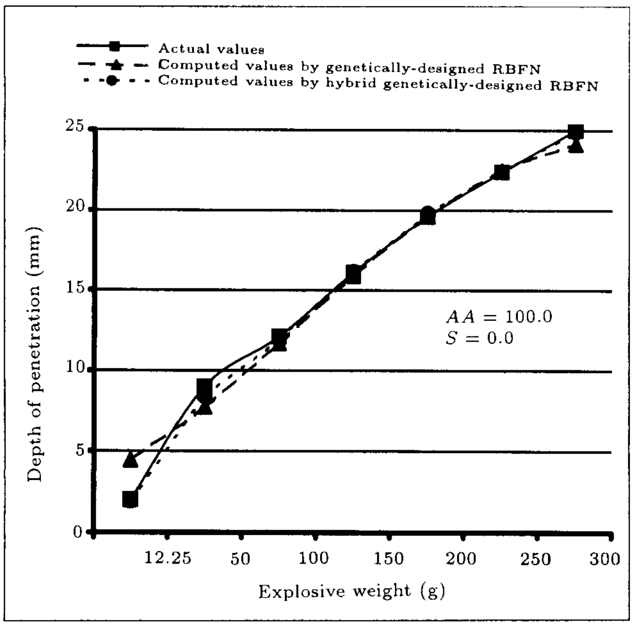

Figure 11. Effect of explosive weight on penetration: Comparison of experimental and trained RBFN computation results.

which have been obtained by joining all the previous figures, present such modeling behavior for these 43 four-input-single-output training data, comparing the actual values taken from experimental observations with those obtained by using RBFN models evolved by simple or hybrid genetic algorithm.

However, in order to demonstrate the prediction ability of such RBFNs, the data have been divided into two different sets, namely, training and testing sets. The training set, which consists of 30 out of

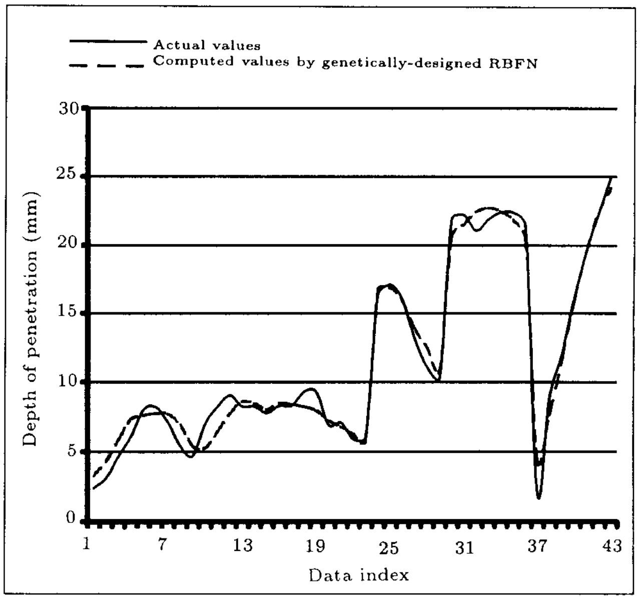

Figure 12. Variation of penetration with data samples: Comparison of experimental and genetically-trained RBFN computation results.

43 inputs-output data pairs, is used for training the RBFN models, using both a simple and a hybrid genetic algorithm. The testing set, which consists of 13 unforeseen inputs-output data samples during the training process, is merely used for testing to show the prediction ability of such evolved RBFN models during the training process. It is clearly evident, from Figures 14 and 15, that both evolved RBFN using simple and hybrid genetic algorithms, can successfully predict the output (DP) of testing data which has not been used during the training process. Moreover, it is again

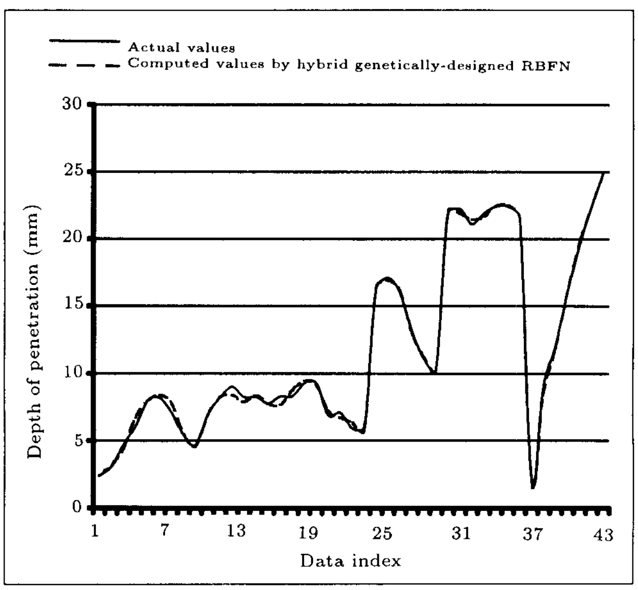

Figure 13. Variation of penetration with data samples: Comparison of experimental and hybrid-genetically-trained RBFN computation results.

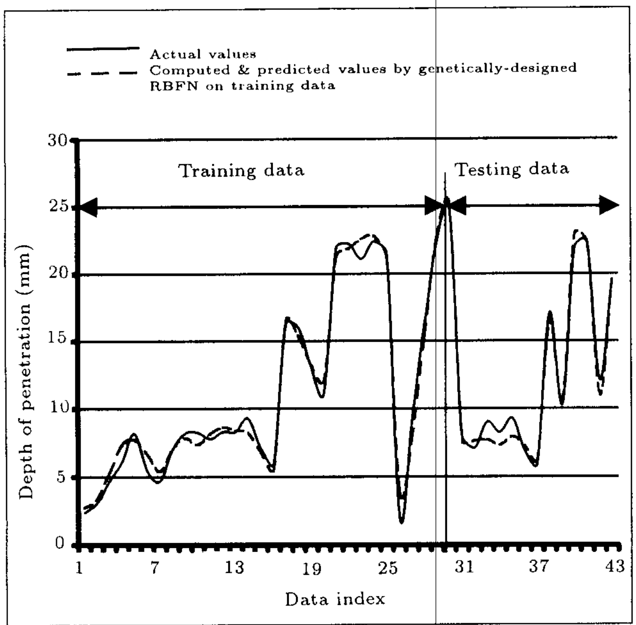

Figure 14. Variation of penetration with data samples: Comparison of experimental and genetically-trained RBFN computation and prediction results.

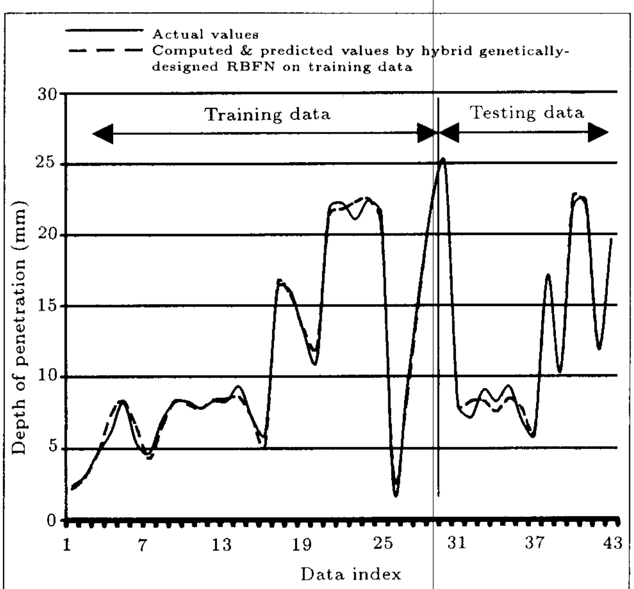

Figure 15. Variation of penetration with data samples: Comparison of experimental and hybrid-genetically-trained RBFN computation and prediction results.

demonstrated that the hybrid genetic algorithm is more effective in the learning process of RBFNs than a simple GA.

CONCLUSION

Radial basis function networks (RBFNs) have been successfully used for the modeling of the very complex process of the explosive cutting of plates by shaped charges. In this way, it has been shown that genetic algorithms provide effective means of optimally designing such RBFNs, in order to predict the depth of penetration according to different input. This has been achieved by dividing the whole data into two different sets, namely, training and testing sets. The training set has been used for learning the parameters of RBFNs, whilst the testing set has only been used to demonstrate the prediction ability of such evolved networks, either by a simple or a hybrid genetic algorithm. Moreover, it has been also shown that the use of a hybrid genetic algorithm for the design of RBFNs to model such a cutting process, is more effective than the use of a simple GA. In particular, Powell's method, as a non-derivative based technique, can be readily augmented into a genetic algorithm to enhance the behavior of the modeling of the complex, multi-input single-output explosive cutting process of plates. Such numerical model can be further used for optimal determination of the values of inputs provided an appropriate objective function is defined. Moreover, the results indicate that the standoff distance has an appreciable effect on penetration and, in fact, an optimum standoff is found to exist. Besides, the depth of penetration was also found to be affected by the apex angle, for which an optimum value was found too.

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