Achievements in Mechanical and Materials Engineering

COMMENT Worldwide Congress on Materials and Manufacturing Engineering and Technology

16th - 19th May 2005
Gliwice-Wisła, Poland

COMMITTEE OF MATERIALS SCIENCE OF THE POLISH ACADEMY OF SCIENCES, KATOWICE, POLAND
INSTITUTE OF ENGINEERING MATERIALS AND BIOMATERIALS OF THE SILESIAN UNIVERSITY OF TECHNOLOGY, GLIWICE, POLAND
ASSOCIATION OF THE ALUMNI OF THE SILESIAN UNIVERSITY OF TECHNOLOGY, MATERIALS ENGINEERING CIRCLE, GLIWICE, POLAND

13th INTERNATIONAL SCIENTIFIC CONFERENCE ON ACHIEVEMENTS IN MECHANICAL AND MATERIALS ENGINEERING

Evolutionary design of generalized polynomial neural networks for modelling and prediction of explosive forming process

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Abstract: Genetic Algorithm (GA) is deployed for optimal design of configuration involved in GMDH-type neural networks which is used for modelling of centre deflection, hoop strain and thickness strain of explosive forming process. In this way, a new encoding scheme is presented to genetically design the generalized GMDH-type neural networks in which the connectivity configuration in such networks is not limited to adjacent layers.

Keywords: Group Method of Data Handling (GMDH), Explosive forming, GAs.

1. INTRODUCTION

Explosive forming has been mostly used to form large and bulky components typically for military applications. Jet engine shroud was manufactured by Ryan aeronautical company by explosive forming [1]. Rohr Corp used this process to make gas turbine shroud, which involved a combination of stretch and draw forming [2]. Explosive forming allowed manufacture of many unique tabular shapes, composite tubes, nozzles and other space age components [3]. In addition explosive forming has also been used for tube plugging, tube expansion, replacements of tube ends, and forming components from welded performs [3].

System identification techniques are applied in many fields in order to model and predict the behaviours of unknown and/or very complex systems based on given input-output data [4]. Theoretically, in order to model a system, it is required to understand the explicit mathematical input-output relationship precisely. Such explicit mathematical modelling is, however, very difficult and is not readily tractable in poorly understood systems. GMDH algorithm is self-organizing approach by which gradually complicated models are generated based on the evaluation of their performances on a set of multi-input-single-output data pairs (X_i, y_i) $(i=1, 2, \ldots, M)$. The main idea of GMDH is to build an analytical function in a feedforward network based on a quadratic node transfer function [4] whose coefficients are obtained using regression technique.

Recently, genetic algorithms have been used in a feedforward GMDH-type neural network for each neuron searching its optimal set of connection with the preceding layer [5, 6]. In the

[6], authors have proposed a hybrid use of genetic algorithm for a simplified structure GMDH-type neural network in which the connections of neurons are restricted to adjacent layers.

In this paper, it is shown that GMDH-type neural network can effectively model and predict the centre deflection, hoop strain and thickness strain, each as a function of important input parameters in explosive forming process. In this way, genetic algorithms are deployed in a new approach to design the whole architecture of the GMDH-type neural networks, i.e., the number of neurons in each hidden layer and their connectivity configuration.

2. MODELLING USING GMDH-TYPE NEURAL NNETWORKS

The formal definition of the identification problem is to find a function $\hat{f}$ so that can be approximately used instead of actual one, f in order to predict output $\hat{y}$ for a given input vector $X = (x_1, x_2, x_3, \ldots, x_n)$ as close as possible to its actual output y. Therefore, given M observation of multi-input-single-output data pairs so that

$$y_i = f(x_{i1}, x_{i2}, x_{i3}, \ldots, x_{in}) \quad (i=1,2,\ldots,M), \tag{1}$$

It is now possible to train a GMDH-type neural network to predict the output values $\hat{y}_i$ for any given input vector $X = (x_{i1}, x_{i2}, x_{i3}, \ldots, x_{in})$, that is

$$\hat{y}_i = \hat{f}(x_{i1}, x_{i2}, x_{i3}, \ldots, x_{in}) \quad (i=1,2,\ldots,M). \tag{2}$$

The problem is now to determine a GMDH-type neural network so that the square of difference between the actual output and the predicted one is minimised, that is

$$\sum_{i=1}^{M} [\hat{f}(x_{i1}, x_{i2}, x_{i3}, \ldots, x_{in}) - y_i]^2 \to \min \,. \tag{3}$$

General connection between inputs and output variables can be expressed by a complicated discrete form of the Volterra functional series in the form of

$$y = a_0 + \sum_{i=1}^{n} a_i x_i + \sum_{i=1}^{n}\sum_{j=1}^{n} a_{ij} x_i x_j + \sum_{i=1}^{n}\sum_{j=1}^{n}\sum_{k=1}^{n} a_{ijk} x_i x_j x_k + \ldots \tag{4}$$

which is known as the Kolmogorov-Gabor polynomial [4, 7]. This full form of mathematical description can be represented by a system of partial quadratic polynomials consisting of only two variables (neurons) in the form of

$$\hat{y} = G(x_i, x_j) = a_0 + a_1 x_i + a_2 x_j + a_3 x_i x_j + a_4 x_i^2 + a_5 x_j^2 \,. \tag{5}$$

The coefficient a_i in equation (5) are calculated using regression techniques [4, 7, 8] so that the difference between actual output, y, and the calculated one, $\hat{y}$, for each pair of x_i, x_j, as input variables is minimized. In this way, the coefficients of each quadratic function $G_j$are obtained to optimally fit the output in the whole set of input-output data pair, that is

$$E = \frac{\sum_{i=1}^{M} (y_i - G_i())^2}{M} \to \min \tag{6}$$

The application of least-squares methods and SVD techniques for multi-regression analysis to find the coefficient embodied in equation (5) in order to minimize equation (6) has been thoroughly given in [6].

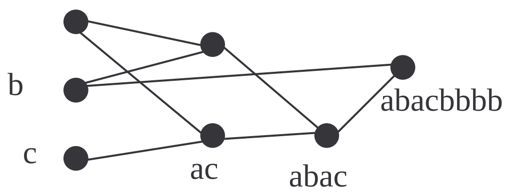
3. THE GENOME REPRESENTATION OF GS-GMDH NEURAL NETWORKS

In the General Structural GMDH (GS-GMDH) neural networks, neurons connections can occur between different layers which are not necessarily very adjacent ones, unlike the CS-GMDH neural networks in which such connections only occur between adjacent layers. For example, a network structure which depicted in figure (1) shows such connection of neuron *b* directly to the output layer. Using the same procedure of defining a chromosome described in the [6], it can now be readily modified to include GS-GMDH networks. This is accomplished by repeating the name of the neuron which directly passing the next layers. In figure (1), neuron *b* in the input layer is connected to the output layer by directly going through the first and second hidden layer. Therefore, it is now very easy to notice that the name of output neuron (network's output) includes *b* twice as *abacbbbb*. In other words, a virtual neuron named *bbbb* has been constructed in the second hidden layer and used with *abbc* in the same layer to make the output neuron *abbcbbbb* as shown in the figure (1). It should be noted that such repetition occurs whenever a neuron passes some adjacent hidden layers and connects to another neuron in the next 2^{nd}, or 3^{rd},or 4^{th},or … following hidden layer. In this encoding scheme, the number of repetition of that neuron depends on the number of passed hidden layers, ñ, and is calculated as $2^{\tilde{n}}$.

The incorporation of genetic algorithm into the design of such GMDH-type neural networks starts by representing each network as a string of concatenated sub-strings of alphabetical digits. The fitness, (Φ), of each entire string of symbolic digits which represents a GMDH-type neural network to model explosive cutting process is evaluated in the form:

$$\Phi = 1/E \tag{7}$$

where *E*, is the mean square of error given by equation (6), is minimized through the evolutionary process by maximizing the fitness Φ.



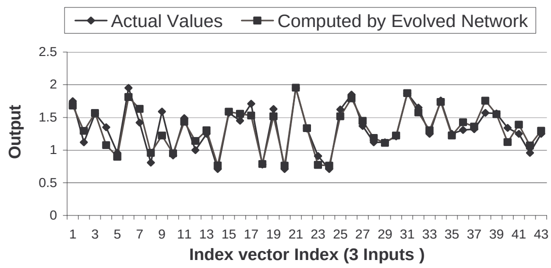


Figure 2. Variation of centre deflection with input data

4. GMDH-TYPE NEURAL NETWORK MODELLING OF EXPLOSIVE FORMING

The parameters of interest in this multi-input single-output system that affect the centre deflection are dynamic yield stress, thickness and charge mass. There has been a total number of 43 input-output experimental data considering 3 input parameters, namely, dynamic yield stress, thickness and charge mass that are given in [9]. The structure of the evolved 2-hidden layer GMDH-type neural network is shown in figure (1) corresponding to the genomes representation of ***abacbbbb*** , in which ***a, b and c*** stand for dynamic yield stress, thickness, and charge mass, respectively. The very good behaviour of such GMDH-type neural network model is also depicted in figure (2).

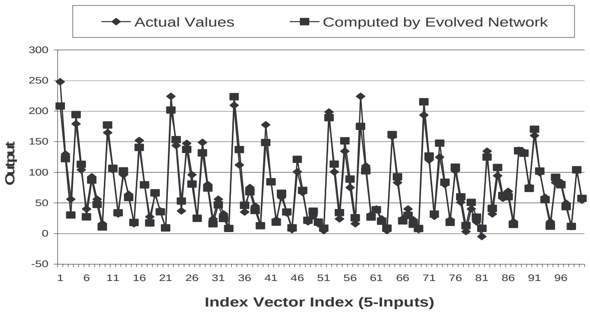


Figure 4. Variation of hoop strain with input data

The centre deflection is then used as an input for modelling of hoop strain and thickness strain in addition to the other important parameters. Such parameters of interest in this multi-input single-output system that affect the hoop strain and thickness strain are dynamic yield stress, thickness, charge mass, centre deflection and distance from centre. There has been a total number of 100 input-output experimental data for hoop strain and thickness strain is given in [9]. The very good behaviour of such GMDH-type neural network models are also depicted in fig. (3) and (4).

5. CONCLUSION

Evolutionary methods for designing generalized GMDH-type networks have been proposed and successfully used for the modelling of the complex process of explosive forming. In this way, it has been shown that GMDH-type networks provide effective means to model the centre deflection, hoop strain and thickness strain. In this way, a new encoding scheme has been presented to genetically design GS-GMDH in which the connectivity configuration in such networks is not limited to adjacent layers, unlike the conventional GMDH-type neural networks. Such generalization of network's topology provides optimal networks in terms of hidden layers and/or number of neurons and their connectivity.

REFRENCES

1. L. Zernow, “Applications of High Velocity Metal Forming (HVMF) in Short Run Production”, Creative Manufacturing Seminars, No. SP62-67, 1962, American Society of Tool and Manufacturing Engineers, Detroit, MI.
2. Michaeal C. Noland, “Designing For the High Velocity Metalworking Process”, Machine Design, Vol.39, aug. 17, 1967, pp. 163-182
3. Paul C. Miller, “HERF Update: High Energy Rate Forming Joins the Productivity Race”, Tooling & Production, Vol. 47, No.7, Oct. 1981, pp. 90-97
4. Farlow, S.J., ed., “Self-organizing Method in Modelling: GMDH type algorithm”, Marcel Dekker Inc., (1984)
5. Yao, X., Evolving Artificial Neural Networks, Proceedings of IEEE, 87(9):1423-1447, Sept., (1999)
6. Nariman-Zadeh, N., Darvizeh, A., Ahmad-Zadeh, R., “Hybrid Genetic Design of GMDH-Type Neural Networks Using Singular Value Decomposition for Modelling and Prediction of the Explosive Cutting Process”, Proceedings of the I MECH E Part B Journal of Engineering Manufacture, Volume: 217, Page: 779 – 790, (2003)
7. Ivakhnenko, A.G., “Polynomial Theory of Complex Systems”, IEEE Trans. Syst. Man & Cybern, SMC-1, 364-378, (1971)
8. Mueller J.-A. and Lemke, F., “Self-Organising Data Mining: An Intelligent Approach to Extract Knowledge from Data”, Pub. Libri, Hamburg, (2000)
9. Gharababei, H., "Modelling of explosive process with GMDH", MSc thesis (in Persian), The University of Guilan, Rasht, Iran