Journal of Engineering Science and Technology
Vol. 11, No. 9 (2016) 1311 - 1320

EXPERIMENTAL STUDY AND MODELLING OF DEFORMATION OF RECTANGULAR PLATES SUBJECTED TO HYDRODYNAMIC LOADING USING NEURAL NETWORK

HASHEM BABAEI[1,]*, TOHID MIRZABABAIE MOSTOFI[1], MAJID ALITAVOLI[1], ASGHAR SAEIDINEJAD[2]

[1]Department of Mechanical Engineering, Faculty of Engineering, University of Guilan, Rasht, Iran
[2]Department of Mechanical Engineering, University of Guilan, Campus 2, Rasht, Iran
*Corresponding Author: ghbabaei@guilan.ac.ir

Abstract

In this paper, experimental responses of fully clamped aluminium and steel rectangular plates are presented subjected to hydrodynamic loading. The GMDH-type neural networks (Group Method of Data Handling) are then used for the modelling of the mid-point deflection thickness ratio of the rectangular plates using the experimental results. The purpose of this modelling is to display how the variations of the significant parameters changes with the mid-point deflection. In addition, the results indicate that dimensionless input variables provide simpler polynomial expressions in comparison with actual physical parameters. It should be mentioned that, for validation of presented model, the yielded results of modelling are contrasted with experimental results. This comparison demonstrates that the results of modelling have satisfying compatibility with experimental results. In general, regarding the presented model, 80% of data are in the reliable range. Hence, utilizing the mentioned equations for modelling of the mid-point deflection of rectangular plates is appropriate.

Keywords: Neural network; Rectangular plate; Hydrodynamic load; Deformation

1. Introduction

High and low rate metal shaping procedures were justly applicable expanded. This materiel had several benefits over regular metal shaping. These consist the capability to use single-sided dies, decreased spring back, and recovered formability [1]. One of the fundamental difficulties widely analysed has been that of a metalliferous rectangular and circular plate fully clamped around its external boundary subjected to transverse impulsive loads.

Nomenclatures

A	Plate area, m^2
C_W	Velocity of sound in water, ms^{-1}
E	Elasticity modulus of plate, $kgm^{-1}s^{-2}$
g	Acceleration of gravity, ms^{-2}
H	Standoff distance of hammer, m
h	Plate thickness, m
m	Hammer weight, kg
V_0	Velocity of dropping, ms^{-1}
W_0	Deflection, m

Greek Symbols

π	Dimensionless parameters
ρ	Material density, kgm^{-3}
σ_y	Static yield stress, $kgm^{-1}s^{-2}$

Abbreviations

GMDH	Group Method of Data Handling

There have been multitude investigation endeavours for theoretical modelling the dynamic and static response and deflection of thin circular and rectangular plates to predict the communication of deflection-thickness ratio as a function of the amount of plate dimension, plate material, impulse, and plate geometry [2].

In recent years, one of the topics of interest to researchers is forming of plates by liquid shock waves. More safety and higher control are benefits of this type of forming [3, 4]. For low and high rate forming, they used drop hammer and shock tube system, respectively. Cirak et al. [4] investigated large plastic deformation of fully clamped circular plates subjected to shocks and detonations by using drop hammer. Also they presented a robust level set based method that integrates a Lagrangian thin shell finite element solver with fragmentation abilities and fracture and an Eulerian Cartesian fluid solver with optional dynamic mesh adaptation. Another research done in this field is Kosing et al. [3] investigation by shock tube system. They predicted the mid-point deflection of the specimens by a theoretical method based on energy approach. So, the predicted mid-point deflections display a good agreement with the experimental results. High speed camera is used to interrogation of deformation process of the ferrous and non-ferrous plates during impact of the liquid shock wave.

System recognition and modelling of procedures using input-output data have ever absorbed multitude investigation endeavours. In point of fact, system recognition materiel is used in multitude fields in order to predict and model the behaviours of unfamiliar and very intricate systems based on given input-output data [5]. Theoretically, for modelling a system, it is needed to realize the explicit mathematical input-output communication exactly. Such explicit mathematical modelling is so hard and is not readily soft in weakly understood systems. Alternatively, soft calculating manners [6, 7], which concern calculation in indefinite surroundings, have reached important consideration. The principal parts of soft calculating, namely, neural network, genetic algorithm and fuzzy-logic have displayed big capability in solving intricate non-linear system recognition and control difficulties. Some investigation endeavours have been developed to use evolutionary manners as efficient tools for system recognition [8-10]. Among these approaches, the GMDH algorithm is self-organizing method by which gently more 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, …, M). In recent years, the application of such self-organizing network results successful usage of the GMDH type algorithm in a wide range area in science, economics and engineering [11].

In this paper, experimental data are used to discover an equation for predicting deflection-thickness ratio using GMDH-type neural network. In this way, input variables are regrouped as dimensionless parameters which are then used to gain the equation of deflection-thickness ratio of fully clamped rectangular plates under hydrodynamic loading.

2. Experimental Tests

The test samples were 310 mm × 260 mm and the thickness of them are changed from 1.0 mm to 3.0 mm. Before being used in impact loading condition, plate samples were not subjected to heat treatment. The samples were clamped in a case, comprising of two (310 mm×260 mm) cases made from 20 mm thick steel plating. The front clamp is connected to water tank (150 mm×200 mm×50 mm) and a vertical cylinder that has length of 0.5 m. The cylinder includes of a stainless steel tube with an internal diameter of 80 mm and an external diameter of 104 mm. The inside of the tube is honed smooth. The experimental arrangement is shown in Fig. 1.

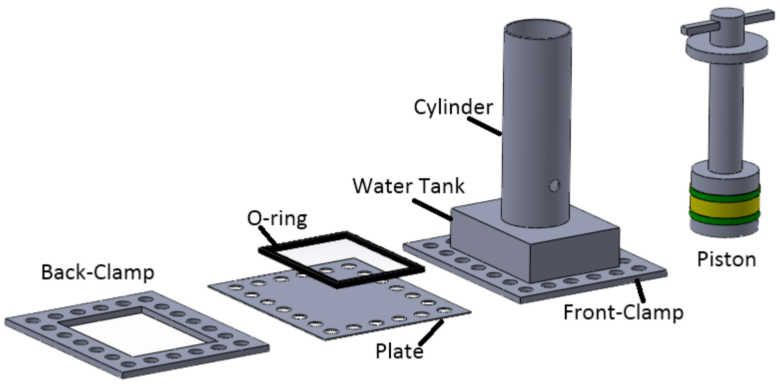

Fig. 1. Experimental test accessories for hydrodynamic forming.

For the low speed metalliferous and non metalliferous shaping in a liquid shock tube, the potential energy of drop-weight testing system is used. After dropping of a hammer with weight of 70.4 kg, the potential energy stored is transformed into kinetic energy of hammer and after incidence hammer to piston, piston rapidly moving and caused to compressed water and then the high-pressure leads to deformation of plate. Photograph and schematic corresponding to experimental set-up are given in Fig. 2.

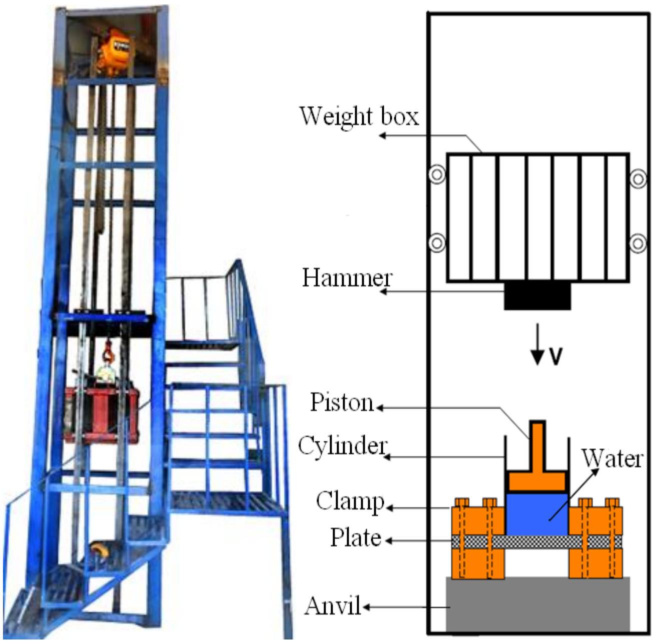

Fig. 2. Photograph and Schematic of experimental arrangement.

2.1. Mechanical properties

Uniaxial tension test samples were provided from aluminium alloy 1100 and steel (St1300) with various thicknesses. To consist the consequence of anisotropy on the quantities of static yield stress, from each sheet there samples were cut in transverse, longitudinal and diagonal directions. The results of uniaxial tension test on samples cut longitudinally display no important difference of those cut transversely and diagonal. The mean average quantities of static yield stress and ultimate tensile stress are computed for different material with various thicknesses. The properties of the various plate materials are summarized in Table 1.

Table 1. Summary of uniaxial tension test results on aluminium and steel.

Material	Thickness of plate (mm)	Mean average static yield stress (MPa)	Mean average ultimate stress (MPa)
Steel	1.0, 2.0, 3.0	289.2	474.5
Aluminium	1.0, 2.0	126.7	152.3

2.2. Experimental results

For the first set of tests, stand-off distance of hammer was held variation from 1.5m to 2.8m for steel plates and 0.15m to 0.7m for aluminium plates. For different material and thickness, the effect of stand-off distance of hammer or the transferred energy was investigated. Results of experimental test are given in Table 2.

Table 2. Results of experimental test under hydrodynamic loading.

Test No.	Material	Thickness of plate (mm)	Stand-off distance of hammer (cm)	Energy (J)	Mid-Point deflection (mm)
1-HB-TMM	St-1300	3	280	1934	22.05
2-HB-TMM	St-1300	2	250	1727	23.98
3-HB-TMM	St-1300	1	250	1727	35.6
4-HB-TMM	St-1300	3	250	1727	20.27
5-HB-TMM	St-1300	3	200	1381	18.13
6-HB-TMM	St-1300	2	200	1381	22.47
7-HB-TMM	St-1300	1	200	1381	31.06
8-HB-TMM	St-1300	3	225	1554	19.42
9-HB-TMM	St-1300	2	225	154	23.68
10-HB-TMM	St-1300	1	225	1554	33.85
11-HB-TMM	St-1300	3	170	1174	15.06
12-HB-TMM	St-1300	2	170	1174	18.2
13-HB-TMM	St-1300	1	170	1174	28.97
14-HB-TMM	St-1300	2	150	1036	18.1
15-HB-TMM	St-1300	1	150	1036	26.81
16-HB-TMM	Al-1100	1	40	276	26.01
17-HB-TMM	Al-1100	2	40	276	14.1
18-HB-TMM	Al-1100	2	50	345	17.01
19-HB-TMM	Al-1100	1	35	242	24.41
20-HB-TMM	Al-1100	2	70	483	22.77
21-HB-TMM	Al-1100	1	25	173	21.77
22-HB-TMM	Al-1100	2	60	414	18.68
23-HB-TMM	Al-1100	1	15	104	14.12
24-HB-TMM	Al-1100	2	30	207	10.7
25-HB-TMM	Al-1100	1	20	138	17.49

By comparing the deformed plate profiles tested at higher stand-off distance of hammer was seen to be more dome than those plates tested at lower stand-off distance. The effect of the hydrodynamic pressure on the central portion of the plate will become more and more larger, relative to the distance of outer edges and more and more, smaller to the angle of incident between the hydrodynamic pressure and the plate at the outer edges. Photograph corresponding to deformed plate are given in Fig. 3.

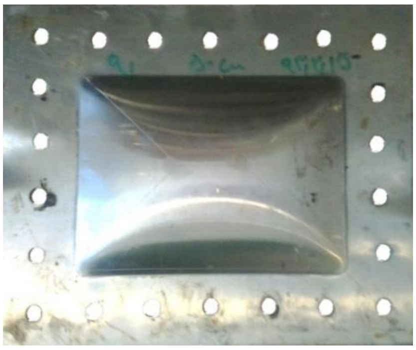

Fig. 3. Photographs of aluminium alloy plate.

The diagram of mid-point deflection versus transferred energy for aluminium and steel plates is shown in Fig. 4. In this figure, effect of thickness is consisted. By increasing transferred energy, the mid-point deflection increases for each material and plate thickness.

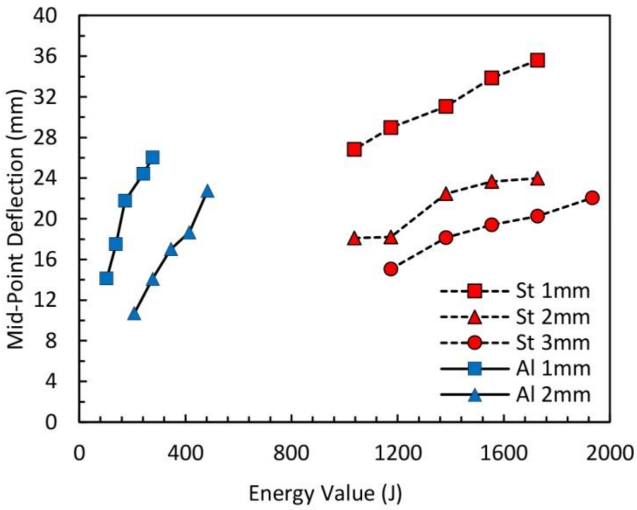

Fig. 4. Measured mid-point deflection versus energy.

3. GMDH-Type neural network modelling of deformation of rectangular plates

The classical GMDH-type neural network modelling can be used for a set of dimensionless parameters based on experimental input-output data in a series of hydrodynamic forming tests given in Table 2. More detail of GMDH-Type Neural Network Modelling has been reported in references [12-14].

Accordingly, a dimensionless set of inputs-output variables used to train the GMDH-type neural network, $\Pi=\{\pi_1,\pi_2,\pi_3,\pi_4,\ldots\pi_k\}$, instead of the set of real physical variables {y, X} ={y, x_1, x_2, x_3... x_n}. Therefore, given M seeing of single output-multi input data pairs that have been transformed to the tantamount dimensionless parameters [13, 14].

So that in Eq. (1) for $i=1,2,3,\ldots,M$:

$$\pi_{1i}=f\left(\pi_{2i},\pi_{3i},\pi_{4i},\ldots,\pi_{ki}\right) \tag{1}$$

Now it is feasible to train a GMDH-type neural network to predict the output quantities $\hat{\pi}_{1i}$ for any given input vector $\left(\pi_{2i},\pi_{3i},\pi_{4i},\ldots\pi_{ki}\right)$, which is in Eq. (2).

$$\hat{\pi}_{1i}=\hat{f}\left(\pi_{2i},\pi_{3i},\pi_{4i},\ldots,\pi_{ki}\right) \tag{2}$$

Now determining a GMDH-type neural network is a problem, so that by minimising the square of difference between the predicted dimensionless output and the actual one, that is in Eq. (3).

$$\sum_{i=1}^{M}\left[\hat{f}\left(\pi_{2i},\pi_{3i},\pi_{4i},\ldots,\pi_{ki}\right)-\hat{\pi}_{1i}\right]^2 \to \min \tag{3}$$

Again, in Eq. (4), the quadratic form of only two variables is used in the form [10] to predict the output π_1 .

$$\hat{\pi}_1 = G\left(\pi_i,\pi_j\right) = a_0 + a_1\pi_i + a_2\pi_j + a_3\pi_i\pi_j + a_4\pi_i^{\,2} + a_5\pi_j^{\,2} \tag{4}$$

In the basic form of the GMDH algorithm, all the possibilities of two independent variables out of total n input variables are taken in order to construct the regression polynomial in the form of Eq. (4).However, for most applications the quadratic form of only two variables is used in the form Eq. (4). Quadratic polynomial in structure of GMDH neural network is optimal selection and it provides a nonlinear mapping between and input and output variables.

The coefficients a_i in Eq. (4) are calculated using regression techniques, so that the difference between actual output π , and the calculated one $\hat{\pi}$, for each pair of π_i,π_j as input variables is minimized. Indeed, it can be seen that a tree of polynomials is constructed using the quadratic form given in Eq. (4), whose coefficients are obtained in a least-squares sense. In this way, the coefficients of each quadratic function G_i are obtained to optimally fit the output in the whole set of input-output data pair, that is

$$r^2 = \frac{\sum_{i=1}^{M}\left(\pi_i - G_i\right)^2}{\sum_{i=1}^{M}\pi_i^{\,2}} \to \min \tag{5}$$

In order to create such independent dimensionless parameters for modelling of deflection W_0 of the fully clamped rectangular plates under hydrodynamic loading, standoff distance of hammer *H* (m), plate thickness *h* (m), hammer weight *m* (kg), plate area *A* (m^2), material density ρ (kg/m^3), elasticity modulus of plate *E* (Pa), static yield stress σ_y (Pa) and velocity of sound in water C_w (ms^{-1}) have been taken into counting.

From this set of input-output parameters, 4 independent dimensionless parameters have been created [15] according to 3 main dimensions (M, L, T) in Eqs. (6)-(9), as follows

$$\pi_1 = \frac{W_0}{h} \tag{6}$$

$$\pi_2 = \frac{H}{h} \tag{7}$$

$$\pi_3 = \frac{mV_0}{Ah\sqrt{\sigma_y\rho}} \tag{8}$$

$$\pi_4 = \frac{E\sqrt{gH}}{\sigma_y C_w} \tag{9}$$

So that in Eq. (10)

$$\pi_1 = f\left(\pi_2, \pi_3, \pi_4\right) \tag{10}$$

It should be noted that the simplest possible dimensionless parameters have been considered according to the involved physical parameters.

In GMDH algorithm, the structures of layers together with neurons' connections are evolved simultaneously with optimum selection of the appropriate coefficients in quadratic polynomials based on "Pre-specified-Network Approach" selection criterion.

In "Pre-specified-Network Approach" approach, number of layers in the network is pre-specified as well as the number of neurons in each of these layers. The main steps of this approach are described as follows:

Step 1: Consider $N_1 = n$ neurons in the first layer from the vector of input variables $\mathrm{Vec\_of\_Var} = \left\{\pi_1, \pi_2, \pi_3, \pi_4, \ldots \pi_n\right\}$, where n is the number of inputs. Set $k = 1$ and $\mathrm{Number-of-Layers} = N_1$.

Step 2: Construct $N'_K = \dfrac{N_K\left(N_K - 1\right)}{2}$ neurons according to all possibilities of connection by each pair of neurons in the layer. This can be achieved by forming the quadratic expression $G\left(\pi_i, \pi_j\right)$ which approximates the output π in Eq. (4) with least-squares errors of Eq. (5) by solving the coefficients.

Step 3: Select the best pre-specified $N_K + 1$ neurons out of these neurons N'_K according to their values of r^2.

Step 4: If $\left(k + 1 \neq N_1\right)$ Then Set $k = k + 1$; $N_k = N_{k-1}$; goto 2. Otherwise END.

It should be noted that only one neuron is selected in the last layer.

For modelling, based on results of experimental tests that are given in Table 2, the single output-multi input set of created dimensionless data according to Eqs. (6) to (9). Figure 5 shows the behaviour of the mid-point deflection thickness ratio, using GMDH-type network model. It is evident from Fig. 5 that the confidence envelope for obtained model is reported as 80% for ±1 displacement–thickness ratio. The structures of GMDH-type network are displayed in Fig. 6. As a result, now it is possible to show the gained polynomial equations for mid-point deflection thickness ratio based on the construction of the GMDH-type neural network displayed in Fig. 6, as follows Eqs. (11)-(14):

$$S = -9.314 + 2420\pi_3 + 0.7058\pi_4 + 45020\pi_3^{\,2} + 0.3456\pi_4^{\,2} + 443\pi_3\pi_4 \tag{11}$$

$$P = 0.09901 + 0.00288\pi_2 + 0.8978S + 0.0000005508\pi_2^{\,2} - 0.002757S^2 + 0.0003674\pi_2 S \tag{12}$$

$$X = 4.895 + 7.777S - 7.519P + 7.176S^2 + 7.449P^2 - 14.613SP \tag{13}$$

$$\pi_1 = -2.8 + 3.95\pi_4 + 1.048S - 1.074\pi_4^{\,2} + 0.00195X^2 - 0.0656X\pi_4 \tag{14}$$

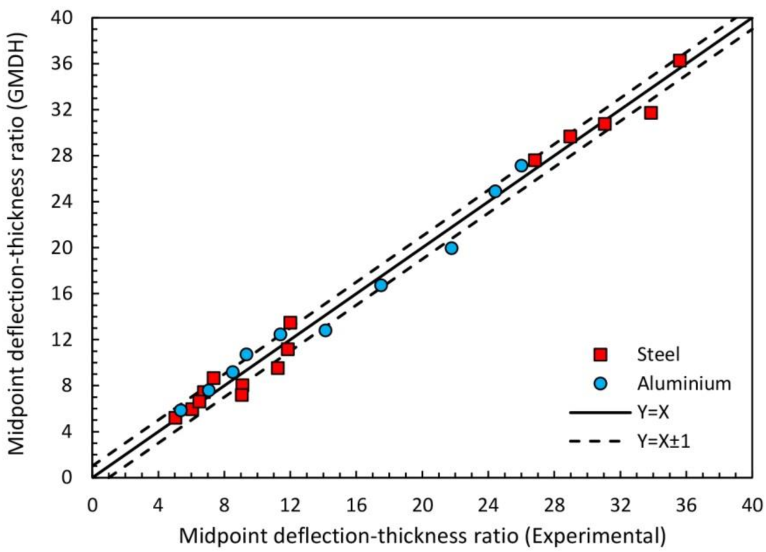

Fig. 5. Comparison of experimental quantities with computed quantities by GMDH-type network.

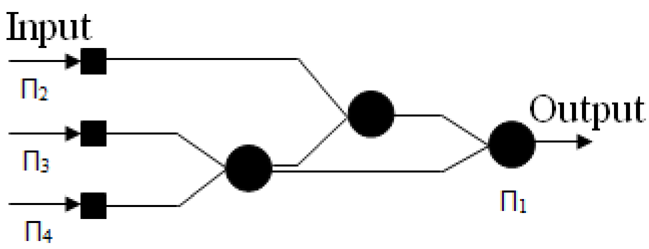

Fig. 6. GMDH-type network for mid-point deflection thickness ratio.

4. Conclusions

In this paper the experimental results show the behaviour of steel and aluminium plates subjected to hydrodynamic loading. Using drop hammer system in experimental section is the novelty of this paper. It should be noted that the process of plastic deformation of plates by drop hammer is inexpensive, low risk and very simple but the quality of deformed plates is as high rate metal forming with this difference that in low rate forming, hydrodynamic pressure causes domical and totally uniform deformation.

The results can prepare a model between applied hydrodynamic load and mid-point deflections. The method for designed GMDH-type networks, used successfully for the modelling of the process parameters of the very intricate process of deformation of rectangular plates subjected to hydrodynamic loading. In this way, it has been shown that GMDH-type networks provide effective means to model mid-point deflection thickness ratio according to different inputs.

References

1. Gerdooei, M.; and Dariani, B. M. (2008). Strain-rate-dependent forming limit diagrams for sheet metals. *Journal of Engineering Manufacture*, 222(B12), 1651-1659.
2. Jones, N. (1987). Impulsive loading of a simply supported circular rigid-plastic plates, Trans ASME. *Journal of Applied Mechanics*, 3, 59-65.
3. Kosing, O.E.; and Skews, B.W. (1998). An investigation of high-speed forming of circular plates in a liquid shock tube. *International journal of impact engineering*, 21(9), 801-816.
4. Cirak, F.; Deiterding, R.; and Mauch, S. P. (2007). Large-scale fluid–structure interaction simulation of viscoplastic and fracturing thin-shells subjected to shocks and detonations. *Computers & Structures*, 85(11), 1049-1065.
5. Astrom, K.J.; and Eykhoff, P. (1971). System identification, a survey, *Automatica*, 7(2), 123-162.
6. Sanchez, E.; Shibata, T.; and Zadeh, L.A. (1997). *Genetic Algorithms and Fuzzy Logic Systems*, World Scientific.
7. Nariman-Zadeh, N.; and Darvizeh, A. (2001). Design of fuzzy systems for the modelling of explosive cutting process of plates using singular value decomposition. *Journal of Materials Processing Technology*, 128(1), 80-87.
8. Kristinson, K.; and Dumont, G. (1992). System identification and control using genetic algorithms. *Systems, Man and Cybernetics, IEEE Transactions on*, 22(5), 1033-1046.
9. Iba, H.; and Garis, H.; and Sato, T. (1996). A numerical approach to genetic programming for system identification. *Evolutionary Computation*, 3(4), 417-452.
10. Porter, B.; and Nariman-Zadeh, N. (1994). Genetic design of computed-torque controllers for robotic manipulators. *International Symposium on Intelligent Control Proceedings, Monterey, CA, USA*, 165-170.
11. Ivakhnenko, A.G. (1971). Polynomial theory of complex systems. *Systems, Man and Cybernetics, IEEE Transactions on*, SMC-1(4), 364-378.
12. Farlow, S.J. (1984). *Self-organizing method in modelling: GMDH type algorithm*. CrC Press, Marcel Dekker Inc.
13. Darvizeh, A.; and Nariman-Zadeh, N.; and Gharababaei, H. (2001). GMDH-type neural network modelling of explosive cutting process of plates using singular value decomposition. *European Simulation and Modelling*, 43(10), 1383-1397.
14. Nariman-Zadeh, N.; and Darvizeh, A.; and Felezi, M.E; and Gharababaei, H. (2002). Polynomial modeling of explosive compaction process of metallic powders using GMDHType neural network and singular value decomposition. *Materials science engineering*, 10(6), 728-744.
15. Taylor, E.S. (1994). *Dimensional analysis for engineers.* Clarendon Press, Oxford.