Improvement of Surface Roughness in Single Point Incremental Forming Process by the Implementation of Controlled Vibration

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HIGHLIGHTS

- Vibration implementation assists metal forming enhancement surface quality.
- Effect of low frequency vibration on forming force.
- Active damper used to control the vibration.

ARTICLE INFO

ABSTRACT

Vibration implementation that assists metal forming has many advantages, such as enhancement of surface equality, reducing the forming force and decreasing the stresses. The technology of single-point incremental forming with all the above-mentioned advantages has been performed with the vibration. This paper focuses on the average surface roughness (Ra) improvement of the final product by using the vibration. The average roughness was found to be affected by vibration of the sheet metal. The combination of vibration produced a better surface quality of the forming shape by using an active damper to control the vibration. For determining the damping ratio, which gives the necessary roughness, an artificial neural network (ANN) was created based on experimental results. A feed forward neural network with Liebenberg–Marquardt back propagation algorithm was utilized for building the artificial neural network model (3-n-1). Confirmation runs were conducted for verifying the agreement between the predicted results of ANN with those of the experimental outcomes. As a result, the product surface quality is increased where the surface roughness was reduced by (18%) from the surface roughness without vibration. The best reduction rate was in the axial forming force at (100 Hz) frequency, where the reduction rate was about (11.64%) from the force without vibration.

1. Introduction

Recently, sheet metal forming technologies must use cost-effectiveness and customizable procedures to satisfy consumer demands while costs and time are held to a minimum in a competitive setting. As a result, researchers have considered examining operational approaches for producing and developing new materials. The research focuses upon the average surface roughness of formed components on AA2024-O sheets to the investigated process parameters, such as instrument diameter, phase size and spindle speed. A roughness tester was used to assess the surface roughness. With the decrease in tool diameter, average roughness was found to increase [1]. Ajay Kumar et al. studied the influence of process parameters including the diameter, step size, and spindle speed upon the average surface roughness (Ra) of the final product on AA2024-O sheets. A roughness tester was utilized for determining the surface roughness. The average roughness was observed to rise as the tool diameter was reduced. A better surface finish of the final product was resulted from the combination of a smaller step size and a larger tool diameter [2]. Single point incremental forming assisted ultrasonic vibration (UVaSPIF) was set upon the plastic deformation in a sheet-metal plate, which involves the deformation of the metal steadily and locally with a vibrating tool (having a hemispherical head) operated via (CNC) milling machine. The ultrasonic excitation of forming tool decreases the vertical aspect of the energy of forming. Response surface methodology (RSM) technique was used to analyze and optimize surface roughness in UVaSPIF. Experiment design, especially the response surface methodology RSM, is commonly utilized to model and optimize the manufacturing method like powder metallurgy, casting and welding [3]. The ultrasonic vibration influences surface roughness, where the decrease of the spring back and axial force of single point incremental forming (SPIF) were demonstrated by Vahdati et al. [4]. Optimization of surface roughness as well as the thickness of the wall was throughout the incremental forming upon the aluminum alloy (AA5052) at the room temperature via governing the forming parameters influence. The results of forming parameters have been studied using design of experiments. V.Mugendiran [5] investigated

the effects of three input parameters (spindle speed, tool feed, and steps size), as well as surface roughness and wall thickness as output parameters. Suresh Kurra et al. [6] built mathematical models in incremental formation that link surface roughness to different process parameters. Three separate machine learning methods were used for this, including Artificial Neural Networks (ANN), Genetic Programming (GP) and Support Vector Regression (SVR). Finally, the outcomes of these three modeling methodologies were compared. Furthermore, a Genetic Algorithm (GA) was used to refine the procedure for the lowest possible surface roughness. Incorporating the ultrasonic vibration into the gradual sheet formation (ISF) method will minimize the surface roughness in addition to the advantages. The effects of ultrasonic vibration on the surface consistency during the forming process, however, are not well understood. Weidong Zhai et al. [7] stated that ultrasonic vibration improves the surface roughness. Mugendiran et al. [8] optimized the sheet thickness and the surface roughness of ISF using three effecting parameters (tool feed, step size and spindle speed). Shanmuganatan and Senthil Kumar [9] explained the manufacturing mechanism of the sheet metal deforming. At wall angle, surface roughness, and layer thinning were studied. Additionally, a metallurgical analysis and FEM simulation were performed. Amrut Mulay et al. [10] developed artificial neural network pattern to expect responses by taking into account operating parameters such as feed rate, tool diameter, sheet thickness and phase depth. M. Oraon and V. Sharma [11] employed the (ANN) technique for predicting the quality of surface using (6) input parameters, including the depth of step, the speed of spindle, the rate of feed, the thickness of sheet and lubrication. The general approach was compared with the experimental data. For the relationship of vibration with roughness, the suitable vibration leads to a momentary separation of the contacting particles, which in turn reduces friction and leads to the smoothness of the resulting surface. In the present work, low frequency vibration is implemented assisting the single point incremental forming process and controlling of this vibration is by using an active damper and then measuring the roughness of the final product. Artificial neural network (ANN) is used for this purpose.

2. Experimental method

SPIF of AL1050 sheet metal was deformed upon a vertical (CNC) milling machine. Vibration responses with a range of frequencies of (20, 40, 60, 80 and 100) Hz were applied by an unbalanced motor attached to sheet metal plank and by using the active damper for controlling the vibration. Figure 1-a shows the CNC milling machine and the rig mounted on the table of the machine. Figure 1-b shows the rig used to fix the sheet metal and the vibration system (the out-of-balance half disk is connected to the dc motor drive used to give vibration, and the active damper is used to control the vibration and speed control). Load cell types were used to measure the vertical forming force (Fz). A DC motor is rigidly bolted to the blank. The exciting frequency can be adjusted by means of the LM2596 DC to DC step down regulator. Figure 2 shows the dc motor and the speed control unit.
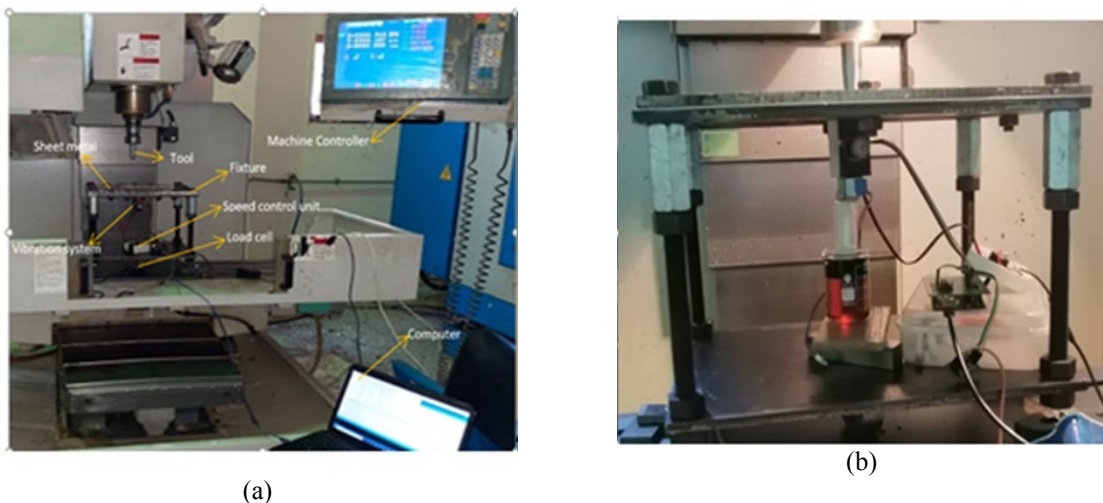

(a)

(b)

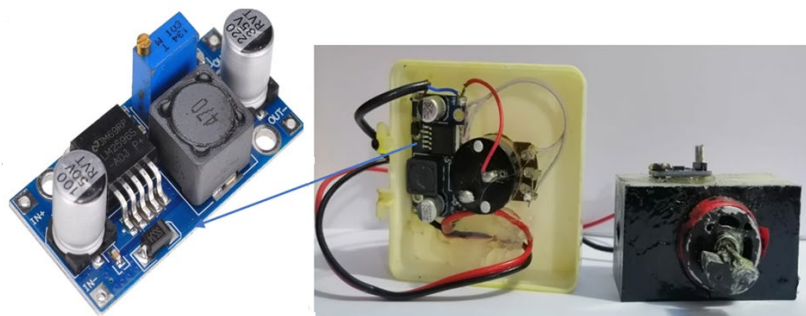**Figure 1:** (a) CNC milling machine (b) vibration system

Figure 2: Dc motor and speed control unit

2.1 Product shape and sheet metal

The final product of SPIF process is a simple cone shape with the (100mm) diameter, (30mm) depth and (45°) wall angle. Figure 3-a shows the dimension of the product shape, and Figure 3-b shows the 3D shape of the cone, which is formed during the single point incremental forming.
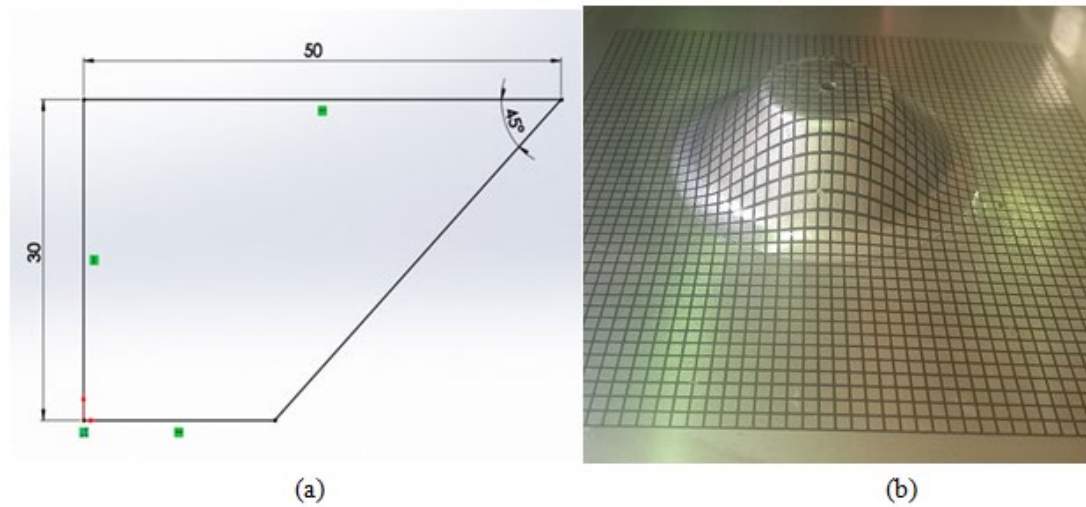

Figure 3: (a) The dimension of the cone shape, (b) The final product shape

2.2 Material and forming tool

The forming tool of (12mm) diameter with a freely rotating ball was used to characterize the formability of Al 1050 sheet, as shown in Figure 4. Using the free rotating ball is a good choice to minimize friction and increase the consistency of the surface. The procedure of (SPIF) is highly appropriate for the sheets processing a slight thickness. A plate with (400mm x 300mm) dimension from Aluminum Al-1050 with 1 mm thicknesses is implemented for this work. The mechanical properties of the metal sheet are given in Table 1. The state Company for Inspection and Engineering Rehabilitation operations (S.I.E.R) conducted a chemical examination. The material's test results are shown in Table 2.

Table 1: The chemical analysis of the aluminum AL-1050

Material		Al%	Si%	Fe%	Cu%	Mn%	Mg%	Cr%	Ni%	Zn%
Al-	Exp	99.5	0.145	0.315	0.013	0.013	0.001	0.001	0.003	0.006
1050	ISO	≤99.5	≤0.25	≤0.4	≤0.05	≤0.05	≤0.05	≤0.03	≤0.03	≤0.05

Table 2: Mechanical properties of AL-1050

Material		Yield Stress (MPa)	Tensile Strength (MPa)	Modulus of Elasticity (GPa)	Elongation%	Poisson's Ratio
Al-1050	Measured	71	86	72	4.5	0.33
	ASTM Standard	65-78	80-100	70-75	3.5-4.2	0.33

2.3 Active damper

It's the damping element in the system throughout which the vibration is controlled. The piston area is varying in the technique to control the damping features. This piston comprises a rotating disc within the principal piston. The body of the piston includes a radial array having (3) similarly sized holes with a circular arc-formed and prepared with an equal interval length way the circle. Figure (5) shows the components of the piston with their dimensions. The rotating disc is linked to the control rod end via a contact surface of the key for limiting the comparative rotation between them. The rod of the piston is a hollow as well as linked to the part of the principal piston by a threaded way. A stepper motor was chosen for changing the location of the disc comparative to the principal component of piston, permitting the active area of flow for controlling via this stepper motor. This motor was used to control the rotation angle between the rotating disc and the principal components of the piston. The damping begins changing via varying the rotation angle, when (φ) is equal to (60) it corresponds to fully-open (the least damping) and when (φ) is equal to (0) it corresponds to fully-closed (maximum damping). The ratio of damping was assessed for a group of the angle of the damper disk. The outcomes are shown in Table 3.

Table 3: Damping ratio for each angle

No.	Damper disk angle	Damping ratio
1	10	0.182
2	20	0.133
3	30	0.0331
4	40	0.0146
5	50	0.0107
6	60	0.0082

Figure 4: Forming tool
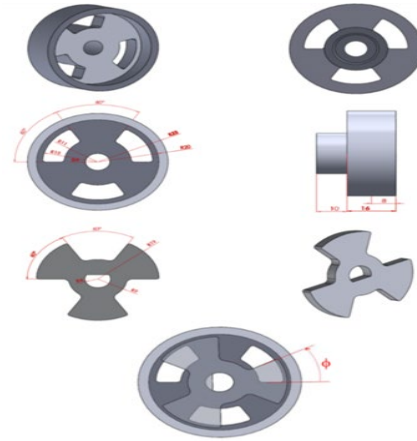
Figure 5: Main piston and rotary disc

2.4 Roughness Test

The surface roughness tests were carried out via a movable tester of surface roughness "Mahr-pocket Surf III" as manifested in Figure 6. In the current investigation, the average roughness (Ra) was calculated since it is commonly used as a parameter of surface roughness. The used device precision is (0.01 μm). The procedure of measurement was implemented via taking the (Ra) average value for (3) line measures with (10 mm) for each specimen.


Figure 6: Roughness tester

3. Estimating damping angle with ANN

ANN stands for artificial neural networks, and it is a computer-based numeric optimization approach. A significant amount of data is needed for training and evaluating a valid model, so a 'standard' neural network requires a very long execution time. In addition, the more neural network architectures and variables give more accurate prediction. The ANN is the most effective and straightforward simulation technique focused on computational techniques that do not necessitate the use of a mathematical model. The input layer, hidden layer, and output layer make up the neural network architecture. Neurons in a hidden layer are changed and all nodes in the succeeding layers are bound to each other. The input layer contains data that are received from an external source. The ANN optimization is done using the MATLAB R2013a software's 'nonoil' wizard. The most critical stage in neural network modeling is determining which ANN topology has the better network architectures. Three parameters are taken into account in the input layer of ANN (frequency, roughness and axial forming force), while the damper angle (ϕ) was taken into account in the output layer variable. The process improved algorithm and output responses are transmitted to Matlab software as the input as well as the aim results, correspondingly, at the beginning of the phase development. The number of neurons in the hidden layer through each layer is used to construct the various networks for creating new weight, bias values, and training the network to improve the optimization, where the algorithm (training) of Liebenberg–Marquardt was employed. It's also the most widely used algorithm since it has the better generalization and convergence with the fewest number of epochs. Figure 7 demonstrates the steps followed in finding the best neural network model. The input and output data that have been estimated from the experimental work and used in ANN are illustrated in Table 4.

Table 4: Experimental data

Runs	Frequency (Hz)	Roughness (µm)	Axial force(N)	Damper angle(º)	Runs	Frequency (Hz)	Roughness (µm)	Axial force(N)	Damper angle(º)
1	20	4.7	372.73	10	19	80	3.89	350.79	10
2	20	4.64	374.36	20	20	80	3.83	356.92	20
3	20	4.5	375.29	30	21	80	3.67	358.84	30
4	20	4.67	376.87	40	22	80	3.45	359.47	40
5	20	4.42	376.78	50	23	80	3.58	361.12	50
6	20	4.56	377.97	60	24	80	3.77	361.97	60
7	40	4.25	367.03	10	25	100	3.57	340.21	10
8	40	4.34	368.81	20	26	100	3.49	344.50	20
9	40	4.24	370.13	30	27	100	3.27	346.00	30
10	40	4.29	371.48	40	28	100	3.06	348.97	40
11	40	4.18	372.18	50	29	100	3.24	350.36	50
12	40	4.13	373.97	60	30	100	3.52	351.68	60
13	60	3.89	360.48	10	31	20	4.8	385.87	0
14	60	4.08	362.35	20	32	40	4.4	372.91	0
15	60	4.03	363.37	30	33	60	3.61	370.19	0
16	60	4.1	363.69	40	34	80	3.79	368.69	0
17	60	3.96	364.14	50	35	100	3.55	360.91	0
18	60	3.91	365.83	60	36	0	4.253	418.45	0
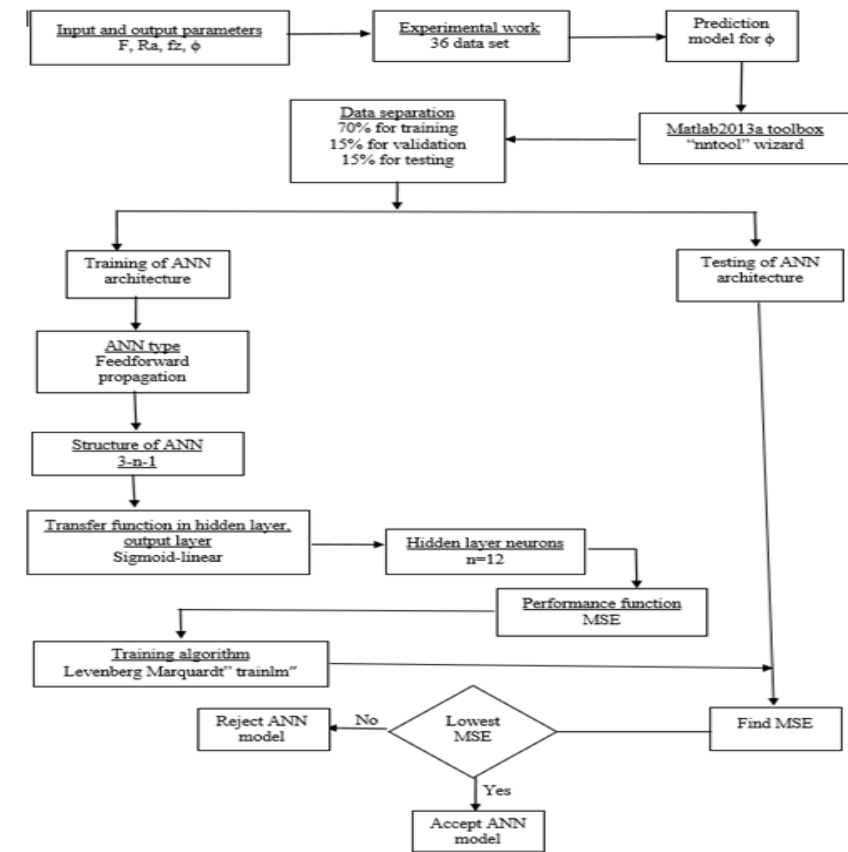
Figure 7: schematic of optimum ANN investigation

4. Results and discussions

4.1 Effect of vibration on surface roughness

Using vibration with the forming process leads to improve the surface roughness. Figure 8 manifests the average surface roughness (Ra) with the application of vibration. The surface roughness of the final cone without vibration is about (4.253µm). It can be observed that the roughness of the surface increases at frequencies of (20 and 40) Hz while it is enhanced at frequencies of (60, 80, and 100) Hz. As vibration is applied to the sheet–tool interface in the local deformation field, it induces an alternating motion. The alternating motion causes elastic–plastic deformation of the asperities of surface, since the hills possess a stronger chance to flow through the valleys. As a result, the product surface quality is increased. From the other point of view, the vibration that led to a static friction was converted to dynamic friction, which eliminates the slippery–sticky behavior. As a result, the surface roughness was improved.
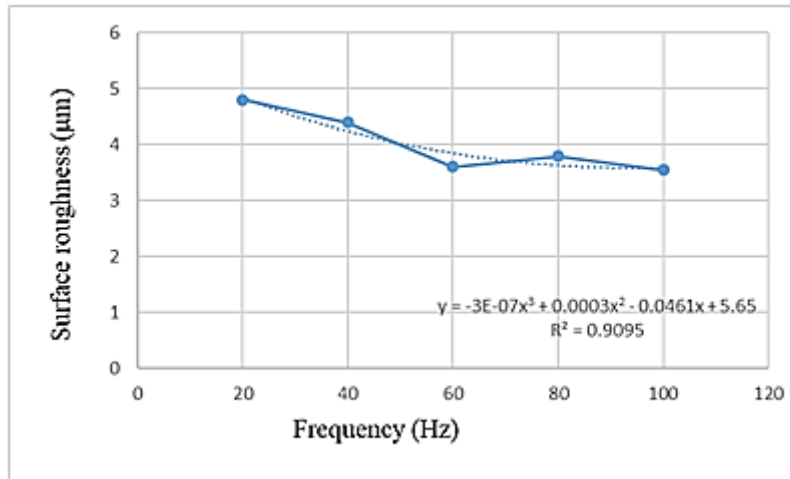
Figure 8: Roughness with applied vibration

4.2 Vertical forming force with vibration

Adding vibration to the SPIF process during forming process has many benefits like reduced vertical forming force (Fz). In SPIF, the effect of different vibration frequencies on the forming force was investigated in Figure 9. It was proven that vibration could reduce the vertical forming force and improve the forming process surface quality. We notice from Figure 9 that the best reduction rate is at (100 Hz) frequency, where the reduction rate is about (11.64%) from the force without vibration. Controlling of vibration by the active damper also improves the deformation force, as shown in Table 4.
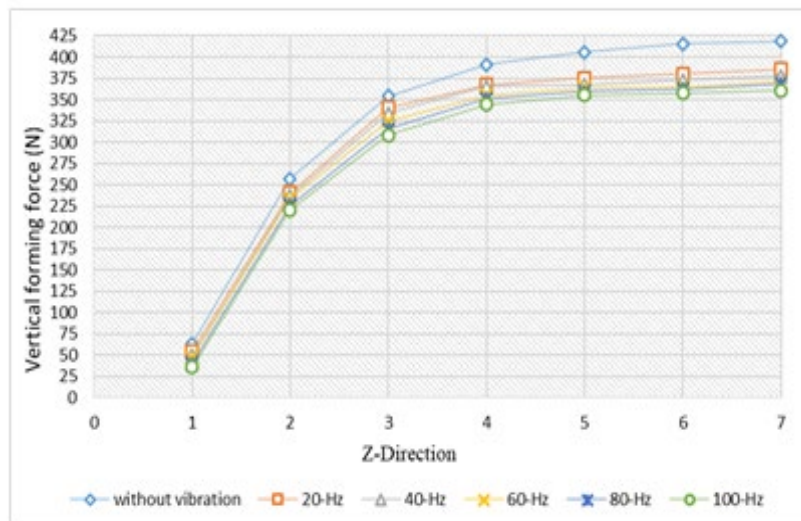

Figure 9: Vertical force with and without vibration

4.3 Controlling of damper angle by ANN

In this section, the model of the neural network was evolved to predict the angle of the active damper which gave the required roughness. The structure of ANN is (3-n-1) for one output neuron, i.e., the angle of the damper is conducted by the aid of the Feed Forward Back Propagation Artificial Neural Network architecture. In this work, Figures 9 evinces the best ability of the model of the neural network to predict (ϕ) as well as the formability with the sigmoid hidden neurons and the linear output neurons. The R-value is started to be 1 and the (MSE) is 1.10283 e-22, which are a sign of a virtuous fitting. R values are one with respect to training, testing, and validation, correspondingly. The performance plot (training, testing, and validation) of the artificial neural network is elucidated in Figure 10. The artificial neural network solution including the performance of training, the state of training, the plot of performance and the plot of regression, correspondingly is indicated in Figures 10(a-d). Regarding Figure 10(c), at (164) epochs, virtuous results as well as the best plot of the regression of iterations are obtained. The best-predicted value was obtained via setting (12) neurons. At epoch (164), the best-fitted value of test data (training, test, and validation) was calculated with an MSE of 3.8907e-22.
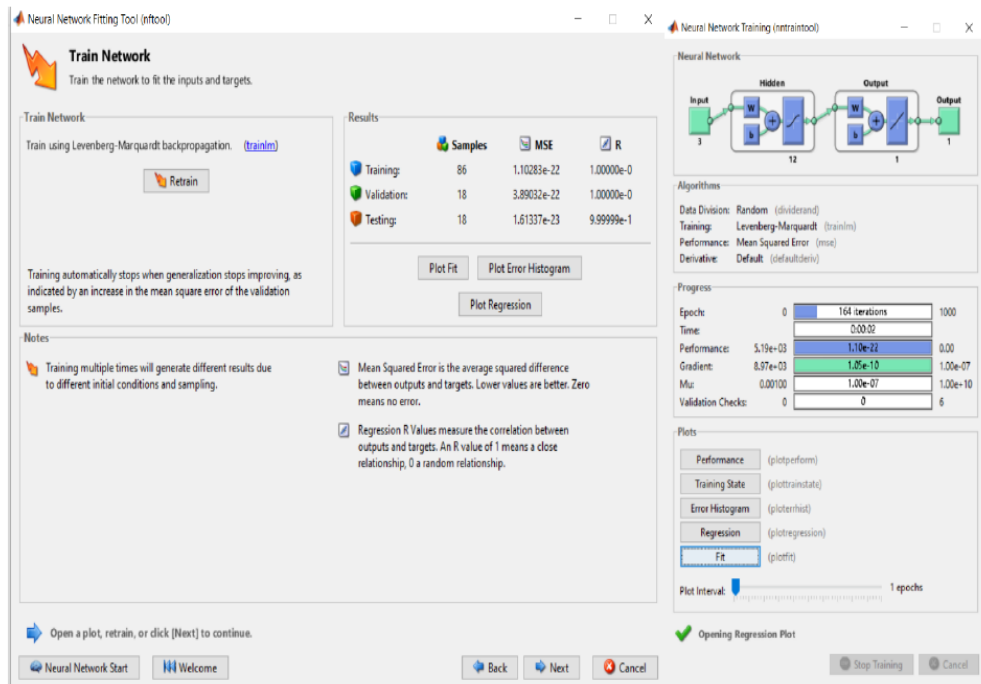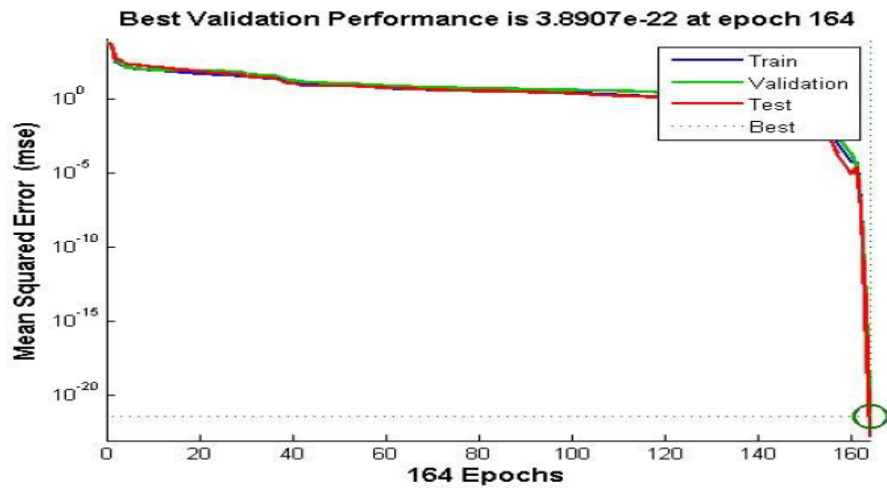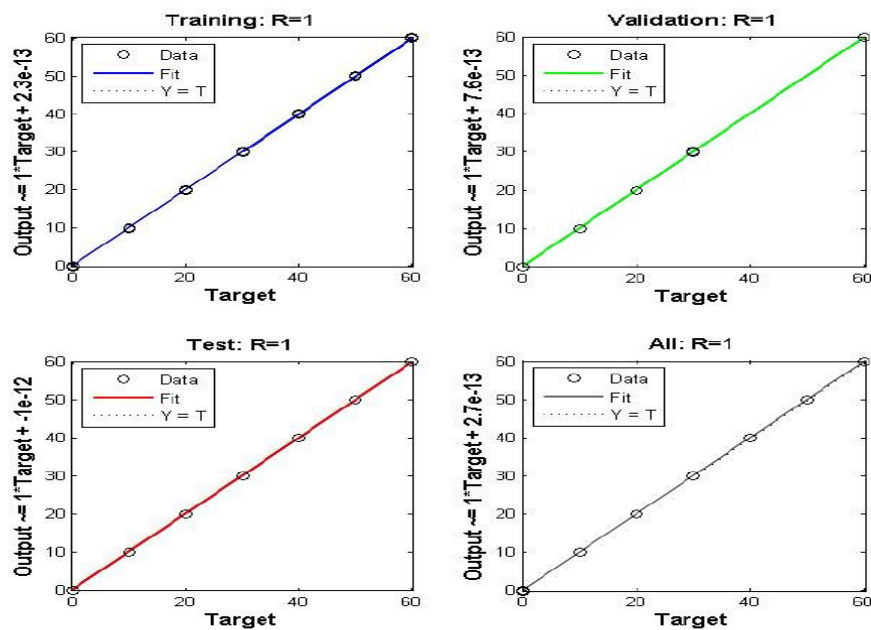
(a)
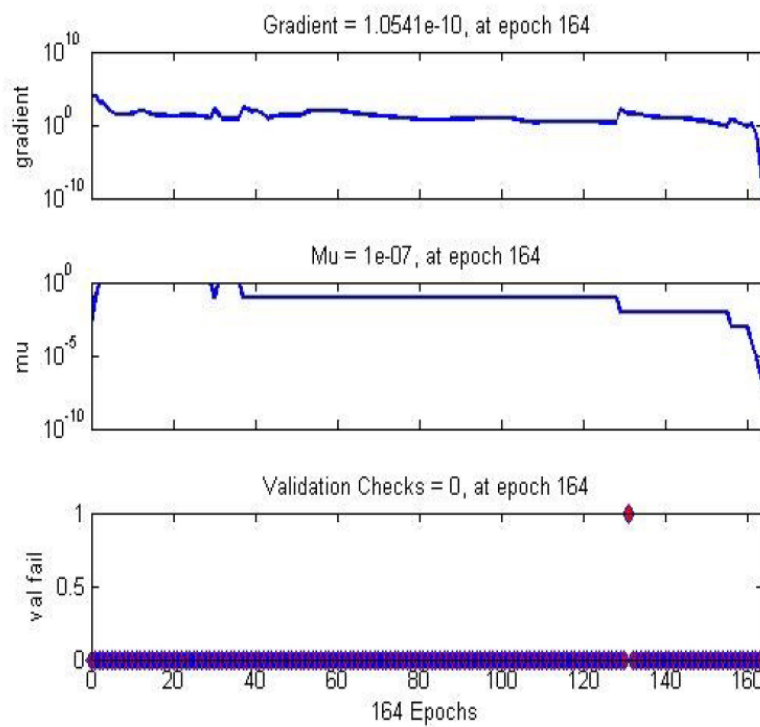
(b)

Figure 10: The artificial neural network results: (a) The plot of training (b)The state of training (c) The plot of performance and (d) The plot of regression

(c)

(d)

Figure 10 Continued

5. Conclusions

1) The axial deformation force decreased with vibration. The good reduction rate is at (100Hz) frequency.
2) Adding vibration assisted with SPIF can improve the surface quality by reducing the surface roughness (Ra).
3) Artificial neural network is able to make an accurate relation between the input parameters and output functions without performing many experiments. The initial prediction for the angle of active damper (ϕ) in SPIF will assist the designers to select appropriate vibration for SPIF, as well as the surface roughness will be accomplished via governing the vibration. The Feed-Forward NN with Back-Propagation learning algorithm was employed to predict the active damper angle with a limited set of experimental data. The predicted active damper angle was obtained with a too close agreement to the measured angle. Thus, artificial neural network can be utilized as a tool to model and to control the output responses prior to performing fresh experimentation. These output responses can be enhanced via choosing an appropriate learning algorithm by a transfer function. The upcoming investigation will concentrate upon prolonging artificial neural network use in the single-point incremental process via utilizing further parameters of forming, the tool geometry effects and the single-point incremental process upon varies materials.

Author contribution

All authors contributed equally to this work.

Data availability statement

The data that support the findings of this study are available on request from the corresponding author.

Conflicts of interest

The authors declare that there is no conflict of interest.

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