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Design Optimization of Components for Additive Manufacturing-Repair: An Exploration of Artificial Neural Network Requirements and Application

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Abstract: The integration of artificial intelligence (AI) in additive manufacturing (AM) technology is currently a promising and leading area of research for component repair and restoration. The Issues of high cost and time consumption for AM repair have been a subject of discussion among researchers in this field of study. Moreover, the potential challenges in dealing with complex components for repair and restoration in the (AM) domain require the establishment of a critical technical platform based on hybrid (AI). At this point, the proposed optimization method must cover all important parameters for the complex configuration of structural components under restoration. For the purpose of this study, a design optimization framework was developed using a MATLAB-SIMULINK mathematical model for AM solution purposes by improving the functionality and integration of monitoring. This improvement is based on facilitating the real-time identification of failures with accuracy and giving a clear monitoring vision according to the intended targets like geometric distortions, residual stresses evaluation, and defect characterization. The improvement involves overcoming a number of challenges such as the pre-fabrication stage by expanding the data repository besides offering a theoretical set of algorithmic with some options that improve the current procedure. Also, this study will conclude and suggest a further framework and new knowledge for restoration and product life cycle extension. This developed ANN can be used at the real pace of modeling the MATLAB-Simulink system and merged with another suitable algorithm to form a hybrid ANN. This model development using a neural network has attained a good manipulation of AM. The predicted data from ANN model that was determined and achieved in this study can be used to facilitate and enhance any further study as base knowledge in merging the ANN with another AI to form a hybrid algorithm.

Keywords: Additive manufacturing, (ANN), hybrid artificial intelligence, design optimization, restoration

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1. Introduction

Until the last few years, the most cutting-edge approach for repairing and rebuilding End of Life (EoL) components of complicated geometries is by adding material layer by layer to create a product using additive manufacturing (AM). Remanufacturing has been viewed as a good technique for recovering deformable components and saving material, time, and energy when compared to the fabrication of a new product. The most common justification for the restoration of components using (AM) after the end of their useful lives, besides cost and time, is environmental sustainability. One of the key goals of creating components for purposes of (AM) repair is to make the recovery of components easier [1].

In order to improve the effectiveness and efficiency of the repair and restoration process, strong integration with process systems is required from the component design standpoint [2]. For the purpose of improving the efficiency and restoration process for (EoL) components; design optimization must be implemented throughout the design and development stage. With respect to the Industrial Revolution (IR) 4.0 mission, the use of additive manufacturing technologies can automate the process of repairing and restoring (EoL) components, making recovering deformable components easier by adding material layer by layer with less wastage and environmental advantages [3].

Numerous optimization methods, such as genetic algorithms, have been developed for high-quality advanced machined components. One of the methods used most frequently in design optimization is a genetic algorithm (GA). Genetic algorithms are Evolutionary Algorithms (EA) that use methods drawn from evolutionary biologies, such as inheritance, mutation, selection, and crossover, also known as recombination. Evolutionary algorithms are a key technique that emerged from (AM) for the planning, designing, and optimization of multi-objective and complicated problems [4]. Through the creation of intelligent and adaptive systems, the integration of (GA) and other AI techniques enables the modeling of real-world issues [5]. In order to enhance and facilitate the (AM) process and make accurate predictions, the robust computational model artificial neural network (ANN), which consists of a network of nodes, is used. Artificial neural networks (ANNs) have excellent characteristics that make them well-suited for handling complicated tasks [6].

In the optimization process using a hybrid algorithm ANN-GA, the type of trigger, number of generations, and population size are essential for making decisions in (GA), while the neuron’s number is used to make decisions in (ANN) [7,8]. However, ensuring that the restoration process is efficient in terms of cost and time which is a key goal of any design optimization methodology, such as (GA). Effective optimization strategies shorten the length and time of thousands of evaluation operations. Reducing computing expenses is the primary goal of the hybrid algorithm during the optimization process [9]. By aiding decision-making and improving the repair performance during the remanufacturing process, the (AI) technique is used to improve and make a good integration in AM restoration. It may be challenging to distill new design thinking that must be taken into account when creating circular products, which is one of the possible causes of the paucity of AI techniques being used in design optimization for repair and restoration. As a result, this element has an impact on the use of AI, which calls for processing enormous amounts of data and information for optimization. Additionally, information and knowledge are needed as the primary inputs for optimization in design for repair and restoration, including the type of damage and severity, type of material, and design requirements [10]. It is therefore necessary to combine this process with big data by using (AI) to develop an integrated optimization design and intelligent AM technology [11].

The neural network data can only move in one direction and has high efficiency and good function generalizing in terms of simplicity of the structure. There are mainly three layers; the input layer, the hidden layer, and the output layer. The most commonly popular training method used is the backpropagation algorithm [12]. The adaptive reclosure scheme for the restoration process by using ANN was presented to find the possibility of estimating the EoL for some industrial parts. The simulation results show that this scheme was able to predict the end of life of the final component [13-14]. In this article, the architecture of (ANN) and their application in repair and restoration in using additive manufacturing are presented and discussed. In order to achieve a suitable level of accuracy, and cost-saving with increased efficiency; Design optimization is an important area of research that requires a comprehensive understanding of the strength and weaknesses in additive manufacturing. On the other part, design optimization is a repetitive process and time-consuming. Consequently, this developed ANN can be used at the real pace of modeling the MATLAB-Simulink system and merged with another suitable algorithm to form a hybrid (NN).

2. Material and Methods

Design optimization of components for (AM) is usually implemented to recover the products to their original properties with high accuracy. The system used was an intelligent neural network and MATLAB - Simulink is adopted to implement this analysis due to the good accuracy of the preprocessing capabilities, and high interaction with data preparation, generation, and visualizations. The first step in this process is modeling the required part as a 3D, then the coordinates of this model are extracted to use as input data for the (ANN) model. As reported by many industries, the common damages to an automotive engine are cracks on the engine block and also damage to other parts. For the purpose of this study, the crankshaft of an automobile engine is used as shown in Fig. 1. The two-dimensional geometry of the crankshaft with the basic dimensions is illustrated in Fig. 2. The carbon steel material of type AISI 4130 is widely used for crankshafts. For properties of the material used in the crankshaft. The properties of this material are listed in Table 1 below.

The ANN algorithm is used to predict the suitable method for compensating the geometry of the deformed part. The flow chart in Fig. 3 illustrates the main steps of this analysis. The main structure of ANN normally consists of four subsections which are hidden layers, neurons in each layer, the activation function, and the loss estimation function as shown in Fig. 4. With the help of the part model developed in the MATLAB-Simulink power systems, four sets of training data are formed that differ in the principle of receiving inputs and corresponding to the output values of training pairs. For the first set, the step of changing each parameter of the block simulating the equivalent system was selected individually, based on the influence and the degree of its change on the resulting form.

To improve the performance of developing a model that has the ability to provide a suitable prediction for the behavior of this process, and to achieve the aim, some steps are necessary such as investigating the model parameters measurement and observing the performance of the model to attain the requirements, and finally analyze the results and compare them with previous literature findings. The structure of ANN contains a Fully Connected Layer. Also, it's connected to a double Long Short-Term Memory LSTM network cell which is a recurrent neural network used in solving sequence prediction problems. Finally, it's connected to the output layer. The proposed NNs, are illustrated in Fig. 5. The ANN will act as a numerical simulation with a low operating velocity. In addition, this suggested network determines the relationship between the re-manufacturing processes attributes (build time and the part mass), and design geometries.

Fig. 1 - The crankshaft of an automobile engine [15]

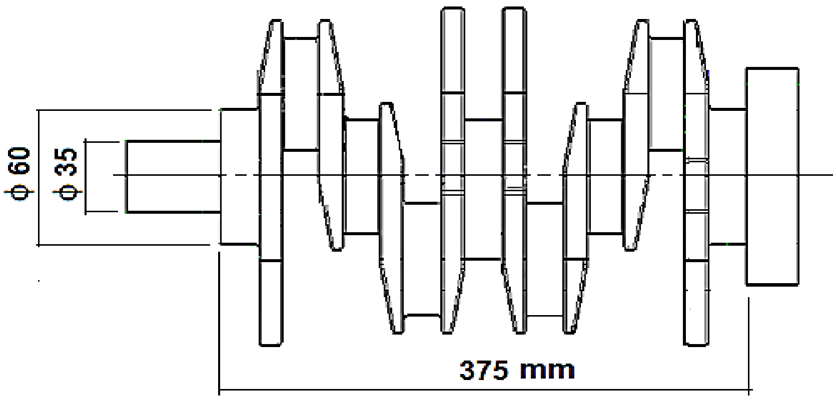

Fig. 2 - The two-dimensional geometry of the crankshaft with the basic dimensions

Table 1 - Mechanical properties of AISI 4130 steel material were used in this work

No.	Properties	Values
1	Young's Modulus of Elasticity	200 Gpa
2	Yield Stress	375 Mpa
3	Expansion Coeff.	0.00012
4	Poisson's Ratio	0.3
5	Density	7340 Kg/m^3.

The second set is using the defined set of process parameters to simulate the AM process. The deformed surface properties and mechanical properties such as the geometry shape, roughness, dimensional deviations, tensile strength, modulus of elasticity, hardness, and yield stress are extracted as the output of the NN model. In additive manufacturing AM, the input criteria in repair for design are to identify the causes of the failure mode of the components. To decide where corrective action needs to be taken, as well as what action needs to be performed and when, so the failure mode effect analysis FMEA method should be examined. In the third set, signals are received at the input (ANN) blocks, then the corresponding distorted values are fed to the scope to form the output (rmse) effective value of the model. Table.2 can be used as input data. Also, it's useful whenever prompt action on some failure types is required. The input data such as material properties that were mentioned earlier in Table 1**,** shape parameters, and layer thickness are the target data that is considered for modeling the network. According to the above methodology flow chart, the first step is to create a database to define the ANN model. The desirable input data of deformed part geometry that will be trained to the network is necessary for accurate output. Fig. 6 illustrates a schematic diagram for the propagation of a forward-trained neural network.

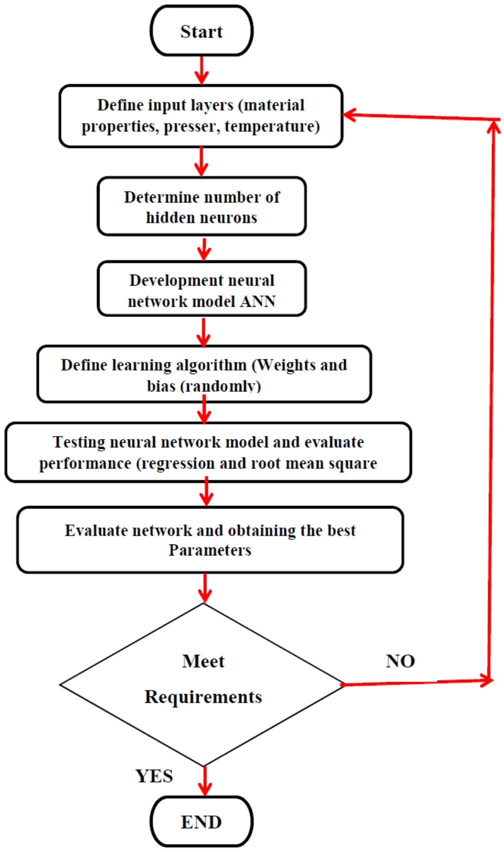

Fig. 3 - Flow chart of implementing artificial neural network ANN analysis using MALAB-Simulink

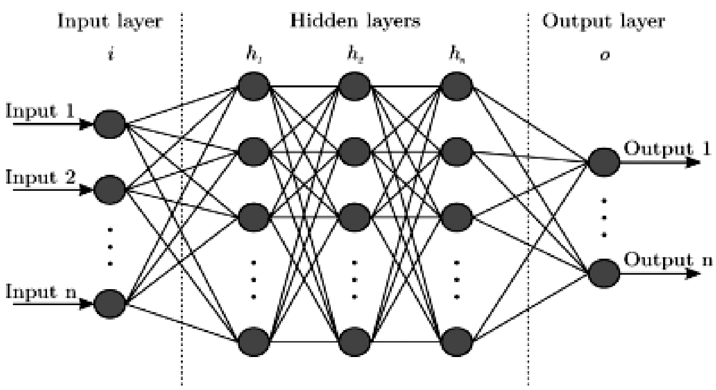

Fig. 4 - Structure of ANN

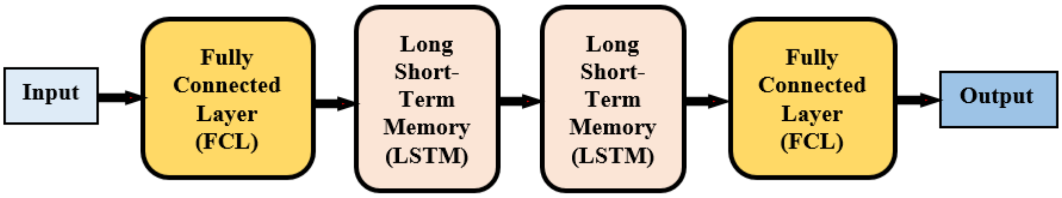

Fig. 5 - The NN fully connected layers are used to predict the deformation

Table 2 - The failure modes and the causes [16-19]

Parts	**The engine block, Crankshaft, Cylinder head**
Failure modes	Fracture, Crack, Broken, Fatigue, Wear, Corrosion, Creep, Burnt, Fastener Failure, Hole.
Causes	Speed, wearing of piston seals, Oil leakage, Temperature, Pressure, Friction, Lubrication, Comparison stress, Tension loads, Bending loads, Density, Vibration, Foreign particles, Wrong using, Connecting, Sealing, Stress concentration, Roughness, Materials, Hardness, Thermal loads, Crankshaft misalignment.

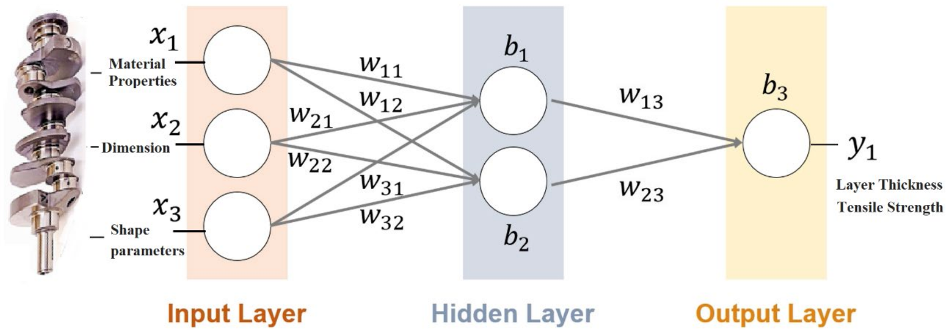

Fig. 6 - The schematic diagram for the propagation forward trained neural network

Weights are usually called Parameters in ANN and link magnitudes between neurons in two adjacent layers. ($W_{i1\text{-}j1}$), ($W_{i2\text{-}j2}$), are connection weights, which represent the strength of a specific node. In ANN, weights are considered the important factors which represent the numerical parameters that determine the impact of neurons on each other and their effects on the output show the strength of a particular node according to the following equations

$$\text{Output} = \Sigma \text{ Weights} \times (\text{Inputs} + \text{Bias}) \tag{1}$$

And weighted contributions of neurons are:

$$\begin{aligned} Y_{net} &= \sum X_{ii} W_{ii} + b_{ii} \\ Y &= f\left(\sum X_{ii} W_{ii} + b_{ii}\right) \end{aligned} \tag{2}$$

Where:
Y_{net} is the summation of weighted data sets
(X_{ij}) is the neuron input, (W_{ij}) is the weight coefficient of each neuron input, and (b_{ij}) is bias.

In the fourth set of data, which is formed based on the three previous sets, artificial neural networks will utilize details of these weights to solve a specific problem. At the real pace of simulation, for each period of the industrial frequency, the values at the inputs and outputs of the ANN are updated 32 times. Therefore, the number of ANN inputs and outputs should be 1. Network Toolbox ANNs have been exported to Simulink as blocks of their models - Neural networks. Now the ANN model with (16) neurons and mean square error MSE as the loss function will be trained to estimate the difference between the input and output. This implemented network is important to achieve the required geometric corrections that will be used later to modify the part geometry according to these findings.

3. Results and Discussion

The design optimization process combines many aspects, including model design, material selection, re-manufacturing parts, and evaluation. The principle of optimization by using the assistance of an artificial neural network here is used for controlling the process by receiving the operation signal to revise it mathematically, improving data analysis, and then feeding it back again to the operation control system to enhance the decision-making. In this analysis, the main influencing parameters such as material properties and shape parameters were taken into consideration as input parameters. The input data for the ANN model was divided to cover all aspects of this process such as testing and validation. This ANN is designed to model the outputs, namely, part dimensions and tensile strength. Consequently, the output of the process is represented as a performance graph. The task of this network is to predict the output, so the performance graphs indicate the quality of this process in terms of error reduction. The method of filtering the results is consist of three-step. The first one is removing the worst datasets, then removing the greatest deviation data from the fit, and finally is disabling all the datasets that appeared not suitable for applications. The ANN construction can be repeated many times to choose the best networks in order to achieve a valid result.

The application of ANN in the AM process involves some procedures such as designing, monitoring, and correlating between process parameters and the final characteristics of the component. Fig. 7 and Fig. 8 show the window of the ANN model under actual running. This window represents the random distribution of the input data and the performance of this model will be estimated based on the mean square error MSE distribution. The linear regression between the actual results and network predicted results can be estimated. Consequently, when the mean square of error MSE is at the minimum value means the result of the ANN model is acceptable. The testing of the system is done by implementing the neural network controller under the simulation process. This simulation involved performing a sequent ANN training, and the model will test the properties of each input parameter to calculate the correct output. This developed ANN can be used at the real pace of modeling the MATLAB-Simulink system and merged with another suitable algorithm to form a hybrid ANN. To obtain the output at each sampling step (according to assumed inputs samples), therefore, the number of ANN outputs should be (1), as in Fig 9.

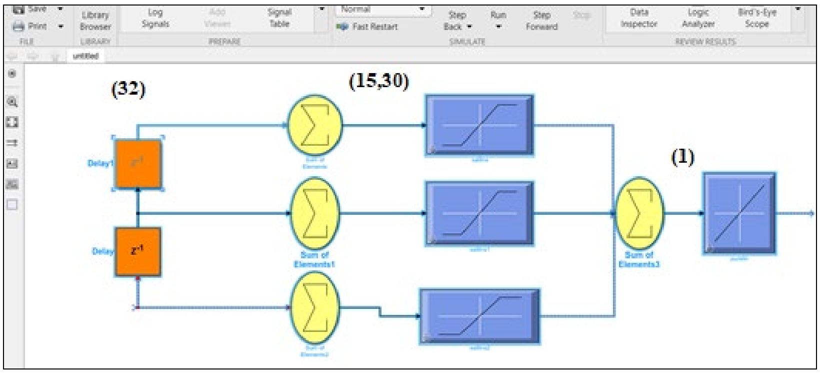

Fig. 7 - The window of the (ANN) model under actual running

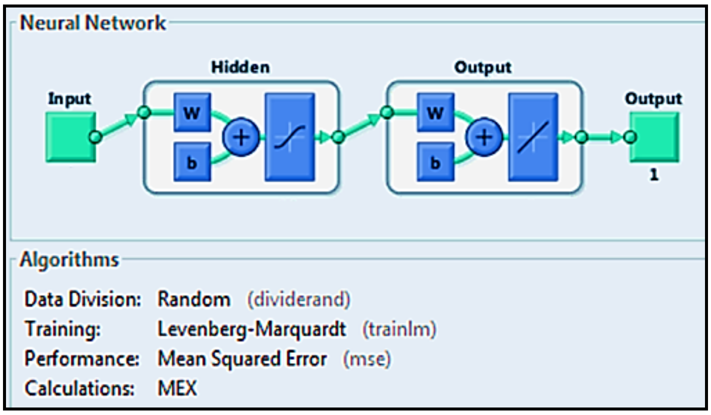

Fig. 8 - Mean square error (MSE) distribution

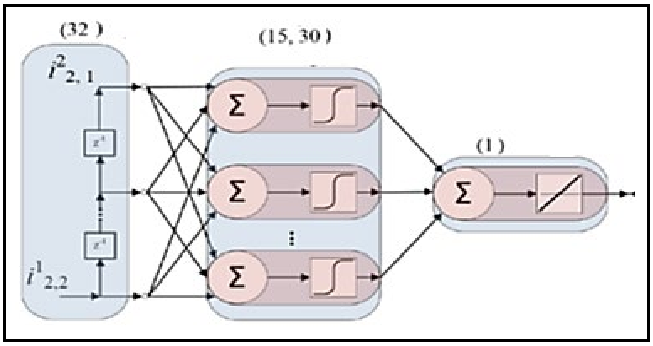

Fig. 9 - Artificial neural network topology

At the actual pace of simulation, for each period of the power frequency, the values at the inputs and outputs of the ANN will be updated (32) times. The positive effect on the resulting accuracy of restoring the shape of the distorted part is identified as an output of the simulation. Pressure and temperature have a high impact on the resulting accuracy of restoring the shape of the distorted parts and consider important input data. The mean of squared errors MSE value is a measure of the performance of the network and is considered an indication of the network performance function. The main function of using MSE is that it squares the error which results in large errors being clearly highlighted, but normally the lower value is the better. It's an absolute value and is used to tell whether the model has become more or less accurate than a previous run. When MSE is close to the minimum value it means that desired outputs are acceptable. Whenever the number of hidden layers and the number of neurons increases, the computational time will increase. The Error Backpropagation algorithm is the common method to calculate their numerical values. Outputs can conclude according to the concealed input values. Mean Squared Error MSE is calculated as follows:

$$MSE = 1/K \times \sum (Y_i - O_i)^2 \tag{3}$$

Where Y_i is the reaction of neuron i, and O_i is the actual value of neuron i. Fig. 10, is the performance plot that illustrates the relationship between the MSE with the number of intervals. This plot indicates that ANN fits the best value after one interval at which validation reached a minimum value. For validation purposes, the comparison was made between the performance curves in Fig. 10 and the similar findings made by [20]. The validation curve in Fig. 11 refers to the training quality in terms of error reduction in the case of underfitting and overfitting. It seems that the regression of the downward curve indicates a low MSE value. It seems from this validation curve in Fig. 11 that the MSE value is achievable and indicates low randomization. In addition, the validation and testing curves indicate the possibility of overfitting after several iterations.

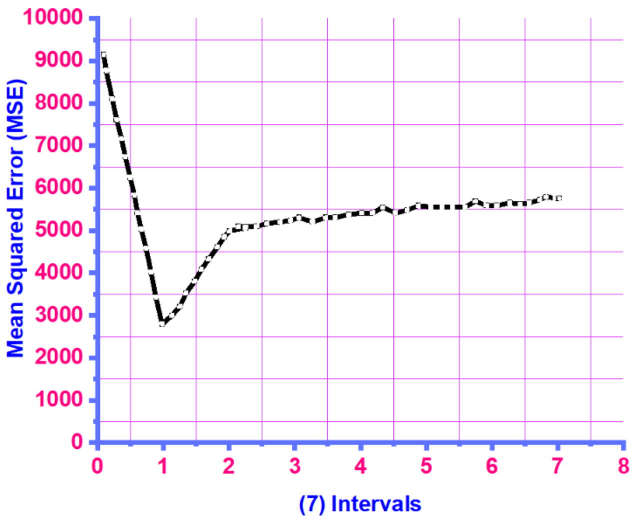

Fig. 10 - (ANN) performance plot of data for layer thickness

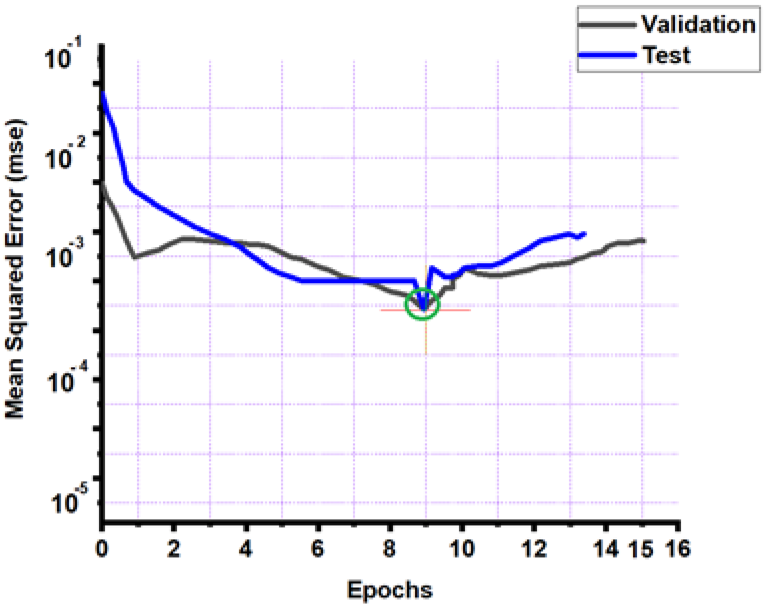

Fig. 11 - (MSE) - Time plot of data for performance validation [20]

In design optimization for repair in the AM process by implementing the ANN learning process, it is recommended to use the MATLAB command line, which allows setting all the changeable parameters of the created ANN at discretion. The undoubted advantage of MATLAB is the ability to export the ANN in Simulink as a model block and share it with other blocks, and therefore, apply it at the real pace of the simulation. Using the interface imposes certain network configuration restrictions and other specific ANN settings, but the speed of the development process can be increased. Besides, preprocessing and post-processing operations are automatically applied to the training dataset and ANN output values. The Neural Network Toolbox package of the MATLAB system provides an intuitive graphical interface that requires a minimum of actions from the user when creating an ANN. The numerical characteristic of the degree of correlation is close to unity, in the case if the ANN was able to approximate the relationship between the input and desired values and significantly less than one if the ANN could not approximate the required dependence.

4. Conclusions

This paper has applied an artificial neural network model to accomplish important modeling and analysis results of this simulation process. The predicted values of the ANN model were evaluated by applying the root mean square error (RMSE). The result's accuracy is indicated by the higher value of the correlation coefficient between the actual outcomes and the predicted output.
The following conclusions are obtained from the study:

- AM will gain many advantages by integrating with ANN and increasing the capability to build parts and solve complicated mathematical models. The combination between AM and NN has an attractive impact on the manufacturing industry. It can be used to restore the distorted shape of the complex component.
- Depending upon the AM task, the capability of the ANN in building an improved algorithms model for the component repair operation relies on the function and carrier efficiency of the hidden layer.
- Developing an accurate ANN model-based mean square error (MSE) can lead to noticeable results. It's considered a necessary step to create a hybrid AI for the purpose of repair or design optimization.
- This new knowledge-based ANN would help manufacturers and designers to make the proper decisions in design optimization of complex components, and lead to saving time, cost, and reducing errors

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