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Optimization of Machining Behaviour of Monel 400 Super Alloy Using ANN and GA Technique

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Abstract

The machining of the nickel-based superalloy Monel 400 has excellent mechanical qualities and may be used in a wide variety of commercial applications. The current study explores the effect of the Surface roughness, primary cutting force, and cutting temperature at the tool work mating point on machining parameters such as cutting speed, feed rate, and depth of cut, and Laser power, which has four levels that are regularly spaced levels. In order to evaluate cutting conditions, a DOE L_{30} orthogonal array and ANOVA were used. A feed forward back propagation artificial neural network (ANN) model with a 4-10-3 architecture trained using a Levenberg-Marquardt (LM) algorithm resulted in a well-organized modelling of the intricate connection between surface roughness, main cutting force, and cutting temperature on machining parameters. This was accomplished through the use of the LM algorithm (R-value of 0.98). In order to predict the optimal turning parameters, the trained network was improved with the use of a genetic algorithm (GA). The ANN-GA technique is the name that has been given to this strategy. Because of the optimization that was done utilizing the ANN-GA approach, there was a discernible decrease in the surface roughness is 11.2% as well as the primary cutting force is about 16%. According to the findings of the analysis of variance, the most significant factor is cutting speed, followed by depth of cut and feed rate.

Keywords

Monel 400, Levenberg-Marquardt algorithm, Artificial neural network, Genetic algorithm

Introduction

Manufacturing refers to the process of transforming raw materials that have not been processed into finished products via the use of a variety of different activities. Different industries have a significant impact on the production of a wide range of components, systems, and products. The constantly evolving industrial sector on today's globe is influenced by a great number of driving factors. Some of the common and resulting reasons are customer satisfaction, a competitive world, and emerging technologies that place an emphasis on the design of equipment and systems to create quality driven goods in an efficient and sustainable manner. The machinability of alloys is increasing as a result of constantly shifting regulations on pollution in order to remain competitive in the engineering industry. It's called a superalloy when an alloy has the ability to keep its intrinsic qualities even after being exposed to a hostile environment for an extended period of time. The machining of superalloys results in the development of extreme heat, enormous cutting pressures, decreased surface quality, great wear, and residual tensions, all of which are characteristics of material that is difficult to process [1, 2]. The findings of previous research indicate that a sizeable decrease in the creation of heat results in a very significant lengthening of the useful life of the instrument. When machining superalloys, using cutting conditions that have been optimized results in an improvement in tool life, a reduction in energy consumption, a lessening of the influence of residual stresses, wear, and heat production, and an increase in machinability.

Monel400 is a copper-nickel solid solution alloy that is extremely resistant to corrosion in acidic and alkaline conditions. It is extensively used in the maritime sector, heat exchanger tubing, nuclear facilities, chemical and hydro-carbon processing units [3]. The machining performance of nickel-based alloys has been the subject of a number of studies, using both traditional and atypical machining procedures. Because nickel alloys have a high heat-resistance property, machining them with conventional tools leads to rapid work hardening, the formation of built-up edge, and a tendency to weld to the tool surface, all of which result in a poor surface finish [4, 5]. This can be avoided by using special tools that are designed to work with nickel alloys. As a result of their high shear strength, they also provide a great resistance to the removal of metal. For the machining of high-strength and high-heat-resistant materials, the use of laser aided machining has the possibility of becoming an effective and unique production technique. As a result, you may find them used in a variety of industries, including the aerospace, medical, nuclear, and automotive sectors [6].

Maity et al. [7] investigated the effects of gas flame heating on the tool life during the hot turning of hardened steel. In order to determine the amount of tool wear, the amount of tool life, and the chip reduction coefficient, an experiment with a full factorial design was carried out. The effect of cutting parameters on tool life was discovered to be greatest at a low value of cutting velocity, followed by feed, depth of cut, and a high value of temperature. Based on these findings, an equation for tool life was developed. Tosun et al. [8] conducted an investigation on the effects of artificial neural networks and regression analysis on the tool wear experienced by cutting tools (ANN). In hot machining, the most important consideration is making sure that the right process parameters are chosen for the machining output parameters. Lee et al. [9] examined machining of high strength material utilizing hybrid machining methods. They employed both heating and cryogenic cooling to increase the tool life. When the conditions were heated, it was discovered that the cutting force was reduced by 65%, whereas it was found to slightly increase during the cryogenic machining process.

This paper deals with the machinability of Monel 400 using laser assisted turning machining and optimizing the process parameters in order to get the optimal value of surface roughness and cutting force.

Materials and Methods

Experimental equipment, material, and cutting tool insert

The "Monel 400" super alloy was machined on a laser-assisted CNC turning machine for the machinability test (with heating of cutting zone by Nd-YAGlaser. The Laser Assisted CNC Turning Machine, also known as a LACNC, typically has a power output of 600 W. The highest spindle speed is 3000 revolutions per minute, and the focal length is 186 millimeters. During machining, the process in which the material is heated with the assistance of a laser beam Due to localized heating with the assistance of the laser beam, the material's strength will diminish, which will ultimately result in decreased cutting forces and surface roughness. As a result, the pace at which material is removed and the life of the tool will both increase. Monel 400 super alloy as work material considered for the present investigation. The hardness of the Monel 400 alloy is 240 VH. The chemical composition for the alloys is given in the following table 1.

Selection of cutting parameters and data analysis

There is not much research work related to the machining of Monel 400 alloy. Hence, we have taken initial values of each process parameters are selected according to tool manufacturing specifications and ASME standards.as shown in table 2.

Surface roughness, cutting force, and temperature measurement

Cutting forces in LACNC turning operations may be measured with the use of a 232 Kistler 6 components Dynamometer (9257B). In addition to measuring the moment MZ, the multi component dynamometer can also measure the three orthogonal components of force (FX, FY, and FZ) operating in any direction on the top plate. The dynamometer's high inherent frequency is a result of its extreme stiffness. Due to the high precision of 0.001, even minute fluctuations in motion may be captured as significant pressure shifts. One uses an infrared thermometer to check the temperature of the joint between the tool and the work piece. Devices that can monitor temperature from a distance are called non-contact type thermometers. (E35B). Following machining, the surface roughness of the workpiece was evaluated using handy surf to compare results from various cutting operations Carbide inserts coated with CNMG120408 were employed as a cutting tool on a LACNC. The investigations are carried out using the central composite design technique. Surface roughness (Ra), primary cutting force (Fz), and metal cutting temperatures (CT) are only a few of the responses that are monitored and analyzed utilizing Design of expert systems (DOE).

Experimental work

The proposed artificial neural network model and genetic algorithm (ANN-GA)

In order to predict the surface quality, metal cutting

Table 1: Shows the chemical composition of Monel 400.

Element	Ni	Mn	Cu	C	O	Si	Fe
Weight (%)	63.07	1.17	29.88	0.3	2.58	0.74	2.26

Table 2: Experimental design of process parameter and their levels.

Parameters	Code	Levels		
		1	2	3
Cutting velocity (V_C) [m/min]	A	30	42.5	55
Feed rate (f) [mm/rev]	B	0.04	0.06	0.08
Depth of cut (doc) [mm]	C	0.25	0.5	0.75
Laser power (W)	D	300	400	500

temperature, and main cutting force that occur throughout the CNC LAM process, a computational model based on an ANN was employed in this investigation.

The model's operation is supposed to mimic that of real-world neural cells. This model is used in order to establish a connection between the input variables and the parameters that are generated from them. Artificial neurons provide the basis of its main structure. Neurons take in a real-number input and calculate their outputs using a wide variety of non-linear functions. These groups of linked nodes are called "edges." The learning process involves changes to the density of synapses and the smoothness of their borders. Connecting neurons across layers is achieved by weights and biases. As long as the necessary adjustments are performed, the NN model may be trained.

In this research, a feed-forward network was trained using the LM method as illustrated in figure 2. Feed-forward neurons have three layers. Input, output, and concealed were the layers. Weights connected all levels. ANN analyzed trail data. Ten neurons make up the one hidden layer in this model. Each input and output layer has four and three neurons. The input and output layers of the network had "logsig" and "purlin," and it had a 4-10-3 topology. depicted in figure 1 After numerous testings', this was selected based on mean absolute percentage error (MAPE).

Equation can be used to assess the output Qi utilising j^{th} neurons at each and every layer.

$$O_j = f\sum_{i=1}^{n} w_{ij}x_i + b_j \qquad (1)$$

Where, f - activation function, n - no of inputs to the j^{th} neurons, w_{ij} - respective weight, x_i - i^{th} output neurons, and b_j - respective bias.

The primary goal function was constructed using equation (1), and its value was improved with the help of a GA. The vast majority of the time, it is used to get solutions that are perfect or about ideal for challenging situations that, in any other

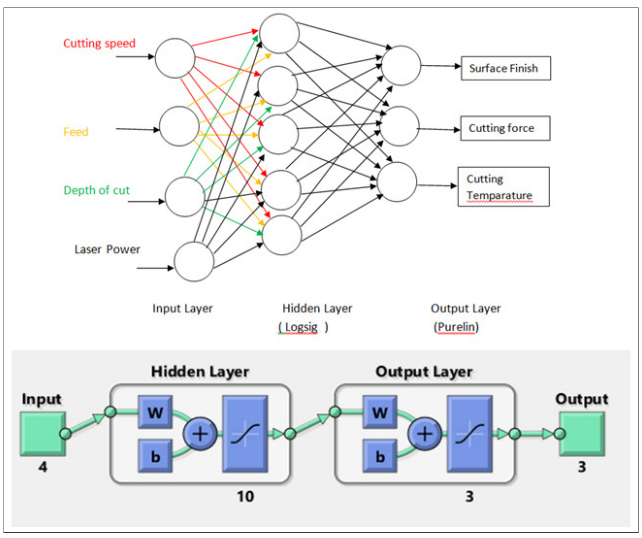

Figure 1: The 4-10-3 ANN architecture developed for turning of Monel 400 for prediction of the surface roughness, main cutting force, and cutting temperature.

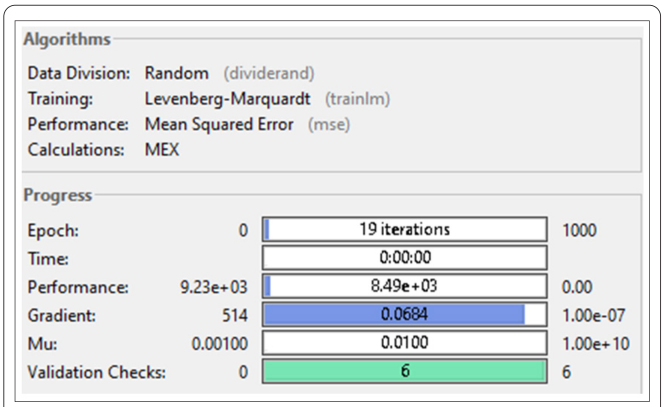

Figure 2: The feed forward network with LM algorithm.

scenario, would take a significantly longer amount of time.

First, the GA uses a pool of potential answers, or "chromosomes," to narrow down the search space. Different permutations of these process parameters are represented by the chromosomes. The most probable solution's feasibility may be evaluated by how well it solves the primary objective function. Over time, the best solution will emerge via a sequence of generations that include biologically inspired processes like crossover and mutation. The fitness of the populations is evaluated at each generational step, and further mutation or genetic exchange is permitted only up to the maximum number of iterations, at which point the process stops. To put it another way, the results of each successive generation are adjusted downward until they fall below the value of the previous generation.

Machinability research of cutting parameters and their detrimental consequences is being optimized as part of the current study in order to decrease surface roughness, primary cutting force, and work piece and tool mating temperature. This optimization is part of the Machinability study.

Subjects to: 30 < A< 55 (m/min),

0.04 <B<0.08 (mm/rev),

0.25<C<0.75(mm) ,300<D<500 (Watts)

The above conditions were fed into GA Toolbox in MATLAB, with variation of all other parameters. The methodology of ANN-GA may be presented by the flow chart shown in figure 3.

Results and Discussion

Modelling and optimization of surface roughness, main cutting force, and cutting temperature

The use of MATLAB, a computer language intended for matrix-based computations, allowed for the more accurate formulation of the ANN model., rapid modelling to predict Ra, main CT on average at the tool-to-work interaction for Monal 400.

A 4-10-3 architecture with logsig'as the hidden layer's activation function and "and "purelin" in the input and output layers' provides remarkably strong modelling capabilities. Following multiple trial runs, MAPE, and R-valve were used as the basis for a 4-10-3 architecture and activation functions

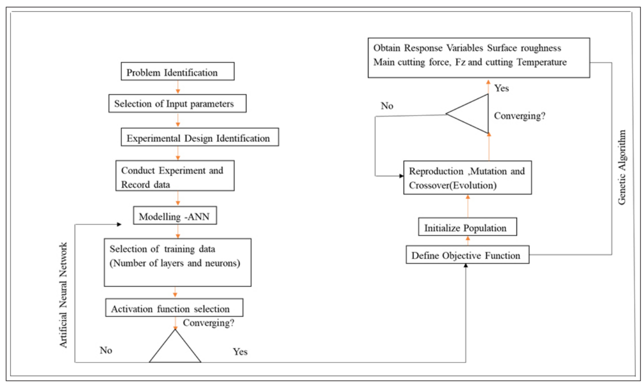

Figure 3: Flow chart for ANN-GA methodology.

for the overall model. In this model, a total of 19 trial sets were needed to train the network, whereas only 6 sets - or 10% to 20% - were taken into account for validation and testing.

Some trail results are shown in table 3. The trail results of 4-10-3 ANN modeling with different architecture we have considered three different training algorithms based on ANN model. Firstly, TRAINLM was used to train and test data in which the best result was obtained at 9 numbers of neurons having R-value of 98.78% which is close to 1. Then after that TRAINGDX algorithm was used for training, testing and validation data in which the best result was obtained at 5 number of neurons having R-value 95.39% showing less noise and also within the acceptable range. Finally, TRAINSCG, algorithm was called to train and test the data in which best outcome was obtained at 5 numbers of neurons with R-value of 97.61%. Hence on capability with all the three-training algorithm, we can say that TRAINLM gives the optimum R-value compared to GDX and SCG. So, for training and testing purposes, the TRAINLM is the best suited training algorithm.

Figure 4 displays the training performance of the current model with the number of epochs19. 2516 has the highest validation performance that has been seen. At the thirteenth epoch, 2597 was seen. The train network's regression graphs showed that the R-value for training, testing, and validation was 0.96, as shown in figure 5. This is well above average and very near to one. This demonstrates how successfully the ANN model correlates the very non-linear relationship between the turning parameters and the surface roughness, main cutting force, and mean cutting temperature. The 4-10-3 ANN architecture's gradient graphs are displayed in figure 6.

Due to the limitations of the machine, the closest combinations to confirm the experimental results are 55 m/min, 0.04 mm/rev, 0.75 mm, 500 watts; 55 m/min, 0.4 mm/rev and 0.25 mm, 500 watts; and 0.04 mm/rev, 30 m/min, 0.04 mm/rev, 0.25 mm, 300 watts for A, B, C, and D, respectively. The average cutting temperature, main cutting force, and surface roughness are observed to be 0.63 m, 112 N, and 210 OC,

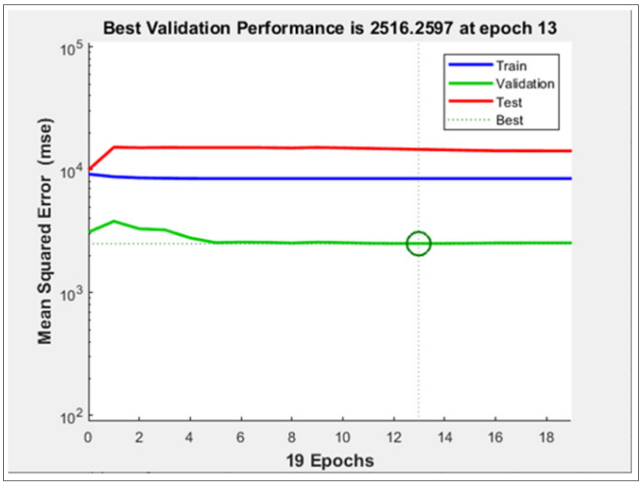

Figure 4: Performance plot for 4-10-3 ANN architecture.

Table 3: Trail results of 4-10-3 ANN modeling with different architecture.

Training Algorithm	No. of nuerons	Training	Testing	Validation	Overall	MSE of best validation performance
TRAINLM	5	0.95615	0.9719	0.94536	0.95453	13635.1111
	6	0.9243	0.94665	0.98129	0.93883	1875.0782
	7	0.77331	0.7327	0.76539	0.75445	15552.0992
	8	0.99138	0.96575	0.99324	0.98759	609.3786
	9	0.99978	0.9622	0.99461	0.98787	353.7937
	10	0.90853	0.75421	0.96612	0.88786	7142.6933
TRAINGDX	5	0.94005	0.97186	0.99372	0.95393	8264.6003
	6	0.80155	0.73097	0.78798	0.78933	9438.4349
	7	0.93416	0.90618	0.95977	0.93385	4232.8233
	8	0.92607	0.97708	0.8891	0.92368	11987.5442
	9	0.95181	0.96203	0.95891	0.95141	3790.1313
	10	0.89402	0.90431	0.91719	0.89516	5729.619
TRAINSCG	5	0.98124	0.96146	0.98406	0.97612	1715.0914
	6	0.94001	0.88628	0.9818	0.93496	1935.9198
	7	0.96051	0.95532	0.90936	0.93496	5727.3866
	8	0.99267	0.92883	0.96285	0.93496	3026.479
	9	0.91391	0.78627	0.93617	0.93496	3723.1343
	10	0.96394	0.94032	0.95156	0.9577	2688.1413

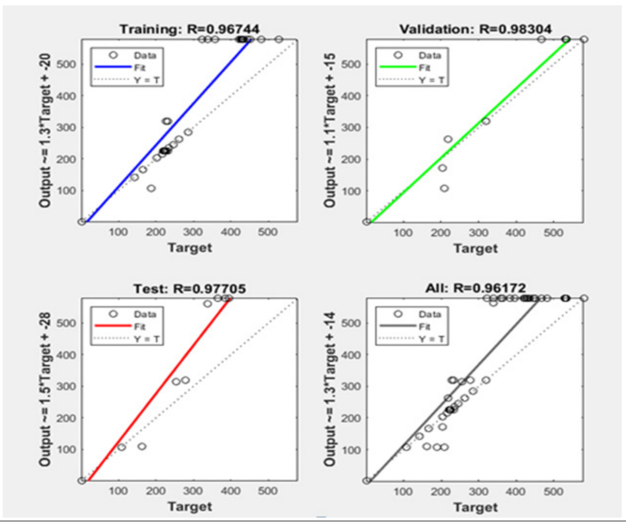

Figure 5: Regression plots for the 4-10-3 ANN architecture.

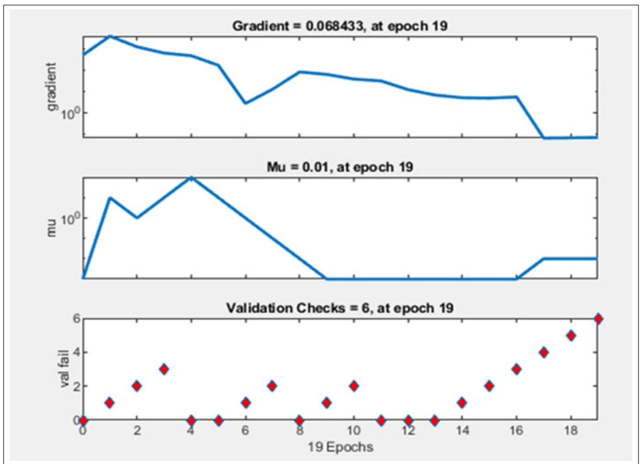

Figure 6: Gradient plots for the 4-10-3 ANN architecture.

respectively. So, the GA results from experiments and predictions correspond quite closely. Thus, the ANN-GA model is a very effective tool for simulating and forecasting the intricate relationships between input parameters and outputs.

A second order regression modelling

The experimental data set aside in table 3 were used to create a second order mathematical regression model. According to the following equations, surface roughness, main cutting force, and cutting temperature can all be calculated.

Surface Roughness (Ra) = -0.01439 * A + 3.881212 * B + 0.670363 * C - 0.00075 * D + 1.472826

Main Cutting force (CF) = -1.28199 * A + 1083.442 * B + 106.3101 * C - 0.17008 * D + 210.2695

Cutting Temperature (CT) = -0.35489 *A + 2468.727*B + 160.2361* C+0.568108* D + 22.8832

Regression statistics data for surface roughness is represented in table 4. It can be seen that the R-square value 95.64% is near to 1. That means the noise is less and it is within the acceptable range. And the ANOVA table for surface roughness corresponds shown in table 5. It is found that the significant value for surface roughness is less than 0.005. It means that the regression values giving best results.

Table 4: Surface roughness summary output.

Regression Statistics	
Multiple R	0.97014013
R Square	0.95646648
Adjusted R Square	0.947087757
Standard Error	0.18965525
Observations	29

Regression statistics data for the main cutting force is represented in table 6. It can be seen that the R-square value 90.26% is near to 1. That means the noise error is less and it is within the reference interval. And the ANOVA table for main cutting force is shown in table 7. It is found that the significant value for surface roughness is less than 0.005. Table 8 and table 9 show cutting temperature summary output of R-square and adjusted R-square values are very close significant factor having less error.

The accuracy for the output parameters using ANOVA here for surface roughness R-square value is 0.95646648, main cutting force for R-square value is 0.902604377 and for cutting temperature R-square value is 0.950300378. The outcome of surface roughness, main cutting force and cutting temperature values' using ANN gives significant results with better efficiency.

Conclusions

In this study, for dry turning of Monel 400, we examined the surface roughness, main cutting force, and metal cutting temperature at the tool work interface. The cutting speed, feed, depth of cut and laser power each had three different

Table 6: Main cutting force summary output.

Regression Statistics	
Multiple R	0.950054934
R Square	0.902604377
Adjusted R Square	0.886371774
Standard Error	15.70885361
Observations	29

Table 5: ANOVA for surface roughness.

	DF	**SS**	**MS**	**F-value**	**Significance F**
Regression	4	3.776925965	0.944231491	20.62485363	1.76615E-07
Residual	24	1.098749897	0.045781246		
Total	28	4.875675862			

Table 7: ANOVA for main cutting force.

	DF	SS	MS	F-value	Significance F
Regression	4	54885.5757	13721.39392	55.60441138	8.61993E-12
Residual	24	5922.433959	246.7680816		
Total	28	60808.00966			

Table 9: ANOVA for cutting temperature.

	DF	SS	MS	F-value	Significance F
Regression	4	204890.1432	51222.5358	24.04512451	4.2656E-08
Residual	24	51126.40853	2130.267022		
Total	28	256016.5517			

Table 8: Cutting temperature summary output.

Regression Statistics	
Multiple R	0.984595092
R Square	0.950300378
Adjusted R Square	0.917017108
Standard Error	46.15481581
Observations	29

levels. These levels were modified in accordance with the DOE L_{30} Orthogonal level design. A feed forward back propagation ANN model that was trained using the LM method produced high regression. The model has a 4-10-3 architecture. The most appropriate training method, TRAINLM, was used in order to train and test the data. The greatest possible result was accomplished by using 9 numbers of neurons and achieving an R-value of 98.78%. The ANN Model could be applied effectively to accurately anticipate and quantify surface roughness, primary cutting force, and metal cutting temperature. This was possible because of the model's flexibility. A hybrid ANN-GA approach was used to forecast. The following diagram illustrates the surface roughness, main cutting force, and cutting temperature conditions that produce the best results. Optimal conditions of surface roughness is 0.64808 µm, cutting speed 55 m/min, feed 0.04 mm/rev, depth of cut 0.75 mm and laser power 500 watts, and predicted optimal conditions of main cutting force is 156.685 N, cutting speed 30 m/min, feed 0.04 mm/rev, depth of cut 0.25 mm, and laser power 500 watts, and also predicted optimal conditions of cutting temperature is 312.604 °C, cutting speed 55 m/min, feed 0.04 mm/rev, depth of cut 0.25 mm, and laser power 300 watts. Hence, The ANN-GA predicted and experimentally obtained results were very closely related. Further a second order regression model was also compared and considered with ANN model. The study proves that ANN-GA will be the most beneficial approach for anticipating different attributes during CNC Laser assisted machining process. Future research work will be conducted towards inclusion of more process parameters such as tool wear, MRR, etc.

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None.

Conflict of Interest

There is no conflict of interest.

Credit Author Statement

Bhukya Rangilal: Study, Conception, Design; Nikhil Bharat: Manuscript - original draft preparation, Writing - review and editing; P.S.C. Bose and C.S.P. Rao: Analysis and Interpretation. All the authors read and approved the manuscript.

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