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Application of Artificial Neural Network: A Case of Single Point Incremental Forming (SPIF) of Cu67Zn33 Alloy

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Abstract
Artificial neural network (ANN), a Computational tool that is frequently applied in the modeling and simulation of manufacturing processes. The emerging forming technique of sheet metal which is typically called single point incremental forming (SPIF) comes into the map and the research interest towards its technological parameters. The surface quality of the end product is a major issue in SPIF, which is more critical with the hard metals. The part of the brass metal is demanded in many industrial uses because of its high load-carrying capacity and its wear resistance property. Considering the industrial interest and demand of the brass metal products, the present study is done with the SPIF experiment on calamine brass Cu67Zn33 followed by an ANN analysis for predicting the absolute surface roughness. The modeling result shows a close agreement with the measured data. The minimum and maximum errors are found in experiment 3 and experiment 7 respectively. The error of predicted roughness is found in the range of –30.87 to 20.23 and the overall coefficient of performance of ANN modeling is 0.947 which is quite acceptable.

Keywords
SPIF, input variable, artificial neural network, surface roughness.

Introduction

Single point incremental forming (SPIF) is an innovative sheet metal forming process in which a hemispherical end tool is used for the deformation on the thin metal sheets. The controlled movement of forming tool defined the accuracy of the SPIF therefore process needed a precise platform i.e. computer numerical controlled machine (CNC). The forming technique is more advantageous for the manufacturing of customized products, rapid prototyping, or low volume production. In the last two decades, several investigations are being made for conceptualizing the process, but still, an optimized processing environment has not been achieved. The authors suggested the positive forming technique in which the forming capability of metal increased due to the plane-strain mode which helps to form complicated shapes with sharp corner/edges (Park and Kim, 2003) and the thickness of the end part is directly proportional to the wall draft angle that should be greater than 30° for the ductile metals (Pohlak et al., 2007). Further, the punch force and sheet thinning rate is reported as the significant parameters in the SPIF (Bahoul et al., 2014). A report is presented that mentioned the futuristic approach and the scope of the SPIF (Oraon and Sharma, 2010). The complex deformation process of SPIF and the achievement of required surface finish of the final product is one of the prime concerns for its acceptance. The linear and quadratic relation of the thickness of metal and the total part depth affects the surface quality (Ambrogio, 2007). The dimensional inaccuracy with varying wall angles due to the spring-back effect is reported in the SPIF of SPCC metal (Luo et al., 2010). An investigation is made on the surface roughness termed as waviness of SPIF Product and declared that the large-scale and small-scale wavy texture marked due to the toolpath and large surface strains respectively (Hagan and Jeswiet, 2004) that could be transformed i.e. wavy to smooth surface achieved by decreasing the vertical step size (Junk et al., 2003). A theory is proposed by the authors in that the surface roughness is defined in terms of amplitude and spacing. The report mentioned that the surface roughness is directly proportional to vertical step size whereas an inverse relation to tool end di-

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ameter and slope angle (Hamilton and Jeswiet, 2010). Subsequently, the effects of feed rate and spindle speed on the SPIF of aluminum Al3003 (H14) are reported in terms of non-contact surface roughness (orange peel effect), thickness deviation, and the microstructural status of the formed part (Hamilton, 2010). The maximum surface roughness (R_z), and absolute surface roughness (R_a) are analyzed in the SPIF of aluminum grade AA7075 by varying the tool end radius, vertical step size, and wall angle (Durante et al., 2010). The medical implants (femoral condylar surface of the knee) is successfully developed through SPIF of Titanium Ti-6Al-4V and observed the effect of punch diameter and lubricants on the surface roughness) (Oleksik et al., 2010) whereas higher tool end diameter along with high tool rotational speed enhanced the surface quality of the SPIFed part, made of carbon steel (DC01), stainless steel (304), and aluminum (A1050) (Radu and Cristea, 2013). It is also reported that the step depth increment is the main input variable, which contributes 63.56% to the surface roughness (Shah and Chaudhary, 2014). Further, the statistical investigation on the SPIF of the aluminum AA1100 is done and confirmed the contribution of the step depth increment (64.19%) and wall thickness (17.23%) on the surface roughness of the formed part (Uttarwar et al., 2015) and found that the high-density lubricant like grease is suitable at low spindle speed whereas low-density lubricant like k-oil, vegetable oil, etc. are favorable at high spindle speed in the SPIF of the Indian standard aluminum grade 19000 (Patel et al., 2015). In the successive investigation, the report of the regression analysis of SPIF of aluminum alloy showed the contribution of tool diameter, spindle speed, step depth increment, and wall angle as 1%, 3%, 27%, and 69% respectively (Khatal et al., 2016). It is also reported that the tool of small end diameter received the high forming forces to the bigger tool diameter in the SPIF when experiments are conducted with constant input variables (Dabwan et al., 2016; Alsamhan et al., 2019). The C-channel, an aerospace part is successfully formed through SPIF of aluminum (Gupta and Jeswiet, 2019) in which a backup plate supported the thin sheet of aluminum for the prevention of the crack. In the SPIF of AA1050-H14 alloy with varying the tool end diameter, feed rate, step size, and sheet thickness, only the thickness of the sheet are found insignificant. The authors also directed that the surface quality is improved with the use of greater tool diameter on SPIF of thin sheet but it is very difficult to control because of contradicting effect of interacting input variables (Dabwan et al., 2020). Results showed that the helical tool path generates homogeneous thinning, and removed the surface scarring of aluminum AA7075-O (Esmaeilpour et al., 2019), and the interaction effect of tool radius and step size, favorably influenced the SPIF (Murugesan and Jung, 2021).

The achievement of goals in the manufacturing processes needed a user friendly-environment but the variation in the results is observed due to various reasons like machine or tool failure, mechanical properties of raw material, lack of experience, etc. therefore a system is needed to predict/forecast the output virtually. Presently, the trend is moving in the direction to develop a hybrid model based on finite element method (FEM), computational tools like data-mining (Xu et al., 2004), neuron-fuzzy logic (Liew et al., 2004) and artificial intelligence techniques like artificial neural network (ANN) (Wang and Lee, 2006). The results of ANN enunciated a tremendous amount of interest in the solution of manufacturing-related problems. In ANN modeling, the output of any forming processes are predicted with the use of historical data therefore a large amount of data is required for training and testing for a valid model (Kecman, 2001).

In the manufacturing process, the outputs are found variable. Consequently, these data are to split into training and testing. Properly trained networks tend to give reasonable answers with inputs that they have never seen. The researchers proposed a variety of ANN network algorithms for the modeling and computational work in manufacturing processes such as calculating the process functional error e.g. mean absolute error (MAE), mean square error (MSE), root mean square error (RMSE), etc. ANN models included feed-forward backpropagation (FFBP), Elman backpropagation (EBP), cascade-forward backpropagation (CFBP), self-organizing map (SOM), and Time-delay backpropagation (TDBP), etc. The feed-forward backpropagation (FFBP) algorithms (Ambrogio et al., 2011; Vahdati et al., 2014; Varthini et al., 2014) are widely utilized by researchers for the prediction of the surface roughness in the SPIF. The forming force is predicted in the SPIF of aluminum AA30003 by ANN modeling and is reported the coefficient performance 0.939 and the mean error of –0.215 (Oraon and Sharma, 2018a) while for surface roughness, it is found as 0.9474 with the mean absolute error (MAE) of 1.068.

Experimental procedure

The surface texture of the end product is one of the important output response that are demanded. In SPIF, obtaining the desired part accuracy and surface roughness is a major issue as it depends on the spring-back effect, step depth increment, and the toughness of the sheet metal.

The copper alloy Cu67Zn33, commonly known as calamine brass is taken for the experiments. The product copper alloys are wildly utilized in the industries due to its rigidity at high load and resistance to wear property. The ultimate tensile strength (UTS) of this material is determined in the automated material test machine 'INSTRON Series IX'. The test-samples are prepared and tested as per American society for testing and measurement (ASTM) standard B-557M. The results of tensile tests are tabulated in Table 1.

Table 1
Taguchi L8 design and measured R_a values

Metals	Cu67Zn33
Stress at Ultimate (MPa)	336.25
Strain at Max. Load (%)	4.43
Stress at Auto Break (MPa)	129.99
Toughness (MPa)	14.23
Maximum Percent Strain (%)	5.96

Six significant input variables are considered for the experiments. The input variables are step depth size (Δz), tool feed rate (f), tool rotational speed (R), wall angle (θ), sheet thickness (T), and density of lubricant (L). The output parameter considered for the analysis is the surface absolute roughness value (R_a). The experiments are performed on a robust machine DT-110 manufactured by Mikrotools Pvt. Ltd., Singapore. A customized forming tool is manufactured. The solid cylindrical rod of medium carbon steel 40C6 is taken for forming tool. One face of the

Table 2
Taguchi L8 design and measured Ra values

Exp.	Δz mm	F mm/min	R	θ	T mm	L Kg/m^3	Ra
1	0.1	20	500	15	0.2	1.5	134.86
2	0.1	20	500	45	0.4	4.9	268.29
3	0.1	100	2000	15	0.2	4.9	156.10
4	0.1	100	2000	45	0.4	1.5	269.83
5	0.7	20	2000	15	0.4	1.5	362.94
6	0.7	20	2000	45	0.2	4.9	378.63
7	0.7	100	500	15	0.4	4.9	360.95
8	0.7	100	500	45	0.2	1.5	369.63

0.7 mm diameter solid rod is grooved hemispherically and a 0.6 mm diameter bearing ball (Bohler W300 alloy) is inserted into the groove to form a hemispherical end. The experiments are designed according to Taguchi's methodology using the L8 orthogonal array. The square pyramid shape of base size 35 mm×35 mm is formed. The level of input variables for the experiment and the output i.e. absolute surface roughness (R_a) is presented in Table 2. The R_a-value of the test samples are measured through atomic force measurement (AFM) technique with 5×magnification.

Estimating Surface Roughness through ANN

In the present study, FFBP neural network 6-6-1 topology is modeled in which an input layer, a hidden layer, and a output layer (Fig. 1) is present. The ANN computation is done by using MATLAB, version 7.10.0 (R2010a) (Fig. 2) in which a three-layer FFBP network is developed.

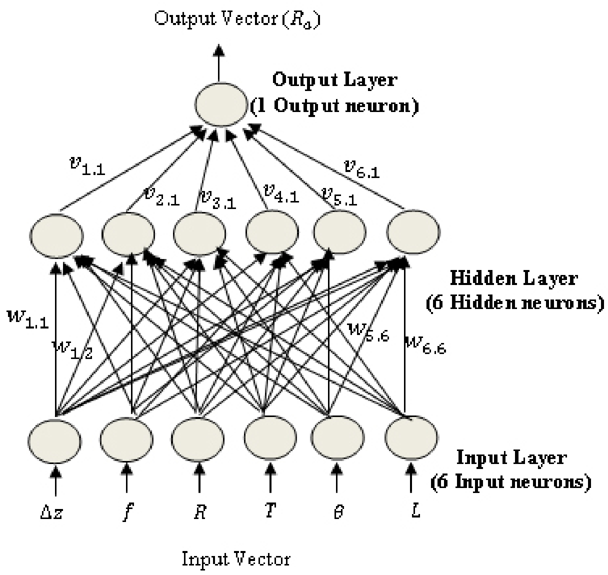

Fig. 1. Structure of three-layer backpropagation neural network

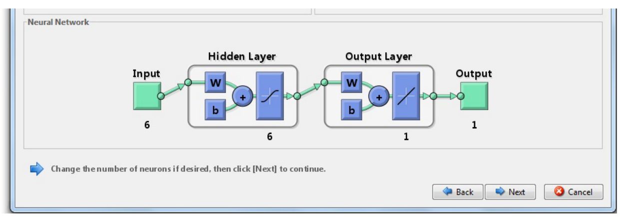

Fig. 2. The network architecture of FFBP

At hidden layer, the hyperbolic tangent sigmoid transfer function (Tansig) and at output layer, the linear transfer function (Purelin) is set. The model is adopted two stopping criteria i.e., the maximum number of iteration (the first activated) and the sufficient accuracy on the test set.

Network Modeling of Surface Roughness

The modeling of ISF through FFBP having the following set parameters is adopted for computation. They are summarized below.

Network: FFBP

Function for Training: TRAINLM

Learning rate: LEARNGDM

Performance: MSE

Training: Levenberg–Marquardt algorithm

No of neurons (n): 0 to 10

During the ANN computation 60%, 20%, 20% of experimental data are segregated for training, testing, and validation respectively without normalizing the input data.

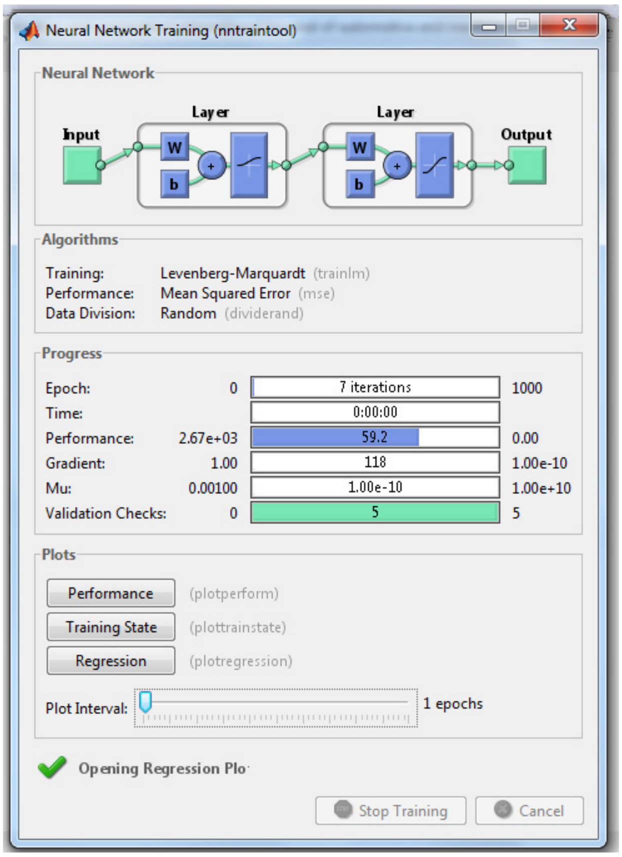

Fig. 3. ANN training performance

The training stopped after 7 iterations because the validation error increased (Fig. 3). Figure 4 showing the train data best validated at epoch 2 with a value of 54.8658 and the test set error and the validation set error have similar characteristics. The regression model indicated the performance index of ANN. The overall R-value comes as 0.947444 (94.7%) which quite acceptable.

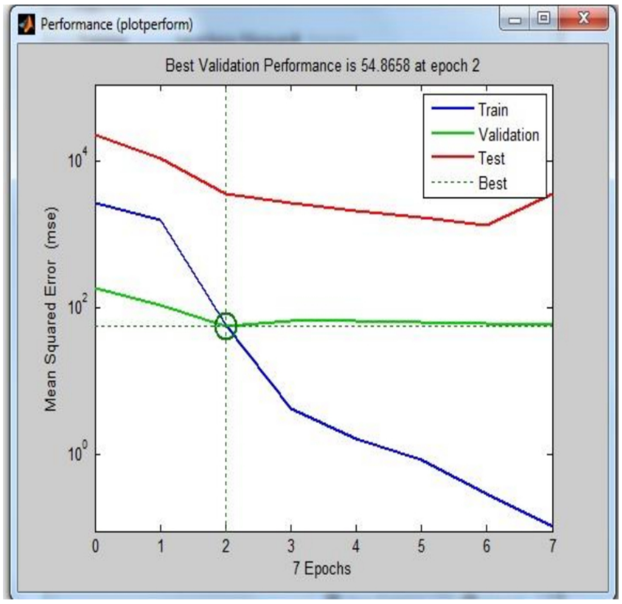

Fig. 4. Validation Plot

Result and discussion

The computational result of the SPIF and functional error is presented in Table 3. The results of the experiments yield good agreement with the predicted R_a-value. The error range of predicted R_a-value is –30.871%–20.23% and the mean functional error is 0.71. Table 3 shows the maximum error in the predicted R_a-value of approx 31% to the measured R_a-value. It is confirming that the achievements of the required surface finish of end product through SPIF by conducting the forming process at 0.1 mm step depth size, 20mm/min feed rate of the tool, 500 RPM, 15° wall angle, and the grease lubricant in the 0.2 mm thickness of CU67Zn33 alloy.

Figures 5 to 10 corresponds to a comparison of experimental R_a-value to predicted R_a-value set yielding an excellent agreement to each other. Figure 5 showed the comparison of experiment R_a value to predicted R_a at variable step depth size. The graph shows that the predicted R_a-value having similar nature to

Table 3
Comparison of R_a-values and calculated error function

Exp.	Ra (Exp.)	Ra (Pred.)	Error	Error (%)	Mean Error
1	134.863	176.497	41.63	–30.871	0.71
2	268.29	272.376	4.086	–1.522	
3	156.102	149.289	–6.813	4.364	
4	269.831	270.174	0.343	–0.127	
5	362.943	348.148	–14.79	4.076	
6	378.637	377.619	1.018	0.268	
7	360.951	287.911	73.04	20.23	
8	369.637	377.594	7.957	–2.152	

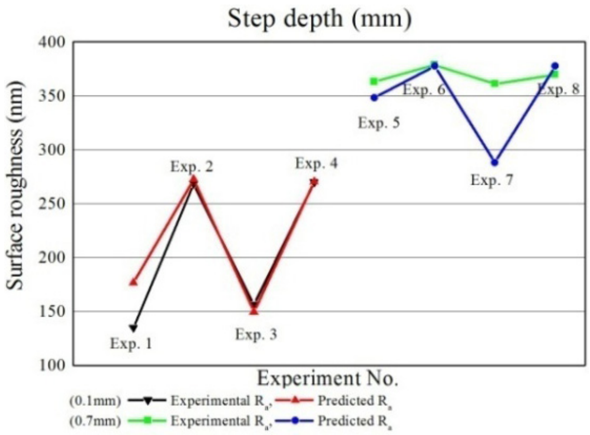

Fig. 5. Comparative results of step depth (Δz)

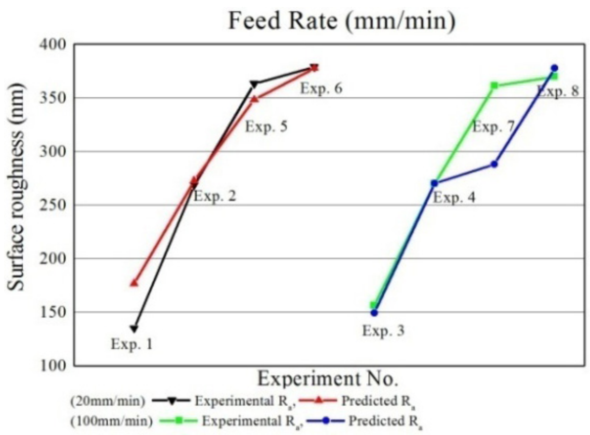

Fig. 6. Comparative results of feed rate (f)

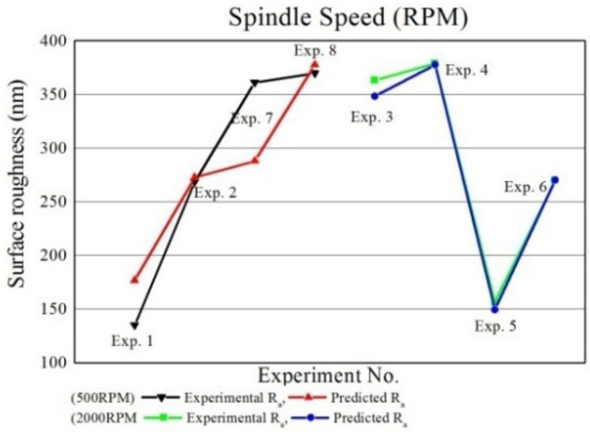

Fig. 7. Comparative results of spindle speed (R)

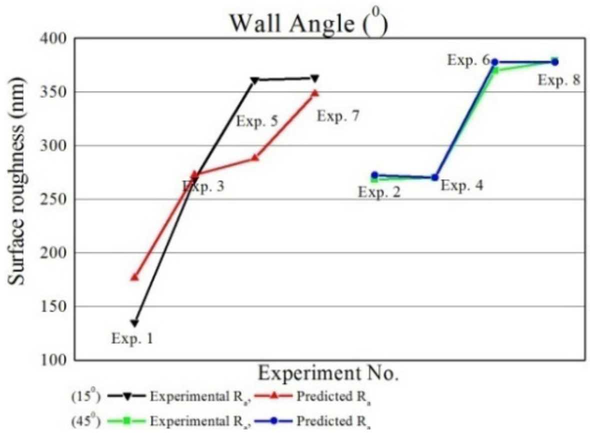

Fig. 8. Comparative results of wall angle (θ)

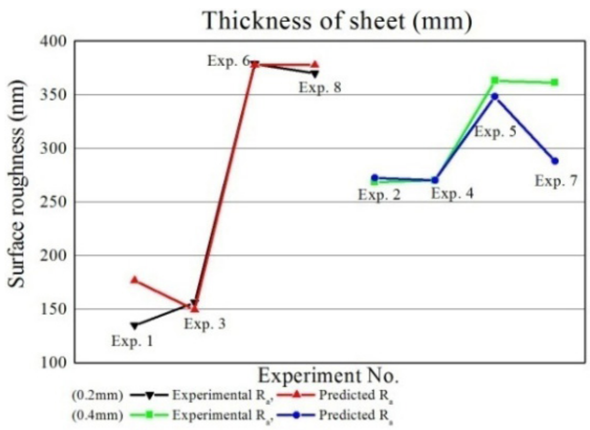

Fig. 9. Comparative results of sheet thickness (T)

experimental R_a in the case of step depth size Δz of 0.2 mm whereas it is diverted severely when the experiment is conducted with 0.7 mm step depth size. The maximum variation of 20.23% is observed in the experimental run 7 to the predicted R_a-value. The variation of predicted R_a value is also affected greatly at 100 mm/min feed rate which is controlled at the lower feed rate i.e. 20 mm/min (Fig. 6). The higher spindle speed i.e. 2000 RPM is recommended for getting the minimum surface roughness when the 0.2 mm thick-

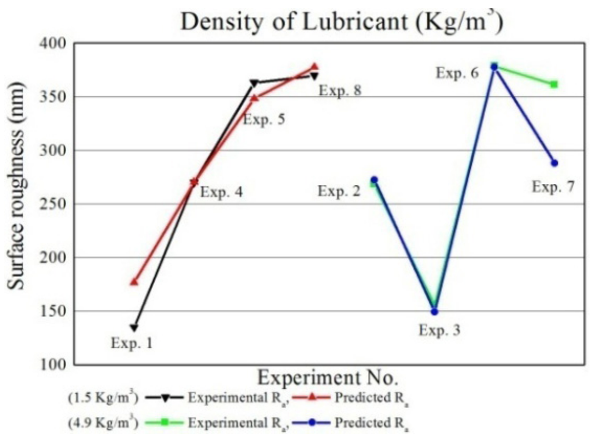

Fig. 10. Comparative results of the lubricant (L)

ness of Cu67Zn33 alloy is deformed through SPIF (Fig. 7). At varying wall angles, the predicted R_a-value greatly deviated from the experimental R_a-value for lower wall angle 15°.

The control of the roughness value, higher wall angle is suitable for SPIF of metal having high hardness (Fig. 8). When the experiment is conducted at 45°, the measured R_a-value is quite closer to the predicted R_a-value. The predicted roughness value is found similar curve to the experimental R_a for the SPIF of 0.2 mm sheet thickness (Fig. 9) and the formability is increased with increasing wall angle. Figure 10 indicated the effect of lubricant in the SPIF of Cu67Zn33 alloy. Applying white grease in the SPIF of Cu67Zn33 alloy presumes the smooth surface finish. The graphite lubricant greatly affected the R_a-value, when the inputs are set at the high step depth size, 100 mm/min feed rate, and 2000 RPM, the coarser surface finish is achieved.

Conclusions

The SPIF of Cu67Zn33 alloy is successfully done and computational work for the prediction of the surface roughness through ANN is presented in this paper. The network structure, modeling, and computational methods of ANN are presented in this paper that is compared with the measured R_a. The predicted R_a-value is found quite closer to the measured R_a. The minimum error of 0.343 nm in experiment 4 and the maximum error of 30.87% in experiment 1 are found. The overall efficiency of 94.7% indicated that the acceptable data is generated with ANN modeling.

The solving technique in ANN is quite simple and efficient. Therefore, ANN can be used as a predictional tool in manufacturing sector too.

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