SURFACE ROUGHNESS PREDICTION OF PARTS PRODUCED THROUGH FUSION DEPOSITION MODELLING

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SUMMARY

With technological advances happening in almost every industry, the manufacturing industry has seen quite a growth in terms of scientific advancements due to incorporation of hi-tech instruments and processes. To cope with the fluctuating demands of manufactured products, companies have adopted 3D printing technology for small-quantity batch production. 3D printing is an additive manufacturing (AM) based techniques that is capable of producing complex shapes, reducing material wastage, and reducing production time. In the present work, different researches which predict the Ra of parts produced through fusion deposition modeling are discussed. The present work consists of all the latest research work that has been conducted to identify the factors impacting the surface finish of products developed through Fusion Deposition Modeling (FDM).

KEYWORDS

Fused Deposition Modelling, Fused Filament Fabrication, Artificial Neural Network, Deep Neural Network, Analysis of Variance

1. INTRODUCTION

FDM is a form of AM in which a filament component has been heated to a semi-molten stage, extruded through a nozzle tip and deposited onto a print bed or a substrate to develop products and objects layer by layer made out of solidified molten filament material. It is a fully automated process and highly used for rapid 3D prototyping.

The filaments used are usually thermoplastic materials including acrylonitrile butadiene styrene (ABS), polyethylene terephthalateglycol (PETG), polylactic acid (PLA) andnylon. The FDM processes are being widely used for research and development purposes with the aim to improve the overall manufacturing process, develop new materials and expand its application to a wide range of engineering applications.

High speed of manufacturing is the prime most reason for manufacturing industries to adopt FDM 3D printing technique, due to which lead time was reduced and prototyping process speed has been enhanced. The availability of a wide range of filament materials in terms of strength, color, and cost becomes a reason for the FDM to gain popularity and the product design becomes easily scalable due to the low cost-to-size ratio. However, the biggest disadvantage of FDM is its low resolution, making it non ideal method of production for small parts that require high detailing due to irregularity in Ra and the need of post-processing to get a smoother finish which can be achieved through vapor smoothing, gap filling, and epoxy adhesion. Since the object was developed layer by layer, the resulting layer is anisotropic in nature.

Since the entire quality of the final produced object depends on its Ra it becomes incredibly significantto find optimum values of parameters impacting the Ra. In other words, Ra or surface finishing is an indicator of the quality of a product and determines the lifespan and proper functioning capability of the product. Keeping this objecting in mind, a research review has been performed in this report discussing different ways of the electing most accurate parameter values that impact Ra and ways of controlling and predicting the Ra values using different machine learning (ML) and Deep Learning Techniques.

RSM (Research surface methodology) is a versatile approach that may be utilised to create mathematical models that anticipate results, examine surface responses using response surface curves to describe how an input variable impacts a response parameter, assess variation in procedural variables values and choose the best variable. In this study, a second-degree linear model has been used to assess the data, evaluate the model's parameters' relevance, compute the mean response and identify the best operating conditions for the control variables that help achieve an optimum response across a certain interest zone.

Another useful technique to improve the quality of a product or a process is the Robust design methodology. The Taguchi approach has been utilised to formulate experiments utilising the orthogonal array method in order to get the most performance out of the 3D printed parts. It is a simple yet efficient technique effective method. In this study, four parameters with three levels each were found using an orthogonal array of L9 (34). The ASTM D638 type IV standard samples were created using 3D printers of the FDM kind. Data was analysed and findings were received. As a consequence, the print pattern (cross), Y-axis orientation (0°), support angle (0°), and side walk are the factors that yield the best results (0.15 mm). The results of this study might serve as a guide for future researchers since they showed that the improved Ra of printed components produced by a FDM machine can be enhanced utilizing the Taguchi technique.

2. PREDICTING RA USING ARTIFICIAL NEURAL NETWORK (ANN)

The most popular advanced ML technique used by researches was found to be the artificial neural network has been further integrated with other ML algorithms to predict the Ra with maximum accuracy of parts produced using fusion deposition modeling. So et al. [4] proposed an ANN-based and non –contact method as shown in Figure 1 to estimate the roughness of a specified surface in SLM (selective laser melting)- customized implants after training and used scan data from femur(thigh)bone. The precision of this model reached close to an impressive 97.2%. In this work, the prediction model was suggested to make an estimate about Ra between consecutive or successively pileslayers/stockpile in a thin wall which was created by wire arc additive manufacturing(WAAM) and this model showed high dependency on process parameters and the DNN(deep neural network)-based bead shape of the preceding processed layer. The CMM (Capability maturity model) that has been inserted and kept a.3D locations point clouds in a thin wall, measured the bead shape. The utilized DNN model used these data as input data which could predict Ra for the given process parameters.

There was one limitation in [4] which prevented it from adequately depicting a full wall. It was recommended to use point clouds and a smoothing technique to expand the cross section to the entire wall area in order to get over this obstacle. A resilient scalar was also employed to lessen the effects of the deviations brought on by the fact that the measurement ranges for each variable changed over course of the study project.

Two very traditional approaches, SVR and regression, were also used in this work but their performance turned out to be quite contrary with that of DNN and according

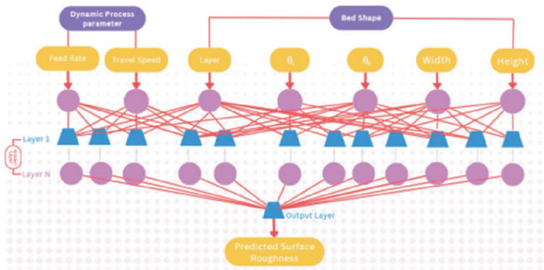

Figure 1. Methodology adopted by [4] for prediction of metal additively manufactured (AM) Rausing DNN

to the speculative findings, DNN performed the best amongst them all the best DNN model came out with a prediction accuracy of as high as 98% and represent enhanced high correlation between the anticipated values and the speculative findings. The prototype proposed and established that this research work could accurately predict Ra when a fresh layer was piled under a variety of bead shapes an dadaptive procedureparameter combinations. The procedural outcomes obtained under a certain variable for operationsr could be then used to seek for the best of it. In a situation where input data was limited a search algorithm or reinforced learning algorithm can be used.

Cerro et al. [10] improvised it model by incorporating various ML algorithms for classification including logistic, regression, multi layer perceptron (MLP), sequential minimal optimization (SMO), Bayes Net, Naive Bayes, J48, logistic model trees and random forest that could predict the Ra of parts manufactured from poly vinyl butyral (PVB) using FDM. Five input parameters were taken into consideration, namely height, print speed, number of perimeters, wall angle and extruder temperature. Sixteen specimens were 3D printed and each part had three sloping surfaces each at an angle of thirty degrees, forty five degrees and seventy five degrees with the horizontal, making forty-eight surface in total. The print values of each part were determined by fraction at doors speculative design. The Ra of each sloping face was measured using a perthometer. Five measurements were taken for each surface and arithmetic mean of the 5 noted values have been used as a final reading. From the obtained speculative values, 40modelswere trained and authenticated using WEKAML/software. And then, ANN was applied along with the selected ML algorithms for the tuning process. Accuracy score and Kappa statistic were the two selected parameters to identify the best algorithm. Fine tuning of the best identified algorithm was performed using bagging, boosting and random subspace ensemble techniques. This was done to identify the most optimized value of input parameters.

It was observed that the best result was generated by the ensemble technique bagging and multilayer perceptron (BMLP)with a Kappa statistic value of 0.9143. The quantity of neurons in the hidden layer were calculated by taking the mean value of input characteristics and number of classes in the output variable. In BMLP, five input characteristics and two classes in the out variable were taken into consideration. It was also observed that for a binary problem simple neural networks gave better results in comparison to complex networks. For the assumed input variables i.e., height of layer, print speed, extruder temperature, number of perimeters and wall angle, the output parameter i.e., Ra comes out to be a discretized value. These values also followed the ISO 1302:1992 standardization plus it was also observed that amongst all the input variables, wall angle and height of layer had a relatively higher influence on the surface finish of the given specimen which was 3D printed.

Like in the previous work, various classifier techniques were employed and data mining approaches were utilized to create the models in [9] to predict the Ra of items produced in PLA using3D FD such as J48 (C4.5), Bayesnet, naive-Bayes, simple logistic, SMOO(SVM), IBk(KNN), KStar, multilayer perceptron (ANN), LMT and random forest. Through a cross-validation process, the models have been evaluated (10-folds). These models were compared against one another using the kappa statistic and the proportion of properly categorized examples. Print orientation, height of layer (LH), extrusion temperature (T), prints speed (PS), print acceleration (PA) and flow were the input variables (F) in the study, out of which flow and height of layer have proven to be crucial for producing a higher surface finish in XY and XZ specimens as it was noted that The PLA printed specimens with very less values of Ra in XY and XZ direction had a flow of 1 110% and a height of layer of 0.16 mm and a pair of spectacles/wearables glasses had been produced using these values as a concrete and immediate application of this study. It may be concluded that the model produced by the multilayer perceptron artificial neural network (MPANN) method is one of the models that best identify the examples as per the Ra, applicable for horizontal and vertical specimens both and LMT was another method that produced models with good outcomes for the current work. There are publications in the literature that also employed various ANN types to forecast the Ra of printed items made using FDM.

Vahabli et al. [8] stated that the surface quality of the manufactured items originates from the layered manufacturing principle and it's limiting factor with FDM process. The surface quality of the manufactured items, that originates from the layered manufacturing principle, is the FDM process' limiting factor. For exact arrangement of the AM process to lessen the Ra of the component formed by FDM, modeling of the Ra distribution has been utilized to optimize the efficient measures prior to the fabrication process. Analytical Ra evaluation has been utilized to enhance the surface texture. Practically such estimates usually fall short of accurately predicting the Ra over the whole potential range of surface build angles.

As a result, an RBFNN has been used in this work to use empirical data obtained from a particular test section. The most crucial component of the intelligent training procedure is the precise modification of the procedural parameters (such as weight connections, biases, spread and the quantity of neurons of the RBFNN model). One optimization algorithm with great convergence performance, quick speed, and a manageable amount of parameters is ICA and the effective parameters were optimized in this approach using ICA. The Ra of the FDM-built items may be estimated with the greatest accuracy and precision using the RBFNN-ICA model. The RBFNN and RBFNN-ICA models had MAPE values of 7.11% and 3.64%,erespectively, and MSE values of 7.48 and 2.27, respectively. The comparison of the suggested models in were used as analytical models that showed the improvement in estimating performance.

The simulation's outcomes verified that the replies of RBFNN-ICA model were more fitting. The sensitivity analysis evaluation of the input parameters and an assessment of the effective variables of RBFNN model were used to investigate the robustness of the RBF network. The suggested layouts performed most advantageous at the highest values of 55 numbers of neuron and 0.3913 for the spread value.

In [11], an ANN model had been discussed that considered the following input parameters—the quantity of neurons, hidden layers, height of layer, in fill density, nozzle temperature and print speed. He also predicted the Ra of FDM products. An speculative matrix of equal Ra was produced for the given parameters by feeding data into an ANN model to evaluate it. 27 tests total were conducted with different input parameters The three readings were mathematically averaged to result in the final reading. It was noted ,similar to the observations, made in previous findings and research work that ANN models handle noisy data more effectively than conventional regression based models.

A chain of input and output nodes connected by one or more layers of hidden nodes makes up an ANN. An ANN model has been developed to forecast the surface as a function of the input parameters using the built-in ANN Tool in MATLAB. For such data, there are input and target variables. The ML algorithm utilized in the ANN model is the Levenberg-Marquardt.(Le-M).algorithm, a return propagation algorithm. The computed MSE (Mean Squared Error) value has been used to calculate the performance of this model.

The collected data from the experiments are divided in a seven is to three (7:3) ratio into training and testing data. Fifteen (%) of this data was utilized to validate the data, fifteen percent has been used for testing, and rest seventy percent for network training. It was observed that quantity of neurons and hidden layers on the ANN model impact its capacity to generate accurate predictions. With an accuracy score close to 0.9, the ANN model with 150 neurons on each of its two hidden layers and one hidden layer could accurately predict the Ra. The height of layer print speed, nozzle temperature, and are all directly and infill density inversely correlated with the Ra. It diminishes as infill density rises. The effect of print speed on Ra increased with height of layer and was stronger at higher one.

A data driven technique has been proposed in [12] for enhancing the surface texture of AM items, employing Ra as a gauge for the quality of the manufactured goods. According to their beliefs, inappropriate Ra optimization could lead to a short product life and poor structural performance. It was also noted that in order to control Ra, an accurate prediction of the outcome of the input process parameter must be made beforehand. So et al. [12] employed a number of analysis techniques, including as DNN and data pre-processing, to forecast Ra. The Ra was determined in the first phase as mean of deviation on both sides of the WAAM product. A gas tungsten arc welding-cold metal transfer, which is an speculative setup, including a robot manipulator, welding power source with a welding torch, and a coordinate measuring device were used to get 3Depointeclouds of the wall surface positioned between two piled layers. The robot and power source controllers were in charge of controlling both the static input process parameters, such as arc length, wire diameter, feeding angle, shielding gas percentage, and flow rate, along with the dynamic input process parameters, such as travel speed, feed rate, and previous layer temperature. Using the aforementioned setup, 27 thin walls along with five layers were generated. The values of the procedural parameters were collected and measured, the bed shape's measurements were noted, and the data was compiled. To speed up model training, prevent accuracy loss, and lessen the impact of deviation resulting from variations in measurement range of the various variables, this data was standardized using a scalar normalization method. This data is then used to train a DNN-based model.

The performance of the DNN model mentioned above has been assessed using the mean absolute percentage error and root mean squared error or MAPE and RSME, respectively. Eighty percent of the data are for training, and twenty percent are for validation. It was found that actual values and expected values had a strong correlation, and the DNN model had a prediction accuracy of almost 98%, higher than the prediction accuracy of the ANN model used in [4]**.** The method presented here can be used to measure Ra when a fresh layer was layered under various bead shapes and dynamic operation settings, pretty similar to the specimen mentioned in previous research work.

The methods suggested in [12] may be used to the field data from operated wire plus arc additive manufacturing (WAAM), which resulted in a mean absolute percentage error (MAPE)of roughly 1.93%. In [13], it was stated that (AM) technologies like FDM have found widespread application in a variety of area of the modern manufacturing sectors, including transportation, aerospace, and medical, due to their capacity to generatecomponents with complex designs in less time and at a lower cost, resulting into their widespread popularity but selecting the input procedural parameters carefully is essential to achieve the best print quality possible. This study presents many approaches, such as response surface methodology, particles warm optimization (PSO) and symbiotic organism search, to identify the ideal parameter settings for improved surface quality—more precisely, the Ra of the FDM printed item. Height of layer, print speed, temperature, and outer shell speed were used as the input parameters, with Ra being considered as the output response. The following research work explored different aspects of FDM.

This study [14] further aimed to predict the Ra of FDM prototypes. Because average roughness is not sufficient, this study aimed to broaden the characterization to include all the roughness characteristics that may be discovered by a profilometric analysis. Along with a theoretical model of the 3D profile, the function of the procedural parameters and part form was supplied. An acceptable geometry was designed and prototyped validation. The data was measured using a profilometer and microscopic investigation was also included. A methodology based on the suggested layout was applied to optimize prototype fabrication in two real-world scenarios.

In [15], it was stated that to further improve the quality of objects made using AM, advance estimation of Ra distribution is essential. However, a rigorous test for model validation and the reasons why surfaces are rough have not been fully assessed. Therefore, the overall goal of the study in [15] is to develop a solid model for predicting the distribution of Ra in FDM, or components of fused deposition modeling, based on empirical data and optimized ANN. The planning stage of the procedure is therefore crucial for optimizing process elements like cost, time, and quality. The procedural parameters are to be selected for which analytical and empirical Ra estimates modeling and methodologies were applied and then in order to provide for a total calculation of the suggested layout, a special test was created. The ANN structure was optimized using both evolutionary algorithms and the trial-and-error approach. The creation of a novel strategy was based on the combination of competitive imperialist algorithms with intelligence algorithms like ANN coupled to particle warm optimization (PSO).

In this wok, Sensitivity analysis has been used to find the process variable that was most helpful. The following model was rigorously tested by building a variety of trench on components and medical case studies, including a molar tooth, cranium, femur and a specifically created hip steam. One of the improvements in Ra distribution modeling that were discussed in this research is the reduction of the total Ra of parts compared to analytical approaches. The introduction of a better method for choosing process parameters in accordance with design criteria is another improvement. Accurate estimates and rapid convergence are hallmarks of the advanced algorithm (PSOICA)-based optimized ANN.

Similarly, Cortes et al. [16] also stated that FDM is the one with the greatest adoption of all the AM techniques used. New materials and processes have been greatly improved for FDM printing in recent years. As a result, FDM may now be used to produce functioning buildings in addition to the quick prototyping it was previously utilized for. For some applications that demand great accuracy, this printing process still is not dimensionally accurate. The most widely employed of all the AM processes, according to [16], is FDM. For FDM printing, new materials and procedures have substantially improved recently. As a result, in addition to the quick prototyping it was previously employed for, FDM may now be used to create functional buildings. This printing technology currently is not dimensionally accurate for some applications that require high accuracy. The work describes a method for increasing the dimensional accuracy of objects made using FDM. First, the Abaqus application has been used to construct a numerical simulation framework for AM procedures and the numerical simulation framework has been used to obtain and analyze the deformations of three distinct geometries.

3D printing is a process that creates three-dimensional items layer by layer using a substance. The manufacturing sector has quickly adapted to the development of 3D printing. However, for various combinations of the input parameters, the material qualities of the produced item vary. Therefore, it is crucial to ascertain the created specimen's qualities. By experimenting with different combinations of the input settings, specimens of ABS that meet ASTM G99 standards have been created in the current study utilizing a 3D printer.

Ra in AM is essential to research, according to [17], as it influences building factors including thickness of layer and building orientation. Some AM machinery had a minimum thickness of layer that did not match the required degree of roughness. Additionally, it produces an unnecessarily smooth surface. This increases the time and expense of building without offering any benefits.

These problems were addressed and a precise Ra was achieved by using a prediction model. Building orientation has been used to predict the Ra using conventional regression models, and the building orientation and thickness of layer were used to apply ANN to estimate the Ra. ANN was created on the basis of speculative study that looked at how thickness of layer and building orientation affected Ra. Some of the data were utilized for training, while others were used for verification. The findings demonstrated that the thickness of layer parameter affects the Ra more than the building orientation parameter. While some of the data were utilized for verification, some were used for training. The results showed that the construction orientation parameter has less of an impact on the Ra than the thickness of layer parameter.

3. PREDICTING RA USING ANN

In this section researches that used variance of analysis (ANOVA) as a method to predict how accurately a model has predicted Ra of parts produced through Fusion deposition modelling have been summarized. [1] found out that Ra, in addition to size and shape, is the most critical factor to consider when evaluating the performance of FDM and the quality of items produced with FDM. In order to create PLA samples using FDM, [1] employed an L16 array with layers differing in thickness from 0.1 mm to 0.4 mm. For thickness of layeres above, surface roughness was discovered to range from 9.102 mm to 10.275 mm. Thickness of layer and deposition head velocity were the factors that had a major influence on Ra according to Sutar et al. [1].

In this inquiry, process's influence factors on Ra were examined using ANOVA and mean effect graphs. The relevance of procedural variables affecting Ra were assessed using the p-value at a 95% confidence level (0.05). A substantial correlation exists between Ra and orientation because p-value for orientation was 0.015, which is less than 0.05 because the thickness of layer and infill p-values density were 0.826 and 0.296, respectively, which are more than 0.05, the other two factors had no impact on Ra. R2 was 98.59% for the Ra data, while R2 corrected came out to be equal to 94.37%. R2 (pred) was 71.50%, which indicated that with the chosen range, the model accounts for 71.50% of the variation in Ra.

Mean effect plots were created in order to clearly show the association between the process parameters under consideration & trend of Ra formed by Sutar et al. [1]. At 0.12 mm, (thickness of layer), the mean Ra is 5.64 m; when layer of thickness is at 0.14 mm, it is 5.41 mm; and at 0.16 mm thickness of layer, it is 5.808 m. As a result, at a thickness of layer of 0.14 mm, the least mean Ra is discovered. Ra increased by 4.12% in comparison to 0.14 mm layer thickness, at 0.12 mm layer of thickness. Ra increased by 7.32% in comparison to 0.14 mm thickness of layer, at 0.16 mm layer thickness. Because thickness of layer in printing is actually height of layer, this suggested that thinner layers produce better surface finishes.

The inference that can be made from Sutar et al. [1] is that the evaluation and prognosis of the operating parameters for 3D printed objects produced using fused deposition modelling are an important parameter to measure quality of the produced parts. The build orientation is crucial for Ra concerns because it significantly affects Ra for the range that was studied in this experiment. The ANOVA findings reveal that p value for build orientation is 0.015, which is less than 0.05, and the Ra (Ra) values range from 2 to 5 m for 0° and 90°. In contrast, Ra values for 45° range from 8 to 10 m.

Similarly Chohan et al. [7] used ANOVA like Sutar et al. [1], but with various print input measures, including orientation angle, infill angle and thickness of layer, were used during experimentation. A mathematical model for prediction has been created using RSM and configurable input parameters. Investigating the impact showing various printing measures on Ra involved the use of the ANOVA, main effect and interaction plots, 3D surfaces, and contour plots. Last but not least, Robust design methodology and RSM approaches were used to optimize Ra (Ra) in parts produced by FDM printing as shown in Figure 2. When the mean Ra and the S/N ratio of the Ra were predicted, it was found that the models could adequately explain the responses within the ranges where the greatest error percent was 14.61% and 18.83%, respectively.

The following inferences are taken from the results of [7]: The ANOVA result demonstrates that thickness of layer has a substantial Ra(Ra) has an effect. On the other hand, angle of orientation and angle of infill are found to have negligible effects on Ra. Thickness of layer contributes 91.827 percent, orientation contributes 6.148%, and infill contributes 2.025%. This demonstrates that subsequent to thickness of layer orientation angle, influences Ra considerably. At thickness of layeres of 0.10 to 0.15 mm, orientation angles of 0 to 5 degrees, and infill angles of 0 to 10 degrees, the reduced Ra is achieved. The Ra increased with infill angle, larger thickness of layer and orientation angle.

The models can accurately predict reactions within the ranges where the maximum error percent is estimated to be 14.61% for mean Ra and 18.83% for S/N ratio of Ra, respectively. At a maximum S/N ratio of 9.72234, the Robust design methodology's ideal mean Ra value is Ra = 0.3265 m. Ra and S/N ratio were found to exhibit individual attractiveness at 0.99268 and 0.91371,

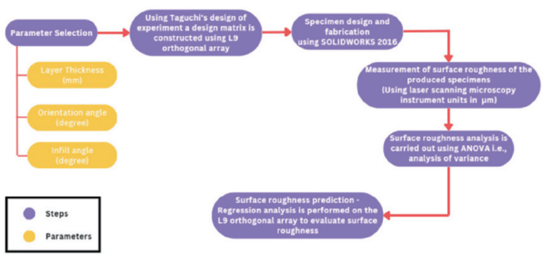

Figure 2. Methodology adopted by [7] to predict & optimize the Ra to evaluate the effects of FDM process parameters on ABS material

respectively. According to the Taguchi technique and RSM optimization, the best combination of printing procedure variables for excellent surface quality is orientation angle is 0°, infill angle is 0° andlayer thickness is 0.1 mm.

Kandananond et al. [2] explored a different methodology to identify the parameters impacting the quality of surface finish of the samples generated. He also undertook a thorough investigation into the FFF printing process utilizing ABS as the filament material. Temperature of the nozzle, the bed and the printing rate were employed as input elements, and the Ra of the samples has been utilised as an output because it is a reaction to the given input parameters. To improve the efficiency of the three-dimensional printing process, the input parameter values were improved by taking the most accurate readings. The selection of an appropriate approach to optimize the result was conducted and an in-depth analysis was performed to identify the components that were assumed to have a high impact on the surface quality were the first studied and second gaps in the literature were studied respectively and thirdly, the base material was coated using a chemical treatment method to enhance the surface finish.

Kandananond et al. [2] also noted that the majority of researchers employed the CCD RSM approach, which required five stages of evaluation for each course of action and required a significant amount of processing time. A test specimen was constructed for the experiment following the ASTM D638 standard. The measurement of the specimen's flatness was the main focus. Prior to being exported to the FFF system, the 3D model of the specimen was divided layer by layer, and then converted to a G Code. The infill density of the specimen was taken as 10% of the rectilinear infill style. It had 8 fused filament layers with a height of 0.3mm each. The extruder had nozzles that were 0.4mm in diameter. The ABS filament's diameter remained at 1.75mm. Only the input parameters—the bed, temperature, nozzle temperature, and printing, speed were changed; everything else was left unchanged. All of the replica sets for the top and bottom surfaces underwent an ANOVA, and the results of the statistical analysis of the anticipated roughness were used to draw conclusions. The Ra was significantly impacted by the printing speed and the bed temperature. The link between Ra and bed temperature was found to be nonlinear. With this, the ideal environment for peak performance was found. In order to get the lowest Ra, The printing speed was set for the bottom surface's Ra. It was set to the slowest possible setting (60 mm/s). And for the top surface, the bed temperature was set as 85 °C (in the middle range). This indicated that the ideal temperature setting for the bed temperature was based on the kind of surface which is selected by the manufacturer.

Li et al. [3] made use of vibrational sensors to extract from each signal channel the minimum, median, mean, maximum, central moment, standard deviation, kurtosis and skewness statistical parameters in the temporal part.

Four frequency-domain features were determined by the vibration sensors, using the fast FFT method (Fourier transform), including the maximum, mean, median and lowest spectral-amplitude. A total of 104 characteristics were obtained from each test. The feature importance determined by the RF algorithm has been used to choose a segment of the features in order to increase computing effectiveness and prevent overfitting.

According to our research, the frequency amplitude of the extruder vibrations, the build plate temperature, and the melt pool temperature all have a substantial impact on the degree of Ra of the 3D printed specimens. The speculative results have demonstrated that, based on Ra assessments and condition monitoring data, predictive models developed using the ensemble learning technique are able to forecast the 3D Ra printed components in real-time. The technique of predictive modelling described in this study forecasts Ra utilizing data from sensors used for condition monitoring as opposed to the existing methods, which used process characteristics like thickness of layer and build direction. Six weak learners were strengthened into one strong learner by the ensemble learning algorithm, leading to better predictions.

A technique focused on ensemble learning for Ra estimation in FFF procedures has been provided in this paper. Li et al. [3] in a similar way it was done in paper Kandananond et al. [2]. Real-time data was gathered using a variety of sensors. From the unprocessed sensor-based signals, a collection the time-frequency domains were a source of characteristics. 40 of the features in the subset were chosen for the use of RF based on feature relevance in order to increase computational efficiency and prevent overfitting. With the aid of the ensemble learning algorithm, the predictive models were trained. Various ML techniques methods, including RF, CART, relative risk regression (RR), AdaBoost, SVR, and RVFL network, were merged in the ensemble learning algorithm. According to the speculative findings, the predictive models could accurately forecast the degree of Ra of 3D-printed specimens. On the basis of RE and RMSE, the ensemble's execution is superior to that of the individual base learners.

Wu et al. [5] like other researchers, used a methodology in which the ML algorithms were fed with the statistical features that were derived from the whole condition monitoring data. A 10-fold cross-validation technique has been used to determine how well the predictive model algorithms had been trained and performed. The original dataset for 10-fold cross-validation, was randomly divided into 10 equal-sized sections. The remaining nine subsets were used as training data, and only one subset of the total of 10 was kept for providing the authenticated information for model testing. After that, results of the ten folds were averaged to produce an estimation.

Data-level fusion is a more basic form of fusion in which several sensors are sources of data which directly input into a ML system. A form of intermediate level fusion that incorporates extracted characteristics is called feature-level fusion. "Decision-level fusion" which is a high level fusion technique collects sensor data after each sensor has assessed a response variable. While the range of the predictive models' relative error rates when trained sources between 0.049 and 0.098 on individual sensor, those of the predictive models built range between 0.082 and 0.044 utilizing the feature-level data fusion method.

The duration between 25% and 35% the constructed period sees a considerable rise in the execution of RFS, support vector regression (SVR), relativeRR, and LASSO. The data from the condition monitoring gathered in the time being, 50% of the complete sample component was manufactured, which was further utilised to train the predictive models, and their relative error rates ranged from 0.047 to 0.042. Between 55% and 100% of the build time saw a near continuous increase in the prediction accuracy of RFs, SVR, relativeRR and LASSO. In the time range between 55% and 100%, the proportional error rates of relative RR and LASSO were marginally lower than those of RFS and SVR.

In Wu et al. [5] research, a ML algorithm-based predictive modelling method for prediction of Ra in FDM procedures was presented. A real-time observation system was created and implemented into a 3D printer using FDM to track the extruder's vibration, temperature, and melt-pool temperature. The sensor data were used to extract a number of statistical features. On each individual sensor measurement, RFs, SVR, relative RR, and LASSO were utilized to train the prediction models. Additionally, by combining data from several sensor sources, data fusion technique were applied to enhance prediction performance. The speculative findings demonstrates that ML algorithms could anticipate the Ra of items produced through additive printing with extremely high accuracy.

4. PREDICTING RA USING RANDOM FOREST

It was noted that Tree algorithms were quite popular to determine the Ra of parts produced through fusion deposition modelling. In [6] decision algorithms (C4.5, random forest and random tree) are utilized for identifying the most accurate model that predicts the surface finish with maximum accuracy in 3D PETG (polyethylene-terephthalate-glycol) parts generated through fused deposition modelling. Height of layer, print speed, extrusion temperature, flow rate and print acceleration were taken as the 5 input parameters and 3 levels were considered. 27 parts (Training parts) and 15 (Test parts) of 25.00mm x 25.00mm x 2.40mm were designed on SOLIDWORKS and then 3D printed through a FDM machine. The surface finish of each 3D printed part was measured 5 times using a (SJ-201) mitutoyo perthometer model and the arithmetic mean of the 5 readings for each part was taken and noted as the final value of Ra of the part. In the data mining stage, the data was collected and cleaned and an exploratory data analysis was performed to identify the most impacting parameters. In the end decision models were applied to generate patterns and a comparison is performed to identify the best algorithm.The collected data was trained on the C4.5 iterative decision tree algorithm which works on the concept of information entropy, Random Tree algorithm and then the Random Forest Algorithm with the aim to understand and predict the most optimum set of parameter values for printing PETG flat specimens, manufactured by FDM. The results of the prediction of Ra,0 and Ra,90 values are noted and observed.

For Ra,0 values, the precision score, recall score and f score obtained using J48 C4.5 algorithm are 0.709, 0.600, 0.650 respectively, using Random forest are 0.807, 0.667, 0.716 respectively and random tree are 0.839, 0.800, 0.816 respectively. Similarly, for Ra,90 values, the precision score, recall score and f score obtained using J48 C4.5 algorithm are 0.733, 0.733, 0.733 respectively, using Random forest are 0.743, 0.800, 0.770 respectively and random tree are 0.933, 0.867, 0.883 respectively.

From the obtained results Barrios et al. [6] concluded that the J48 C4.5 algorithm was able to classify training data set nicely however the algorithm wasn't successful to predict values for test data due to overfitting problems, Random Forest showed better results in comparison to J48 as shown in Figure 3. While, the random tree algorithm gave the most precise results for Ra 0& Ra 90 with the least computation time in comparison to the previously used algorithms.

To enhance the accuracy achieved by others, Cerro et al. [10] used a combination of a variety of ML algorithms for classification, such as logistic regression, MLP model of Artificial Neural Network, sequential minimal optimization, Bayes Net, Naive Bayes, J48 model, logistic model trees, & random forest. With the aim to create models which can predict Raof parts made of polyvinyl butyral resin (PVB) using FDM. The five input parameters

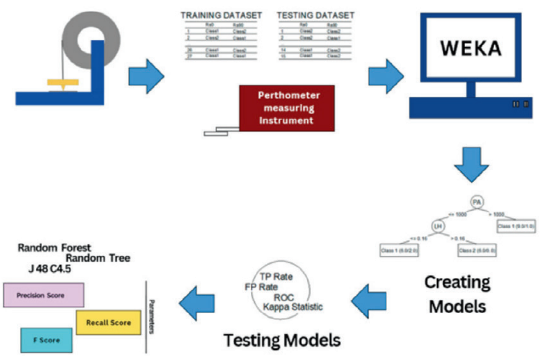

Figure 3. Methodology adopted by [6] to train the ML models with the training data & predict surface finish

were print speed, height, wall angle, extruder temperature & number of perimeters. The 16 examples that were 3D printed each had 3 sloping surfaces, at an angle of thirty, forty-five and seventy five degrees respectively with the horizontal. The print values of each component were obtained using a fractionated orthogonal speculative design.

Perthometer utilizes to calculate the Ra (Ra) of each slope face of the produced parts. Each surface was measured five times, with the arithmetic mean of the five recorded values being utilised as the final measurement. 40 models were developed and authenticated using WEKA ML software using the speculative results. For the tuning procedure, ANN has been used in addition to the chosen ML methods. The two metrics chosen to determine the most effective algorithm were accuracy score and the kappa statistic.

Boosting, bagging, and random subspace ensemble approaches were used to fine-tune the best identified methodology. This was done to determine the input parameter value that was most optimal. The ensemble technique BMLP, with a kappa statistic value of 0.9143, was found to produce the best results. The number of classes in the output variable and the mean value of the input characteristics were used to compute the quantity of neurons in the hidden layer. In BMLP, 2 classes in the output variable and 5 input characteristics were taken into account. The height of layer& wall angle had the greatest impact on the surface finish of the 3D printed specimen out of the considered input parameters.

5. PREDICTING RA USING KNN

There were a few researches that used K-Nearest Neighbors (KNN) to predict Ra. Barrionuevoet al. [19] observed that the manufactured components produced by the Directed energy deposition (DED) method in had uneven surfaces, which required additional subsequent optimizations to gain the required overall surface finish, measurement accuracy and geometrical precision. In [19] KNN ML technique is used to estimate Ra. Stellite-6 is used as an AM material in powder & wire form, and then create single-track and multi-layer depositions producing wall like edifices to create the surface-roughness data for training the K Nearest Neighbour model. It was observed that surface irregularity & roughness enhances as micro-plasma power supply increases and For both wire and powder AM material, the feed rate reduces as the traverse speed of the deposition head increases. The Ra of the walls produced by the AM material in powder form was lower (between 118 and 149 m) than that produced by the material in wire form (between 195 and 227 m).

The prediction error of the k nearest neighbour method to predict the Ra for powder form was obtained to lie between 6.2 and 2.8% and for wire form of AM material to be between 5.8 and 2.3%. This showed how the KNN algorithm could accurately predict Ra. The prediction error can further be decreased by enhancing the training data set as shown in Figure 4.

On the other hand, [18] predicted that the relative density of 316L stainless steel samples made by the SLM process using seven supervised ML regressors namely: the multi-layer perceptron, SVM, random forest, gradient boosting, decision tree, KNN, Gaussian process. A data set of 112 data points & cross-validation with 5 folds has been used to determine the best model & regressor errors. An index of merit is determined along with optimized values of the statistical metrics that includes Root Mean Square Error ('RMSE'), Mean Absolute Deviation ('MAD') & standard deviation, the accuracy of the predictions was assessed.

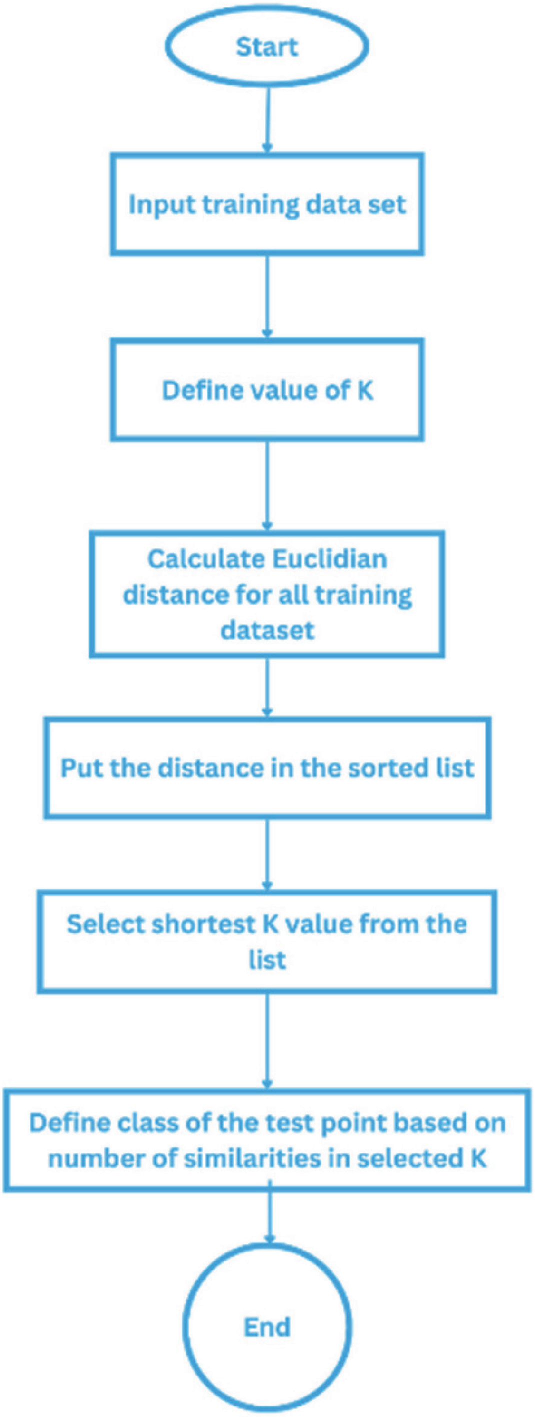

Figure 4. Methodology adopted by [19] to train the KNN model to predict Ra

Kumar et al. [20] discussed that the most important element that significantly affects Ra among the criteria evaluated is thickness of layer. The results of the trial runs demonstrated that low thickness of layer and a 0° construction orientation result in the best surface quality. A FDM printer is used to create a variety of test items utilising nylon carbon fiber (PA-CF) filament. Environmentally friendly, nylon-based PA-CF contains 20% carbon fiber. Having filament with a high finish printing effect and good print quality. The test pieces are made using 1.75 mm diameter (PA-CF) filament.

In [20] average Ra has been used as the output response value for examining surface excellence (Ra). According to ASTM standard D695, the test pieces in a cubical shape that were manufactured. A 3D model of the test piece is created using CAD software and it is then converted into an STL standard format. In order to create a GCODE file for an FDM machine, the STL produced file is then imported into the slicer program. The summary of open literature review has been given in Table 1, as shown below:

Table 1. Comparison study for the reviewed papers

Paper Number	Authors	Methods Used
1	Chinmay et al.	ANOVA, The relevance of process parameters on Ra is assessed using the p-value at a 95% confidence level
2	Karin et al.	ANOVA, RF, AdaBoost, CART, SVR, RR, and RVFL network, Box Behnken RSM method
3	Zhixiong et al.	RF, AdaBoost, CART, SVR, RR, and RVFL network A fast Fourier transform (FFT) technique to extract four (4) frequency-domain properties from the vibration sensors, including the maximum, median, mean, and minimum of the spectral-amplitude has been used.
5	Dazhong et al.	A 10-fold cross-validation method was employed to assess how well the predictive model the algorithms had trained performed A real-time monitoring system was created and implemented into a 3D printer using FDM to track the extruder's vibration, temperature, and melt-pool temperature

(continued)

Table 1. Continued

Paper Number	Authors	Methods Used
6	Juan et al.	Decision algorithms (i.e., C4.5, random forest, and random tree) are utilized for identifying the most accurate model that predicts the surface finish with maximum accuracy in 3D PETG. Height of layer, print speed, extrusion temperature, flow rate and print acceleration were taken as the 5 input parameters.
7	Amanuelet al.	ANOVA, A mathematical model for prediction has been created using response surface methods (RSM) and configurable input parameters
8	Ebrahimet al.	RBFNN and RBFNN-ICA Neural Network
9	Min et al.	Predict the Ra of items produced in PLA using 3D FD such as J48 (C4.5), Bayes net,naive-Bayes, simple logistic, SMO(SVM), IBk(KNN),KStar, multilayer perceptron (ANN), LMT, and random forest.
11	Satishet al.	ANN model's the Levenberg Marquardt (Le-M) algorithm, has been used and input parameters include-quantity of neurons, hidden layers, height of layer, infill density, nozzle temperature, and print speed
12	Min et al.	DNN based model is used to enhance the surface quality of AM items
13	Mohdet al.	ANN, RSM, PSO, symbiotic organism search (SOS)
14	Alberto et al.	ANN, In two real-world situations, a methodology built on the suggested model has been used to optimize prototype fabrication
15	Ebrahimet al.	ANN, PSOICA (particle swarm optimisation, imperialist competitive algorithm)
16	Cortés et al.	ANN, The numerical simulation framework is used to obtain and analyze the deformations of three distinct geometries
17	Mohamed et al.	ANN, The Ra was predicted using regression models based on the building orientation
18	Mohamed et al.	The relative density of 316L stainless steel samples made by the SLM process using seven supervised MLregressors namely: the multi-layer perceptron, SVM, random forest, gradient boosting, decision tree, KNN, Gaussian process.
19	Germánet al.	Used KNN to predict Ra of components produced by the Directed energy deposition (DED)
20	Pravinet al.	A FDM printer is used to create a variety of test items utilising nylon carbon fiber (PA-CF) filament. Environmentally friendly, nylon-based PA-CF contains 20% carbon fiber. Having filament with a high finish printing effect and good print quality. The test pieces are made using 1.75 mm diameter (PA-CF) filament.

6. CONCLUSIONS

As the manufacturing industry is highly being influenced by the advance and hi tech FDM technology, the number of researches happening in the domain are exponentially high. This present work has collectively summarized the methodologies adopted by various researchers and scientist who with their knowledge and domain expertise have successfully been able to come up with algorithms that can effectively identify properties that have an impact on the Ra. The results obtained through various suggested methodologies can help the system operator to set these parameters to the optimized values in order to enhance the surface finish of the manufactured good and bring uniformity in mass produced good with minimum surface finishing requirement saving a large amount of capital required post production.

It was noted that FDM was quantified using various technologies and ML models like ANOVA, CCD RSM Method, RF, K-Nearest Neighbours, AdaBoost, SVR, RVFL network, DNN and various ANN models in order to draw relationship between identified input parameters like bed temperature, nozzle temperature, extrusion rate, flow etc and the out parameter i.e., Ra. The models were also analyzed using error metrics and error terms like RMSE and RE etc.

The best result was shown by paper So et al. [4], in which a prediction model to predict Ra between successively piles layers in a thin wall created by WAAM was suggested, followed by the papers which used a Deep neural network model. It was identified that more traditional predictive models like regression, Decision trees, Random Forests and SVR gave less accuracy in comparison to the accuracy of the predictions made using the DNN model. The best DNN model has a good correlation between the real and predicted values and a prediction accuracy of roughly 98%. It was observed that models that incorporated ensemble techniques of bagging and boosting on ANN model of MLP i.e., multilayer perceptron gave high accuracy with a Kappa statistic value of 0.9143 as seen in [10].

It was also noticed that decision level fusion which is a high accuracy data level fusion type in which the sensor data is put into the ML model to be trained only after the sensors have assessed the response variable, gave higher accuracy in comparison to a simple predictive model when assessed using ANOVA method. This finding is supported by the results observed in [5] and [3].

The results and accuracies obtained in the above-mentioned researches can further be improvised by increasing the input dataset. Since most of the papers used a data set with entries in the range 25 to 30, the chance of over fitting and under fitting are quite high making the result questionable. Higher the input data set greater is the precision in the results obtained. Using advanced Artificial Intelligence techniques and Image processing techniques can help in harnessing the available online data to train and build models that can predict Ra with high accuracy and with least data preparation time.

As the number of researches is increasing, more innovative and improvised models are being developed and worked upon. The current work presented in this review has combined all the key findings of methodologies suggested and developed by various researches and future scope have also been discussed successfully.

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