A Neural-Fuzzy System for Predicting the Areal Surface Metrology Parameters

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Abstract: With the increasing demand for faster manufacturing, Industry 4.0 has now only started to contribute towards streamlining the manufacturing processes. Despite the availability of high dimensional manufacturing data, a significant amount of time is still spent on testing the end products. Therefore, with a drive to substitute these inspection processes with a "*digital twin*", this paper presents a framework for predicting the optimal surface metrology parameters such as force and vibration, required to achieve the desired surface roughness of an end product. Firstly, an Adaptive Neuro-Fuzzy Inference System (ANFIS) was designed to predict the surface roughness using vibration, force and temperature. A low RMSE of 0.07 was obtained between the predicted and desired surface roughness. This model was then reverse engineered to predict the optimal surface conditions (force, vibration and temperature) required to achieve the desired surface roughness. For this, optimisation was applied to minimise the error between the target and predicted surface roughness. This framework will help manufacturing industries to discard frequent in-depth product inspection processes in favour of this "*digital twin*" due to the possibility of achieving right-first-time production.

1 INTRODUCTION

Manufacturing is an ever-developing sector that continuously strides towards accuracy to ensure the efficient production of goods. Therefore, industries are now adopting Multistage Manufacturing Process (MMP), which involves performing multiple operations such as forming, machining and assembly in a series to create the end product(Yang et al., 2010).

To meet the growing demand for customer-centric products, there has been a rising focus on product quality. Due to this, a significant amount of time is spent on the testing of end products to ensure that they meet the stringent customer requirements. Therefore, the demand to substitute these processes with an alternative has given birth to the field of surface metrology. This field focuses on the measurement of small-scale characteristics such as amplitude, spacing and shape of features of a manufactured product (Yang et al., 2010). These surface properties are correlated to the function of a manufactured product and thus play an important role in predicting its behaviour over time. Therefore, exploiting surface metrology data can help discard these physical inspection processes and still meet the stringent environmental and economic constraints to achieve 'right-first-time production'. With the continuous advancements in data acquisition technologies, industries are now equipped with cutting edge sensors for measuring surface properties such as vibration, force and temperature throughout the MMP. Therefore, applying Artificial Intelligence (AI) techniques can help discover new and not so obvious patterns, which can then be used to design data-driven models for simulating these manufacturing processes. As a result, these models can help compute the optimal surface parameters such as force and vibration required to achieve the desired surface quality such as roughness thus simplifying the product inspection process. By providing better insights into the manufacturing processes, these models can further contribute to the diagnostics and prognostics of a product, thus reducing costs and achieving better customer satisfaction. Considering the above advantages of using AI for surface metrology, this paper presents a systems engineering framework, capable of predicting the optimal surface conditions required for achieving the desired surface roughness. To achieve this, an ANFIS model was first developed to predict the surface roughness using surface parameters such as vibration. This model was then reverse-engineered and optimised to predict the optimal surface parameters required to achieve the desired surface roughness.

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2 LITERATURE REVIEW

2.1 Rise of Surface Metrology

Achieving a good surface finish ensures that the customer desired tribological properties such as high fatigue strength, corrosion resistance and aesthetic appeal are met to a high accuracy(Yang et al., 2017). However, excessive surface finishing can lead to increased costs of manufacturing and degraded mechanical properties. As a result, it is important to devise models that can predict the optimal surface metrology parameters required to achieve such properties to a high degree of accuracy. (Acayaba and de Escalona, 2015) developed an ANN model comprised of two hidden layers, to predict the surface roughness of stainless steel in turning. This model achieved an accuracy of 98% thus inspiriing to use an ANN based technique in this paper for predicting surface roughness. This research also compared the results against regression models and as expected, ANN performed better due to a lower Mean Squared Error (MSE). In another research (Abbas et al., 2018), a multi-layer perceptron based ANN model was designed to predict the surface roughness of magnesium alloys used in aviation products. Using the cutting speed and depth of cut of the tool as inputs, this model achieved a reliable prediction accuracy of 1.35%.

With advancement in AI techniques, an intelligent framework combining ANFIS and Genetic Algorithm (GA) was developed to predict the surface roughness of a thermally drilled hole in galvanised steel (Kumar and Hynes, 2020). Using the spindle speed and angle of tool as inputs, the ANFIS model predicted the surface roughness which was then used by GA to minimise an objective function. This framework achieved a correlation of 0.99 and RMSE of $2.4\text{x}10^{-6}$ between the predicted and experiment value.

The above research work shows the advantage of using AI based frameworks for predicting surface roughness of manufactured products. Another research showcased the correlation between surface roughness and surface metrology parameters such as force and vibration (Rao and Murthy, 2018). Hence, this paper presents a new system for intelligent manufacturing that combines the above discussed insights and techniques thus highlighting its novelty. This framework utilises and learns from surface metrology data to better predict the surface roughness value of a manufactured product as a measure of surface quality.

2.2 ANFIS

ANFIS is a feed-forward adaptive neural network which uses a fuzzy inference system through its structure.Being a combination of fuzzy logic and neural network, it provides the advantages of both these modelling techniques in a single framework i.e. a powerful interpolator which is transparent and can deal with uncertainty intrinsically. Such integration is beneficial because the fuzzy logic manages the imprecision and uncertainty while the neural network ensures adaptation. The research defined in Section 2.1 shows the popularity of using ANN in surface metrology and thus, it was decided to use MATLAB ANFIS editor ($anfisedit$) for predicting surface roughness.

Overview: The rest of the paper is organised as follows. Section 3 describes the experimental setup. Section 4 and 5 explain and compare two ANFIS models for predicting surface roughness of end products. Section 6 describes the reverse-engineering framework that computes the optimal surface parameters. Section 7 presents the concluding remarks.

3 EXPERIMENTAL SETUP

A total of seventeen blocks of material steel EN24 were manufactured in the Advanced Manufacturing Research Centre (AMRC) facility in Sheffield, UK, where they underwent MMP. These blocks were first heat treated for hardening and then tempered at high temperatures to produce blocks that possessed similar mechanical but different surface properties. Here, the average temperature was measured using thermocouples but only once as a discrete value for every block. Then, milling and turning (referred to as $Operation1$ and $Operation2$) were performed on these blocks. During this, the vibration and force values were measured using a dynamometer and accelerometer in three axes i.e. X, Y and Z but were sampled at different rates thus generating differently sized datasets. A typical 3D surface plot for the surface metrology measurement of a part is shown in Figure 1. After MMP, a Coordinate Measuring System (CMS) was used to measure surface properties called *Surface Areal Parameters*. These parameters characterise the full 3D surface of a product and are standardised in the ISO 25178 (Specifications, 2012). This contains a list of industry-standard surface areal parameters. The two popular parameters are *Sa* and *Sq* and have been described in Table 1. A single discrete value of both of these was recorded by the CMS as a measure of surface roughness for every block.

Table 1: Selected areal parameters as defined in the ISO documents. It should be noted that the data is sampled uniformly along the x and y axes. z(x, y) represents the measured height at location (x, y) (Specifications, 2012).

Symbol	Name	Formula	Notes
Sa	Arithmetic Mean Height	$\frac{1}{A}\int\int\lvert z(x,y))\rvert dxdy$	Arithmetic mean of the absolute of the ordinate values within a definition area (A).
Sq	Root Mean Square Height	$\sqrt{\frac{1}{A}\int\int z^2(x,y)dxdy}$	Root mean square value of the ordinate values within a definition area (A).

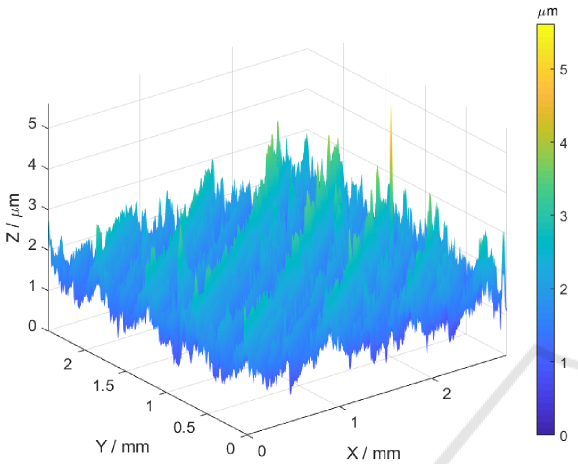

Figure 1: Typical surface metrology measurement of a part. This is a 3mm x 2.5mm surface patch with a sampling density of 100 samples per mm(Papananias et al., 2019).

4 MODEL 1: BIN DIVISION

(Rao and Murthy, 2018) showed that vibration measurements were widely used across industries to predict surface roughness of manufactured products due to a high correlation between these parameters. Hence, to produce a simple but reliable model, only vibration was considered as a useful feature for predicting the surface roughness. Since *Sq* had a higher statistical significance than *Sa*, therefore it was considered an ideal representation of surface roughness.

4.1 Data Mining

The vibrations during MMP were recorded in three axes i.e. X,Y and Z and an average correlation of 0.87 was observed between these values. Hence, to exploit this knowledge, Principal Component Analysis (PCA) was applied. This reduced the data dimensionality by replacing the three axes dataset with a single PCA generated dataset thus reducing model complexity without losing any relevant information. Also, when analysing this PCA'd vibration dataset, it was identified that $Operation1$ data oscillated between -1 and 1, while $Operation2$ data oscillated between -6 and 6. Therefore, these datasets were then normalised between 0 and 1 to ensure that the training features were scaled equally thus reducing the risk of producing a biased model. The above techniques (*PCA and Normalisation*) were applied to the vibration data obtained during both the Operations for all 17 blocks.

4.2 Sample Size Reduction

The above techniques improved the data quality, however, the I/O dataset was still unequally sized. This was because the vibration data was a continuous-time series dataset, however, the *Sq* data was a discrete dataset recorded only once for every block. To train a model, it is important to create a training dataset containing equally sized input and output data. Thus, the following approach was taken:

- **Input Data:** The vibration dataset was first divided into eight equally sized sub-datasets called as 'Bins'. Then, the mean vibration value was calculated for each of these eight 'Bins'. As a result, this technique affiliated each block with eight vibration values, irrespective of the original dataset size. This ensured that every block had the same number of vibration sample values.
- **Output Data:** The *Sq* dataset size was increased by repeating the same *Sq* value eight times per block thus affiliating these values to each of eight mean vibration values as shown in Figure 2.

The above processes were applied to the vibration dataset obtained for each block during both $Operation1$ and $Operation2$. This resulted in an equally sized I/O dataset and hence fit for training.

4.3 Overarching Model Architecture

Since all seventeen blocks were identical and underwent the same Operations, it was decided to combine the newly processed vibration data of all the seventeen blocks obtained from Operation 1 together and similarly combine the newly processed vibration data of all blocks obtained from Operation 2 together. This allowed utilising the vibration data of both Operations separately for training the model. Figure 3 shows this model architecture which is a Two Input Single Output ANFIS model. A total of 136 samples were generated and randomised such that 76% of it were used for training the model and the rest for testing.

4.4 Further Analysis

Data Filtering: To reduce the effect of outliers, Savitzky Golay filter was applied to the dataset. However, this degraded the performance significantly as evidenced by a high RMSE value of 2.34.

Bin Size Adjustments: The performance degraded with increasing the *Bin* size (example to 15) possibly due to overfitting. Reducing the *Bin* Size (example to 4) also led to reduced performance due to underfitting. Hence, *Bin* size of eight was considered optimal.

4.5 Results and Discussion

The correlation plot in Figure 4 shows that the predicted *Sq* values are scattered in the close vicinity of the correlation line thus evidencing a good performance. Correlation of 0.85 and RMSE of 0.12 was achieved, thus showing the model's capability for predicting *Sq* values to high accuracy. The generalisation of this model can be evidenced by the training data response. A correlation of 0.90 and an RMSE of 0.08 was achieved thus confirming the absence of overfitting. Furthermore, a linear regression model and a 2 layer feed-forward ANN were designed and used as benchmarks to compare the performance. Both these models obtained a higher RMSE and a lower correlation value thus showing an inferior performance. Therefore, ANFIS was the preferred technique.

5 MODEL 2: STATISTICAL FEATURE EXTRACTION

Despite showing a good performance, "Model 1" posed the following limitations. Firstly, applying "Bin Division" as explained in Section 4.2 led to a huge reduction in vibration dataset, thus losing useful information Secondly, the duplication of *Sq* values meant providing misleading data to train the model. Hence, inspired by (Papananias et al., 2019), the following strategy was adopted.

5.1 Data Mining

Based on (Papananias et al., 2019), it was found that parameters such as force, vibration and temperature were highly correlated to surface roughness. Therefore, these features were used for eliciting a new model i.e. *Model 2* for predicting surface roughness

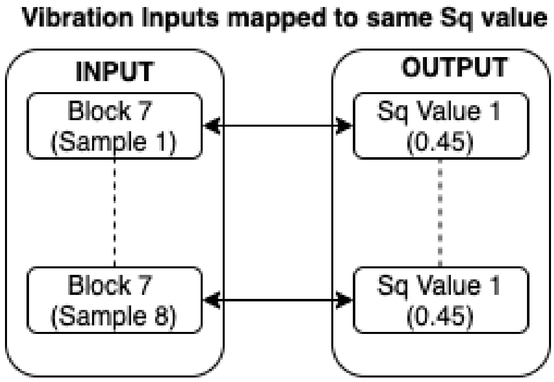

Figure 2: Shows the duplication of Sq values for Block 7, Operation 1. Here, the different vibration values are mapped to the same Sq value.

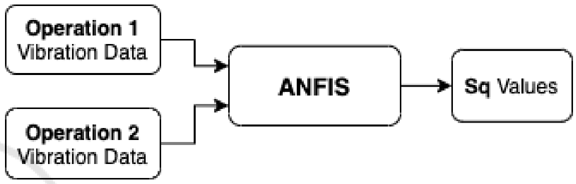

Figure 3: Shows an ANFIS model i.e. 'Model 1' designed to predict the *Sq* values using vibration data.

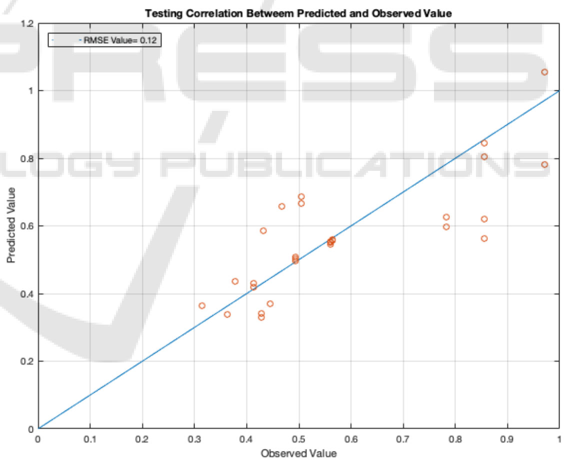

Figure 4: Testing data shows a near linear relationship b/w the 'Model 1' predicted and observed *Sq* value.

of end products. Inspired from paper (Papananias et al., 2019), it was decided to use *Sa* instead of *Sq* as a measure of surface roughness.

Data Set: Vibration and Force, both were continuous time-series data while temperature and *Sa* both were discrete values recorded once for every block. Unlike *Model*1, where the focus was to utilise the actual values of the continuous time-series data, this method instead focused on utilising the statistical features of the continuous time-series data as follows.

Technique: The Root Mean Square (RMS) and Mean value of both 'Force' and 'Vibration' datasets were calculated for every block. For example, Block 1 had (RMS and Mean) 'Force' values and (RMS and Mean) 'Vibration' values affiliated to it. This feature extraction technique was applied to both $Operation1$ and $Operation2$ datasets, thus generating eight values of 'Force' and 'Vibration' for every block. The temperature was a single value measured only once across both $Operation1$ and 2 for every block. Hence, the final training dataset comprised of 17 sample values due to 17 blocks and each sample was associated with the above mentioned nine features. Following such a technique, ensured that the input and output datasets could now be mapped easily without having to either reduce the input dataset or duplicate the output values. *Hence, this technique embedded in an ANFIS framework highlights the novelty proposed by this paper.*

5.2 Overarching Model Architecture

Figure 5 shows the proposed system architecture. The nine feature dataset as described above was subjected to some feature extraction techniques and was then used as input to an ANFIS model for predicting the *Sa* value. The proposed model is a three-input single-output Sugeno based ANFIS. This architecture overcame the limitations of 'Model 1' as now each block was linked to nine distinct features, all mapped to a single *Sa* value thus avoiding any duplications.

5.3 Feature Extraction

To remove any biases, the sample dataset was randomised. Furthermore, it was identified that the vibration, force and temperature data were all scaled differently. Therefore, to ensure equal contribution to the model design, they all were normalised to a comparable scale i.e. between 0 and 1. Having nine input features but only 17 data samples, such a dataset was considered unfit for model training. Therefore, PCA was applied to reduce the dimensionality and retain the useful information of the removed features;

PCA Method: The four vibration values (i.e. RMS and Mean from both Operation 1 and 2) were first collected together and then subjected to PCA thus reducing the dimension of vibration dataset from four to one. The same method was then applied to the four force associated features thus reducing their dimensionality to one. Following this method, the dimensionality of the training dataset was reduced from nine features at the start to three input features, i.e. PCA'd Vibration, PCA'd Force and Temperature as shown in Figure 5. Due to the small sample size (i.e. seventeen samples), it was decided to utilise 13 samples for training i.e. a 76% and 24% split of the data.

Verification and Validation

Multiple Runs: The developed ANFIS model was executed 100 times such that the original dataset was randomised in each run thus producing a different RMSE and Correlation value. This was done to evidence the generalisability of the model. Therefore to evaluate the performance, average RMSE and Correlation values were calculated.

K-Fold Cross Validation: Despite the reduced dimensionality, such a low number of data samples posed the risk of overfitting. Hence, 4 Fold Cross-validation was applied. The performance was evaluated by calculating the average Correlation and RMSE value obtained in each fold. This was used to evidence the model's diversity and robustness.

5.4 Results and Discussion

An average correlation and RMSE of 0.87 and 0.09 was obtained on running the model 100 times using the testing data thus showing acceptable performance. Figures 6 and 7 show the best predicted and observed *Sa* values obtained among the 100 runs using testing and training data. A low RMSE of 0.07 and 0.05 shows the high accuracy of the predictor. Furthermore, the results obtained from the 4-Fold cross-validation also showed a high correlation and a low RMSE value for both the training and testing dataset, thus evidencing model's generalisability. The 3D surface plots between the input and output, corresponding to this single best run are shown in Figure 8 and Figure 9.These plots are non-linear and within the data minimum and maximum ranges thus suggesting that no obvious extrapolation occurred. Furthermore, a linear regression model and a 2 layer feed-forward ANN were designed and used as benchmarks to compare the performance. Both these models produced a higher RMSE and a lower correlation value than the ANFIS model thus showing an inferior performance.

Comparison between Model 1 and Model 2

$Model2$ achieved a lower RMSE and a higher Correlation value. Some other differences were as follows:

- $Model1$ followed a "Bin Division" approach, utilising the actual dataset values thus leading to information loss. While $Model2$ utilised the statistical features of the dataset to predict the surface roughness and thus the preferred choice

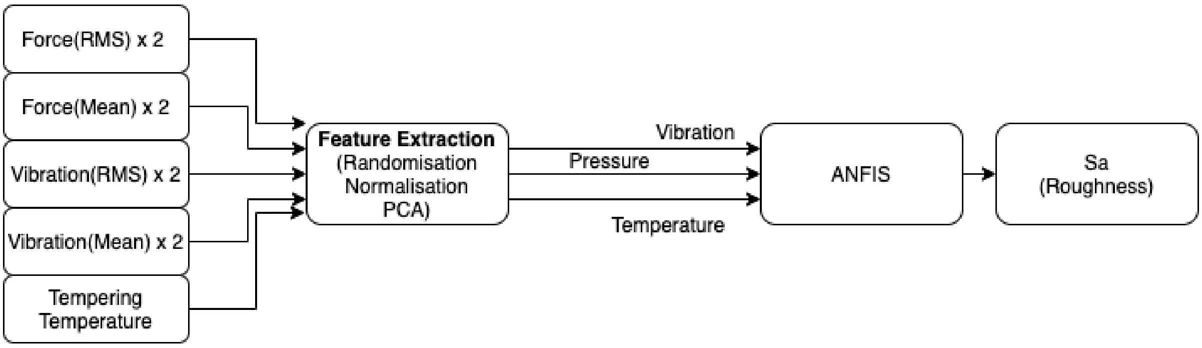

Figure 5: Shows the system architecture of ‘Model 2’.

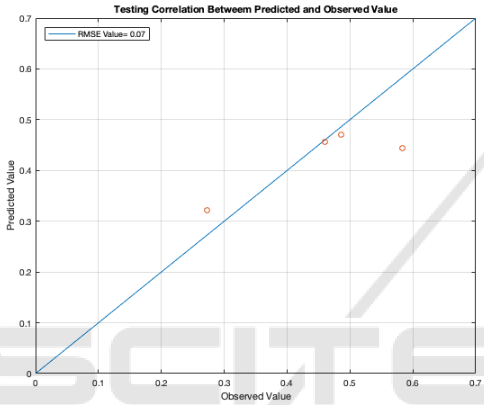

Figure 6: Testing data shows a linear relationship b/w the ‘Model 2’ predicted and observed *Sa* value.

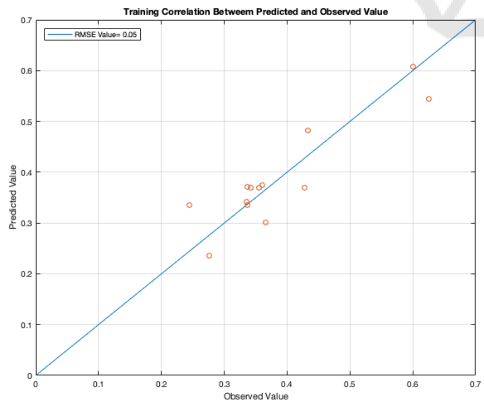

Figure 7: Training data shows a linear relationship b/w the ‘Model 2’ predicted and observed *Sa* value.

- Unlike *Model*1, *Model*2 did not require to duplicate the output values i.e. surface roughness values, thus generating an unbiased training dataset

6 OPTIMISATION FRAMEWORK

6.1 Motivation

The above proposed ‘ Model 2’ was capable of predicting the surface roughness i.e. *Sa* value, given surface metrology parameters as input. However, to achieve right-first-time production, it was required to design a framework, such that given a target *Sa* value as an input, the framework could predict the optimal surface metrology values required to achieve that target. Therefore, the following framework was designed in which the ‘Model 2’ was reverse-engineered. To achieve this, multi-objective optimisation was applied to minimise the error between the customer desired and model predicted *Sa* value until the error value was below a defined threshold.

6.2 Objective Function

Genetic Algorithm (GA) was used for optimising two objective functions. The first objective was to minimise the error between the customer desired and model predicted *Sa* value. The second objective was to minimise the Standard Deviation (SD). Therefore, multiple predictors were designed which were variations of ‘Model 2’ . Inspired from (Mason et al., 2017), these objective functions were also normalised to minimise the risk of biasness during optimisation. Mathematically;

$$\text{Objective 1} = \left(\frac{SaTarget - MeanSaValue(x)}{SaTarget}\right)^2 \quad (1)$$

$$\text{Objective 2} = \left(\frac{STDSaValue(x)}{SDEstimate}\right)^2 \quad (2)$$

where, ‘*MeanSaValue*’ calculated the average of the *Sa* value predicted by the multiple models; ‘*STDSaValue*’ calculated the SD using the *Sa* value

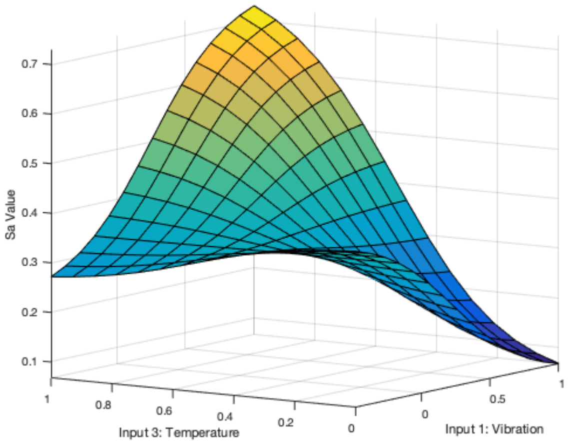

Figure 8: Shows 3D surface plot of Temperature and Vibration against *Sa* values.

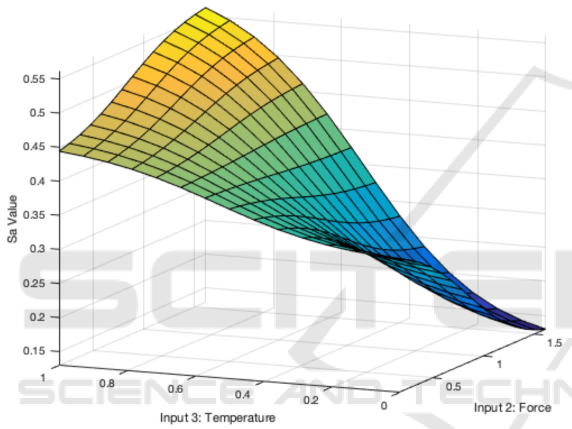

Figure 9: Shows 3D surface plot of Temperature and Force against *Sa* values.

predicted by the multiple models; '*SDEstimate*' was set to 1000 (Mason et al., 2017). '*SaTarget*' was the customer desired *Sa* value.

6.3 System Architecture

Figure 10 shows the framework used for reverse-engineering the proposed ANFIS model. Seven ANFIS predictors were designed by varying the Membership Functions(MFs) such as 'Bell' and 'Sigmoid'.
In the first iteration of this framework, GA generated a random set of solution and passed this solution set to the seven ANIFS models as an input. This solution set represented the nine features as described earlier in Figure 5. In each iteration, the seven variations of 'Model 2' used the GA produced solution set to predict seven *Sa* values. These seven values were then used to calculate the mean *Sa* value and SD which were then passed to the optimiser(GA). Using these values, the optimiser produced a new set of solutions, with an aim to minimise the error objective.

6.4 Implementation

Method 1: MATLAB function called *gamultiobj* was used for multi-objective optimisation. The objectives were specified in two separate equations (Section 6.2) but were optimised simultaneously. This produced Pareto solutions. Figure 11 shows that the solutions for *Sa* of 0.37, minimised the objectives to achieve a low MSE in the range of 0.4 and 10^{-8}.

Method 2: Inspired from paper (Mason et al., 2017), the two objective functions were combined to form a single function and each objective was assigned a weight vector to quantify their priorities. This provided more control over optimisation by allowing to generate solutions of interest directly rather than Pareto solutions;

$$\text{Objective} = w1 * (Objective1) + w2 * (Objective2) \quad (3)$$

where $w1$ and $w2$ were the weights assigned to each objective and were varied between 0 and 1. This was because the objectives themselves were normalised between this range of values.

6.5 Results and Discussion

Both 'Method 1' and 'Method 2', produced very similar results. However, there was a qualitative difference between the two methods.

Method 1: This is beneficial for solving generic problems, where the decision-maker (usually analysts) are unable to determine the priority order of the different objectives as they are debatable and not stringent.

Method 2: This is beneficial for solving problems where analysts can prioritise objectives according to their goal by manipulating weights of each objective
For the proposed surface metrology problem, 'Method 1' was preferred as it provides analysts with the flexibility to choose the optimal solution that meets their goals from a range of Pareto solutions.

7 CONCLUSIONS

The increasing demand for customer-centric products is difficult to meet when a significant amount of time is still spent on the testing of end products. Therefore, with a drive to substitute these inspection processes with a *'digital twin'*, this paper presented

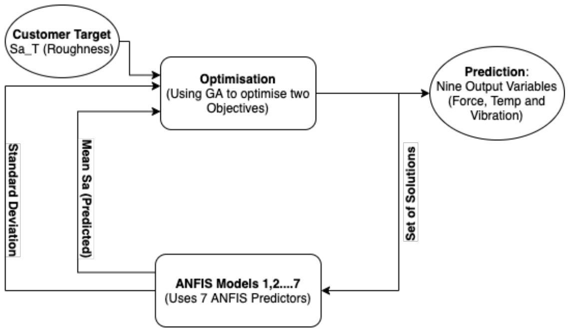

Figure 10: Shows the reverse-engineered framework developed for achieving right first time production.

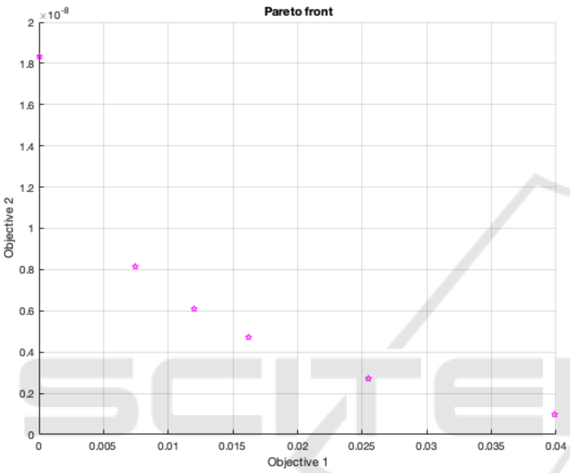

Figure 11: Pareto-Optimal solutions obtained using 'Method 1' where target *Sa* value was set to 0.37.

an intelligent framework to predict the optimal surface metrology parameters required for achieving the desired surface roughness of an end product. This was a two-stage process:

Stage 1: A 3 I/O ANFIS model was designed to predict the surface roughness of an end product using surface parameters such as vibration and force. Using statistical features of these parameters in an ANFIS model showcases the novelty.

Stage 2: 'Model 2' was then reverse-engineered to compute the optimal surface metrology values such as force and vibration required to achieve the desired surface roughness value. An optimisation framework was developed where GA was applied to minimise the error between the predicted and target roughness.

Limitation and Future Work: 'Model 2' was derived using the data collected from seventeen experiments only. Such a low sample size does not guarantee a reliable model and hence, more data shall be collected for robust validation. Due to limited data, the model was only tested within a limited range of target values. Hence, the model shall be tested with a wide range of target values. Another case study shall also be conducted to establish emphatically that the proposed framework for digital twin establishment is generic to a wide range of manufacturing systems. Finally, other modelling techniques such as SVM and Deep Learning will be explored as ANFIS can be restrictive in problem-specific parameter tuning.

To summarise, developing such a framework for predicting the surface roughness, will help manufacturing industries to discard the in-depth product inspection process thus saving on processing time and costs.

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