Deployment of a Multi-Objective RSM-ANFIS Approach for FFF Process Optimization using Thin-Film PLA Specimens

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Abstract— **This study seeks to unify the advantages of response surface methodology (RSM) and a machine learning (ML) technique, namely adaptive neuro-fuzzy inference system (ANFIS) by way of hybridization to demonstrate the benefits of a selective, performant-driven multi-objective optimization approach. Optimality is derived using performance measures such as print time deviation, dimensional accuracy, specimen mass, surface roughness as well as tensile strength. FFF process parameters such as infill speed, layer thickness, nozzle temperature and raster width are used to derive an I-optimal design of experiment (DOE) methodology. Major findings emanating from this study reveal under-building in geometrically constrained regions of printed parts such as in the orthogonal Z-direction in accordance with thin-film ASTM D882-18 standards. Additionally, such constraints heavily reduce the efficiency of raster deposition due to the increased reliance of sub-optimal toolpath process planning caused by automatically generated geometric code. In contrast, advantages in utilizing a combined modelling approach to combat these challenges are seen, which shows improvements on average of 73.50% when using the RSM-ANFIS technique in comparison to the RSM model. Evidence from combining these models for improved prediction confirm the potential for advancing FFF process optimization using ML driven techniques to tackle future manufacturing challenges.**

I. INTRODUCTION

Fused filament fabrication (FFF) is an additive manufacturing (AM) technique, built on the foundations of rapid prototyping and fused deposition modelling (FDM). It creates three-dimensional (3D) products using a vertical, layer-by-layer stacking approach. Since its development in the 20th century, the FFF process has witnessed continued growth in global market, obtaining a net worth of approximately USD 16.16 billion in 2025 [1]. Its feasibility in numerous industries at scale like aerospace, automotive, food and beverage as well as medical has been testimony to the increasing volume of pertinent research and publications according to bibliometric studies like Yorke and Chowdary [2]. Notably, a key facet, which has primarily driven FFF to its success has been the utilization of predictive strategies for the process optimization of 3D printed (3DP) part performance.

By definition, these strategies have stimulated success in both research and application through the use of mathematical and computer programmed algorithms for synthesizing input and output data, expressed as process parameters and performance measures. Historically, conventional prediction models have been developed using statistical and orthogonal methods such as response surface methodology (RSM) and Taguchi to name a few [3]. Lately, with advancements in artificial intelligence (AI), fuzzy based machine learning (ML) techniques by way of neural networking have demonstrated strong potential in handling more complex datasets while establishing more robust predictions for decision-making strategies when compared to conventional approaches.

Research undertaken by Kumar, et al. [4] highlighted the Taguchi approach, which was used to predict optimal dimensional accuracy using process parameters such as layer thickness orientation angle and raster width. Multi-objective optimization was deployed using a genetic algorithm (GA) approach in conjunction with regression analysis to develop a polynomial objective function which was used as a prediction model for deriving optimal correlation between process parameters and performance measures in varying orthogonal directions. Meanwhile, RSM was used in studies like Jawad, et al. [3] to multi-objectively optimize part performance such as tensile strength by deploying distinct design of experiment (DOE) methodologies such as central composite design (CCD), along with predictive models by way of desirability and transformation functions.

Comparatively, ML driven techniques have demonstrated feasibility of their predictive models in publications involving the use of artificial neural network (ANN) and adaptive neuro-fuzzy inference system (ANFIS) approaches. Built on the concept of supervised learning and fuzzy logic systems, research from Chowdary and Ali [5] leveraged the use of several ANN prediction models to forecast the process parameters needed for optimizing surface roughness, hardness and tensile strength of 3DP parts. In tandem, similar studies mirrored these methods by deploying ANFIS based prediction models for the optimization of stress, strain and elastic modulus. Luis-Pérez and Buj-Corral [6] expressed their multi-objective optimization approach by way of ANFIS but for predicting FFF process attributes such as dimensional accuracy and surface roughness using materials like virgin polylactic acid (PLA) and composites such as glass fiber-reinforced polypropylene (PP).

Inherently, statistically-driven conventional as well as emerging prediction modelling using ML driven techniques have demonstrated capability in deriving optimal parametric conditions for maximizing or minimizing performance measures toward respective applications. However, such models have not come without their challenges. For instance, RSM based models have shown affluence toward experiments

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involving low-order, non-linear polynomial interactions between process parameters according to findings in Kumar, et al. [4] compared to analytical datasets where higher-order parametric interactions have been prevalent.

By contrast, experimental analyses containing highly non-linear and fuzzy-oriented uncertainties among datasets have successfully illustrated the efficacy behind ANFIS based ML models. This was touted by Oladipo and Sun [7] who deployed several combinations of process optimization approaches including GA, particle swarm optimization (PSO) and Harris Hawks Optimization (HHO) with ANFIS prediction models, fostering comparative success. In this regard, however, ML based models like ANFIS have required more fine-tuned structuring in its data sets, particularly where poor parameter-performance correlation has existed. In addition, the algorithmic design of neural networks along with systematic strain on computational resources have also presented challenges in advancing the use of ML driven techniques. Furthermore, 3DP parts of complex geometries have exacerbated the effects of process parameters on part performance due to the need for increased sensitivity in positional accuracy from dimensional constraints. These barriers have contributed to increased fuzziness in the correlation of experimental datasets, thereby presenting hurdles in accurately predicting part performance when using conventional approaches, particularly in the face of limited, experimental resources.

In retrospect, though there have existed numerous studies which have investigated the applicability of conventional or ML based models, this study sought to apply these models to constrained geometric environments in order to investigate the hidden layers that have critically influenced the correlation between FFF process parameters and part performance. Additionally, the research emanating from this work sought to exploit the applicability of defuzzification found in ML techniques such as ANFIS in order to overcome the challenges found through process optimization strategies – the combination of which has not been prevalently seen due to the subscription to larger, less sensitive geometric standards such as ASTM D638. Hence, given the structural differences between the algorithms of predictive models, it was therefore prudent to investigate the possibility of integrated strategies toward maximizing the capability of prediction models for performance-oriented scenarios using a multi-objective approach.

II. RESEARCH METHODOLOGY

The flowchart outlined in Fig. 1 represents the steps executed in this research.

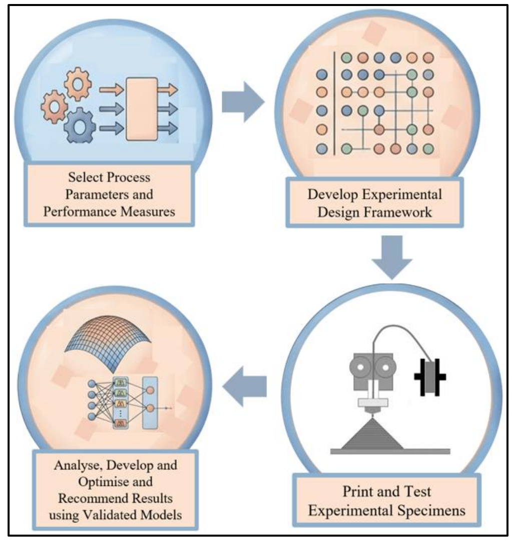

Figure 1. Methodology flowchart

A. Selection of Process Parameters

Key process parameters, as illustrated in Fig. 2 were selected with the aim of maximizing sensitivity of FFF performance measures based on past research [3]. This was conducted under the hypothesis that increasingly stimulated results invoked observable performance differences of data synthesis between prediction models prior and subsequent to optimization and validation.

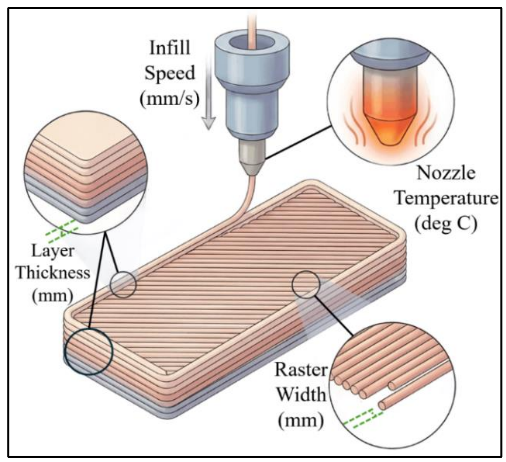

Figure 2. FFF process parameters

Dimensional accuracy (ΔZ) in the Z-direction and print time deviation (ΔPT) were selected to analyze the reproducibility of estimated measurements, particularly under varying parameters of infill speed (IS), layer thickness (LT) and raster width (RW) [8]. Information contained within their signed conventions was valuable for understanding under- and over-estimations, which superseded the choice to utilize absolute values of the experimental data. Simultaneously, the consumption of filament resources, expressed as specimen mass (M) as well as surface roughness (SR) and tensile strength (TS) were chosen to observe the constrained effects invoked by process parameters such as IS and nozzle temperature (NT) [9].

B. Development of Experimental Design Framework

In accordance with, ASTM D882-18, a thin-film cuboidal beam was designed using PLA as the specified material. As shown in Fig. 3, this design was modelled in SolidWorks version 2023 software and selected to compound the conditions of the hypothesis by limiting positional behavior of printer mechanics. It was also chosen to confine the use of process parameters within a restricted geometric space unlike similar experimental procedures which use thicker designs of other standards such as ASTM D638 and ASTM D3039 [10].

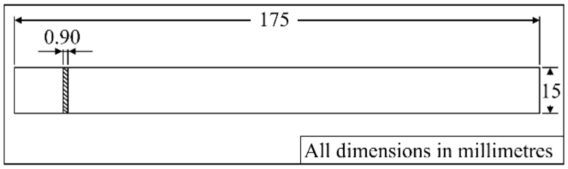

Figure 3. Designed specimen

Based on experimental trials, the lower (L1) and upper (L4) boundaries of each process parameter was established and presented in Table I. These were used for the development of the Design of Experiments (DOE) framework within the Design-Expert version 13 software.

TABLE I. Controlled process parameters

Process Parameters	**Units**	**Levels**			
		L1	L2	L3	L4
Infill Speed (IS)	mm/s	35	40	45	50
Layer Thickness (LT)	mm	0.10	0.15	0.20	0.25
Nozzle Temperature (NT)	ºC	195	200	205	210
Raster Width (RW)	mm	0.45	0.50	0.55	0.60

Highlighted in Table II, an I-optimal DOE framework of 40 experiments was chosen based on its predicated success in satisfying suitable combinations of process parameters as well as its capability in supporting datasets for non-linear prediction models. A larger dataset was considered but not used so as to retain the research aim of evaluating the capability of the RSM-ANFIS approach in a constrained experimental environment.

TABLE II. I-optimal DOE framework

No.	**IS**	**LT**	**NT**	**RW**
	mm/s	mm	C	mm
1	45	0.10	205	0.50
2	45	0.25	210	0.45
3	40	0.25	195	0.50
4	40	0.20	200	0.55
5	35	0.25	210	0.60
6	45	0.10	195	0.50
7	35	0.20	200	0.45
8	45	0.25	200	0.45
9	50	0.25	210	0.55
10	40	0.15	205	0.45
11	35	0.20	210	0.50
12	50	0.20	195	0.45
13	40	0.15	195	0.45
14	50	0.15	205	0.50
15	40	0.20	200	0.55
16	40	0.25	200	0.55
17	35	0.25	205	0.45
18	45	0.10	195	0.50
19	45	0.15	195	0.60
20	50	0.10	210	0.45
21	50	0.15	205	0.50
22	40	0.10	210	0.55

a. The acronyms IS, LT, NT, RW, ΔPT, M, SR and ΔZ represent the terms Infill Speed, Layer Thickness, Nozzle Temperature, Raster Width, Print Time Deviation, Specimen Mass, Surface Roughness, Dimensional Accuracy and Tensile Strength respectively.

TABLE II. I-optimal DOE framework (continued)

No.	**IS**	**LT**	**NT**	**RW**
	mm/s	mm	C	mm
23	50	0.20	195	0.45
24	50	0.25	210	0.55
25	45	0.20	200	0.55
26	50	0.10	210	0.55
27	35	0.20	210	0.50
28	45	0.15	210	0.60
29	35	0.15	195	0.60
30	35	0.10	195	0.55
31	40	0.20	200	0.55
32	35	0.10	205	0.50
33	35	0.10	205	0.60
34	35	0.25	195	0.45
35	45	0.20	200	0.55
36	50	0.25	195	0.60
37	45	0.15	210	0.60
38	50	0.10	200	0.60
39	35	0.10	200	0.45
40	35	0.25	210	0.60

a. The acronyms IS, LT, NT, RW, ΔPT, M, SR and ΔZ represent the terms Infill Speed, Layer Thickness, Nozzle Temperature, Raster Width, Print Time Deviation, Specimen Mass, Surface Roughness, Dimensional Accuracy and Tensile Strength respectively.

C. *Printing and Testing of Experimental Specimens*

Subsequent to DOE finalization, job files for each specimen were prepared using exported STL computer aided model (CAD) files using the ideaMaker version 4.3.3.6560 software. In following, all specimens were printed and tested for data analysis using the apparatus in Fig. 4.

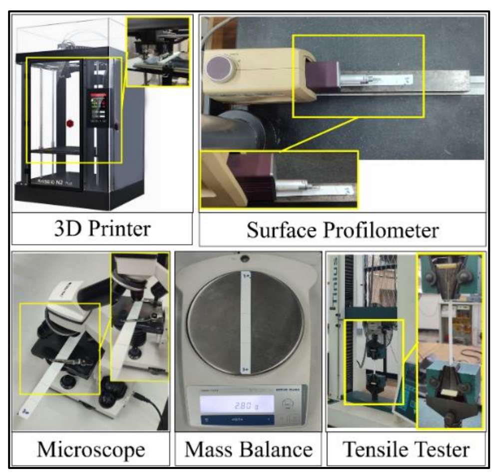

Figure 4. Experimental setup

Performance measures of ΔPT and M were obtained using a stopwatch and precision mass balance, while tests for ΔZ, SR, TS and microscopy were conducted using transcribed annotations along the X-Y plane of each specimen.

D. *Analysis, development and optimization of models*

Tabulation of performance measures for each specimen was followed by data analysis using analytical plots alongside an analysis of variance (ANOVA) technique to derive statistically-driven parameter-performance correlated observations. Development and validation of RSM as well as ANFIS models were conducted to evaluate accuracy of prediction using parameters that were within and outside of the DOE framework. As shown in Fig. 5, multi-objective optimization using a non-dominated sorting genetic algorithm II (NSGA-II) was deployed to derive optimal performance measures through a combined, hybridized objective function of RSM and ANFIS models. This approach was validated against an RSM only NSGA-II optimized function to evaluate the capability of a hybridized integration of prediction models when compared to optimization scenarios in a geometrically constrained environment where a limited experimental dataset was provided.

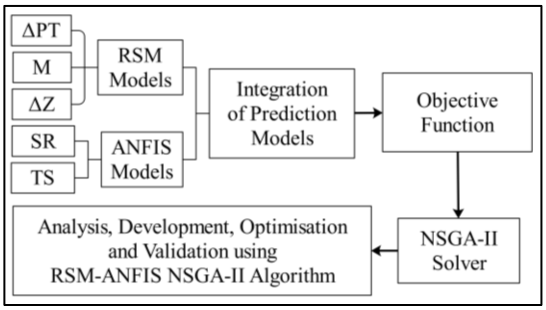

Figure 5. Multi-Objective Optimization Framework for the Integration of RSM-ANFIS Models into the NSGA-II Solver

III. ANALYSIS OF EXPERIMENTAL DATA

Print time deviation, ΔPT denoted a negative signed convention across all specimens, which indicated that the actual print time was less than that of the estimated. Illustrated in Fig. 6, analysis of experimental data using a main effects plot further suggested correlation between the number of layers and rasters along the X-Y-Z planes with geometric information in toolpath steps for printing each specimen. An increase in one or both parameters reduced the positional information generated within the geometric code (G-code), thereby reducing the complexity of the design and increasing the accuracy in estimating total print time [11].

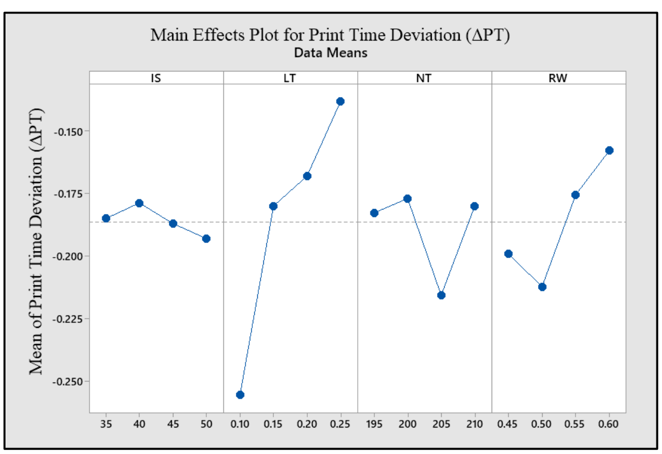

Figure 6. Main effects plot of process parameters on print time deviation

Analysis of M in Fig. 7 highlighted increased efficiency of filament deposition as RW and NT increased while a slow IS was maintained. Further observation described this relationship to be attributed to the effects of higher thermal energy on improved deformation of filament flow rate. Additionally, smaller LT, along with a reduced RW improved stacking efficiency, thereby allowing for better utilization of space, especially in the Z-direction.

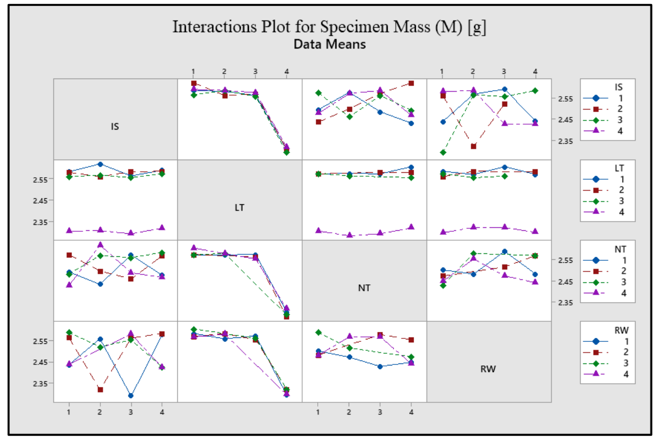

Figure 7. Effects of interacting process parameters on specimen

Dimensional accuracy, ΔZ demonstrated a negative signed convention for all experimental data, mirroring similar mathematical attributes to that of ΔPT. Notable changes in ΔZ occurred in the Z-direction with negligible findings in the X and Y orthogonal directions. From Fig. 8, analysis suggested that deviations from the nominal thickness was a result of under-building due to shrinkage from thermal contractions of filament, melt flow rate and layer stacking errors caused by increased LT and RW. Furthermore, observations indicated that divisibility between nominal and layer thickness also influenced part height accuracy, where the mathematical ratio using lower (Level 1) and intermediate boundaries (Levels 2 and 3) contributed to smaller deviations compared to the upper boundary (Level 4).

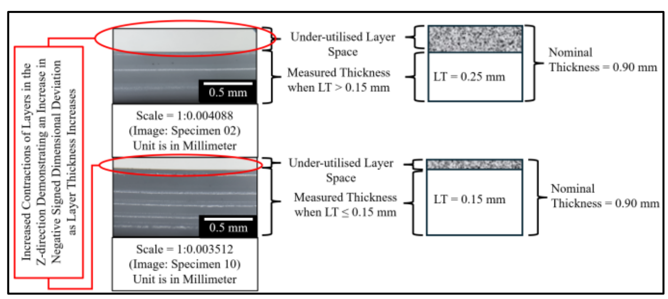

Figure 8. Microscopic analysis of negative signed dimensional deviations due to under-building

The effects of process parameters on SR were dominantly observed when analyzing LT and RW as highlighted in Fig. 9. Increasing layers initially contributed to an increase in SR, until an inflexion occurred. This inflexion however, was observed to not be a result of LT independently but due to correlating effects as NT. Higher thermal gradients influenced better interlayer bonding despite increased elliptical dimensions of filament, thus ensuring more uniform distribution along the X-Y plane. In contrast, increasing RW was observed to increase SR as a result of the staircase effect, which led to additional instability to sustain filament extrusion width, particularly at higher NT.

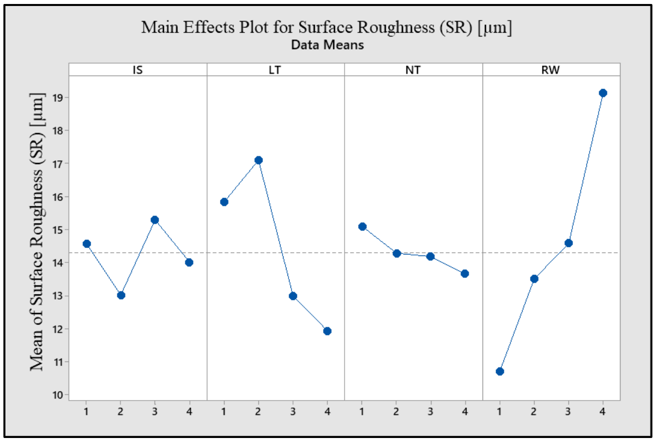

Figure 9. Main effects plot of process parameters on surface roughness

Analysis extracted from tensile test experimental data shows correlation between reductions in TS with increasing LT, NT and RW. Interestingly, these findings aligned with similar effects seen on ΔZ and M. This suggested that the effects induced by under-building through shrinkage and thermal cooling had cascading consequences on process part performance. Furthermore, positional accuracy due to toolpath algorithms evidently affected interlayer bonding and by extension, the location of stress concentrations in the specimens. Surface level microscopic examination in Fig. 10 illustrated this observation, which was unanimous across all printed specimens.

Discontinuities across the top layer profile was inherently detected due to the uniformity of the design, which was not seen in the past research that utilized dog-bone-oriented designs [12]. Constraints within the Z-direction was postulated to also influence geometric characteristics seen along the X-Y plane in accordance with challenges in G-code toolpath steps previously described. As a result, it was noted that aforementioned effects of process parameters and geometric toolpath were primary attributors to tensile test performance compared to previous studies that underscored stress build-up due to grip strength of tensile testing apparatus.

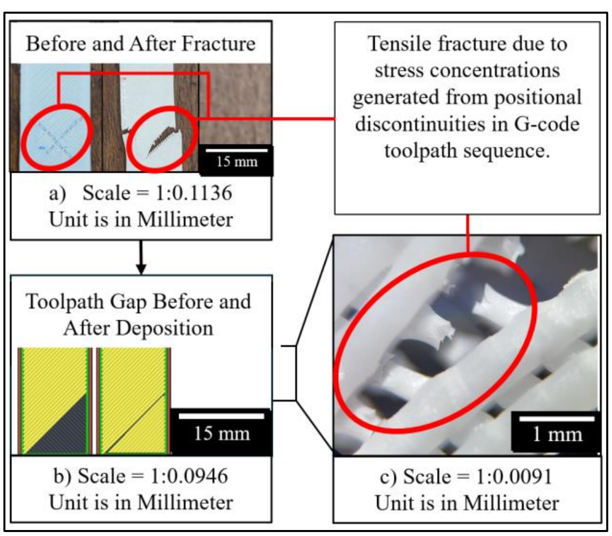

Figure 10. Microscopic examination of tensile test fracture profile

IV. DEVELOPMENT AND EVALUATION OF MODELS

Reliability of the RSM-ANFIS hybrid performance was evaluated by comparing validation data with that of an RSM only model subsequent to process optimization. Although an ANFIS only technique was also considered, challenges arose due to increased requirements in system resources and computational requirement imposed by the ANFIS model for computing the current volume of experimental data. Refinement of the RSM and ANFIS models, particularly for hybrid integration was therefore applied to combat this challenge by programming the objective function to only query the ANFIS models once instead of multiple times for each iteration during the genetic algorithm's cycles. As a result, optimization became equitable to an RSM-only NSGA-II approach.

Cross validation was performed by way of a Fuzzy C-means Fuzzy Maximum Likelihood Estimation (FCM-FMLE), in which 75% of the experimental dataset was used to train the model while 25% was used to error validate. This was conducted for the SR and TS experimental data by iterating on the number of clusters and number of rules per cluster in order to derive a sufficient quantity of trainable parameters across 200 generational epochs. These iterations were done until an adequate root mean squared error (RMSE) for SR (3.274) and TS (24.718) was obtained when compared to other cluster methods that were used, namely Grid Partition (Triangular, Trapezoid and Gaussian). the root mean squared error (RMSE). From this, external test validation was conducted to assess predictive performance using default and randomized process parameter settings in the job slicing software, both of which were outside of the DOE dataset. This validation gave a prediction accuracy between 2.97% and 5.23%, confirming model robustness. Regression equations were subsequently integrated into an objective function, as shown in the following algorithm under equations 1 through 7. This used a combination of coefficients (A through E) and variables (x) as representation of the process parameter inputs into their respective RSM and ANFIS prediction models. A backward elimination technique was used to improve parametric terms for RSM while backpropagation in conjunction with least squares estimation was chosen to train and tune the experimental data using the ANFIS technique.

Objective Function

$$y = \text{ObjectiveFunction}(x) \quad (1)$$

RSM Models

$$\Delta PT = A + B(x_1) + C(x_2) + D(x_3) + E(x_4) \quad (2)$$
$$B(x_1)\cdot C(x_2) + C(x_2)\cdot D(x_3) \ldots - C(x_2)\cdot E(x_4) - C(x_2)^2$$

$$M = A + B(x_1) + C(x_2) + D(x_3) + E(x_4) + B(x_1)^2 - C(x_2)^2 - E(x_4)^2 \quad (3)$$

$$\Delta Z = A + B(x_1) + C(x_2) + D(x_3) + E(x_4) + C(x_2)^2 \quad (4)$$

ANFIS Models

$$SR = \text{evalfis}(x, SR.fis) \quad (5)$$
$$TS = \text{evalfis}(x, TS.fis) \quad (6)$$

Where: x, x_1, x_2, x_3, x_4 represent the process parameter inputs into the RSM and ANFIS models

Multi-Objective RSM-ANFIS Function Vector

$$y = \begin{bmatrix} RSM_{\Delta PT} \\ RSM_{M} \\ RSM_{\Delta Z} \\ ANFIS_{SR} \\ ANFIS_{TS} \end{bmatrix} \begin{matrix} \dashrightarrow \text{Minimize } \Delta PT \\ \dashrightarrow \text{Minimize } M \\ \dashrightarrow \text{Minimize } \Delta Z \\ \dashrightarrow \text{Minimize } \Delta SR \\ \dashrightarrow \text{Maximize } TS \end{matrix} \tag{7}$$

Comparative validation against the alternative approach, namely RSM was conducted using the RMS-ANFIS hybrid model. This was conducted by analyzing the absolute errors between the predicted (Pre) and actual (Act) responses of optimal performance measures (PM) as highlighted in Table III. By calculating the relative average for the RSM as well as RSM-ANFIS error %, an improvement of 73.50% in prediction accuracy when using the hybridized approach was achieved. This was notably observed due to increased percentage error when predicting SR and TS by way of RSM only. Such error values were suggested to be consequential from instabilities earlier discussed, which were due to inconsistencies in roughness as a result of insufficient interlayer bonding under the effects of increased RW, inadequate toolpath sequencing and poor thermal cooling. Additional fuzziness in the experimental data due to these inadequacies in parameter-performance interaction was noted to be a primary cause toward not only poor statistical fit of SR and TS RSM models, but by extension unreliable prediction capability, which the ANFIS technique was able to mitigate during its data tuning and training stages.

TABLE III. Validation of prediction models

Models	PM	Optimal Responses		
		Pre	Act	|Error %|
RSM	ΔPT	-0.16	-0.13	0.64
	M [g]	2.50	2.28	8.80
	ΔZ	-0.16	-0.16	0.10
	SR [μm]	7.38	10.73	45.34
	TS [N]	299.68	360.00	20.13
RSM-ANFIS	ΔPT	-0.15	-0.15	0.97
	M [g]	2.31	2.32	0.43
	ΔZ	-0.15	-0.16	0.35
	SR [μm]	8.81	9.52	8.05
	TS [N]	316.59	331.60	4.74

V. CONCLUSION

The current research was presented in attempt to give credence to the consideration of a hybridized model for improved prediction in process optimization. Following laboratory tests, preliminary experimental analysis revealed shortcomings in applying universal application of a single model compared to a hybridized approach. Most notably, these efforts demonstrated that not all numerical data exist equally, in that the sensitivity of process part performance, depending on the application and associated measure requires careful consideration into the type of techniques that are used for optimization and prediction. Although conventional techniques like RSM have demonstrated historical prowess, observations from this research revealed opportunities for improvement. In addition, future research is required to address the challenges faced in ANFIS modelling in order to determine the feasibility of hybridization in lieu of its computational requirements when compared to conventional techniques. Nevertheless, the findings of this research provide evidence that advances the methods used for multi-objective optimization toward industrial application.

VI. ACKNOWLEDGEMENTS

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