Development of a bi-directional multi-input-multi-output predictive model for the fused deposition modelling process using co-active adaptive neuro-fuzzy inference system

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Abstract. In the automated manufacturing industries, modelling and prediction of the process parameters of additive manufacturing plays an important role. This paper proposes a computationally intelligent method using coactive-adaptive neuro-fuzzy inference system to establish relationships between the process parameters and the responses, in both forward and backward directions, for the fused deposition modelling process. Experimental data have been statistically analyzed and regression equations have been generated to produce large training samples. The model has been built using six inputs each with non-linear Gaussian membership function distributions, and three responses, each with linear membership function distributions for the forward-directed mapping. Similarly, three inputs and six outputs from the same training data set have been used to formulate the backward-directed inference model. The parametric study for the used back propagation algorithm has been conducted and validation has been accomplished with the optimal settings using actual experimental data.

Keywords. Additive manufacturing, fused deposition modelling, C-ANFIS, forward mapping, backward mapping.

1. Introduction
Fused deposition modelling (FDM) is the most popular additive manufacturing technology (AMT) in which prototypes and functional parts, especially, with complex geometry, are manufactured by adding mainly plastic materials in semi molten state layer after layer directly from the three-dimensional (3D) computer-aided design (CAD) data [1, 2]. It has been gaining popularity as it minimizes cycle time to a great extent [3]. The quality of a part produced, solely depends on the adjustment of different process parameters viz. layer thickness, percentage of infill and infill pattern, build direction, road width, air gap, raster angle, raster pattern, etc. Hence, modelling of such a process by establishing relationship between input and output parameters is very important. There has been untiring efforts from the research community for the last couple of decades or so in this direction.

Kumar and Jain [4] studied the variation of compressive strength as a function of the inputs. They developed an empirical model of the compressive strength based on the stated process...
parameters using second order regression method of response surface methodology (RSM). Singh et al. [5] reported the effects of material composition, infill percentage and print speed upon mechanical properties of the printed prototypes using analysis of variance (ANOVA) method. They also figured out the optimal settings of process parameters using the same. Keles et al. [6] investigated the variation of mechanical reliability of printed acrylonitrile butadiene styrene (ABS) with build orientation. They used Weibull analysis for quantifying the variation of tensile strength. Similar to them, Onwubolu and Rayegani [7] studied the effects of part orientation, layer thickness, raster width, raster angle and air gap on tensile properties of test specimens using design of experiments (DOE). Sood et al. [8] conducted the experiments based on central composite design (CCD) and developed empirical models relating the responses and the process parameters using regression analysis and validated them using ANOVA analysis. They determined the optimal process parameters using response surface plots. Zhang and Chou [9] used finite element analysis (FEA) as well as regression analysis to model responses of FDM based on process parameters. Lee et al. [10] employed the Taguchi method to determine the optimal FDM process parameters for achieving the desired performance in terms of elasticity and flexibility. Cantrell et al. [11] used a novel method for mechanical characterisation of ABS and polycarbonate printed parts. They determined the extent of anisotropy present in the 3-d printed parts. To study the behaviour of directional properties, they used 2-d digital image correlation (DIC) with varying build orientation and raster angle. Qattawi et al. [12] studied the independent effects of the input parameters on the responses of the fabricated parts experimentally. Further, they proposed to model the FDM parts using FEA that utilised the apparent density of the parts. Another remarkable work was reported by Mohamed et al. [13]. The authors studied the influence of critical input parameters on responses using Q-optimal RSM. Further, they determined the optimal process parameters with the help of multi-objective optimization using composite desirability function. Liu et al. [14] experimentally studied the effects of inputs on evaluation indices of mechanical properties of FDM parts such as tensile, flexural and impact strength using the Taguchi method. They applied the gray relational analysis for determination of the optimal process parameters.

The output responses as reported in most of the studies were observed to have a complex non-linear relationship with the input parameters. Statistical based RSM, regression and ANOVA were mostly used for developing such models, which has natural limitations with respect to the extent of non-linearity and optimization capabilities.

Raju et al. [15] applied a hybrid evolutionary algorithm based on particle swarm optimization and bacterial foraging optimization (BFO) in order to optimize the process parameters that would result in the desired output responses, namely flexural modulus, tensile strength, hardness and surface roughness. Panda et al. [16] studied the effects of inputs on tensile, impact and flexural strength of the test specimen. They carried out experimental investigations with the help of CCD method and were able to determine the empirical relationship between the responses and the process parameters using RSM. They also suggested theoretical combination of the optimal parameter settings using BFO that would result in good strength simultaneously of multiple categories.

Fuzzy inference systems have been tried to address the input-output relationship problems involving incomplete and imprecise data in real world with considerable cases of reported success. Srivastava et al. [17] formulated an empirical relationship between the input process parameters and the outputs using RSM. They utilised fuzzy logic for multi-objective optimization of the process parameters. Sahu et al. [18] also employed fuzzy reasoning based approach in order to optimize the process parameters, so as to achieve the desired dimensional accuracy of the manufactured parts. Peng et al. [19] considered, filling velocity, extrusion velocity, line width compensation and layer thickness as the input variables and warp deformation, dimensional inaccuracy, and build time as the output variables. They converted the three output variables
to a single comprehensive variable using fuzzy inference system. They further formulated a relation between the input variables and the comprehensive output variable using second order RSM. They verified their methodology using artificial neural network (ANN). The drawback of such a fuzzy reasoning system is that it uses a static inference mechanism and fuzzy rules are to be manually entered and edited prior to the reasoning process, which relies on trial and error and hence, not systematic. The ANN method used in the same literature did not use the concept of fuzzy logic. Hence, the authors of the same felt the need for a dynamic inference engine in the form of an adaptive neuro-fuzzy inference system (ANFIS) to overcome the aforementioned issues.

The literature survey reveals that regardless of the approaches adopted, the studies were strictly concentrated on the forward mapping of the input-output parameters, which involves determination of the output parameters from the known set of inputs. To the best of the authors’ knowledge no significant study has been reported on backward mapping of the input-output parameters. It is reported that backward mapping model cannot be accurately obtained by using statistical regression because of the presence of multi-collinearity among the responses [20]. This has necessitated the usage of technique like coactive-ANFIS (C-ANFIS) in order to achieve the same.

This work proposes a computationally intelligent method using C-ANFIS to establish input-output relationship of an exemplary FDM experimental process reported in past literature [13] captured in both forward and backward mappings. Various toolboxes and libraries are available for developing ANFIS architecture. However, to handle the issue of multiple-input-multiple-output problem, the model has been custom-developed to tailor any other specific need and kept open for extendibility. In the same literature, layer thickness (LT), air gap (AG), raster angle (RA), build orientation (BO), road width (RW) and number of contours (NC) have been considered as the independent input process parameters and build time (BT), feedstock material consumption (FMC) and dynamic flexural modulus (DFM) have been regarded as the dependent process outputs.

A forward mapping model has been first developed using C-ANFIS architecture, which predicts three responses for a given set of values of six input parameters. The data generated from regression equations for the three responses have been used as training set. The trained model has been tested on the real experimental data in order to validate the developed model. The training of the C-ANFIS model has been carried out using the traditional gradient based approach. Parametric study of the algorithmic constants, namely, number of membership functions and learning rate, has been carried out after which the optimal parameters have been selected. The prediction results of all the responses have been captured in order to validate the developed model using the test data. Similar procedure has been adopted for developing the backward mapping model where three inputs have been represented by BT, FMC, and DFM, and six outputs have been similarly reused from the inputs of forward model. Similar testing has been carried out for validation purposes.

The remaining article is segmented as follows: The methodology has been described in 2. Statistical modelling and data generation has been dealt in 2.1 and conceptualization and development of computational intelligence (CI) based models are explained in the subsequent subsections (2.2 and 2.3). Simulation results for both forward and backward mappings are presented and discussed in 3. Finally, some conclusions are reported in 4.

2. Methodology
2.1. Statistical modelling and data generation
For conducting experimental investigations on the FDM process, a Q-optimal (also known as IV-optimal) design has been adopted. A statistical regression model has been developed using Minitab software by feeding the experimental data. The same experimental data was
originally used by Mohamed et al. [13] to describe the FDM process responses in terms of the input parameters with a high value of goodness of fit and subsequently carry out optimization. Regression equations of uncoded type have been produced by applying RSM on the experimental data set [13]. 95% confidence interval has been adopted and stepwise backward elimination method of all available terms for selection has been applied. For the development of any computationally intelligent model especially involving evolutionary algorithms, a large number of training samples is often placed as a compulsory prerequisite. In order to cater to this need, hypothetical levels have been created keeping the lower and upper bounds of input parameters intact. 3072 numbers of data have been generated using all the possible combinations of input parameter levels as depicted in Table 1. This has been done essentially to get maximum coverage within the range of experimental design space.

Table 1. Levels of input parameters

| Input Parameters       | Coded Symbols | Units | Levels Considered |
|------------------------|---------------|-------|-------------------|
| Layer thickness        | A             | mm    | 0.127 0.2159 0.3302 |
| Air gap                | B             | mm    | 0 0.15 0.35 0.5   |
| Raster angle           | C             | degree | 0 22.5 52.5 90    |
| Build orientation      | D             | degree | 0 37.5 67.5 90    |
| Road width             | E             | mm    | 0.4572 0.4935 0.5419 0.5782 |
| Number of contours     | F             |       | 1 4 7 10          |

The experimental data have been used as test cases for the validation purpose of the computational models of both forward and backward mapping [13].

2.2. C-ANFIS modelling for forward and backward mapping

As the name suggests, ANFIS typically amalgamates the benefits of neural network capable of learning with substantial accuracy with the fuzzy reasoning which works pretty well for incomplete and imprecise data of real world problems [21]. For handing multiple responses there are two variants of ANFIS – first, multiple ANFIS (MANFIS) which has as many as separate multiple ANFIS modules as the responses and second, C-ANFIS which houses all the responses as output nodes in one single ANFIS module. In this study, C-ANFIS has been adopted for developing the models. The six independent process parameters have been used as inputs whereas the three dependent process responses have been provided as the outputs for developing the forward mapping model. The C-ANFIS architecture for forward mapping model is shown in Figure 1. The backward mapping of the process parameters has been achieved by swapping the inputs and outputs of the physical process model. Three dependent responses have been provided as the input parameters to the C-ANFIS model, whereas the six independent process parameters have been kept as outputs of the model (Figure 2). The C-ANFIS architecture can be understood by following the layout of the layers and nodes contained therein and their contributions for producing the final outputs from a set of inputs, and thereafter, applying the learning algorithms for the parameters of the membership functions for both inputs and outputs. The layers are described here in this sub-section while the training algorithms are discussed in the following sub-section.

Layer 0: This layer consists of the input variables of the problem.

Layer 1: This layer consists of the membership functions for all the inputs. The membership function, \( \mu \), selected for this work is a gaussian function, as shown in Equation 4, which has two
parameters viz. $m$, the mean and $s$, the standard deviation. These parameters are known as premise parameters. These parameters are usually initialized using a clustering mechanism. For this model, fuzzy-C-means (FCM) clustering algorithm has been employed. The experimental input training data after normalization are fed to FCM for initializing the parameters based on clusters or centroids and number of membership functions[22]. The basic idea of FCM is illustrated using the Equation 1, 2, and 3.

$$J_{FCM} = (U, V) = \sum_{i=1}^{c} \sum_{k=1}^{N} \sum_{p} ||x_k - v_i||^2$$  \hspace{1cm} (1)$$

where, $v_i$ is the centroid of $i$th cluster. The partition matrix and centroid are updated by Equations 2 and 3.

$$\mu_{ik} = \frac{1}{\sum_{j=1}^{c} \frac{d_{ik}^2}{d_{jk}^2}^{1/p}}$$ \hspace{1cm} (2)$$

$$v_i = \frac{\sum_{k=1}^{N} \mu_{ik} x_k}{\sum_{k=1}^{N} \mu_{ik}}$$ \hspace{1cm} (3)$$

These parameters are adjusted via a supervised learning process through back propagation. The type and number of membership functions of each input variable is same, with only the premise parameters set at different initial values.

$$\mu = \frac{1}{1 + e^{-\frac{1}{2} \times (x-m)^2}}$$ \hspace{1cm} (4)$$

$$n = n_i \times m_f$$ \hspace{1cm} (5)$$

where, $n$ is the number of nodes, $n_i$ is number of input variables and $m_f$ is the number of membership functions for each input. The number of membership functions has to be selected on the basis of the performance of the model during training. For simplicity, in Figure 1, two membership functions are shown. The actual model of forward mapping has a higher value than this.

**Layer 2:** This layer can be thought of as the product layer, symbolized by $\pi$, where each membership function value of one input is multiplied by the membership function values of all the other inputs cumulatively. The respective membership functions of all the inputs are connected as constituents of each inference rule for the model. There can be several ways to combine each input membership function with another. The full factorial combination would generate $m_f^{n_i}$ number of rules. This would make the system less responsive during training as it would require enormous computational power and memory. The value of a node representing each rule, contains the combined firing strength $\mu_{rule}$ of the rule obtained by multiplying all the membership function values of this rule, as shown in Equation 6,

$$\mu_{rule} = \mu_1 \times \mu_2 \times \mu_3 \ldots \times \mu_{ni}$$ \hspace{1cm} (6)$$

where, $\mu_i$ is membership function value of $i$th input variable.

**Layer 3:** This is a normalization layer, symbolized with $N$. This essentially normalizes the firing strength of each rule by simply dividing the respective firing strength by the summation of all the firing strengths. All the nodes in this layer are connected to all the nodes in the previous layer by the virtue of the mathematical summation operator in the denominator, as shown in Equation 7,

$$\mu_{normal(i)} = \frac{\mu_{rule(i)}}{\mu_{rule(1)} + \mu_{rule(2)} + \mu_{rule(3)} \ldots + \mu_{rule(m_f)}}$$ \hspace{1cm} (7)$$
where, $\mu_{\text{normal}(i)}$ is the normalized firing strength for ith rule and $\mu_{\text{rule}(i)}$ is the firing strength of the ith rule, and similarly, $\mu_{\text{rule}(mf)}$ is firing strength of the last i.e. mfth rule.

Layer 4: These nodes are connected with previous layer by one to one mapping. Additionally, each node has connections with all the input variables. “Takagi and Sugeno” type of fuzzy inference mechanism, which is mostly followed for majority of ANFIS models, has been adopted here. In this case, six inputs along with one normalized firing strength value produces the total value for each node in this layer. This value is obtained using some linear coefficient terms known as consequent parameters as shown in Equation 8. The number of consequent parameters is one more than the number of input variables used in the model.

$$ f_{\text{rule}(i)} = \mu_{\text{rule}(i)}(p_{i1}a + p_{i2}b + p_{i3}c + p_{i4}d + p_{i5}e + p_{i6}f + p_{i7}) \quad (8) $$

where, $f_{\text{rule}(i)}$ is the value of node in layer 4 representing output or consequence for ith rule and $p_{i1}, p_{i2}, ..., p_{i7}$ are the consequent parameters for ith rule and $a, b, ..., f$ are the values of the input variables considering total six input variables.

Layer 5: This layer comprises of output nodes. The number of nodes is same as the number of responses used in the model i.e. three. In this layer, the consequent outputs from the previous layer are summed up and the final output value is produced, which is shown in Equation 9. Each output node is connected with all the nodes in the previous layer, where, $f_{\text{final}}$ is the final output value.

$$ f_{\text{final}} = f_{\text{rule}(1)} + f_{\text{rule}(2)} + ... + f_{\text{rule}(mf)} \quad (9) $$

2.3. Computational intelligence-based approaches for training

In the C-ANFIS model, learning has two passes – forward and backward. Here, batch mode of learning has been implemented which means, one forward and one backward pass for the entire training set is considered as an epoch. Two algorithms have been used for training the traditional C-ANFIS model viz. back propagation (BP) and recursive least square (RLS), which has made this a hybrid training process. BP has been used for training the premise parameters by computing the ordered derivatives of the errors obtained in the previous iteration propagated from layer 5 to layer 2. RLS method has been used to train the consequent parameters of layer 5 on each forward pass.
BP algorithm works on gradient-based steepest descent method. The adjustment of the independent variable is done in the direction of slope defined by tangent on the current position. This is mathematically expressed by Equations 10 through 14 considering the current scenario,

\[ \Delta p = -\eta \times \frac{\partial E^2}{\partial p} \]  
\[ \frac{\partial E^2}{\partial p} = \frac{\partial E^2}{\partial O_5} \frac{\partial O_5}{\partial O_4} \frac{\partial O_4}{\partial O_3} \frac{\partial O_3}{\partial O_2} \frac{\partial O_2}{\partial O_1} \frac{\partial O_1}{\partial p} \]  
\[ E^2 = (t - o)^2 \]  
\[ \frac{\partial E^2}{\partial O_5} = -2(t - o) \]  
\[ \eta = \frac{sl}{\sqrt{\sum \frac{\partial E^2}{\partial p}}} \]  

where, in Equation 10, \( \Delta p \) is the required update in parameter \( p \) and \( \eta \) is the learning rate; the computation of \( \frac{\partial E^2}{\partial p} \) is shown in Equation 11; In Equation 12, \( E^2 \) is the squared error, \( t \) is the actual value and \( o \) is the obtained output; similarly \( \frac{\partial E^2}{\partial O_5} \) is computed as shown in Equation 13.

The learning rate is computed by Equation 14, where \( \sqrt{\sum \frac{\partial E^2}{\partial p}} \) is the square root of the sum of the partial derivatives with respect to each premise parameter for each input variable and \( sl \) is the step length which is a value less than 1 and is to be determined by a parametric study.

The partial derivatives shown in Equation 11 are calculated as follows:

\[ \frac{\partial O_5}{\partial O_4} = 1 \]  
\[ \frac{\partial O_4}{\partial O_3} = p_1 + p_2b + p_3c + p_4d + p_5e + p_6f + p_7 \]  
\[ \frac{\partial O_3}{\partial O_2} = \frac{1}{(\sum \mu)} - \frac{(\sum \mu - \mu_i)}{(\sum \mu)^2} \]
where, $\sum \mu$ is the sum total of the values of nodes in layer 2. $\mu_i$ is the output containing the firing strength of the node of interest. This derivation can be obtained from the relationship given in Equation 7).

$$\frac{\partial O_2}{\partial O_1} = \frac{O_2}{O_1}$$

(18)

For a node which has more than one connection to the nodes in the following layer, the ordered derivative of the said node is computed as the summation of the actual ordered derivative for each connection.

$$\frac{\partial O_1}{\partial m} = -\frac{1}{(1+\zeta)^2} \times [\zeta] \times \left[ -\frac{1}{2} \times 2 \left( \frac{x - m}{s} \right) \times \frac{-1}{s} \right]$$

(19)

where, $m$ is the mean parameter, $x$ is the value of the input variable corresponding to the particular node and $\zeta$ is calculated from Equation 20.

$$\zeta = e^{-\frac{1}{2}(\frac{x - m}{s})^2}$$

(20)

$$\frac{\partial O_1}{\partial s} = -\frac{1}{(1+\zeta)^2} \times (\zeta) \times \left[ -\frac{1}{2} \times 2 \left( \frac{x - m}{s} \right) \times \frac{-(x - m)}{s^2} \right]$$

(21)

RLS has been implemented to determine the values of consequent parameters in layer 5. Rather than solving Equation 22 directly, the consequent parameter values are iteratively solved by applying a numerical method for all the samples, using Equations 23 and 24.

$$(A^T A)^{-1} A^T B = P^*$$

(22)

$$S_{i+1} = S_i - \frac{S_ia_{i+1}a_{i+1}^T S_i}{1 + a_{i+1}^T S_i a_{i+1}}$$

(23)

$$P_{i+1} = P_i - S_{i+1} a_{i+1} (b_{i+1}^T - a_{i+1}^T P_i)$$

(24)

where, $P_0 = 0, S_0 = \gamma I$, $\gamma$ is a large number, $a_i^T$ is the ith line of matrix $A$, $b_i^T$ is the ith element of vector $B$, $P^* = \hat{P}_N$ and $N$ is number of training samples. The generated data from regression have been used for training the custom-developed C-ANFIS model. Traditional ANFIS works on multiple-input-single-output (MISO). That is why, a fully customized ANFIS development effort has been felt necessary to implement the multiple-input-multiple-output (MIMO) architecture [23], as required in this case. The complete procedure of development of the expert system is summarized in the form of a flowchart shown in Figure 3.

3. Results and Discussions
3.1. Simulation results for forward mapping
The optimal parameters of the traditional training algorithm have been determined by a careful parametric study, in which one parameter has been varied within a certain range and others have been kept fixed for training the model. The fixed parameters have been initialized with some recommended values and updated with the optimal values in the subsequent steps (Table 2). The optimal value of a parameter has been chosen as such to yield minimum RMSE, as shown in Figure 4.
Figure 3. Flowchart describing the complete procedure of expert system development

Table 2. Parametric study of the forward mapping model

| Training algorithm | Parameter varied | Range of variation | Parameters kept fixed | Optimal value of the varied parameter |
|--------------------|------------------|--------------------|-----------------------|---------------------------------------|
| BP-RLS             | $m_f$            | [2, 9]             | $s_l = 0.01$          | 9                                     |
|                    | $s_l$            | [0.001, 0.1]       | $m_f = 9$             | 0.013                                 |
The model has been tested against the experimental test data with the traditional training algorithm, consisting of the optimal parameters determined from the parametric study. The mean absolute percentage errors (MAPEs) of each response along with the overall MAPE have been obtained in order to determine the accuracy of the algorithm for predicting each response specified in the model [24]. The comparison is shown in Figure 5.

3.2. Simulation results for backward mapping
The parametric study of the backward mapping model has been carried out along similar lines as that of the forward mapping model. The details of the parametric study are shown in Table 3. It has been noted in many training instances with BP, the over learning of it by running for a large number of iterations thereby reducing the training RMSE has eventually resulted in higher values of testing MAPE. Hence, testing MAPE has been used as an index to determine the optimal parameters instead of RMSE, as shown in Figures 6.

| Training algorithm | Parameter varied | Range of variation | Parameters kept fixed | Optimal value of the varied parameter |
|--------------------|------------------|--------------------|----------------------|--------------------------------------|
| BP-RLS             | $mf$             | [5, 20]            | $sl = 0.01$          | 7                                    |
|                    | $sl$             | [0.01, 0.1]        | $mf = 7$             |                                      |
|                    |                  |                    | iterations = 1000    |                                      |
|                    |                  |                    | $mf = 7$             |                                      |
|                    |                  |                    | iterations = 1000    | 0.01                                 |
Figure 6. Parametric study of backward mapping model trained with BP-RLS

Figure 7. Results of prediction in backward mapping model

The comparison of all the training algorithms has been done in similar fashion as that of the forward mapping model, which is shown in Figure 7.

It is evident that BP & RLS has produced the least overall MAPE of 35.61, in spite of the fact that for some responses individually it has produced better results for prediction.

4. Conclusions

Forward and backward mapping models of the FDM process involving six process parameters and three responses have been successfully achieved using a customized C-ANFIS model. The developed models have been trained by the data generated from the regression equations and tested on the experimental data. The prediction accuracy has been the maximum in case of FMC and minimum for BT in predictive model with the forward mapping with an allowable overall MAPE less than 8%, while the backward mapping revealed the maximum accuracy in case of B (Air Gap) and maximum for C (Raster Angle) with a disappointing overall MAPE of 35.61%. It is evident that the backward mapping model is not adequately capable of predicting all the outputs (input conditions) with reliable accuracy/confidence level. Hence, the present study will be extended to carry out a comparative study of the various types of membership functions used in the C-ANFIS model. Optimization of the number of membership functions will be carried out using some dedicated optimizer.

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