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Intelligent Digital Twin Applications for Feature-Based Parameter Selection in Additive Manufacturing

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Abstract: - The current industrial transition coins additive manufacturing and smart machines towards digital manufacturing. Wire arc additive manufacturing method is one such potential method with the aid of industrial robots with less buy-to-fly ratio. In the present work, a systematic framework is adopted for feature-based auto-selection of process parameters with the advent of machine learning models and with the implementation of digital twin. The performance of the proposed model was validated by building a thin wall structure with the proposed technology. Forward and reverse implementation of strategies were adopted to determine suitable parameters for the required feature. Implementation of these optimal parameters with the proposed methodology adopts the generative model framework. A thin wall structure was fabricated with the novel framework. The thin wall structure characterization was performed to determine the structural integrity developed and found to be superior to conventional bead formation methods.

Keywords: Buy-to-fly ratio, Machine learning, Robot-assisted WAAM, ML model, Digital twin

1. Introduction:

The Industrial Revolution coined the term digital manufacturing with the aid of current cutting-edge technologies. The current industry was proactively looking for an alternative to conventional manufacturing methods to chop down the overall cost of production. A substantial alternative considered to be adopted by the industry is additive manufacturing(AM).

Simultaneous simulation and processing of integrated production demands Digital Twin(DT), that meets the requirement of enhanced productivity[1].

The prospective aspects of this potential method are renowned for its beneficial aspects such as reduced production time, overall cost, post-processing, and with no or less pre-processing operations[2]. From the times of recent past years automation was playing a crucial role in the manufacturing sector. Especially AM is renowned for its potential applications in diverse applications. Particularly AM is considered a potential alternative to conventional manufacturing as it has emerged in rapid prototyping as well as the repairing of the huge functional part. Additionally, AM offers less buy-to-fly ratio instead of using unnecessary feedstock [3]. Due to the flexibility of the ease of operation involved in the AM, it has drawn the attention of many researchers across the globe. The terms for the AM are Rapid prototyping, Additive technology, Additive manufacturing, 3D printing, free-form fabrication, Layered manufacturing, and direct digital manufacturing are often interchangeably used, and are advanced for industrial sustainability.

The sensed data is used for manufacturing with accurate and high precision with reduced material utilization, energy as well as minimal toxic products. Adoption of AM technology in the manufacturing of a product where material deposition occurs in a layered fashion with the aid of computer control[4]. The integration of AM technology enhances production without compromising the quality aspect[5]. The advent of AM was that the transition of prototyping to functional part design in view of enhanced features like flexibility, material efficiency, and versatility are desirable, especially in lightweight components manufacturing sector such as the automobile industry and aerospace industry[6]. Even though AM supports rich set of materials library, metal based AM

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methods are more commercially used in the industry. Based on the ease of doing classification of Metal AM methods Power based and feed based are the main streams the current research is ahead[7]. The AM methodologies such as WAAM is considered as a deposition of direct energy (DDE) method, where electric energy is used to melt the filler wire and that fused material deposits as one layer after another to devolop the part or object as indicated in the Fig.1.

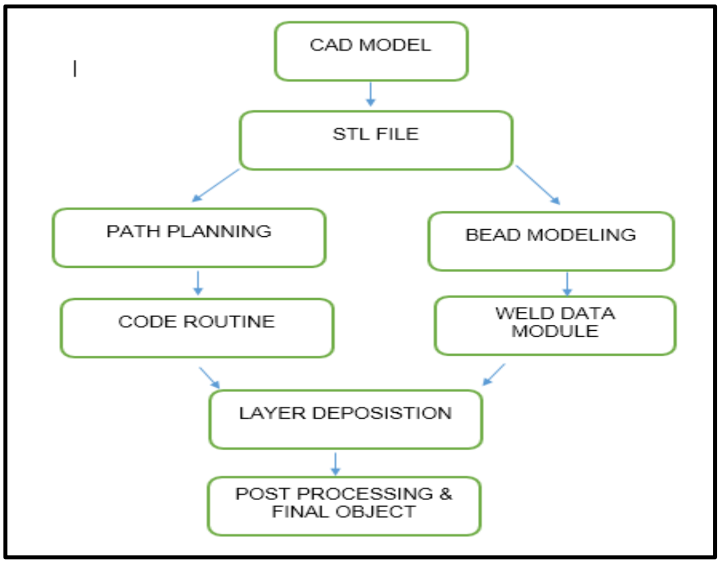

Fig.1.Steps involved in WAAM.

The build quality conren of a part or object relies on the process quality and nature of the building, further, the strength and structural quality depend on bead quality in each layer. The deposition of individual beads in each layer influences the build quality of the part. In AM the object was built in an orderly layered fashion. In the process of deposition as layers for a complex geometrical feature there exist certain errors visual chordal effect or stair-step effect, to overcome these problems the weld bead height needs to be decreased that increasing dimensional accuracy and surface roughness with high deposition time and vice versa with the features if the height of the weld bead was decreased[8]. For large-scale production, the deposition time needs to be decreased and for the small-scale objects surface roughness and dimensional accuracy should be focused. Few research works were carried out on the adaptive weld bead with the feature of variation in dimensional characteristics [9]. The usage of ML methods with bead modelling as path planning for the deposition of single weld beads make an attempt that includes machine learning models in additive manufacturing[10]. Certain studies on single weld bead geometry optimization were performed with the validation of the WAAM process in simulation environments such as Simufact and ANSYS[11]. The formation of an adaptive weld bead depends upon the process parameters like current, voltage, weld feed supply speed, and weld deposition speed. The build quality completely relies on the mentioned properties. In the automation process, based on the weld bead to be formed, the optimal set of input process parameters called weld data in ABB IRB 1520 MIG welding robot, needs to be identified[12]. There are certainly other things to monitor in the WAAM process apart from the weld data, heat input, and power consumption[13]. Numerous strategies of path planning for the WAAM process have been addressed in the literature[14]. The process of WAAM to build the objects requires an effective way of material distribution through several overlapping beads[15]. With the use of a mid-axis path of deposition and optimal step size, multi-beads at multi-levels are formed to build the thin wall [16]. The offset gap between the top and bottom beads is determined using the algorithm of center lines calibiration [17]. The path optimization algorithms in the WAAM process is presented to accomplish the requirements of the robot[18]. With the advent of SVM algorithms integrated with machine learning methods are used to form an adaptive weld bead in the process of automation[19]. The prediction of layer-wise weld pool conditions makes use of convolutional neural networks (CNN) and hybrid deep learning methods with recurrent neural network models(RNN)[20][21]. The use of the above models deals with digital image information and processing of the weld bead to measure the dimensional characteristics. Defects like void formation, crack propagation, material discontinuity, porosity, and entrapment of foreign particles in the process of fusion are determined by a high-resolution digital single-lens reflex(DSLR) vision system[22]. Online monitoring of weld bead deposition is a vital factor to consider in the process compensation of weld geometry apart from the post weld of deposited weld beads[23]. Apart from the image processing, the use of three dimensional data deliberated from the CAD model of the object provides more realistic digital data[24][25]. Integration of internet of things and cloud data for manufacturing leads to sustainability of the product [26]. Industry 4.0 has coined the terms smart machines such as robots with the use of digital data can additively manufacture the objects for sustainable product development. It has also transformed the manufacturing sector towards the automation from the conventional methods, with the aid of additive manufacturing (AM) technology[27].

The present work intends to design a framework for the automation of the WAAM process using machine learning techniques. The developed model will be able to deliberate weld data that can be directly used by the welding robot to fabricate the thin wall. Based on the object to be built as layers the automation system uses the proposed model and prints the metal object layer-wise. The proposed model utilizes data points that stored in the cloud, where pre weld bead characterstic data with sutiable path plan approches are selected from master data base. The master database consists of single weld bead geometry weld data with different proportions that mix of process parameters are taken into consideration. Multi-weld beads with multi-level and mixed-level strategies are considered to maintain the data points. The optimal path plan was taken from the online slicing tools that are integrated with the model. A supervised ANN model is used to estimate the weld data from either slice data of the CAD model from the experimental data. The forward neural network model is used in the present study. To reduce the overall cost for production power consumption was considered in ANN modeling, in addition to the surface roughness of each weld bead also provided to reduce the further post-processing or no post-processing operations. To facilitate the user, simulation is used to monitor the overall process through robot-interfaced studio software. Integrated IoT-based digital manufacturing with the aid of the ML model with a mechatronics approach is deployed in the present work as shown in Fig. 2

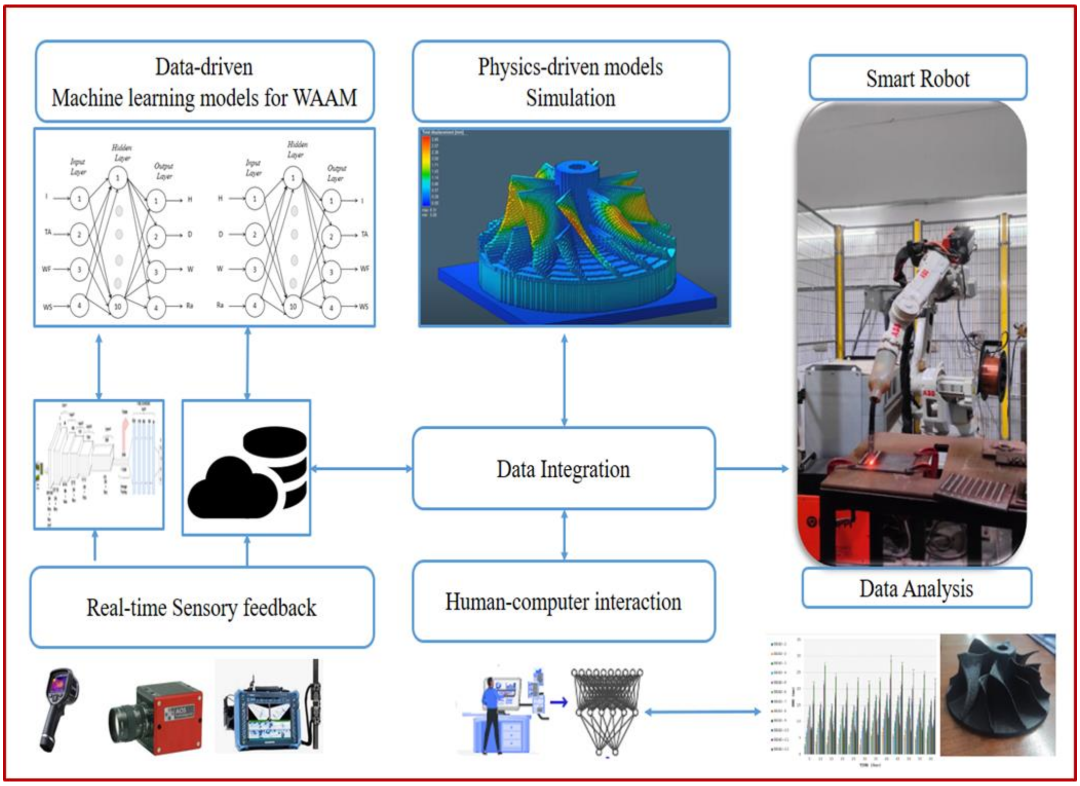

Fig.2. Implementation of Digital Twin in WAAM Process

2. Experimental Methodology:

The proposed model framework was carried out using an industrial welding robot in the Center for Robotics. The deployed welding robot is a six-axis industrial robot that can be controlled by the either ABB robot studio or by a manual teach pendant which was attached to the robot. The L16 design of experimental weld beads are deposited on a mild steel plate of dimensions 150mm X 300mm X10mm that is considered as substrate. The mild steel substrate plate was clamped firmly to resist the deformation that arises in the process of weld bead deposition due to the cyclic thermal stress induced in the substrate. The electric arc was used to melt the ER70S-6 of industrial steel grade filler wire of diameter 1.2 mm in the process. The supply of shielding gas was maintained at 20 liters per minute. The halting time of 5 seconds per bead was maintained for the homogeneity of the built structure.

Based on the model of the weld bead to be deposited the weld parameters were chosen by the proposed model. The proposed model can be able to estimate the weld data that consists of feed, weld speed, and torch angle. Based on the experimental data inference from experiments with different weld parameters is considered to maintain the master data management system. Single-weld beads and multi-weld beads with fully overlapped, half overlapped conditions were taken into consideration for experimentation to feed the proposed model.

Each variation of feature has a minimum of sixteen experiments both in single and multi-weld beads with both conditions. Hence, each feature selection was done by the optimization method employed in the process. Further, with the optimized weld parameters the weld bead dimensional characteristics such as height, width, depth of the deposited weld beads are determined measured individaully, and the entire data module is made available for the master data management system as shown in Fig.3 via cloud points.

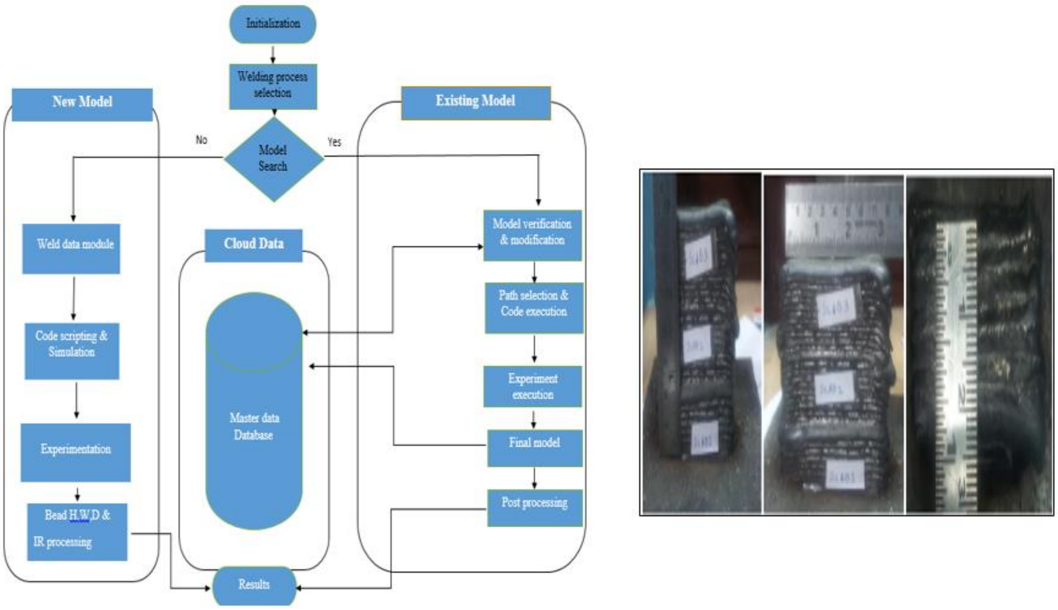

Fig.3. Model-based feature selection process to built layers as thin wall structure.

A thin wall structure of dimensions 75 mm X 20 mm X 70mm deposited on substrate plate of thickness as presented in Fig 3.

2.1 Feedforward ANN model:

The effect of weld parameter data on the weld bead geometry was nonlinear which was a tedious task for the analytical method. To model the relation precisely, supervised machine learning techniques such as artificial neural networks are deployed. Generally, the ANN model consists of input data and corresponding out data, and computing nodes with the synapse or weights between the both as shown in Fig.4. This model was able to interpret the non-linear model that builds the relationship between input data as weld data and out data as weld bead characteristics. Feed forward back propagation method was chosen with TANSIG (tangent sigmoid) as the transfer function of the proposed ANN model. To train the proposed model TRAINLM (Leven Berg-Marquardt backpropagation) training function was adopted, with the gradient descent with momentum weight and bias(LEARNGDM) learning mechanism. The deployed ANN model consists of four input nodes at the input layer one hidden layer with ten neurons and the output layer of ten nodes as shown in Fig.5

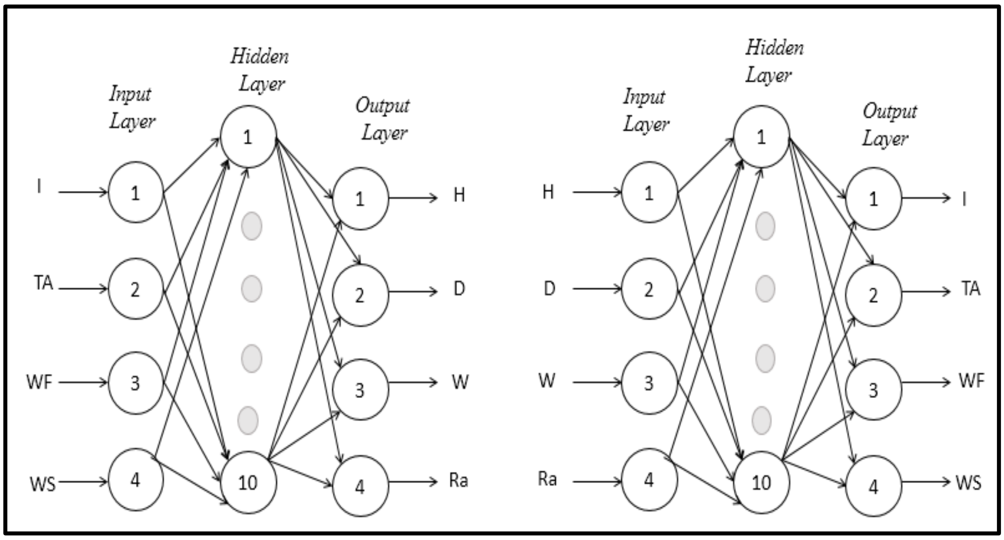

Fig.4. ANN models used in the present work

The optimal set of weld data parameters along with the weld bead characteristics is used in the forward modeling of the ANN model. Along with the experimental data, the slicing information was also provided to the ANN model to estimate the weld bead characteristics. A set of sixteen designs of experiments presented in Table 1 was used for training the ANN model that maps the input process parameters to weld bead characteristics with the synapse between the both. 80% of the experimental data was used to train the ANN model and the rest 20% was used to test the model. The network model was validated with the optimized set of HTLBO results as shown in Fig.9

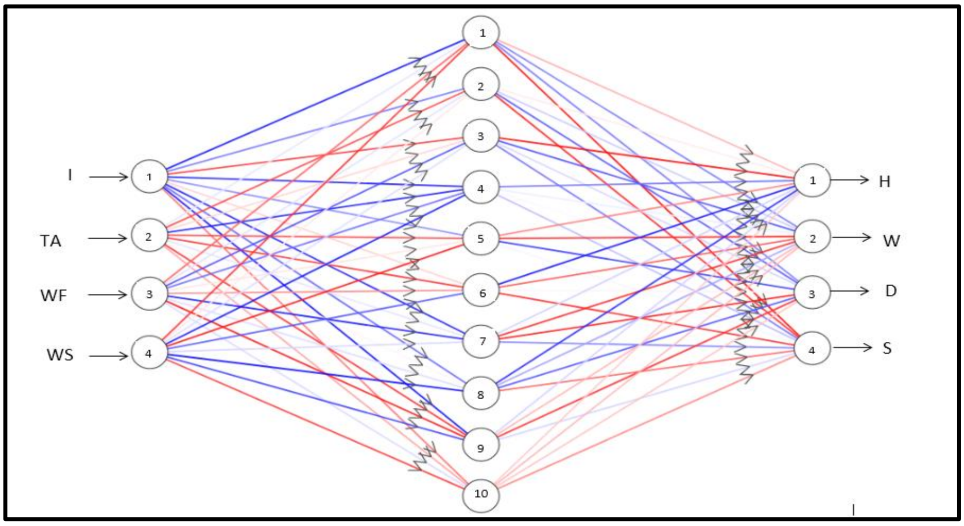

Fig.5. Multi-Layer Preceptor of 4-10-4 ANN model

Table.1. A set of sixteen design experiments.

Exp.No.	I	TA	WF	WS	H	D	W	SRa
1	150A	90^0	6	0.5	3.609	1.364	6.641	0.504
2	150A	90^0	7	0.6	3.746	1.401	5.642	0.719
3	160A	90^0	4	0.4	4.208	1.749	7.525	0.568
4	160A	60^0	6	0.6	4.313	1.634	6.427	0.516
5	160A	60^0	7	0.5	4.452	1.657	7.115	0.612
6	170A	60^0	4	0.5	4.188	1.916	7.543	0.601
7	170A	60^0	5	0.6	4.257	1.925	6.491	0.318

8	170A	90^0	7	0.4	3.881	2.144	7.463	0.852
9	180A	60^0	6	0.4	4.961	2.137	7.907	0.484
10	150A	60^0	5	0.4	3.790	1.256	8.582	0.601
11	150A	60^0	4	0.3	4.483	1.192	8.867	0.565
12	170A	90^0	6	0.3	3.743	2.097	8.524	0.509
13	180A	90^0	5	0.5	3.602	2.464	7.631	0.416
14	180A	90^0	4	0.6	3.599	2.502	7.397	0.564
15	160A	90^0	5	0.3	4.587	1.786	9.499	0.624
16	180	60^0	7	0.3	5.007	2.256	9.276	0.862

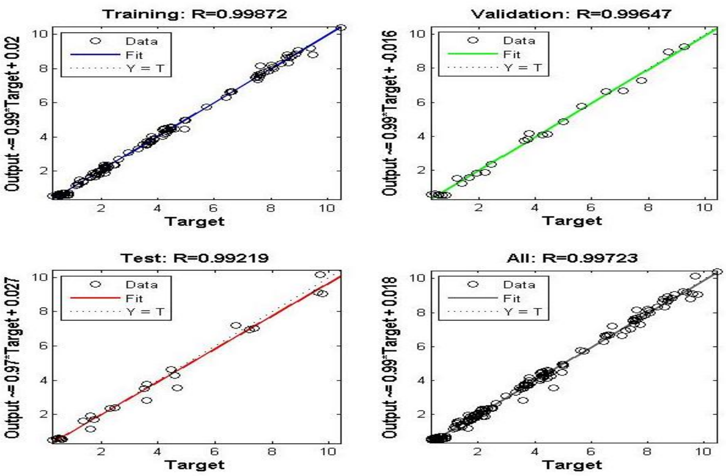

Fig.6. The proposed model training and validation regression graph.

The proposed ANN was modeled in MATLAB with an R^2 value of 99.8 with training and was validated with an R^2 value of 99.6, as shown in Fig.6 The model was tested with the optimized set of HTLBO and the close R^2 was found to be at 99.2. The overall performance of the ANN model R^2 was found to be 99.7 as shown in Fig.7

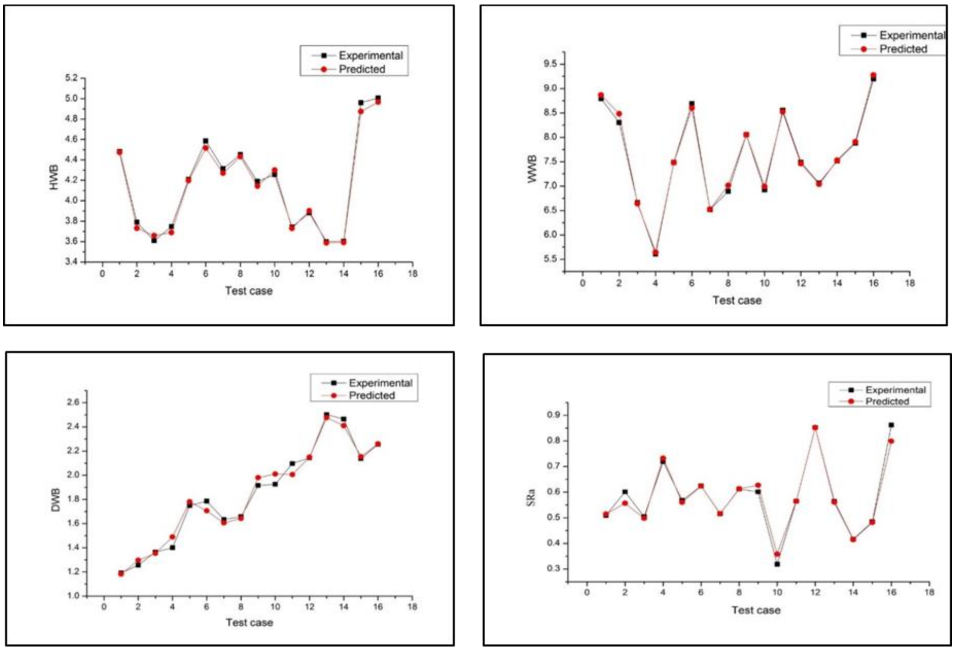

Fig.7. The performance of the proposed model with height,width,depth and surface roughness

2.2 Reverse mapping ANN model:

In the present work reverse mapping feed-forward ANN model was used to predict the weld data as shown in the Fig.8 A feed-forward multilayer preceptor model of the 4-10-4 ANN model was used in the reverse mapping**.**

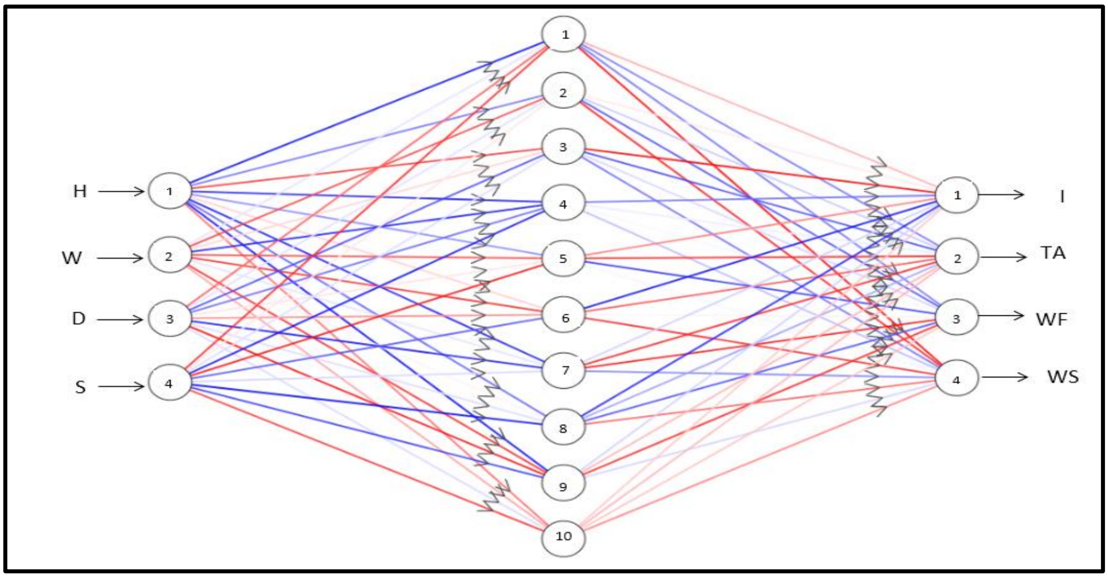

Fig.8. Reverse mapping ANN model

Table.2. Comparison of desired and ANN predicted geometry

Exp.No	Desired bead			Predicted bead		
	H	D	W	H	D	W
1	4.4830	1.1920	8.8670	4.4750	1.1822	8.8670
2	3.7900	1.2560	8.5820	3.7318	1.2968	8.4820
3	3.6090	1.3640	6.6410	3.6588	1.3538	6.6410
4	3.7460	1.4010	5.6420	3.6886	1.4895	5.6420
5	4.2080	1.7490	7.5250	4.1984	1.7805	7.4825
6	4.5870	1.7860	9.4990	4.5171	1.7060	8.5990
7	4.3130	1.6340	6.4270	4.2711	1.6061	6.5270
8	4.4520	1.6570	7.1150	4.4322	1.6429	7.0150
9	4.1880	1.9160	7.5430	4.1452	1.9799	8.0543
10	4.2570	1.9250	6.4910	4.3005	2.0099	6.9910
11	3.7430	2.0970	8.5240	3.7302	2.0061	8.5240
12	3.8810	2.1440	7.4630	3.9008	2.1495	7.4630
13	3.5990	2.5020	7.3970	3.5875	2.4770	7.0397
14	3.6020	2.4640	7.6310	3.5914	2.4096	7.5310
15	4.9610	2.1370	7.9070	4.8749	2.1535	7.9070
16	5.0070	2.2560	9.2760	4.9667	2.2591	9.2760

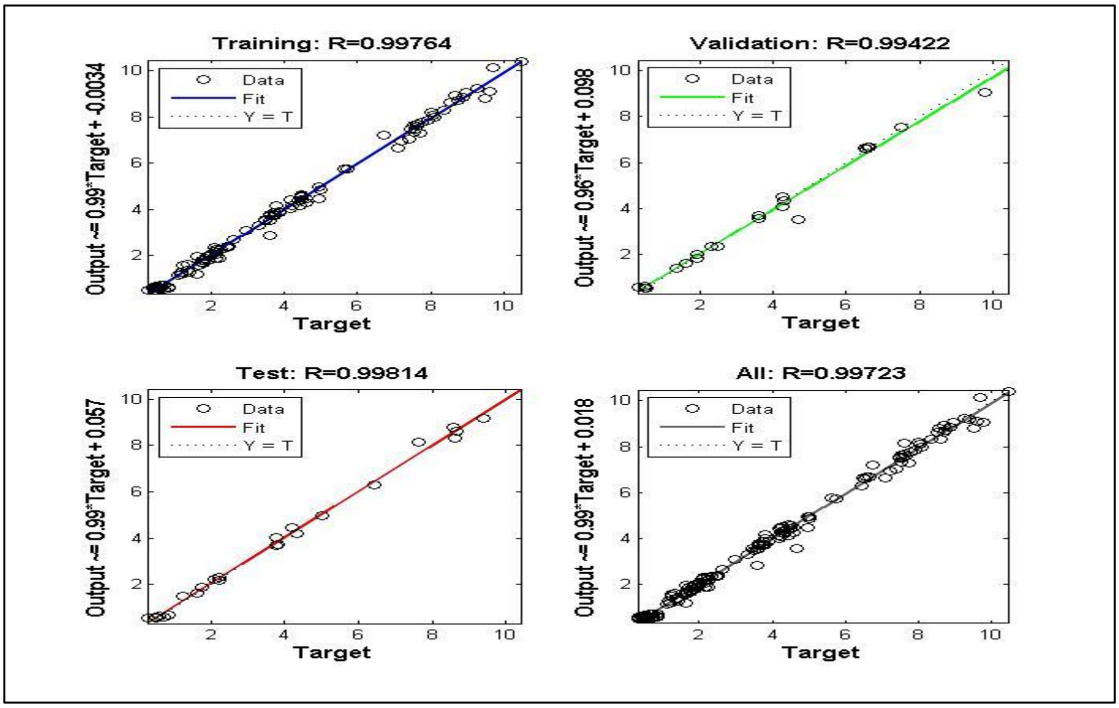

Fig.9. The proposed model training and validation regession graph.

Table.3. Reverse mapped ANN model predicted geometry

S.No.	Current (I)		Torch Angle (TA)		Weld Feed (WF)		Weld Speed (WS)	
	Exp.	ANN	Exp.	ANN	Exp.	ANN	Exp.	ANN
1	150	150.221	90	87.828	6	5.977	0.5	0.513
2	150	150.193	90	89.920	7	6.924	0.6	0.584
3	160	159.150	90	87.803	4	3.943	0.4	0.396
4	160	160.083	60	60.002	6	5.894	0.6	0.596
5	160	170.640	60	61.024	7	6.752	0.5	0.492
6	170	169.808	60	63.388	4	3.890	0.5	0.480
7	170	170.258	60	65.614	5	5.106	0.6	0.591
8	170	170.113	90	82.769	7	6.896	0.4	0.417
9	180	180.933	60	61.281	6	6.027	0.4	0.393
10	150	150.628	60	60.322	5	5.034	0.4	0.397
11	170	150.799	90	87.255	6	5.828	0.3	0.292
12	150	150.512	60	59.334	4	3.763	0.3	0.291
13	180	180.000	90	86.958	5	5.880	0.5	0.497
14	180	180.793	90	82.972	4	4.848	0.6	0.592
15	160	159.312	90	87.043	5	5.059	0.3	0.291
16	180	179.834	60	64.378	7	6.626	0.3	0.299

3. Results and Discussions:

The forward ANN model was used to predict the bead geometry as shown in Table.2 with an R^2 value of 0.992 which means the error on mapping of output to input was in acceptable range.

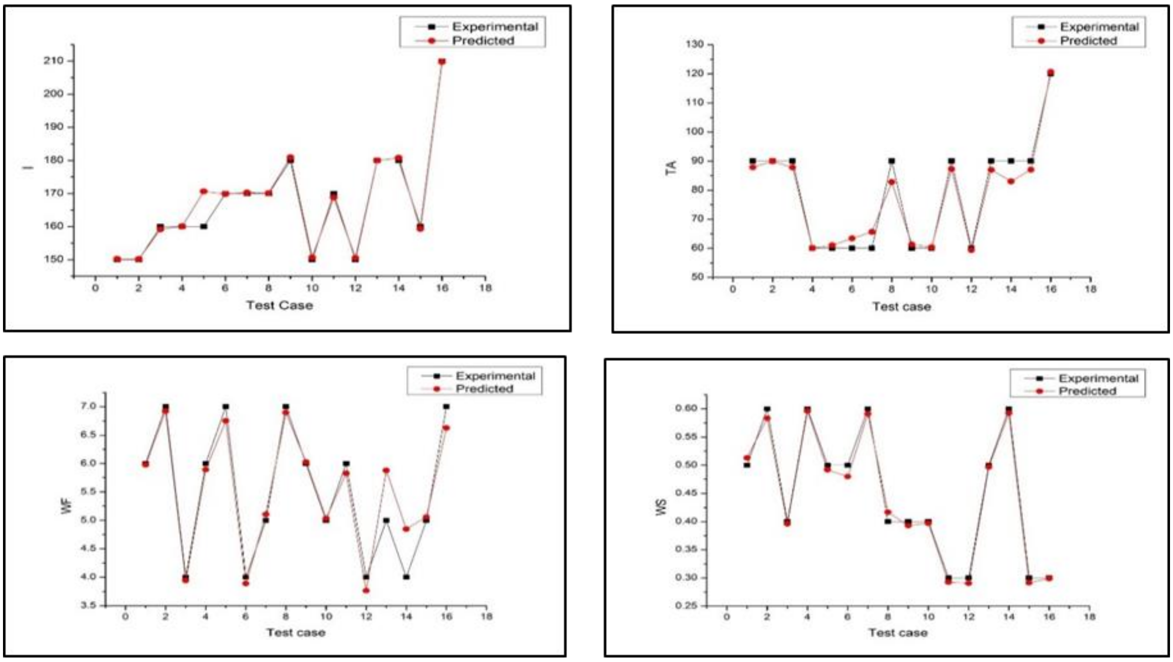

Fig.10. The performance of the proposed model with current, torch angle, feed, and weld speed.

The reverse mapping ANN model was used to predict the set of process parameters such as corresponding current, weld torch angle, supply feed, and speed of the weld as shown in Table.3, for the specified bead geometry, R^2 value as 0.997 which means the error on mapping of output to input was in acceptable range and the model performance as shown in Fig.9& Fig. 10.

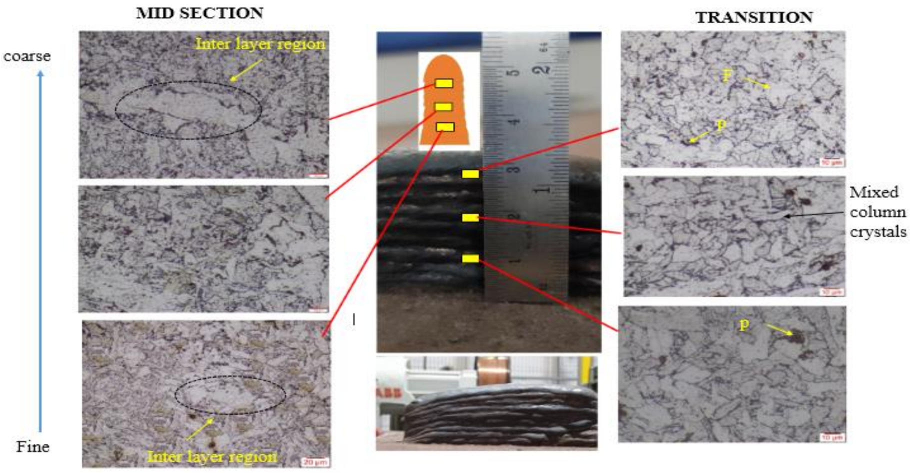

Fig.11. Micro structures of thin wall at layer midsection and transition

Table.4. Hardness value at the labelled locations of the weld bead

S.No.	Location				
	A	B	C	D	E
1	174	165	156	169	177
2	169	166	162	169	177
3	170	166	164	171	181
Average BHN	**171**	**165.66**	**160.66**	**169.66**	**178.33**

It was observed that the hardness was high on the top layer and decreased from the top of the structure. Initially substrate possessed no thermal history and also for initial layer deposition the heat conduction is higher in the substrate, hence the cooling rate of initial layers in slab-1 was higher. For the case of slab-2 layers, the presence of thermal history due to the slab-1 layers accumulating more heat and the rate of cooling was low compared to the previous slab hence this leads to a decrease in hardness as shown in Table.4. For the case of slab-3, the heat accumulation was relatively low compared bottom two slabs, and hence the hardness was relatively higher from the previous slab.

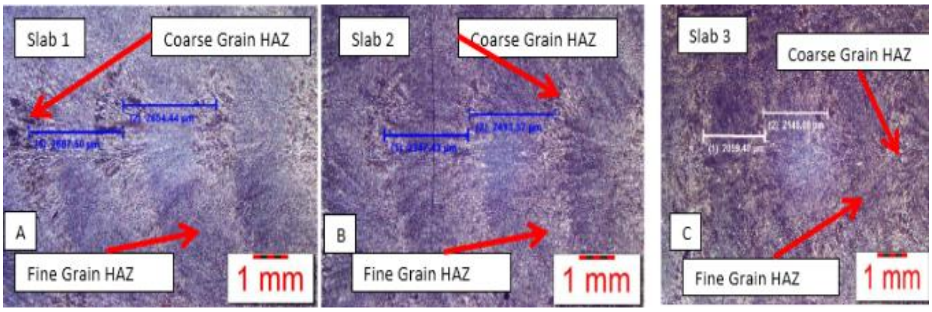

Fig.12. Inner layer formation in the microstructure of three slabs

It can be observed that the formation of coarse grains in heat-affected zone volume is high in the first slab when compared with the second slab and third slab shown in Fig.11. The formation of coarse grains is due to the heat input of that particular slab. Similarly, the formation of coarse grains is high in the second slab compared to the third slab as shown in Fig.12

4. Conclusions:

The objective of the present work is to frame a systematic approach with the use of machine learning for the auto-selection of process parameters with the use of a Hybrid ANN model. The performance of the proposed model is validated with the experimental thin wall structure formation. The significant outcomes of the proposed model are as follows.

1. Initially, the ANN feed-forward model is used to predict the out responses of the weld bead characteristics and are validated with the orthogonal array of sixteen design of experiments.
2. The reverse mapping feed-forward model predicts the input machining process parameters and is validated with the formation of thin wall structure weld bead layers.
3. It can be inferred that the formation of coarse grains in heat-affected zone volume is more in the first slab when compared with the second slab and third slab.
4. The deposited weld bead Dimensional accuracy relies on parameters such as the weld speed of the torch and feed of the filler material.
5. It was also observed that hardness is high on the top layer and decreases from the top to bottom layers of the structure, due to the accumulated heat.

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