Application of Deep Neural Network in Estimation of the Weld Bead Parameters

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Abstract—We present a deep learning approach to estimation of the bead parameters in welding tasks. Our model is based on a four-hidden-layer neural network architecture. More specifically, the first three hidden layers of this architecture utilize Sigmoid function to produce their respective intermediate outputs. On the other hand, the last hidden layer uses a linear transformation to generate the final output of this architecture. This transforms our deep network architecture from a classifier to a non-linear regression model. We compare the performance of our deep network with a selected number of results in the literature to show a considerable improvement in reducing the errors in estimation of these values. Furthermore, we show its scalability on estimating the weld bead parameters with same level of accuracy on combination of datasets that pertain to different welding techniques. This is a nontrivial result that is counter-intuitive to the general belief in this field of research.

I. INTRODUCTION

The automation of the welding processes witness a significant advancement in recent decades. This, in turn, introduces a dramatic improvement on the manufacturing productivity and its efficiency. As the interest in automation of this field of industry continues to grow, the needs for quality research on reducing the manual modification of its parameters by human operator becomes indispensable. The intelligent monitoring of the welding process helps increase the precision and accuracy of the various aspects of its final outcome (e.g., the geometry of the weld beads). Furthermore, it helps determine if the driving parameters of the welding system requires readjustment. As a result, the overall performance of the system and consequently its welding quality improves significantly.

[6] uses the term Direct Weld Parameters (DWP) to refer to the geometrical description of the welding pool. The depth of penetration, the width of the weld bead, and the transverse cross-sectional areas are some of the examples of DWPs. Moreover, [1] shows the quality of these parameters are directly influenced by the control of the Indirect Weld Parameters (IWP). They include the voltage, the current, the torch traveling speed, the wire feed rate, and the arc gap. An investigation of the relationship between DWP and IWP is found in [20].

The study of the welding process and its related parameters can be broadly divided into two main fields of research. These are the estimation of the values of the weld parameters and the sensitivity analysis of these parameters. The sensitivity analysis refers to the prediction of the effect of the changes in welding process parameters on the final welding quality. It is applied on a number of welding techniques such as Gas Metal Arc Welding (GMAW) [10], Submerged Arc Welding (SAW) [12], [25], [22], and Tungsten Insert Gas (TIG) Welding [23]. On the other hand, the estimation problem attempts to predict these parameters, given the IWP.

In this article, we focus on the problem of the estimation of the welding process parameters.

There exists a rich body of research on estimation of the weld process parameters and its final outcome. [4] represents an early trial of static model, based on the heat flow. More specifically, it expresses the welding contour as a function of electrode velocity, heat input, and the material properties. Moreover, many researchers apply sophisticated mathematical models to capture this relationship. This includes factorial design [18], [9], [16], linear regression [24], [10], multiple regression analysis [19], response surface methodology [17], [8], Taguchi method [13], [15], or a combination of genetic algorithm and artificial neural network [27].

In particular, the recent achievements in application of artificial neural network (ANN) on modeling the welding process brings a remarkable progress in this area. They are successfully utilized to investigate the modeling of the welding process, the process control, and the estimation of the quality of the weld beads [7]. [26] uses ANN to model the arc welding process. This model achieves satisfactory results on the prediction accuracy of the weld bead parameters as compared to the conventional control systems. [21] uses back-propagation and counter-propagation to analyze the relationship between the input process parameters and the geometry of the weld bead in TIG welding. [3] studies the application of the self-organizing map (SOM) in monitoring and quality evaluation of the GMAW welding. [5] applies back-propagation on modeling and estimation of the weld bead parameters in Shielded Metal Arc Welding (SMAW).

In this article, we present a deep learning approach to estimation of the bead parameters in welding tasks. The deep networks learn through realization of the feature hierarchies with features from higher levels formed by the composition of those at the lower levels [28]. They are successfully used in a variety of applications ranging from natural language processing [29] to document recognition [31] and traffic sign classification [30]. An overview of the application of the deep network along with the challenges on training these architectures are found in [32] and [28], respectively.

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The scarcity of real welding data makes the analysis of the performance of proposed approaches difficult. The process of collecting such data is cumbersome and time-consuming. It requires hours of tedious welding by skilled welders. This is followed by long hours of manual measurement and cross sectional cutting to ascertain the weld bead parameters on a given workpiece. Moreover, there are a number of different welding techniques (e.g., arc and submerge arc weldings) whose applications are only appropriate for a certain type of welding tasks.

We compare the performance of our deep neural network architecture with a number of selected studies in the literature. In particular, we choose [26], [27], [22] for this purpose. These selected articles form a reliable representatives of the trends of the study in this field over the past two and half decades. More specifically, [26] is the seminal paper that first introduces the application of the single hidden layer neural network in estimation of the weld bead parameters. Furthermore, [22] applies a curvilinear approach to estimation of these parameters. Moreover, [27] proposes a single hidden layer neural network in combination with genetic algorithm to predict the weld bead parameters.

Additionally, the welding data of these studies are publicly available through their respective articles. They pertain to three different welding techniques. More specifically, [26] provides a dataset of size 42 on arc welding process. A dataset of size 28 is presented in [22]. It corresponds to submerged arc welding technique. The two tables that are included in [27] pertain to A-TIG welding process. These are comparatively large datasets with 120 data each. Furthermore, they correspond to the application of A-TIG welding on two different types of materials. These are 304LN stainless steel and 316LN stainless steel.

Our contributions are as follows. First, we introduce the potentials that the deep neural networks can offer to the solution concept of the estimation of the weld bead parameters. To the best of our knowledge, this is the first attempt to apply deep neural computation in this field of research. Second, we show that its simple implementation achieves a considerable improvement over the results that are presented in the literature. In addition, its results do not require any additional post optimization processing as it is suggested by some of the reports in this field [27]. However, we acknowledge the fact that our approach is not the definite solution but an early step towards potentials that deep neural network can provide to estimation and analysis of the weld bead parameters. We are hopeful that it provides the researchers in automation of the welding processes with an opportunity to broaden their consideration on existing methodologies to advance the reliability of the performance of these systems.

The remainder of this article is organized as follows. Section II elaborates on formulation of our deep neural network architecture. We present the results of our case studies on a selected list of literature in section III. Section IV presents conclusion and future direction of this research.

II. NEURAL ARCHITECTURE

We model our neural architecture as a four-hidden-layer deep network. We assign an equal number of neurons to each of these layers. In this architecture, the neurons of every preceding layer are fully connected to those of the succeeding layer via their corresponding weight matrices. Fig. 1 depicts this network. In this figure, we omit the neural units of the layers for simplicity. The inputs to this network are the welding process parameters. These are the current, the voltage, and the torch speed.

The first three hidden layers of this architecture utilize Sigmoid function to produce their respective intermediate outputs. As a result, the output values of these layers are bounded within [0, 1] interval. Whereas, the last hidden layer uses a linear transformation to generate the final output of this architecture. This transforms our deep network model from a classifier to a non-linear regression model. In other words, our architecture produces real-valued numbers to estimate the actual weld bead parameters. These outputs pertain to the depth of penetration and the width of the weld beads, respectively.

We train our deep network using feed-forward with back-propagation procedure. In addition, we use a constant momentum factor in calculation of the gradient of the weight matrices. This encourages their downhill movement during their updates. Furthermore, we formulate a linear cost function that utilizes the output of this network to minimize its discrepancy with the actual weld bead parameters in training data. Additionally, we regularize this cost function with the weighted sum of the weight matrices of every layer to prevent its over-fitting.

Let $X$ denote the set of input parameters to the network. Furthermore, let $Y$ be the set of weld bead parameters in training data. In addition, let $H^{(i)}$, $i = 1, \ldots, 4$, represent the $i^{th}$ hidden layer of this architecture. Moreover, let $\Theta^{(i)}$, $i = 1, \ldots, 5$, be the weight matrices that connect every preceding layer to its successor. This includes the connection between the input layer $X$ to $H^{(1)}$ and the hidden layer $H^{(5)}$ to the output layer $Y$. There are three steps involved in formulation of our deep neural network. These are minimization of the cost function, feed-forward computation, and weight updates through back-propagation. We explain these steps in the following subsections.

A. Cost Function

During the training process, we are interested in weight matrices that minimize the discrepancy between the estimated values of the weld bead parameters by this neural network.
architecture in contrast to their actual values in training data. Moreover, it is important to prevent the training process from overfitting on the training data. This increases the accuracy of the network in predicting the new weld bead parameters that do not come from the training set. Furthermore, this cost function needs to take into account the real-valued output of the last layer of our architecture. Therefore, we formulate our cost function as a regularized sum of the squared error of the output of the network and the actual bead parameters in the training data:

$$J = \frac{1}{2m}[\Vert Y - Y' \Vert^2 + \lambda \displaystyle \sum_{l=1}^{L-1} \displaystyle \sum_{i=1}^{p(l)} \displaystyle \sum_{j=1}^{q(l)} (\Theta_{ji}^{(l)})^2]$$

where $Y'$ is the estimated values of the weld bead parameters that are calculated by our neural architecture. $m$ is the total number of training data. The second term in (1) is the regularization term that incorporates the sum of the squared of the weight matrices of all the layers in the network. This helps prevent the network from overfitting on the training data. $\lambda$ is the regularization constant. $L$, $p(l)$, and $q(l)$ refer to the total number of hidden layers along with the row and the column dimensions of the weight matrix at $p^{th}$ layer, respectively.

B. Feed-Forward

The values that are generated at every hidden layers are:

$$z^{(i)} = (H^{(i-1)})^T \times \Theta^{(i)}$$

$$H^{(i)} = \frac{1}{1 + e^{-z^{(i)}}}, \quad i = 1, \ldots, 4$$

with $H^{(0)} = X$ in (2). These values correspond to the application of the Sigmoid transformation on the input as we move forward through layers of the network and towards the output layer. It is worth noting that we add an extra column with all whose entries equals to 1 to the input and the hidden layers to count for the bias term. This is why we do not explicitly include this term in (2). This also explains the starting indices of the last two summation operations from 1 in (1). The final output of this network is the linear transformation of the values at the last hidden layer i.e., $H^{(4)}$:

$$Y' = (H^{(4)})^T \times \Theta^{(5)}$$

where $\Theta^{(5)}$ is the weight matrix that transforms the values at the last hidden layer onto the final estimates of the bead parameters.

C. Back-Propagation and Weights Update

Equation (4) shows the final estimates of the values of the weld bead parameters by our neural architecture. The discrepancy between this generated output and the actual weld bead parameters in training data is:

$$\delta^{(Y)} = Y - Y'$$

We use this value to update $\Theta^{(5)}$:

$$\Delta^{(5)} = ((\delta^{(Y)})^T \times H^{(4)}) \times \gamma$$

$$\Theta^{(5)} = \Theta^{(5)} + \frac{1}{m} (\alpha \times \Delta^{(5)} + \lambda \displaystyle \sum_{i=1}^{p(5)} \displaystyle \sum_{j=1}^{q(5)} \Theta_{ji}^{(5)})$$

where $m$ is the total number of training data. $p(5)$ and $q(5)$ refer to the dimensions of the weight matrix of the output layer, as shown in Fig. 1. Equation (5) is the gradient of the output layer and $\gamma$ is a constant that acts as the momentum to encourage the downhill move of the gradient values. We use $\gamma = 0.9$ throughout our experiments. Furthermore, $\alpha$ and $\lambda$ are the learning rate and the regularization factor, respectively. Similarly, the updates of the weight matrices $\Theta^{(4)}$, $\Theta^{(3)}$, and $\Theta^{(2)}$ are:

$$\delta^{(i)} = (\Theta^{(i)})^T \times \delta^{(i+1)} \times (H^{(i)} \times (1 - H^{(i)})), \quad i = 5, \ldots, 3$$

$$\Delta^{(i-1)} = ((\delta^{(i)})^T \times H^{(i-1)}) \times \gamma$$

$$\Theta^{(i-1)} = \Theta^{(i-1)} + \frac{1}{m} (\alpha \times \Delta^{(i-1)} + \lambda \displaystyle \sum_{i=1}^{p(i-1)} \displaystyle \sum_{j=1}^{q(i-1)} \Theta_{ji}^{(i-1)})$$

where $(H^{(i)} \times (1 - H^{(i)}))$ in (8) is the gradient of the Sigmoid function at the $p^{th}$ hidden layer. The weight update for $\Theta^{(1)}$ closely follows (8) through (10) except that $H^{(1)}$ is replaced by $X$ in (7):

$$\delta^{(2)} = (\Theta^{(2)})^T \times \delta^{(3)} \times (H^{(2)} \times (1 - H^{(2)}))$$

$$\Delta^{(1)} = ((\delta^{(2)})^T \times X) \times \gamma$$

$$\Theta^{(1)} = \Theta^{(1)} + \frac{1}{m} (\alpha \times \Delta^{(1)} + \lambda \displaystyle \sum_{i=1}^{p(1)} \displaystyle \sum_{j=1}^{q(1)} \Theta_{ji}^{(1)})$$

The training process starts with the feed-forward calculation of the estimated output of the network. This is followed by the updates of the weight matrices through the back-propagation. Next, we calculate the cost function using the recently calculated output of the network and the updated weight matrices. This procedure continues until a given number of iterations is met.

III. CASE STUDY

We compare the performance of our deep neural network architecture against a number of selected studies from the literature. In particular, we choose [26], [27], [22] for this purpose. These articles form a reliable representatives of the trends of research in this field over the past two and a half decades. More specifically, [26] is the seminal paper that first introduces the application of the single hidden layer neural network in estimation of the weld bead parameters. Furthermore, [22] applies a curvilinear approach to estimation of these parameters. Moreover, [27] proposes a single hidden layer neural network in combination with genetic algorithm to predict the weld bead parameters.

Additionally, the welding data of these studies are publicly available through their respective articles. These data pertain
to three main welding techniques. More specifically, [26] provides a dataset of size 42 on arc welding process. A dataset of size 28 is presented in [22]. It corresponds to submerged arc welding technique. The two tables that are included in [27] pertain to A-TIG welding process. These are comparably large datasets with 120 data each. Furthermore, they correspond to the application of A-TIG welding on 304LN stainless steel and 316LN stainless steel, respectively. Throughout our case study, we use the following abbreviations to refer to each of these datasets:

1) $T_{1990}$: dataset that is provided by [26] on arc welding process.
2) $T_{2008}$: dataset that is presented by [22] on submerged arc welding process.
3) $T_{2010}^{(1)}$ and $T_{2010}^{(2)}$: the two datasets in [27] on A-TIG welding on 304LN stainless steel and 316LN stainless steel, respectively.

A. Training Setup

We use 80% of data of each of these datasets for training purpose. We keep the remaining 20% for testing. These values are selected at random from each of these datasets. Moreover, we use the current, the voltage, and the torch speed as inputs to our neural architecture. These welding process parameters constitute the common features in [26], [22], [27] whose data are utilized throughout this case study. Similarly, we train our model on estimating the common weld bead parameters in these articles. They are the depth of penetration and the width of the weld beads, respectively. These choices of input and output parameters make the comparative analysis of the performance of our model in contrast to the above literature plausible. Furthermore, we compute two separate sets of weight matrices $\Theta(i)$, $i = 1, . . . , 5$. As a result, the weight matrices to estimate the depth of penetration and the width of the weld beads are different.

We train our model through a number of training phases with varying iterations. More specifically, we train this network using 1000 through 6000 iterations where each setting of the number of iterations correspond to a different training phase. This is to choose the best meta-parameters that fit our architecture with respect to a given dataset. These parameters are the learning rate $\alpha$, the regularization factor $\lambda$, and the number of neural units at each hidden layer of our network. However, we use a fixed momentum $\gamma = 0.9$ throughout these training phases. It is worth noting that we assign same number of neurons to all the hidden layers.

We initialize these meta-parameters from their respective predefined sets of values at the commencement of every training phase. For instance, we initialize $\lambda$ to a value that is selected from $[0, 0.001, 0.003, 0.009, 0.01, 0.03, 0.09, 0.1, 0.3, 0.9, 1, 3, 10, 20, 30, . . . , 100]$ and $[2, . . . , 10]$ to initialize the $\alpha$ and the number of neural units of the hidden layers, respectively. This process is performed through a series of nested loops in our implementation. We update these meta-parameters if the result of the estimate of the weld bead parameters in a training phase outperforms the previous result.

Table I shows the final values of these meta-parameters along with the best number of iterations for depth of penetration. Similarly, Table II corresponds to their values in estimating the width of weld bead. The last column of these tables shows the size of each of the corresponding dataset for comparison. These tables reveal the overall simplicity of our deep network architecture. More specifically, the number of neural units of each of the hidden layer of this network is between 2 to 5 neurons. This expedites its convergence since less computational units results in smaller weight matrices at each layer. Furthermore, its computation favors a setting where the regularization term is excluded. This is evident in the $\lambda$ entry of these tables with whose values mostly zero. This suggests that our model does not suffer from over-fitting in general. The only exception to this observation is $T_{2008}$ [22]. This is mainly due to the small size of this dataset (28 data in total) which can lead to over-fitting during a particular training phase. Moreover, the maximum number of iterations to train this network does not exceed 4000. However, its variation does not exhibit any correspondence with the size of the given datasets. As a result, any conclusion on the effect of the size of the dataset on training process in these cases are not warranted. However, the learning rate $\alpha$ exhibits a comparably higher variations in these tables. This is indicative of high variance among the values of the depth of penetration and the width of the weld beads in training data.

| Dataset | No. Neurons | $\alpha$ | $\lambda$ | Iterations | Size |
|---------|-------------|----------|-----------|------------|------|
| $T_{1990}$ | 5 | 50.0 | 0.0 | 4000 | 42 |
| $T_{2008}$ | 4 | 10.0 | 0.09 | 1000 | 28 |
| $T_{2010}^{(1)}$ | 5 | 10.0 | 0.0 | 2000 | 120 |
| $T_{2010}^{(2)}$ | 3 | 40.0 | 0.0 | 4000 | 120 |

| Dataset | No. Neurons | $\alpha$ | $\lambda$ | Iterations | Size |
|---------|-------------|----------|-----------|------------|------|
| $T_{1990}$ | 5 | 50.0 | 0.0 | 4000 | 42 |
| $T_{2008}$ | 4 | 10.0 | 0.3 | 3000 | 28 |
| $T_{2010}^{(1)}$ | 2 | 30.0 | 0.0 | 1000 | 120 |
| $T_{2010}^{(2)}$ | 4 | 10.0 | 0.0 | 4000 | 120 |
B. Results

Tables III through VI show the result of the performance of our deep network architecture on the test data in comparison with the single hidden layer net [26], the curvilinear model [22], and the combination of single hidden layer network and genetic algorithm [27]. The test data pertains to a 20% subset of entire values of each of these datasets that are selected at random. However, we are unable to use the exact same test data in these articles since the authors do not report these values. The row entry DNN of these tables are the results obtained by our deep neural network. We choose Root Mean Squared Error (RMS) and the percentage of Prediction Error (PE) to report our results. The main reason to choose these two values are to enable the comparative analysis of our results with respect to the selected literature. More specifically, [26] reports the percentage of prediction error. Whereas, [22] and [27] provide RMS as the measure of accuracy of their models.

A comparison between the PE in Table III reveals that the standard deviation of the differences between these values is above one standard deviation. As a result, the reduction of the percentage of the prediction error by our model on this dataset is significant. Additionally, the RMS values that are calculated by our model are considerably small on this dataset (in the scale of millimeter). However, we are unable to confirm the significance of these values since [26] does not provide any report on RMS values of their one-hidden-layer network.

We notice the same trend of improvement on the entries of Tables IV through VI. The PE values that are calculated by our model on these datasets are below 2.55%. Moreover, it considerably improves upon the RMS values in Table IV. It reduces these values to almost half their values in [22] as it is evident in the entries of this table. The same observation on reduction of the values of the RMS is valid in case of Tables V and VI. However, the latter improvements are within one standard deviation of the RMS reported in [27].

| Penetration(mm) | Width |
|-----------------|-------|
| Value           | Value |

Hence, its statistical significance is not warranted.

An interesting observation on the results of the performance of our deep neural network architecture is its stability on estimating the weld bead parameters, irrespective of the dataset that is used. In particular, the differences between the RMS and the PE values that are generated by our model in Tables III through VI are within one standard deviation of one another. In other words, our deep neural architecture is capable of adjusting to different settings of input parameters to estimate the values of the output parameters within an acceptable range of accuracy.

C. Scalability on Combined Datasets

In this section, we analyze the performance of our model on combination of these datasets. In particular, we report the RMS and the PE values of our deep network on the following two datasets:

1) $T_{2010}^{(1,2)}$: is the combination of $T_{2010}^{(1)}$ and $T_{2010}^{(2)}$ in [27].
2) $T_{all}$: combines all these datasets into one.

We choose the same ratio of 80% train data and 20% test data on these two new datasets. The test data is selected at random after combining all the values in one large dataset. Tables VII and VIII show the best fit of meta-parameters for these datasets. An interesting observation to note is the increase in the number of neural units on combination of these datasets as compared to Tables I and II. Such an increase in the number of neural units in hidden layers is due to the increase of the size of the resultant combined datasets. The value of $\lambda$ for estimating the width of the weld beads in Table VII is also slightly higher than those in Tables I and II. It suggests that our model is more susceptible to over-fitting on estimating the width of the weld beads in this combined dataset. However, the learning rate $\alpha$ remains in the same range as in Tables I and II.

Table IX provides the RMS and the PE values that are calculated by our deep network on these combined datasets.
TABLE VII
BEST SET OF META-PARAMETERS TO ESTIMATE THE DEPTH OF PENETRATION ON COMBINATION OF DATASETS.

| Dataset | No. Neural Units | α | λ | No. Iterations |
|---------|------------------|----|----|----------------|
| $T_{2010}^{[1:2]}$ | 7 | 30 | 0.0 | 4000 |
| $T_{all}$ | 9 | 19 | 0.001 | 4000 |

TABLE VIII
BEST SET OF META-PARAMETERS TO ESTIMATE WIDTH OF THE WELD BEAD ON COMBINATION OF DATASETS.

| Dataset | No. Neural Units | α | λ | No. Iterations |
|---------|------------------|----|----|----------------|
| $T_{2010}^{[1:2]}$ | 4 | 10 | 0.9 | 1000 |
| $T_{all}$ | 7 | 30 | 0.0 | 2000 |

Although these values are slightly larger than those calculated on separate datasets by our model, their differences are within one standard deviation from one another. This is an interesting observation that challenges the general belief in this field of research. In particular, it shows that a deep neural network is capable of discovering the pattern that can exist among the weld bead parameters that pertain to different types of welding processes. However, this observation requires further investigation.

IV. CONCLUSIONS

In this article, we present a deep learning approach to estimation of the bead parameters in welding tasks. We show that the linear transformation of the output layer enables our deep network to behave as a non-linear regression model to generate real-valued estimate of the weld bead parameters. A comparison between our model and a selected number of results in the literature show a considerable improvement in reducing the errors in estimation of these values. Furthermore, we show its scalability on estimating these values with the same level of accuracy on combination of datasets of different welding techniques. This is a nontrivial result that is counter-intuitive to the general belief in this field of research.

The RMS entries of Tables III through IX reveal that the estimate of the depth of penetration always yields a better result as compared to that of the width of the weld beads. Moreover, this observation holds true in case of our deep network architecture as well as methodologies that are adapted by the selected literature in this case study. Furthermore, the same behavior is noticeable in the results obtained from the combined datasets. The future direction of this research pertains to analysis of this peculiar behavior to realize the possibility of further reduction of the errors on estimation of the width of the weld beads.

In this study, we apply our approach to the data that pertains to three different welding techniques. This is mainly due to scarcity of data on other welding techniques. We are hopeful to find data on other variety of welding techniques to realize the utility of our model on broader welding applications. Moreover, it is interesting to investigate the performance of our model on the results of the multi-pass welding processes once its data is available.

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