Expert System for Manufacturing Process

Project report submitted in partial fulfillment
of the requirements for the degree of

Bachelor of Technology
in
Computer Science and Engineering

by

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CERTIFICATE

This is to certify that the project entitled "Expert System for Manufacturing Process" submitted by Ashish Gupta(16ucs048), Nimish Gupta (16ucs119), Raja Singhal (16ucs151), Abhishek Upadhyay (16ucs013) in partial fulfillment of the requirement of degree in Bachelor of Technology (B. Tech), is a bonafide record of work carried out by him/her at the Department of Computer Science and Engineering, The LNM Institute of Information Technology, Jaipur (Rajasthan) India, during the academic session 2018-2019 under my supervision and guidance and the same has not been submitted elsewhere for award of any other degree. In my/our opinion, this thesis is of the standard required for the award of the degree of Bachelor of Technology (B. Tech).

Advisor: Dr. Bharavi Mishra

Advisor: Dr. Manoj Kumar

Date

Dedicated to My Family, Friends and Teachers.

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Abstract

A smart welding automation system has been used to improve the weld quality, reduce the time for the decision, minimize the number of trial and error, and avoid the requirement for a highly qualified and experienced professional welders (Any welder can weld easily and efficiently).

The main purpose of this project is to improve and verify all possibility of the desired characteristics of the weld bead by a programmed system. For this work, experimental data were obtained under laboratory conditions, using an industrial welder or robot that made welds with the submerged arc-welding process.

Welds were made with different values of voltage, current, wire feed rate, nozzle to plate distance and different type of material and the following output parameters were measured from the weld bead: bead width, reinforcement, and penetration. As of now, environment conditions (like temperature, humidity, air, pressure, etc.) are not taken into account for this model.

A feed-forward artificial neural network, fully connected and supervised learning using backward propagation, was created from the experimental welding data. After comparing the results with other geometric parameter prediction methods and models like Recurrent Neural Network (RNN), Linear Regression and Artificial Neural Networks (ANN), ANN is able to predict the required weld bead structure parameters with less error and complexity. The mean square error between the actual output and predicted output was calculated for finding the loss (error) in each iteration of training for getting better accuracy of this model.

In our system what we are going to do is that we take the desired output for welding in the real world as input for our system and bring the output that will be served as the input needed in the real world to get the actual desired output.

Due to less experimental data we generate dummy data for deep learning. As of now, we got 79% accuracy in our final model And with the increase in the number of data accuracy will definitely increase. Currently, we've applied some existing model to test how it works so that we will be able to choose a good model.

Keywords: Weld parameter prediction, Submerged Arc Welding, Artificial neural network, Dummy data generation, Regression.

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Chapter 1

Introduction

1.1 System Overview

Welding is the process by which two pieces of metal can be joined together. The process of welding doesn't merely bond the two pieces together as in brazing and soldering, but, through the use of extreme heat and sometimes the addition of other metals or gases, causes the metallic structures of the two pieces to join together and become one. There are a number of different welding methods, including spot welding, metal inert gas (MIG), and tungsten inert gas, which are forms of gas metal arc welding, arc welding, and gas welding, to name a few. Welding can be done underwater. Weld bead geometry is an important factor in project engineering since it influences the plan and decides the expenses of steel structure and mechanical devices. The width and height of the reinforcement of the weld bead may prejudice the operation of equipment and a small weld penetration may jeopardize its resistance.

1.2 What is Manufacturing Systems?

In the context of the presented research, we define manufacturing system design as follows: manufacturing system design covers all aspects of physically arranging and operating a manufacturing system. Physically arranging the system includes equipment selection, facility layout, work design (manual and automatic), standardization, design of material and information flow, etc. Operation includes planning, scheduling, and execution of orders, the manufacturing system must manufacture.

1.3 Role of Parameters

Process parameters in welding are key variables affecting the production process. Parameters are attributes that are monitored to detect deviations in standardized production operations and product output quality or changes in Welding Quality Attributes. Those attributes with a higher impact on Weld should be prioritized and held in a stricter state of control. The manufacturer should conduct tests to set acceptable range limits of the determined parameters and define acceptable process variable variability. Operational conditions within this range are considered acceptable operational standards. Parameters have an important role in the manufacturing of products. It can be anything either obtained from the environment (nature) or by the process.

1.4 Type of Parameters

In our system, there are two kinds of parameters:

1. **Direct Parameter:**
    a. Voltage (V)
    b. Nozzle to plate distance (NPD)
    c. Welding speed (WS)
    d. Wire feed rate(WFR)
2. **Indirect Parameter:**
    a. Temperature
    b. Humidity
    c. Pressure etc.

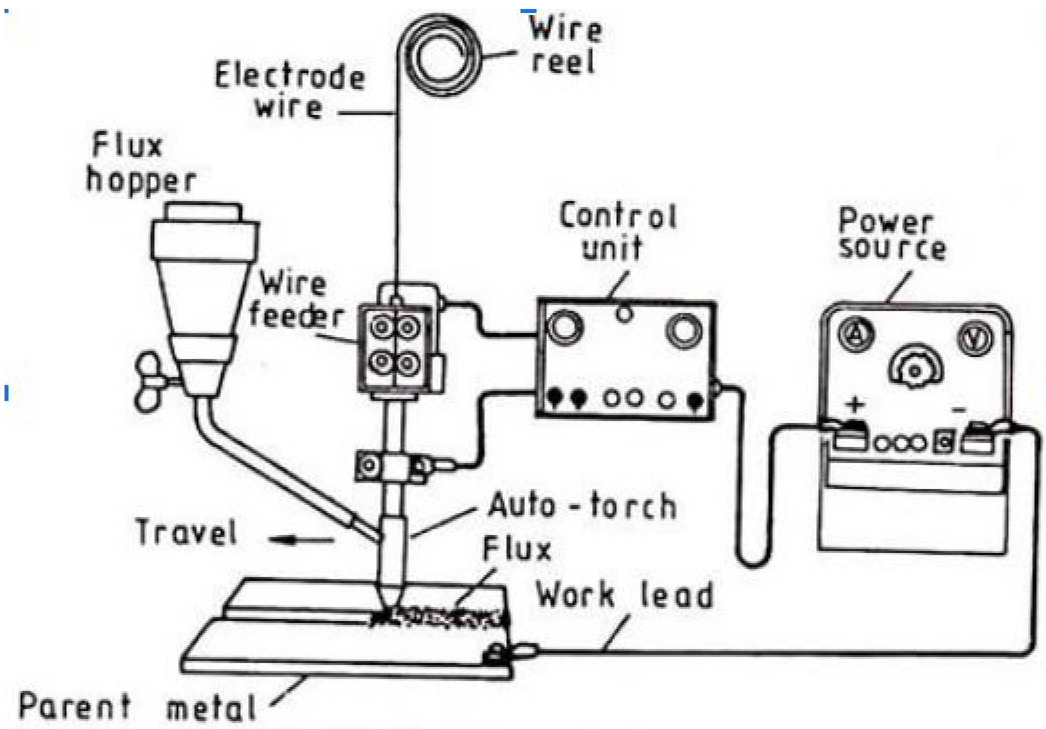
1.5 What is Welding?

Welding is a fabrication or sculptural process that joins materials, usually metals or thermoplastics, by using high heat to melt the parts together and allowing them to cool causing fusion. Welding is distinct from lower temperature metal-joining techniques such as brazing and soldering, which do not melt the base metal.

In addition to melting the base metal, a filler material is typically added to the joint to form a pool of molten material (the weld pool) that cools to form a joint that, based on weld configuration (butt, full penetration, fillet, etc.), can be stronger than the base material (parent metal). Pressure may also be used in conjunction with heat, or by itself, to produce a weld. Welding also requires a form of shield to protect the filler metals or melted metals from being contaminated or oxidized.

Many different energy sources can be used for welding, including a gas flame (chemical), an electric arc (electrical), a laser, an electron beam, friction, and ultrasound. While often an industrial process, welding may be performed in many different environments, including open air, underwater, and in outer space. Welding is a hazardous undertaking and precautions are required to avoid burns, electric shock, vision damage, inhalation of poisonous gases and fumes, and exposure to intense ultraviolet radiation.

1.6 Schematic Diagram for The SAW Process



Source:http://www.yourarticlelibrary.com/welding/submerged-arc-welding/submerged-arc-welding-saw-equipment-and-applications/96695

1.7 Problem and Current Scenario

In the Industry, there is the 7000+ type of steel are available and each steel type has own different property. Welding output is going to be varying at a different location due to the change in environmental condition. The same grade of steel variation in chemical composition leads to change in various welding output property due to its different property.

In present, welding is not an automated process. It is done on the basis of trial and error theory with the help of highly qualified professionals, in which they use their experience and knowledge of previous experiments and theories to weld the metals to get a perfect weld. Otherwise, they have to do a lot of calculations regarding input parameters (voltage, wire feed rate, nozzle to plate distance and welding speed) to get a perfect weld.

Problem is, even after years of development in many industries as well as in transportation and also we are reaching unimaginable heights in terms of construction of massive skyscrapers and structures, we are not able to get efficient output of basic need of every industry which is welding of machines and structures which acts as base in achieving these unreachable heights in any industry. The process of welding is still based on a very old methodology which is the trial and error method which does not guarantee the success rate and efficiency of the process. We basically use previous knowledge and methods to achieve perfect weld with the help of highly qualified professionals irrespective of the fact whether this process is a repeatable/success or not.

1.8 Solution For the Given Problem

As there is a great requirement of welders for welding but due to some reasons it can’t be fulfilled. So we’re designing an expert system using deep learning to overcome this problem. We use previous welding data for designing our system and make predictions accordingly. By using this model we can increase the quality of welding, minimize the process of trial and error, ensures process repeatability. As we learn from our experience, so our model will. The welder will input his requirement and get the result which will be used to get a required weld.

Chapter 2

Welding Dataset Introduction

2.1 Sample Dataset

Voltage (volt)	Welding Speed (mm/s)	Wire feed Rate (mm/s)	NPD (mm)	Bead Width (mm)	Penetration (mm)	Reinforcement Height (mm)
32.5	51	15.5	32.5	10.8	2.7	1.1
37.5	51	15.5	32.5	14.3	3.2	1.4
32.5	51	23.16	32.5	10.8	2.9	2.2
37.5	51	23.16	32.5	14.2	4	1.5
32.5	67	15.5	32.5	10.5	2.2	1
37.5	67	15.5	32.5	10.6	2.3	2.2
32.5	67	23.16	32.5	10.4	2.9	1.9
37.5	67	23.16	32.5	11.5	3.3	1.2
32.5	51	15.5	37.5	9.4	2.2	1.9
37.5	51	15.5	37.5	12.8	2.9	1.2
32.5	51	23.16	37.5	9.4	2.7	3.1
37.5	51	23.16	37.5	12.8	3.9	2.4
32.5	67	15.5	37.5	9	2.6	1.5
37.5	67	15.5	37.5	10.1	2.5	1.8
32.5	67	23.16	37.5	9.1	3	2.7
37.5	67	23.16	37.5	9	3.4	1.8
30	59	19.34	35	8	1.9	2.1

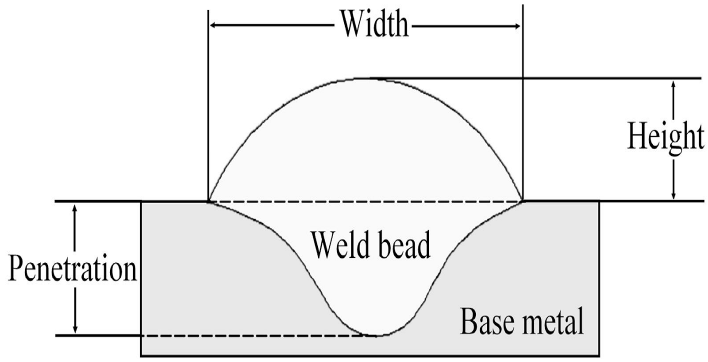
Above grid shows the sample of our dataset that we have used in our model. We collected data by exploring many research papers, our data set contains input parameters and output parameters. From research papers, we picked data relevant to our system. The data that we have picked is already been used and tested in some research paper so the chances of getting faulty value is very low. The dataset that we have collected for our model is not from single research paper it is collected after analyzing more than 150 research papers on Submerged Arc Welding. We have also used crawler to collect dataset from different websites like science direct and more. There are several parameters that we have used in our dataset as input or output according to the need of model.

2.2 Parameters Used

The parameters that we are going to be used in our model are the inputs and outputs of our model. The parameters used are Bead-Width, Penetration, Reinforcement height, Voltage, Welding speed, Nozzle to Plate Distance, Wire Feed Rate.The parameters that we are going to use as input in our system are actually the desired output that we need in real world welding. So in our system what we are going to do is we take the desired output for welding in the real world as input for our system and bring the output that will be served as input needed in the real world to get the actual desired output.

2.3 Input / Output Parameters Used in Our Model

- **Input parameters:**
  - Bead-width (W)
  - Reinforcement height (H)
  - Penetration (P)
- **Output parameters:**
  - Voltage (V)
  - Wire Feed Rate (WFR)
  - Welding Speed (WS)
  - Nozzle to Plate Distance (NPD)



Source:https://www.mdpi.com/1424-8220/16/9/1500/htm

Now for further discussion we are going to discuss the input and output parameters.

2.3.1 Input Parameters

1. **Bead-Width**

The bead-width of a weld is the maximum width of the deposited weld metal. It is directly proportional to the arc properties of the weld metal. It is also directly proportional to the arc current, welding voltage, electrode diameter and inversely proportional to the welding speed. A proper bead-width eliminates the lack of sidewall fusion defect. It is observed that bead-width enhances with increase in arc voltage and melting rate increases.

2. Reinforcement height

It is the bead height above the surface of the plate. The reinforcement influences the strength of the weld and wire feed rate. Increasing the wire feed rate increases the weld reinforcement irrespective of welding current and polarity. Reinforcement is inversely proportional to welding voltage, welding speed and diameter of the electrode.

3. Penetration

Penetration is the maximum distance from the surface of the base plate to the depth of fusion. Penetration is influenced by welding current, welding speed, weld polarity, and electrode stick out . Penetration is directly proportional to the welding current and inversely proportional to the welding speed and diameter of the electrode. Increase in thermal conductivity of the weld metal decreases penetration. Deepest penetration is achieved with D.C. Electrode Positive (DCEP) polarity than D.C. Electrode Positive Negative (DCEN) polarity. A stable arc increases penetration because the arc wander is minimized allowing more efficient heat transfer.

2.3.2 Output parameters

1. **Voltage**

The voltage is a deciding factor for the shape of the weld bead cross- section. Augmenting the voltage at constant current results in a wider, flatter, and reduced penetration, leading to reduced porosity caused by rust on steels. Raising in arc voltage beyond the optimum value leads to an enhanced loss of alloying elements affecting the metallurgical and mechanical properties of the weld metal. Arc voltage beyond the optimum value produces a wide bead shape and decreased penetration that is prone to cracking and increased undercut.

2. **Wire Feed Rate**

Wire feed rate is the rate to feeding wire into the SAW machine for welding process. We use WFR in mm/sec represent the how much length of wire we melt in per second for welding.

3. **Welding Speed**

It is the rate at which the arc moves along the joint to be welded and influences the heat input per unit length of the weld. The welding speed is the most influencing factor on weld penetration compared to other parameters except welding current. Enhancing the welding speed diminishes the heat input and less filler metal is deposited per unit length of the weld leading to less weld reinforcement and a lesser weld width. Increased welding speed results in undercutting, arc blow, cracking, porosity and uneven bead shape. Excessive welding speed also results in lower heat affected zone and finer grains. Slow welding speed facilitates escape of gases from the molten metal, thereby reducing porosity. The bead width is inversely proportional to the welding speed at any current.

4. Nozzle to Plate Distance(NPD)

The NPD influences the development of the weld pool by changing the arc length and welding current. The arc length is decided by the welding voltage and NPD. An increase in arc length due to an increase in NPD increases the bead width because of the widened arc area at the surface of the weld. Increase in arc length reduces the reinforcement height because the same volume of filler metal is us

Figure-5 shows the schematic of contact tube-to-work distance

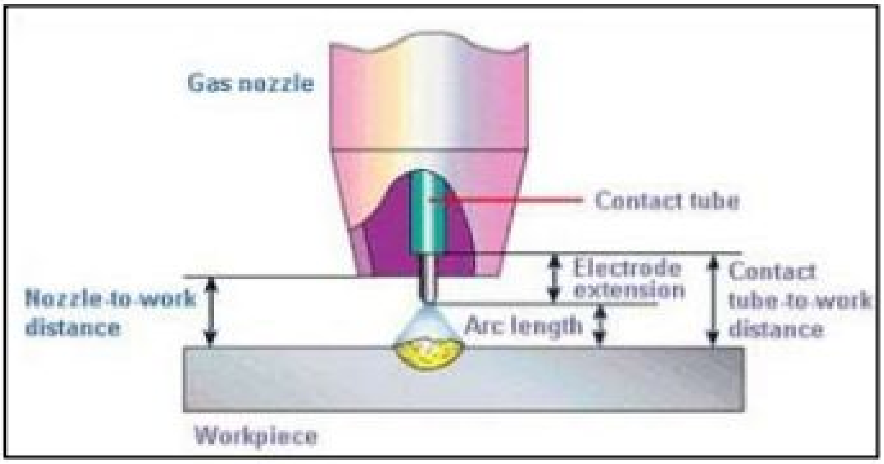


Fig. 5: Contact tube-to-work distance

Source:https://image.slidesharecdn.com/wis5process-04new-160823035304/95/wis5-process-04-new-41-638.jpg?cb=1471924443

The above figure is showing what is called as nozzle to plate distance here plate is considered as work site and the term is called as nozzle to work distance in the diagram.

2.4 Effect of Output Parameters on Input Parameters

1. Voltage

Arc voltage has an important effect on the weld bead shape and the depth of penetration; the precise effect being dependent on the joint preparation. Bead on plate welds and square edge close butt welds have increased bead width and dilution as the arc voltage increases, although the depth of penetration is relatively unaffected. Increasing the arc voltage may lead to lack of fusion in the root as the wide arc will not reach the bottom of the root. Reducing the voltage, in this case, will increase the depth of penetration as the narrow arc column is more easily able to reach the bottom of the preparation.

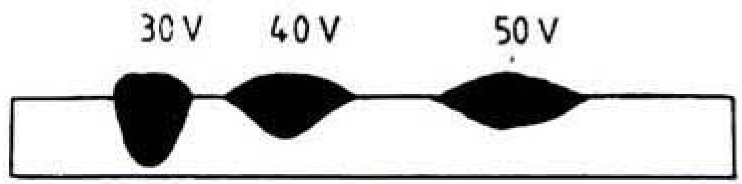


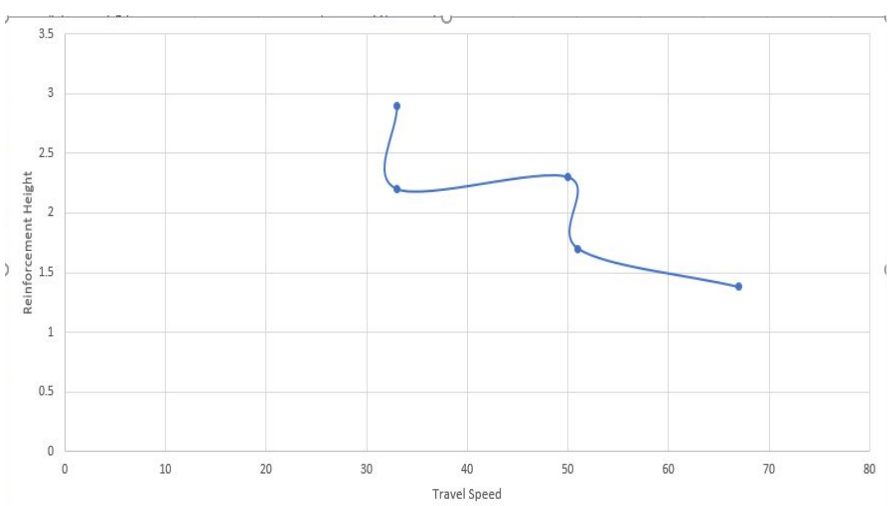
Fig. 8·6 Effect of arc voltage on bead shape and size.

Source:http://cdn.yourarticlelibrary.com/wp-content/uploads/2017/01/clip_image002-37.jpg

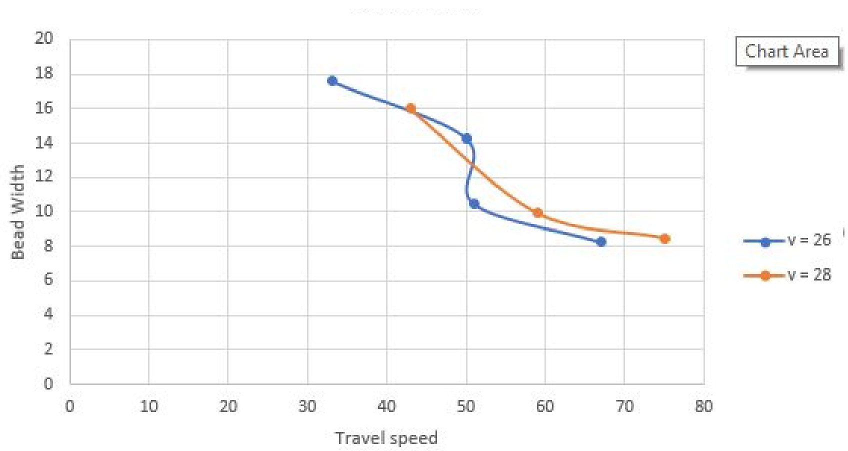
2. Welding speed

Bead size is inversely proportional to welding speed at the same current. Higher speeds reduce bead width, increase the likelihood of porosity, and if taken to the extreme, produce undercutting and irregular beads. At high welding speeds, the arc voltage should be kept low to minimise the risk of arc blow. If welding speed is too low burnthrough can occur. A combination of high arc voltage and low welding speed can produce a mushroom-shaped weld bead with solidification cracks at the bead sides. For a given arrangement of wires and wire diameters, welding speed is limited by the welding current which can be tolerated by the flux. Some fluxes are specially formulated to allow high speed operation. Higher speeds are possible with multiple wire operation or by holding a more acute electrode angle.The welding speed is the most influencing factor on weld penetration compared to other parameters. Enhancing the welding speed diminishes the heat input and less filler metal is deposited per unit length of the weld leading to less weld reinforcement and a lesser weld width.

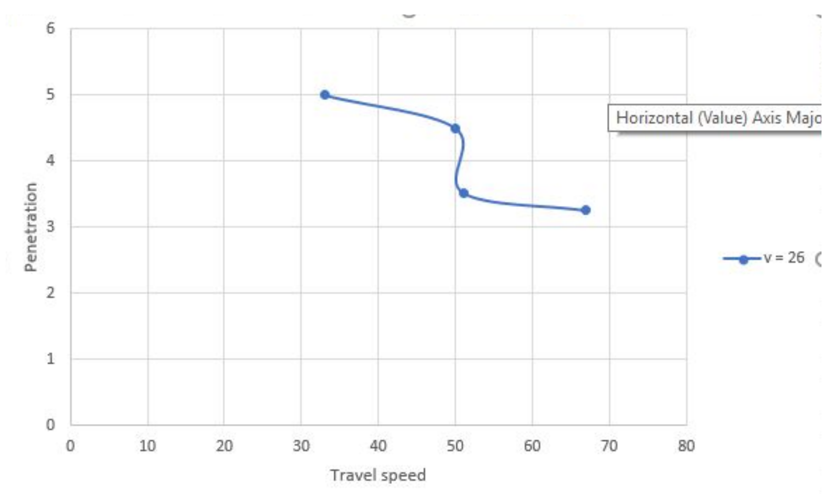
Graph-1 (Reinforcement height(on y-axis) and Travel speed(on x-axis))



Graph-2 (Bead width(on y-axis) vs Travel speed(on x-axis))

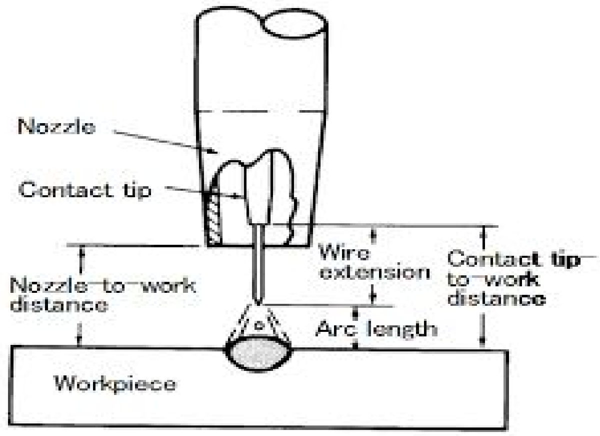


Graph-3 (Penetration (on y-axis) vs Travel Speed(on x-axis))



The graphs that are shown above are plotted with respect to welding(travelling) speed at constant voltage to measure the variation of different input parameters with respect to welding speed. The graph we have plotted above is showing that the relationship between our parameters is highly non-linear and dynamic.

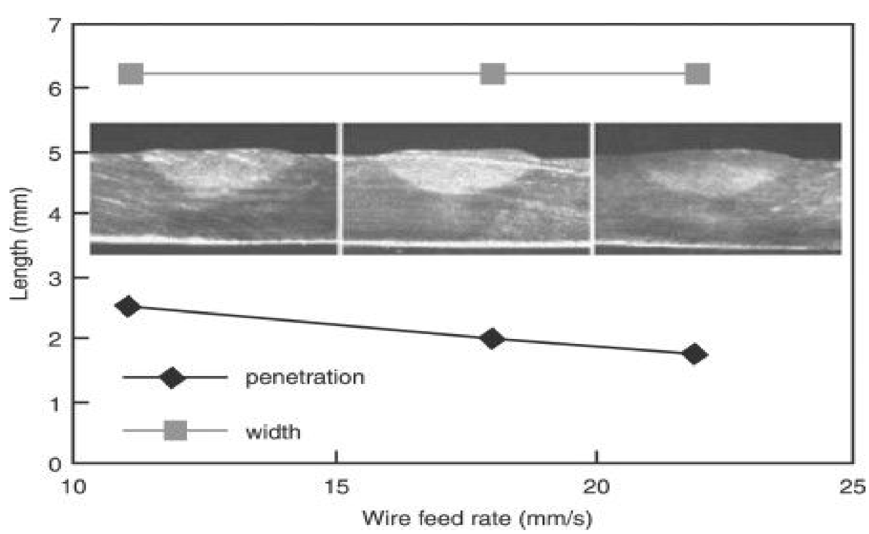
3. Nozzle to Plate Distance



Source:https://bit.ly/2LXBfn5

As shown in figure if the distance between nozzle to plate increases it will result in an increase of arc length which results in uneven bead shape because the heat input per unit length is change. Also the bead-width increases because of the widened arc area at the surface of the weld. As the arc length increases the reinforcement height decreases because the filler material that we are using is now going to be spread over a larger area as compared to before because the arc length increases.

4. Wire Feed Rate



As shown in figure wire feed rate is going to affect the penetration on the working material as the wire feed rate increases the depth of penetration decreases. Increasing the wire feed rate increase the weld reinforcement irrespective of the welding current and polarity of electrode. Also the bead width remains constant as shown in figure it doesn't change with increase or decrease of wire feed rate.

Chapter 3

Dummy Dataset Generation

As of now dataset has only 150-200 lines of data which is not enough to apply deep learning or any prediction algorithm. So our main issue of getting less accuracy (68%) in first attempt is less amount of data. After searching for more data on the internet, we decided to generate dummy dataset.

Now below steps are taking place to generate dummy dataset.

3.1 Regression for getting relation b/w inputs and outputs:

Regression is used to getting relation between inputs (W, H, P) and outputs (V, WS, NPD, WFR). We generate mathematical formula for bead width, penetration and reinforcement height in terms of voltage, welding speed, nozzle to plate distance and wire feed rate. Regression is applied on 32 lines of data which is collected by doing real experiments on the welding machine.

We tried linear regression as well as polynomial regression of degree 2 on this dataset as we discuss about dataset, we know the relationship is not linear between the parameters so polynomial regression is much better than linear for this type of data. We get more accurate results and much better R^2 (coefficient of determination) value in polynomial regression. Below are R^2 values for W, H, P in both types of regression.

Higher R^2 values (near to one) represent good results.

- Linear Regression:
  - R^2 value for W = 0.84
  - R^2 value for H = 0.55
  - R^2 value for P = 0.70
- Polynomial Regression (degree 2):
  - R^2 value for W = 0.97
  - R^2 value for H = 0.88
  - R^2 value for P = 0.79

After using polynomial regression separately for all inputs (W, H, P) we get below mathematical relations-

```
Bead Width(W) = -8.56868188206372 + (-1.79187724*V) +
(0.967760085*WFR) + (6.62476469*WS) + (-0.0803223064*NPD) +
(0.0990754705*V*V) + ( 0.00378289474*V*WFR) + (-0.266346154*V*WS) +
(-0.0175*V*NPD) + (-0.0125511543*WFR*WFR) + (-0.0599696356*WFR*WS) +
(0.00302631579*WFR*NPD) + (0.155029981*WS*WS) + (-0.07*WS*NPD) +
(0.0182083011*NPD*NPD)
```

```
Penetration(P) = 27.4885068600134 + (-0.815323235*V) +
(0.0472846968*WFR) + (-1.844236*WS) + (-0.181596644*NPD) +
(0.01243447*V*V) + ( -0.00592105263*V*WFR) + (0.0153846154*V*WS) +
(0.00075*V*NPD) + (0.00662939947*WFR*WFR) + (-0.00227732794*WFR*WS) +
(-0.000789473684*WFR*NPD) + (0.0206472284*WS*WS) +
(0.0253846154*WS*NPD) + (-0.0010419392*NPD*NPD)
```

```
Height(H) = 34.5668034706068 + (-1.19858268*V) + (-0.167141485*WFR) +
(-2.39260516*WS) + (-0.125375251*NPD) + (0.0196979434*V*V) + (
0.00222039474*V*WFR) + (0.0122596154*V*WS) + (-0.002875*V*NPD) +
(0.00580464577*WFR*WFR) + (-0.000632591093*WFR*WS) +
(-0.00203947368*WFR*NPD) + (0.0839948675*WS*WS) +
(0.00788461538*WS*NPD) + (0.00220668375*NPD*NPD)
```

3.2 Generate values for V, WFR, WS and NPD

We already get formulas for W, H, and P but we need values of V, WFR, WS and NPD for generating W, H, P using above formulas. We used given range (in reference research papers) for generating values for these output. For making things totally random (Because randomization is reduce the biasing of the dataset), we use python random function for generating 1500 values within given range. We generate 1500 values because we need 1500 lines of dataset by using 32 lines of actual data.

All values are random so there may be a chance where some rows can be duplicate (for two rows values for all outputs is the same). So we removed all duplicate rows to maintain quality of dataset.

3.3 Real VS Dummy dataset

Using above formulas and generated values of outputs we successfully generated 1500 lines of dummy data which can be used for better predictions.

Now let's compare dummy data with real data.

Voltage (V)	Wire feed Rate (mm/s)	Travel Speed (mm/s)	Nozzle to plate distance (NPD/mm)
26	15.5	8.5	32.5
30	15.5	8.5	32.5
26	23.1	8.5	32.5
30	23.1	8.5	32.5
26	15.5	11.1	32.5
30	15.5	11.1	32.5
26	23.1	11.1	32.5
30	23.1	11.1	32.5
26	15.5	8.5	37.5
30	15.5	8.5	37.5
26	23.1	8.5	37.5
30	23.1	8.5	37.5
26	15.5	11.1	37.5
30	15.5	11.1	37.5
26	23.1	11.1	37.5
30	23.1	11.1	37.5

For the above values of V, WFR, WS, NPD (from 32 lines of real dataset) these are actual and dummy values of W, H, P are :-

Actual values

H (mm)	P (mm)	W (mm)
1.7	3.52	10.15
1.51	3.4	13.37
2.32	4.75	11.05
1.85	4.1	15.64
1.38	3.25	8.28
1.18	3.18	10.1
1.5	3.52	9.15
1.82	3.33	9.86
1.61	3.85	10.66
1.48	3.6	14.45
1.92	4.1	12.38
1.8	3.8	15.96
1.37	3.2	8.7
1.1	3	9.28
1.75	4.1	9.01
1.5	3.88	10

Dummy values

H (mm)	P (mm)	W (mm)
1.753151368	3.797078008	10.09636714
1.551901367	3.574578009	14.02553381
2.079861582	4.589126948	11.3902987
1.946111581	4.186626949	15.43446537
1.282262979	3.147470854	8.88430684
1.208512978	3.084970855	10.04347351
1.596473193	3.894519793	8.993238402
1.590223192	3.652019794	10.26740507
1.701901369	3.639578012	11.05220047
1.443151368	3.432078013	14.63136714
1.951111583	4.401626952	12.46113203
1.759861582	4.014126953	16.1552987
1.33351298	3.319970858	8.930140167
1.202262979	3.272470859	9.739306835
1.570223194	4.037019798	9.154071729
1.506473194	3.809519798	10.0782384

By analyzing the above two tables we can say that our dummy dataset is not bad. We can use this dataset for future model predictions until we get a huge amount of real data.

We applied these all steps (3.1, 3.2, 3.3) on three different dataset of size 32 and generate 1500*3 = 4500 lines of dummy data which is enough for deep learning and we used this data in our model which is described in chapter 4.

W, H, P formula for dataset-2

```
Bead Width(W) = 12.6588017419633 + (0.0000201233821*V) +
(-0.0000789141587*WFR) + (0.000360332854*WS) + (0.00000616246625*NPD)
+ (0.00142876013*V*V) + ( 0.014264596*V*WFR) + (-0.0209221162*V*WS) +
```

```
(-0.00394023675*V*NPD) + (-0.00378787962*WFR*WFR) +
(-0.0193839549*WFR*WS) + (-0.00120891277*WFR*NPD) +
(0.00576532566*WS*WS) + ( 0.00980004214*WS*NPD) +
(0.000308123312*NPD*NPD)
```

Penetration(P) = 2.13539943069859 + (0.0000258799915*V) +
(-0.0000734656427*WFR) + (-0.00156084859*WS) + (0.000242569049*NPD) +
(0.0018374794*V*V) + (0.00124454086*V*WFR) + (0.0139031912*V*WS) +
(-0.00822503161*V*NPD) + (-0.00352635085*WFR*WFR) +
(0.0265673725*WFR*WS) + (-0.00367256637*WFR*NPD) +
(-0.0249735774*WS*WS) + (-0.0232697008*WS*NPD) +
(0.0121284525*NPD*NPD)

Height(H) = 2.87864710921001 + (0.000015125142*V) +
(0.000164558398*WFR) + (-0.000619736599*WS) + (-0.0000127537538*NPD)
+ (0.00107388508*V*V) + (-0.0074836944*V*WFR) + (0.00487032142*V*WS)
+ (0.00131157338*V*NPD) + (0.00789880311*WFR*WFR) +
(-0.00258915402*WFR*WS) + (-0.0005357933*WFR*NPD) +
(-0.00991578558*WS*WS) + (-0.00373830594*WS*NPD) +
(-0.00063768769*NPD*NPD)

W, H, P formula for dataset-3

Bead Width(W) = 4.63902900259104 + (1.21716335*V) + (-1.2568034*WFR)
+ (0.0136765879*WS) + (-0.40132148*NPD) + (0.02300516*E2) +
(-0.0144940804*V*V) + (0.00448698774*V*WFR) + (-0.00126804143*V*WS) +
(0.000928479285*V*NPD) + (-0.000484600518*V*E2) +
(0.0480117036*WFR*WFR) + (-0.0445520491*WFR*WS) +
(-0.0191510245*WFR*NPD) + (-0.000713150613*WFR*E2) +
(-0.0444052872*WS*WS) + (0.0412139171*WS*NPD) + (0.00274909793*WS*E2)
+ (0.0107736782*NPD*NPD) + (-0.000734826036*NPD*E2) +
(0.0000223585489*E2*E2)

Penetration(P) = -46.5350363270301 + (0.376782808*V) +
(0.602010392*WFR) + (8.35344964*WS) + (-0.0375444658*NPD) +
(0.0632123528*E2) + (-0.0160888925*V*V) + (0.00450195649*V*WFR) +
(-0.0209592747*V*WS) + (0.0410828626*V*NPD) + (-0.000691678434*V*E2)
+ (-0.0084732882*WFR*WFR) + (-0.031992174*WFR*WS) +
(0.00587891299*WFR*NPD) + (0.000303222825*WFR*E2) +

```
(-0.344922279*WS*WS) + (-0.0606685495*WS*NPD) +
(0.000670786263*WS*E2) + (-0.0206055698*NPD*NPD) +
(-0.00161773187*NPD*E2) + (-0.0000343628561*E2*E2)
```

Height(H) = -8.12193662335733+(0.0376867113*V) + (0.153379398*WFR) +

```
(-0.184965901*WS) + (0.611086168*NPD) + (0.00965598994*E2) +
(-0.00225562694*V*V) + (-0.00243362474*V*WFR) + (0.0036065777*V*WS) +
(0.00492828885*V*NPD) + (-0.0000721052788*V*E2) +
(-0.00298324853*WFR*WFR) + (0.052765501*WFR*WS) +
(-0.00486724948*WFR*NPD) + (-0.000356056237*WFR*E2) +
(-0.073590031*WS*WS) + (-0.0052868446*WS*NPD) +
(0.000024078885*WS*E2) + (-0.0121475078*NPD*NPD) +
(0.0000120394425*NPD*E2) + (0.00000607968265*E2*E2)
```

Chapter 4

Automation Process

4.1 Model selection

We tried some popular deep learning models on this data set and pick the most suitable one model.

1. Linear Regression
2. RNN (Recurrent neural network):
3. ANN (Artificial neural network):

4.1.1 Linear Regression

Linear Regression is a machine learning algorithm based on **supervised learning**. It performs a **regression task**. Regression models a target prediction value based on independent variables. Different regression models differ based on – the kind of relationship between dependent and independent variables they are considering and the number of independent variables being used.

Linear regression performs the task to predict a dependent variable value (y) based on a given independent variable (x). So, this regression technique finds out a linear relationship between x (input) and y(output). So linear regressions are meant to describe linear relationships between variables. So, for a nonlinear relationship, **this model is not good.** that's why this model can't be used for this data. it also has some limitations like it will give only **many to one output** but we are trying to create a model for multiple outcomes.

4.1.2 RNN (Recurrent Neural Network)

A recurrent neural network is a type of Neural Network commonly used in speech recognition and Natural Image Processing. RNN is designed to recognize data's sequential characteristics and predict the next likely scenario. They make use of internal memory for remembering inputs. Because of their internal memory, RNN is able to remember important things about the input they received, which enables them to be very precise in predicting what's coming next. This is the reason why they are the preferred algorithm for sequential data like time series, speech, text, financial data, audio, video, weather and much more because they can form a much deeper understanding of a sequence and its context, compared to other algorithms.

Using Long Short Term Memory(LSTM) a type of RNN, we got 33% of accuracy and 120 unit loss function (MSE) value which is not acceptable for any prediction models. Also, LSTM depends on the previous output to get new output and our model doesn't require this and also LSTM is best for time-dependent input values, so we then implement ANN on our dataset. RNN is a type of ANN.

In the first phase of this project, we selected an Artificial Neural Network as our prediction model for submerged arc welding.

We choose ANN because of the following reasons:-

- We have a non-linear relationship among our dataset (can be seen from the above image)
- Our model requires multiple outputs for multiple inputs
- ANN is good for numerical value prediction.

Now let's see what is ANN:-

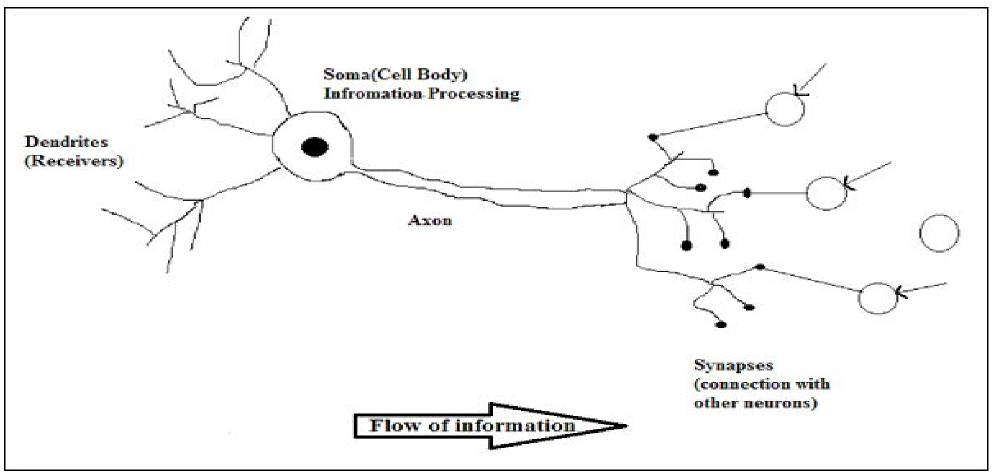
4.1.3 ANN (Artificial Neural Network)

An Artificial Neural Network is a mathematical model based on the biological neural network. ANNs consist of many interconnected processors known as neurons that perform summing function. The Neuron is the core unit of any ANN, which takes numerical input and produce numerical output.

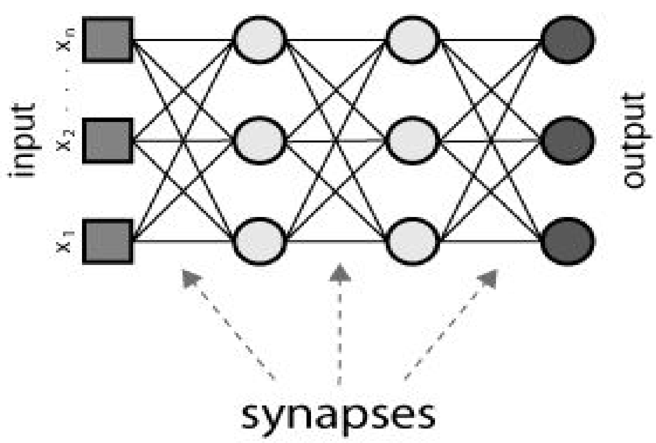
Similarities between ANN and BNN(Biological Neural Networks):

Biological Neural Network (BNN)	Artificial Neural Network (ANN)
Soma (Cell Body)	Node
Dendrites	Input
Synapse	Weights or interconnection
Axon	Output

Diagrams showing similarities between ANN and BNN:-



Source: https://www.tutorialspoint.com/artificial_neural_network/images/schematic_diagram.jpg



Elements of ANN

- **Input Layer:** There is only one input layer in the network, it may have more than one node. Provides information from the outside environment to network. No computation is performed on this layer.
- **Hidden Layer:** All types of computation are performed in the hidden layer. There can be zero or more hidden layer in the network.
- **Output Layer:** There is only one output layer in the network, it may have more than one node.

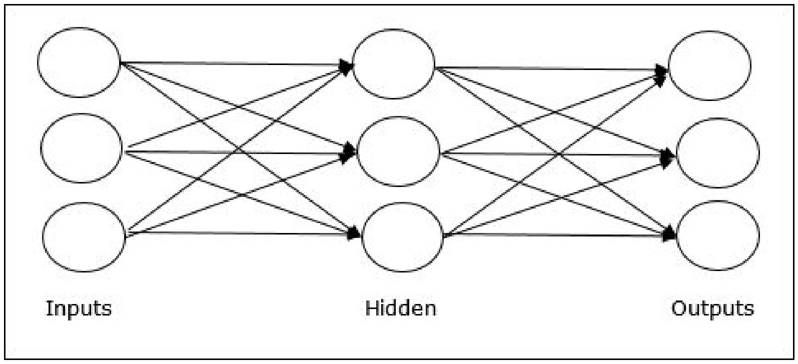
Implementation of ANN

Processing of ANN depends upon the following three building blocks :−

- Network Topology
- Adjustments of Weights or Learning
    - Supervised learning
    - Error & Loss Function
    - Optimization
- Activation Functions

4.1.3.1 Network Topology

- A network topology is the arrangement of a network along with its nodes and connecting lines.
- **Multilayer Feedforward network:** All the nodes in a layer are connected with the nodes of the previous layers. The connection has different weights upon them. The signal can only flow in one direction, from input to output. This network has one or more layers between the input and the output layer, it is called hidden layers.



4.1.3.2 Adjustment of Weights or Learning

- Learning, an artificial neural network, is the method of modifying the weights of connections between the neurons of a specified network. We used supervised learning for our model.

- **Supervised Learning:**
  This learning is done under supervision. This learning process is dependent on the teacher or supervisor. During the training of ANN under supervised learning, the input vector is presented to the network, which will give an output vector. This predicted output vector is compared with the desired output vector. An error signal is generated if there is a difference between the actual output and the desired output vector. On the basis of this error signal, the weights are adjusted until the actual output is matched with the desired output.For supervised learning process, our ANN-based model uses the Back Propagation algorithm.

  - **Back Propagation Algorithm:**
    The training of Back Propagation will have the following three phases-
    1. **Feed Forward Phase:** Data sends from the input layer to the output layer using a feed forward network. Data flow only in one direction in the network.
    2. **Back Propagation of error:** In this system, the mean square error between the actual output and predicted output was calculated and sent back to all layers.
    3. **Updating of weights:** Update weights according to error using optimizer functions.

- **Error and Loss Function:**

  Error is calculated as the difference between actual output and predicted output, and the function used to compute error is called loss function. The model learns by the loss function. One widely used loss function is MSE(Mean Square Error), which calculates the square of the difference between actual and predicted value. We need to minimize the error for more accurate predictions. It is done by Back Propagation. The current error is propagated backward to the previous layer, where weights are modified. Weights are modified using the function called Optimization Function.

- **Optimization Function:-**

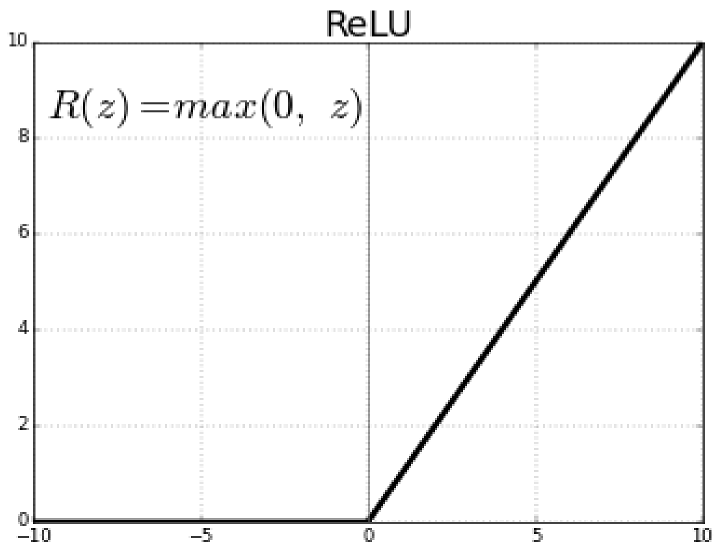
  Optimization algorithms help us to minimize (or maximize) an Objective function (another name for Error function). It is used to update weight and biases, which will reduce the error of the model. They calculate Gradient, a Gradient measures how much the output of the function change if you change input a little bit. The higher the gradient, the steeper the slope and more fast the model can learn. If the gradient becomes zero model stops learning. We've used **Adam**, (Adaptive Moment Estimation). Adam is a popular algorithm in the field of deep learning because it achieves good results fast.

4.1.3.3 Activation Function:-

Activation function decides whether a neuron should be activated or not. Just like our brain decides that for a particular activity, which part of our brain will activate more. An artificial neuron calculates the 'weighted sum' of its inputs and adds a bias. Now the value of net input can be any anything from -inf to +inf. According to this range, activation function decides whether a neuron is activated or not. Higher value in range means a higher chance of activation. Weight decides how fast the activation function will trigger whereas bias is used to delay the triggering of the activation function. This helps the model in a way that it can fit best for the given data. The purpose of the activation function is to introduce non-linearity into the output of a neuron. We use **ReLU** as an activation function for this model.

ReLU (Rectified linear unit):

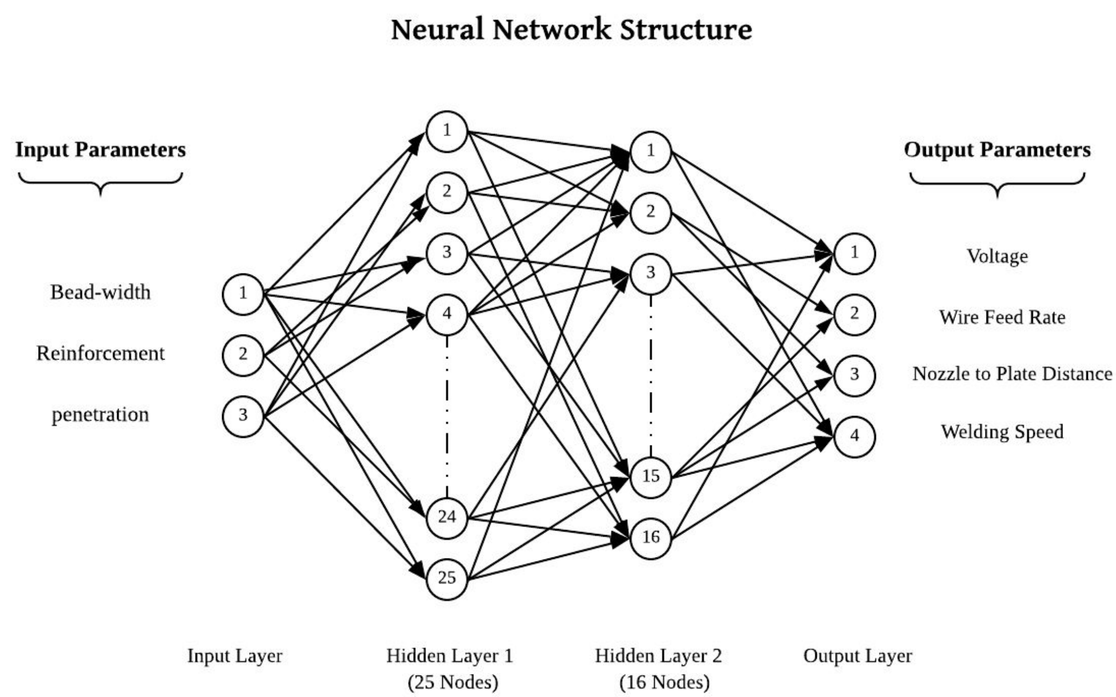
The ReLU is the most used activation function in the world right now. Since it is used in almost all the deep learning models. The range of this activation function is 0 to infinity which means the output of this ReLu function can be 0 to infinity. If the output is 0 that means the neuron will not activate.



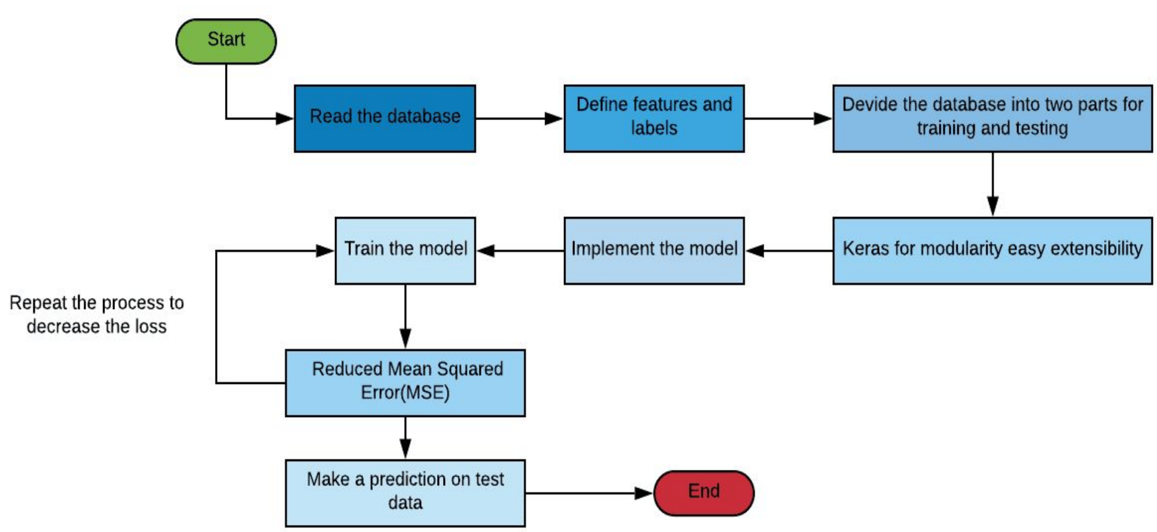
Source: https://miro.medium.com/max/357/1*oePAhrm74RNnNEolprmTaQ.png

Z: value of net input for a neuron **R(z):** output of the activation

Compare to other activation functions, which requires computing an exponent. The huge advantage of using ReLU is dealing with big networks with many neurons, it can significantly reduce both training and evaluation times.



4.2 Process Diagram



Working Procedure

Step-1: Studied a numerical data set.
Step-2: Decide inputs and outputs and also checked if there is a dependency between variables and there exist dependency between them.
Step-3: Divide the dataset into training and testing data, we chose 80% of the data for training and 20% for testing.
Step-4: To make layers we used Sequential model of Keras. Keras is a high-level Neural Networks API based on python. It is user-friendly and modular in nature. We use Sequential model because it is a linear stack of layers.
Step-5: Implemented the model having:

- One input layer (with 3 neurons)
- One hidden layers (with 10 neurons)
- One output layer (with 4 neurons)
- 10 forward passes (**epochs**) of training data with batch size = 1
- **Activation function**: Rectified Linear Unit (ReLU) is used for this system.
- **Optimizer**: Adam is used as an optimizer for this model.
- **Loss function:** Mean squared error (MSE)

Step-6: Now model starts learning.
Step-7: In each pass, the model learns and calculates Reduced Mean Squared Error(MSE), {MSE=actual output - desired output}
Step-8: To make the model more accurate ie minimizing the error model repeats Step-6 and Step-7
Step-9: Make a prediction on test data
Step-10: End

After the implementation of the model according to the above-stated steps, we get an accuracy of 79%

4.3 Actual Output Vs Predicted Output

Actual and Predicted Outputs					Input for Our System		
	Voltage	Travel Speed(mm/s)	Wire feed Rate(mm/s)	NPD(mm)	Bead Width (mm)	Penetration (mm)	Reinforcement Height(mm)
Actual-1	33	6	24.5	29.5	11.69	3.74	3.34
Predicted-1	33.18	7.45	24.36	29.31			
Actual-2	48	7.5	25.5	30.5	15.49	9.42	2.78
Predicted-2	47.08	7.5	25.76	30.86			
Actual-3	45	8.5	20.5	25.5	13.16	5.15	2.15
Predicted-3	44.35	8.62	20.86	25.78			
Actual-4	45	9.5	21	26	13.30	5.31	1.75
Predicted-4	44.35	9.12	20.96	25.78			
Actual-5	38	8.5	22	27	12.98	6.69	2.70
Predicted-5	40.91	8.18	22.15	27.42			
Actual-6	35	8	22	27	12.56	6.35	2.88
Predicted-6	36.37	8.02	22.55	27.71			
Actual-7	48	10	26.5	31.5	14.96	6.69	2.69
Predicted-7	47.92	9.95	25.76	30.87			

Chapter 5

Conclusion and Future Scope

5.1 Conclusion

Welding plays an important role in our daily life and still, we are stuck with the old methodology of trial and error which sometimes costs us in time, efficiency and manpower. And in this world of automation, we just tried to automate the welding process in order to help welder to obtain the required weld.

So, in order to automate the welding, we tried some popular deep learning models like Linear Regression, RNN and ANN, but by using the first two models we are still not able to get the more accurate output. By using ANN we are able to predict more accurate output to get required weld.

However, in our current implementation, using ANN is quite simple in which database is divided into two parts for training and testing then it starts implementing the model, train the model to reduce the error rate then predict the test results which are more accurate compared to others. By using ANN, the results are in our favour i.e. accuracy of our model is approximately 78% which is quite good.

The ANN was able to predict with considerable accuracy, the output parameters proposed. The use of models based on neural networks really has excellent results, and as it requires large computational resources are an excellent option to make our expert system for welding even simpler. The use of Voltage(V), Wire-feed rate, Nozzle to plate distance(NPD) and welding speed as output parameters was a key point to improve the Bead-width, Reinforcement height, penetration prediction.

Using the weight of each input data on the network would present even better results because the network itself would define the relationship between the elements and its influence in the welding formation.

5.2 Future Scope

As after dummy data generation accuracy is not very good for welding, so this model still needs future improvements. Also temperature and surrounding plays an important role in welding process which is not taken into account in this model. After integration of all three datasets, we will need more powerful algorithm for better prediction. We will have to replace dummy dataset to real experimental data for perfect prediction which can be used in welding without any risk.

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