

# Coupled Finite Element and Artificial Neural Network Modeling of Hot Extrusion in Aluminum–Copper Bimetallic Rods

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## Abstract

The hot extrusion of Al-Cu bimetallic rods has been found to be an encouraging way to get superior electrical and thermal properties along with lower material cost and weight. The study presents a coupled thermo-mechanical finite element analysis of Al-Cu bimetallic rods during hot extrusion by using the software package ABAQUS, and attention was focused on the punch force, material flow, and thermal gradient zones. The results of this analysis were found to show excellent agreement during hot extrusion of Al-Cu bimetallic. Analysis of various parameters such as the ratio of extrusion, initial billet temperature, friction coefficients, and copper sheath thickness showed that the extrusion ratio, initial billet temperatures, friction coefficients, and copper sheath thickness contribute significantly to the levels of forming loads. Additionally, extreme thermal gradients were determined to exist in the copper sheath and Al during hot extrusion because of the considerably large thermal resistance of Al in comparison to that of copper. An important approach in this study was to use artificial neural networks based on the feed-forward concept of back-propagation to optimize the predicted results. From this analysis, it was found that the predicted results were excellent and showed good resemblance to FEM results in terms of punch force. Additionally, it was found that the billet temperatures were significantly influential in reducing the amount of forming loads during hot extrusion of Al-Cu bimetallic.

**Keywords:** Thermo Mechanical Coupling, Hot Extrusion of Al–Cu Bimetallic Rods, Finite Element Simulation, Punch Force–Displacement Analysis, Thermal Gradient Across Al–Cu, Artificial Neural Network.

## 1. Introduction

Recently, the critical increase in the application and industrial use of bi-material extruded materials has resulted in an increase in the focus of scientific research in the concerned area. Because of this rising trend in scientific research in the concerned area, scientists and researchers have been motivated and encouraged to cover the concerned topic from different viewpoints and perspectives. As a result of this rising trend in scientific research in the concerned area, the research work in the concerned area has significantly increased and covered different aspects [1].

Copper has traditionally found many uses in various fields of engineering and industry owing to several desirable properties such as good thermal and electrical conductivity, sufficient strength, corrosion resistance, and ease of manufacturability, to name a few. However, despite the several desirable properties, such as good electrical conductivity, the density of copper does create some constraints on its usability for the parts of structure designed for lighter weights. Also,

copper is typically known to be costlier compared to some other metals. In these regards, the use of aluminum has been gaining acceptance as a complementary material to copper due to the significant lower density and lower cost that it can deliver. By incorporating the properties of aluminum and the properties of copper together in a bimetallic structure, a better solution can be engineered with the benefits of using the properties of copper in a manner in which the demerits of using the properties of copper can be overcome. Such structures can serve as an effective substitute for an element entirely made up of copper. These types of bimetallic systems are especially appealing since they make it possible to achieve considerable weight savings and reduction in cost of production, while still retaining the basic physical property demands for metallic parts. In essence, weight savings and cost-cutting benefits, which can reach as high as 30% and 50%, respectively, in comparison to conventional copper system designs, can now be realized due to the addition of aluminum in these copper systems [2,3].

Extrusion processes are normally divided into a few groups, depending on the temperature range in which the deformation is carried out; the cold, warm, and hot extrusion processes are normally considered. The selected temperature regime plays a critical role in governing material flow behavior, the required forming loads, and the overall efficiency of the process. Within operations involving metal forming, the interaction at the interface between tooling surfaces and deforming material is of particular importance. Friction arising at this contact zone significantly influences key aspects of the process, such as the magnitude of the applied forming force, the durability and service life of dies, and the final surface finish and quality of the formed product. Consequently, careful consideration of temperature and interfacial conditions is responsible for achieving reliable and high-quality extrusion outcomes [4].

Many studies have been conducted to develop metal extrusion process. In a related work, an in-depth analysis was performed on the extrusion of aluminum-copper bimetallic parts during processing conditions where copper was preheated to a temperature of about 320°C. The experiment involved different extrusions by using two different extrusion ratios and different die geometries that have varying angles. Thermo-mechanical numerical analysis showed that as the extrusion ratio increases, there is an equalization in the hardness value of the extruded area, coupled with the increased hardness value of the extruded product. Furthermore, it can be observed from the data that as the angle of the die increases, there is an overall reduction in the extrusion force required for the process. Further analysis also showed that the rate of copper layer reduction happens in a specific angle range, identified to be between 19° and 45°. Considering the effects on the flow, hardness, and extrusion load, the optimal extrusion process happens for an angle close to 45°. Yang & Han, on the other hand, analyzed the deformation area in the extrusion of two curved metal bars using the Finite Element Method [5].

A friction factor was determined using an inverse analysis method based on comparisons between a developed theoretical expression concerning hot extrusion forces and a number of experimental extrusion processes by Bakhshi Jooybari [6]. Tokuno investigated the deformation processes involved during the extrusion of monolithic metallic rods as well as rod shapes involving composite materials, extensive research was carried out [7]. Great attention was focused on the assessment of the influence of the differences in hardness values of the inner core materials in relation to the outer layer upon material flow processes, deformations, and overall extrusion behavior. Story et al. emphasized the role of forming force during hydrostatic extrusion [8]. Avitzur et al. investigated how extrusion force is dependent on the ratio between core radius and thickness as well as on material strengths in clad extrusion [9]. Yamaguchi et al. studied extrusion limit dependence on volume fraction and flow-stress ratio under hydrostatic extrusion conditions [10]. Byon et al. developed a die design optimized for clad extrusion through two-dimensional finite element

calculations [11]. Park et al. used two-dimensional finite element calculations and experimented on Al/Cu extrusion processing of aluminum and copper alloyed as a tube under hydrostatic loading conditions [12].

Similarly, Park et al. analyzed rod-type Al/Cu clad metal extrusion processes via two-dimensional finite element calculations, getting their experimental confirmations [12]. Huang et al. simulated the forward extrusion of an Al-Cu bimetallic rod by Deform-2D and results were obtained regarding stress, strain, velocity, die load, and the final height aspect ratio [4]. The simulated results agreed well with the upper bound solution and the experimental results by Hwang and hence the validity of the model was confirmed [13]. The effect of sheath thickness, die exit diameter, and die temperature in the finite element simulation results of the temperature, stress, and strain rates has been analyzed by [14]. The result showed that the rod extrusion process can be done effectively with a thick copper sheath and a large die outlet, while the simulated values of the extrusion force were found to be accurate when the lubricant used in the experiment was carbon-oil. Montazerolghaem et al. employ finite element simulations to investigate the process of hydrostatic extrusion of bimetallic wires compared with the direct extrusion process [15]. The results indicated that increasing the value of the friction factor and the amount of cross-sectional area reduction led to the enhancement of the required force during the extrusion process. As the die friction during the hydrostatic process gets reduced concurrently with the uniform deformation, longer bimetallic wires with uniform coating thicknesses could easily be produced. In addition, the initial form of the bi-material stock exerts a large effect on the cross-sectional stability of the extruded rod, as indicated by the experiment conducted by Kazanowski [16].

The microscopy results show the complicated interface observed between the alloys AA2014 and AA6063. In certain research, due to the HCP structure of Mg-alloys comparing to aluminum, containing less slip systems, defects occur during high extrusion ratio hot extrusion processes at a constant speed. Sound sheets may be obtained by using the multi-speed method (MSM); however, it is significant to determine when the first speed starts. Orthogonal array designs were conducted on AZ31 and AZ61 Mg-alloys by using artificial neural networks for estimating material temperature and speed change effect [17]. Grain size evolution in extruded AA6XXX profiles affects their mechanical, thermal, and surface properties. Traditional microstructure control methods are often time-consuming and costly. This study presents an innovative approach that combines FEM simulation with experimental microstructure measurements to train an artificial neural network (ANN) for grain size prediction. A hollow AA6060 profile was extruded and its grain size distribution measured. Experimental data were compared with FEM simulation results from QForm software, and the ANN was trained using these outputs to predict the final microstructure. The proposed method showed good accuracy and provides a faster, more sustainable, and cost-

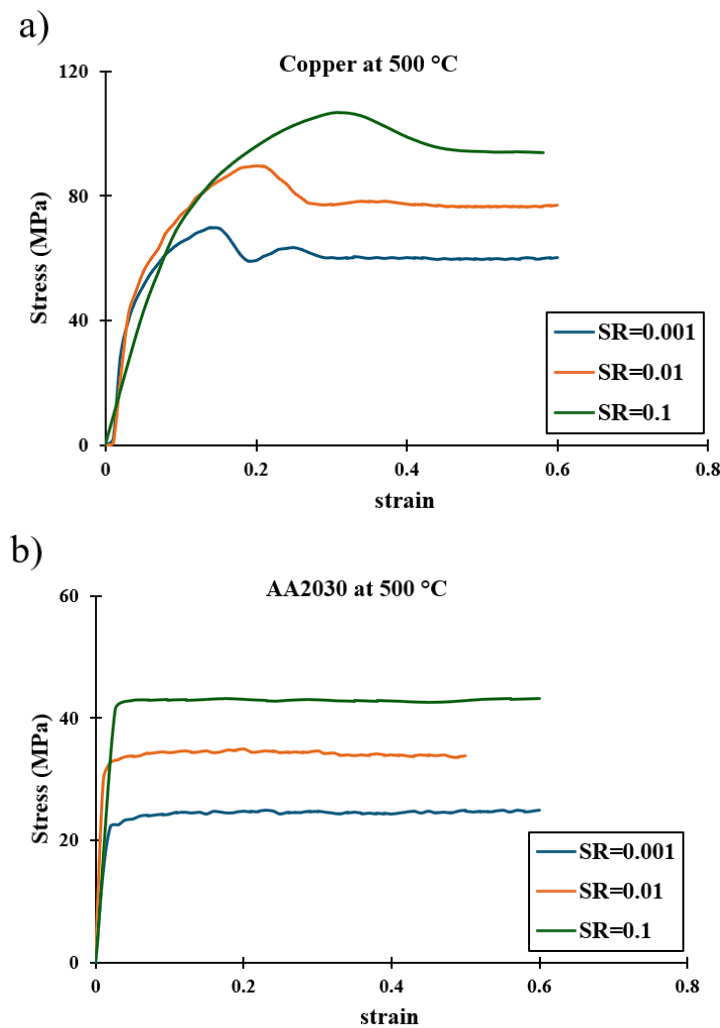
effective alternative to conventional approaches, aiding the optimization of the extrusion process for AA6XXX alloys [18].

The hot extrusion process for the production of aluminum-copper bimetallic rods was considered. The proposed numerical solution was first verified by comparing it with a solution based on a trained neural network. The results showed a strong correlation between the predictions and outputs. The numerical solution was carried out using ABAQUS software. Additionally, the influence of important factors, namely the diameter of the composite rod, the friction coefficient between the die and the aluminum-copper bimetallic rod, the rate of extrusion, and the temperature at which the materials have initially been set, during the hot extrusion process, was also investigated. The solution acquired was applied as input data during the training process of the neural network.

## 2. Numerical Modeling

The process of direct extrusion was modeled using the ABAQUS software. The heat transfer coefficient of  $20 \text{ kW/m}^2$  was considered between the interfaces of the billet, punch,

billet, and dies, and between the interfaces of the sheath and core materials. The energy fraction that is converted into heat due to the deformation process was considered to be 0.9 [19]. The meshing qualities during finite element analysis play a crucial role, and the effectiveness of analysis results heavily relies on this particular factor. In this analysis, high-quality meshing was carried out, and the analysis was done to test the sensitivity of the results with an increase in the mesh density. The analysis showed that with variations in the range of 3000 to 5000 elements, there was no significant influence on the output values, and the results remained stable. This indicates that the mesh used has a good quality level and that there is an optimal trade-off between analysis effectiveness and efficiency. Hence, it may safely be concluded that there are no significant errors during the analysis and that the analyses carried out are precise. From the given figures, it is observed that for AA2030 aluminum alloy, the stress value depends on the strain rate after crossing the yield point at various temperatures. In addition, the graph showing the values of true stress with strain for pure copper under compression testing is given in Figure 1.



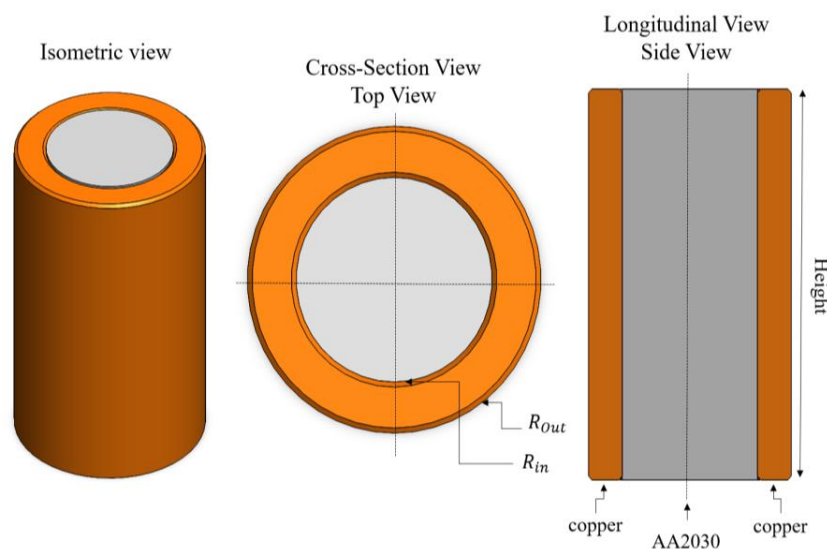
**Figure 1:** The true stress–true strain curve of a) pure copper and b) AA2030 at the different strain rate

In the hot extrusion technique, because of the use of high pressure and high temperature while pushing the material towards the die, the use of only the industrial oil as a lubricant is not very effective because the lubricating nature of industrial oil gets reduced at high temperatures. Graphite possesses higher temperature and mechanical stability compared to the industrial oil. The use of graphite in the industrial oil helps the industrial oil to work as a carrier that helps in ensuring the uniform distribution of the graphite particles at the interface of contact. Based on this aspect, the composite material of graphite and industrial oil can be regarded as a good alternative material for the hot extrusion technique because it possesses the potential for a decrease

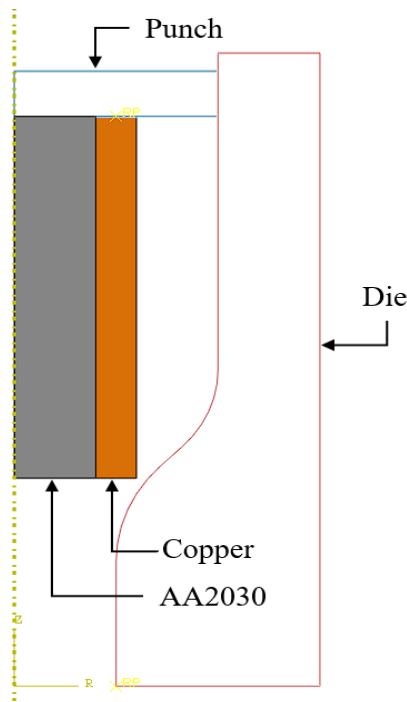
in the extrusion force and the die wear ratio and a positively affected final product. Table 1 presents the input parameters of the bimetallic rod considered for the numerical simulation. In addition, Figure 2 schematically illustrates the assembly configuration and the relative positioning of the components. The assembly model of the composite billet containing its core as well as the sheath, along with the die and punch, was created in the Abaqus software. This model is created in such a way that the geometry and positions of each component reflect the reality of the hot extrusion process. Figure 3 shows a schematic view of the assembly of the billet, die, and punch in the Abaqus software.

Parameter	Unit	Value
Bi-material height	mm	20
Core material radius ( $r_c$ )	mm	3.9
inside material radius ( $r_s$ )	mm	3.95
outside material radius ( $r_o$ )	mm	6
Extrusion ratio (R)	-----	1.45
Die angle	°	45
Extrusion speed ( $v_0$ )	mm.s <sup>-1</sup>	10

**Table 1: Parameters Used for Initial Simulation Model**



**Figure 2: Schematic diagram of bi-metal rod as AA2030 core and Pure Copper sheath**



**Figure 3:** Assembly model of the composite billet, die, and punch developed in Abaqus

In this simulation, several input parameters were introduced to more realistically model the hot extrusion process. These parameters include variations in the inner and outer radii of the copper sheath, which in effect determine the outer diameter of the aluminum core, initial billet temperatures, variations in friction conditions between the billet and the

die, and variations in extrusion ratios. This data was used to determine their effect in the thermal and mechanical modeling of the bimetallic rod in a hot extrusion process, and the data obtained will be used to form a comprehensive basis in the analysis of this process, as tabulated in Table 2.

Sim. no.	$R_{AA}$ (mm)	$R_{Copper}$ (mm)	Extrusion Ratio	Temperature (°C)	Friction
1	3.9	2.1	1.45	400	0.1
2	3.9	2.1	1.2	400	0.1
3	3.9	2.1	1.35	400	0.1
4	3.9	2.1	1.45	500	0.1
5	3.9	2.1	1.45	600	0.1
6	3	3	1.2	400	0.1
7	5.1	0.9	1.2	400	0.1
8	3.9	2.1	1.2	500	0.2
9	3.9	2.1	1.2	500	0.15
10	3.9	2.1	1.2	500	0.1
11	3	3	1.2	500	0.1
12	3	3	1.35	500	0.1
13	3	3	1.45	500	0.1
14	3	3	1.2	600	0.1
15	3	3	1.35	600	0.1
16	3	3	1.45	600	0.1
17	5.1	0.9	1.2	400	0.15
18	5.1	0.9	1.2	400	0.2
19	5.1	0.9	1.35	500	0.1
20	5.1	0.9	1.45	600	0.1

**Table 2: Chosen Simulation Schedules for Investigation of Hot Extrusion Process**

### 3. Neural Network Modeling

ANNs are computational models that draw inspiration from the organizational principles of the human brain and have recently gained prominence as powerful data-driven analytical frameworks. Owing to their capability to receive, process, and interpret large volumes of information, these models find extensive applications in a wide variety of complex problem-solving scenarios. One of the key strong points of ANNs is their adaptive learning capability, which enables them to map complex nonlinear relationships within data sets and to utilize the learned knowledge in solving a variety of problems in a reliable manner. Therefore, ANNs find immense applicability in retrieving meaningful information from complex physical and engineering data. The most commonly used architecture in ANN is the Multi-Layer Perceptron, which consists of three fundamental building blocks: the input layer represents the interface through which the measured variables or feature vectors are fed into the network. The information is then propagated sequentially through one or more hidden layers where intermediate transformations and feature extraction occur. It is then combined at the output layer to generate the network response or prediction vector. The interconnectivity of the processing units, which are called neurons, is governed by adjustable synaptic weights. The process of training the network mainly aims at adjusting these weights in a systematic way to achieve a minimum prediction error. Several learning algorithms, with the back-propagation method being the most popular, are applied iteratively to update the synaptic weight so that the network learns an accurate functional relationship between input and output data. Each neuron performs an internal computation, which involves calculating a weighted summation of the incoming signals, followed by passing the sum through a nonlinear activation function, as mathematically expressed in Equation (1) [20,21].

$$y_j = f\left(\sum_{i=1}^n w_{ij}x_i + b_j\right) \quad (1)$$

Where  $x_i$  is the inputs to the neuron,  $w_{ij}$  is the corresponding synaptic weights,  $b_j$  is the bias term,  $f$  is the activation function applied to the weighted sum,  $n$  is the number of inputs to the neuron. During the training phase, the neural network is provided with multiple sets of input-output pairs. An iterative optimization algorithm systematically updates the synaptic weights to ensure that the network's predicted outputs  $o_j$  closely approximate the corresponding target outputs  $d_j$  for each input pattern. For a network with

$J$  total outputs, the training process seeks to minimize the discrepancy between predicted and desired values by reducing the mean squared error (MSE), as formulated in Equation (2) [22]. This approach ensures that the network progressively learns the underlying relationships within the dataset, improving its predictive accuracy across all outputs.

$$\text{MSE} = \frac{1}{J} \sum_{j=1}^J (o_j - d_j)^2 \quad (2)$$

The Back-Propagation algorithm has been widely recognized in the literature as an essential training algorithm for artificial neural networks because it makes it possible to systematically decrease the Mean Squared Error (MSE) by means of iterative adjustment of connection weights in the network [23]. The Back-Propagation algorithm is utilized in this study to describe the nonlinear thermo-mechanical phenomenon during the hot extrusion of aluminum-copper bimetallic rods. The learning process is repetitive in the three cycles identified. During the feed-forward phase, the input variables that are associated with the hot extrusion process are fed into the network. Based on the present values of the weights and the biases of the network that have been generated randomly, the activation of the nodes is calculated systematically layer by layer until the output variables have been determined.

The output variables are the present estimate of the extrusion response by the network. The second stage is the error back propagation stage, where the outputs are compared with the target outputs, and the error is analyzed. The error is then propagated back into the network, which enables the contribution of the weight and bias of each neuron to the overall error of the prediction to be measured. The weight update component uses the error function gradients from the previous backward pass in order to update the weights and biases based on an optimization method like gradient descent. This is carried out in the direction which maximizes the error reduction in the network. The above three steps of computation are considered one whole learning cycle of the neural network model. All these steps are repeated until a certain stopping criterion, representing acceptable predictive accuracy, is achieved. The established neural network model developed in previous works is applied in this study with the input of necessary parameters of hot extrusion in an effort to accurately calculate the punch force in the hot extrusion process of aluminum-copper bimetallic rods, as depicted in Figure 4 [24].

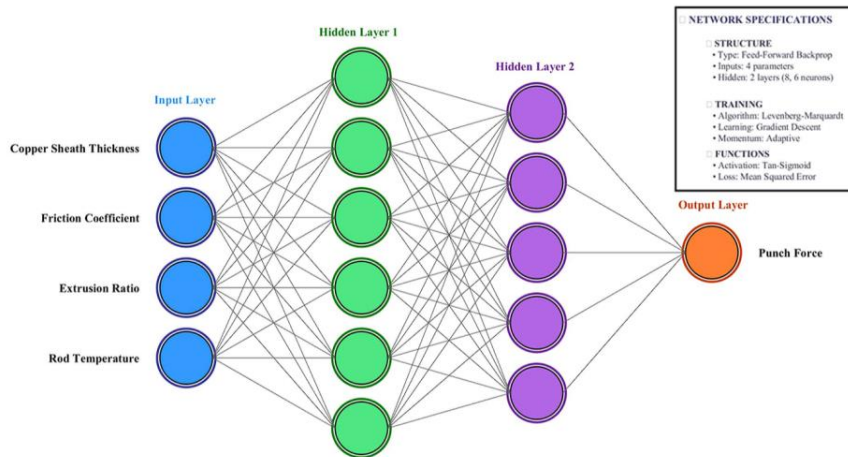


Figure 4: neural network structure

The key process parameters of the hot extrusion of aluminum–copper bimetallic rods, including the initial temperature of the bimetallic billet, the thickness of the copper sheath, the extrusion ratio, and the friction coefficients at the die–billet interface, were defined according to the scenarios listed in Table 2 and used as input variables for training the neural network. The extrusion process was numerically analyzed

using the finite element method implemented in ABAQUS, and the corresponding outputs, including the punch force, were obtained from the simulations. The resulting input–output data pairs employed for testing and validating the performance of the neural network are summarized in Table 3.

Sim. no.	$R_{AA}$ (mm)	$R_{Copper}$ (mm)	Extrusion Ratio	Temperature (°C)	Friction
1	5.4	0.6	1.45	400	0.1
2	5.4	0.6	1.2	400	0.1
3	5.4	0.6	1.35	500	0.1
4	4.2	1.8	1.45	500	0.1
5	4.2	1.8	1.2	600	0.15

Table 3: Summary of Test Data Used for Neural Network Evaluation

For the current study, a customized computational environment was designed in MATLAB for developing the proposed Artificial Neural Network (ANN) approach with Back-Propagation Algorithm (BPA) to simulate and predict the thermo-mechanical properties of the hot extrusion process. Back-propagation-type feed-forward networks are considered to be one of the most universally accepted approaches in the area of metal forming process simulation, primarily due to the robust generalization potential of the method, along with the availability of many more mature training algorithms, like Gradient Descent, Quasi-Newton, Conjugate Gradient, Stochastic Approximation, and Levenberg-Marquardt optimization algorithms, among others, as stated in [5,25].

In the proposed work, the transfer function for the sigmoid and hidden layers was chosen as the tangential sigmoid transfer function, and the Levenberg-Marquardt algorithm was chosen as the training function because of its fast convergence speed and higher efficiency associated with the training of medium-sized feed-forward networks [24]. In this proposed work, to avoid overfitting and ensure proper prediction of the hot extrusion process, the early stop method was introduced during the training process. In this

method, the available data set was divided into two subsets: the first was the training set, which was used for consecutive adjustments of the network weights and constant terms associated with the interconnecting network connections, and the second was the validation set, which was used for monitoring the generalization ability of the trained networks.

During training, the training and validation errors both decrease; when overfitting commences, the validation error begins to increase. When this phenomenon indicates a specific number of epochs, the training process automatically stops, and the optimal trained network parameters associated with the minimum validation error were all stored as the best trained network. Before inputting the data to the backpropagation network, some preprocessing work on the input and output variables needed to be carried out in order to improve the stability of the data in the numerical system. In this regard, all input and output data related to the hot extrusion process were normalized on a given scale from -1 to 1 based on the normalization process described by Equation (3) above. This is an efficient way to improve the training process in the network.

$$X_i = 0.1 + 0.8 \left( \frac{X - X_{\min}}{X_{\max} - X_{\min}} \right) \quad (3)$$

where  $X$  represents the original dataset,  $X_{\min}$  and  $X_{\max}$  denote the minimum and maximum values of  $X$ , respectively, and  $X_i$

is the normalized value corresponding to each data point of  $X$ . The architecture of the artificial neural network and the functions employed in the final model are summarized in Table 4.

Network	Feed-forward back propagation network
Training function	Levenberg–Marquardt
Learning function	Gradient descent with momentum weight & bias learning function
Transfer function	Tan sigmoid function
Performance function	Mean squared error
Number of input layer unit	4
Number of hidden layers	2
Number of output layer unit	1

**Table 4: The ANN Architecture and Functions**

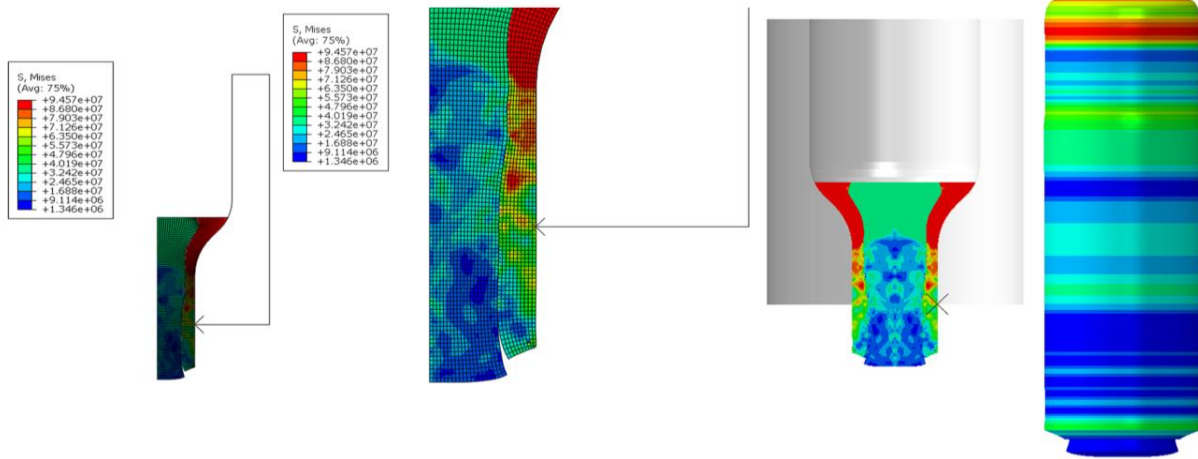
#### 4. Results

The hot extrusion process for a copper/aluminum AA2030 bimetallic composite rod has been examined by a two-dimensional thermo-mechanical simulation using the FE package ABAQUS™. To simulate large deformations, the Arbitrary Lagrangian-Eulerian (ALE) method with automatic re-meshing has been used. The model has been validated for various extrusion conditions to ensure the possibility to simulate the realistic extrusion process with sufficient accuracy. In simulation, both thermal and mechanical processes were coupled, and the effects of temperature, strain, and strain-rate on the flow phenomena of thermo-viscoplastic materials were accurately considered. As there is substantial heating due to friction contact and plastic flow, a coupled thermal-mechanical simulation was necessary to determine accurately the temperature rise in the bimetallic billet. In this context, using ABAQUS explicit, both temperature and displacement variables are simulated simultaneously, and this is quite helpful as there are large differences in temperatures among the die, punch, and bimetallic billet. The die and the punch are modeled as rigid bodies, while their Young's modulus was considered to be 200 GPa. By incorporating the heat transfer analysis into the process, a realistic representation of the thermal extrusion process was obtained. By considering the deformation modes, a comprehensive dataset can be obtained, which captures the amount of force and heat flux generated during the process [26].

Results for the simulation of the present model are shown in Figure 5. In comparison, pure copper is acknowledged as a softer material than aluminum alloy. This relative softness of

copper causes it to deform more in the sheath, relative to the harder and stronger aluminum alloy core during a bimetallic hot extrusion process as the billet exits the die. Therefore, during extrusion, the copper sheath is stretched and naturally flows over the aluminum core. This behavior allows copper to protect and cover the core material, hence coming up with a final structure of a bimetallic rod comprising an aluminum core and copper sheath. This distribution of material does not depend on the mechanical properties difference between the two metals only but also on the die geometry, interfacial friction conditions, deformation rate, and process temperature.

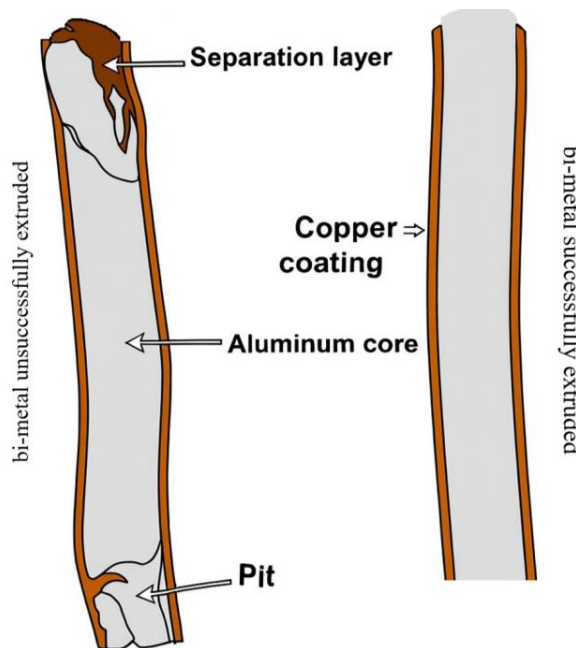
The interaction of these factors fixes the uniformity of the copper sheath over the aluminum core and the range of thickness variation along the rod length. In the central region of the extrudate, the thickness ratio between the core and sheath remains almost constant. At the initial and final regions of the rod-particularly toward the end of the extrusion process-the aluminum core shows slight protrusion due to differences in material flow and the distribution of stress, which becomes visibly apparent. These characteristics are critical for the quality control of the final product because the uniformity in copper coating and the minimization of core protrusion directly influence the mechanical properties, electrical conductivity, and dimensional tolerances of the bimetallic rod. Therefore, selection of precise process parameters and optimized die design might provide an opportunity to fabricate the bimetallic rods with a stable and uniform copper sheath, along with better functional performance.



**Figure 5:** Finite element simulation results of the bimetallic hot extrusion process, illustrating the material flow and deformation behavior of the aluminum alloy core and the copper sheath

Figure 6 schematically shows the hot extrusion process under ideal and improper conditions. The ideal case is characterized by no traces of PIT (interfacial trapping) or layer separation, and material flow is well-controlled and uniform. In contrast, an improperly conducted material flow is one that may lead to excessive core protrusion, layer

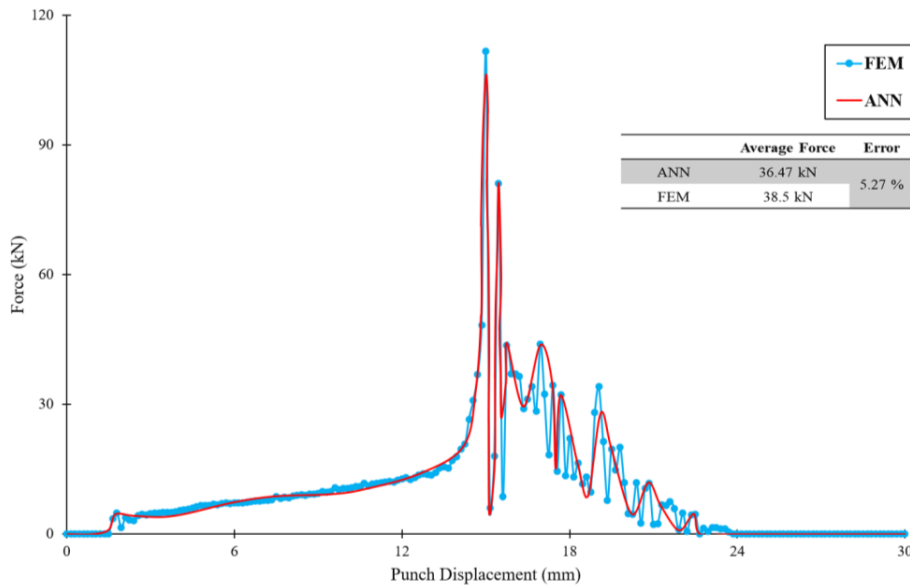
separation, and uneven sheath distribution that ultimately adversely affects both the surface quality and the dimensional accuracy of the rod. From the above comparison, correct die design, proper selection of process parameters, and careful control of the key variables constitute the only way to obtain good-quality bimetallic rods.



**Figure 6:** Schematic of the hot extrusion process showing ideal material flow and improper flow

The result of the applied force on the displacement of the punch and subsequent deformation of the bimetallic rod was simulated computationally and modeled using an artificial neural network (ANN) model. This is depicted graphically in Figure 7, showing the comparative simulation result and ANN model of the variation of the applied force during the hot extrusion process. From the result, it is possible to assess and verify the accuracy of the ANN model. Further, the result

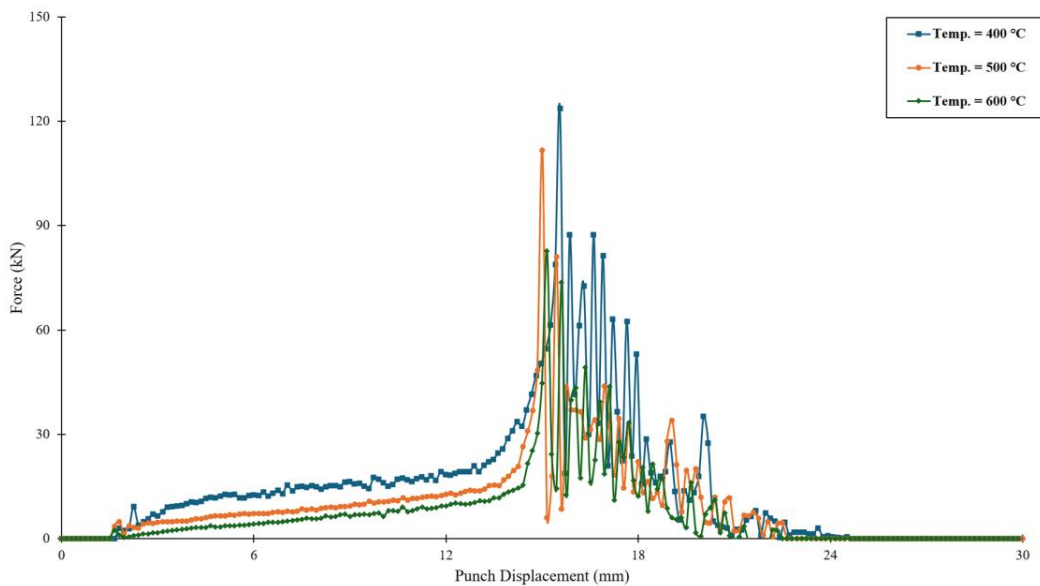
of the variation of the applied force helps understand the deformation of the rod. From the result, it can be visually confirmed that the precise simulation modeling and the trained ANN model can predict the deformation of the rod and the result of the applied force correctly. Hence, the application of the ANN model for the design of bimetallic extrusion is a practical solution.



**Figure 7:** Comparison of the punch force and deformation of the bimetallic rod between simulation results and ANN predication

As the temperature of the bimetallic rod rises during the hot extrusion process, the yield strength and flow stress values reduce; hence, the punch force required for the material movement will reduce. This causes the force-displacement plot for the punch to shift to lower levels with a softer slope as the material becomes softer. In the tail portion of the plot, the force falls off rapidly because the material moves

through it smoothly without any friction. Hence, the plot for the punch force will shift from one that is steeper with a higher point to one with a lower point and is softer. Figure 8 above shows the force displacement for the punch, while Figure 9 below shows the temperature contours generated from the FE simulation.



**Figure 8:** Variation of punch force with displacement during the hot extrusion of the bimetallic rod

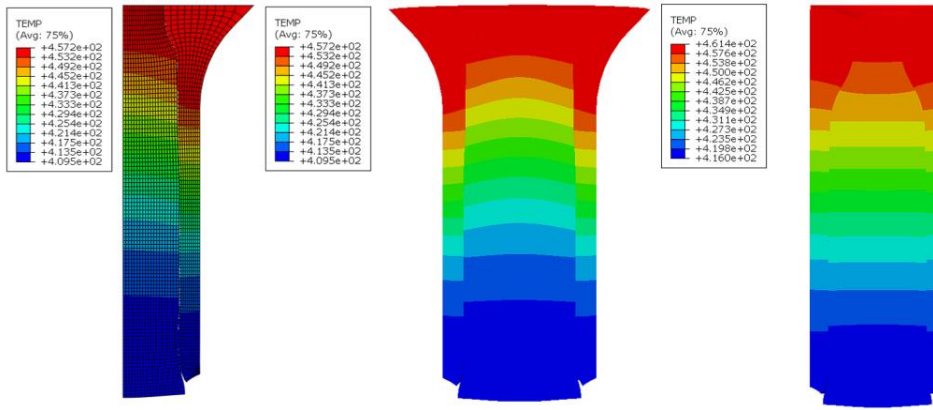
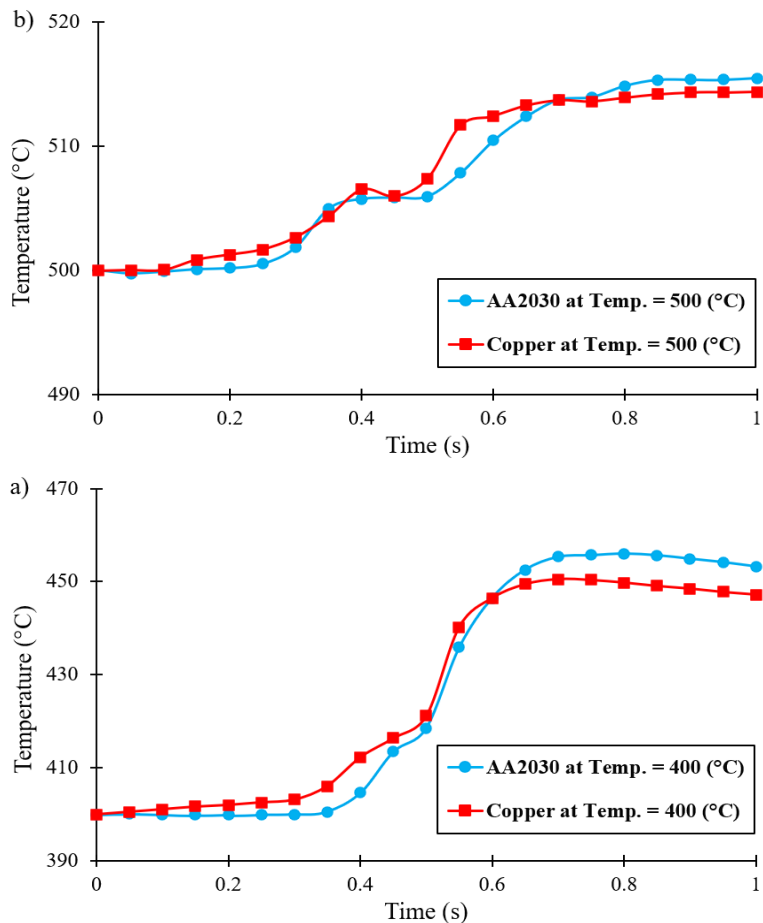
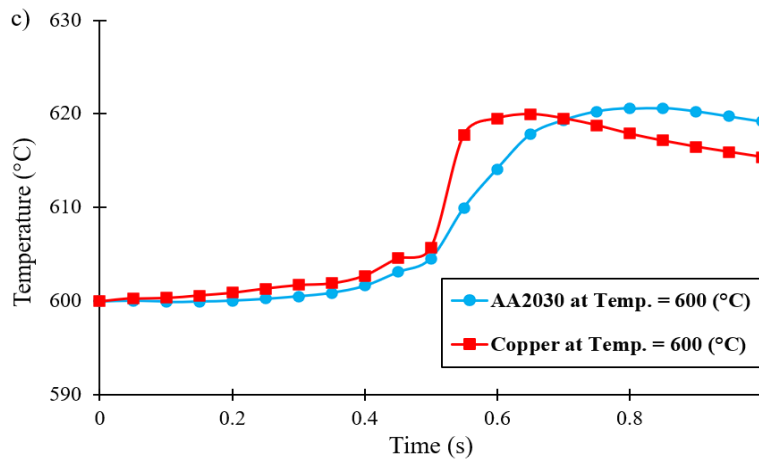


Figure 9: Temperature contours obtained from the finite element simulation of hot extrusion

Generally, the temperature variation in hot extrusion starts with a sharp rise due to frictional heating and plastic work. After this, there is a quasi-steady state where there is a slight variation in temperature around a certain equilibrium level. Finally, at the end of the hot extrusion process, there is a gradual reduction in temperature because of low deformation rates and dominant convective heating to the die and surroundings. As a result of this variation, with increased temperatures of the initial billet, there is a shift in the whole temperature variation to higher levels, with a decrease in the time to reach thermal equilibrium. The temperatures also attain higher values with increased maximum temperatures; however, there is no effect on the

general variation. In this bimetallic rod, there is accelerated heating and cooling for the copper sheathing because of higher conductivities. There is also a delay in the absorption of heat by the aluminum core. As such, there is a maximum thermal gradient exhibited by the core and copper sheathing in the middle process. Additionally, because the copper sheathing is in contact with the ambient environment once it leaves the die, there is a faster reduction in temperatures on the copper sheathing surfaces compared to those at the aluminum core. Such effects influence the final bimetallic rod. Figure 10 shows the temperature variations as a function of time for the bimetallic rod with initial temperatures of 400, 500, and 600 °C.





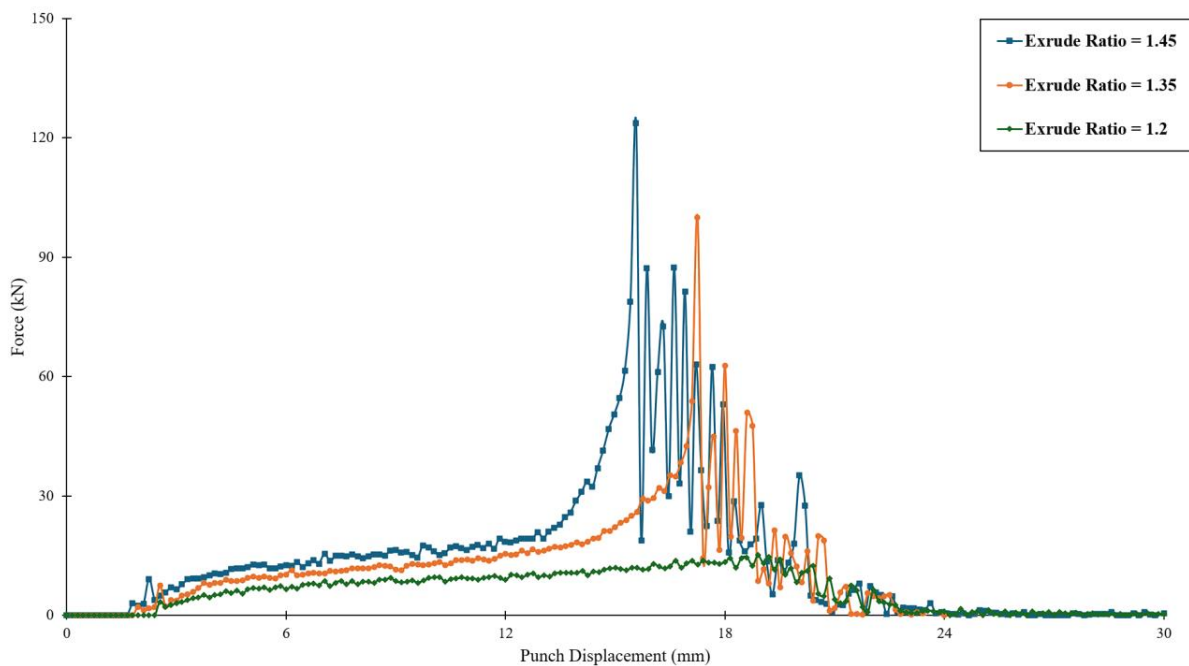
**Figure 10:** Temperature variations over time for the bimetallic rod at initial billet temperatures of a) 400, b) 500, and c) 600 °C

An increase in the extrusion ratio is defined by Equation (4).

$$R = \frac{A_i}{A_f} \tag{4}$$

That R is extrusion ratio,  $A_i$  is initial area and  $A_f$  is final area in extrusion process. The larger the reduction of area is, the greater the effective strain and, thus, the average flow stress of the material, which both contribute to the necessary increase in punch force. Of practical significance is the taller initial peak in the force–displacement curve as the flow of material commences and the uniform zone forms, and the quasi-steady region is elevated due to increased plastic work and more extensive friction. The region of high force also spreads over a larger displacement with decreasing exit

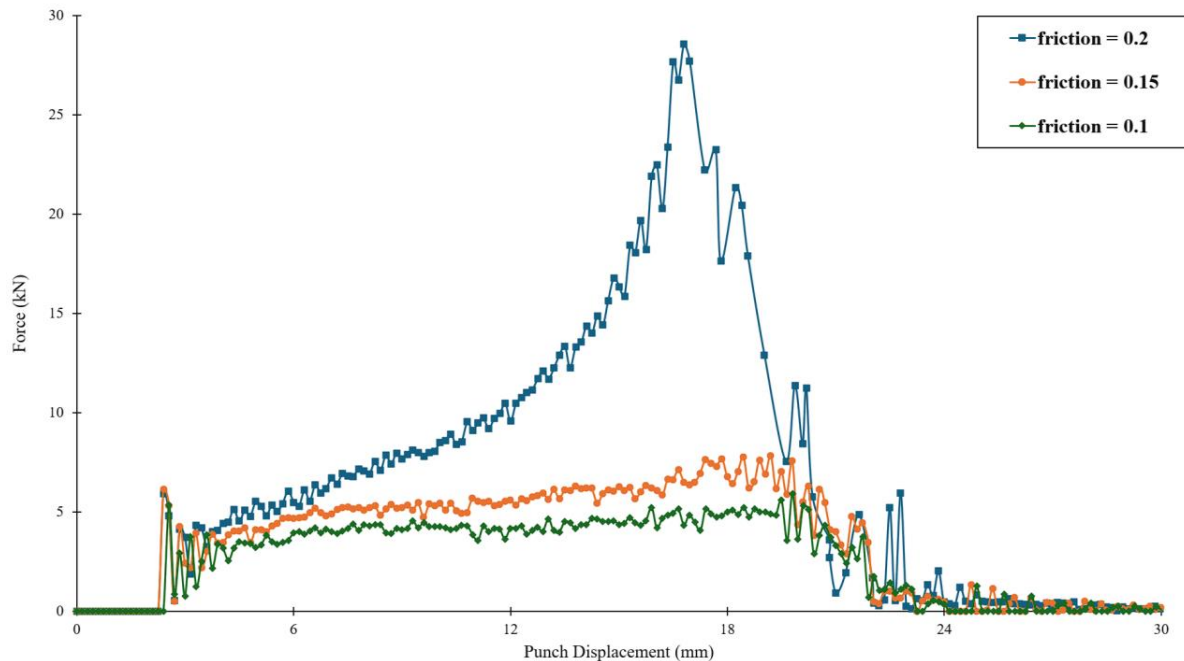
cross-section. Frictional contributions and redundant work become greater for larger extrusion ratios, as demonstrated, unless compensation is accomplished through higher temperatures, improved lubrication, or favorable die geometry. In the case of bimetallic rod, as the ratio of extrusion is increased, the harder constituent material, say the aluminum alloy core, plays a more dominant role in governing the force level, while the softer sheath, say copper, deforms to a greater degree of elongation. The result, the sensitivity of the punch force to thermal conditions and friction now becomes more pronounced and apparent. The variations in punch force with displacement, considering changes in the extrusion ratio and the friction coefficient between the bimetallic rod and the die, are presented in Figures 11 and 12.



**Figure 11:** Variation of extrusion force as a function of punch displacement for different extrusion ratios

The increase in the friction coefficient between the copper sheath and the die (generally between the bimetallic material and the die) leads to a substantial increase in the force of the punch during the extrusion process since some of the energy will go to overcoming the resistance due to contact between the two materials. Consequently, the force displacement curve moves upwards, the peak before reaching the quasi-

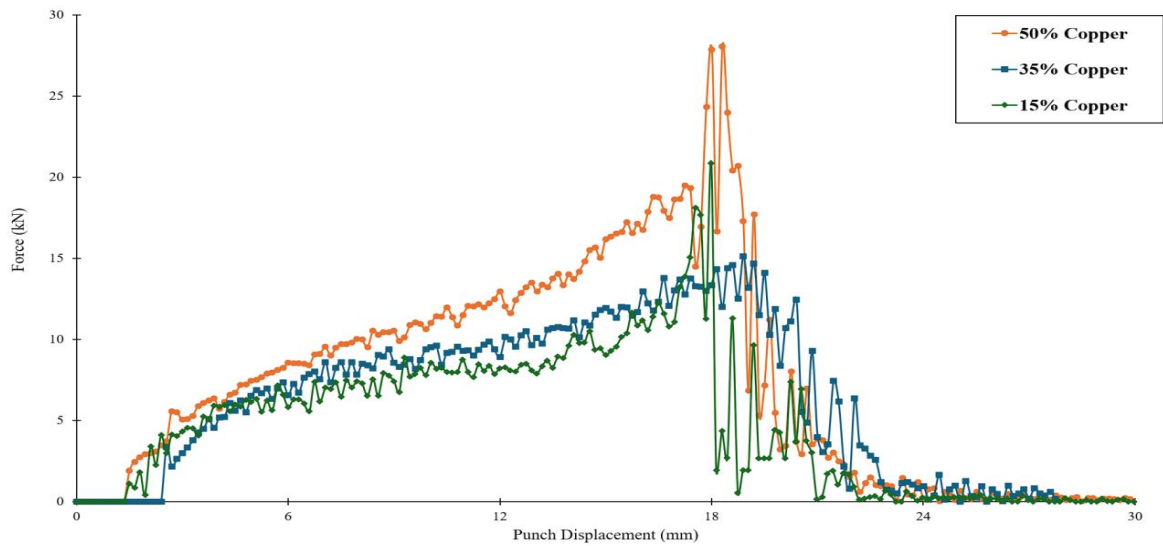
stable area becomes higher, and the area will stabilize at a higher point. Additionally, the rate at which the force reduces at the end of the process will be slower due to friction. The copper sheath will experience a greater effect because of its area of contact with the die. This can affect the quality of the resulting bimetallic material.



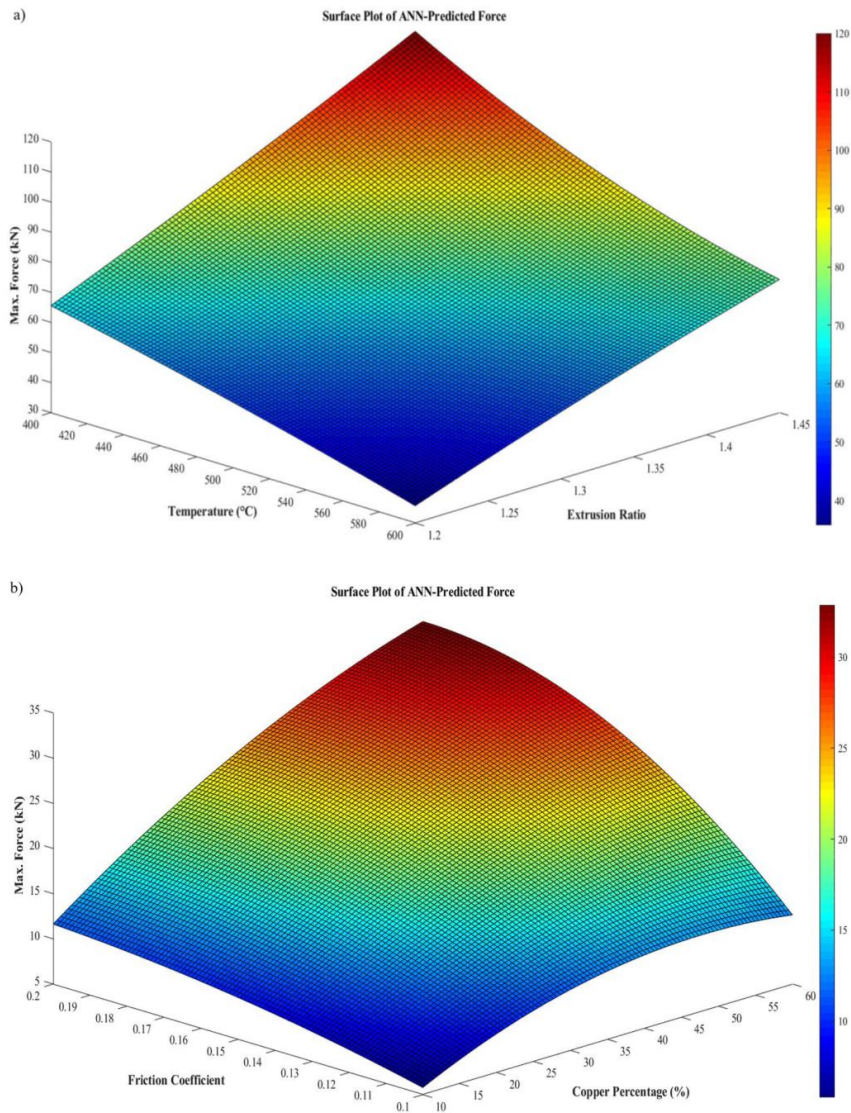
**Figure 12:** Effect of higher friction coefficient on punch force–displacement curve in bimetallic extrusion

When the total diameter of the bimetallic rod remains constant but the value of the thickness percentage of the copper layer varies (15%, 35%, and 50%), the process of the punch force can be understood as follows. In the 15% thickness case, the area of interaction with the die and the amount of the copper layer undergoing deformation are small, leading to less friction, hence the lowest magnitude of the punch force during the whole process. Consequently, the first force peak is of shorter duration, and the rate of force reduction at the end of the extrusion process is faster. With the increase of the sheath thickness by 35%, a greater amount of the copper contributes to the plastic deformation and the contact area with the die also increases. As a result, the friction forces and the plastic work increase, and the punch force remains at a medium value. In this scenario, the first peak of the force-displacement graph increases relatively,

and the graph moves to a higher position. In the case of a 50% copper sheath, the maximum volume of copper will deform, and the contact between the copper sheath and the die will be at its maximum. This will cause a substantial increase in the level of friction and unnecessary deformations, resulting in the maximum force during the punching process. The first maximum will be more noticeable, and the reduction will be more gradual towards the end. In general, the outcomes of the experiment reveal that the increase in the thickness fraction of the copper sheath causes the force of extrusion to increase, and the differences among the initial peak force and the steady-state force for the thicknesses of 15%, 35%, and 50% copper sheath thicknesses are clearly identifiable. The punch force changes for the different thicknesses of copper sheath thicknesses are shown in Figure 13.



**Figure 13:** Variation of punch force as a function of punch displacement for different copper sheath thickness fractions (15%, 35%, and 50%) in the bimetallic rod extrusion process



**Figure 14:** ANN-predicted punch force showing the effects of a) billet temperature, extrusion ratio and b) friction, and copper sheath percentage

To this end, the artificial neural network predictions for the hot extruded bimetallic rod comprehensively analyzed a series of conditions: The force variations can be quantified as related to key parameters including initial billet temperature and extrusion ratio, showing how each of these factors affects the shape and slope of the punch force curve. In addition, the variation in friction coefficient between billet and die and the effect of the percentage coverage of the copper sheath on the required extrusion force are all represented graphically in Figure 14. These plots show in detail what influence each parameter has on the extrusion force and how the material behaves, therefore providing a solid basis for optimizing the hot extrusion process of bimetallic rods.

## 5. Conclusion

In the current work, the hot extrusion of aluminum-copper bimetallic rods is analyzed using a coupled thermal and mechanical simulation via a two-dimensional FE simulation carried out using ABAQUS software, as well as an ANN prediction model approach. The two-dimensional FE simulation carried out using ABAQUS software was able to analyze the coupled thermal and mechanical characteristics of hot extrusion successfully. The result obtained showed that more deformation occurs for copper than for aluminum, thus ensuring proper encapsulation of aluminum material with suitable processing parameters. The parametric analyses suggested that raising the initial billet temperature helps decrease the extrusion force because of the reduction in flow stress, but the higher extrusion ratios, friction values, and values of the copper sheath thickness result in higher values of the forming load and peak force. Further, there was a notable temperature gradient at the interface of the Al-Cu because of the difference in the thermal conductivity of the materials that could affect the material integrity at the interfaces. For enhancing the calculation efficiency and accuracy, an ANN model trained with data from FE simulation was used for estimating the punching force in varying conditions of hot extrusion. This ANN model predicted results in close agreement with those from numerical analysis, authenticating the accuracy of utilizing data-driven analysis. Thus, it is established that the present FE-ANN approach is an efficient analysis tool for hot extrusion processes of Al-Cu bimetallic rods.

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