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# Using Finite Element Process Simulation to Design and Simulate an Optimal Preform Mold with Neural Networks and Continuous Genetic Algorithm

**Houshang Hamidi Monfared[1], Seyyed Mohammad Kazemi[*2]**

1.Bachelor's degree from Sharif University of Technology, Tehran, Iran

Email: hamidia76@yahoo.com

**2.**Department of Civil Engineering (Geotechnical), Azad University, Islamshahr Branch, Tehran, Iran

info.s.m_kazemi@acceptyar.com

s.mohamad_K@yahoo.com

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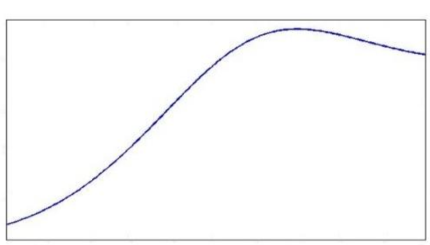
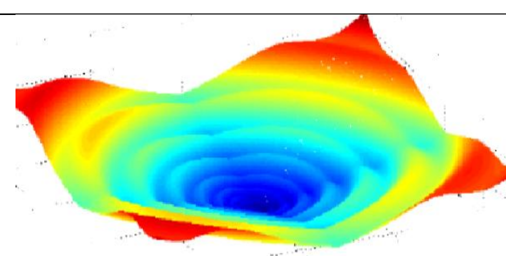
**Abstract**

In the forging process, if the shape of the final part is complex, the raw material cannot be transformed into the shape of the final part in one forging step; therefore, the use of preform molds is essential. An optimal preform mold is a mold that can meet the design criteria. Design criteria include producing a defect-free part with the least volume of raw material, the least plastic strain, the least force required to perform the process, and also completely filling the final mold. In this research, using the ability of the continuous genetic algorithm to generate Cartesian paths, first several different preform mold shapes are produced using mathematical functions. Then, using finite element simulation of the process, the optimal mold selection criteria are calculated. From the information obtained from the simulation, the artificial neural network is trained so that it can predict the results of the simulation process. This network and design criteria are used for the objective function in the continuous genetic algorithm. Finally, the best shape of the preform mold is calculated by the continuous genetic algorithm, which is a mathematical function and is obtained by plotting this function in the Cartesian coordinates of the mold shape. Next, this method is used for a part with an H-shaped cross-section to examine its efficiency. The optimal preform mold for the part is calculated and its forging results are extracted by the continuous genetic algorithm. Also, finite element simulation is performed for the optimal mold to compare its results with the results obtained from the continuous genetic algorithm. Finally, the success of using this method was proven.

**Keywords**: Optimal preform mold - Finite element method - Artificial neural networks - Continuous genetic algorithm

## 1-Introduction

The forging process holds a prominent position among manufacturing methods due to its ability to produce components with **excellent mechanical properties** while minimizing material waste. In forging, the initial material, often with a relatively simple geometry, undergoes **plastic deformation** through one or more operations to achieve a final product with a relatively complex configuration. Forging typically requires relatively expensive tooling. Consequently, the process is economically attractive either when a large number of parts are produced or when the required final mechanical properties can only be achieved through a forging process. In **closed-die forging**, the raw material is deformed under immense pressure within the die cavity. However, when the final part geometry is complex, the desired deformation cannot be accomplished in a single stage. Attempting to produce complex parts in one step often leads to **critical defects** such as incomplete die fill, **lap/folding formation**, improper material flow, and a sharp increase in forging forces, which consequently reduces die life (1, 2). To overcome these challenges, the use of one or more **preform stages** before the final operation is essential. The primary objective of **preform die design** is to control material flow in such a way that the initial material is converted into an optimal geometry for the final stage. An **optimal preform** must ensure adherence to critical design criteria: the absence of defects in the final part, minimization of raw material consumption, **uniform plastic strain** for enhanced mechanical properties, reduction of the required forging force, and guaranteeing **complete final die fill**. Traditionally, preform design has relied heavily on the **experience** of engineers and the costly **trial-and-error** method, which significantly increases both production time and cost (3, 4, 5). In recent decades, with significant advances in computational power, process simulation using the **Finite Element Method (FEM)** has become a powerful and standard tool for analyzing and evaluating metal forming processes. Software packages like **DEFORM** and **ABAQUS** enable accurate modeling of material flow, temperature distribution, strain, and stresses, as well as the prediction of defect occurrences. FEM effectively replaces physical trial-and-error, offering deep insight into the process mechanics. Nevertheless, the process of optimizing the preform shape through iterative FEM simulations remains a major **computational challenge** due to the time-consuming nature of each simulation run. To accelerate and rationalize the design process, **Artificial Intelligence (AI)** methods and **Metaheuristic Optimization Algorithms** have been introduced. These novel approaches, particularly the integration of **Artificial Neural Networks (ANN)** with the **Genetic Algorithm (GA)**, have shown great potential in overcoming the computational limitations of the standalone FEM approach (6, 7, 8, 9). **Artificial Neural Networks (ANNs)** are capable of creating a **surrogate model** (or metamodel) of the complex physical process. Using limited and targeted data generated by FEM simulations, the ANN is trained to rapidly predict the non-linear relationship between preform geometric parameters (input) and performance criteria (output), such as forging force or die fill, with acceptable accuracy. This approach significantly reduces the need for computationally expensive, repetitive FEM simulations during the optimization phase (10, 11, 12). The **Genetic Algorithm (GA)**, an optimization technique inspired by natural evolution, is a highly effective tool for searching large and complex design spaces. GA is well-suited for solving **non-linear, multi-objective optimization problems**, such as preform shape optimization, where the goal is the simultaneous reduction of several performance metrics (e.g., force, material waste, and strain) (13). One of the most important optimization variants is the **Continuous Genetic Algorithm (CGA)**. This method offers the capability to optimize continuous problems. Abuhomour et al. presented a method using CGA to optimize the trajectory of robot arms. This method is applicable to generating **Cartesian paths**, or in other words, curves in Cartesian coordinates. In any problem where the solution takes such a form, this method can be employed to find the optimal solution (14, 15). In some continuous optimization problems, the solution is a smooth, continuous surface or curve. Examples include finding the optimal trajectory for robots and the solution to a differential equation. Regarding forging preforms, if the die shape is modeled as a surface, the solution can be obtained using two-dimensional mathematical functions; however, if the die shape is modeled as a curve, one-dimensional mathematical functions are used to solve the problem. Figure (1) shows an example of a curve solution, and Figure (2) shows an example of a surface solution.

|  |  |
|---|---|
| **Figure (1) Example of a Curve Response** | **Figure (2) Example of a Surface Response** |

Since the component selected for **preform die design** is **axisymmetric** (axially symmetric), its preform shape is represented by a **curve**. Therefore, the subsequent discussion focuses on the **curve-shaped die geometry**. One study introduced a method for executing the steps of the **Continuous Genetic Algorithm (CGA)** using the **Hyperbolic Tangent** and **Gaussian** mathematical functions. In this approach, the curves for the **initial population** as well as the **crossover and mutation** stages were all generated using these functions. Their method is highly applicable to problems where there is no prior knowledge regarding the shape of the solution curve (16). Several examples of mathematical functions that can be utilized in this context are presented in Figure (2).

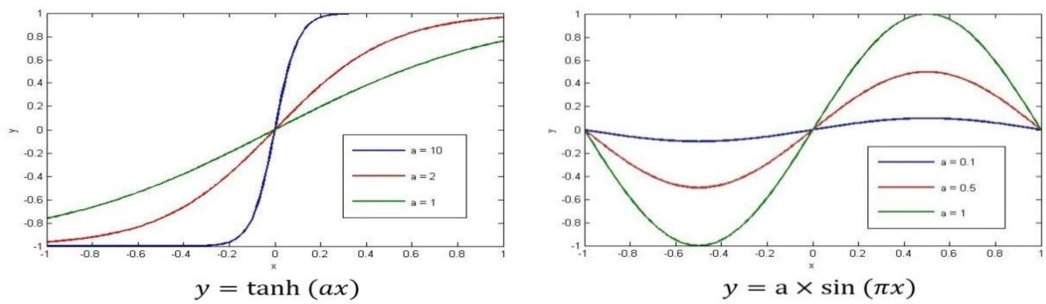



**Figure (3) Two examples of mathematical functions**

By modifying the parameters of these functions, various distinct curves are produced. For **preform die design** in **axisymmetric components**, estimating the preform shape is simpler because the final die shape is known. Forging experience indicates that the preform shape bears a strong resemblance to the final die; thus, its estimation is not unduly challenging. It suffices to use functions that generate a shape close to the final die to produce the preform curve. The curve shape changes as the parameters of these functions are varied. Furthermore, a combination of several functions can be used to achieve the desired shape. By varying the parameters of these functions, numerous states for the curve shape are generated, and the role of the **Continuous Genetic Algorithm (CGA)** here is to find the **optimal set of parameters** for the utilized mathematical functions to yield the **optimal curve shape**. Recent research has demonstrated that the integration of **Intelligent Techniques** and **Simulation** is the key to achieving high-performance optimal designs. For instance, multiple studies have successfully employed the **FEM-ANN-GA** combination for optimizing the forging process. In an approach similar to the current research, the capability of the **Continuous Genetic Algorithm (CGA)** to generate **Cartesian paths** and model preform shapes using mathematical functions has been proven (14). This method allows the entire preform shape to be optimized as a **continuous function**, instead of optimizing limited parameters, thereby offering greater flexibility and accuracy in designing the optimal geometry. In this integrated approach, the predictions from the **Artificial Neural Network (ANN)**—trained on **FEM data**—are utilized as the **Objective Function** for the Continuous Genetic Algorithm. This research presents a **comprehensive and integrated methodology** for the optimal preform die shape design in the forging process. This approach is founded on leveraging the complementary strengths of **Finite Element Method (FEM)** for generating precise data, **Artificial Neural Networks (ANN)** for creating a rapid prediction model (**Surrogate Model**), and the **Continuous Genetic Algorithm (CGA)** for searching and determining the most optimal preform geometry (modeled as a **mathematical function**). Finally, the effectiveness of this advanced approach will be investigated and validated using a key industrial component with an **H-shaped cross-section**, where preform design is challenging due to the complex geometry (6). The comparison between the final **FEM simulation results** of the optimal preform and the predictions from the hybrid model will validate the efficacy of this intelligent methodology in enhancing product quality and reducing production costs in the forging industry.

**2. Research Methodology**

The research methodology employed in this study is an **integrated and intelligent methodology** based on the synergy of three powerful tools: the **Finite Element Method (FEM)**, **Artificial Neural Networks (ANN)**, and the **Continuous Genetic Algorithm (CGA)**. The main goal is to convert the preform design problem into a **mathematical optimization problem** and solve it using an intelligent approach. This process is executed in several primary, structured stages:

**1. Definition of Criteria and Design Space**

- **Design Criteria (Objective Function):** First, the required technical criteria for selecting the optimal preform die are precisely defined. These criteria include minimizing the volume of raw material (flash reduction), minimizing non-uniform **plastic strain**, minimizing the process **force requirement**, and ensuring complete final die cavity fill and the absence of defects like folding. These criteria are ultimately incorporated into the **Fitness Function** of the Genetic Algorithm.
- **Preform Geometry Modeling:** To establish the design space, the capability of the **Continuous Genetic Algorithm (CGA)** for **Cartesian path generation** is utilized. In this phase, the preform die shape is modeled as a **continuous mathematical function**. The parameters of this function (e.g., polynomial coefficients or **Bezier curve** parameters) are considered the **design variables (genes)** for the Genetic Algorithm. Initially, several different shapes are randomly generated using the mathematical functions.

**2. Data Generation and Finite Element Simulation (FEM)**

- **Process Simulation:** The preform shapes generated in the previous step are analyzed using FEM-based simulation software (such as **DEFORM** or **ABAQUS**). The forging process (e.g., hot or cold forging) is simulated for each preform geometry.
- **Result Extraction:** From the results of each simulation, the quantitative data required for evaluating the design criteria (such as maximum forging force, generated **flash volume**, and effective strain distribution) are extracted and collected. This dataset (including the mathematical parameters of the preform shape as inputs and the FEM results as outputs) is used to **train the surrogate model**.

**3. Development of the Surrogate Model with Artificial Neural Networks (ANN)**

- **Neural Network Training:** The data obtained from the FEM simulations is used to train an **Artificial Neural Network**. The goal of ANN training is to create a **Surrogate Model** that can predict the design criteria (FEM results) with very high speed and acceptable accuracy, given the mathematical parameters of the preform shape. This effectively eliminates the need for time-consuming FEM simulation in every iteration of the optimization process.
- **ANN Validation:** The accuracy of the trained neural network is assessed using a test dataset that was not used during the training process, ensuring the model possesses adequate **generalization capability**.

**4. Preform Shape Optimization with Continuous Genetic Algorithm (CGA)**

- **Model Integration:** The trained **ANN model** replaces the FEM simulation process and is incorporated as the **Objective Function** (or a component of the fitness function) within the Continuous Genetic Algorithm.
- **Optimization Execution:** The **CGA** is executed with the aim of optimizing the fitness function. By searching the space of mathematical parameters, the algorithm finds a set of parameters that results in a preform simultaneously satisfying the defined criteria (minimum force, minimum waste, etc.).

- **Optimal Shape Calculation:** Finally, the **best individual** (the optimal set of mathematical parameters) determined by the CGA is selected as the **mathematical function for the optimal preform die shape**. The optimal geometric shape is obtained by plotting this function in Cartesian coordinates.

**5. Case Study and Validation**

- **Practical Application (H-Shaped Case Study):** The developed methodology is applied to a specific industrial component with an **H-shaped cross-section**. The optimal preform die shape for this part is calculated by the CGA.
- **Final Validation:** To confirm the accuracy and effectiveness of the **hybrid method (FEM-ANN-CGA)**, a final FEM simulation is performed for the determined optimal preform die. The results of this FEM simulation (including forging force, strain distribution, and die fill status) are directly compared with the results predicted by the Continuous Genetic Algorithm (using the ANN model). This comparison proves the success of the proposed method in achieving the optimization objective and validating the accuracy of the intelligent models.

**3. Optimal Preform Die Design Using Neural Networks and Continuous Genetic Algorithm**

To obtain the preform die shape for forging components, **mathematical functions** that are capable of generating the die geometry can be utilized. The optimal shape is subsequently determined using the **Continuous Genetic Algorithm's (CGA)** ability to optimize continuous problems.

Using the CGA in optimization necessitates repeated analyses of the process (e.g., 1000 times) under different conditions to find the best preform shape. Given that **Finite Element analysis is a time-consuming process**, repeated iterations would require an excessive amount of time. To reduce the time required to find the optimal preform die, the use of **Artificial Neural Networks (ANNs)** is rational. Thus, instead of running the FEM analysis for the process repeatedly, a network is designed and trained to provide the necessary results promptly.

Figure (2) shows the component under study with its dimensions . The dimensions are in millimeters (mm). For modeling this component in **ABAQUS**, **one-quarter of the total part** is considered due to symmetry, as shown in Figure (4) .

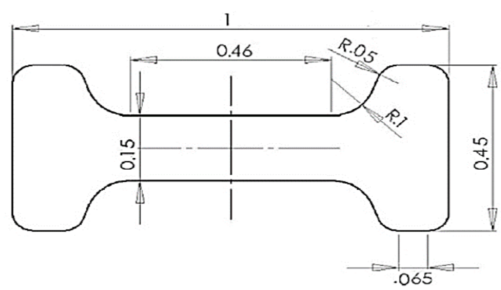



**Figure (4) Geometry of H-shaped piece**

Given the component's geometry, its **final die** is modeled as a **curve**, as depicted in Figure (4) . The **preform die** for this component will also be **curve-shaped**, similar to the final die. Naturally, a narrow **flash gutter** will be included in the final die to improve **material flow** and allow excess material to be expelled as **flash**.

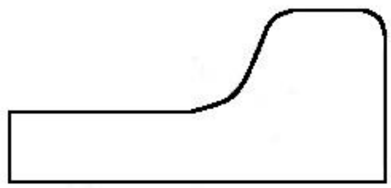


**Figure (5) Required Component Geometry for Abaqus Modeling**

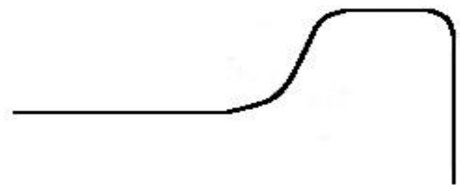


**Figure (6) Final Die Shape**

**Calculation of Raw Material Volume**

To calculate the volume of the **raw billet**, it is essential to consider that during the forging process, a portion of the component's surface oxidizes, and **flash** is formed. Therefore, if the raw material volume is considered equal to the final part volume, cavities will be observed after the process (8).

Various rules and formulas exist for calculating the initial raw material volume, mostly based on the oxidation rate and the amount of flash generated. Since none of these formulas offer sufficient accuracy, the volume of the initial raw material in this study was determined by **trial-and-error**. The raw billet for this die is considered a cylinder with a height of 0.9 meters and a radius of 0.3 meters. Since the raw billet is also **axisymmetric**, only **one-quarter** of the component is used for modeling, which is represented as a rectangle with a height of 450 mm and a width of 300 mm.

**3-1. Material Characteristics and Preform Die Geometry Design**

This section of the research addresses three main axes: determining the **physical properties** of the raw material at the process temperature, defining the **number of preform stages** required for the component under study, and the **mathematical modeling** of the preform die geometry for the optimization process.

**1. Raw Material Physical Properties and Process Conditions**

The raw material selected for this research is **AL2014 Aluminum Alloy**. Since the forging process is performed at a high temperature, specifically **400∘C**, the material's mechanical properties must be accounted for at this temperature.

| **Feature** | **Value** |
|---|---|
| Material Type | AL2014 |
| Process Temperature | 400∘C |
| Initial Yield Stress (σs) | 23.7 MPa |
| Poisson's Ratio | 0.33 |
| Elastic Modulus | 27.9 GPa |

**Plastic Stress-Strain Relationship:**

The constitutive relationship governing the material's plastic behavior is expressed as a **power law function** of plastic strain ($\epsilon$):

$\sigma=\sigma s+C\epsilon m$

Where:

- C (**Strength Coefficient/Flow Constant**) is 1.02×108 MPa.
- m (**Strain Hardening Exponent**) is 0.11.

This relationship is considered for modeling the material behavior in the **Finite Element Method (FEM)** simulation.

**2. Determining the Number of Preform Stages**

For forging processes with complex final part geometries, defining the optimal number of preform stages is crucial to prevent defects. In this research, for the studied component with an **H-shaped cross-section**, the method proposed by Thomas, based on the **height-to-width ratio** of the forged part, is employed.

Given the dimensions of the H-shaped component used in this study, the height-to-width ratio falls within the range of 2 to 3. Consequently, **only one preform stage is required**. Thus, the entire forging process will consist of two stages: the **preform die stage** and the **final die stage**.

**3. Mathematical Modeling and Preform Die Design Parameters**

**A) Mathematical Function for Preform Shape Generation**

To model the preform die shape and introduce geometric variability for the optimization process, the preform geometry is estimated as a **continuous mathematical function**. This curve shape is formed by the combination of **two Hyperbolic Tangent functions** that connect at point m.

The general form of the function models the preform geometry as a function of the width coordinate (x) and the height coordinate (y). This function contains the coefficients a1, a2, and the connection point m, which are used as the **design variables** (primary input parameters) for the **Continuous Genetic Algorithm (CGA)**.

**B) Preform Dimensions and Function Mapping**

Since only one preform stage is required, the preform die shape is considered an intermediate state between the initial billet (symmetric rectangle) and the final part (H-shape).

- **Preform Width:** The average width between the initial billet (300 mm) and the final part (500 mm), which is **400 mm**, is selected.
- **Preform Height:** Half of the height change of the final part (150 mm), which is **75 mm**, is considered.

Ultimately, the mathematical functions used are mapped to be within the width range [0,400] and the height range [0,75], forming the final relationship (4-4) of the optimization problem. Varying the parameters a1, a2, and m creates a wide variety of curve shapes (similar to Figure (4-5) in the original text) that cover the search space of the Genetic Algorithm.

**C) Problem Input and Output Parameters**

The design criteria for selecting the optimal die include: **die fill percentage**, **required process force**, **plastic strain magnitude**, and **raw material volume**. These criteria are divided into two categories: input parameters (those modified by the designer) and output parameters (process results that must be optimized):

- **Input Parameters:**
  - **Raw Billet Width (Discrete Variable):** To regulate the raw material volume, the billet width is selected as **20 discrete, predefined values** between 300 mm and 305 mm (e.g., 300, 300.25, 300.5, etc.), instead of a continuous value. The Genetic Algorithm must find the optimal state among these 20 discrete values.
  - **Preform Shape Parameters (a1,a2,m):** These are the **primary continuous variables** for generating the die's geometry.
- **Output Parameters (Criteria):**
  - Maximum required force (to reduce forging costs).
  - Component plastic strain magnitude.
  - Die fill percentage.
  - Raw material volume.

**Method of Drawing the Shape in Software (Abaqus)**

For simulation in **Abaqus** software, the continuous preform shape curve is modeled using the coordinates of **21 points** (resulting from dividing the width into 20 segments). To eliminate sharp corners at the connection points of the segments, the **spline command** is used. Due to the two-dimensional nature of the shape and software limitations, the 21 points are divided into **7 sections** (each containing 3 points), and then the curve is smoothed using the **spline command and ensuring tangency** at the connection points, achieving an acceptable geometry for forging dies.

## 4. Problem Solving

In this section, the command to solve the problem is executed. A printout of the inputs and applied boundary conditions can also be generated before the operation begins. Here, the **default settings** of the software are used for problem solving, and the solution command is issued.

### 4-1. Displaying Problem Solving Results

This section presents the results obtained from solving the problem. The software provides various options for this purpose, allowing different results to be viewed visually or extracted numerically. Tools for plotting various graphs as needed are also available. In this research, **three output parameters** must be obtained from the simulation; the method of extracting them is presented below.

The first parameter is **Maximum Plastic Strain**. Plastic strain is represented as **PEEQ** in Abaqus software. Figure (7) shows the **plastic strain contour** for this model, with a maximum value of 10.316

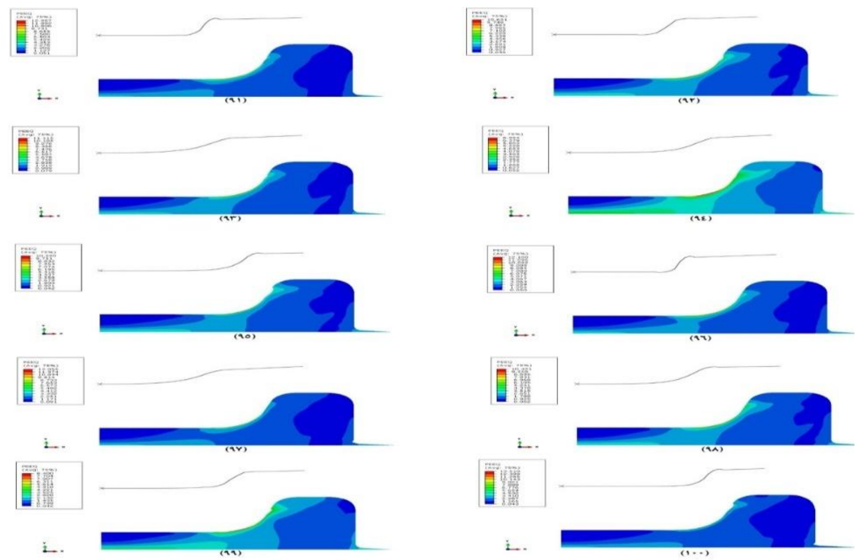


**Figure (7) Plastic Strain Contour for the Simulated Model**

The second parameter that must be obtained from the process simulation is the **Die Fill Percentage**. As observed in Figure (5), due to the small volume of material or an unsuitable preform die, as well as the loss of some material as flash, the final die is not completely filled. It should be noted that a tool exists in Abaqus to calculate the volume of a closed part. However, since the component is modeled here as **axisymmetric**, it has symmetry in two directions, which results in the part being "open" in those two directions, making it impossible to calculate its volume using the built-in Abaqus tool.

In this research, the **analysis tool in Photoshop** (1) is used to determine the die fill percentage. Initially, the results from Abaqus software are saved in **PNG format** with a resolution of 1056×453. Then, in Photoshop, the flash area is first removed, and the **number of pixels** of the final part is calculated using the analysis tool. By comparing this pixel count with the pixel count of the completely filled final die, the **die fill percentage** is obtained. Using this method, the die fill percentage for this model was obtained as **99.36%**.

The third parameter obtained from the simulation is the **Maximum Force Required for Forging**. As observed in the figure [referencing Figure 5-9 in the original thesis structure], the maximum force can be determined by plotting the **force applied to the final die versus time**. The maximum required force for this model is **226 MegaNewtons (MN)**.

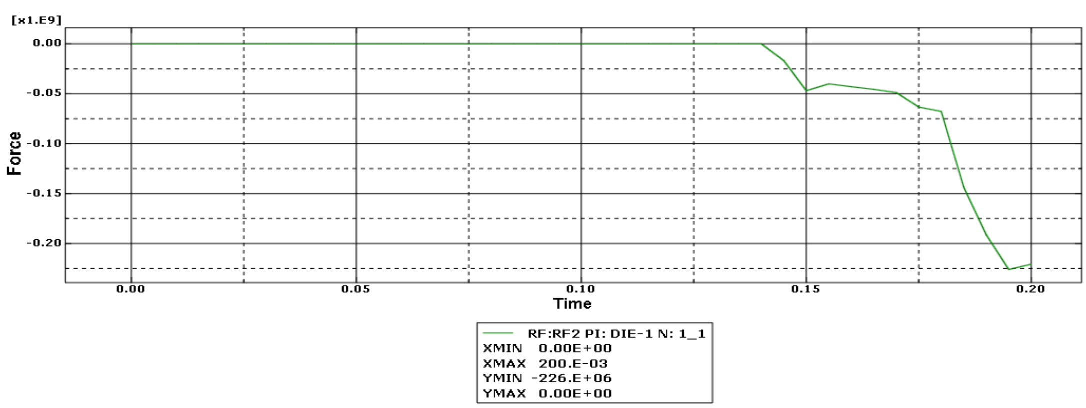



**Figure (8) Force vs. Time Diagram for the Final Die**

**5. Simulation, Intelligent Modeling, and Optimization of Preform Die**

**5-1- Finite Element Method (FEM) Simulation and Result Extraction**

Three key output parameters were extracted from the simulations to evaluate the performance of the preform dies:

| Parameter | Description | Measurement Method & Example |
|---|---|---|
| **Maximum Plastic Strain (PEEQ)** | Indicates the **plastic deformation** in the part. | Its value is read directly from the plastic strain contour in **Abaqus** software (e.g., in one case 1.316×10−x). |
| **Die Filling Percentage** | Due to axisymmetric modeling and the part being open in Abaqus software, calculating the part volume with internal software tools is not possible. To resolve this, a creative method was used involving the analysis tool in **Photoshop** software. The filling percentage is calculated by comparing the number of pixels in the filled area of the final part with the number of pixels in the completely filled die (after flash area removal) (e.g., 99.36%). | |
| **Maximum Forging Force Required** | This parameter is obtained by plotting the force versus time diagram (like Figure 5-9) and represents the **maximum force consumed** in the process (e.g., 226 **Mega Newtons** (MN)). | |

- Finally, FEM simulation was performed for **100 cases** (a combination of shape parameters and raw billet width), and the necessary results were extracted to train the neural network.

**5-2- Optimization with Artificial Neural Networks and Continuous Genetic Algorithm (ANN & CGA)**

**1. Design and Training of Artificial Neural Network (ANN)**

- The neural network is designed as a **high-speed surrogate model** for predicting forging results (FEM outputs) and is trained using **MATLAB** software.
- In this research, a multi-criteria **objective function** is defined in MATLAB so that its minimization by the Genetic Algorithm leads to finding the optimal die.

**6. Finding the Optimal Preform Die State by Neural Network and Continuous Genetic Algorithm**

**6-1- Designing and Training Several Neural Networks and Selecting the Appropriate Neural Network**

- Several neural networks with different **topologies** are designed. These networks are then trained, and the optimal network is selected based on performance indicators to continue the research process.
- Of course, to train the network, the data must first be **normalized**.

**6-3-1- Data Normalization**

- Because the range of variation in the data is small, normalization is used to put the range of all data at one level, which increases the accuracy and reduces the error of the neural network. Data normalization means scaling them within a specified range.
- Among the commands used in MATLAB software to normalize neural network data is the **`mapminmax`** function. This function scales the data within the desired range.
- In this research, this function is used to scale the problem's input and output data in the range **[0, 1]**. Note that subsequently, whenever a new input needs to be entered, that input must be scaled in the desired range, and whenever a new output is needed, the output is returned to its original value using the inverse command of this function.

**6-2- Selecting the Optimal Network**

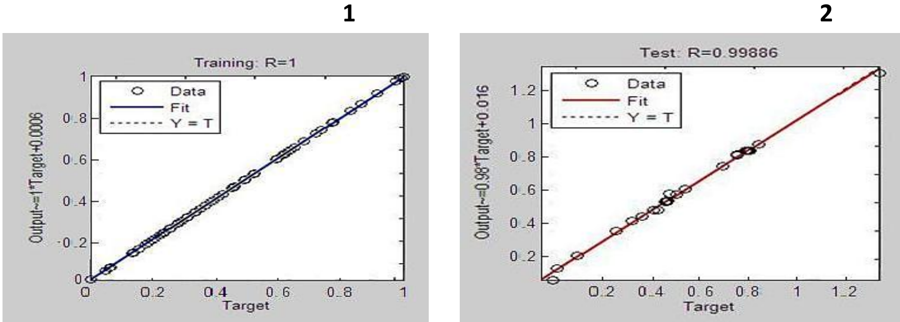
**Table (2)** shows the results of running the network for several different topologies. As is clear, the network with layers **3, 40, 20** (i.e., the network with two hidden layers of 40 and 20 neurons) has the **best MSE** and **correlation coefficient**.

**Table (2) Results from running networks with different topologies**

| ow | Topology | MSE | Correlation Coefficient | Minimum Error | Maximum Error |
|---|---|---|---|---|---|
| | 3, 12, 5 | 0.0089 | 0.87 | -0.33 | 0.47 |
| | 3, 15, 12 | 0.0023 | 0.97 | -0.14 | 0.35 |
| | 3, 21, 18 | 0.00022 | 0.94 | -0.21 | 0.10 |
| | 3, 40, 20 | 0.000005 | 0.99 | -0.03 | 0.05 |

Figure (9) shows the correlation coefficient graph for the training and testing state of the network, and Figure (10) shows the network performance.

1 2 3



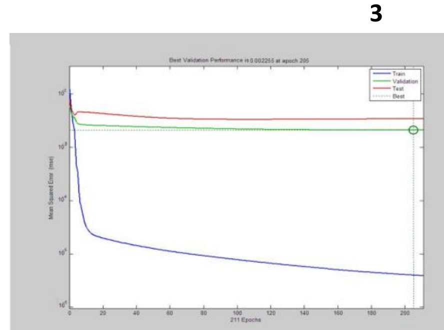



**Figure (9) Correlation Coefficient Diagram for Training and Testing State of 3, 40, 20 Network**

**Figure (10) Performance Diagram of 3, 40, 20 Network**

**6-3- Using Continuous Genetic Algorithm to Find the Optimal Preform Die State**

- In this section, an **objective function** is first defined for the Genetic Algorithm based on the design criteria. Then the Genetic Algorithm parameters are selected, and the optimal preform die state is obtained by running the algorithm.

**6-3-1- Defining the Objective Function**

- As mentioned before, the goal of designing an optimal preform die was stated as designing a die that could **completely fill the final die** with the **minimum raw material volume**, **minimum plastic strain**, and **minimum required force**.
- The parameters: *final die filling percentage*, *maximum plastic strain*, and *maximum force* must be extracted from the neural network and then applied to the objective function. Therefore, the variables of the objective function are first **normalized** and then applied to the Genetic Algorithm. Also, due to the normalization of the inputs and outputs of the neural network, the weight of all parameters is equal.
- Each of these four parameters can have a different value for the mold designer. Thus, a different coefficient can be considered for each or specific conditions can be applied. In this research, the status of these parameters is considered as follows:
  - The final die filling percentage **must** be between 99.90% and 100%. In this case, the die is completely filled. It is worth noting that dies with a filling percentage less than 99.90% are **not acceptable** at all. For this purpose, a condition is placed in the objective function that if this criterion is not met, the other criteria are not checked, and the objective function value is considered a large number (value **20**).
  - The coefficient for **maximum plastic strain** is considered to be **2**.
  - The coefficient for **maximum force** is considered to be **3**.
  - The coefficient for **raw billet width** is considered to be **5**. The reason for this is the high cost of obtaining the raw billet.
- As noted, the final die filling percentage is the **most important** criterion, and the maximum plastic strain coefficient is the **least important** criterion.
- Considering the conditions, the objective function is applied as a computer program in MATLAB software. This program will be as follows:

```
If area%<99.90%
 then fitfunc=20
 else fitfunc=5×width+3×force+2×peeq
end
```

- Since the Genetic Algorithm tool in MATLAB software seeks to find the **minimum** of the objective function, the minimum value obtained for the objective function will be the optimal state of the problem.

**6-3-2- Selecting the Continuous Genetic Algorithm Parameter Values**

- In this stage, the values or states of the algorithm parameters must be determined. These parameters include the initial population size, the fitness evaluation method, and the termination conditions of the algorithm. These parameters were applied as follows:
  - The **initial population size** is considered to be **25**.
  - The **fitness evaluation method** is selected as the **Rank** method.

- The **Roulette Wheel** method is considered for the selection stage.
- The **algorithm termination condition** is considered to be **150** generations.
- The rest of the parameters are set to the software's default state.

**6-4- Optimal Preform Die Found by Continuous Genetic Algorithm**

- Figure (11) shows the diagram of fitness convergence and the best generation obtained. It should be noted that, to ensure the results of the Genetic Algorithm and to avoid the results being a **local minimum**, the Genetic Algorithm was run about **20 times** to ensure the correctness of its results.

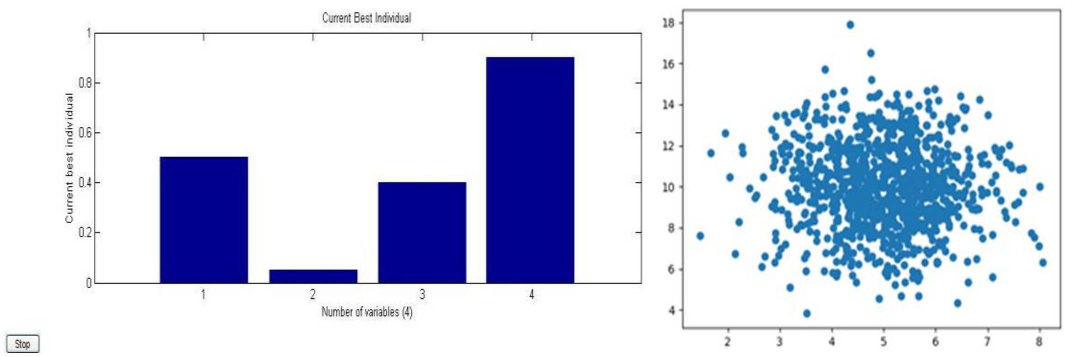



**Figure (11) Fitness Convergence and Best Generation**

- **Table (3)** shows the results of the Finite Element simulation of the optimal preform die compared to the Genetic Algorithm results. As observed from the results, the difference between the neural network results and the Abaqus results is **very small**. This means that the neural network is well-designed and can predict the process well.

**Table (4) Comparison of Finite Element Simulation Results with Genetic Algorithm Results**

| Results Source | Die Filling Percentage | Maximum Plastic Strain | Maximum Force (MN) |
|---|---|---|---|
| Abaqus | 99.96% | 8.895 | 270 |
| Genetic Algorithm | 100.06% | 8.887 | 271 |

- Figure (12) shows the cross-section of the raw part for the optimal state at the end of the final die application stage.

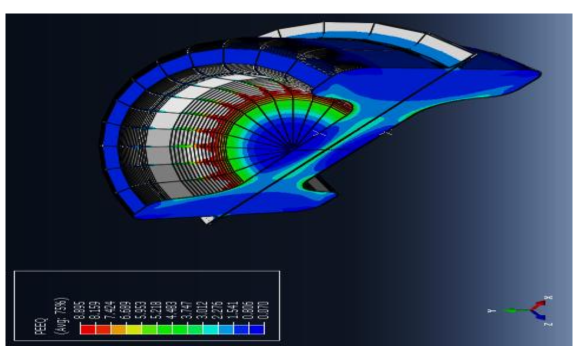


**Figure (12) Cross-section of the Part for the Optimal State at the End of the Final Die Application Stage**

**7. Optimization Results and Validation**

- The **Continuous Genetic Algorithm** was run **20 times** (to ensure it did not get trapped in a local minimum) and specified the best generation (optimal state).
- The optimal preform die was extracted as mathematical parameters (a1, a2, and m) and the optimal raw billet width (e.g., 302.5 mm).

**Table (5) Optimization and Validation Results**

| Parameter | Raw Billet Width | | 1 | 2 | Die Filling | Max Plastic Strain | Max Force (MN) |
|---|---|---|---|---|---|---|---|
| **CGA Result (Actual)** | 302.5 | 05.8 | .6 | 3.9 | 10 0.06% | 8.887 | 271 |
| **FEM Result (Optimal)** | 302.5 | 05.8 | .6 | 3.9 | 99. 96% | 8.895 | 270 |

**8. Conclusion**

- The design of the preform die in the forging process of complex parts has always been presented as a difficult, time-consuming, and costly problem. This research successfully presented and applied an **intelligent and integrated methodology** based on the combination of **Finite Element Method (FEM) simulation**, **Artificial Neural Networks (ANN)**, and **Continuous Genetic Algorithm (CGA)** to overcome these challenges.
- The results of this research showed that using the capability of the Continuous Genetic Algorithm to produce and optimize geometric shapes as a continuous mathematical function provides a powerful tool for defining the preform design space.
- By using accurate and limited data generated by FEM simulations, the Artificial Neural Network was trained as a **high-speed surrogate model** to predict the process performance criteria for any suggested shape. This effectively eliminated the time and computational limitations of performing repeated Finite Element simulations in the optimization phase.
- The Continuous Genetic Algorithm, using the ANN model as its fitness function, was able to quickly calculate the **most optimal preform shape**. This optimal shape guaranteed the simultaneous realization of several conflicting design goals; including the production of a defect-free part (such as complete filling of the final die), minimizing raw material consumption (reducing flash), and reducing the required process force.
- The comparison of the Finite Element simulation results (Abaqus) for the optimal preform die with the neural network results (Genetic Algorithm) showed a **very small difference** (such as a difference of 1 Mega Newton in maximum force). This confirms the successful design of the neural network in accurately predicting the process results and the effectiveness of the hybrid method (FEM-ANN-CGA) in finding the optimal state.
- In the case study section, by applying this method to an **H-section part**, the optimal preform shape was extracted. The final validation by performing the Finite Element simulation for this optimal die showed that the obtained FEM results had a **high correlation** with the predictions of the hybrid model (ANN/CGA). This agreement proved the success and effectiveness of the proposed method in the optimal and automated design of forging preform dies, marking an important step towards the intelligent and efficient production processes in metal forming industries.

**References**

[1] Huang, D., & Chen, F. (2019). Efficient shape optimization using continuous genetic algorithm and a dynamic metamodel approach. Engineering Optimization, 51(7), 1185–1204.

[2] Kim, J. H., & Lee, S. Y. (2023). Hybrid optimization methodology for 3D forging preform design using FEM, ANN, and evolutionary algorithms. Journal of Materials Processing Technology, 311, 117865.

[3] KhaliliGheidari, Shiva., (2025). Optimization of Process Design Time in a Distributed Multi-Factory Environment Using Genetic Algorithms to Organize the Process and Support the Development of Technical Designs for Part Production Based on Information Available in the Production Database and Process Mining, EKSPLORIUM – Buletin Pusat Teknologi Bahan Galian Nuklir , Volume 46No. 2, June2025: 933–954. DOI: https://doi.org/10.52783/eksplorium.326

[4] Li, X., Wang, Y., & Zhang, J. (2020). Multi-objective optimization of hot forging parameters using an integrated surrogate model based on Kriging and NSGA-II. Structural and Multidisciplinary Optimization, 62(4), 1839–1852.

[5] Park, Y. C., & Choi, D. H. (2023). Integrated preform design and optimization for closed-die forging using design of experiments and a genetic algorithm. Journal of Mechanical Science and Technology, 37(6), 2841–2850.

[6] Zhong, H., Chen, X., & Xu, W. (2021). Review on the application of artificial intelligence in metal forming processes: Modeling, optimization, and control. CIRP Annals - Manufacturing Technology, 70(2), 527–540.

[7] Ghasemi, E. and Kazemi, S. M. (2025). Designing an intelligent competitive online network model in order to improve business efficiency by using online capabilities in small and medium-sized companies using structural equations.. International Journal of Nonlinear Analysis and Applications, 16(11), 87-99. doi: 10.22075/ijnaa.2024.34127.5092

[8] Wang, Z., Sun, B., & Chen, X. (2022). Preform shape optimization of H-beam forging based on the combination of finite element analysis and a machine learning surrogate model. International Journal of Advanced Manufacturing Technology, 120(1-2), 173–185.

[9] Shiva Khalili Gheidari. (2025). Design and Training a Routing Model for Predicting E-Commerce Logistics Distribution Systems in Transportation and Delivery of Educational Goods for Students Using Existing Algorithms, Big Data Analysis, and Machine Learning Methods . Pegem Journal of Education and Instruction, 15(3), 330–360.

[10] Park, Y. C., & Choi, D. H. (2023). Integrated preform design and optimization for closed-die forging using design of experiments and a genetic algorithm. Journal of Mechanical Science and Technology, 37(6), 2841–2850.

[11] Zhong, H., Chen, X., & Xu, W. (2021). Review on the application of artificial intelligence in metal forming processes: Modeling, optimization, and control. CIRP Annals - Manufacturing Technology, 70(2), 527–540.

[12] Bita Aramesh, INVESTIGATION OF THERMODYNAMIC MODELS AND HEAT TRANSFER DURING LASER RADIATION IN TEETH TISSUE, Journal of Population Therapeutics & Clinical Pharmacology,31 (09), 1362-1377, 2024 . https://doi.org/10.53555/kqp0mj79

[13] Bita Aramesh, Artam Enayat, Melika Method for Reconstructing and Revealing Metal Areas in Real Raw Data (Cyanogram Improved with Tooth Filling Materials) To Reduce the Effect of Various Distortions in Two-Dimensional Scan Images of Spiral-Shaped Metal Implants and Dental P, Power System Technology, Vol. 48 No. http://dx.doi.org/10.52783/pst.811

[14] Badri M, Kazemi S M, Rahimi H, (2025), Presenting the behavioral model of citizens in selection of trip vehicle with emphasis on how to go to work, Case Studies on Transport Policy Volume 19 , 101304. https://doi.org/10.1016/j.cstp.2024.101304

[15] Patel, V., & Singh, A. (2024). A Convolutional Neural Network approach for rapid prediction of forging defects and preform geometry. Manufacturing Letters, 38, 45–50.

[16] Ghasemi, M., & Mohammadi, A. (2017). Prediction and optimization of hot forging process parameters using artificial neural networks and finite element simulations. The International Journal of Advanced Manufacturing Systems, 3(1), 1–12.

[17] Al-Ani, A., & Hassan, S. (2018). Optimized preform design for a complex aluminum alloy forging part using finite element simulation and genetic algorithm. Metals, 8(10), 820.

[18] Chen, J., Li, Y., & Zhao, M. (2016). Review of intelligent approaches in metal plastic forming based on neural networks and optimization algorithms. Journal of Manufacturing Science and Engineering, 138(10), 100801.

[19] Huang, D., & Chen, F. (2019). Efficient shape optimization using continuous genetic algorithm and a dynamic metamodel approach. *Engineering Optimization, 51*(7), 1185–1204.

[20] Kim, J. H., & Lee, S. Y. (2023). Hybrid optimization methodology for 3D forging preform design using FEM, ANN, and evolutionary algorithms. *Journal of Materials Processing Technology, 311*, 117865.

[21] Li, X., Wang, Y., & Zhang, J. (2020). Multi-objective optimization of hot forging parameters using an integrated surrogate model based on Kriging and NSGA-II. *Structural and Multidisciplinary Optimization, 62*(4), 1839–1852.

[22] Wang, Z., Sun, B., & Chen, X. (2022). Preform shape optimization of H-beam forging based on the combination of finite element analysis and a machine learning surrogate model. *International Journal of Advanced Manufacturing Technology, 120*(1-2), 173–185.

[23] Patel, V., & Singh, A. (2024). A Convolutional Neural Network approach for rapid prediction of forging defects and preform geometry. *Manufacturing Letters, 38*, 45–50.

[24] Ghasemi, M., & Mohammadi, A. (2017). Prediction and optimization of hot forging process parameters using artificial neural networks and finite element simulations. *The International Journal of Advanced Manufacturing Systems, 3*(1), 1–12.

[25] Al-Ani, A., & Hassan, S. (2018). Optimized preform design for a complex aluminum alloy forging part using finite element simulation and genetic algorithm. *Metals, 8*(10), 820.

[26] Chen, J., Li, Y., & Zhao, M. (2016). Review of intelligent approaches in metal plastic forming based on neural networks and optimization algorithms. *Journal of Manufacturing Science and Engineering, 138*(10), 100801.