Optimizing extrusion processing of Al-Mg-Si alloys by machine learning

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Abstract

This work explores an approach to optimize microstructural development in thermomechanical aluminum processing using neural networks. The intricate industrial process involves continuous casting, homogenization heat treatment, reheating, forming (extrusion), and artificial aging. For a given geometry and chemical composition, the microstructural evolution of the material during this process chain defines the end-product properties. Our primary focus is on integrating a neural network combined with an optimization algorithm to precisely regulate thermomechanical processing parameters, enhancing processability and end-product quality while minimizing scrap generation in pursuit of Zero Defect Manufacturing.

A neural network architecture predicts grain size distribution based on extrusion process parameters and in-situ conductivity measurements. The dataset is derived from in-situ measurements of conductivity of six different aluminum alloys during homogenization, implicitly carrying microstructural information, and from finite element simulations of the extrusion process coupled with physically based microstructure simulation.

The optimization algorithm, using Gradient Decent, dynamically adjusts key parameters for the extrusion process, such as ram speed, billet temperature, and tool temperature. The algorithm converges consistently across different initializations to optimized parameters that match the parameters in the simulation, which shows that the optimization works and the model is robust to local minima.

Keywords

Zero Defect manufacturing (ZDM), Quality management, Process Optimization, Metal extrusion

1. Introduction

In the realm of aluminum production, a robust correlation has been established between the conditions of heat treatment and the processability (e.g., extrusion, rolling, forging) as well as the final properties of the resulting product [1], [2]. In particular, the extrusion process is important for the material's performance and quality, which also depends on the microstructure [3]. Information about the material's microstructure can be extracted via ex-situ measurements like microscopy [4].

Many approaches to finding optimized process parameters use statistical methods, as demonstrated in [5], which employs 27 experiments to determine the optimized parameters. These "trial and error"-methods result in scrap generation, as destructively tested sample parts need to be

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manufactured for process verification. Other approaches, such as those described in [6],utilize finite simulation models for predicting the quality of the metal.

Besides that, data availability increases in general in the industry with the emerging trend of the Internet of Things (IoT) and the advancement of artificial intelligence methods, the data-driven approach has become a more easily available and important tool to use [6]. Building on this trend, this paper shows a proof of concept of the integration of an optimization process for microstructural development in Al-Mg-Si alloys with machine learning, particularly neural networks, to finely control the extrusion process. A similar approach for optimized rolling schedule for desired mechanical properties with in-situ measurements was shown by [7]. Another similar data driven approach shows the process parameter optimization for the aluminum alloy casting in [8].

Such process optimization holds the potential to steer the process towards an optimal window, ensuring both enhanced processability and improved end-product properties while minimizing scrap generation. By adjusting parameters in the extrusion process such as temperature and ram speed, the neural network optimization seeks to bring about a substantial increase in productivity within an industrial setting.

2. Material and Methods

2.1. Data and Machine Learning

A neural network was developed with the goal of predicting the grain size distribution within an alloy profile. To facilitate the training of the algorithm, a comprehensive dataset was curated encompassing extrusion process parameters. These parameters were derived from a finite element simulation of the extrusion process, as detailed in [9], [10]. The dataset includes crucial factors such as grain size, grain element position, ram speed, billet temperature, and tool temperature. The simulations were conducted for six different materials, and for each material, 245 simulations were performed with different parameter combinations [10], providing an extensive range of data for the machine learning. The extrusion process was simulated for identical Al-Mg-Si profiles, specifically targeting 6060, 6005A, and 6082, as well as non-standard variations of these alloys with higher Fe content [11].

In addition, in-situ conductometry measurements were incorporated, involving both real and imaginary parts of impedance, along with the sensor temperature. These in-situ measurements were systematically carried out during the homogenization process of six Al-Mg-Si wrought alloys and implicitly carry information about the microstructural evolution during the heat treatment [11].

Each measurement curve within the dataset comprised a substantial 800 datapoints. To optimize computational efficiency, accelerating convergence and avoid overfitting, a one-dimensional convolutional autoencoder (1d-CAE) was employed for dimensionality reduction [12], [13]. This technique allowed condensing the measurement curves down to just 12 essential features. All of the ensembled data can be seen in the following Table 1:

Table 1. Summary of data for grain size prediction

Features	Range	Sequence Length
Ram Speed [mm/s]	1.0, 2.0, 4.0, 8.0, 12.0	1
Billet Temperature [°C]	460, 470, 480, 490, 500, 510, 520	1
Tool Temperature [°C]	460, 470, 480, 490, 500, 510, 520	1
Temperature of the Sensor [°C/min]	1 Measurement	3
Imaginary Curve of Impedance [Ω/min]	1 Measurement	6
Real Curve of Impedance [Ω/min]	1 Measurement	3
Element Coordinates of the profile	1507 (X|Y)-Coordinates	2 (X|Y)
Grain Size [µm]	≈ 1.5 … 360	1

The neural network architecture, as illustrated in Figure 1, consisted of an input layer with 17 inputs, three hidden layers, each containing 64 neurons, and an output layer for grain size prediction. Linear layers and leaky rectified linear [14] unit activation functions were employed in the network

structure. This comprehensive approach facilitated the efficient prediction of grain size distribution based on the provided features seen in table one (except the grain size, which is the prediction target).

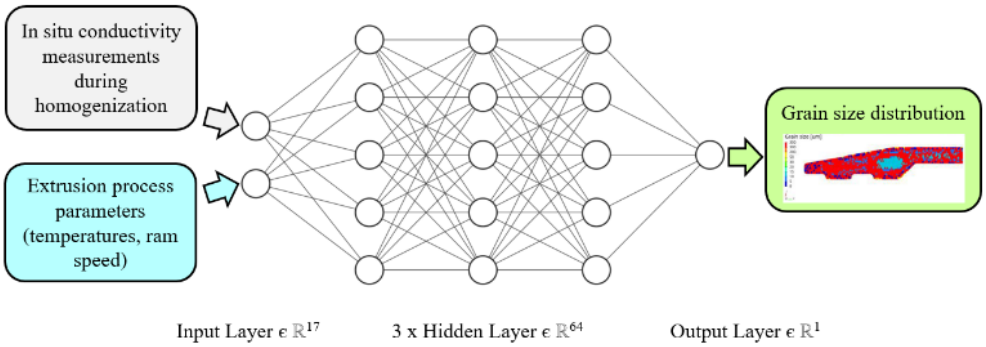

Figure 1: Neural Network Architecture for predicting the grain size distribution based on extrusion process parameters and in situ conductivity measurements

2.2. Optimization Algorithm

To determine the optimal parameters for the model and minimize the objective function (also called cost function or loss), the Gradient Descent optimization algorithm was employed in conjunction with the Adam Optimizer [15], [16]. This combination leverages adaptive learning rates and momentum for enhanced convergence efficiency. The entire process chain, from input variables through the Neural Network (NN) to the objective or loss function (see Figure 2), comprises differentiable functions. This continuity enables the application of the Backpropagation method. The general workflow of the gradient descent optimization is shown in Figure 2.

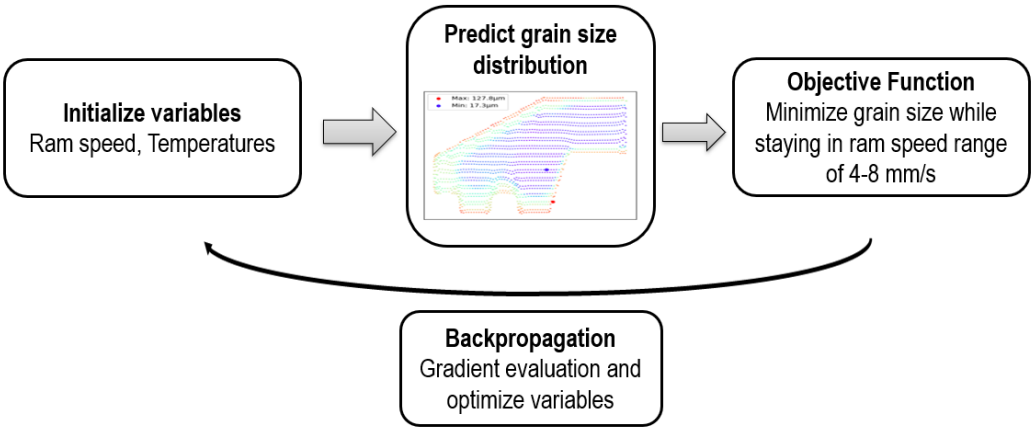

Figure 2: Process chain of the optimization algorithm

The first step of the algorithm involves initializing the variables that should be optimized. The objectives for optimization are the process parameters, including ram speed, billet temperature, and tool temperature of the extrusion process. These parameters are the input for the neural network model, which, alongside known material properties obtained from the measurements (see 2.1), predicts the grain size distribution of the alloy profile. The grain size distribution forms a component of the objective function, the target for minimization.

The second component consists of constraints for the process parameters. The goal is to predict the smallest possible grain size distribution with a process parameter combination within an extrusion ram speed of 4–8 mm/s. Additionally, the model should not extrapolate on the data but find the best set of parameters within its known range. Therefore, in addition to the ram speed constraint, the temperatures are also constrained between 460–520°C.

For the constraints, the following regularization function is implemented, used to regulate the three process variables (ram speed, billet temperature, and tool temperature) in the desired range:

$$regularization(x) = tanh\ tanh\left(\frac{x - width + \epsilon}{\epsilon}\right) * c + tanh\ tanh\left(\frac{-x + \epsilon - (width - 1)}{\epsilon}\right) * c + 2c \quad (1)$$

Here in equation (1), ***width*** is a constant parameter affecting the position and width of the area to regulate, while $\boldsymbol{\epsilon}$ is used to smooth the function, and $\boldsymbol{c}$ scales the output of it. Combining the regularization functions for the process parameters and the model for the grain size distribution that should be minimized, the objective or loss function looks as follows:

$$Loss = NN(r, t_1, t_2) + regularization(r) + regularization(t_1) + regularization(t_2) \quad (2)$$

Here, $\mathbf{r}$, $\mathbf{t_1}$ and $\mathbf{t_2}$ are respectively the ram speed, tool temperature, and billet temperature, while NN stands for the Neural Network, and Loss represents the objective function in equation (2). After evaluating the objective function, the optimization algorithm evaluates the gradients and optimizes the process parameters through backpropagation.

3. Results and Discussion

To test the optimization algorithm in conjunction with the neural network for predicting grain size distribution, eight different optimization runs were conducted using various initial values for the process parameters. After that, the optimized parameter get compared to the simulation data. The results, including the optimized parameters and the corresponding final grain size distribution, are presented in Table 2:

Table 2. Optimized Parameters - ram speed (r) [mm/s], tool temperature (t_1) [°C] and billet temperature (t_2) [°C] - from different Initializations of the Optimization

Starting Value [r, t_1, t_2]	Optimized Parameters [r, t_1, t_2]	Average Grain Size [µm]
[2.1, 466, 466]	[4.03, 461.34, 461.59]	52.32
[3.2, 472, 472]	[4.03, 461.34, 461.59]	52.32
[4.3, 478, 478]	[4.03, 461.34, 461.59]	52.32
[5.4, 484, 484]	[4.03, 461.34, 461.59]	52.32
[6.5, 490, 490]	[4.03, 461.34, 461.59]	52.32
[7.6, 496, 496]	[4.03, 461.34, 461.59]	52.32
[8.7, 502, 502]	[4.04, 461.34, 461.59]	52.35
[9.8, 508, 508]	[4.04, 461.34, 461.59]	52.35
[10.9, 514, 514]	[4.04, 461.34, 461.59]	52.35

The results indicate that, irrespective of the initialized parameters, the optimized parameters consistently converge to approximately 4 mm/s, 461°C, and 461°C. The consistent convergence of the neural network towards the same optimized process parameters across various initial conditions suggests that the model possesses a robust and reliable capability for parameter optimization. The resilience to different initializations indicates that the network model is less susceptible to local minima.

In Table 3, simulation values are listed, showing the temperatures for achieving the smallest Grain Size Distribution in the simulation from [9] for each simulated ram speed.

Table 3. Smallest average grain size for each ram speed from the simulation data of [9]

Process Parameter [r, t_1, t_2]	Average Grain Size [µm]
[1, 460, 470]	41.86
[2, 460, 460]	45.74

[4, 460, 460]	**51.15**
[8, 460, 460]	**58.84**
[12, 460, 460]	65.4

The relevant ram speeds of the simulations are 4 mm/s and 8 mm/s, as that is the regulated area of the optimization algorithm. The values of the optimized parameters, calculated using the optimization procedure, with 4 mm/s, 461°C, and 461°C, align with the simulation parameters from [9] of 4 mm/s, 460°C, and 460°C. Additionally, the prediction of the average grain size between the neural network with 51.15 µm and the simulation from [9] with 52.33 µm aligns.

In summary, the algorithm converges consistently across different initializations to optimized parameters that match the parameters in the simulation, which shows that the optimization works and the model is robust to local minima.

4. Conclusion

This study introduces a proof of concept for a data-driven approach, utilizing neural networks and an optimization algorithm, to optimize the extrusion process of Al-Mg-Si alloys. Other approaches for process optimization use statistical methods with trial and error experiments or attempt to simulate the quality of the extruded alloy [5], [6]. Our optimization approach with machine learning advocates the possibility to eliminate these 'trial and error' methods without the need for simulations by leveraging microstructural information contained in in-situ conductivity curves alongside process parameters such as time/temperature curves and extrusion parameters. Using this data, the neural network predicts the microstructure of the alloy. Furthermore, this model serves as the objective function for the optimization algorithm, dynamically adjusting key parameters. The optimized process parameters consistently converge to values aligned with simulations, which serve as ground truth data, indicating successful optimization.

Despite the challenges posed by limited real-world data availability and the reliance on simulation-driven training, our approach demonstrates robustness in converging towards optimized parameters closely aligned with simulated results. This suggests the potential applicability of our optimization framework in industrial settings.

Future research will focus on accumulating larger datasets of real process data, which could aid in predicting additional product properties beyond grain structure. Furthermore, with these real-world data, the optimization model should be again tested and verified.

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Declaration on Generative AI

The author(s) have not employed any Generative AI tools.

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