Prediction of tool failure in metal hot extrusion process using artificial neural networks

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Abstract. The variation of tool performance and nonuniform process parameters in metal forming are some of the factors that complicate the tool life modeling and analysis of such processes. In this work, a brief discussion about machine learning in analyzing metal extrusion process as well as tool life modeling, and an implemented work of using machine learning to predict failure modes for H13 Steel die used in 6063 Aluminum hot extrusion process is presented. The analysis is conducted on a set of steel dies used in 6063 aluminum hot extrusion process. The data for the failed dies used in this work is collected from a local hot extrusion manufacturer. Using artificial neural network, the prediction of the die failure modes was modeled. Moreover, the model's accuracy and improvement recommendations are presented.

Introduction

Metal extrusion process is one of the most preferable forming processes since it enables the production of relatively complex cross sections with good surface finish [1] . In addition, it provides the flexibility of using the same press for different materials and final cross-sections by using different dies. Due to its excellent deformability as well as considerable strength properties, Aluminum is one of the most widely used working material in this process [2]. Extrusion can be classified as cold or hot process depending on the initial temperature of the billet to be extruded [1]. In hot extrusion, the working material is preheated above the recrystallization temperature [3], to allow processing with lower power requirements and extrusion time. Next, the preheated billet is forced within a chamber through a die to achieve the final end profile.

Along with the initial billet temperature and the extrusion force [4], there are multiple parameters related to the process, material, and geometry such as ram speed, friction at the interfaces, extrusion ratio, number of cavities, metallurgical condition of the billet and deformation characteristics of the tool and working material [5]. The relationship between the input parameters and the extrusion performance exhibits a non-linear correlation [6]. Therefore, it is important to identify an optimum parameter set. An optimum set of process parameters are required to guarantee a final product with acceptable quality while maintaining an efficient power consumption and a long die life [7].

Optimizing the extrusion process parameters and die life as well as studying the metal flow behavior and temperature distribution are the main areas of research in this process [8]. Among all the extrusion process research areas, die life optimization and modeling plays a vital role for the feasibility of the overall process since rapid die failure is a major factor that affects the profitability. For each die replacement, the costs of press down-time, costs of die elements fabrication or refurbishing, and costs of die handling and assembly are all increased [8]. Also, frequent die wear damages are reflected on the final product quality.

The prediction and optimization of die life could be done through a variety of systematic approaches, and they can be divided mainly into three groups as analytical-based models, experimental-derived models, and numerical computation models. Several experimental works have been done to investigate the die life in hot metal extrusion by these methodologies. Akhtar et. al. [9] used a statistical approach and proposed a regression model to predict the die life. A few researchers [10], [11] used Monte Carlo to predict the extrusion die fracture failure and to correlate the stochastic nature of various fatigue and wear related die variables to die life. Simulation based approaches are also used to predict the die life. Akhtar et al. [12] employed finite element (FE) simulations to analyze the extrusion process parameters. Li et al. [13] used FE simulations to study the wear failures in the extrusion dies. Redl et al. [14] also implemented a FE simulation to provide a numerical description of the mechanical and thermal loading during the extrusion process.

Current works from literature show a lack of appropriate tools in predicting the die failure modes in extrusion. Huge data sets required for accurate statistical approaches and time limits associated with FE simulations are some of the common issues. Machine learning approaches provide an alternative solution to predict die failure in hot extrusion. Artificial neural networks (ANN) is one such approach and has been shown to provide excellent predictive capabilities when compared to experimental and simulation results. ANN models give excellent predictive capabilities along with huge time savings when compared to numerical approaches [15]. Bhadeshia [16] has discussed applications of ANN models in materials science. Flow behavior at room and elevated temperatures has also been predicted using ANN models [17], [18]. Cyclic and static loading and damage has also been predicted using ANN models [19], [20]. In addition to these, machine learning approaches such as ANN, GA, and fuzzy learning have also been used in manufacturing processes [21]–[23]. For metal extrusion, several researchers have used ANN to predict the extrusion load [24]–[26]. While a few researchers have used machine learning approaches for die design [27], [28]. However, none of the studies focused on predicting failure modes for hot extrusion dies. In this work, a data driven ANN model is used to analyze die failures during hot extrusion process. The data was collected for H-13 steel dies used in extrusion of aluminum 6063 billets. Results show that ANN can be used for prediction of die failure modes.

Die Failure Mechanisms

Since the final extrudates profitability and quality are directly related to the die performance, comprehensive knowledge about the die failure mechanisms and modes is the key to achieve long die life. Tool-based and operation-based failure reasons are the two main categories for the most influencing factors on die life [8]. Die geometrical and material specifications as well as die manufacturing and surface treatment history are examples of the first category, where billet material and microstructure (recycled or pure) properties with equipment capability and operational settings are examples of the second category [8].

The commonly encountered failure mechanisms in metal extrusion due to those factors are fracture, wear, and deflection [29]. Fracture could be caused by fatigue loading or by thermal and mechanical loading [30]. Wear is induced by several reasons, such as adhesion, that gradual deterioration of the die surface [31]. Deflection occurs after heavy plastic deformation which may alter the shape of the die components [29]. During the service lifetime of the die, various damage types might overlap and act at the same time, which generates mixed modes of failure, with one significant factor. The correlated defects and failure types to the mentioned mechanisms are categorized and listed in Table 1.

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Table 1: Failure types for each failure mechanism [29]

Failure Mode	Failure Types
Fracture (F)	Bearing chip-off (BCO), Corner crack (CC), Die broken/cracked (DB/DC), Bearing broken/cracked (BB/BC), Cavity broken (CvB), Tongue broken/cracked (TB,TC), Detail broken/Path broken/Tip broken/Screw broken/ (DtB)
Wear (W)	Bearing wash-out (BWO), Dimension change/oversize/overweight (DimC/OS/OW)
Deflection (D)	Cavity/die deflected (CvD/DD), Tongue deflected (TD)
Mixed mode (Mx)	Mixed mode (Mx)
Miscellaneous (Msc)	Bearing/cavity damage (BDm/CvDm), Corroded (Crd), Die Modified (DMod)
Mandrel failure(M)	Mandrel broken/cracked/deflected (MB/MC/MD), Web Cracked (WC)

Artificial Neural Network Model

Machine learning (ML) is one of the modern techniques that facilitates the understanding of the available data to draw practical conclusions. In theory, it is the field of study that intended to let computers learn without being explicitly programed where different methods and algorithms are implemented depending on the nature of the problem, number of variables and the suitable model [32]. The field of ML is highly diverse and categorizing its techniques can be achieved in different ways. One widely accepted approach is to separate the ML methods into three main domains as supervised learning, unsupervised learning, and reinforcement learning [33]–[36]. A good structuring of ML domains with some examples of their methods as well as their overlapping are presented in Fig. 1 [37].

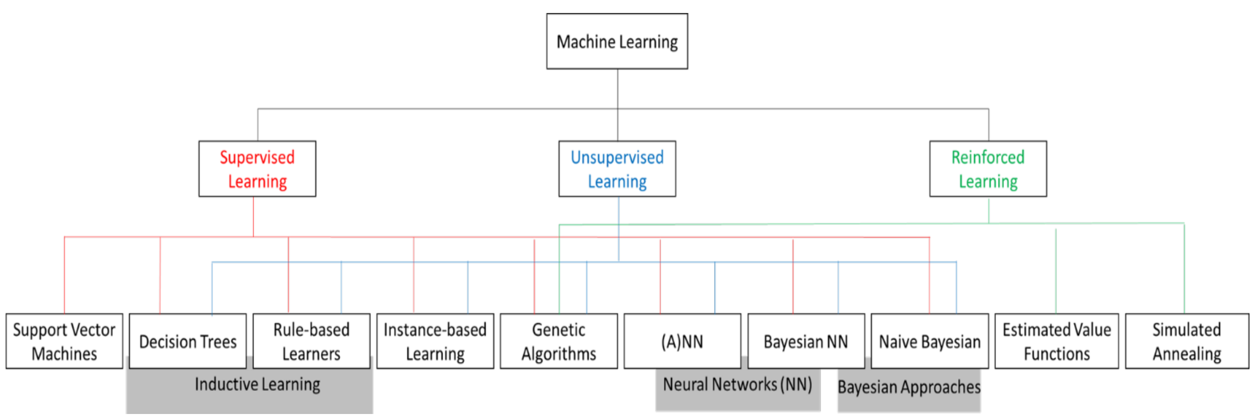

Fig. 1: Machine learning domains and examples [37]

In machine learning, the nature of problems usually depends on a knowledgeable source that states the assumptions and identification sets to train the algorithms [37] The most common techniques in supervised learning, as per the author's observation, are support vector machines (SVM), decision trees (DT), genetic algorithms (GA), and artificial neural network (ANN).

In this work, an ANN model was used to predict the failure modes for failed dies during hot extrusion. Data used in this work was gathered from Aluminium Products Company © (ALUPCO). The collected data for 135 failed H13 steel dies was sorted according to die type, profile, billet quality, nitriding history and failure history. A total of 89 data sets were used in this study. The failure modes were the outputs from the ANN model as shown in Table. 1 [29]. The final dataset used in this work was broken down into training (70%), validation (15%) and testing (15%) sets. It should be mentioned that the extrusion ratio (R) and Secondary Billet percentage (S%), were calculated as:

$$R = \frac{Area\ of\ original\ billet}{Area\ of\ extruded\ billet} \tag{1}$$

$$S\% = \frac{No. of\ secondary\ billets}{Total\ No. of\ extruded\ billets/die} \tag{2}$$

Results and discussion

The output of the artificial neural network (ANN) model was defined as the failure mode for the die. Several ANN models with different neurons and hidden layers were analyzed in multiple iterations to investigate the mean square errors (MSE) with the train, test and validation runs. Fig. 2 shows the iterations of the optimal ANN model. The graph shows the least MSE at 5th iteration. A breakdown of the error distributions for the optimal model is shown in Fig. 3. Error distributions show maximum predictions with near zero error showing reasonable accuracy of the proposed ANN model. A non-skewed distribution shows a well selected model but due to low accuracy, the model needs more work to get better predictions.

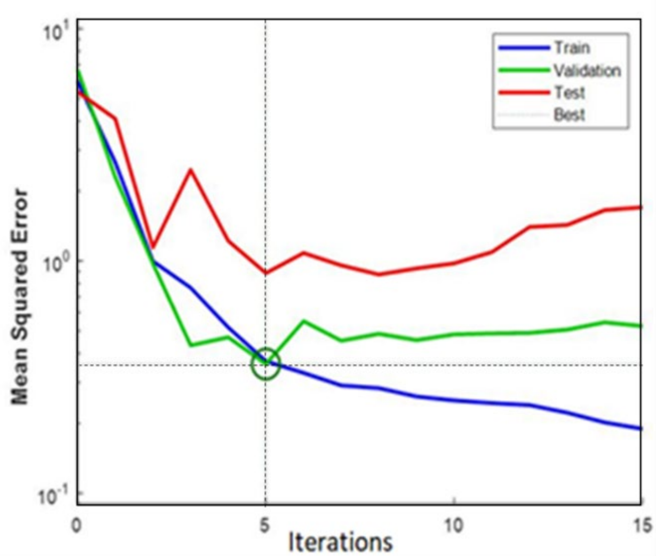

Fig. 2: Proposed ANN model accuracy as per MSE

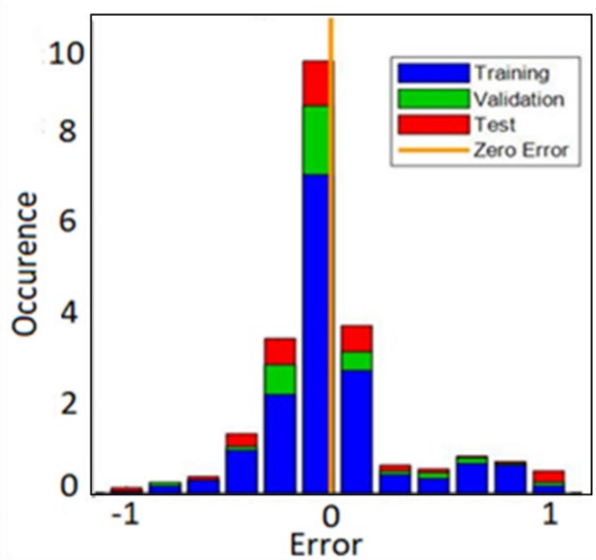

Fig. 3: Proposed ANN model errors analysis

The model predictions along with experimental observations are shown in Fig 4. The linear line shows the correctly matched predictions. Results from the ANN model shows a training accuracy of 70% while testing and validation showed 50% accuracy respectively. However, the overall data set showed an accuracy of 67%. This low performance of the proposed model is highly associated with the choice of input parameters as well as the algorithm suitability for the current conditions. Involvement of more process parameters, such as billet temperature and ram speed, rather than the reliance on geometrical factors enhance the model training ability. Also, integrating other ML methods, such as SVM and GA, with the current ANN algorithm to add more flexibility and proper tuning could improve the model performance and give better results.

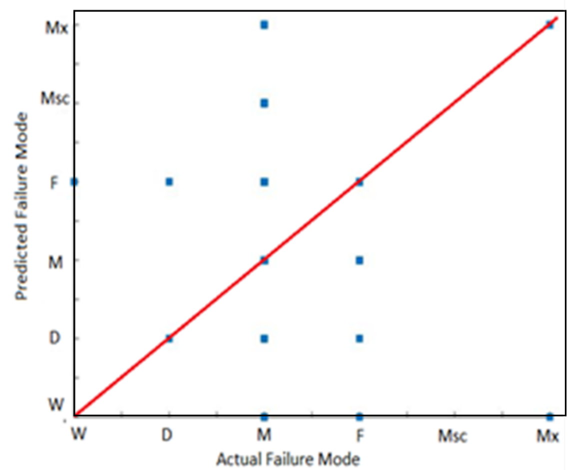

Fig. 4: Proposed ANN model validation

Conclusions

Metal extrusion process parameters are related to each other in a nonlinear manner. The optimization of these parameters is paramount to achieve extrudate with acceptable quality in an efficient power consumption and long die life. Predicting die failure mode is one such factor that that guarantees high productivity. In this work, a machine learning artificial neural network (ANN) model was used to predict the failure mode of extrusion dies. Compared to analytical, experimental, and numerical approaches machine learning based approaches provide a flexible and cost-efficient solution to this problem. A set of 89 data points were used to train, test and validate the ANN model. The input parameters to the model were the die type, cavities, and billet quality whereas failure mode was defined as the output. Results from the proposed model showed a 67% accuracy. It is proposed that the model predictions can be improved with additional parameters such as billet and die temperatures.

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