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Predicting Extrusion Process Parameters Using Neural Networks

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Abstract**—**The objective of this paper is to estimate realistic principal extrusion process parameters by means of artificial neural network. Conventionally, finite element analysis is used to derive process parameters. However, the finite element analysis of the extrusion model does not consider the manufacturing process constraints in its modeling. Therefore, the process parameters obtained through such an analysis remains highly theoretical. Alternatively, process development in industrial extrusion is to a great extent based on trial and error and often involves full-size experiments, which are both expensive and time-consuming. The artificial neural network-based estimation of the extrusion process parameters prior to plant execution helps to make the actual extrusion operation more efficient because more realistic parameters may be obtained. And so, it bridges the gap between simulation and real manufacturing execution system. In this work, a suitable neural network is designed which is trained using an appropriate learning algorithm. The network so trained is used to predict the manufacturing process parameters.

Keywords**—**Artificial Neural Network (ANN), Indirect Extrusion, Finite Element Analysis, MES.

I. Introduction

ONE of the greatest challenges in the design of an actual extrusion operation is to obtain realistic manufacturing process parameters prior to plant execution. However, the conventional finite element analysis does not consider the manufacturing process constraints in its modeling and hence, the process parameters obtained through such an analysis is more theoretical and not realistic enough. This is one of the chief reasons why simulations are not widely accepted by industries for the determination of process parameters for their manufacturing execution systems. Moreover, very less amount of work has been done to bridge the gap between simulation and reality. Therefore, a new approach to obtain more realistic process parameters following the finite element analysis is the need of manufacturing industries. This research tries to bridge this gap between the Finite Element Simulation and the results required by manufacturing execution systems (MES). To do so, artificial neural network is used as a middleware between the results of finite element analysis and the manufacturing execution system to map the FEA results to realistic process variables.

Linear programming and other numerical methods have been used to tackle this problem of estimation of realistic extrusion process parameters. However, due to the inherent time consuming nature of such methods, quick and rapid problem solving as desired by industries have not been achievable. Also, these mathematical models, when presented with a new set of data, do not yield desired results. Additionally, today, the process development in industrial extrusion is to a great extent based on trial and error and often involves full-size experiments, which are both expensive and time-consuming. The use of ANN will reduce the calculation times and it is aimed at eradicating the full-size experiments that have to be carried out prior to actual production processes.

In this work, a suitable neural network is designed which is trained using the Levenberg-Marquardt learning algorithm. The network so trained is used to predict the process parameters for new finite element analysis derivatives. Finally, the performance efficiency of the network in achieving desired process parameters is studied.

II. Background

Sivaprasad, Venugopal, Davies and Prasad [3] have identified the optimum process parameters using finite element simulation. They discuss the use of processing map with the output of the finite element analysis to design the process. Tibbetts and Ting-Yung [4] have used optimization technique for a direct extrusion machine. Their work is related to product optimization with focus on surface quality and micro-structural uniformity of product. They have presented a model which is derived directly from the mathematical description of the physical phenomena present. Hansson, in her Ph.D. thesis [5], has used finite elements method for the simulation of stainless steel tube extrusion.

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Most other extrusion process simulations have been done for food industries like by Lertsiriyothin and Kumtib [6], and plastic or polymer manufacturing units such as by Salazar [7].

The finite element models provide the needed information for theoretical analysis but cannot be applied directly to the manufacturing execution system because the results are not realistic enough. Bajimaya et. al. [8] has tried to obtain realistic parameters by making use of manufacturing process dynamics in the simulation of an extrusion plant. Following the completion of finite element analysis, ANN based estimation of process parameters yields a direct solution for the real process in that realistic process parameters can be recognized directly and quickly. The ANN based estimation of extrusion process parameters dealt with in this research is thus found to be new and novel in the area of bridging the gap between theoretical derivations from simulations to realistic measurements that may be applied to a manufacturing execution system.

III. Indirect Extrusion Process

Extrusion is a plastic deformation process in which a block of metal, called the billet, is forced to flow by compression through the die opening of a smaller cross-sectional area than that of the original billet [4] as shown in Fig. 1. In indirect extrusion process, the die at the front end of the hollow stem moves relative to the container, but there is no relative displacement between the billet and the container as depicted in Fig. 1. Therefore, this process is characterized by the absence of friction between the billet surface and the container, and there is no displacement of the billet center relative to the peripheral regions.

Extrusion can be cold or hot. In this paper, we consider the hot extrusion process. In hot extrusion, the billet is preheated to a certain temperature to facilitate plastic deformation.

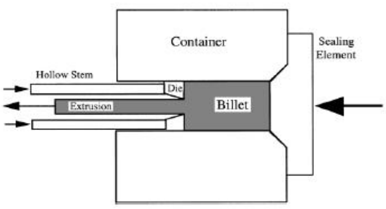

Fig. 1 Indirect extrusion mechanism

The properties of the extruded aluminum shapes are affected greatly by the way in which the metal flows during extrusion. The metal flow is influenced by several factors which are as follows:

a. the temperature of billet, $\theta_{preheat}$
b. the temperature of container
c. the extrusion pressure, $P_{T(ER)}$
d. velocity of extrusion, $V_{extrusion}$
e. the size of billet (length and diameter)
f. the extrusion ratio, ER

For a particular extrusion process, the size of billet and the extrusion ratio are constant. Extrusion ratio (ER) is the ratio of container bore area to the total cross-sectional area of extrusion. Therefore, the main factors affecting an extrusion process include the extrusion temperature, the extrusion pressure and the velocity of extrusion. These three variables, which make the principal extrusion process parameters, are obtained through empirical calculations such as the popular Avitzur method [12]. These empirical calculations make use of the outputs of finite element analysis that consist of flow stress, strain, strain rate and shear stress to obtain the process parameters. However, these empirical methods do not give appropriate results for all ranges of inputs. Thus, the industry lacks a method that offers them a solution to a wide variety of inputs.

IV. Interdependence between Extrusion Variables

During the operation of an extrusion plant, while extrusion is taking place, billets will be waiting for their turn to get loaded to the container for extrusion. In hot extrusion, the billets are preheated. It should be assured that the next billet in queue is heated to the required preheat temperature ($\theta_{preheat}$) during the time (τ_{wait}) it waits in the queue. For efficient heat usage, τ_{wait} would be approximately equal to the sum of the time taken by the current billet to be extruded ($\tau_{extrusion}$) and the time taken for the change of die ($\tau_{dieChange}$). Therefore, considering the time taken to preheat to be $\tau_{preheat}$,

$$\tau_{preheat} = \tau_{wait} = \tau_{extrusion} + \tau_{dieChange}$$

Temperature is one of the most important parameters in extrusion. The flow stress (σ) is reduced if the temperature is increased and deformation is therefore, easier, but at the same time, the maximum extrusion speed is reduced because localized temperature can lead to incipient melting temperature.

The response of a metal to extrusion processes can be influenced by the speed of deformation. Increasing the ram speed produces an increase in the extrusion pressure. The temperature developed in extrusion increases with increasing ram speed.

Thus, it is important to determine the optimal values of the principal extrusion variables for a specified extrusion ratio (ER) such that, while on the one hand, the aluminum billet does not reach its solidus point ie, it's melting temperature, and on the other hand, efficient extrusion is assured.

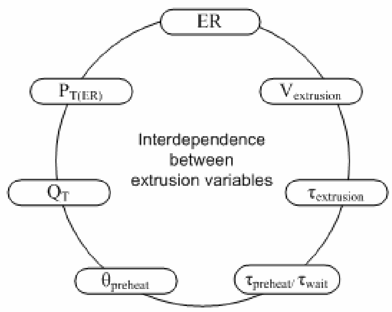

Fig. 2 Interdependence between extrusion variables

Determination of ram speed ($V_{extrusion}$) is another important thing for a particular extrusion ratio. The ram speed affects the extrusion time ($\tau_{extrusion}$). The preheat time ($\tau_{preheat}$), in turn, is related to the extrusion time. The extrusion time is used to decide the amount of heat (Q_T) that a waiting aluminum billet should be given to reach the preheat temperature ($\theta_{preheat}$) during the period of its waiting time (τ_{wait}).

The actual pressure exerted on the ram is the total pressure required for a particular extrusion ratio (ER) given by:

$$P_{T(ER)} = P_D + P_F + P_R$$

where, P_D is the pressure required for the plastic deformation of the material. P_F is the pressure required to overcome the surface friction at the container wall friction, dead metal zone friction, and die bearing friction. P_R is the pressure required to overcome redundant or internal deformation work.

Each of the above may be represented in functional form as:
$P_D = \mathbf{f}$ (flow stress σ, strain ε)
where, the flow stress $\sigma = \mathbf{g}$ (strain ε, strain rate, temperature of material T).
Here, strain $\varepsilon = \ln(A_C/A_E)$ where, A_C = area of container and A_E = area of extrusion
$P_F = \boldsymbol{\varphi}$(billet diameter D, length of billet L)
$P_R = \boldsymbol{\psi}$ (flow stress σ)

The extrusion pressure, $P_{T(ER)}$, is thus dependent upon the size of the billet, the extrusion ratio, the temperatures of billet and container, flow stress and the strain rate of aluminum of which the first two remain constant for a particular extrusion process.

These variables that affect the extrusion process are functionally related to each other. Attempts have been made to equate them to each other but these attempts have failed to incorporate all the variables as such since there exists a non-linear functional relationship between them. In particular, the relationships between the stress, strain, strain rate and the shear stress obtained from the finite element analysis to the extrusion temperature, pressure and velocity required by the manufacturing execution system have been found to be non-linear. Hence, in this work, an effort has been made to map them to each other by means of artificial neural network.

IV. Methodology

The mapping of finite element analysis (FEA) outputs to the realistic extrusion process parameters is a function approximation problem. Additionally, there is a non-linear functional relationship between the FEA outputs and the extrusion process parameters. This makes artificial neural network based mapping most suitable for the solution of such problems because neural networks are best suited for function approximation problems where the inputs and outputs are related through non-linear functions. In this research, MatLab is used to design a suitable neural network. A feed-forward neural network with back propagation is used. The network consists of two layers. The first layer, which is the hidden layer, is triggered using the sigmoidal activation function whereas the second layer, which is the output layer, is triggered using the linear activation function as shown in Fig. 3. A network of two layers, where the first layer is sigmoid and the second layer is linear, can be trained to approximate any function.

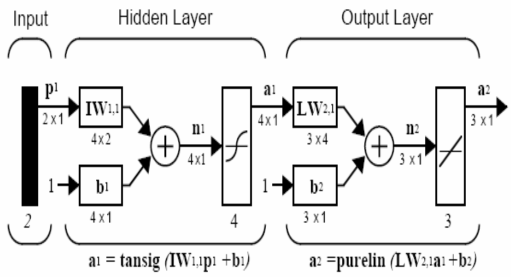

Fig. 3 A two-layer feed forward network

The network is trained using a suitable supervised learning algorithm, in this case, the Levenberg-Marquardt algorithm. In the case of supervised learning, the network is presented with both the input data and the target data called the training set. The network is adjusted based on comparison of the output and target values until the outputs match the targets as shown below in Fig. 4. In other words, the learning rule is used to adjust the weights and biases of the network in order to move the network outputs closer to the targets.

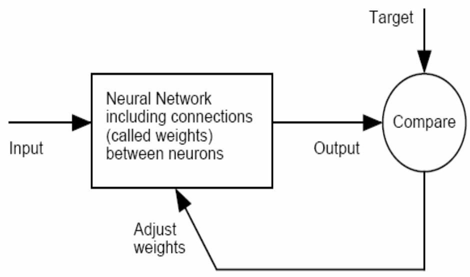

Fig. 4 Input-Output Comparison

The trained network is then used to predict the process parameters for the production of new products following their finite element analysis. These parameters are then sent to virtual commissioning for the validation of process parameters. The complete architecture for the implementation is shown in Fig. 5.

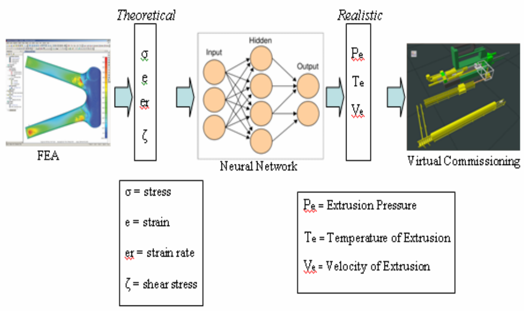

Fig. 5 The implementation architecture

V. Implementation

To carry out the implementation, a suitable neural network was designed. The network has two layers. The first is a hidden layer that has sigmoidal activation function and the second is an output layer that has linear activation function. The hidden layer is designed to have sixteen nodes whereas the output layer has three nodes, one each for the extrusion pressure, temperature and velocity. The network is presented with inputs and targets and trained using the Levenberg-Marquardt supervised back-propagation learning algorithm. The inputs include stress, strain, strain rate and the shear stress. The targets include extrusion pressure, temperature and velocity. The training curve using this algorithm is shown in Fig. 6.

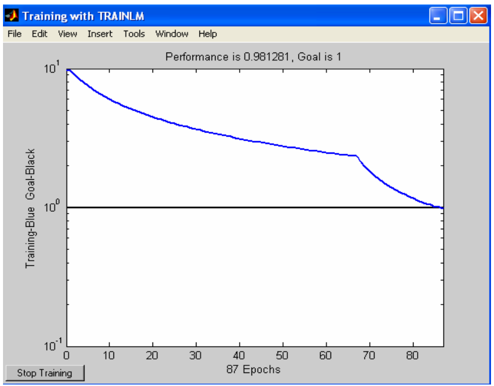

Fig. 6 The training curve

The available data is divided into two subsets; a training set, to construct the neural network model, and an independent validation set to estimate model performance in the deployed environment. However, dividing the data into only two subsets may lead to model overfitting. As a result, and as discussed later, crossvalidation is used as the stopping criterion in this study and, consequently, the database is randomly divided into three sets: training, testing, and validation. In total, 80% of the data are used for training and 20% are used for validation. The training data are further divided into 70% for the training set and 30% for the testing set.

The way the data are divided can have a significant impact on the results obtained. Like all empirical models, ANNs are unable to extrapolate beyond the range of their training data. Consequently, in order to develop the best possible model, given the available data, all patterns that are contained in the data need to be included in the training set. Similarly, since the test set is used to determine when to stop training, it needs to be representative of the training set and should therefore also contain all of the patterns that are present in the available data. If all the available patterns are used to calibrate the model, then the most challenging evaluation of the generalization ability of the model is if all of the patterns are also part of the validation set. Consequently, it is essential that the data used for training, testing, and validation represent the same population. In order to achieve this in the present study, several random combinations of the training, testing, and validation sets are tried until three statistically consistent data sets are obtained. The statistical parameters considered include the mean, standard deviation, minimum, maximum, and range. Despite trying numerous random combinations of training, testing, and validation sets, there are still some slight inconsistencies in the statistical parameters for the training, testing, and validation sets that are most closely matched (Table I). This can be attributed to the fact that the data contain singular, rare events that cannot be replicated in all three data sets. However, on the whole, the statistics are in good agreement and all three data sets may be considered to represent the same population.

The performance goal was 1. The actual performance reached was 0.981281. This goal was reached in 87 number of epochs.

After the network was trained, it was used for the prediction of realistic extrusion process parameters. The graphs comparing outputs (the predicted data) and targets (the actual data) for the extrusion pressure, extrusion temperature and velocity of extrusion are shown in Figs. 7, 8 and 9 respectively.

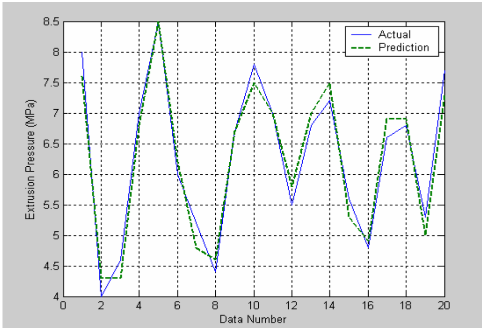

Fig. 7 Graph showing outputs versus targets for extrusion pressure

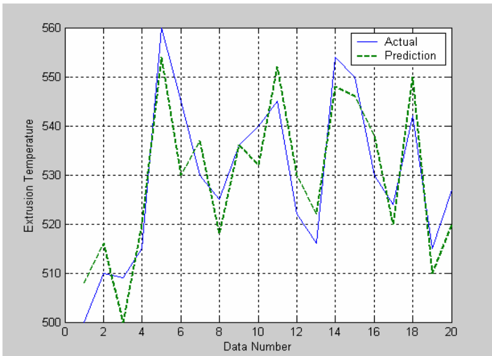

Fig. 8 Graph showing outputs versus targets for extrusion temperature

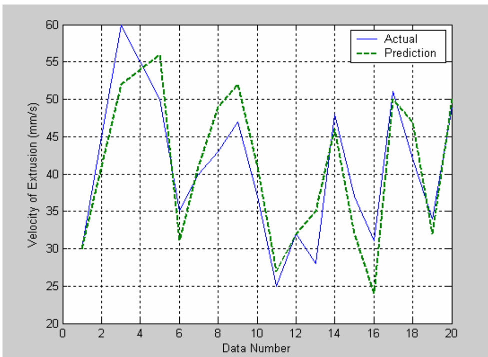

Fig. 9 Graph showing outputs versus targets for velocity of extrusion

The sum of mean square error (MSE) and the sum of mean absolute deviation (MAD) were used to evaluate the performance of the network. The MSE is defined as the difference between the actual observations and the response predicted by the model and is used to determine whether the model does not fit the data. As can be seen from Table I, the MSE and MAD are within the limits of acceptable error. This proves the feasibility of the use of neural network for the prediction of extrusion process parameters within acceptable limits.

TABLE I
PERFORMANCE EVALUATION

	Ac. Error	MSE	MAD
Pressure	1	0.915	0.892
Temperature	10	6.223	6.541
Velocity	10	7.466	7.339

VI. CONCLUSION

Finite element simulations have been widely used to derive the extrusion process parameters. However, such simulation studies have been limited to academic research only. This is because finite element simulation results are highly theoretical as they do not consider the constraints encountered in a real manufacturing process. In this research, a middleware made from artificial neural network is used to bridge this gap between finite element simulation and real manufacturing execution system. And so, this research aids in the determination of more realistic process parameters that may be used by a real manufacturing system.

Also, it has been found that the outputs of the finite element analysis and the real extrusion process parameters are related through a non-linear function. The mapping of the finite element outputs to real process parameters is thus a function approximation problem. Artificial neural networks are best suited to solve such industrial problems. This research proves and paves a new avenue in the determination of realistic extrusion process parameters by the use of artificial neural network. This method, in the future, may be further applied to other manufacturing processes as well.

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