Cascade-Correlation Neural Network Modeling of the Abrasive Flow Machining Process

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Abstract

This paper presents some preliminary work for modeling the abrasive flow machining (AFM) of automotive engine air intake manifolds using a cascade-correlation neural network approach. AFM has not been widely used because of the lack of theoretic support for the complex behavior of the process. Currently, this process can only be monitored subjectively by the plant engineers and is not suited for mass production of manifolds. The objectives of this research are to improve the functional performance of automotive engines and to enable cost effective process control of the AFM process. A neural network model is used to capture the nonlinear relationship between the AFM media and the specified outgoing air flow rate by using part characteristics such as surface finish and weight and process parameters such as media temperature. This model allows the prediction of when the machining process should be terminated to meet the air flow specification and can be used as an off-line controller for the process. A leave-one-out cross validation method is used to validate and demonstrate the performance of the model in predicting the specified outgoing air flow rate for new values of the independent variables.
Keywords: Abrasive Flow Machining, Neural Network, Cascade Learning, Process Control, Engine Manifold, Cross Validation.

1. Introduction

The manufacture of precision parts emphasizes final finish machining operations, which may account for as much as 15% of total manufacturing costs. Proper finishing can dramatically improve product performance while reducing direct labor costs [1, 2]. Abrasive flow machining (AFM) has the potential to provide a high precision and economical means of finishing parts.

AFM is a nontraditional finishing process that is used to deburr, polish or radius surfaces of critical components. It was initially developed for deburring aircraft valve bodies. Current applications include the aerospace, automotive, electronic, medical component and die-making industries. AFM can process many selected passages on a single workpiece or multiple parts simultaneously. Inaccessible areas and complex internal passages can be finished economically and productively [1, 2, 3]. However, AFM has not been widely used because of the lack of theoretic support for the behavior of the process. In order to understand the process, a large range of process parameters such as extrusion pressure, media viscosity, media rheology, abrasive size and type, part geometry and others must be taken into consideration.

An air intake manifold is part of automotive engines (see Figure 1). It consists of 12 cylindrical “runners,” through which air flows (shaded in Figure 1). These runners are of complex geometries. The manifold is attached to the throttle body in the engine through a large hole (middle front of Figure 1). Engine manifolds are too complex to be economically machined by conventional machining or grinding, and are typically sand cast. In modern engines, manifolds are most likely to be made of aluminum. The sand cast cavities have rough and irregular surfaces that retard air flow, particularly at the passage walls. This imperfect finish has a significant detrimental impact on the performance, fuel efficiency, and emissions of automotive engines [4].

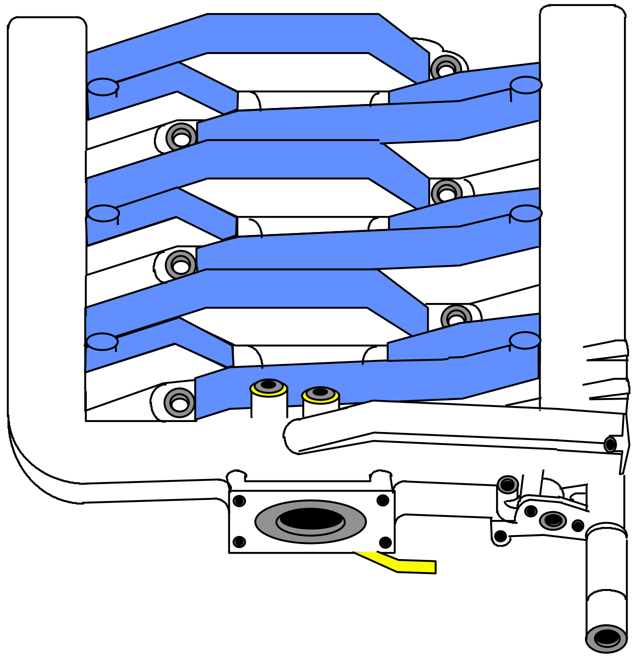

Figure 1. Drawing of Air Intake Manifold.

AFM can finish sand cast manifolds so that the interior passages are smoother, more uniform and can achieve more precise air flow specifications. This can increase engine horsepower and improve vehicle performance. However, the AFM process is not currently economical for mass production of manifolds. Currently, in order to AFM engine manifolds, technicians preset values for the total volume of media that will be extruded through the manifold and the hydraulic pressure based on their experience. After this operation is finished, they clean the manifold and test the outgoing air flow. If specifications have not been made, they will repeat the process until the manifold achieves the desired air flow requirements. On the other hand, if the manifold is overmachined, they will have to scrap the part.

This paper describes the preliminary development of a neural network model as an off-line controller for abrasive flow machining of automotive engine manifolds. For a given set of cast manifold characteristics such as incoming average air flow, incoming weight, throttle body diameter (i.e., the diameter of the large hole at the bottom of the drawing in Figure 1) and surface finish, and machining parameters such as extrusion pressure and volume of media extruded, this model will accurately predict when the AFM process has achieved the specified air flow requirements for engine intake passages. It will be able to adapt to changes in the process variables (i.e., abrasive flow material properties, fluid temperature, degradation of the fluid through repeated use, and ambient temperature and humidity). This project is currently underway and this paper reports preliminary results.

2. Abrasive Flow Machining Process

AFM is the removal of material by a viscous, abrasive laden semi-solid grinding media flowing under pressure, through or across a workpiece. The process is abrasive only where the media flow is restricted. Generally, the media is extruded through or over the workpiece with motion usually in both directions. The velocity of the extruded media is dependent upon the principal parameters of viscosity, pressure, passage size, geometry and length [5, 6]. Places that have the greatest restriction will produce the largest grinding forces. Four main types of abrasives are used in AFM. These are aluminum oxide, silicon carbide, boron carbide and diamonds. The AFM process acts in a manner similar to grinding or lapping where the extruded abrasive media gently hones edges and surfaces. It is particularly useful when applied to workpieces containing passageways that are considered to be inaccessible with conventional deburring and polishing tools [2, 3, 5, 6].

Previous research on the AFM process include Fletcher et al. [7], Davies and Fletcher [8], Williams and Rajurkar [9, 10], Williams et al. [11], Petri et al. [12] and Lam and Smith [13, 14]. Fletcher et al. investigated the thermal and fluid flow properties of polymers used in AFM. They showed that the rheology of the media contributes significantly to the success of the AFM process [7]. Davies and Fletcher studied the relationship between the rheological characteristics of several mixtures and their associated machining parameters. They concluded that both the viscosity and the grit ratio affect the temperature and pressure drop across the workpiece. They identified temperature as an important variable in the AFM process due to its effect on the viscosity [8]. Williams and Rajurkar showed that media viscosity and extrusion pressure significantly determine both surface roughness and the material removal rate. The authors indicated that the major improvement in surface finish takes place within the first few cycles. Their later work proposed methods to estimate the number of dynamic active grains involved in cutting and the amount of abrasive grain wear per stroke [9, 10]. Williams et al. presented an experimental and qualitative analysis of the distribution of metal removal in multiple hole finishing applications. They found that using AFM on a workpiece with one center hole and four outer holes resulted in thirty more percent in metal removal in the center hole than in the outer holes. They also studied metal removal and surface roughness characteristics per cycle for a single hole part and concluded that the most pronounced change in the bore diameter and surface roughness occurred on the first cycle [11].

However, each of these studies considered only a subset of the process parameters and ignored other critical parameters. Petri et al. developed a predictive process modeling system for the AFM process that relates all of the critical parameters using strictly empirical techniques, namely neural networks [12]. Their system addressed process settings for AFM for a variety of products and material types. The research in this paper focuses on one particular product type (*viz*., engine manifolds), like Lam and Smith [13, 14], but with the demand of more precise control to meet stringent specifications and with the consideration of a larger set of process parameters.

3. Neural Networks for Process Modeling

Analytical models that explain a highly non-linear relationship with interactions among process variables are often difficult to obtain. Moreover, there are no analytical models that capture the dynamics of the entire abrasive flow machining process. Artificial intelligence techniques, such as neural networks and expert systems, have been increasingly used to successfully model complex process behavior in areas where adequate analytical models are unavailable.

The use of neural networks is motivated because of their accommodation of non-linearities, interactions, and multiple variables. Neural networks are also tolerant of noisy data and can operate very quickly in software. Unlike statistical models, which generally require assumptions about the parametric nature of the factors (which may or may not be true), neural networks do not require *a priori* assumption of the functional form of the model. Some of the recent work in using neural networks for modeling manufacturing processes include [12-18].

4. Neural Network Model Development

A neural network based process controller for abrasive flow machining of engine manifolds was developed for a consortium including an AFM manufacturer and a U.S. automotive manufacturer. The first objective of this research is to improve the functional performance of U.S. automotive engines, hence generate the economic benefits of reduction in fuel consumption. The second objective is to enable predictive process control of the AFM process, with an understanding of the relationship between the AFM media to the specified air flow rate of the engine manifolds. This understanding may be useful in controlling and optimizing the AFM process for parts similar to the manifold.

Four major tasks were undertaken to develop the model: (1) identification of the key process variables, (2) data collection, (3) preliminary neural network development, and (4) model validation.

4.1 Process variables

The first step was to determine which process variables were critical to the AFM process and should be included as process input parameters to the neural network. Table 1 summarizes these process variables. Some of these variables may not be independent of each other. The development of the predictive model was an attempt to capture the behavior of both the independent and interaction effects of these variables so that it can accurately predict the flow of the orifice fluid (*viz*., air) through the manifold. The main categories of process variables are:

- Incoming part **-** weight, surface finish, air flow, throttle body diameter
- AFM machine setting **-** pressure, volume of media extruded, number of passes, media flow rate
- Media condition **-** grit, freshness, media temperature, part temperature
- Ambient conditions **-** temperature, humidity

Table 1. Process Variables.

Process Variables	Definition
Incoming weight	The shipped weight of the manifold
Throttle body diameter	The diameter of the throttle body orifice
Surface finish	The surface roughness inside the throttle body orifice
Runner airflow	The airflow rate through each paired runner
Variability of runner airflow	The variability of airflow rate among the 6 pairs of runners
Ambient temperature	The temperature in the plant
Ambient humidity	The humidity in the plant
Production sequence	The sequence of the production during the day
Number of parts prior to current part	The number of parts machined prior to the current part in a work day
Media condition	The condition of the media (cutting ability, contamination level)
Hydraulic pressure	The extrusion pressure of the media
Volume of media extruded	The volume of media extruded through the part
Media flow rate	The rate of media flow through the part
Number of passes	The number of cycles of the AFM machine piston
Media temperature	The temperature of the media
Part temperature	The temperature of the part

There is variability among the incoming parts due to the limitations of the sand casting process. The total volume of media extruded and the pressure for the AFM processing is preset by the operator depending on his judgment of when the manifold reaches air flow specifications. These two machine settings determine the number of passes needed and the media flow rate for the process. The ambient conditions impact the condition of the media. The primary variables of media condition are extremely important. The media starts new with a amount of grit and no impurities. Over time, impurities enter into the media from the metal being AFM'ed and the grit becomes less abrasive. This has a profound impact on the AFM process, however measurement of media condition during processing is impossible. Another change in media condition occurs daily. The behavior of the media depends partially on its temperature. At the beginning of a day, the media is cold, however after repeated processing, it becomes heated. The sequence of production and the number of parts machined prior to the current part (Table 1) are very crude approximations to this heating effect. Time of production was divided into five periods beginning in the morning (period 1) and ending with the work day (period 5). Each part was assigned to one of these periods depending on its time of production. The number of parts machined prior to the current part is simply a counter for another measure of the changing characteristics of the media during a work day.

The outcome variables of interest are all specific to the manifold:

- Average air flow per runner
- Surface finish
- Weight
- Throttle body diameter

While all of these outcome variables define the state of the finished manifold, the primary specification is the first one - average air flow per runner through the manifold. It is this specification that the model described here targets.

4.2 Data set

Production data on the variables described in Table 1 (except the ambient conditions and the media condition) was collected by the company's technicians. Fifty eight observations were collected. For the processing variables (i.e., pressure, volume of media extruded, media flow rate and media temperature) which were collected on a per pass basis during the AFM process, additional statistics such as: the range, the median, the average, the gradient and the standard deviation were derived to represent some of the dynamics during the AFM process. A first order stepwise regression model was developed using the entire data set to identify the statistical significant variables for the neural networks. Regression results indicated that these variables can explain 87.00% of the variance of the outgoing average air flow. Input variables to the networks include the following: incoming average air flow, median of media flow rate, range of media temperature, range of part temperature, standard deviation of volume of media extruded, average pressure and the number of parts machined prior to the current part. The outcome variable studied was outgoing average air flow.

4.3 Cascade-correlation neural network

The neural network architecture for predicting the outgoing average air flow of engine manifolds was created using the cascade-correlation learning algorithm, available in the software package of NeuralWorks. The training parameters and the maximum number of epochs were selected through experimentation and examination of preliminary networks. A cascade-correlation learning algorithm was used because it learns very quickly and the network determines its own size and topology [19]. This algorithm starts off with no hidden neurons, with only direct connections from the input units to the output units. Then the hidden neurons are added one at a time, and the purpose of each new hidden neuron is to predict the current remaining output error in the network. Unlike the traditional backpropagation learning algorithm, the hidden neurons are allowed to have connections from the pre-existing hidden neurons along with the connections from the input units. Figure 2 illustrates a typical cascade architecture.

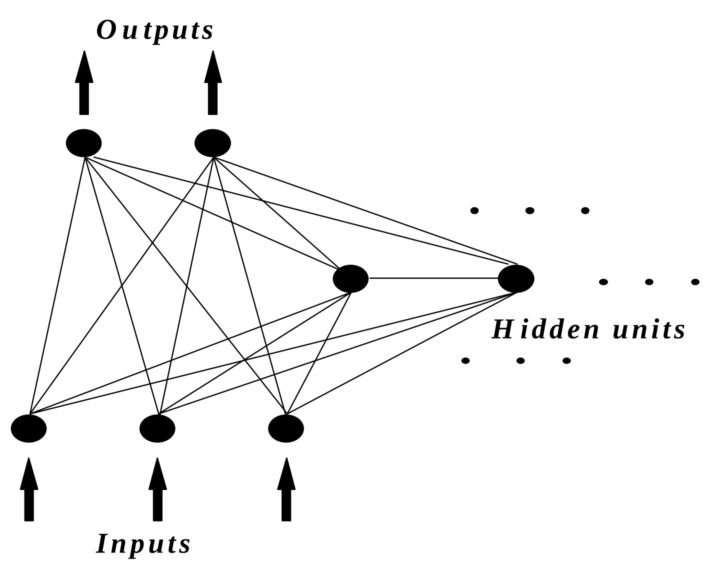

Figure 2. A Typical Cascade-Correlation Neural Network.

The final network architecture had 7 inputs, one hidden layer with 10 neurons, and a single output. The learning rate was fixed at 0.10 and the unipolar sigmoid transfer function was used.

5. Results and Discussion

A leave-one-out cross-validation approach, using the entire data set for model evaluation, was used [20, 21]. Despite the computational effort, this approach was chosen in favor of a grouped cross-validation approach because it provides a better estimate of the performance of the final network especially when the amount of data is scarce. This approach required building fifty eight validation networks with each trained on fifty seven observations and tested on the left-out observation. Each validation network has a different left-out data point and combining all the left-out data points for all the validation networks exhausts the entire data set. All of the validation networks were built using parameters identical to those of the final network described above with an upper bound of 10 hidden neurons.

Figure 3 verifies that the final network has nearly unbiased generalization to all combinations of the independent variables used in this study. Figure 4 shows the leave-one-out cross-validation networks and their predictions on each left-out data point against the actual observed outgoing average air flow.

The final network was able to predict the outgoing average air flow with a mean absolute error of 0.0972 (0.0569%) and a root mean square error of 0.1358 (0.0794%). The R-squared (coefficient of determination) value of the final network, which was estimated by the validation networks, is 0.8741 which means that the network can explain about 87 percent of the variance in the outgoing average air flow.

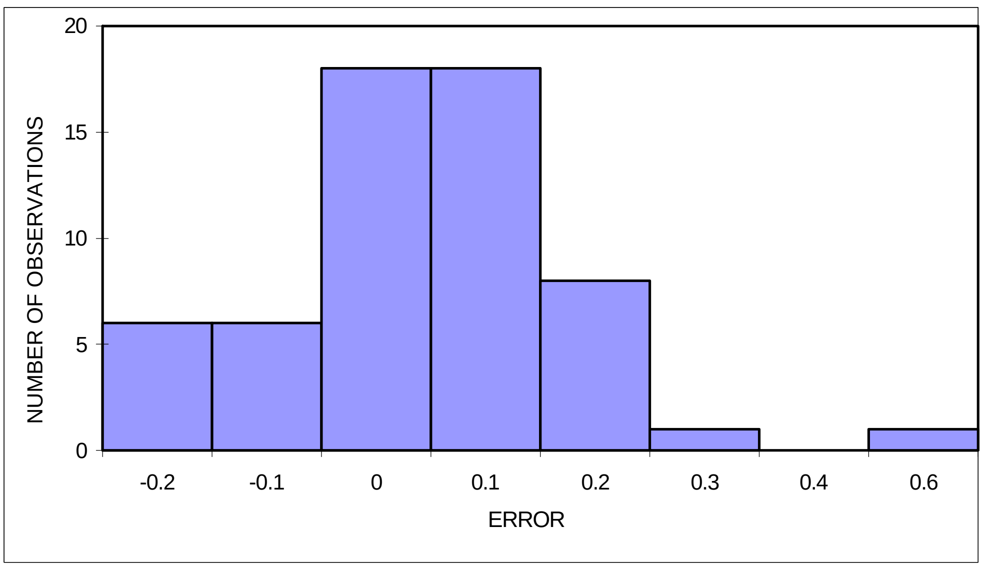

Figure 3. Histogram of Residuals of Leave-one-out Cross-Validation.

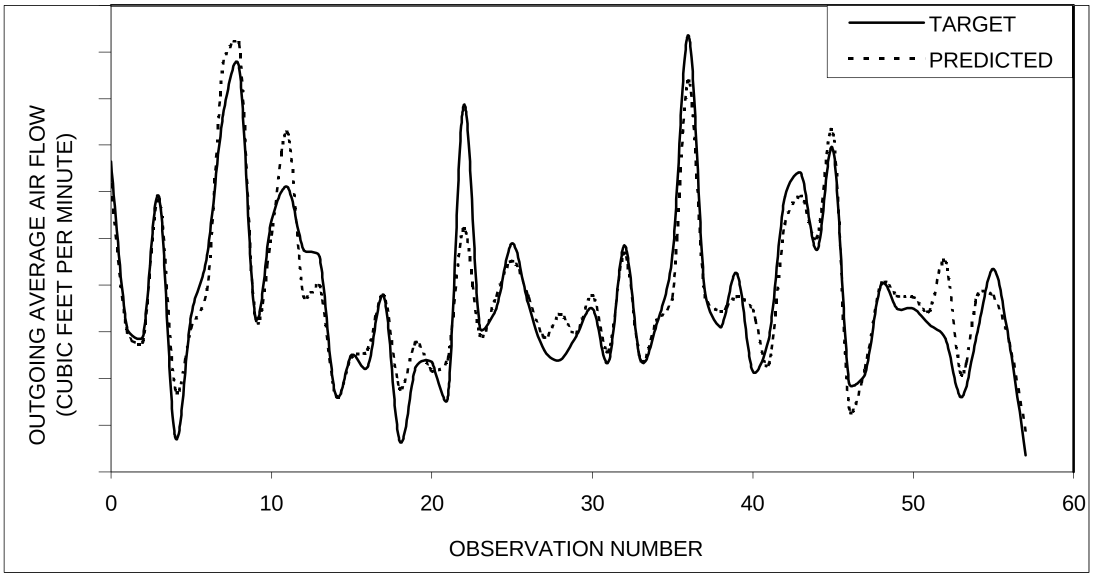

Figure 4. Performance on Leave-one-out Cross-validation: Predicted Against Target Outgoing Average Air Flow.

6. Conclusion

The cascade application network outperforms the first order stepwise regression model. This indicates that some of the nonlinear relationship among the variables are captured in the network model. Moreover, it also performs better than the backpropagation network illustrated in Lam and Smith [14].

The model will be improved with additional information from Table 1 that is expected to be monitored. The main area not adequately addressed by this preliminary neural network is the condition of the media. The inputs concerned with the media condition are: media temperature, part temperature and the number of parts machined prior to the current part. These measures only provide a crude surrogate for media condition. Also, as the data set expands to more observations, including experimental data which will be collected over the entire range of interest for each variable, the neural network predictive model should improve in precision.

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