Neural Network Modeling of Abrasive Flow Machining

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Abstract

This paper discusses the preliminary development of a neural network-based process monitor and off-line controller for abrasive flow machining of automotive engine intake manifolds. The process is only observable indirectly, yet the time at which machining achieves the specified air flow rate must be estimated accurately. A neural network model is used to estimate when the process has achieved air flow specification so that machining can be terminated. This model uses surrogate process parameters as inputs because of the inaccessibility of the product parameter of interest, air flow rate through the manifold during processing. The primary project participants are Extrude Hone, Ford Motor Company and the University of Pittsburgh.

Keywords: Abrasive flow machining, neural networks, process monitoring, process optimization, engine intake manifold.

Introduction

The manufacture of precision parts emphasizes final finish machining operations, which may account for as much as 15% of the total manufacturing costs [12, 13]. Abrasive flow machining (AFM) is a nontraditional finishing process that is used to deburr, polish or radius surfaces of critical components. It has been applied in the aerospace, automotive, electronic 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 [12, 13]. AFM is being used to finish air intake manifolds for the Ford Contour SVT [14] as part of this project.

The air intake manifold (Fig. 1) is that part of an engine that directs the flow of air from the throttle body to each of the (in this case twelve) intake valves. Air flows into the manifold through a single large orifice, where it is then divided into twelve “runners” that lead to the intake valves. The complex geometry and internal passages of the manifold dictate manufacture by sand casting, if the component is to be metallic. Injection molded plastic is a generally more expensive option. It has previously been determined that the Ford Contour SVT intake manifold will be an aluminum alloy.

An optimal intake manifold would deliver precise, predetermined quantities of air to each of the intake valves during each cylinder's intake cycle. To obtain such an outcome for each of the many thousands of intake manifolds to be produced demands an innovative final machining method. Sand casting is not capable of producing finish parts to the high dimensional tolerances required and traditional final finish machining processes are not suitable for the interior passages of the intake manifold. In addition to the low dimensional tolerances of the air flow passages in the as-cast manifold, sand casting leaves rough, irregular surfaces that retard air flow and generate turbulence making the manifold even less optimal. It has been demonstrated that AFM can finish the sand cast manifolds so that precise air flow specifications are met and the roughness of internal passages is greatly reduced. However, the AFM process is not currently economical for mass production of manifolds because the target specification — air flow rate through the manifold with a given pressure differential — is not measurable during processing. This necessitates operator intervention and iterative processing of parts.

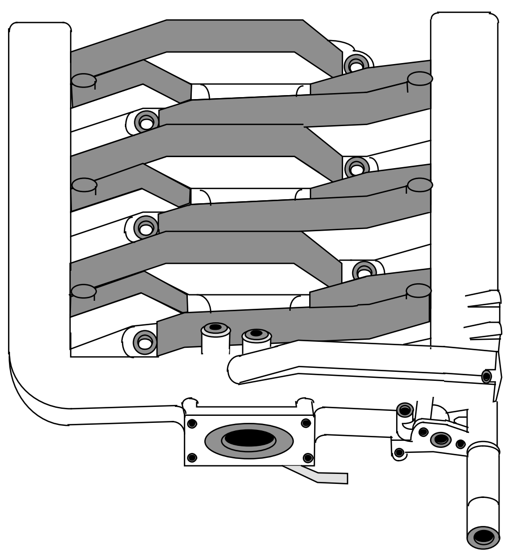

Figure 1. Drawing of Air Intake Manifold.

This paper describes the preliminary development of a neural network-based process monitor and off-line controller for abrasive flow machining of engine manifolds. For a given set of as-cast manifold characteristics and a set of machine parameters this model will predict when the AFM process has achieved the specified air flow requirements for engine intake passages. This project is currently underway and this paper reports preliminary results.

Background

The 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. 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 [3]. Four types of abrasives are commonly 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, 8, 11, 13].

Previous research on the AFM process include Fletcher et al. [4], Williams and Rajurkar [16, 17], Williams et al. [18], and Petri et al. [10]. Fletcher et al. studied 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 [4]. Williams and Rajurkar showed that media viscosity and extrusion pressure significantly determine both surface roughness and 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 [16, 17]. Williams et al. presented an experimental and qualitative analysis of the distribution of metal removal in multiple hole finishing applications. They also studied metal removal and surface roughness characteristics per cycle for a single hole part and found that the most pronounced change in the bore diameter and surface roughness occurred on the first cycle [18]. Petri et al. developed a predictive process modeling system for the AFM process that relates the critical parameters using strictly empirical techniques, namely neural networks [10]. 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) but with the demand of precise control to meet stringent specifications.

Neural Networks for Process Modeling

Analytical models that explain a highly non-linear relationship with interactions among process variables are difficult to obtain. Moreover, there are no analytical models that capture the dynamics of the entire AFM process. Artificial intelligence techniques, such as neural networks and expert systems, have been increasingly used to successfully model complex process behavior in areas where 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, and in real time in hardware. Statistical models, such as linear regression, require assumptions about the parametric and functional nature of the factors which may or may not be true. Neural networks do not require such assumptions and are data-driven models. Recent work in using neural networks for modeling manufacturing processes include [1, 3, 9, 10, 15, 19].

Model Development

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

Key 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 process model is an attempt to capture the behavior of both the independent and interaction effects of these variables in order to accurately predict the flow of the air through the manifold. The main categories of process variables are

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

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 individual runner
VARIABILITY OF RUNNER AIRFLOW	The variability of airflow rate among the 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
MEDIA CONDITION	The condition of the media (cutting ability, contamination level)
HYDRAULIC PRESSURE	The extrusion pressure of the media
MEDIA TEMPERATURE	The temperature of the media
NUMBER OF PASSES	The number of cycles of the AFM machine piston

There is variability among the incoming parts due to the limitations of the sand casting process. The number of passes of AFM processing is done interactively by the operator depending on his judgment of when the manifold reaches air flow specifications. The ambient conditions can impact the condition of the media, and characterizing media condition is important. The media starts new with an 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 affects the AFM process. However, measurement of media condition during processing is not practical. 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 production sequence (Table 1) is a rough approximation to this heating effect. Time of production was divided into six periods beginning in the morning (period 1) and ending with the work day (period 6). Each part was assigned to one of these periods depending on its time of production.

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

- **Total air flow**
- **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 - total air flow through the manifold. It is this specification that the model described here targets.

Data Set

Production data based on a subset of the variables described in Table 1 was collected by the company's technicians. Ninety eight observations were collected on the following seven input variables: incoming part total air flow, incoming part air flow variability over the runners, incoming part weight, total AFM processing time, total volume of media used during processing, average hydraulic pressure during processing and production sequence. The outcome variable studied was outgoing part total air flow.

Preliminary Neural Network Development

The neural network architecture, training parameters, and stopping criteria were selected through experimentation. The transfer function was the unipolar sigmoid and a traditional backpropagation learning algorithm was used because it is known as an universal approximator when used with a nonlinear continuous transfer function with at least one hidden layer [5, 6]. The final network architecture had seven inputs, one hidden layer with seven neurons, and a single output as shown in Figure 2.

Results And Discussion

A five-fold cross-validation approach which used the entire data set for model evaluation was used [20]. The available data was divided into five mutually exclusive groups after randomizing the entire data set. Five networks with parameters identical to those of the final network described above were built, with each using four groups of the data as a training set, and the remaining one as a test set. Figure 3 verifies that the final network has unbiased generalization to all combinations of the input variables used in this study. The *x*-axis is in units of cubic feet per minute. Figure 4 shows the five-fold cross-validation networks and their predictions on each 20% test set against the actual observed outgoing average air flow. The *x*-axis is in processing order, and shows the predicted results of each of the five folds on the hold-out data set (the test set). The test sets are concatentated to produce Fig. 4. The *y*-axis is in cubic feet per minute of total airflow.

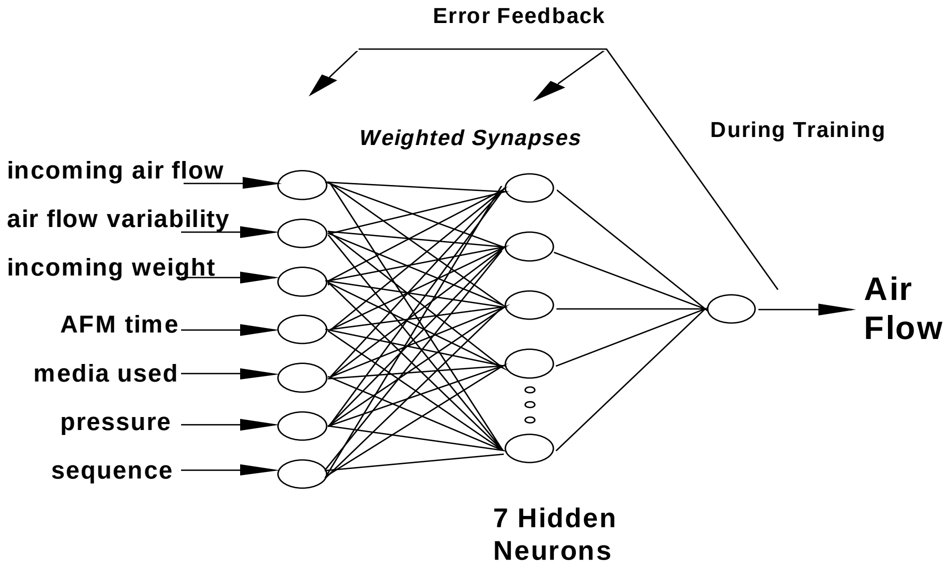

Figure 2. The Neural Network Architecture, Inputs and Output.

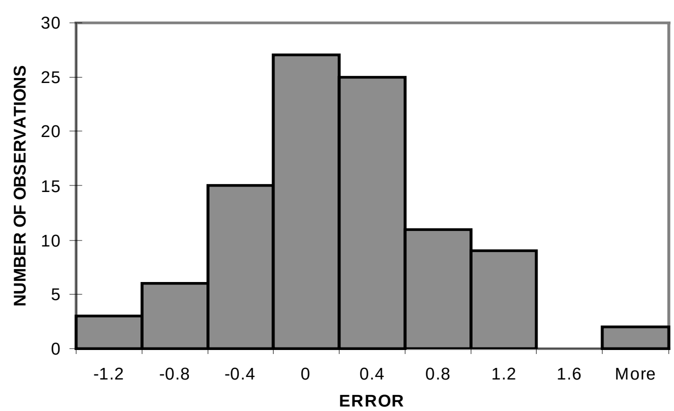

Figure 3. Histogram of Residuals of Five-Fold Cross-Validation.

The final network was able to predict the outgoing average air flow with a mean absolute error of 0.4873 (0.28%) and a root mean square error of 0.6386 (0.37%). The R-squared (coefficient of determination) value of the final network is 0.6527, which means that the network can explain about 65 percent of the variations in the outgoing average air flow. This figure is not high enough for use during production. The R-squared value for a stepwise linear regression using the same data set was slightly less than this value, indicating the appropriateness of a non-linear model.

The model will be improved with additional information from Table 1 that is expected to be monitored. One main area not addressed well by this preliminary neural network is the condition of the media. The only input describing media condition is the categorical measure of production sequence. This is a very crude surrogate for media condition. It is anticipated that advanced techniques, such as acoustic emissions, may be able to characterize media condition quite accurately and in real time. This will significantly improve the accuracy of the controller. Also, as the data set expands to more observations, the neural network model should improve in precision.

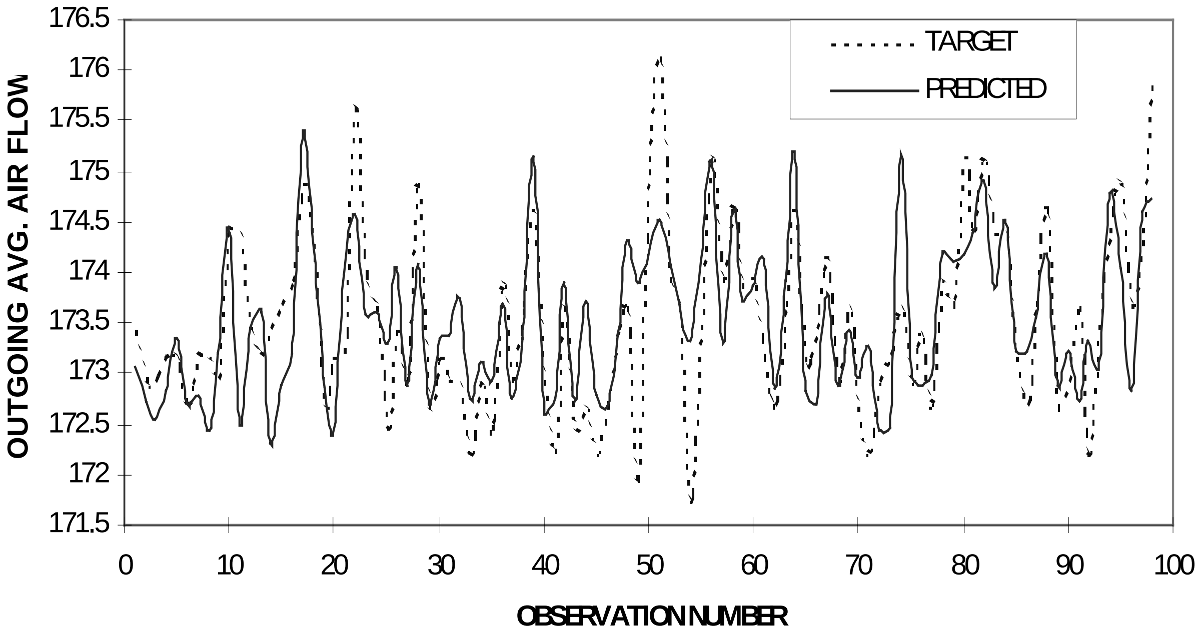

Figure 4. Performance on Five-fold Cross-validation: Predicted Against Target Outgoing Average Air Flow.

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