# PROCESS MONITORING OF ABRASIVE FLOW MACHINING USING A NEURAL NETWORK PREDICTIVE MODEL

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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.

**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) has the potential to provide 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 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]. However, AFM has not been widely used because of the lack of theoretic support for the behavior of the process. A large range of process parameters such as extrusion pressure, media viscosity, media rheology, abrasive size and type, grit size and grit type, part geometry, and others (such as the highly non-Newtonian nature of the AFM "fluid") must be taken into consideration when developing an application.

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 that control the volume of air ingested 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 impact on the performance, fuel efficiency, and emissions of automotive engines [14].

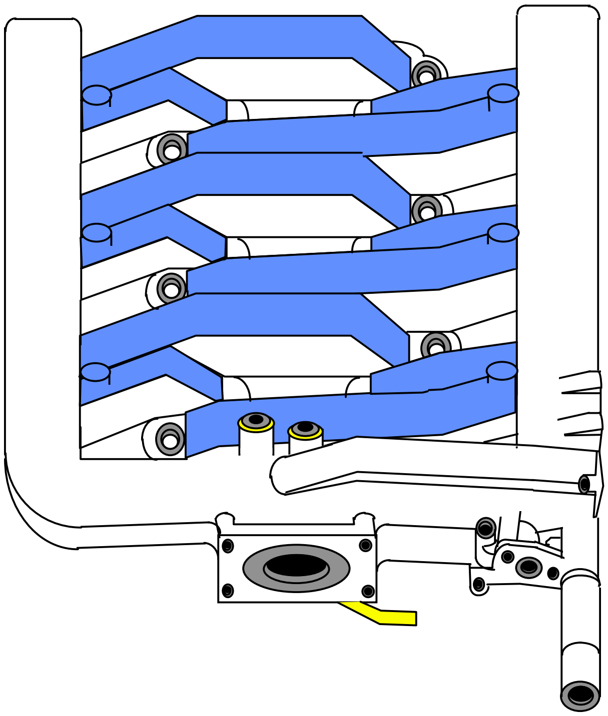

Figure 1. Drawing of Air Intake Manifold.

AFM has the potential to finish the sand cast manifolds so that the interior passages are smoother, more uniform and can achieve more precise specifications regarding air flow. However, the AFM process is not currently suited to mass production of manifolds. Currently, in order to AFM machine engine manifolds, technicians have to stop the process and test the intermediate air flow and repeat the process until the manifold achieves the desired air flow requirements.

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 cast manifold characteristics such as incoming average air flow, incoming weight and surface finish, and an initial setting of machining parameters such as extrusion pressure and displacement, 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.

## 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 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 [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].

However, each of these studies considered 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 [10]. Their system addresses process settings for AFM for a variety of products and material types. The research in this paper focuses on one particular product type (i.e., engine manifolds) but with the demand of more 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 abrasive flow machining process. Artificial intelligence techniques, such as neural networks and expert systems, have been increasingly used to successfully model 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. 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. Recent work in using neural networks for modeling manufacturing processes include [1, 3, 9, 10, 15, 19].

## MODEL DEVELOPMENT

A prototype neural network based process monitor and 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.

**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 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, number of passes
- Media condition **-** grit, freshness, temperature
- Ambient conditions **-** temperature, humidity

Table 1. Anticipated 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 considerable 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 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 (Table 1) is a very crude 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 for predicting the outgoing average air flow of engine manifolds, training parameters, and stopping criteria were selected through experimentation and examination of preliminary networks trained. The transfer function was the unipolar sigmoid. 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 7 inputs, one hidden layer with 7 neurons, and a single output.

## 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 2 verifies that the final network has unbiased generalization to all combinations of the independent variables used in this study. Figure 3 shows the five-fold cross-validation networks and their predictions on each 20% test set 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 0.4873 (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 model will be improved with additional information from Table 1 that is expected to be monitored. The main area not addressed well by this preliminary neural network is the condition of the media. The only input concerned with the media condition is the categorical measure of production sequence. This is a very crude surrogate for media condition. Also, as the data set expands to more observations, the neural network model should improve in precision.

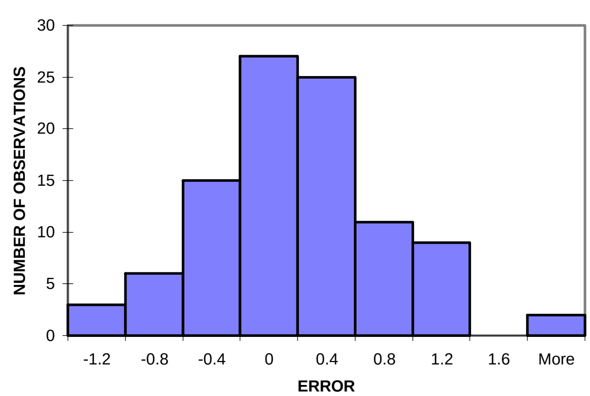


Figure 2. Histogram of Residuals of Five-Fold Cross-Validation.

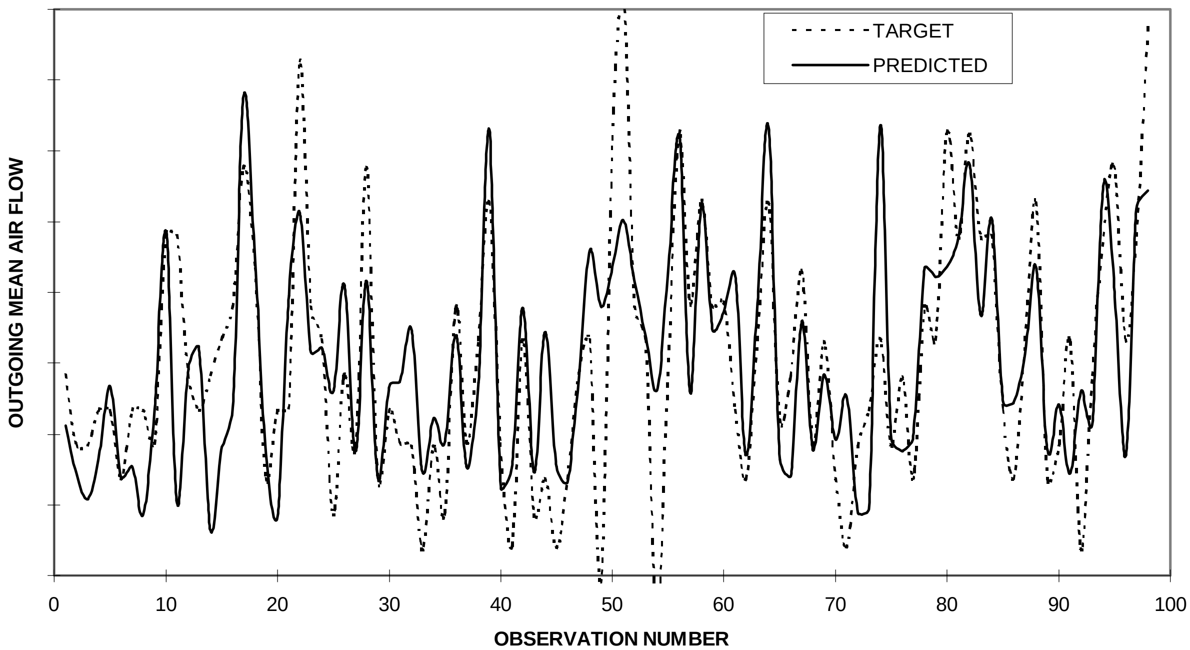


Figure 3. Performance on Five-fold Cross-validation: Predicted Against Target Outgoing Average Air Flow.

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## BIOGRAPHICAL SKETCHES

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