Journal of Advances in Science and Technology

Vol. VI, Issue No. XI, November-2013, ISSN 2230-9659

AN INTERNATIONALLY INDEXED PEER REVIEWED & REFEREED JOURNAL

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Journal of Advances in Science and Technology
Vol. VI, Issue No. XI, November-2013, ISSN 2230-9659

Nural Networks Modeling Strategy: A Study on Abrasive Flow Machining Method

Ashvini Kumar

H.O.D (Mechanical) Sityog institute of Technology Aurangabad Bihar

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 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.

Abrasive Flow Machining (AFM) is an effective way to polish unsymmetrical surfaces and interior structure of parts, which are difficult to reach by conventional machining. The material to be machined may be cylindrical or any complex shape. Various process parameters are Material Removal Rate, Machining Time, and Abrasive Mesh size that affects the performance of AFM. The objective of this paper is to study the effects of process parameter related to it such as material removal rate, surface finishing etc.

In recent years, several papers on machining processes have focused on the use of artificial neural networks for modeling surface roughness. Even in such a specific niche of engineering literature, the papers differ considerably in terms of how they define network architectures and validate results, as well as in their training algorithms, error measures, and the like. Furthermore, a perusal of the individual papers leaves a researcher without a clear, sweeping view of what the field's cutting edge is.

Hence, this work reviews a number of these papers, providing a summary and analysis of the findings. Based on recommendations made by scholars of neurocomputing and statistics, the review includes a set of comparison criteria as well as assesses how the research findings were validated. This work also identifies trends in the literature and highlights their main differences. Ultimately, this work points to under explored issues for future research and shows ways to improve how the results are validated.

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INTRODUCTION

Abrasive flow machining (AFM) was developed by Extrude Hone Corporation, USA in 1960. There are three types of AFM machines that have been reported in the literature: one way AFM, two way AFM and orbital AFM. Commonly used AFM is Two-way AFM in which two vertically opposed cylinders extrude medium back and forth through passages formed by the work piece and tooling as shown in Fig.1.

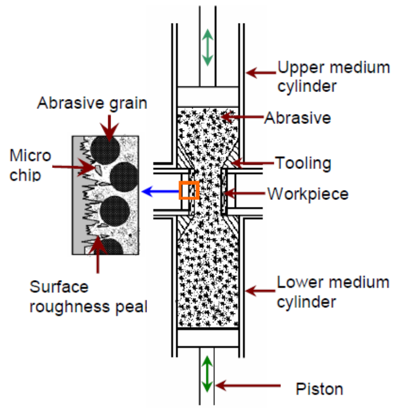

Fig.1. Principle of material removal mechanism in two way AFM process

AFM is used to deburr, radius and polish difficult to reach surfaces by extruding an abrasive laden polymer medium with very special rheological properties. It is widely used finishing process to finish complicated shapes and profiles. The polymer abrasive medium which is used in this process, possesses easy flowability, better self deformability and fine abrading capability. Layer thickness of the material removed is of the order of about 1 to 10 µm.

Best surface finish that has been achieved is 50 nm and tolerances are +/- 0.5 µm. In this process tooling plays very important role in finishing of material, however hardly any literature is available on this () of the process. In AFM, deburring, radiusing and polishing are performed simultaneously in a single operation in various areas including normally inaccessible areas. It can produce true round radii even on complex edges. AFM reduces surface roughness by 75 to 90 percent on cast and machined surfaces. It can process dozens of holes or multiple passage parts simultaneously with uniform results.

Also air cooling holes on a turbine disk and hundreds of holes in a combustion liner can be deburred and radiused in a single operation. AFM maintains flexibility and jobs which require hours of highly skilled hand polishing can be processed in a few minutes; AFM produces uniform, repeatable and predictable results on an impressive range of finishing operations.

Important feature which differentiates AFM from other finishing processes is that it is possible to control and select the intensity and location of abrasion through fixture design, medium selection and process parameters. It has applications in many areas such as aerospace, dies and moulds, and automotive industries.

The manufacture of precision parts emphasizes final finish machining operations, which may account for as much as 15% of the total manufacturing costs. 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. AFM is being used to finish air intake manifolds for the Ford Contour SVT as part of this project.

The air intake manifold (Fig. 2) 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 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.

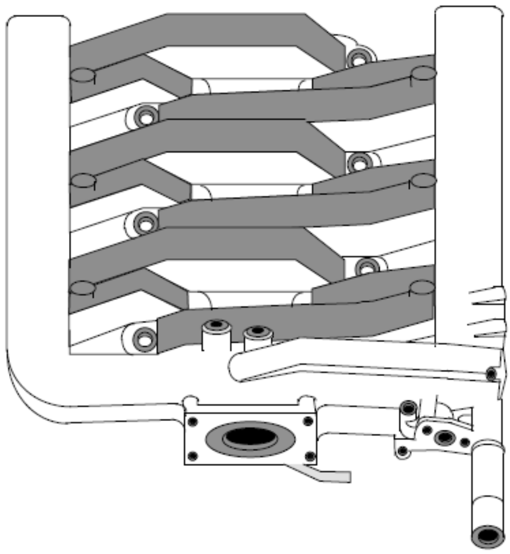

Figure 2. Drawing of Air Intake Manifold.

BACKGROUND

Limited efforts have been done towards enhancing the productivity of AFM process with look upon to superior quality of work piece surface. AFM process has a greater potential of being used to deburr, radius, polish and remove recast layer of component. Basically there are three types of AFM processes. One way, Two way and Orbital AFM. Commonly we use two way AFM. In two way AFM process consist of two cylinder stocks, one from the lower cylinder pumping an Abrasive laden medium throughout and one from the upper cylinder makes up one process.

The polymer abrasive medium which is used in this process possesses trouble-free flow ability, better nature deformability and excellent abrading capacity. For the finishing of the components which have complex unsymmetrical shape/profile, holes and undercut, a need is being felt to expand finishing operations which can produce parts with superior quality performance and higher productivity. AFM is one of such method. The various parameters affecting the process are described here and the effect of the key parameters on the performance of process has been studied. Material Removal Rate and Surface Finish are the two major output parameters.

The AFM Method : 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. 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 debarring and polishing tools.

Neural Networks 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.

LITERATURE REVIEW

Fletcher et al. studied the relationship between medium rheological properties and the AFM process. Shear rate of the polymer increases when it passes through the restriction (or reduced cross sectional area). Capillary rheometer is used to find the relationship between wall shear stress and shear rate for medium viscosity of polyborosiloxane medium.

They concluded that coefficient of viscosity decreases but shear stress increases as shear rate increases. Variation of wall shear stress with time is also studied. They also concluded that greater finishing action could be achieved as a result of longer piston stroke durations, due to higher wall shear stress generated. Jain and Jain proposed a generalized back propagation neural network model and a second network which parallelizes the augmented Lagrange multiplier (ALM) algorithm. The model determines optimal finishing parameters by minimizing a performance index subject to appropriate operating constraints.

Sarah et al. presented a neural network model as an off-line controller for AFM of automotive engine manifold to predict when the AFM process should be stopped to achieve the required airflow rate through manifold body. Ramandeep Singh et al. Abrasive flow machining (AFM) is a relatively new non-traditional micro-machining process developed as a method to debur, radius, polish and remove recast layer of components in a wide range of applications. Material is removed from the work-piece by flowing a semi-solid viscoelastic/plastic abrasive laden medium through or past the work surface to be finished. Components made up of complex passages having surface/areas inaccessible to traditional methods can be finished to high quality and precision by this process. The present work is an attempt to experimentally investigate the effect of different vent/passage considerations for outflow of abrasive laden viscoelasic medium on the performance measures in abrasive flow machining. Cylindrical work-piece surfaces of varying cross-sections & lengths having different vent/passage considerations for outflow of abrasive laden viscoelastic medium have been micro-machined by AFM technique and the process output responses have been measured. Material removal, MR and surface roughness, Ra value are taken as performance measures indicating the output responses. Experiments are performed with significant process parameters, such as concentration of abrasive particles, abrasive mesh size, number of cycles and media flow speed kept as constant on brass as work material. The results suggest that the work-piece surfaces having single vent/passage for media outflow have higher material removal and more improvement in surface roughness in comparison with work-piece surfaces having multiple vents/passages and the performance measures decrease with increase in the number of vents for media outflow.

Abrasive flow machining (AFM) is a process for the production of excellent surface qualities of inner profiles that are difficult to access and outside edges, as well as for deburring and edge rounding. The grinding medium used in AFM consists of a polymer fluid, the so-called base, in which the abrasive grains are bound.

The grinding medium is pressed along the contours at a defined pressure and temperature. Depending on the respective machining task, different specifications of media are used. The description of process-related material removal mechanisms requires the knowledge of material removal mechanisms in AFM. Based on findings in flow mechanism, analyses have been made on material removal mechanisms. The objective of the investigations at the Institute for Machine Tools and Factory Management - IWF in Berlin is to trace correlations capable of influencing the work result.

Jose Cherain et al. Abrasive flow machining (AFM) process is a non-traditional finishing process used for polishing and radius difficult to reach surfaces by the abrading action of the abrasives. The material to be machined is taken in the form of a cylinder. The abrasives are taken in the work piece and rotated at high RPM.AFM can be used to produce high surface finish. Various process parameters are abrasive size, Machining time, Hardness of abrasives and speed of abrasives. The experimental result reveals that the efficiency of the process strongly linked to the mechanical properties of the machined material and machining time. This technique offers good surface finish without affecting closesest geometrical tolerances of materials.

R.S. Walia et al. Limited efforts have been done towards enhancing the productivity of Abrasive Flow Machining (AFM) process with regard to better quality of work piece surface. In recent years, hybrid-machining processes have been developed to improve the efficiency of a process by clubbing the advantages of different machining processes and avoiding limitations. In the present study, the abrasive flow machining was hybridized with the magnetic force for productivity enhancement in terms of material removal (MR). The magnetic force is generate around the full length of the cylindrical work piece by applying DC current to the solenoid, which provides the magnetic force to the abrasive particles normal to the axis of work piece. The various parameters affecting the process are described here and the effect of the key parameters on the performance of process has been studied.

DEVELOPMENT MODEL OF NEURAL NETWORK

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.

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. 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.

2. Data set : Production data on the variables 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.

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. Figure 3 illustrates a typical cascade architecture.

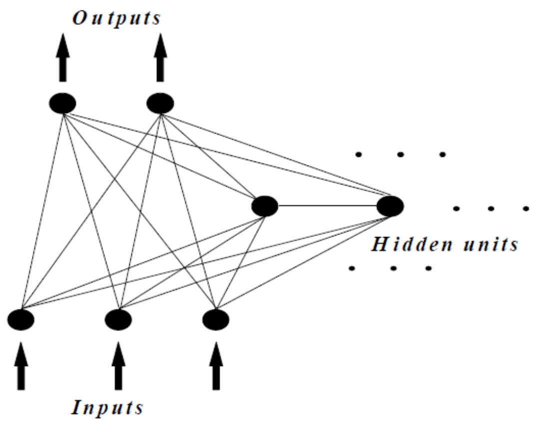

Figure 3. A Typical Cascade-Correlation Neural Network.

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.

EXPERIMENTAL RESEARCH IN ABRASIVE FLOW FINISHING

Process parameters and their influence : Experimental investigations have been carried out by various researchers to investigate the effects of process parameters like extrusion pressure, number of cycles, viscosity, abrasive concentration and grain size on the output responses namely, surface finish and material removal during AFM.

Rhoades experimentally investigated the basic principle of AFM process and identified its control parameters. He observed that when the medium is suddenly forced through restrictive passage then its viscosity temporarily rises.

Significant material removal is observed only when medium is thickened. The amount of abrasion during AFM depends on design of tooling, extrusion pressure, medium viscosity and medium flow volume.

All these parameters ultimately change the number of particles interacting with the workpiece and the force acting on individual abrasive grain. A higher volume of medium flow increases number of interacting abrasive grains with the workpiece, hence more abrasion takes place. Number of cycles depend on the velocity of medium, during a given time period. Flow pattern of medium depends on its slug (medium exiting the workpiece) flow speed, medium rheology and passage size (cross-sectional area). AFM can be used in industrial applications such as precision deburring, edge contouring, surface finish, removal of thermal recast layers, etc..

Process modeling and optimization : Williams and Rajurkar developed a stochastic model of AFM generated surfaces by using Data Dependent Systems (DDS) methodology. They have estimated the ratio of surface roughness peak to valley height (Rz) to centerline average surface roughness value (Ra) by DDS methodology and found to be between 1.4 and 2.2 for the AFM process. It was established in their research that AFM finished surface profiles possess two distinct wavelengths, a large wavelength that corresponds to the main path of

abrasive while the small wavelength is associated with the cutting edges. Good agreement is found between the primary frequency ranges obtained in DDS modeling and those derived from spectral analysis function. It is stated that these frequency bands are related to different material removal modes in AFM; consequently, the mechanism of material removal in AFM is considered to consist of ploughing responsible for creation of characteristic flow lines and micro-cutting. They also proposed an expression for estimating the abrasive grain wear and the number of active grains (Cd). The estimated value of Cd is used as a cutting life criterion for abrasives. For small number of cycles its value should remain fairly stable but with more and more processing the abrasive particles may fracture thereby increasing the Cd value.

The downturn of Cd value indicates that the medium has absorbed too much work piece material and need replacement. Jain et al. also carried out simulation of finished surface profile and material removed considering the interaction of abrasive grains with workpiece.

Monitoring of AFM process : For online monitoring of material removal and surface roughness in AFM process, Williams and Rajurkar applied acoustic emission technique (elastic stress waves generated by the rapid release of strain energy within a material due to a rearrangement of its internal structure is called "acoustic emission"). In a full factorial experiment, the effect of extrusion pressure, medium viscosity, abrasive grit size, number of cycles, and work piece material was investigated on material removal, root mean square of acoustic emission signal (AERMS), and surface roughness improvement. From the above parameters only grit size showed insignificant affect on material removal. They studied acoustic emission signals for grinding to analyze the mechanism involved in AFM and found that the acoustic emission signal is highly dependent on the characteristics of the initial surface roughness of the workpiece. The AERMS of the signal is sensitive to extrusion pressure and other AFM process parameters, which affect material removal.

CONCLUSION

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.

It is generally applied to finish complex shapes for better surface roughness values and tight tolerances. It is possible to increase the performance of conventional AFM by providing additional motion to the media. But the major shortcoming of this process is slow finishing rate. So continuous efforts are being made to increase finishing rate, improve surface texture and to some extend to improve MRR. If higher the Extrusion pressure and speed of the piston higher will be the material removal rate and surface finish.

AFM is a well established advanced finishing process capable of meeting the diverse finishing requirements from various sectors of applications like aerospace, medical and automobile. It is commonly applied to finish complex shapes for better surface roughness values and tight tolerances. But the major disadvantage of this process is low finishing rate. So continuous efforts are being made to increase finishing rate, improve surface texture and to some extend to improve MRR. To achieve an accurate and efficient finishing operation without compromising the finishing performance, understanding of inter relationship between various input parameters and output responses that influence the process performance. This leads to identification of various optimal finishing conditions from the infinite number of combinations and their modeling.

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