# Data driven unit manufacturing process (UMP) model for monitoring specific energy in surface grinding process

Zhaoyan Fan*, Sai Srinivas Desabathina

*Team Leader: Zhaoyan.fan@oregonstate.edu

Affiliation: School of Mechanical, Industrial and Manufacturing Engineering

Oregon State University

Corvallis, OR, USA

## 1. INTRODUCTION

Manufacturing industry is placing increasing pressure on the environment [1]. US manufacturing sector is alone responsible for 36% of Carbon dioxide emissions within the US industrial sector [2]. To address this issue production/manufacturing engineers have to develop sustainable manufacturing practices. According to US EPA, the primary characteristic of any sustainable manufacturing practice is to conserve energy and natural resources [3]. Being a methodology to access the details in the manufacturing processes, Unit Manufacturing Process (UMP) models is able to serve a solution to identify and monitor the factors influencing the energy consumption.

Compared to the other traditional machining methods such as milling or lathing where energy is mainly consumed by chip formation grinding is considered as one of the largest energy consuming machining operation. Specific energy, defined as the amount of energy required to remove unit volume of material in unit time period, is one of the most generally used parameters to evaluate the energy consumption and efficiency in manufacturing processes. In any machining operation, the interaction between the cutting edges and the material determines the specific energy. In grinding process, cutting edges are embedded on the grinding wheel surface in random order. The stochasticity of the cutting edges makes it highly difficult to develop accurate analytical UMP models. It is also difficult to capture the dynamics of the grinding process such as change in cutting edge concentration, wheel loading using analytical UMP models. These factors have established the motivation to develop data models. Developments of microelectronics and multiple sensor data fusion technique has made it feasible to develop data models by combining the information from multiple low-cost sensors for accurate parameter estimation. This document demonstrates an indirect approach to estimate the grinding specific energy by fusing vibration, acoustic emission (AE) and energy consumption signals measured by sensors embedded in the part fixture and machine powers supply units. A mathematical model was established based on Artificial Neural Network (ANN) as a representative of the physical system to correlate the measured features with specific energy. Experimental study has been conducted to validate the developed technique on a commercial grinding machine. The graphical representation of the developed mathematical model is generated using UMP builder tool. The same UMP builder tool generates the XML file of the graphical representation of the UMP model. Equations governing the mathematical model is represented in Predictive model markup language (PMML) in the same XML file. All the mathematical models are established on MATLAB and Neural Designer platforms to automatically generate the PMML file.

## 2. SENSING SYSTEM AND MODELING

A sensorial platform is designed based on a conventional grinding machine infrastructure. Four sensors measuring current, voltage, vibration and AE are designed to systematically monitor the vibration of in process signals from three energy consumption stages at control unit, motors and grinding execution.

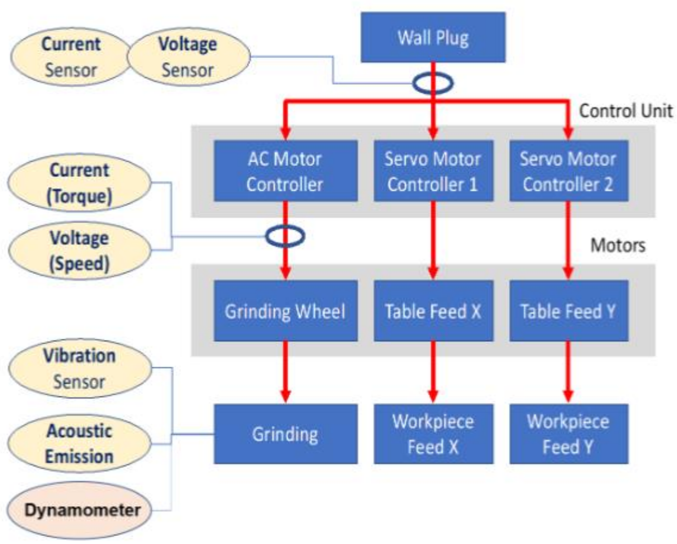


**Figure 1: Configuration of the sensing system**

A dynamometer was mounted on the moving table as a reference means to measure the tangential cutting force $F_t$ for estimating the specific energy. Physically, the specific energy was defined as:

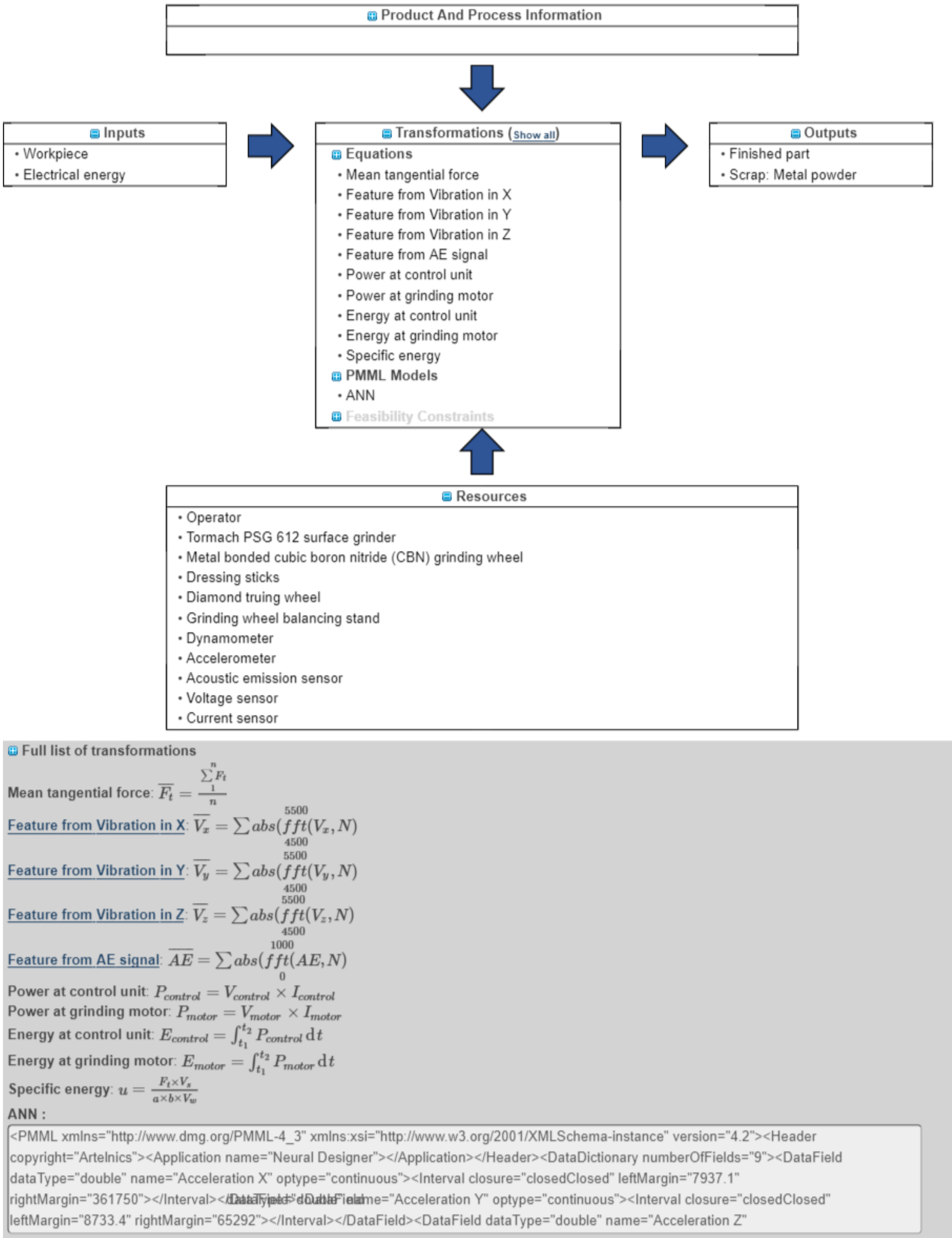


**Figure 2: Graphical representation of UMP model**

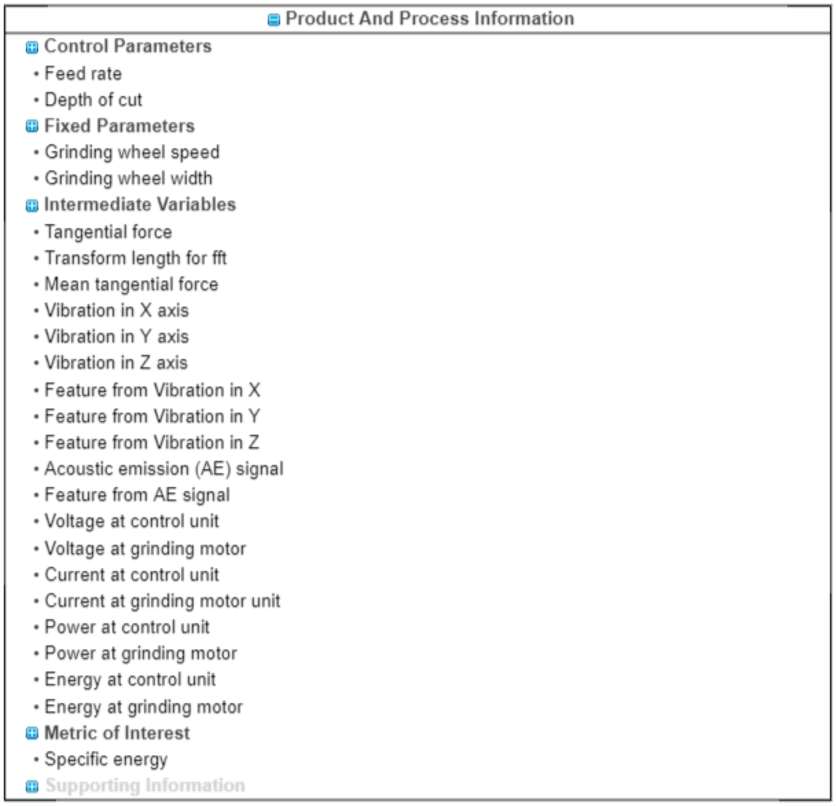


**Figure 3: Expanded representation of product and process information used in the UMP model**

$$u_i = F_t V_s / Q_w \tag{1}$$

where $V_s$ *and* $Q_w$, are the wheel speed and volumetric removal rate that can be obtained from machine settings. ANN is used to fuse the features extracted from all the sensorial data and estimate the specific energy. ANN is composed of interconnected processing neurons arranged in three different types of layers; input layer, hidden layer and output layer. Through the input layer, the network receives the independent variables and the estimate of dependent variable is delivered through the output layer. Every connection in an ANN is assigned a weight *w* to quantify its relative importance with respect to the other connections. Mean square error function *E(w)* of the network is dependent on these weights. ANN maps the relationship between independent and dependent variables through iterative adjustment of all weights in the network until *E(w)* is minimized. Levenberg-Marquardt algorithm was used to minimize *E(w).*

## 3. EXPERIMENTAL VALIDATION

The developed technique is implemented on Tormach PSG 612 personal surface grinder. Considering the three levels for depth of cut and moving table speed as seen in Table 1, there are 9 combinations tested in the experiment. By repeating each combination for 7 times, a total of 63 sets of data were collected. Before moving from one combination to another grinding wheel is trued, dressed, and balanced to maintain consistent cutting condition at every combination. The experimental setup is based on the scheme presented in the fig. 1. The setup involves a pair of current and voltage sensors installed on the power supply line from wall plug to control box unit, while another pair is installed on the supply cable from control box unit to grinding motor. The total energy and that consumed by the motor for a grinding cycle at both the stages are features extracted from the voltage and current sensors. The accelerometer mounted on the part (workpiece) fixture measures part vibration along the tangential direction (x-axis) and normal direction (z-axis). The Acoustic Emission (AE) sensor is placed close to the point of the grinding execution to record the acoustic wave generated. For the accelerometer and AE sensors, specific frequency bands associated with the wheel rotation speed and grits density on the wheel were selected for calculating the average power, by averaging the magnitude of all frequency components in the selected bands. Dynamometer is installed on the horizontal moving table as an alternative means to measure the specific energy according to Eq. (1). Table 1 summarizes the feature vectors extracted from the process signals

**Table 1: Summary of features extracted from raw data**

| Raw Data | Features extracted |
|---|---|
| Voltage and current | Energy consumption during grinding |
| Accelerometer (x-z) | Average power in freq. band 4.5-5.5 kHz |
| AE sensor | Average power in freq. band 0-1.0 kHz |
| Machine setting | Depth of cut |
| Machine setting | Feed rate |

The ANN model was trained using 45 data sets sampled from the experiment, which was randomly chosen from the total 63 sets pool. The rest 18 data sets were used for testing the model and quantitatively evaluate the accuracy, as shown in Fig. 4The mean estimation accuracy obtained in the testing phase is 72.94%. From the plotted linear fit line of the test data, as shown in Fig. 4, it is seen that the estimated results are more accurate in the high specific energy level than that in the low level range. This is due to the signal-to-noise ratio of sensor data is low when the specific energy is low, i.e. at low feed speed or shallow cutting depth. This trend is confirmed in the results comparing the accuracy at different feed rate, as shown in Fig. 5. It is seen that the best performance is achieved at a feed rate of 66.3mm/sec with mean estimation accuracy of 87.36% and least performance at a feed rate 23.4mm/sec with mean estimation accuracy of 53.75%.

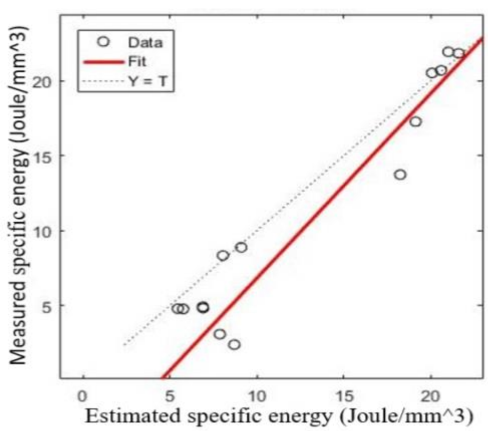


**Figure 4: Correlation plot of ANN for test phase**

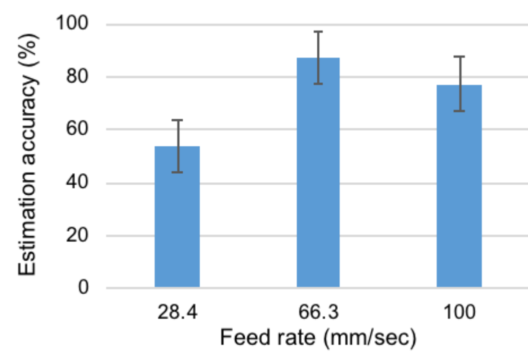


**Figure 5: Estimation accuracy at different feed rates**

## 4. CONCLUSION

A multi-sensor data fusion UMP model was established based on artificial neural network(ANN) algorithm for estimating specific energy during grinding process from in-process parameters. An experimental study was conducted on commercial grinding machine using acoustic, vibration, current and voltage sensors. Results show a mean estimation accuracy of 72.94%, indicating the feasibility of using a UMP model for estimating the specific energy toward clean energy manufacturing.

## REFERENCES

[1] Duflou, J. R., Sutherland, J. W., Dornfeld, D., Herrmann, C., Jeswiet, J., Kara, S., Hauschild, M., and Kellens, K., 2012, “Towards Energy and Resource Efficient Manufacturing: A Processes and Systems Approach,” CIRP Annals, **61**(2), pp. 587–609.

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