Parameter Prediction Using Machine Learning in Robot-Assisted Finishing Process

Bobby K Pappachan
School of Mechanical and Aerospace Engineering,
Nanyang Technological University, Singapore
Email: kbobby@ntu.edu.sg

Tegoeh Tjahjowidodo
School of Mechanical and Aerospace Engineering
Email: ttegoeh@ntu.edu.sg

***Abstract*— In finishing processes equipped with real-time pro- cess monitoring, analyzing real-time data acquired is vital to ensure product quality and safety compliance. The quality and dimensions of a finished product is often times dictated by the process parameter set initially. However, changes in parameter occurs whenever an unexpected event such as an equipment failure or voltage fluctuations occurs. This could result in a finished product with a below par quality and subsequently delays in production due to rework or machine downtime. With an indirect monitoring method to continually monitor these parameters such as spindle speed, these occurrences can be minimized. Here lies in the benefit of an integrated parameter prediction model, which is able to detect deviation from normal operation early, hence enabling the capability of delivering actionable insights in a real-time basis to shop-floor engineers. This paper presents a parameter prediction method tested successfully on data acquired from a robot-assisted deburring process.**

***Index Terms*—finishing, gradient descent, back propagation, actionable insights**

I. Introduction

In machining and finishing processes, having a control over the material removal rate (MRR) is a capability, machinist and floor managers constantly strive to achieve. In principal, MRR is dependent on three main parameters namely depth of cut (D), width of cut (W) and speed or feed rate (S) and is calculated as,

$$MRR = D * W * S \ cc/min \tag{1}$$

Machinists use this relationship to determine the process parameters and use the parameters as program inputs to run the machine or robot. Several algorithms and mathematical models exist to optimise the input parameters but a gap exists in real-time monitoring of these parameters[1]. Some OEMs, these days equip machines and robots with in-built sensors to monitor these parameters but the disadvantage here is that the data is accessible only locally and user-defined features are difficult to implement. In addition, the proprietary format restricts communicating with other machines and data logging very tedious. Development towards sensor integration into machine tools have taken place in the past 10 years. These concepts have not been successful enough because the spindle or end-effector must be characterised to isolate machine dynamics from the actual process[2]. Off-the-shelf sensors such as tachometer monitors speed, but deploying such relatively bulky sensors in a machining environment would introduce additional constraints for tool-work piece interaction[3]. Besides, there exists no sensor with direct sensing capability to measure depth of cut (D) and width of cut (W). An indirect approach is hence necessary to deduce the parameters from the acquired sensor data.

Sensor based process monitoring and data analysis has been successful in delivering status of any specific machining process with regards to the tool or work piece and also acts as an enabler for real-time process control[4]. The capability of deducing process parameters real-time will eventually result sensors to be a regular feature in future manufacturing equipment. A combination of sensor data acquisition and intelligent sensor data processing algorithms will expedite the usage of sensor-based process monitoring in current manufacturing scene. Majority of the research work published on sensor based monitoring focuses towards machining tool and work piece condition monitoring. For instance in [5], sensor signal feature is extracted to monitor tool wear and in [6], a combination of signature extraction technique and neural network is used for tool condition monitoring. Using sensor signal features to train machine learning algorithm is the approach most research works have adopted to perform predictive analysis from incoming sensor data. Decision making support systems has become a fundamental building block in predictive maintenance based applications along with a number of cognitive computing methods. The different computing paradigms include fuzzy logic, neural networks, genetic algorithms and hybrid systems.

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In [7] a recurrent neural network (RNN) approach is used on sensor signal processed using wavelet transform to estimate flank wear while a fuzzy logic approach to estimate tool wear is seen used in [8]. It is worth noting that, the applications in which these techniques are used are mostly in the area of output prediction and tool condition monitoring. In most research works, estimation of machining parameter is not an interest under focus. However, the capability of accurately estimating process parameter real-time would pave way for a feedback control loop to facilitate dynamic process control. A literature survey of past predictive analysis research work published was conducted and only 2% of the surveyed literature actually performed parameter estimation. The result is shown in Figure 1 in the form of pie chart. The sampling size for the survey was 65 research publications published in the period 2000-2010[9].

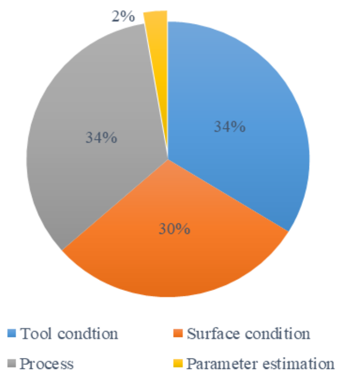

Figure 1. Parameter estimation research

With the increase in number of connected devices in the shop floor and the introduction of industry 4.0 driven production standards, the demand for smarter industrial robots and manufacturing equipment is set to only increase. For a control algorithm to be robust, having a grip on the machine parameters is imperative to deliver consistent performance from the smart manufacturing equipment. This has motivated the authors to perform the associated research work for parameter estimation. In the following section a background on parameter estimation is presented. Section 3 covers the data analysis and modelling analysis of experimental data acquired.

II. Parameter Estimation

A typical sensor based process monitoring system is depicted in Figure 2. As shown in figure, Parameter estimation plays a crucial role in sensor based process monitoring system and it constitutes three main components; signature extraction, signature level classification and parameter prediction.

A. Signature Extraction

Sensor signal generated from a source contains embedded information regarding the source, which might correspond to spindle or work piece interaction[10]. This embedded information can be extracted using signal processing and signature extraction techniques. Selecting a suitable signal processing routine largely depends on the type of application and the depth of information available. In applications where the information regarding tool or work piece integrity is required, a time-domain approach is generally used[11].

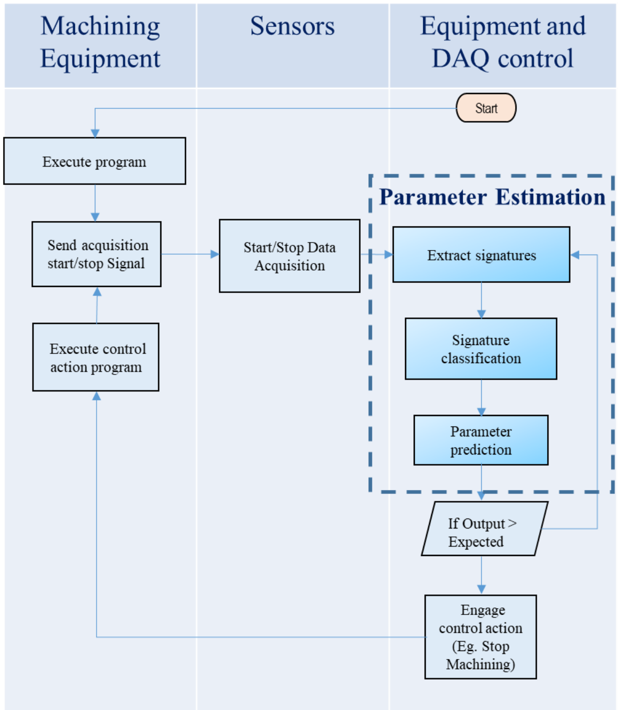

Figure 2. Sensor based process monitoring system

If the objective is towards continual monitoring, a frequency domain approach is more apt as Frequency-domain analysis of sensor data has better performance in terms of latency compared to time-domain approach. A deviation from normal behaviour happens generally as a gradual process and if a certain frequency is indicative to a variation in parameter of interest, by monitoring the particular frequency continually will be able to track and alert undesirable outcomes. Whereas if time-domain method for monitoring and detection of such an event is used, latency problems will result in delayed alerts and the damage or anomaly to the work piece would have already occurred, ruling out the possibility of any actionable preventive feedback. Time-domain analysis however requires less processing and computational effort to deduce an insight whereas more often than not frequency-domain analysis needs the support of machine learning algorithms to classify and interpret the information embedded within sensor data. Table I shows a list of signatures that can be extracted from the sensor data.

TABLE I. Time-domain and Frequency-domain Features

Time-domain	Frequency-domain
Mean, average, magnitude, magnitude, standard deviation, skewness, kurtosis, crest factor, peak-peak range	Fourier coefficients, power spectrum, mean frequency, variance, skewness, kurtosis, dominant frequency

A systematic data analysis and correlation study has to be conducted before down-selecting the appropriate feature to facilitate indirect monitoring. In many machining processes, transient mechanical events can induce noise into the sensor data. Filtering methods are usually employed to separate undesired elements from the coherent information[12]. Data pre-processing techniques like filtering and feature normalisation are essential to ensure data integrity. A prediction model will behave as a generalised one if data integrity is maintained and will avoid problems caused due to overfitting.

Several optimisation techniques exist to select a feature that can represent the feature space approximately. One such technique is to calculate the correlation coefficient of the feature of interest with the parameter that needs to be indirectly monitored. A correlation coefficient value close to 1 denotes that the feature as representing the feature space approximately. In the context of this research, time domain features such as skewness, kurtosis, standard deviation and average were extracted and frequency domain features such as average energy in a power spectrum and welch spectrum estimate were extracted. Welch estimate exhibited the highest correlation coefficient of 0.78 (Fig. 3). As seen in Fig. 3, three distinct clusters, approximately represents the three different states (RPM) of the process. Welch power spectrum is estimated by performing a transform of successive time series data and averaging the periodograms of each segment or frame. Welch spectrum $S_x(w_k)$ is defined as,

$$S_x(w_k) = \frac{1}{K}\sum_{m=0}^{K-1} Px_m, M(k) \tag{2}$$

$$Px_m, M(k) = \frac{1}{M}\left|\sum_{n=0}^{N-1} x_m(n)e^{-\frac{2\pi nK}{N}}\right|^2 \tag{3}$$

where $m = 0,1, \ldots K, K$ = total number of frames or segments.

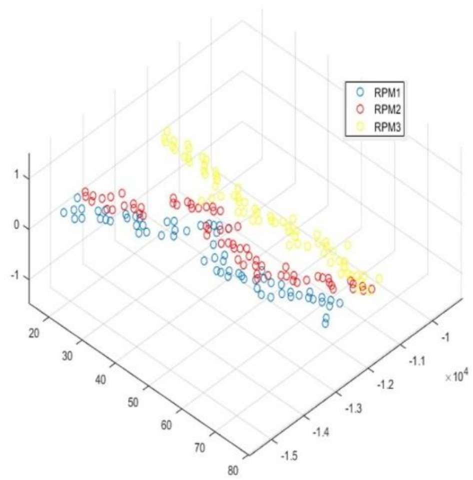

Figure 3. Feature space of Welch Estimate

B. Actionable Insights

Manufacturing industry has evolved considerably since the introduction of steam powered machines; with the most recent addition being computer assisted manufacturing or, automation. Industrie 4.0 is believed to be the next wave of change, brought about by factors such as increased computational power at low cost, speed of data flow and connectivity. This factors when coupled with the availability of machine and operational data and advanced data analysis can provide actionable insights to reduce downtime, rework and also assist in predictive maintenance.

Machine learning models can be trained effectively using the signatures extracted from sensor data in a machining cell. Parameters such as speed and feedrate although is set initially; due to fluctuations in voltage and other influencing factors, is prone to inconsistencies in terms of maintaining the set parameter. Predictive models can be employed to accurately monitor these parameters real-time while the process is running. If the parameter deviates more than the acceptable range, an actionable insight can be generated. The operator may decide to act on the insight to take any corrective actions or escalation if necessary. These insights can be in linguistic form or as an alert, interpretations of which can be pre-defined by the operator and stored in a database (Fig. 4).

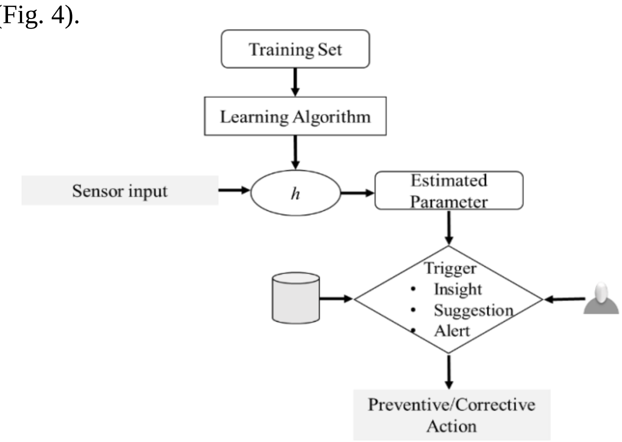

Figure 4. Decision making support system

The hypothesis that fits the prediction model is given as h defined as,

$$h_\theta(x) = \theta_0 + \theta_1(x) + \cdots \theta_n(x) \tag{4}$$

Variables $\theta_1, \theta_2, \ldots \theta_n$ are weights that need to be tuned to obtain optimum value where n is total number of features. Optimisation algorithms such as gradient-descent, back propagation and neural networks have been used widely in applications involving medical diagnosis[13], fintech[14] and asset classification purpose using image processing. In this research gradient descent and back propagation algorithms are used to indirectly monitor RPM of a spindle and depth of cut. The comparison between the results are also analysed and presented in the following section.

III. Parameter Prediction from Experimental Data

The experiment setup is as shown in Fig. 5. The setup comprises of an ABB IRB 6660 robot with a PDS Colombo spindle mounted on the end-effector. A replica of a combustor casing boss hole is used as the work coupon and the objective is to remove the burrs formed on hole until a chamfer is formed. An accelerometer is mounted on the spindle to capture the vibrations during the process and subsequently used for signature extraction and modelling. A total of 550 sets of data was collected. This is to simulate production scenario where changes in RPM occurs randomly. Since these variations are inadvertent, simulating the scenario in a laboratory setup will help to collect corresponding sensor data with coherent information. Three different parameter setting was used for RPM and sensor data was acquired to train the model.

Accelerometer data was acquired at 40 kHz sampling rate and to reduce computational complexity was resampled to 1000 samples. A laser measuring equipment was used to measure the chamfer after each cycle of machining.

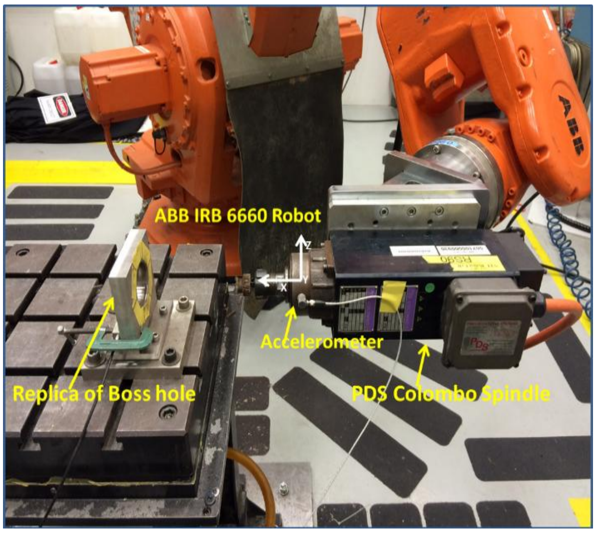

Figure 5. Experiment setup

A. *Machine learning model*

The sensor data collected was used train two different machine learning models based on gradient descent optimisation and neural networks algorithm respectively. Signatures extracted for training were time domain features average and skewness and frequency domain feature welch power spectrum. Gradient descent algorithm optimises the function which is characterised by the three features and tunes the weights $(\theta_1, \theta_2, \theta_3)$ iteratively thus minimising the cost function. The cost function is defined as,

$$J(\theta) = \frac{1}{2m}\left[\sum_{i=1}^{m}(h_\theta(x^i) - y^{(i)})^2 + \lambda\sum_{j=1}^{n}\theta_x^2\right] \quad (5)$$

m = Total training examples
$h_\theta(x^i)$ = Predicted value derived using (4) for three features
y = Actual measured value and,
λ = Regularisation factor

A total of 550 sets of data was used with 80% (440) used for training and the remaining 20% for validation. This ensures that the model developed is generalised and emulates a representative feature space of the available data. In addition, regularisation factor will further improve model accuracy by reducing the possible impact created by a feature with relatively low correlation coefficient. For neural network model implementation, gradient descent optimisation was used in combination with back propagation algorithm. The neural network architecture consists of 1 input layer with 3 units representing three features, 1 hidden layer with 25 neurons or units and one output layer with one unit which is the predicted value. The hidden layer and the hidden units has an error associated with it and back-propagation algorithm minimises this error by propagating the output layer back to the hidden layer. The error in output layer (L) and j^{th} unit is obtained as,

$$\delta_j^L = \frac{\partial J(\theta)}{\partial a_j^L}\sigma'(z_j^L) = a_j^L - y_j \text{ , where } a_j^L = (h_\Theta(x))_j \quad (6)$$

$$\delta_j^{L-1} = \frac{\partial J(\theta)}{\partial a_j^{L-1}}\sigma'(z_j^{L-1}) = (\Theta^{(L-1)})'\delta_j^L\sigma'(z_j^{L-1}) \quad (7)$$

Error in the previous layer is given as in (7) and so forth. As the error is propagated to layers before the output layers, the weights associated with the layers gets perturbed consequentially improving the cost function and optimisation occurs faster. The cost function plots of both gradient descent and neural network algorithm is shown in Fig. 6.

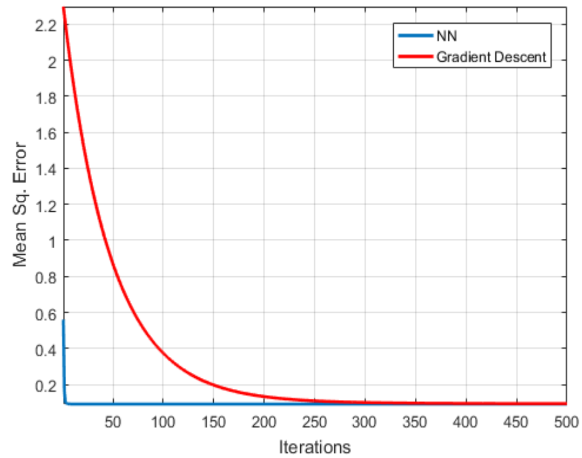

Figure 6. Cost Function plot (NN and Gradient Descent)

B. *Model Validation and Results Analysis*

As seen in figure 5 the mean square error of both the algorithms is close to 9e-2. Validation of the model was performed on 110 sets of data which was not used for training. Evaluation of the model prediction was done in terms of the average prediction accuracy for each of the validation data set as given in (8) where m is the total number of validation data sets.

$$\frac{1}{m}\sum(100 - \frac{|measuredVal - predictedVal|}{measuredVal} * 100) \quad (8)$$

Neural network algorithm showed a better performance with a maximum accuracy of 95.38% and gradient descent had a prediction accuracy of 93.97%. Both the algorithms involved random seeding for initialisation of weights that undergoes optimisation and hence the accuracy relies on the training data set used for each iteration. For each iteration he training set for each iteration was selected randomly from the available data set and the remaining 110 sets were used for validation. The model accuracy rates of neural network and gradient descent algorithms across 20 iterations are shown in figure 7.

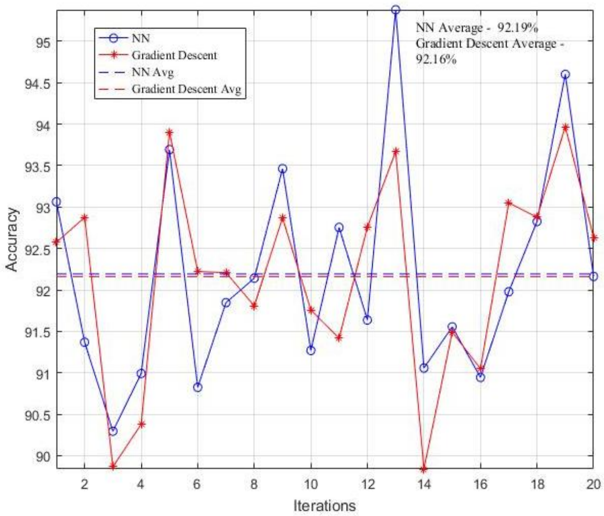

Figure 7. Model prediction accuracy across 20 iterations

Using back propagation algorithm in combination with gradient descent, the number of iterations required for optimising the cost function was considerably lower.
Prediction accuracy of neural networks algorithm was also higher than gradient descent with an average prediction accuracy of 92.19%.

IV. Conclusion

In a typical manufacturing shop floor, several machining, assembling cells becomes part of a product's manufacture. These cells often are operated independent using proprietary controllers. Deploying a universal sensor based indirect monitoring and parameter prediction would enable operators to keep track of machine health in a more centralised manner. Since the sensors are available off-the-shelf, relatively cheaper and smaller in size, the implementation cost incurred is minimal and practical constraints to tool-workpiece interaction is also minimised. This provides the motivation for this research work to develop a sensor based monitoring and parameter prediction model that can be easily deployed on industrial robots or CNC's. With parameters such as feedrate and depth of cut also determined, MRR can be predicted using equation (1). The same model can be also used to predict the output parameters such as product dimensions, surface finish etc.

With emerging Industry 4.0 standards, predictive maintenance practices has immense potential to add business value to manufacturing industry by reducing unnecessary downtime. Additionally, integrating a parameter control strategy is believed to further increase the business benefits by reducing rework and improving dimensional tolerance of the finished product.

Conflict of Interest

The authors declare no conflict of interest.

Author Contributions

Bobby K Pappachan conducted ideation, DOE, data analysis, machine learning, validation and original draft preparation. Tegoeh Tjahjowidodo provided overall guidance, supervision, funding acquisition and draft review.

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Bobby K Pappachan: I completed B.Eng. in Electronics and Communication from Karunya University, Coimbatore-India (2005-2009) and M.Sc. in Signal Processing from NTU-Singapore (2010-2012). Currently, I work as a technologist at the Rolls-Royce @ NTU Corporate lab and leads a project that focuses on conducting in-process monitoring and prediction in robot-assisted finishing processes. I have more than 5 years' experience in applied research focusing on machine learning and sensor based data analysis in the aerospace industry. In a capital heavy industry like manufacturing; to bring about innovation or changing conventional practices, is difficult not only because of the capital investments, but also due to factors like lengthy deployment periods, process redesign and a prevailing skepticism on results and return of interest(ROI). However I believe that, with machine learning and the entire discipline of AI, these challenges for innovation in manufacturing can be tackled since the infrastructure essential for AI based approach is already mature and adaptation of it will require minimal investment. It is hence of top-most priority to me that data based research adds business value to whichever target industry, and I am determined to adopt applied research practices to motivate myself towards achieving this goal in my future research endeavors.

Dr Tegoeh Tjahjowidodo: Tegoeh obtained his PhD from Katholieke Universiteit Leuven, Belgium in 2006. Formerly he obtained his master degree from Institut Teknologi Bandung, Indonesia. During his study, he was involved in a lot of researches, particularly on non-linear dynamics of friction.

He was a Senior Researcher at Flanders' MECHATRONICS Technology Center (FMTC) in Belgium, a research center bridging academic research and industrial know-how in mechatronics since 2006. In this research centre, he was involved in several projects, mainly in developing a model-based diagnosis methodology of mechatronic systems and noise reduction techniques in machineries. Presently he works as Associate Professor at Nanyang Technological University. His research interests include nonlinear dynamics, modeling, identification and control.