AN INVESTIGATION TO IMPROVE THE PERFORMANCE OF PORTABLE INTELLIGENT SYSTEM IN A DISTRIBUTED NETWORK

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ABSTRACT—
A low cost adaptive control system called Portable Intelligent System (PIS) was designed to improve the machining accuracy by reducing the dimensional variations in a component being machined in a CNC milling machine. This system can be mounted as an auxiliary device on an existing CNC machine. The PIS consists of portable modular fixture (PMF), laser detection system (LDS) and adaptive control system (ADS). The workpiece which need to be machined is mounted on the PMF. The LDS is used to collect real-time machining data. The ADS uses real-time machining data and determine the dimensional variations from engineering specification (called as delta). Based on the delta value, ADS makes the decision to reduce the dimensional variations via PMF. The decision making algorithm used in the system is feed forward back propagation neural network. The initial design of PIS uses default ANN parameters to monitor and control the dimensional variations found in the component. This paper aims to further investigate and improve the performance of PIS, thus able to improve the machining capability closer to six sigma quality level. In addition, an attempt was made to implement the PIS solution in a distributed manufacturing network. From the study, it was concluded that optimum ANN parameters helped to improve the performance of PIS, thus able to improve the machining capability closer to six sigma quality level. In addition, a framework was developed to deploy the PIS solution in a distributed network. In other words, this type of technology can be implemented in one part of the world and the machining can be controlled in the other part of the work at fraction of cost.

KEYWORDS— Adaptive control system; low cost automation; precision machining; CNC milling machine; six sigma; artificial neural network; portable intelligent system; distributed network.

INTRODUCTION
Customers demand high quality products at low cost. A high quality product implies tight tolerances in the manufacturing processes. The tight tolerances define the dimensional variations found in the machined surface. For instance, a component needs to maintain consistent thickness throughout the machined surface within a specified tolerance specification. With the current technology, CNC machine tools are able to machine the components within the tolerance specifications but the machined surfaces are not even (uneven surface). Nithyanandam et al. [1] demonstrated such uneven surfaces found in components machined using all CNC machine tools. This unevenness is called as dimensional variations or error. Figure 1 shows such uneven surface found on a sample component being machined using CNC milling machine.

Fig. 1. Dimensional Variations in a sample component.
A product consists of several components. Manufacturers accept a component as good quality when the dimensional variations fall within the tolerance specification, even though the surface of the component is not even (as shown in Fig 1). Taguchi et al. [2] stated that any dimensional deviations from the specified mean value of a component’s dimension is cost to quality. When each component is having such dimensional variations, then the final product could face cumulative dimensional variations or cumulative error. This could lead to malfunction of a product over the period of its usage. Therefore, each and every component needs to be machined with tight tolerance and closer to the targeted mean or targeted value.

To machine the components with tight tolerance, a low cost adaptive control system called portable intelligent system (PIS) was developed. This system consists of portable modular fixture (PMF), laser detection system (LDS) and adaptive control system (ADS). The ADS consists of artificial neural network (ANN), micro-controller and business intelligent (BI) unit. In ANN, feed forward back propagation neural network algorithm was used with default parameters. Figure 2 shows the working principle of the PIS solution. The step-by-step development of this system was elaborately discussed in the initial study [3]. Figure 3 shows the experimental outcome of that study - comparison of machining conditions between conventional machining and PIS machining.

Fig. 2. Working principle of portable intelligent system.

Fig. 3. Dimensional variations in Traditional machining vs. Existing PIS machining.

Even thought PIS helped to machine the components at tight tolerance but not to the six sigma quality level. Therefore, an investigation was carried out to improve the performance of PIS. For this, various ANN parameters such as number of hidden layers, number of neurons in the hidden layers, type of transfer function, ratio between training and test datasets are investigated in detailed. Then, an attempt...
was made to implement this solution in a distributed network. The details of these findings are well documented in this paper.

**LITERATURE REVIEW**

Factor of Safety (FOS) is a major factor to be considered in designing and manufacturing components for automobiles and aerospace industries. The ultimate aircraft structural FOS is defined as the ratio between design ultimate load to design limit (or actual applied) load on the structure and it is usually equal to 1.5 for U.S. military and commercial aircraft [4]. From the design perspective, proper fit of components in assembly is a natural way of improving FOS. This implies designing components to tight tolerances. Practically achieving this tight tolerances involves the use of precision machining to reduce the dimensional variations. However, it is difficult to machine the components to tight tolerance using traditional machining processes.

Artificial Intelligence offers a wide range of possibilities for the improvement of manufacturing processes. Many researchers [5 - 14] have done extensive research in the field of Machine Learning (ML) and Artificial Neural Network (ANN). In manufacturing applications, usually they are used for the prediction and control of machining parameters in manufacturing processes.

Machine Learning is the use of various algorithms and programs to mimic the process of learning. A computer program is said to learn from experience E with respect to some class of tasks T and performance measure P, if its performance at tasks in T, as measured by P, improves with experience E [15]. Among these algorithms, Artificial Neural Network (ANN) is widely used in manufacturing applications. MatLab [19] suggested using back propagation neural network algorithm for prediction in manufacturing applications. Peng et al. [16] used an ANN based Machine Learning approach to model and predict emission of NOx in coal power plants.

The function of artificial neural network (ANN) is to imitate human brain for the implementation of the functions such as association, self-organization and generalization. It can approximate any functions more efficiently and thus it is suitable for modeling any non-linear process [15].


**EXPERIMENTAL ARRANGEMENTS**

A preliminary study [3] was carried out in Makino CNC milling machine with Aluminum 6061 as the work piece and ZCC carbide tip end mill cutter as the tool. The ANN algorithm was modeled using MatLab with default values (ANN parameters). Figure 4 shows the experimental setup of the PIS system. The process capability of the existing PIS was determined close to 4.4 sigma. Therefore, an investigation was required to optimize the system to six sigma quality level.

A laser detection system was used to implement this solution in a distributed network. The ANN algorithm was modeled using MatLab with default values (ANN parameters). Figure 4 shows the experimental setup of the PIS system. The two laser sensors (Keyence LK-H027) are mounted on the spindle head of the CNC milling machine, which helps to measure the machining condition in real-time. The workpiece is mounted on the portable intelligent system and the machining operation starts. The laser sensors collect the workpiece thickness via Keyence 5001 controller and stored into a centralized database. Figure 5 shows the working principle of the laser detection system. The alignment of these sensors depends on the accuracy of the machining. Figure 6 shows the alignment of the laser detection system setup.

![Fig. 4. Experimental Setup with existing PIS.](image)

![Fig. 5. Working principal of laser detection system.](image)

![Fig. 6. Alignment of Laser heads.](image)
net\(_j\) is the output of the network.

In each layer, ANN network calculate the activating function \(f_a\) by tangent hyperbolic, which is expressed in Equation (2) at \(j\) th neuron:

\[
O_j = f_a(\text{net}_j) = \frac{1 - e^{-\text{net}_j}}{1 + e^{-\text{net}_j}}
\]  

(2)

With these information, neural network is trained with random generated weights \(W_{ij}\). This network continues to train itself in a loop until the mean square error (MSE) attains the lowest possible value among the targeted value and the network output. This MSE is expressed as shown in Equation (3)

\[
\text{MSE} = \sum_{m=1}^{m} \sum_{k=1}^{k} (D_{mk} - O_{mk})^2
\]  

(3)

where,

\(D_{mk}\) is the targeted network;
\(O_{mk}\) is the desired network;
\(k\) is the number of neurons in the output layer; and
\(m\) is the overall number of dataset.

When the network is trained, the weights between the neurons are adjusted dynamically using the Equation (4).

\[
W_{ij}(t) = \eta \delta_i O_j + \alpha W_{ij}(t-1)
\]  

(4)

where,

\(\eta\) is learning rate to control the stability of the network;
\(\alpha\) is the momentum rate of the network; and
\(t\) is the number of iterations.

C. Adaptive control system application

In the initial study, adaptive control system was developed using MatLab with ANN algorithm. In the ANN, default parametric values were considered. The performance of the system depends on the ANN parameters and the response time taken between MatLab and the machining reaction. With these setup, the system performance was too slow and many times, the system was deadlock.

Therefore, in the current study, the adaptive control system (ADS) was developed using Microsoft Visual Studio with Aforge.Net ANN libraries. This new ADS determines not only optimum cutting parameters required for the study but also the optimum ANN parameters dynamically. Figure 8 shows the new ADS application main menu (called as PIS Business Intelligence application). In the main menu (setup screen), target (desired) value, upper control limit, lower control limit and precision machining requirements are entered. Doering [18] suggested that 75% control on upper limit and lower limit specification may lead to precision machining.

The optimization of PIS started with the selection of ANN parameters. Table 1 shows the ANN parameters considered for the case study. The optimization targeted the speed (performance) of the ANN algorithm and the prediction accuracy.

| TABLE I. INITIAL ANN PARAMETERS FOR OPTIMIZATION |
|-----------------|--------------|
| Parameter       | Values       |
| No of Hidden Layers | Range {1-50} |
| Hidden Layer Neurons | Range {2-20} |
| Transfer Function | Sigmoid, Tanh |
| Function Parameter | Range {1-10} |
| Ratio between training set and testing set | 0.5 to 0.99 |

The input layer for this network are given as cutting speed and feed rate. Table 2 shows the design of experiments conducted during initial study [17]. With this data, network is trained in "for" loop with Table 1 conditions.

### Table II. Thickness Data of the Initial Study

<table>
<thead>
<tr>
<th>Feed Rate (mm/sec)</th>
<th>Cutting Speed (m/min)</th>
</tr>
</thead>
<tbody>
<tr>
<td>34</td>
<td>57</td>
</tr>
<tr>
<td>76</td>
<td>94</td>
</tr>
<tr>
<td>113</td>
<td></td>
</tr>
</tbody>
</table>

For this, maximum error distribution curve was plotted against number of hidden layers, number of neurons in the hidden layers, type of transfer function and ratio between training and testing data set. Figures 9, 10 and 11 shows the error distribution curve for number of hidden layers, number of neurons in the hidden layers and transfer functions respectively for a sample data.
Fig. 9. Error distribution over number of hidden layers for given study.

Fig. 10. Error distribution over number of neurons in a hidden layer for given study.

Fig. 11. Error distribution for different Transfer Functions and \((\alpha)\).

The real-time data point (A, B, etc. of Figure 5) collected by laser detection system is also pooled with the above data in the centralized database. With these data, the new ADS determine the optimum cutting parameters and optimum ANN parameters are determined in real-time for each given condition, as shown in Figure 12.

With these information, the portable intelligent system machining operations starts. The new ADS application predicts the cutter tool movement (up or down) based on the dimensional variations (delta). For instance, the ADS predict the data point B based on data point A (as seen in Figure 5) and sends the signal to portable modular fixture via Netduino microcontroller.

D. Portable modular fixture

The Aluminum 6061 material is placed on the portable modular fixture, which is mounted on the High Speed Makino CNC milling machine table. This portable modular fixture uses Oriental NX-4 servomotor to move it in the linear direction perpendicular to dimensional variations exists on the machined surface. When the dimensional variation (say data point A in Figure 5) is measured above the targeted value (positive value), then the servomotor of portable modular fixture rotates in anticlockwise direction at a distance of delta (data point A minus targeted value). Similarly, when the dimensional variation is measured below the targeted value (negative value), then the servomotor of the portable modular fixture rotates in the clockwise direction at a distance of delta (targeted value minus measured value).

E. Implementing in a Distributed Network

It is assumed that the machining conditions are within the private network (intranet environment). An attempt was made to implement the low cost adaptive control system in two methods: (a) Client/server model; (b) Embedded programming model.

In the first method, the portable modular fixture was located in one location and the rest of the portable intelligent system components were at different location, as shown in Figure 13. With this setup, the single setup controls several CNC machines. In other words, this setup may be useful for similar machining conditions. The drawback of this model was that more dimensional variations found in the machining conditions and it was difficult to control. This is because machines are not in identical conditions.

In the second method, the portable modular fixture and microcontroller are placed in one location and the rest of the components of portable intelligent system were located in different location, as shown in Figure 14. In this setup, each machine can be controlled independently.

F. Experimental setup

Three sets of experiments are conducted in this study. The first experimental setup was conducted using conventional machining. The workpiece was placed on the High Speed Makino CNC milling machine. From the preliminary study, the optimum cutting speed and feed rate were determined, which was used in these experiments. A sample of 10 components (Aluminum 6061 material with 100 mm length, 80 mm width and 25 mm depth) are machined to maintain 2 mm thickness (as shown in Figure 1). Digital micrometer was used to measure the thickness of the workpiece.
The second experimental setup was conducted using earlier version of portable intelligent system (using MatLab). In this, the workpiece was placed on the portable intelligent system, which was then mounted on High Speed Makino CNC milling machine. Similar experiments were conducted and the workpiece thickness was measured using laser detection system. The third experimental setup was conducted using low cost adaptive control system. In this setup also, the workpiece was placed on the portable intelligent system, which was then mounted on High Speed Makino CNC milling machine. Similar experiments were conducted and the workpiece thickness was measured using laser detection system.

RESULTS AND DISCUSSIONS

In the first experimental setup, optimum cutting parameters were determined as 94 m/min as cutting speed and 6.8 mm/sec as feed rate. In the second experimental setup, optimum cutting parameters were determined dynamically based on machining conditions (real-time data collection using laser detection system). In the third experimental setup, optimum cutting parameters and optimum artificial neural network parameters were determined dynamically. The optimum cutting parameters were determined as 38 m/sec as cutting speed and 5.1 mm/sec as feed rate (see Figure 12). Similarly, the optimum ANN parameters were determined as shown in Table 3.

**TABLE III. **OPTIMUM ANN PARAMETERS FOR PRECISION MACHINING

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Values</th>
</tr>
</thead>
<tbody>
<tr>
<td>No of Hidden Layers</td>
<td>1</td>
</tr>
<tr>
<td>Hidden Layer Neurons</td>
<td>11</td>
</tr>
<tr>
<td>Transfer Function</td>
<td>Sigmoid</td>
</tr>
<tr>
<td>Function Parameter</td>
<td>1</td>
</tr>
<tr>
<td>Ratio between training set and testing set</td>
<td>98:2</td>
</tr>
</tbody>
</table>

Figure 15 shows the resultant (dimensional variations) of all three experimental setups.

CONCLUSIONS

The earlier version of portable intelligent system is a low cost automation (LCA) can be mounted on a CNC milling machine, which can act as plug and play device. This system uses MatLab with default ANN parameters. It helped to machine the components up to 4.4 sigma quality level. With the fine tuning of ANN parameters, the updated portable intelligent system demonstrated to machine the components to closer to six sigma accuracy. An attempt was successfully made to launch this PIS solution in two methods of distributed network: client/server model and embedded programming model. When this solution is implemented using a single CNC machine, then embedded programming model could provide better results at affordable cost. When several CNC machines are involved, then client/server model works better.

Further studies will be needed to expand the scope of the optimized PIS solution to support other machine tools such as CNC Lathes, etc. In addition, an attempt could be made to integrate this solution into the existing CNC machine tools with the help of OEMs.

REFERENCES


