Enhancing the Accuracy of a CNC Machine Using Artificial Neural Networks
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Abstract
Traditionally, geometric errors of CNC machine axes are rectified by means of calibration with subsequent calculations of compensation values applied directly in a machine controller or with the aid of parameterised kinematic error models. The main drawback of these methods is that they require a calibration process, which may not economically viable. In this research, the proposed approach is based on software compensation with the aid of Artificial Intelligence.

Two artificial neural networks, namely the Global Neural Network and the Global Vector Neural Network were applied. The artificial neural networks were derived from the data obtained in the drilling of a large number of holes, in a random sequence, in test plates. The coordinates of the drilled holes were then measured with the aid of a CMM to determine geometric errors. A genetic algorithm was used to train the neural networks on previously drilled holes. The network generated predicted errors, based on which compensation values were then determined and applied in subsequent drilling tests.

Keywords
CNC Machine, Geometric Accuracy, Neural Networks, Evolutionary Computing

1 INTRODUCTION
Computer Numerically Controlled (CNC) machining centres are used in all sectors of modern industry as the core of flexible, advanced and reconfigurable manufacturing systems. As part of a research project in low-cost automation, a special purpose 3-axis CNC machine of a gantry type was developed to be used as a platform for a reconfigurable machining centre for manufacturing of moulds and dies [1, 2] (see Figure 1). The stroke lengths are 350 mm, 270 mm and 170 mm for the X, Y and Z machine axes respectively. The machine can be equipped with different workheads including: conventional milling spindle, high-speed spindle and an electric discharge machining unit.

Figure 1 - CAD model of the machine

In order to enhance the displacement accuracies of the machine axes, a software compensation strategy, based on neural networks, was developed and evaluated. The main focus of this study was limited to the development of a compensation strategy for linear displacement errors within the X-Y working plane, as they were considered to be the most significant for this type of machine and its applications. Two types of neural networks were developed and compared through both cutting test and direct measurement by a laser interferometer.

2 THEORETICAL BACKGROUND
Errors affecting machine components are classified into two categories, namely dynamic errors and quasi-static errors. Dynamic errors are the result of machine vibrations, controller error, and/or spindle motion error; affecting the micro characteristics (for example surface finish) of the workpiece [3 - 7]. Quasi-static errors are time varying errors between the work-tool and the workpiece related to the hardware of the CNC machine and are comprised of three general classes, specifically cutting force induced errors, thermal/temperature induced errors and geometric/kinematic errors [7 - 12].

The enhancement of quasi-static errors can be addressed by two main strategies, namely hardware compensation or software compensation. Hardware compensation adopts the approach of applying error avoidance techniques during the design and manufacture of the CNC machine. However, this can prove to be costly and may lead to over designed CNC machines [5, 8, 11]. Software compensation on the other hand does not endeavour to avoid the inherent errors of the CNC machine; rather it enhances the absolute accuracy
of the CNC machine through error minimisation, offering effective, efficient and economically feasible error correction and accuracy enhancement.

Wang et al. [6] developed a kinematic error model to compensate for 21 geometric and thermal errors of a 3-Axis Cincinnati Milacron Horizontal CNC machine. The use of software compensation to reduce quasi-static errors that affect the accuracy of a CNC machine has been extensively addressed. Jung [7] presents a parameterised error model and on-machine measurement to minimise the geometric errors of a 3-Axis vertical CNC machine.

The above mentioned techniques make use of a theoretical compensation strategy based on direct measurements and the application of transformation matrices and linear interpolation to derive required compensation values. The alternative approach outlined in this research is to utilise artificial neural networks to predict geometric inaccuracies within the working volume of a machine, and correct them through software compensation.

Artificial neural networks (ANN) are the algorithmic modelling of a biological neural system through the interconnectivity of multiple artificial neurons (AN). The ANN accepts input vectors from either the environment or from AN contained within the ANN. The input signal is strengthened or weakened by the individual AN in order to calculate the output signal. Common applications of ANNs involve the modelling of complex input-output relationships or establishing patterns within data. In the case of the neural network based compensation strategy, data obtained during the measurement of linear errors by a laser interferometer and electronic level, in addition to data obtained during cutting tests, can be employed to train the networks.

For example, for machine tools, Fines [13] compared the compensation of the X-axis through an ANN based strategy and through the CNC machine’s controller strategy. End point compensation was employed to evaluate the efficiency of the neural network based compensation strategy and the displacement error compensation capability of the CNC machine’s control system. Displacement errors during compensation were directly measured by a laser interferometer.

Raksiri and Parnichkun [4] proposed an offline error compensation model for a 3-Axis ARD-TB400 CNC machine. Geometric and cutting force-induced errors of the CNC machine are predicted via a feed forward backward propagation ANN. Veldhuis and Elbestawi [14] developed a neural network based compensation model for the geometric and thermal error of a 5-Axis Vertical CNC machine focusing on the compensation of the Z-Axis and A-Axis; an individual feed forward backward propagation network was developed for each axis. Supervised learning was adopted for training the ANN, with training sets developed from results simulated using a kinematic model of the CNC machine and from results measured by thermocouples.

3 COMPENSATION STRATEGY

3.1 Artificial Neural Networks Compensation Strategies

Several ANN morphologies and sizes were investigated in a preliminary study, with the two most successful approaches discussed here. The first approach will be referred to as the Global Neural Network (GNN). The NN was trained to predict a global error within the X-Y working plane of the machine, not considering the previous movement in the machining process or the error associated with that movement. The only input to the network is thus the drilling position. This approach corresponds to neural network approaches followed by previous researchers [4,11,14].

The second approach is referred to as the Global Vector Neural Network (GVNN). The GVNN is trained to predict a global error within the X-Y working plane of the machine, based on both the drilling position and the direction of motion. A direction-of-motion indicator was adopted by a previous researcher [14]. The motivation for this approach is that the displacement error may be affected by the machine movements required to reach that position from a previous position because of backlash. The inputs to the GVNN are thus the drilling position and a normalized vector indicating the direction from the previous position.

Separate ANNs were developed for both the X- and Y- axes linear displacement errors. This is attributable to separate output vectors required for the linear displacements, as the laser interferometer employed during calibration is not able to measure multiple error components. The division of the data employed for the formulations of training and validation data sets, and the development of separate ANNs to predict the X-axis and Y-axis linear displacement, were adopted for all further experiments conducted. A single hidden layered Feed-forward Neural Network was employed for the basic structure of the ANNs developed, with the Sigmoid Activation Function incorporated for the hidden layer and the Linear Activation Function for the output layer.

All ANNs explored in this research are fully connected from the input layer to the single hidden layer to the output layer. The output vector for all ANNs developed comprised of a single output value providing the linear displacement compensation value to be applied to the desired machine axes position.

The neural network based compensation strategy is based on end-point compensation. Therefore, the machine code describing the X and Y co-ordinates is pre-processed and adjusted according to the
predicted error (PE) by the developed ANNs. The process can be described as follows: the network is supplied with the code (L) describing the machining process in terms of x-coordinates and y-coordinates. Suppose Lx is the list of points defining the position of the X-axis during the machining process, and Ly is the list of points defining the position of the Y-axis. Then the predicted linear displacement error at a position (0, 0) for the GNN is defined as follows:

\[ PE_x = F_{NN}(0, 0) \]
\[ PE_y = F_{NN}(0, 0) \]  

and for the GVNN at (0, 0) as follows:

\[ PE_x = F_{NN} \left( \frac{L_x(0) - L_x(i - 1)}{\sqrt{(L_x(i) - L_x(i - 1))^2 + (L_y(i) - L_y(i - 1))^2}} \right) \]
\[ PE_y = F_{NN} \left( \frac{L_y(0) - L_y(i - 1)}{\sqrt{(L_x(i) - L_x(i - 1))^2 + (L_y(i) - L_y(i - 1))^2}} \right) \]

Where: FNN is the activation function for the respective neural network.

Consequently the predicted linear displacement error for every element i in L can be calculated for the GNN as described below:

\[ PE_x(i) = F_{NN}(L_x(i), L_y(i)) \]
\[ PE_y(i) = F_{NN}(L_x(i), L_y(i)) \]

and for the GVNN:

\[ PE_x(i) = F_{NN} \left( \frac{L_x(i) - L_x(i - 1)}{\sqrt{(L_x(i) - L_x(i - 1))^2 + (L_y(i) - L_y(i - 1))^2}} \right) \]
\[ PE_y(i) = F_{NN} \left( \frac{L_y(i) - L_y(i - 1)}{\sqrt{(L_x(i) - L_x(i - 1))^2 + (L_y(i) - L_y(i - 1))^2}} \right) \]

3.2 Neural Network Training

Training of the neural networks was achieved with a generic algorithm. The training data was acquired from a large number of holes drilled in two plates. A total of 526 training points were included in the training set, with the validation set consisting of 263 points.

To determine the final architecture of the ANNs, small to moderate sized networks were examined with varying numbers of hidden neurons contained within the hidden layer. For every configuration of the ANN a series of 10 tests were conducted, where the network was trained against the data obtained during the linear displacement error tests. In each test the ANN was re-created, with the initial weights and biases of all the neurons randomly initiated.

The appropriate number of hidden neurons for each of the neural networks was determined in preliminary experiments. The following number of hidden neurons was used in each neural network respectively: 5 neurons in the Global NN (X-axis); 8 neurons in the Global NN (Y-axis); 7 neurons in the Global Vector NN (X-axis); 5 neurons in the Vector NN (Y-axis).

4 EXPERIMENTAL PROCEDURE

The test plates were mounted on the machine table using dowel pins as shown in Figure 2. The machining process consisted of drilling a series of up to 152 holes, to a depth of 2mm, within the 350mm x 270mm working area of the CNC machine. Each hole was initially drilled with a 9mm slot drill at a spindle speed of 1000rpm and a feed rate of 100mm/min, and secondly with a 10mm slot drill at a spindle speed of 1000rpm and a feed rate of 50mm/min. A feed rate of 800mm/min was employed for movement between commanded X-Y co-ordinates. By repeating the machining operation and reducing the feed rate of the second drill process, the majority of the machined material would be removed by the first drill operation. This would reduce the cutting force-induced errors experienced during the repeat operation.

The drilled points’ coordinates were selected at random and varied from points selected for the previous tests in order to eliminate the occurrence of a “best-fit” model. In addition, movements between holes could be one of eight possible axis motions as holes were drilled in varying incremental movements. Subsequently, even if the location of a hole was identical on two different test plates, the approach to the location of the hole would vary.

5 RESULTS

Figures 3 and 4 illustrate the error maps developed for the X-axis by the GNN and the GVNN respectively, detailing the target linear displacement errors (scatter plot) which were experimentally measured and the predicted linear displacement errors (surface plot) which were produced by the neural network. The target error points include both...
the training data points and the validation target points. It can be seen from Figures 3 and 4 that variations occur between the predicted errors and the target errors. However, the results illustrate that the GNN and GVNN are successfully generalising the input data because the surface plots follow the general trends of the scatter plots, even those points that were not used for training.

![Figure 3 - Error map for the X-axis produced by the GNN](image1)

![Figure 4 - Error map for the X-axis produced by the GVNN](image2)

Generally, the accuracy of an ANN is determined by its ability to approximate or generalise a function, in other words minimise the error between the desired or target output of the ANN and the predicted output. The validation test confirmed the capabilities of the developed ANNs as discussed below.

6 EVALUATION AND VALIDATION

6.1 Neural Networks Validation

The validation set was acquired to determine the generalisation ability of the neural network by drilling a completely new set of holes in the 3rd plate using the predicted errors and required compensations. The obtained cross-validation graphs, shown in Figures 5 and 6, demonstrate that the developed ANNs have the ability to capture the general trends in the training data. Trend lines are included to demonstrate the correlation. Note that these graphs do not present information regarding to accuracy of the compensation, but rather illustrates the neural network’s performance on unseen data.

6.2 Evaluation of the Compensation Strategy using the Machined Plates

The neural network based compensation model was evaluated by comparing the actual absolute coordinates of the machined holes, measured by a CMM with an accuracy of 0.1 μm, and the programmed coordinates. The first test plate was drilled without any compensation producing the errors shown in Table 1 in the uncompensated column. The final (third) test plate, which was drilled with the compensations, had significantly smaller errors, indicating that the neural network based compensation method improved the position accuracies of the X and Y axes by approx. the factor of two.

<table>
<thead>
<tr>
<th>Machine Axis</th>
<th>Uncompensated</th>
<th>Compensated with Neural Network</th>
</tr>
</thead>
<tbody>
<tr>
<td>X</td>
<td>66.8</td>
<td>30.1</td>
</tr>
<tr>
<td>Y</td>
<td>132.9</td>
<td>45.2</td>
</tr>
</tbody>
</table>

**Table 1 - Average displacement errors before and after the compensations**

6.3 Evaluation of the Compensation Strategy using the Direct Measurements

Direct measurements of the accuracy of linear displacements along the X and Y axes were taken with the aid of a Renishaw XL-80 Laser Interferometer [15]. Measurements were conducted for both forward and reverse translation with measurements obtained at 25mm intervals along the respective axis. Firstly, axial displacements without compensations were measured. The X-axis displacement errors, shown in Figure 7, accumulate, which can be attributed to mechanical and/or electrical/electronic errors of the drive. While the Y-axis displacement error map, shown in Figure 8, exhibits a pattern, which can be explained by geometric inaccuracies, slack and/or deflection in the ballscrew-nut system.
It can be seen that for the X-axis, the neural network compensation method reduced the errors within a 30 μm range. However, the displacement errors for the Y-axis were overestimated by the network, which can be attributed to the fact that the errors for the Y-axis in combined movements were significantly larger than in the singular movement along the axis, possibly due to the X-Y axes squareness error.

7 CONCLUSIONS

In this research, the accuracy of a special purpose CNC machine was enhanced through the utilisation of software compensation of geometric errors, based on artificial neural networks. In order to evaluate the compensation strategies, cutting tests were performed, in which a large number of holes were drilled randomly within the machine workspace, and then measured with the aid of a CMM to determine the actual machine geometric errors after compensation. Hence, the reduction in the displacement errors in the X-Y plane was solely investigated. Drilled holes were selected at random, with eight possible axes motions occurring between sequentially machined holes. Besides the simplicity of the procedure and relatively low costs, the other important advantage of a compensation strategy using ANN is that both axes movements are executed using interpolation. Therefore, combined errors of displacement, straightness and squareness can be accounted for and compensated.

Two artificial neural networks, namely the Global Neural Network and the Global Vector Neural Network were applied as the compensation strategy. The artificial neural networks were trained with larger data sets that represent the approach to a data point from different angles and the errors associated with that approach. In addition, the training data supplied to the artificial neural networks represents the linear displacement error associated with the motion of either a single or two axes. The Global Neural Network and Global Vector Neural Network reduced the average machine error by 55% and 66% respectively for the X-axis, and 65% and 55% respectively for the Y-axis, during the final cutting test.

The performance of the compensation strategies was further evaluated with a laser interferometer measuring uncompensated and compensated positions of the X and Y axes. Single axis linear displacement error testing revealed that the neural network based model improved the accuracy of the X-Axis by 70% and the repeatability by 50%. It did not, however, improve the accuracy and repeatability of the Y-Axis. It appears that the network overestimates the Y-axis errors and generates large predicted values. Therefore, further investigation into the development of Y-Axis compensation values by the neural network would have to be performed. However, based on the
results of the combined movements of the axes, the network compensation strategy demonstrated significant improvements in the accuracy of both axes.

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9 REFERENCES

10 BIOGRAPHY
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