Neural Network Contour Error Prediction of a Bi-axial Linear Motor Positioning System

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Abstract: In the article a method of predicting contour error using artificial neural network for a bi-axial positioning system is presented. The machine consists of two linear stages with permanent magnet linear motors controlled by servo drives. The drives are controlled from a PC with real-time operating system via EtherCAT fieldbus. A randomly generated Non-Uniform Rational B-Spline (NURBS) trajectory is used to train offline a NARX-type artificial neural network for each axis. These networks allow prediction of following errors and contour errors of the motion trajectory. Experimental results are presented that validate the viability of the neural network based contour error prediction. The presented contour error predictor will be used in predictive control and velocity optimization algorithms of linear motor based CNC machines.

1 INTRODUCTION

Multi axis machines are widely used in industrial manufacturing in the form of numerically controlled machine tools (CNC) and robots. Each mechanical axis is driven by a linear or rotary feed drive. Composition of their movements constitutes the output motion trajectory of the machine's end effector (i.e. milling tool, laser head, welding head, gripper) also called a toolpath. Position commands for each feed drive are generated by interpolating the given tool path according to pre-planned or on-line generated velocity profiles.

In order to enhance machine performance much attention has been given to improving the motion planning process by developing new feedrate profile generation algorithms. Several authors propose using optimization algorithms to generate an optimal feedrate profile (Xu et al., 2018; Ni et al., 2018; Zhang et al., 2019). An optimal feedrate profile maximizes speed while simultaneously respecting the feed drives' and machine's constraints in order to shorten machining time. Most approaches neglect the influence of machining errors in the feedrate planning process. Machining errors are often defined as contour errors which are the minimum distances between the reference toolpath and actual tool positions (Ramesh et al., 2005; Tang and Landers, 2013) as shown in figure 1. Some authors propose including error constraints in the feedrate planning process but usually use simplified models that do not accurately predict actual following errors (Jia et al., 2017).

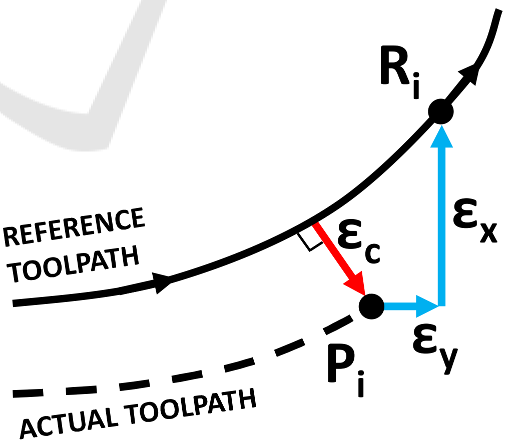

Figure 1: Contour error definition. ε_c - contour error, $\varepsilon_{x,y}$ - axis following errors, R_i - toolpath reference point, P_i - actual toolpath point.

Optimizing feedrate with respect to contour error constraints is especially important for machines that utilize linear motor feed drives such as laser cutters. These machines can achieve very high speeds

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and accelerations which significantly reduces machining time. At the same time they simultaneously need to ensure accurate toolpath following. Most multi axis machines use permanent magnet rotary synchronous motors which produce rotary motion and torque. Some mechanism is usually required to convert rotation into linear motion. These are usually ballscrews, racks and pinions or toothed belts sometimes with an additional reduction gear. Permanent magnet linear synchronous motors produce linear motion directly without the need for additional mechanisms. This has the advantage of greatly simplifying the machines construction and eliminating backlash and compliance in the feed drive which leads to decreased following errors. On the other hand the linear motor does not have the mechanical advantage provided by these mechanisms and has to drive the machines mass directly. Linear motors are controlled using the same field oriented control techniques used in rotary motors therefore the same servo drives can usually be used.

The authors previously developed a feedrate optimization method which accounts for contour error for traditional ballscrew driven machines (Erwinski et al., 2016; Szczepanski et al., 2017). A fundamental requirement for such an algorithm is an accurate predictor which can predict the contour error generated by the feed drive (both the servo drive and the mechanical part). It is important that the parameters of the predictor used are easy to identify and can be easily ported to any machine with any servo drive. The main contribution of the paper is the development of a contour error predictor that can perform a multi-step-ahead prediction of the contour error based on a velocity demand input signal. The proposed predictor is a non-linear black-box input-output model that accounts for the dynamics of both the servo drive and mechanical components of the linear motor feed drive. This predictor will be used in a multi-axis machine feedrate optimization algorithm to constrain the maximum contour error by adjusting the feedrate profile. The authors will implement this approach for linear motor based machines which will be an extension of their previous works.

2 BI-AXIAL LINEAR MOTOR POSITIONING SYSTEM

The linear motor positioning system used in this research consists of two linear motor positioning units representing X and Y axes of a multi-axis machine. The positioning units use Tecnotion TM6 iron core flat linear motors mounted on an aluminium chassis with linear roller guideways. The motors are controlled by Kollmorgen AKD-P00307 servo drives with feedback provided by Renishaw optical linear scales. The high resolution feedback provides positioning accuracy of around 0.01 micrometre. The positioning units' servo drives receive position, velocity or torque commands from a PC-based numerical controller via EtherCAT fieldbus (Jansen and Buttner, 2004; Paprocki et al., 2018). The PC controller runs TwinCAT 3 real-time control software on a standard Windows 10 operating system. Special real-time mechanism implemented in TwinCAT such as processor core isolation ensure hard real-time operation of the CNC controller. This allows for implementation of typical PLC or CNC controllers in software without any dedicated hardware extensions. TwinCAT also implements a real-time EtherCAT communication stack and driver which enables deterministic communication with many commercial automation equipment such as servo drives or input output devices.

TwinCAT also enables the user to implement custom real-time control programs in C++. This approach was used in this research to develop a trajectory interpolator for both linear axes. The intepolator generates position commands in 250 microsecond intervals and sends them over EtherCAT to the drives to realize the reference motion trajectory. The developed software can also send direct commands to the drive over Ethercat to initiate the device, perform homing, clear errors and change between position, velocity and torque modes according to the Can in Automation CIA402 device profile. The picture of the linear motor positioning system test stand is shown of figure 2 and its schematic is shown of figure 3.

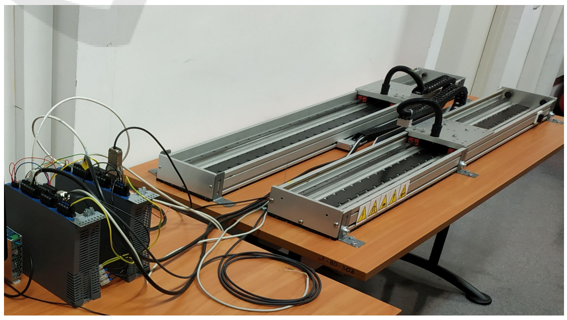

Figure 2: Linear motor positioning system test stand.

The linear motor motion path is defined as a third order Non-Uniform Rational B-Spline (NURBS) (Piegl and Tiller, 2012). Such path description is often used in CNC machining because of guaranteed continuity, ability of local shape modification and ability to easily describe complex shapes (Heng and Erkorkmaz, 2010; Liu et al., 2015). Interpolation of NURBS

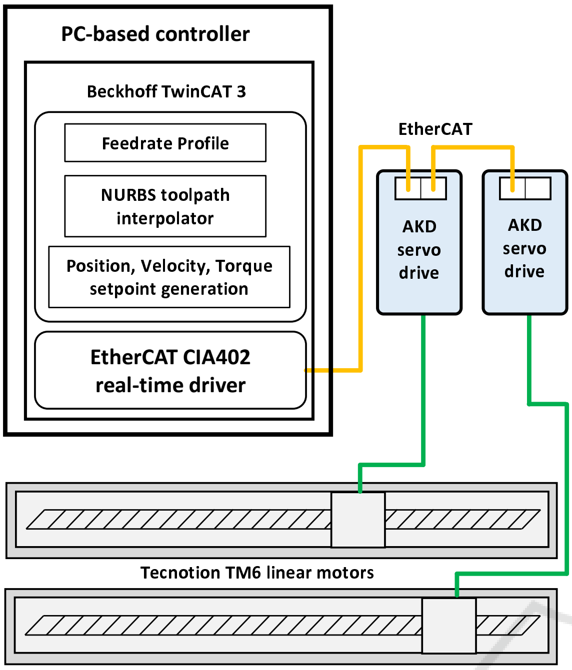

Figure 3: Linear motor positioning system test stand schematic.

toolpaths is performed according to a predefined, optimized polynomial feedrate profile. This allows to maximize drive capabilities without violating their speed and acceleration limits.

3 LINEAR MOTOR FEED DRIVE MODEL

Main factors that contribute to the dynamics of the linear motor positioning system are the mass of the motor and carriage attached it and guideway friction. Due to lack of a drive train effects such as backlash or compliance do not influence the positioning accuracy. An additional effect typical of flat iron core linear motors is the cogging force. This force is due to the attraction between the motor's iron core and the permanent magnets and is dependent on their relative position. This causes a periodic force ripple the frequency of which is proportional to the motor speed and magnet pitch (distance between adjacent magnet poles).

The cogging force has significant effect on positioning accuracy mainly at low speeds. Because this effect depends only on motor position it can be mapped and eliminated by using static feedforward compensation. This functionality is implemented in the Kollmorgen AKD servodrives and was used in this research to significantly eliminate its effect on positioning accuracy.

Friction force is influenced by several friction components. When the drive tries to move the motor from standstill it has to overcome static friction. Then as the speed increases the friction force drops and after reaching a certain speed rises again. This is called the Stribeck effect and the velocity at which the friction minimum is reached is the Stribeck velocity. Friction then increases as a linear function of speed and this component is called the viscous friction. There is also a constant velocity independent component called the Coulomb friction which depends only on mass. Friction is usually assumed to be symmetric for positive and negative velocities. This is not always the case if the motion unit is inclined or the guideways are not exactly parallel to each other. A block schematic of the linear motor feed drive is presented in figure 4.

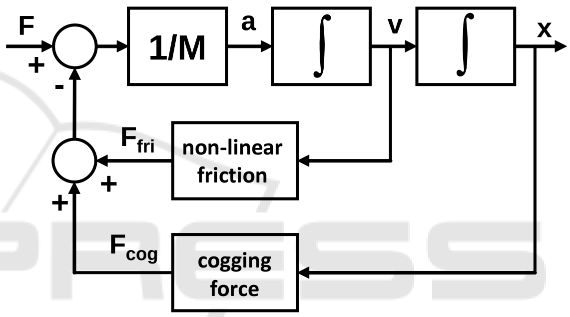

Figure 4: Linear motor model, M - motor and carriage mass, a - motor acceleration, v - motor speed, x - motor position, F_{fri} - friction force, F_{cog} - cogging force.

In order to identify the Linear Motor Feed Drive Model a series of experiments were performed on the system. In order to identify carriage mass a current step command of 2A was issued and actual velocity was measured. Total carriage and motor forcer mass was identified using MATLAB System Identification Toolbox to be 3.61kg. In order to identify friction a series of constant positive and negative velocity movements were performed in velocity mode from 0.1 mm/s to 2000 mm/s. Motor current was measured for each run in order to determine the friction force. This current was averaged to eliminate any force ripples and multiplied by the motor force factor Kf equal to 39. The resulting friction map is shown in figure 5.

It can be clearly seen that for large velocities from about 500mm/s the viscous does not increase linearly with the increase in speed as is usually assumed. The discrepancy between a linear friction characteristics and actual friction curve is significant at large speeds. For 2 m/s the actual friction current is 20% smaller than a linear friction model would predict. The linear motor also has a large static friction requiring about

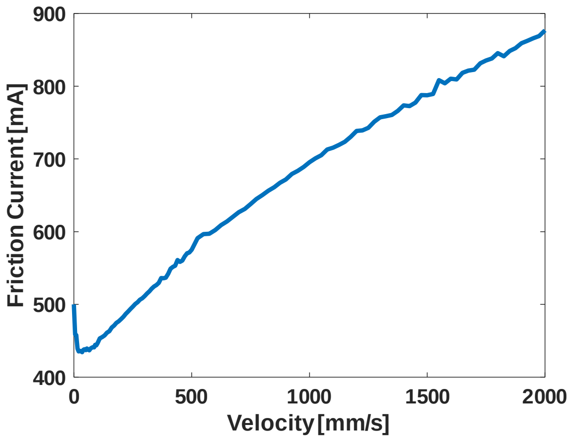

Figure 5: Current due to friction as a function of velocity.

500mA current to start motion. This was identified by generating a ramp current command and recording the amount of current at which the motor starts to move. This is caused by large magnet attraction forces and lack of mechanical advantage offered by traditional drive train mechanisms.

Cogging force was also identified during constant velocity movement of 5 mm/s. Because this effect is depends motstly on motor position a current versus position table can be recorded and used for feedforward compensation. Figure 6 presents the drive current as a function of position. The period corrensponds to distance of 12mm which is the distance between north and south poles of the permanent magnet track.

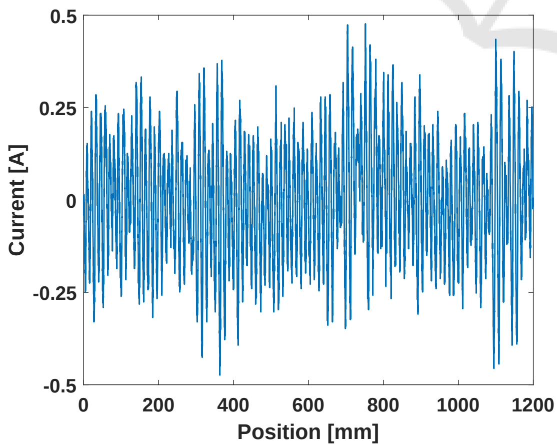

Figure 6: Linear motor (Tecnotion TM6) current due to cogging force at constant speed of 5 mm/s in velocity mode.

It is clear that the linear motor positioning system although mechanically very simple has non-linear characteristics. Identification of a model presented in fig. 4 is time consuming and requires switching the drive to velocity and torque modes. This is not always possible on commercial multi-axis machines. Also when using off-the-shelf servo drives the actual controller structure is not always precisely known. Due to these problems a black box modelling approach is used instead in order to obtain following and contour error predictions.

4 NARX NEURAL NETWORK CONTOUR ERROR PREDICTION

In order to obtain contour error predictions of a linear motor positioning system with NURBS motion path definition following error prediction of each axis have to be determined first. Predicted following errors are combined with information about local toolpath geometry to obtain and estimated contour error. The structure of a neural network contour error predictor is shown in figure 7.

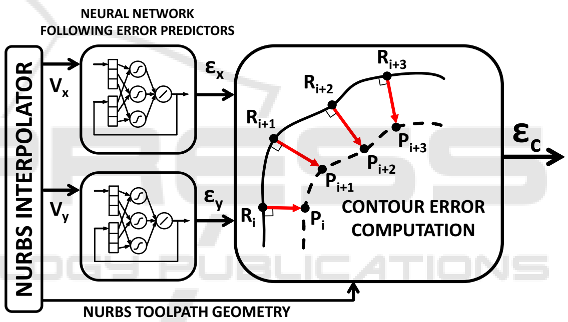

Figure 7: Structure of neural network prediction block.

Prediction of axis following errors is performed by using a Non-Linear Auto Regressive Exogenous Input Neural Network (NARX). Such networks differ from traditional multi-layered perceptrons (MLP) by adding a feedback between output and input layers and delays in the input layer. This allows to model non-linear dynamical systems. An example of a NARX neural network used for following error prediction is presented in figure 8. Reference velocity obtained from differentiating polynomial toolpath and feedrate profile is used as input.

Training the network is a process of minimizing the mean squared errors based on error backpropagation. Training of the NARX following error predictor is performed first in series-parallel form where the network feedback is disconnected and target series (following error) is fed into the network along the input signal (reference velocity). In this form standard static network training algorithms are used (Xie et al., 2009). Training is finished when the prediction error

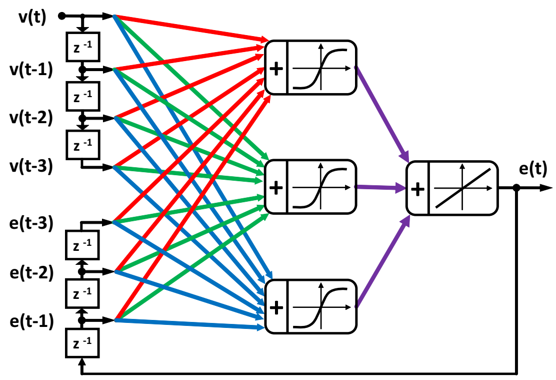

Figure 8: Example structure of a NARX neural network used for following error prediction.

stops decreasing. The feedback is then reconnected and training is continued in parallel form. In this form dynamic training algorithms such as backpropagation through time have to be used. These are more computationally demanding and are sensitive to initial weight values (Horne and Giles, 1995). Weights obtained from the series-parallel training phase are used as initial guess for parallel training which gives good initial values and decreases total training time. Training is finished when the prediction error does not change significantly for some period of time. MATLAB Neural Network Toolbox function TRAINBR is used to train the network.

If motion paths are defined as Non-Uniform Rational B-Splines (NURBS) or other polynomial curves the contour error cannot be computed exactly and has to be estimated (Uchiyama et al., 2011). Several contour error estimation techniques for free-form toolpaths have been proposed (Yeh and Hsu, 2002; Huo et al., 2012; Sencer et al., 2009; Chen et al., 2008). All of these are either simple estimates which have large errors for curves with high curvatures or are computationally demanding. In one interesting algorithm proposed in (Zhu et al., 2013) the contour error vector is approximated by a Taylor series which yields accurate estimates without high computational demand. This method was chosen for developing the contour error predictor. The contour error is estimated using the following closed form formula:

$$\vec{\varepsilon}_c = \left[-\vec{c} - \frac{1}{2}\frac{\kappa(\hat{c}\cdot\hat{n})(\hat{t}\cdot\vec{\varepsilon}_t)\hat{t}}{1-\kappa(\hat{c}\cdot\hat{n})} \right]\cdot\vec{\varepsilon}_t \tag{1}$$

$$\hat{c} = -\frac{\vec{\varepsilon}_t\cdot\hat{t}}{\sqrt{||\vec{\varepsilon}_t||^2-\vec{\varepsilon}_t\cdot\hat{t}}}\hat{t} + \frac{1}{\sqrt{||\vec{\varepsilon}_t||^2-\vec{\varepsilon}_t\cdot\hat{t}}}\vec{\varepsilon}_t \tag{2}$$

where: κ - toolpath curvature at the reference point, $\hat{t},\hat{n}$ - tangent and normal unit vectors at the reference point, $\vec{\varepsilon}_t$ - following error vector. Curvature, tangent and normal vectors can be computed using the following formulas:

$$\kappa = \frac{||C'(u)\times C''(u)||}{||C'(u)||^3} \tag{3}$$

$$\begin{aligned} \hat{t} &= \frac{C'(u)}{||C'(u)||} \\ \hat{b} &= \frac{C'(u)\times C''(u)}{||C'(u)\times C''(u)||} \\ \hat{n} &= \frac{\hat{b}(u)\times C'(u)}{||\hat{b}(u)\times C'(u)||} \end{aligned} \tag{4}$$

where: $C'(u), C''(u)$ - are first and second derivatives of the NURBS toolpath position vector with respect to the toolpath parameter u obtained from the NURBS interpolator.

5 EXPERIMENTAL RESULTS

In order to generate training data for training the contour error predictor a NURBS trajectory was constructed by randomly generating curve control points in the whole positioning system travel range between 0 and 1200mm in both axes. The toolpath used is presented in figure 9.

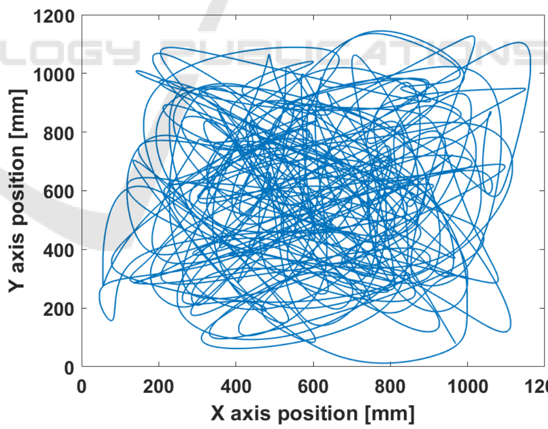

Figure 9: Randomly generated NURBS curve motion path used for neural network training.

A feedrate profile was generated which forced high variations and values of velocity,acceleration and jerk in each axis while simultaneously keeping them within safe limits. The maximum values of velocity, acceleration and jerk were set to $2500mm/s$, $25000mm/s^2$ and $500000mm/s^3$ respectively. This was done to sufficiently capture following error dynamics and avoid drive saturation and positioning system damage. The motion path was executed using the feedrate profile using the PC-based controller controlling the linear motor positioning system. Axis velocity demand and actual following error for each axis were recorded and transfered to MATLAB. Datasets of velocity demand (input) and following error (target) were generated with 455559 samples (at 0.25 ms sampling rate) for both X and Y axes. The velocity demand signal and following errors are shown on figures 10 and 11. Only the first half of each dataset was used as a training set. The second half was used for validation.

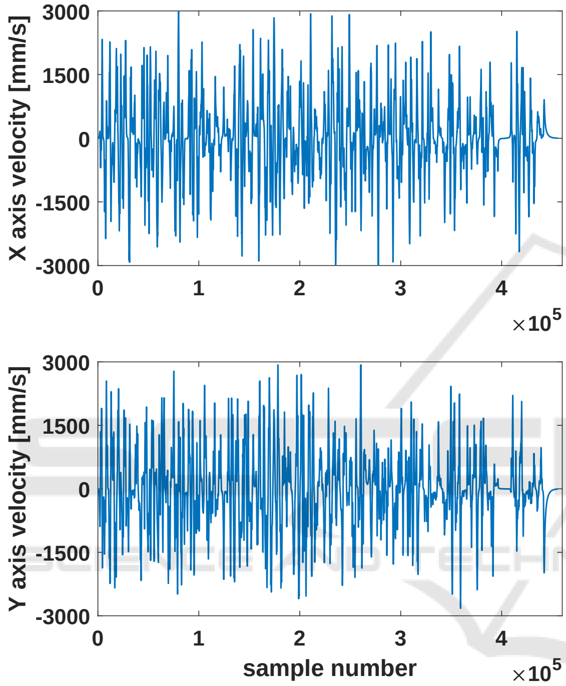

Figure 10: Velocity demand for x and y axes (input values) used in training and testing.

Training was performed for each axis NARX neural network multiple times in order to determine the best network architecture (trial and error approach) by using an automated script in MATLAB. Each network was trained first in series-parallel mode and then further trained in parallel mode. A training period of 2000 epochs and 4000 epochs in the series-parallel and parallel mode respectively was used. A NARX neural network with 5 input, 4 feedback delays and 6 sigmoid hidden neurons was chosen as the following error predictor for X and Y axes. This network structure achieved the lowest following error prediction mean squared error. Prediction mean squared error of 6.59e-4 mm and 4.75e-4 mm was achieved for the X and Y axis respectively. If only series-parallel training was to be used, the training would complete much faster but at the cost of much worse mean squared prediction error (5e-1 mm average).

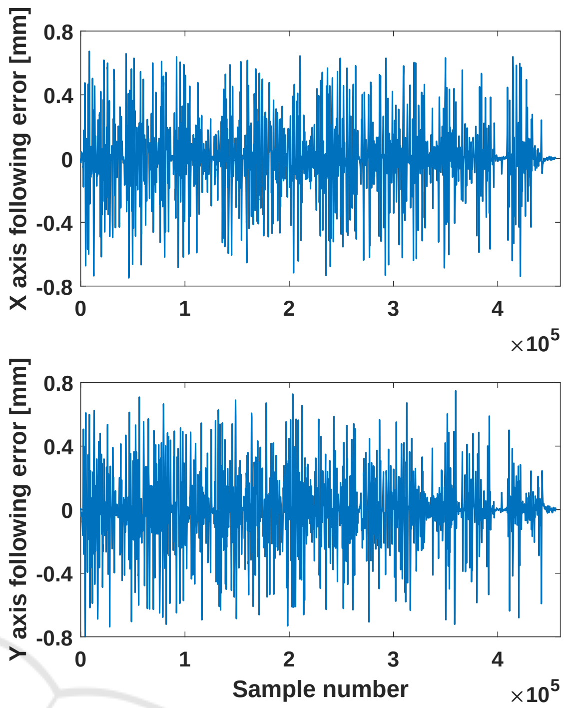

Figure 11: Following error for x and y axes (target values) used in training and testing.

In order to test the contour error prediction error for a typical trajectory another toolpath was used. The obtained neural network contour error predictor was used to verify contour error prediction accuracy of a butterfly curve (figure 12). An appropriate feedrate profie with the same limits as stated above was generated. The curve was run on the linear motor positioning system and actual contour error was computed and compared with values predicted from the proposed predictor.

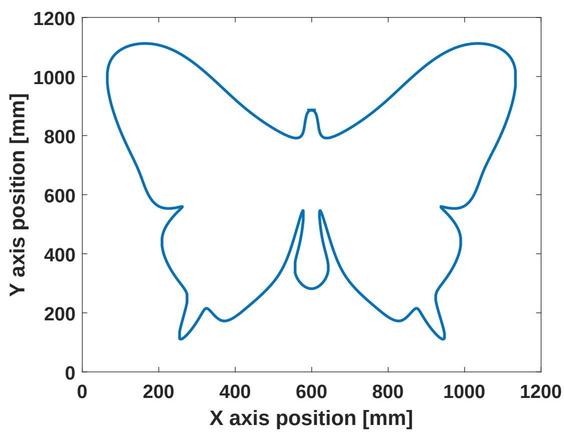

Figure 12: Butterfly NURBS curve motion path.

Figure 13 presents a comparison of following and contour error resulting from realizing the actual motion path and predicted using the NARX contour error predictor. The mean squared error (MSE) of contour error prediction is 2.6921e-04 mm. It can be seen that the predictor is able to accurately predict actual following errors and by extent the actual contour error. It should be noted that the test toolpath was not used in the neural network training process and the accurate prediction is due to neural network generalization abilities.

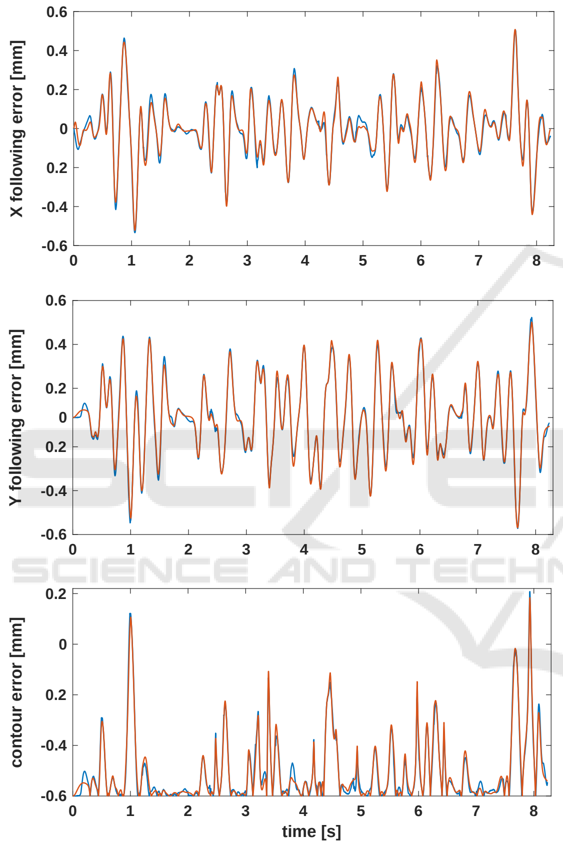

Figure 13: Predicted (orange) and actual (blue) following error and contour error for validation dataset (butterfly curve).

6 CONCLUSION

The article presents a contour error predictor for a biaxial linear motor positioning system based on neural networks. Experimental results are presented which show that linear motor exhibits non-linear dynamics mainly due to non-linear friction at very low and very high speeds. Due to complexity of identifying particular friction components and potentially incomplete information about the commercial drive control structure a black box approach to predicting contour error is proposed. This approach uses NARX neural networks to predict following errors of each axis. This in turn is used to estimate contour error based on local motion path geometry.

Experimental results show good accuracy in predicting contour error of a NURBS motion path. Major advantage of this approach is the quick and easy identification procedure. Actual toolpaths can be used with following errors obtained during normal machine operation. Identification experiments in velocity and torque modes are not required. The neural network can generalize and accurately predict actual following and contour errors for toolpaths not used in the training process.

The main contribution of this paper is developing a fast and easy to use method to predict contouring error in multi axis positioning systems such as CNC machine tools. Compared to other modelling techniques in literature this approach can use following error data collected during normal machine operation. This allows considerable time savings because dedicated identification experiments in velocity and torque modes are avoided. The contour error predictor will be used to develop an on-line feedrate optimization method for linear motor based multi axis machines. Using The contour error predictor can also be used for predictive control of such machines. Predictive techniques require a model to generate an optimal control signal. The proposed predictor in the form of NARX neural networks is easy to implement and computationally efficient.

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REFERENCES

Chen, X., Yong, J., Wang, G., Paul, J., and Xu, G. (2008). Computing the minimum distance between a point and a nurbs curve. *Computer-Aided Design*, 40(10):1051–1054.

Erwinski, K., Paprocki, M., Wawrzak, A., and Grzesiak, L. M. (2016). Pso based feedrate optimization with contour error constraints for nurbs toolpaths. In *2016 21st International Conference on Methods and Mod-*

els in Automation and Robotics (MMAR), pages 1200–1205. IEEE.

Heng, M. and Erkorkmaz, K. (2010). Design of a nurbs interpolator with minimal feed fluctuation and continuous feed modulation capability. *International Journal of Machine Tools and Manufacture*, 50(3):281–293.

Horne, B. G. and Giles, C. L. (1995). An experimental comparison of recurrent neural networks. In *Advances in neural information processing systems*, pages 697–704.

Huo, F., Xi, X.-C., and Poo, A.-N. (2012). Generalized taylor series expansion for free-form two-dimensional contour error compensation. *International Journal of Machine Tools and Manufacture*, 53(1):91–99.

Jansen, D. and Buttner, H. (2004). Real-time ethernet: the ethercat solution. *Computing and Control Engineering*, 15(1):16–21.

Jia, Z.-y., Song, D.-n., Ma, J.-w., Hu, G.-q., and Su, W.-w. (2017). A nurbs interpolator with constant speed at feedrate-sensitive regions under drive and contour-error constraints. *International Journal of Machine Tools and Manufacture*, 116:1–17.

Liu, H., Liu, Q., Zhou, S., Li, C., and Yuan, S. (2015). A nurbs interpolation method with minimal feedrate fluctuation for cnc machine tools. *The International Journal of Advanced Manufacturing Technology*, 78(5-8):1241–1250.

Ni, H., Hu, T., Zhang, C., Ji, S., and Chen, Q. (2018). An optimized feedrate scheduling method for cnc machining with round-off error compensation. *The International Journal of Advanced Manufacturing Technology*, 97(5-8):2369–2381.

Paprocki, M., Wawrzak, A., Erwinski, K., and Klosowiak, M. (2018). Flexible pc-based cnc machine control system. *Mechanik*, 91(4):299–303.

Piegl, L. and Tiller, W. (2012). *The NURBS book*. Springer Science & Business Media.

Ramesh, R., Mannan, M., and Poo, A. (2005). Tracking and contour error control in cnc servo systems. *International Journal of Machine Tools and Manufacture*, 45(3):301–326.

Sencer, B., Altintas, Y., and Croft, E. (2009). Modeling and control of contouring errors for five-axis machine tools. part i: Modeling. *Journal of manufacturing science and engineering*, 131(3).

Szczepanski, R., Erwinski, K., and Paprocki, M. (2017). Accelerating pso based feedrate optimization for nurbs toolpaths using parallel computation with openmp. In *2017 22nd International Conference on Methods and Models in Automation and Robotics (MMAR)*, pages 431–436. IEEE.

Tang, L. and Landers, R. G. (2013). Multiaxis contour control—the state of the art. *IEEE Transactions on Control Systems Technology*, 21(6):1997–2010.

Uchiyama, N. et al. (2011). Contouring controller design based on iterative contour error estimation for three-dimensional machining. *Robotics and Computer-Integrated Manufacturing*, 27(4):802–807.

Xie, H., Tang, H., and Liao, Y.-H. (2009). Time series prediction based on narx neural networks: An advanced approach. In *2009 International conference on machine learning and cybernetics*, volume 3, pages 1275–1279. IEEE.

Xu, G., Chen, J., Zhou, H., Yang, J., Hu, P., and Dai, W. (2018). Multi-objective feedrate optimization method of end milling using the internal data of the cnc system. *The International Journal of Advanced Manufacturing Technology*, pages 1–17.

Yeh, S. and Hsu, P. (2002). Estimation of the contouring error vector for the cross-coupled control design. *IEEE/ASME Transactions on Mechatronics*, 7(1):44–51.

Zhang, Y., Ye, P., Zhao, M., and Zhang, H. (2019). Dynamic feedrate optimization for parametric toolpath with data-based tracking error prediction. *Mechanical Systems and Signal Processing*, 120:221–233.

Zhu, L., Zhao, H., and Ding, H. (2013). Real-time contouring error estimation for multi-axis motion systems using the second-order approximation. *International Journal of Machine Tools and Manufacture*, 68(5):75–80.