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Data-Driven Thermal Deviation Prediction in Turning Machine-Tool - A Comparative Analysis of Machine Learning Algorithms

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Abstract

Thermal error significantly impacts the machining precision of machine-tools. Thermal deformations in the machine-tool structure caused by the various machine heat sources is at the origin of this phenomenon. In order to ensure the expected quality of the parts, manufacturer have to run the machine-tools for hours before start producing in order to reach the machine thermal stability. This heating phase has a high negative impact on the machine productivity on one hand and on its ecological footprint on the other. This paper presents a data-driven approach to model and predict the thermal error in order to correct the tool reference position accordingly. The automatic adjustment of tool position allows to produce parts with the expected quality and precision regardless of the thermal state of the machines, which substantially increase their productivity. For this purpose, temperature sensors as well as high precision tool position measurement instruments are deployed on a Tornos SwissNano4 machine-tool. A set of experiments are conducted to collect data related to these two measurements. Four major Machine Learning algorithms are trained using a subset of the collected data and tested with the remaining data subset. Quantitative and comparative analysis shows that three of the four algorithms have a prediction with a mean Absolute Error (MAE) below 1μm and a Correlation Coefficient higher than 90%. Even classical linear regression models are able to predict the thermal error with high accuracy. Advanced Machine Learning techniques show high potential to provide a better prediction accuracy.

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Keywords: Thermal error; Machine Learning; Machine-Tools; High precision manufacturing; Industry 4.0.

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1. Introduction

1.1. Context and problem statement

Energy Efficiency, while keeping a high level of productivity, becomes a major competitive advantage in the machine-tool sector. For Turning machine-tools in general and Swiss-Type Lathe in particular, the preheating phase which lasts up to 8 hours represents an important potential to increase the energy efficiency of machines. The preheating phase is intended to bring the machine-tool to a thermal stability in order to guarantee the precision of tool positions and, therefore, the precision of the machining operations. The temperature increase at different components of the machine-tool (spindle, machining zone, axes, etc.) leads to a deformation of some of the components, which directly influences the reference position of the Tool Center Point (TCP). This phenomenon is called thermal deviation or thermal error [1]. In order to mitigate the impact of the thermal deviation, machine-tool users run the machine, either while machining material or without material, during hours in order to reach the thermal stability. Predicting the thermal error in order to compensate it in real-time through correction of tool reference position would suppress or at least drastically reduce the preheating time [2]. This paper presents a holistic approach and an end-to-end system for modelling and, therefore, predicting the thermal error of Swiss-type lathe machine-tools. The developed system allows to automatically correct the reference position of the Tool Center Point at any thermal condition, which suppresses the need for a long preheating phase of the machines while guaranteeing high precision machining.

1.2. Related work

To our knowledge, the most exhaustive research related to the thermal compensation problem is carried out by the IWF team (Institut für Wekzeugmaschinen und Fertigung) at ETH Zurich (Switzerland) [3]. In [5] the IWF team presents an adaptive approach for the control and compensation of thermal error on 5-axis machines. The thermal error estimation is based on a "phenomenological" model which makes use of differential equations. In this research, the authors take into account only a reduced number of thermal sources to validate the approach. By considering a larger number of thermal sources and given the complexity of the behavior of each of these sources, mathematical modeling becomes very complex. Our research clearly demonstrates that the "data-driven" approach leveraging machine Learning techniques to model the thermal behavior of machine-tools is a relevant complement to the deterministic approaches recommended by IWF for the prediction of thermal error. Furthermore, in [4] the same team studied the use of Kalman filters in order to take into account historical data related to the thermal behavior of the machine-tool in order to refine the quality of the thermal error prediction. However, the used Kalman filter can only incorporate short-term history into the predictive models. Our proposed approach overcomes this limitation by training Machine Learning models using long-term and short-term historical data gathered at various thermal and machining conditions and situations.

Several other research papers presented results for data-driven and machine Learning based thermal error prediction [7, 9, 8]. In particular, [10] and [11] used similar approaches to ours. The thermal error prediction in [10] is based on two techniques: Adaptive Neural Network (ANN) and Adaptive Neurofuzzy Inference System (ANFIS). Both techniques have been compared in terms of prediction accuracy. The results showed that the ANFIS technique over perform the ANN one. However, the results are based on only two machining experiments: one for training the model and the other one for testing it. Further, the models are validated on machine-tools with relatively large thermal deviation (around 50 μm). The prediction accuracy expressed in Root Mean Squared Error (RMSE) exceeds 2.8μm.

The results presented in [11] are obtained using a modified version of the Adaptive Neurofuzzy Inference System (ANFIS). Though the prediction accuracy there is higher than in [10] (RMSE = 0.65 μm), the number of experiments used to validate the technique is still the same: only two. Our research work leads to a set of Machine Learning techniques which prediction results overcome the results of the above-cited papers while using data from six different experiments. Further, we present also a comparative analysis of different Machine Learning techniques to predict the thermal error of a high precision machine-tool which maximal thermal deviation does not exceeds 8μm.

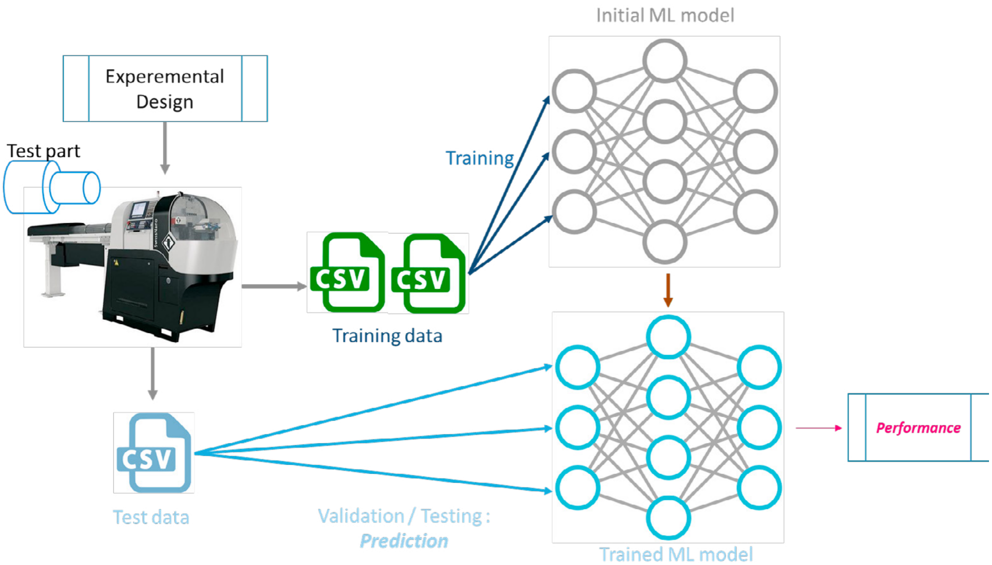

Fig. 1. Overall concept of data-driven thermal error prediction. A set of experiments (machining of parts) is first designed and executed. A subset of he collected data during machining is used to train Machine Learning models. The remaining data subset id used to test and validate the prediction accuracy.

2. Machine Learning Based Thermal Deviation Prediction

2.1. Overall concept

The main objective of this paper is to evaluate the thermal error prediction accuracy of different Machine Learning techniques. The overall concept of the evaluation process is depicted in Figure 1. The concept is composed of the following steps:

1. A set of machining experiments are designed. An experiment consists in running a machining program on machine-tool and collect the relevant data
2. Each designed experiment is executed on the machine-tool
3. Relevant data are collected for each experiment. The main data collected are a) Tool position and b) a temperature vector as will explained below.
4. The data set is divided in two subsets: a training subset and a test subset.
5. For each of the Machine Learning technique to be evaluated:

   (a) Train the Machine Learning model using the training data subset
   (b) Test the model using the test data subset
   (c) Calculate prediction accuracy metrics: Mean Absolute Error (MEA) and Correlation coefficient (R)
   (d) While MAE and R are not satisfactory and number of iteration is less than a max_iteration

      i. Fine tune the model
      ii. Go to step 5.a

6. Compare the accuracy of the different Machine Learning techniques

2.2. Machine Learning techniques

The following supervised Machine Learning techniques have been considered in our comparative analysis. For all techniques, we used an implementation from the Python Machine Learning library *scikit-learn* [12].

- *LinearRegression()*: which implements classical least squares Linear Regression. Linear regression is one of the most known and the simplest techniques of statistics and machine learning. Concretely, linear regression is a model that assumes a linear relationship between the input variables (in our case, the temperature vector) and the single output variable (in our case, the tool position). More specifically, that output can be calculated from a linear combination of the input variables [13].
- *DecisionTreeRegressor()*: which uses decision trees structures and the ID3 algorithm [14] for regression purposes. Specifically, the ID3 algorithm used in our work starts with selecting a small subset of the training data from the experiments that is called it window and constructs a decision tree with this data subset. The constructed tree correctly classifies all data in the window (matching temperature to tool position). Then, the constructed decision tree is used to verify whether the remaining data are correctly classified. If yes, the process terminates. Otherwise, falsely classified data are added into the *window* and a more complex decision tree is reconstructed. This process is iterative repeated until an acceptable classification/regression precision is met.
- *MLPRegressor()*: Which uses Multi-Layer Perceptron (MLP) also known as a neural network with hidden layers. The Multilayer Perceptron is the most known and used Artificial Neural Network (ANN) type [15]. MLP is an artificial neural network that is composed of at least three layers: one input layer, one output layer and at least one intermediate layer also known as hidden layer. The hidden layers allow MLP to learn non-linear functions. In our case, the used MLP has 100 hidden layers. One of the important parameters of MLP is the activation function that is often a linear function that maps the weighted inputs to an output for each neuron of the network. For this work, the Rectified Linear Unit (ReLU) [16] has been used.
- *ElasticNet*: which is based on a regularized regression method. Elastic net linear regression [17] technique combines two regression techniques: a) lasso [18] and b) ridge [19] regression methods by identifying their respective shortcomings in order to enhance the regularization of statistical models. Concretely, the Elastic net uses the penalties from the lasso ($L1$) and ridge ($L2$) techniques to regularize regression models. In our case, both penalties are equally considered: $L1 = L2 = 0.5$.

The ANFIS method could not be considered in our comparative study because *scikit-learn* does not provide an implementation for this type of models. The author will consider ANFIS method in future work with own implementation of the models.

3. Experimental Set-Up

3.1. Test Machine-Tool

The experiments are conducted on a Tornos SwissNano4 machine-tool [20], a 5-axis SwissType Lathe designed to meet the demand for small manufactured parts requiring very high precision.

3.2. Temperature Measurements

The temperature vector is measured using 8 sensors placed on relevant positions of the SwissNano4. Thermo-mechanical analysis has been conducted in order to find out the SwissNano4 components that mostly impact the thermal behavior of the machine. Table 1 List of the placements of the 8 thermal sensors.

3.3. Tool Position Measurements

For high precision machine-tools like Tornos SwissNano4, measuring the tool position with high precision is a challenging task. We conceived and set up a high precision tool position measurement method based on probing. We

Table 1. List of thermal sensors.

Sensor	Placement
$T1$	Chassis right
$T2$	Support Axis Z
$T3$	Spindle carrier
$T4$	Spindle motor
$T5$	Chassis central
$T6$	Support Axis Y
$T7$	Ambient temperature
$T8$	Machining zone

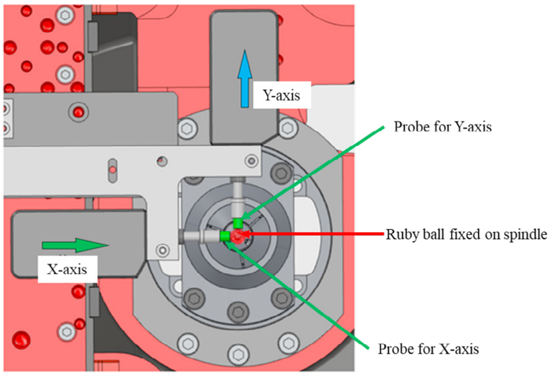

Fig. 2. Tool position (X, Y) measurement using probing. Touch probes are attached on both axis X and Y in order to measure the relative distance to the spindle.

used a TESA axial probe GT21. The probe is installed so that it measures exactly the X and Y positions of the tool tip relatively to the spindle. This measurement technique is only possible if the machine-tool is heated without machining. Indeed, we observed that the SwissNano4 thermal behavior is comparable if we run a machining program with or without raw material. The only difference is the thermal stability time that is longer when heating the machine without machining. Figure 2 illustrates the tool position measurement principle. As it will be shown later, this measurement technique allows us to achieve high precision tool position measurements.

4. Experiments and Data

In order to collect enough data to train the different Machine Learning models, we conducted six different experiments. For each experiment, the temperature values of the 8 thermal sensors as the tool position in X and Y are continuously collected. The experiments have been conducted over two weeks period in order to cope with different weather conditions. The ambient temperature is an impacting factor of the thermal behavior of machine-tools that should be taken into consideration. Different duration of the experiments have been also taken into account in the experiment design in order to cope with various usage patterns of the machine. It is to be noted that each experiment starts with cooled status of the machine. The interval between two experiments is at least six hours, which allows the machine to cool down.

Figure 3 shows the collected data during Experiment 6. The plots clearly shows the high correlation between the temperature and the tool position.

Table 2. List of conducted experiments.

ID	Duration (h)	Spindle speed (rpm)
1	2	8000
2	10	8000
3	10	8000
4	9	8000
5	26	8000
6	24	8000

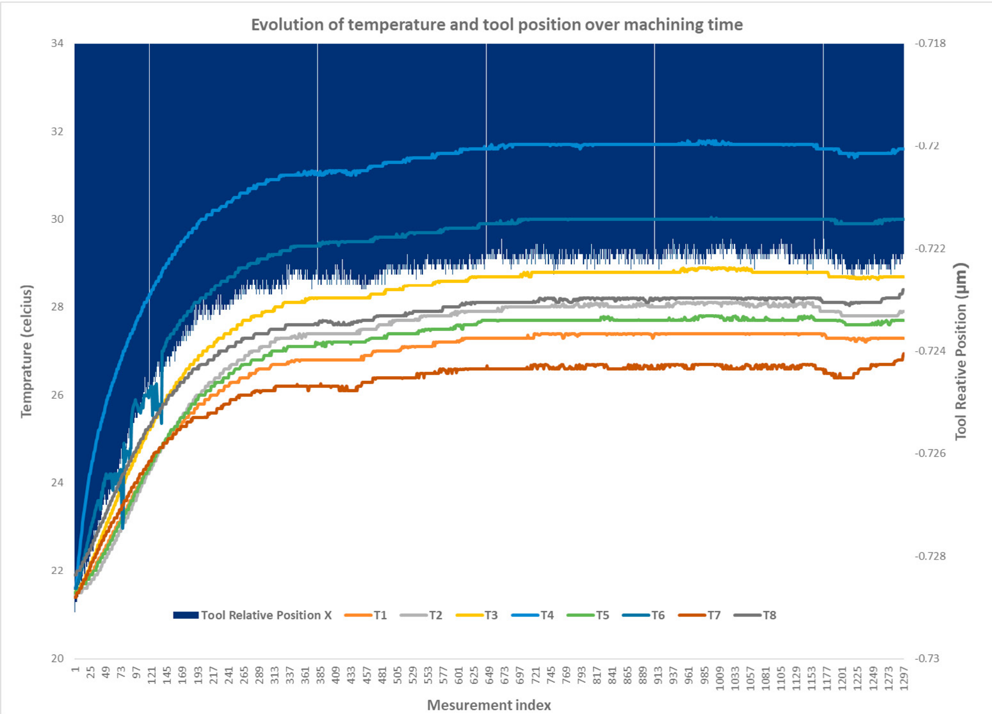

Fig. 3. Temperatures and tool position evolution over the experiment time. The X-axis (Measurement index) is an indexed representation of time. A measurement (temperature and tool position) is consolidated (average) every 30 seconds. The left Y-axis represents the temperature in Celsius and the right Y-axis represents the relative tool position in μm.

5. Results

In order to evaluate the performance of the four Machine Learning techniques presented in 2.2, we trained all models with data of experiments 1 to 5 and tested each of them using data from experiment 6. The following tuning actions have been carried out:

- *LinearRegression()*: No tuning has been carried out. The default parameters of skit-learn implementation have been used as are.
- *DecisionTreeRegressor()*: No tuning has been conducted. The default parameters of skit-learn implementation have been used as are.
- *MLPRegressor()*: Only the parameter $random_{s}tate$ has been tuned. It determines random number generation for weights and bias initialization. In our tuning, we explored and evaluated the prediction accuracy using 10000 different values of the parameter $random_{s}tate$ (1...10000). We then selected the value providing the most

accurate prediction. The structure of the neural network (number of layer, number of nodes per layer) has not been tuned.

- *ElasticNet*: No tuning has been conducted. The default parameters of skit-learn implementation have been used as are.

Figure 4 illustrates the prediction results of the different Machine Learning techniques on both axis X and Y. For each graphic (a ... h), the measured tool position (over time) for experiment 6 is drawn in blue, whereas the predicted value is drawn in orange.

To quantitatively evaluate and compare the accuracy of the different prediction algorithms, we us two metrics:

- Mean Absolute Error *MAE*
- Correlation Coefficient *R*

Table 3 summarizes the prediction accuracy of the different algorithms on both axis X and Y. Except *LinearRegression()*, all algorithms have an MAE below 1μm and a Correlation Coefficient higher than 90%. It is noticeable that the classical linear regression technique has the best accuracy performance. The high quality, high precision measurement of tool position as well as the thermal behavior repeatability of the SwissNano4 explains part of this high prediction accuracy. Both *MLPRegressor()* and *ElasticNet()* achieve high prediction accuracy level even without or with very minimal fine-tuning of the models.

Table 3. Prediction accuracy of the different algorithms for both axis X and Y expressed in Mean Absolute Error (MAE) in μm and Correlation Coefficient R.

Algorithm	MAE (μm)	R (%)
LinearRegression() on X	0.44	99.0
LinearRegression() on Y	0.49	91.7
DecisionTreeRegressor() on X	0.97	89.2
DecisionTreeRegressor() on Y	1.16	77.5
MLPRegressor() on X	0.86	99.1
MLPRegressor() on Y	0.61	91.0
ElasticNet() on X	0.45	99.2
ElasticNet() on Y	0.52	93.9

6. Conclusions

In this paper, we tackled the data-driven thermal behavior modelling and prediction of machine-tools in a high precision manufacturing context. Four major Machine Learning techniques have been analyzed and compared in terms of prediction accuracy. The major conclusions that can be drawn from our research work are:

- The high precision measurement of tool position is a success factor in building predictive thermal behavior models for high precision machine-tools.
- High precision tool position measurement is best achieved when the machine-tool is heated without machining. In the absence of constraints and perturbations due to machining, more tool position measurement options are available. The absence of machining does not noticeably impact the thermal behavior of the machine-tool.
- Probing is a relevant, reliable and precise method to measure the tool position and thus the thermal errors of machine-tools if the above conditions are considered.
- The quality of the so obtained data (tool position and thermal measurement) allow a high accurate prediction of the thermal behavior of high precision machine-tools like the SwissNao4. Even the classical linear regression models provide a high level of prediction accuracy.

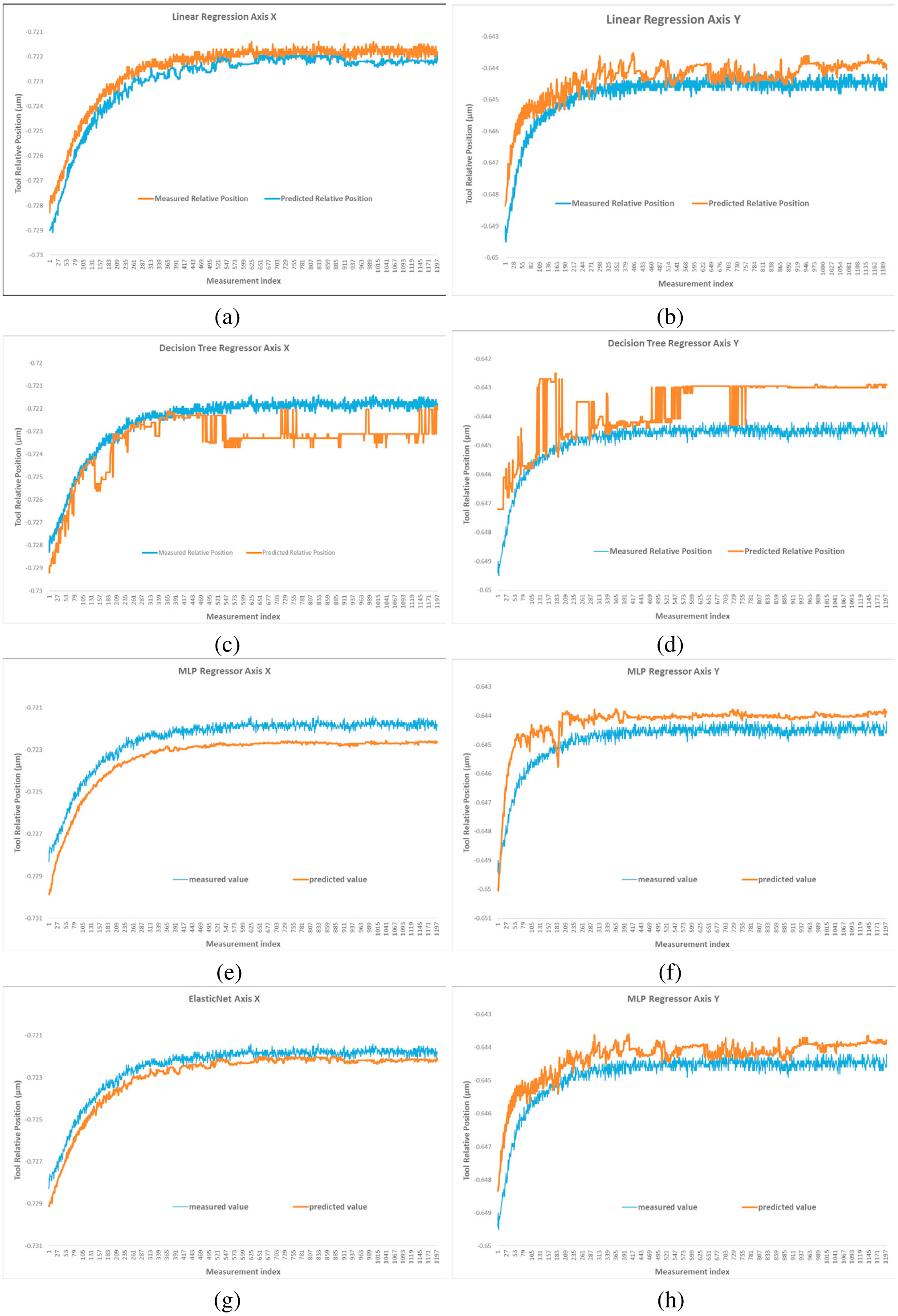

Fig. 4. Results. For each of the graphs (a) to (h) the blue curve represents the really measured tool position and the orange one represents the predicted tool position. For the each of the graphs, the graph's X-axis represents time evolution of the experiment in and indexed manner (1 consolidated measurement every 30 seconds) and the graph's Y-axis represents the relative tool position. (a) and (b) represent the prediction results using the linear regression method for the machine's X- and Y- axis respectively. (c) and (d) represent the prediction results using the Decision Tree regression, (e) and (f) represent the prediction results using the MLP regression and (g) and (h) represents the prediction results using ElasticNet regression.

- More advanced Machine Learning models like Multi-Layer Perceptron (MLP) achieve high prediction accuracy level even without major fine-tuning effort. More fine tuning related to the structure of the MLP (number of layers, number of nodes per layer, etc.) is expected to increase the prediction accuracy level of such techniques.

Future work is expected to include more Machine Learning techniques into our benchmark. In particular, the Adaptive Neurofuzzy Inference System (ANFIS) technique will be considered, given the results presented in previous work. Further, the authors will extend the performance evaluation methodology to include cross-experiment validation in order to cope with variability of the experiment conditions.

Acknowledgements

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