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Predicting geometric tolerance thresholds in a five-axis machining centre

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Abstract

NC-Checker is a software tool used for monitoring and validating the geometric performance in modern machining centres. Threshold settings allow the Manufacturing or Maintenance Engineer to customise the tool based on specific job or industry tolerance requirements. In order to perform effective long-term monitoring, this has the potential to skew the perceived health state of the machining centre as presented in the NC-Checker benchmark reports. This study brings attention to this fact and its relevance in the pursuit of enhanced levels of automation for geometric performance monitoring tools, in preparation for the machine shop's transition to Industry 4.0. A sense-check function is proposed to identify unusual alterations based on historical data, utilising a support vector machine methodology to develop a predictive classifier. The models achieved predictive accuracy scores of 87.5% during validation, acquisition of a suitable testing set is under way and the predictive models will be evaluated upon completion.

Key Words: Support vector machine, In-process inspection, CNC machining, Geometric performance, Condition monitoring

1 Introduction

Enhancing production through intelligent automation is becoming increasingly important in the advanced manufacturing sector, driven in-part by recent advances in the *Industry 4.0* movement, with its fundamental requirement for data and analytics as a core capability [1]. Of the four design principles set out for implementing Industry 4.0 [2], the two which this research will consider relate to information transparency - analysing the physical system through means of on-line data collection - and providing technical assistance to the Manufacturing or Maintenance Engineer. Application of machine learning to the performance monitoring and optimisation of machining centres provides a unique opportunity to fulfil these principles.

NC-Checker [3] is a software tool developed by metrology software products ltd., for data collection and benchmarking of geometric performance in CNC machining centres. It runs a series of probing cycles on a datum point of a sphere within the machine volume, revealing the errors inherent in the system. It is then possible to compare these errors against both nominal positions and the typical operational conditions, using this data to assess the likelihood of quality part production but also to track any changes in geometric performance over time. Herein, *geometric performance* refers specifically to the level of component error present in the system, as identified in the NC-Checker analysis process, and affecting finished part quality. Due to a variety of error sources [4] present in machining operations, it is not possible to guarantee identical geometric performance at all times, and it is observed that geometric performance tends to drift over time. As such, machining centres undergo regular maintenance to ensure they are performing within the acceptable tolerances.

One key functionality of NC-Checker is the ability to set threshold limits on each tested parameter, providing the operator with a simple system to determine whether the machining centre is in a satisfactory state for operation or not. This is facilitated by the production of a *benchmark report*, the resultant output of the NC-Checker performance monitoring procedure. Generally, the ability to edit these thresholds is restricted to the Manufacturing or Maintenance Engineer and is determined by the required precision of the part in current production. Through interference with the tolerance thresholds, there is the possibility of distorting the actual health state of the machining centre as perceived in the benchmark report. This can have implications for finished part quality if the operator is using NC-Checker as a go/no-go system, as is often the application of the software tool. In order to achieve effective monitoring of machining centre geometric performance with this system, it is pertinent to explore the issue.

An approach to the geometric performance monitoring of five-axis machining centres, utilising NC-Checker as a data acquisition system, is introduced in this paper. Consideration is given to the phenomenon of *threshold bias* (see Section 2.4) as an immediate application of the research. More holistically, the prospect of automating the fault diagnostic and prognostic processes are discussed, with the greater objective of informing a condition-based maintenance strategy via the synergy of on-line inspection data with contemporary machine learning paradigms.

This paper is structured as follows. Section 2 describes the methodology of the study, covering firstly the data collection technique, then the concerns of threshold bias and construction of the predictive models. Section 3 describes and presents the results of the support vector machining classifiers. Section 4 then discusses these results, the issues outlined in the paper and sets out the prospect for further research.

2 Methodology

2.1 Data acquisition

A large gantry head-head five-axis machining centre was investigated in this study. A number of different options were explored in the selection process, but this particular operation was selected due to the high consistency of the data collection being carried out by the team responsible. At the time of contact, six months of legacy data were available, collected at roughly one-week intervals with minimal deviations from this schedule. The individual tests carried out had all been performed and recorded in their entirety, which was a crucial prerequisite for the data analysis procedure.

There are a number of operational factors to consider with respect to the selected machining centre, which have implications for the presented results and comparability with industrial examples. These are described below.

2.1.1 Research environment

Based in a primarily research environment, the studied machining centre does not generally follow the same operational patterns as would be seen with similar systems in industry. Of most concern are trials involving the testing of tools to destruction, which is the primary research application of the machining centre. This involves introducing sustained and excessive levels of force to the system, which is unlikely to occur in an industrial setting under normal conditions. The fatigue process for structural components under loading is well documented [5], and the same principles will apply to the machining centre's structural loop under excessive loading conditions. Thus, the research environment has potential to exacerbate errors incurred in the system, increasing the risk of operational problems such as mechanical breakdown or extensive maintenance requirements.

Due to the relatively small dataset available, this conversely presents some benefit to the study. More extreme variability in the data can be attributed to amplification of the geometric performance deterioration, in essence enhancing the meaningfulness of each measurement in the limited dataset. This characteristic of the data provides worthwhile insight into the machining centre's geometric performance, and is sufficient for preliminary investigations and objectives of the study at this point in the research. Clearly, though, the preference is for an extensive set with a high resolution of data points relative to the observable trends, which will be sought as a priority for future developments of the work.

2.1.2 Known calibration issues

Throughout the acquisition period of the legacy data, it was apparent to the operator that there were a number of problems with the machining centre requiring extensive maintenance activity. A later investigation, with support from the equipment supplier, diagnosed the issue as a faulty component located in the machine's structural loop, and the issue was rectified. Recent corrections have improved the performance of the machining centre significantly. For the dataset currently applied in this study, however, the fault is still present, and manifests itself in a pronounced effect on the accuracy of the rotary C axis. This is apparent in the results of the benchmark reports, where the measured deviation is observed to be consistently and abnormally higher than the pre-set tolerances.

Throughout the collection period and until the issue was diagnosed, the operational team took a pragmatic approach and continued research whilst applying ongoing maintenance actions to maintain the usability of their machining centre. This was acceptable practice as the trials conducted over the collection period were not adversely affected by the machining centre's geometric performance. As they were distinctly aware of the issue affecting the rotary C axis (see Section 2.2 for an explanation of the machining centre axes) and monitoring it regularly, they chose to halt updates to the tolerance threshold. This has implications for the analysis methodology employed in this study, and adjustments to compensate are discussed further in Section 2.3.

2.1.3 Extreme alterations to the tolerance thresholds

Due to the calibration issues described above, and the inconsistent mode of application required in a research - as compared to production - environment, the machining centre has undergone a programme of maintenance to correct and enhance its operability. Part of this programme involved extensive alterations to the tolerance thresholds that are saved in NC-Checker and used to determine the pass/fail aspect of the report. Although it must be noted that regular threshold alterations like this are uncommon in industry, it raises a point of interest for exploration, discussion and advice where the practice has the possibility to occur.

2.2 The benchmark wheel

The standard presentation of the report produced by NC-Checker is the *benchmark wheel*, an example of which can be seen in Figure 1. The wheel is interactive and provides the option to click through individual results, visualised as spokes on the wheel, for detailed reports and data. Each spoke represents an independent feature which directly affects the geometric performance, thus the feature is defined as a measurement of error in a particular aspect of the machining centre. Key features of interest to this study are the linear X, Y and Z axes, and the rotary C axis. These govern the cutting tool's ability to move accurately around the machine volume, with the linear axes relating to simple positional movements and the rotary axes describing a rotation of the tool relative to the part being machined. The ability to provide rotation in two axes, in addition to the linear movements, is the requirement for a machining centre to be regarded as having five-axis capabilities. Rotary axes are denoted as A, B and C, with the axis of rotation being parallel to the linear X, Y and Z axes, respectively. The position on the spoke indicates the extent of deviation from a given feature's nominal position, always located at 0.0000. Tolerance thresholds are set by the Manufacturing or Maintenance Engineer and provide maximum (always positive) and minimum (can be negative or 0.0000, depending on the test) limits. Should a measurement exceed its tolerance threshold, the software will notify the operator and indicate that the machining centre has failed the geometric performance test, often requiring attention before the operation is permitted to proceed.

2.3 Pre-processing

As this study currently represents the initial investigation phase of the overall research project, only the data included on the benchmark wheel was extracted and stored for analysis. This approach allowed the research to present an alternative visualisation procedure to the *trend analysis* tool that comes as part of the NC-Checker package. Contained within the benchmark reports, however, is a much more extensive dataset which will be incorporated into the analysis at a later stage. This provides the opportunity for future expansion of the research, using the methodologies established in this study as the foundation. In particular, incorporating expert knowledge on the

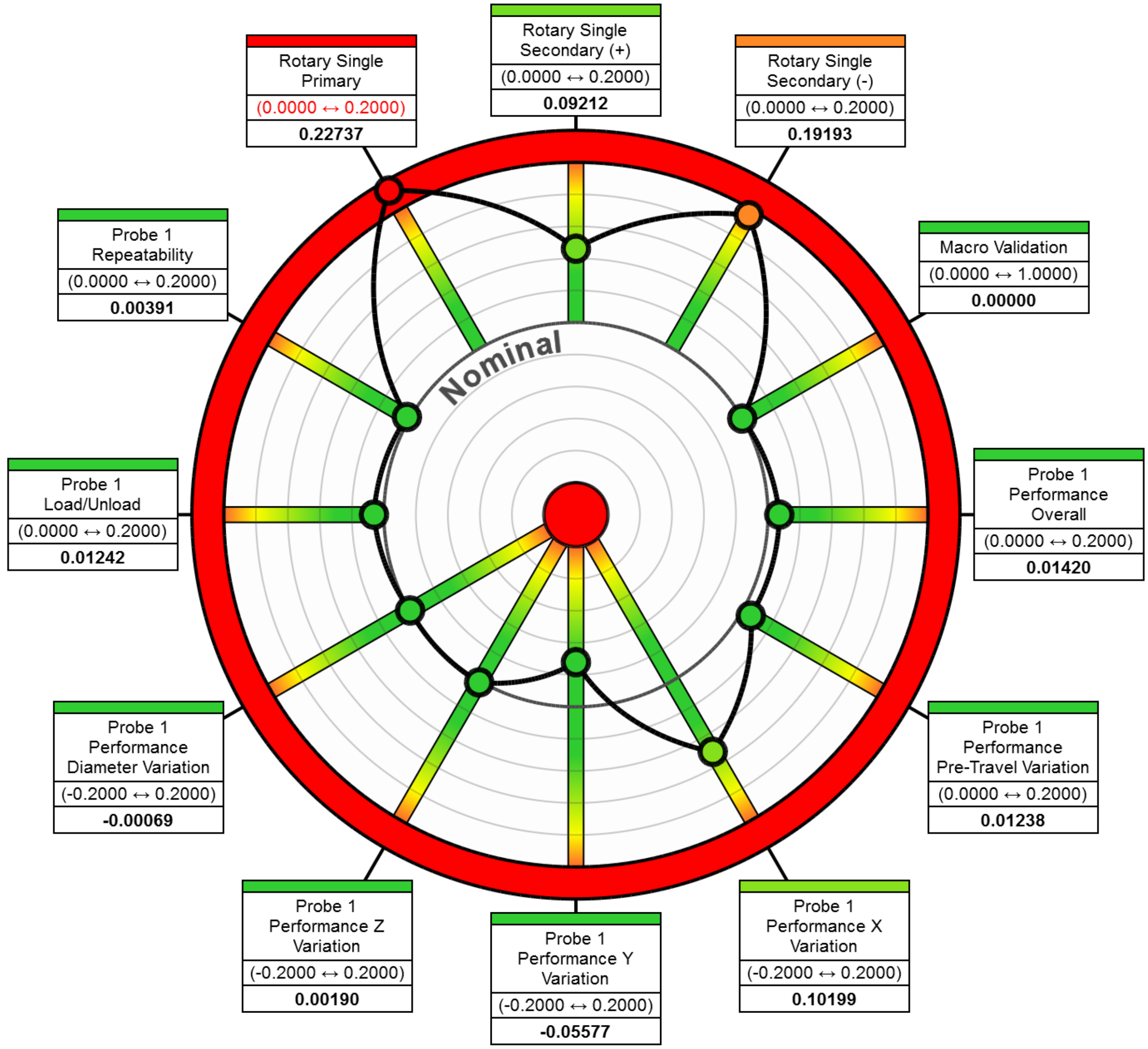

Fig. 1: Benchmark report presentation of data used in this study

report characteristics to pattern recognition tools has promising potential for developing an automated fault diagnosis system, which the research team will will be explored in the near-future.

Damage classifications were assigned to each of the data points. The output of a given parameter is considered a *fail* if the measured value exceeds the engineer-determined threshold *for that particular test instance*; in such a case, the data point receives a classification of damage, encoded as a value of one. Similarly, an output which does not exceed the threshold is considered a *pass*; these data points receive a classification of healthy, encoded as a value of zero.

Here, it is important to again note the effect on the rotary C axis measurements caused by the faulty component, as previously discussed in Section 2.1.2. A practical solution was employed involving maintaining awareness of the issue, though in the raw data it is simply presented as persistent failure. As the damage classes have been assigned based on thresholds determined by engineering judgement, this characteristic of the data collection must be considered and accounted for. An amendment was added to raise the threshold for this parameter by 20%, which, given the

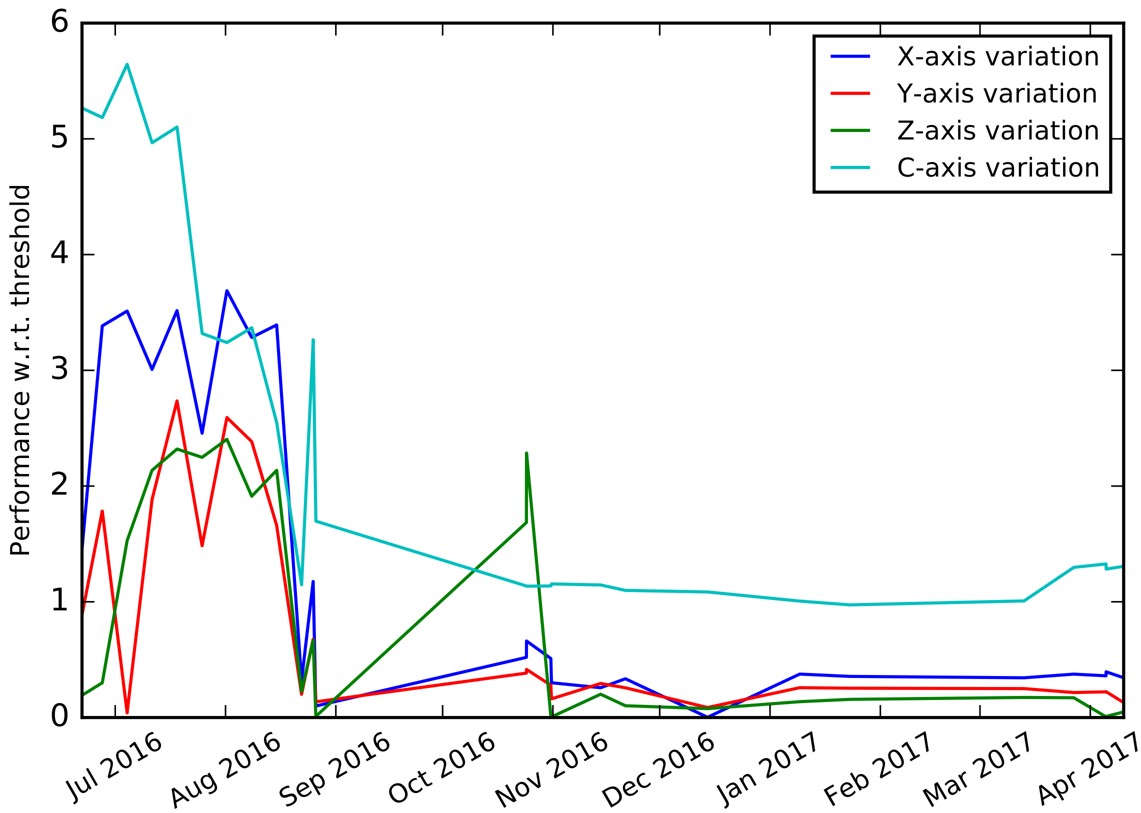

Fig. 2: Geometric performance variation over time, as a function of tolerance threshold

circumstances, provides a more realistic representation for the operator's judgement of an acceptable limit. It should be noted that this value was estimated based on the point at which the operating team ceased amendments to the tolerance thresholds, and the time-series trend entered the perceived period of stability as observed in Figure 2. Thus, the reader should be aware of a level of uncertainty introduced to the analysis from this action.

2.4 Time-series graphical representation

Visualisation of the data as a time-series provides an insight into the effects of altering the tolerance threshold, and the skew it can impart on the perception of the data. Figure 2 shows the geometric performance as a function of the tolerance threshold set by engineering judgement. Performance values above *1* indicate a parametric failure in the benchmark report. From this graphical representation, it would not be unreasonable to deduce that the machining centre appears faulty in the months of July and August, but subsequent corrections then led to an extended period of generally stable, healthy operation. From this point, the linear axes plateau close to their nominal positions and the rotary C axis maintains its position around a performance value of *1*.

However, different observations are made by comparing these trends with the actual, measured deviations as shown in Figure 3. In the linear Y axis, for example, it can be seen that the absolute, measured deviations have a relatively low level of variance throughout the data collection period as a whole. This contrasts sharply with the performance indicated in Figure 2, where there is a clear shift from perceived unacceptable levels in July and August to acceptable in the months that follow. This characteristic is largely apparent in all of the axes, whereby Figure 2 suggests significant performance improvements but similar trends are not observable in the absolute, measure values as seen in Figure 3.

This effect on the graphical representation is caused by the inherently variable nature of the tolerance thresholds.

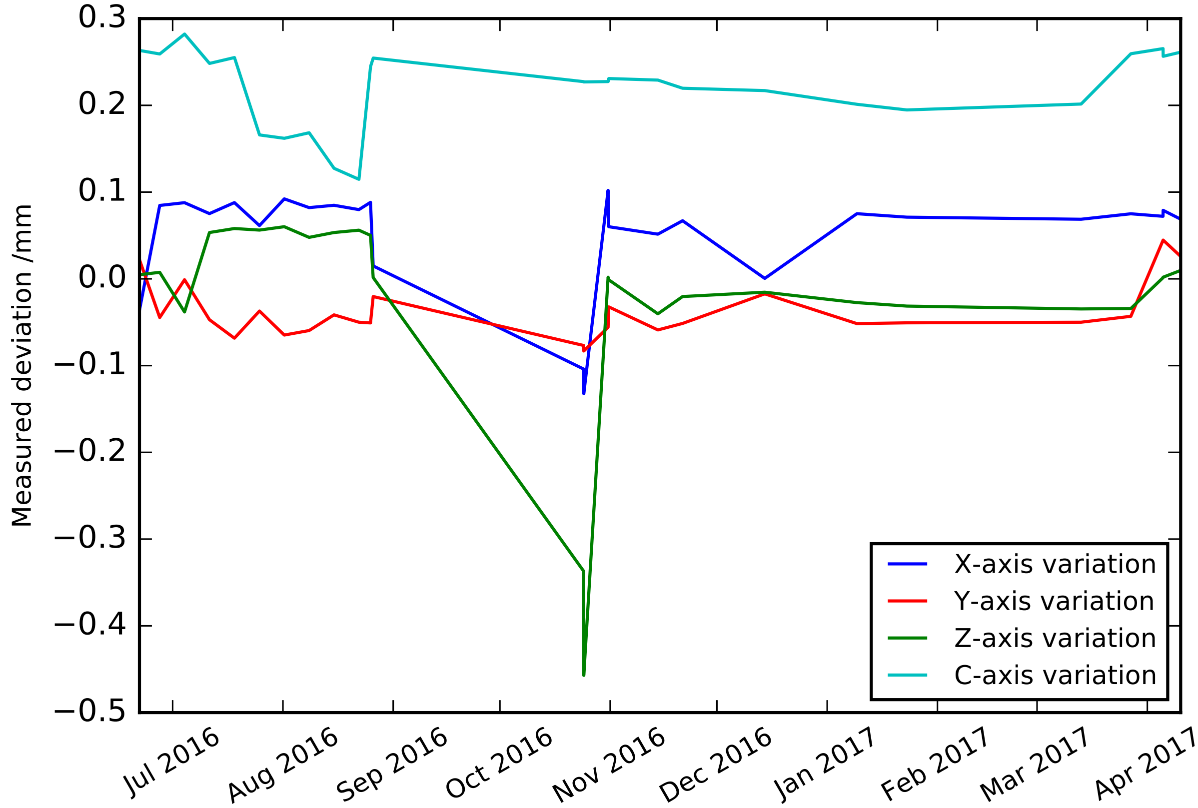

Fig. 3: Geometric performance variation over time, absolute measured values

Consider, for example, the C axis deviations as captured in early August, in comparison with those captured in mid November. Figure 2 presents considerable failure in August with a performance value of *3.24* and a much more acceptable value of *1.15* in November, suggesting the geometric performance has improved over time. Seen in Figure 3, the absolute, measured deviation for August is *0.16mm*, but in November is *0.23mm*. In absolute terms, then, the interpretation is that geometric performance has worsened.

This contradiction of geometric performance induced by variable tolerance thresholds and human interaction - the phenomenon of threshold bias - is the basis for the argument of this paper. Although it must again be noted that this is not necessarily a common practice in an industrial setting, altering the tolerance thresholds can lead to skewed perceptions of the machine health state which machining centre operators and engineers should be aware of. Moreover, it is a characteristic of the data which must be considered in future research with the intention of increasing levels of automated monitoring. There is no standard threshold setting that is relevant for all parts. For example, parts produced for aerospace applications may require stricter tolerances than those produced for the automotive industry, or indeed certain parts within the same industry may be more critical than others. The intricacy is that the tolerance thresholds must be included to consider the absolute measurements meaningful; ultimately though, it is the absolute measurements alone which provide the necessary information for effective and proper monitoring of overall geometric performance.

2.5 Modelling

Four parameters were selected from the dataset for analysis in this study, concerning the measured deviations in linear axes X, Y and Z; and measured deviations in rotary axis C (representing the rotation potential about the linear Z-axis). Rotary axis A was omitted from this study due to a number of missing data points, which would have adversely affected the analysis and data continuity in the study. The data were split into two sets, one comparing linear X with linear Y and the other linear Z with rotary C, conducted to allow visualisation and direct parametric comparison. Class labels were assigned to all data points, as described in Section 2.3. The data points were randomly shuffled and split by a three-fold cross validation with stratified sampling, for homegeneity and to ensure adequete representation of the training data [6]. Due to the relatively small dataset, a Bayesian optimisation procedure may be more appropriate for this problem, permitting the use of all training examples for both model fitting and comparison [7]. It must be noted that, for evaluating and confirming the model's predictive capability, an independent test set will always be required, and caution should be exercised with this approach to avoid the possibility of overfitting. This is an element for exploration in further research from this paper and has not been considered at this stage. The training set was then fed into a support vector machine (SVM) for predictive classification, including an optimisation step for the model hyperparameters C (soft margin parameter) and γ (kernel length scale) [8]. Following this, the model score was evaluated against the validation set and discarded if it did not meet a specified minimum threshold of 80% correct classifications. This process was repeated until representative models were found, both X vs. Y and Z vs. C achieving scores of 87.5% correctly classified data points.

3 Results

Figures 4 and 5 present the models to predict the likely classification of a measured data point, based on past events as determined by engineering judgement. Modifications to the engineer-determined thresholds for acceptable performance are represented by the coloured rectangles; whilst the black decision boundary separates the two classification regions predicted by the SVM. Data points for the measured values are visually separated into + and o markers, for a benchmark pass and fail respectively. Note that some measured values with a classification of 'pass' in Figure 5 exceed the maximum engineer-determined threshold. This is the due to the permitted increase in C axis tolerance threshold, discussed in Section 2.3. A value at the nominal location *[0, 0]* was also included in the training sets, based on the knowledge that this value will always be deemed acceptable by engineering judgement.

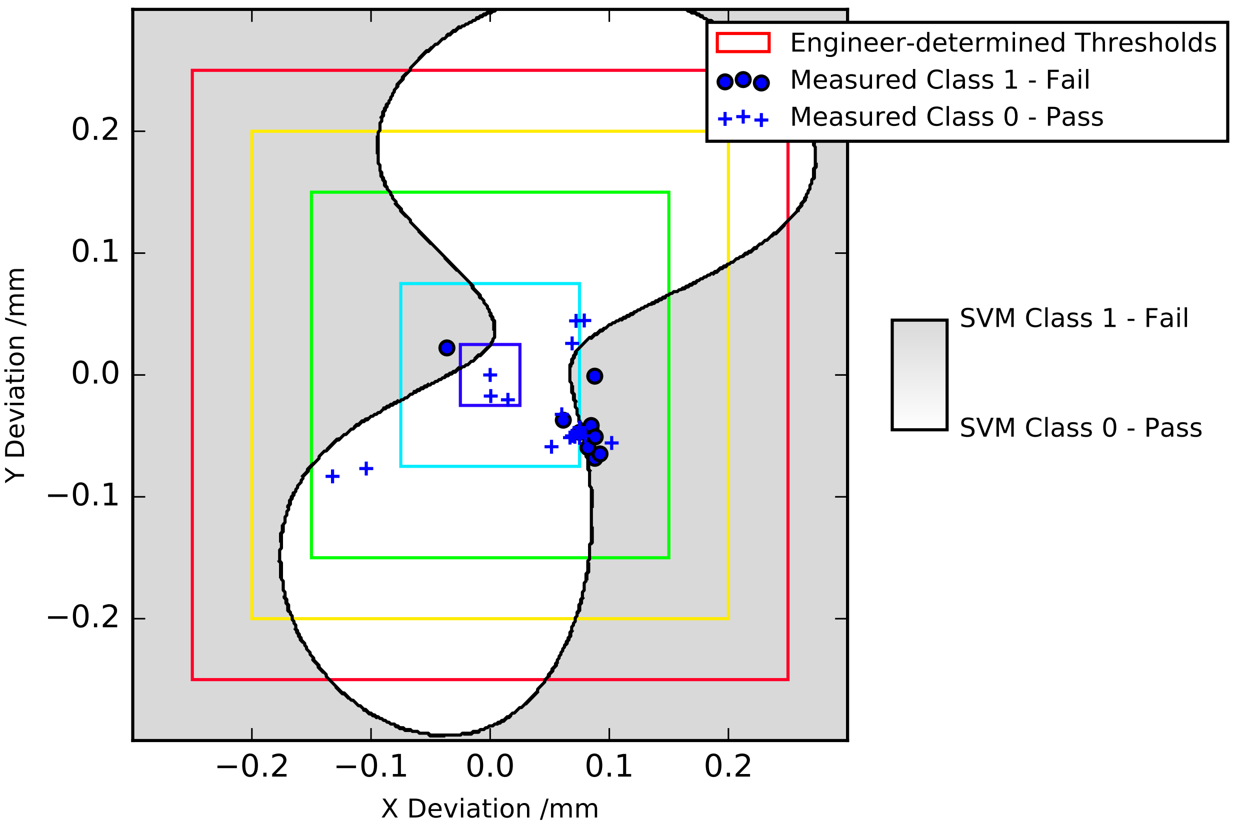

Fig. 4: Predictive classification of parametric health states, comparing linear X and Y axes

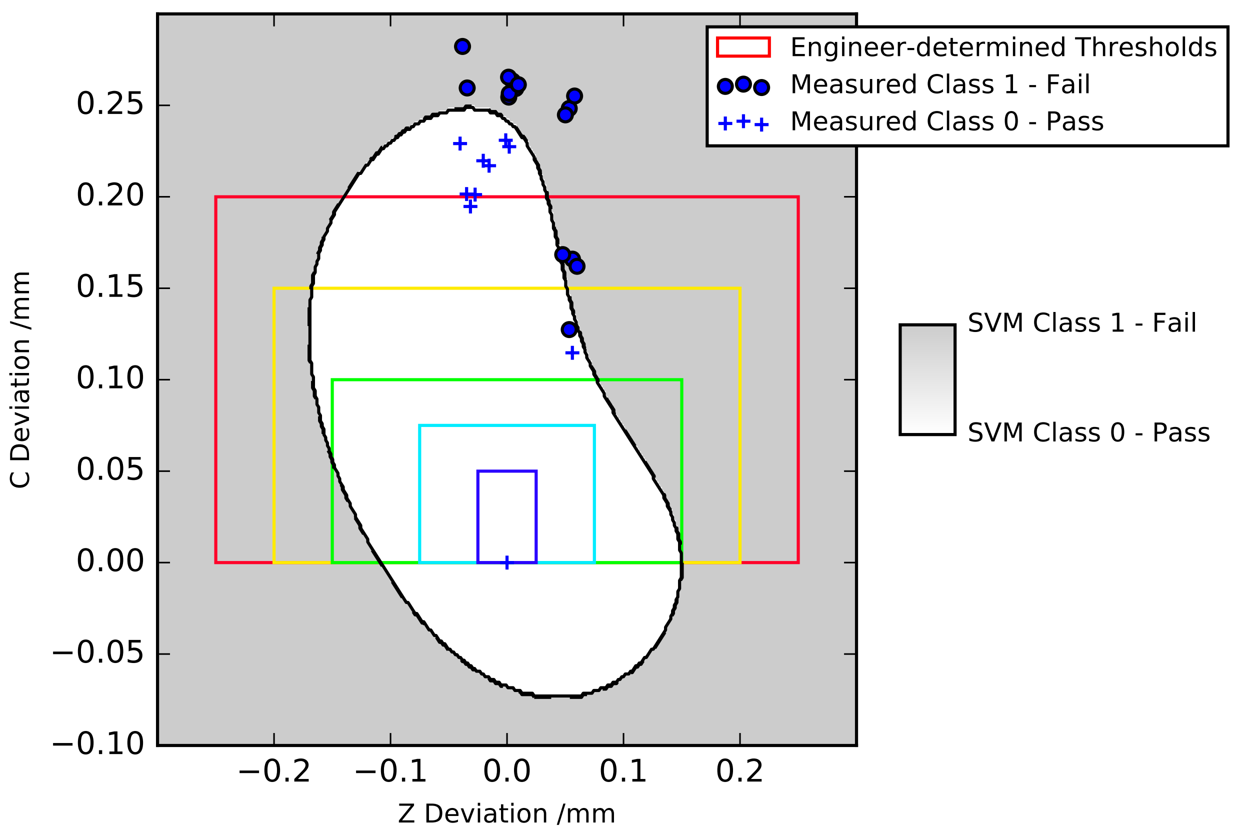

Fig. 5: Predictive classification of parametric health states, comparing linear Z and rotary C axes

4 Discussion and further research

From the analysis, it is reasonable to deduce that modifications to the threshold values can skew perceptions of the machining centre health state. In Figure 4, a cluster of measured data points classified by the engineer as ‘failed‘ is observed, interspersed with three further ‘pass‘-classified data points. The actual operation as observed at these data points is near-identical with respect to the X and Y axes, so in the context of overall machining centre performance it would be more sensible to be grouped into a single class. Furthermore, it would be logical to assume that a tight cluster of data points represents a stable operating condition, as all parts produced in these states are subject to similar conditions.

Clearly, deviation from nominal geometry is of the highest importance when assessing machining centre performance; however, it is also worth considering the stability of the system and the effects that this can have on finished part quality. Figure 5 shows a consistent grouping of data points with just one outlier; however, in Figure 1 the data points classified as ‘pass‘ show considerable dispersion. Again, this weakens the argument for relying on engineer-determined thresholds for monitoring the overall system performance.

The SVM models can be used to predict the classification of future measured data points as determined by engineering judgement. Due to applications-based problems out of the researchers’ control, a dedicated set of testing data was not available at the time of writing. This will be sought and used to evaluate model performance in the near-future. As abnormal classifications could lead to a reduction in finished part quality and be difficult to interpret at a human level, it is hypothesised that this will have benefits in informing the threshold-setting requirement through automatic identification. The approach provides a means of sense-checking the threshold-setting procedure and the potential for optimising the tolerance requirements based on individual machine-specific characteristics, minimising the requirement for calibration and subsequent machine downtime.

Further to this, the establishment of models describing the normal operating condition of the machining centre is highly relevant to the development of an automated fault diagnostic and prognostic tool. With respect to this objective, the critical aspect raised in this paper is that of threshold bias. As geometric performance monitoring does not entirely conform to the traditional formulation of a damage detection problem, classifications in the training data must be derived from, at least in some part, an engineer’s interaction with the system. The primary source of this information is in the legacy data threshold settings. In order to develop an effective monitoring tool, it is imperative to ensure these inputs accurately reflect the genuine health state of the machining centre, and are not adversely affected by threshold bias.

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