Adaptive decision support for suggesting a machine tool maintenance strategy: from reactive to preventative

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Abstract

Purpose – To produce a decision support aid for machine tool owners to utilise while deciding upon a maintenance strategy. Furthermore, the decision support tool is adaptive and capable of suggesting different strategies by monitoring for any change in machine tool manufacturing accuracy.

Design/methodology/approach – A maintenance cost estimation model is utilised within the research and development of this decision support system. An empirical-based methodology is pursued and validated through case study analysis.

Findings – A case study is provided where a schedule of preventative maintenance actions is produced to reduce the need for the future occurrences of reactive maintenance actions based on historical machine tool accuracy information. In the case-study, a 28% reduction in predicted accuracy-related expenditure is presented, equating to a saving of £14k per machine over a five year period.

Research limitations/implications – The emphasis on improving machine tool accuracy and reducing production costs is increasing. The presented research is pioneering in the development of a software-based tool to help reduce the requirement on domain-specific expert knowledge.

Originality/value – The paper presents an adaptive decision support system to assist with maintenance strategy selection. This is the first of its kind and is able to suggest a preventative strategy for those undertaking only reactive maintenance. This is of value for both manufacturers and researchers alike. Manufacturers will benefit from reducing maintenance costs, and researchers will benefit from the development and application of a novel decision support technique.

Key words: Machine tool calibration, decision support, maintenance

1 Introduction

Machine tools are powered mechanical devices used in both subtractive and additive manufacturing to convert raw materials into a desired component. Machine tools come in a variety of different configurations and sizes which is often determined by their intended use. The design and configuration of a machine tool is chosen for a particular role and is different depending, amongst other things, on the volume and complexity range of the work-pieces to be produced. A common factor throughout all configurations

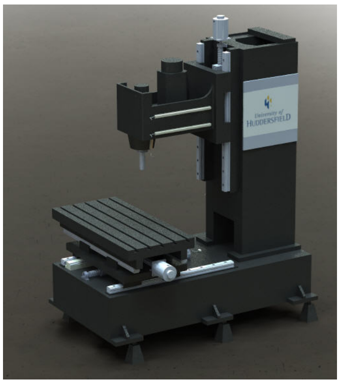


Figure 1: Three-axis C-Frame machine tool.

of machine tools is that they provide the mechanism to support and manoeuvre the functional position, and sometimes the orientation, between the cutting tool and workpiece. The physical manner by which the machine moves is determined by the machine's kinematic chain (Moriwaki, 2008). For example, accurate manufacturing of medical implants requires a small precise working volume, so could be served by a machine with a working volume of 300mm^3 where the small component is driven around the cutting tool. Conversely, the machining of aeroplane wing components requires a larger precise working volume. An example C-frame three-axis machine tool is presented in Figure 1.

In a perfect world, a machine tool would be able to move to predictable points and orientations in three-dimensional space, resulting in a machined artefact that is geometrically identical to the designed part. However, due to tolerances in the production of machine tools and wear during operation, this is often difficult to achieve mechanically. Quasi-static errors are the geometric positioning errors resulting from the movement of the machine tool's axes that exist when the machine tool is nominally stationary. Machine tool error mapping is the process of quantifying these errors (Schwenke et al., 2008; Longstaff et al., 2014) so that predictions, as well as improvements of part accuracy can be made via numerical analysis and compensation.

Machine maintenance is a fundamental process required to maintain the quality of measuring machines. It can also be applied to the production process to help control output quality and maintain the credibility of the machine tool for measurement, such as in-process probing (Achelker et al., 2014). The aspect of machine tool maintenance addressed in this paper is the use of calibration actions to monitor and maintain manufacturing accuracy. Full machine tool calibration requires measurement of a number of error sources. There are 21 sources of geometric error for a 3-axis machine tool, with more on complex machines such as a five-axis machine. Large complex five-axis machine tools can typically take up to one week of measurement time.

The reason for *preventative* calibration of an instrument, machine tool or any other machine is that their performance can drift over time and usage in both their mechanical and electrical response. When considering machine tool accuracy, some reasons for this change are due to the bedding in and wear of components, as well as collision.

The prescribed interval between calibrations tends to be subjective; a fixed "annual" calibration is sometimes adopted as part of a quality paper-trail. A more common approach is *reactive* calibration that is undertaken where a change is detected in the consistency of the machine's output. Such detection can be part of the manufacturer's Statistical Process Control (SPC) applied to the measurement of the final components. Preventative calibration actions are performed to maintain a machine's manufacturing capability and detect any potential problems before they become significant enough to result in the production of parts which are not fit for purpose. In this paper, machine tool capability refers to both availability and the machine's ability to perform machining operations which are within a tolerance limit (Motorcu and Güllü, 2006). When defective parts are discovered, a reactive calibration action will be performed to identify the fault within the machine tool and implement corrective action. Another type of calibration action is a *quick check* measurement which allows the machine tool owner to get a quick indication of the machine's error with little financial implications.

Both preventative and reactive calibration actions have different associated costs and are better suited to different situations. However, there is currently a lack of a formal process which can help the manufacturers to decide which calibration strategy they should choose for a given situation. Currently, manufacturers are implementing maintenance strategies based on their experience and formal guidance from machine tool providers. However, these processes are often rigid and expensive, resulting in small manufacturers not adopting a preventative maintenance strategy due to the high cost. There is a need for a hybrid approach whereby preventative maintenance can be performed to minimise the need for expensive reactive action whilst minimising the costs associated with performing preventative maintenance.

In this paper, a novel *decision support system* is presented which allows manufacturers to predict the cost of both calibration strategies and provide them with the knowledge to make the best decision in terms of minimising financial cost and maximising machine accuracy. This presented decision support system requires the input of manufacturing costs, measurement costs, and scrap and rework costs. These costs are secondary values based upon a set of primary inputs. The implemented decision support system is able to inform a manufacturer as to the best preventative calibration plan based on their historic information, perform sensitivity analysis to highlight the potential impact of uncontrollable costs (e.g energy costs), and to adapt any suggested maintenance strategy based on monitoring the machine's machining accuracy. For example, if a machine's accuracy is seen to be decreasing, then additional calibration actions will be schedules, whereas if the accuracy is stable, costly calibration actions will be replaced with quick check calibration actions, resulting in a decrease in maintenance costs.

This paper presents the development and empirical analysis of a decision support system able to suggest preventative calibration strategies. As illustrated in Figure 2, this research forms a series of subcomponent within a larger programme of research whereby the a cost estimation model is established and tested. Aspects of the methodology used in the research presented in this paper are (4) development of the decision of support systems, and (5) performing empirical analysis of the developed technique. Both (4)

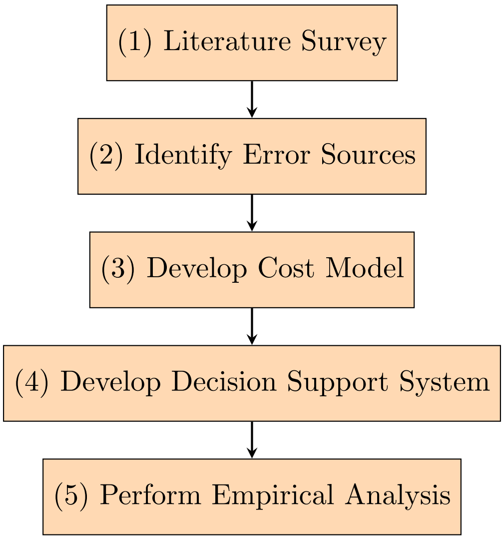


Figure 2: Research methodology flowchart

and (5) are dependent on all previous stages. In stage 3 a mathematical derivation of a cost function that forms the basis of a strategy for scheduling machine tool calibration is then presented in detail, based on machine tool accuracy tolerance boundaries. A UK machine tool maintenance company provided expertise and data throughout the development process. Coding of all the algorithms was undertaken in order to fully test the costing model and replicate how it would be applied for a machine tool in a production situation.

In stage 4 of Figure 2, a decision support system is developed on top of the costing model. The decision support system also takes historical data regarding the number of historic calibration actions, as well as whether they are preventative or reactive. The decision support system has been developed to reason with historical calibration information to determine a cost effective future strategy. Following the development of the decision support model, empirical analysis is then performed based on historical data acquired from an industry partner of this research.

The paper is organised as follows: in the first section a survey of related work related to the automation, establishment of cost, and optimisation of machine tool maintenance. This then leads to the production of a mathematical model capable of calculating the cost for both predictive and reactive calibrations. This mathematical model is used for core analysis in the presented decision support system. The decision support system is capable of processing a manufacturer's historical preventative and reactive calibration actions and deriving a preventative-only maintenance plan to minimise the overall accuracy cost. A case study is then presented to demonstrate the feasibility of the technique as well as demonstrating the importance of sensitivity analysis.

2 Related work

There is a wealth of literature describing and quantifying the detrimental financial impact of machine tool downtime in manufacturing (Farrell and Maness, 2005) and processing environments (Fox et al., 2008). Crumrine and Post (2006) state that manufacturers could lose from 5% to 20% of their productivity capacity due to machine downtime. Whether planned or unplanned, such lost production is intuitively costly to manufacturing organisations. They also estimate that 80% of industrial facilities are unable to estimate their downtime accurately, and suggested that many facilities underestimate their total downtime costs by as much as 200-300%. The great majority of machine tool unavailability is the result of planned downtime that occurs due to required maintenance. "Although unplanned downtime may account for 10% of all downtime, its unexpected nature means that any single downtime incident may be more damaging to the industry, physically and financially, than many occurrences of planned downtime" (Vision Solutions, 2008). To put this into a financial context, typical hourly rates for machine tools are estimated between £65 and £125 per hour.

Manufacturing development needs to be supported by effective and efficient maintenance. The maintenance function has become more complex, involving technical and management skills and requiring the flexibility to cope within a dynamic business environment. Emphasis should be made on carefully implementing a well-considered maintenance strategy since simply following an unjustified strategy can lead to significant negative impact in terms of wasted time, money and morale (Henderson, 2013). The purpose of maintenance management is to reduce the adverse effects of breakdown and to maximise the production system availability at minimum cost (Löfsten, 2000). With the increasing complexity of modern CNC machine tools, the correct maintenance policy is ever more critical to the ability of the manufacturing organisations to compete. In this respect, operations management, especially maintenance management, is taking on a wider organisational strategic role (Simões et al., 2011).

A significant amount of research and development has been performed into improving maintenance processes in regards to manufacturing using machine tools. Carlos et al. (2008) provide a case study demonstrating the importance of selecting the correct maintenance strategy. Although the research demonstrates the importance of performing adequate maintenance operations, it does not consider the translation from a reactive to a preventative only strategy, which subsequently can be optimised based on machine tool accuracy information. Salonen and Deleryd (2011) discuss the cost associated with poor maintenance and proposed a framework, with no empirical validation, on maintenance improvement. Although it is a conceptual framework, it does not address the need to reduce the reliance on expert knowledge. Furthermore, the technique is not adaptive, nor does it have suggestive capabilities to assist a manufacturer in translating from a reactive to a preventative maintenance strategy.

Early work presented by Al-Sultan and Duffuaa (1995) utilises a mathematical programming technique (mixed integer programming) to adaptively monitor and change the maintenance schedule. However, the system is based purely on production demands and does not pay any attention to energy costs, nor is based on the accuracy capabilities of the machine tool. Zhou and Liu (2016) present a technique to optimise preventative maintenance based entirely on degenerating manufacturing systems. There model is focused on the loss of manufacturing accuracy and workpiece accuracy. Although their system is based on historical data, it focusses on determining how long before a maintenance activity is required. It does not consider the scheduling of such actions to maintain a preventative only strategy for a manufacturer who may have previously operated reactively, nor does it take into account energy requirements. The system presented in this paper aims to assist the manufacturer in translating to a preventative only maintenance strategy, which is subsequently updated through active monitoring of machine accuracy. The novelty of this approach is further confirmed by reviewing the research surveys where a comprehensive survey does not identify a system able to solve the challenges presented in this paper Ansari et al. (2016); Basri et al. (2017).

In previous work, researchers have produced expert systems capable of modelling the process of machine tool calibration (Parkinson et al., 2011) and provide the mechanism to use domain-independent automated planning to generate a calibration plan, minimising the requirement for expert knowledge (Parkinson et al., 2012b), and produce both temporal and cost efficient plans (Parkinson et al., 2012a, 2014). However, the model is measurement-oriented and takes no consideration of manufacturing costs, nor the frequency of performing calibrations. Further research investigated the potential of extending this model to include manufacturing costs in a two-stage approach where the individual measurements were planned and minimised, and then the proposed calibration was optimised (Shagluf et al., 2014a). Although these tools are useful in assisting in the producing and cost-estimating of calibration plans, they do little to assist the user in adapting their current calibration plan to one which is more systematic, as well as gaining a better understanding of potential costs given changes in the manufacturing landscape.

The advantages of using decision support systems for scheduling, planning and optimising strategies has been explored by many researchers in difference disciplines. For example, Qu et al. (2012) present the use of a decision support system for scheduling patient appointment in the medical domain. Equally, as significant, Plaza and Turetken (2009) discuss the importance of planning as essential components of project management. This includes highlighting the considerable effort and time that goes into planning so that acceptable results are delivered within the constraints of time, budget, and other resources. This is interesting work which is pertinent to the work presented in this paper. Research has also been conducted into using decision support systems for production planning. For example, Farrell and Maness (2005) present the use of a database approach used to create a programming-based decision support system that can be used to analyse production planning issues. Another interesting and relevant work presented by Khataie et al. (2011) includes the development of an activity-based costing and management method which is integrated into a decision support system. This work is of particular interest as the use of an activity-based costing system aligns to the research presented in this paper.

Expert systems have been widely used in manufacturing and maintenance (Palma et al., 2010; Tran and Yang, 2012). For example, recent work has seen the integration of decision support systems for integrating manufacturing and product design into supply chain networks (Wang and Hsiao, 2014). This work is particularly interesting as it considers uncertainty surrounding customer demand, production, and supply times. The use of a decision support system for selecting machine tool in a flexible manufacturing cell (Taha and Rostam, 2011; Nguyen et al., 2014) is another significant use of a decision support system in manufacturing. This paper successfully uses a hybrid approach to suggest the best machine tool to use to increase overall performance (accuracy and time). The hybrid approach makes use of fuzzy analytic hierarchy process and preference ranking organisation methods. Decision support tools have also been implemented for specific manufacturing processes. For example, recent work utilised a decision support system to aid with strategic and operational decision-making during steel manufacturing (Melouk et al., 2013). Other decision support systems have also demonstrated the potential to encode past experience to further optimise any decision (Ghattas et al., 2014).

All these works demonstrate significant potential and motivate the use of a decision support system for selecting machine tool calibration strategies.

3 Mathematical model

A mathematical model has previously been derived which breaks the maintenance cost estimation process down into logical sub-stages. The model's previous use is for calculating the cost model associated with different machine tool accuracy maintenance strategies. This paper aims to further utilise the model to produce a decision support system that can enable the choice of optimal strategy for varying manufacturing conditions. An overview of the model follows. The full details can be found in (Shagluf et al., 2015). This previous work presented the development of the mathematical model, whereas in this work the model is used for the cost calculation which feeds into the decision support system.

To motivate the need for the maintenance cost model, as well as to aid with justifying the logical subsections of the presented model, Figure 3 is provided to illustrate an example run to fail scenario for the reader. In the figure it can be seen how the part accuracy is steadily increasing beyond the tolerance limit until the post process inspection identifies non-conformance. Manufacturing has continued to the time when non-conforming parts started to be produced and identification. The parts manufactured during this time-frame will subsequently need to be reworked or have to be scrapped. There are also other significant costs arising from the downtime of the machine tool whilst error mapping and corrective action take place.

The below list summarises sections of the mathematical model:

- **Cost per part:** This represents the cost of raw materials or semi-finished parts that come to the machine for processing. It forms an important component of

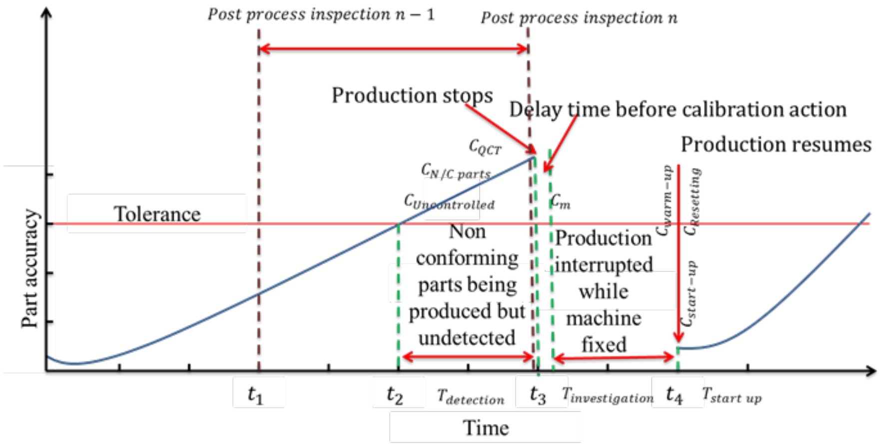


Figure 3: Run to fail scenario and related costs

the model, since it directly affects the cost of any scrap, reworks or opportunity cost while the machine is not in production. The material costs can be divided into both direct and indirect cots. The latter are those that are not directly added to the product but are costs which contribute towards the final value of the manufactured part. For example, machine tool oil and lubricant are used during machining processes, but not directly purchased for a particular job. An example of a direct cost is the raw materials for manufacturing. The cost per part is directly affected by variable manufacturing parameters such as energy costs, raw material costs, time to manufacture, etc. For this reason, the decision-making process must be a "live" tool to respond to changes in these inputs.

- **Cost of the uncontrolled period:** This is the cost associated with producing parts which are not under accuracy control. It has a direct relationship with the time taken between the machine starting to producing non-conforming parts due to the machine going out of acceptable tolerance and the point at which this situation is detected. This cost will be influenced by the response to a non-conforming part; an out of tolerance part may be either reworked or scrapped. The cost of scrapping a part related to the *cost per part*.

- **Cost of external impact:** In addition to the internally-costed waste associated with scrapping or reworking a non-conforming part, there is an external impact of delivering defective parts to a customer. The cost includes cost of shipping, fines and penalties, rework-costs by customers, etc. There may be significant additional consequences such as loss of contracts due to reputation harm due to unsatisfied customers (Shagluf et al., 2013).

- **Quality control costs:** Quality control is concerned with monitoring quality while the product or service is being produced. As stated by Kumar et al. (1998), "the costs of quality are essentially the costs of failures or defects and trying to avoid failure of such as inspection and training." In the produced model, quality control time related to quality inspection is considered. This usually involves skilled workers to interpret acquired measurement data to identify the fault. Decisions on how these costs are borne will be influenced by how close the quality-control loop is, both physically and temporally, to the point of production.

- **Machine error mapping costs:** Machine error mapping is the process of measuring the geometric errors of the machine tool (Zhu et al., 2012). Since the machine can/will also change with temperature, this can be extended to the repeated mapping required to ensure the accuracy of machines over a long-term period. In this model, the cost of error mapping includes the labour required to complete the measurements, opportunity cost associated with the (non-producing) time taken for measurement of the machine and the time required to resume production after measurement. The last of these includes re-setting fixtures, inserting offsets, etc.

- **Machine tool accuracy costs:** The costs described above enable a realistic cost prediction of the different aspects of both predictive and reactive calibration. However, many aspects of the model are reliant on historical information to allow for good estimates of the probability of various input factors. For example, when deciding which calibration strategy is going to be the most effective, knowledge is required regarding the expected number of episodes of machine non-conformance which will occur in a given time-frame. The number of regular calibrations is also unknown and will often depend on company policy. This aspect of the model equation is to be used to calculate the total accuracy related costs, which then forms the output upon which the decision support system can provide its recommendations.

The below equation provides the high-level calculation used to calculate the final accuracy related costs. Table 1 provides a description of each term within the equation. A full description and justification of how each term is calculated is provided in (Shagluf et al., 2015).

$$
\begin{aligned}
&CV_{total\ accuracy\ costs} \\
&\quad = CV_{uncontrolled} + CV_{nonconformance\ part\ impact} \\
&\quad + (CV_{qc\ mc\ error\ mapping} \times QV_{regular\ calibration}) \\
&\quad + (CV_{qc\ ipi} \times QV_{qc\ ipi\ parts} + CV_{qc\ mc\ validation\ checks}) \\
&\quad + (CV_{react\ detect\ non\ conformance} \times QV_{incidents\ of\ failure}) \\
&\quad + (CV_{quick\ check} \times QV_{quick\ check})
\end{aligned} \tag{1}
$$

4 Decision Support

In the previous section, a model is discussed that can be used to estimate the cost of maintaining machine tool accuracy through preventative or reactive strategies. The model

Term	Description
$CV_{total\ accuracy\ cost}$	total machine tool accuracy related costs
$QV_{incidents\ of\ failure}$	total number of reactive incidents
$QV_{regular\ calibration}$	number of preventative calibration actions
$CV_{nonconformance\ part\ impact}$	total cost of producing non-confirming parts
$CV_{uncontrolled}$	cost of uncontrolled production whilst machine is out of tolerance
$CV_{qc\ mc\ error\ mapping}$	is the cost value of regular machine measurement
$CV_{qc\ ipi}$	is the cost of any in process inspection
$QV_{qc\ ipi\ parts}$	number of parts in the batch to be inspected
$CV_{qc\ mc\ validation\ checks}$	number of validation checks required
$CV_{react\ detect\ non\ conformance}$	costs incurred during the reaction to detect non-conformance
$QV_{incidents\ of\ failure}$	total number of reactive incidents
$QV_{quick\ check}$	total number of quick check incidents
$CV_{quick\ check}$	cost incurred for a quick check action

Table 1: Nomenclature for error mapping related equations

presents the interesting possibility of being able to predict and inform a manufacturer of potential accuracy related costs, based on the parts that they are manufacturing as well as their current maintenance strategy. In most cases, the manufacturer will have limited control over the cost of the part. This is because it is often determined by their client's requirements, and external factors such as raw material and energy have a significant influence. However, their maintenance strategy is something under their control that can optimised to improve profitability. Previous work by the authors has demonstrated the potential of using this model to calculate the financial cost associated with different calibration strategies (predictive and reactive) (Shagluf et al., 2014b). The work presented in this section is to utilise this model in a decision support system, which is capable of informing the user as to the implications of choosing between different maintenance strategy, as well as illustrating the sensitivity of the chosen strategy to any change in parameters (e.g. energy cost). Some of these parameters are fixed or slow-changing (e.g. cost of labour) while others are relatively volatile, such as energy price. The DSS must be sufficiently flexible to assist the end-user in choosing and reviewing their calibration strategy. This includes helping to determine the following:

1. If the manufacturer does not currently have a maintenance strategy, provide them with the potential cost of using a preventative calibration strategy, highlighting the potential effect of increasing resource costs. This will allow them to make more informed decisions when trying to identify a suitable strategy.
2. If the manufacturer has a calibration strategy, calculate the total accuracy related costs based on their current maintenance strategy and any available historical

information regarding the machine's performance. This will also consider the potential of increasing resource costs and demonstrate the effect on their current maintenance strategy.

3. Identify if it is feasible to produce a predictive maintenance strategy that would prevent as many reactive calibration actions as possible. This will also provide the user with the predicted cost should any resource costs change.

4. Monitor the execution of a maintenance strategy and make modifications to both preserve manufacturing capability and minimise economic impact.

4.1 Inputs

In order to calculate the total accuracy related costs, the system requires the manufacturer to provide inputs related to the parts that are being manufactured, information for the cost calculation of uncontrolled periods, costs incurred during quality control, and machine tool error mapping costs. The correctness of these inputs is important as any erroneous values would result in an incorrect cost calculation and could result in the suggestion of an incorrect maintenance strategy. However, most of the required information would be readily available, and if it is not, the use of sensitivity analysis can aid the manufacturer in understanding the potential impact of changing resource costs on their calibration strategy. In addition to specifying cost information, information regarding the required tolerance is provided. This tolerance limit is then used to compare the results of a calibration action to aid the manufacturer in adjusting their calibration plan to minimise financial cost while maintaining manufacturing equipment availability.

4.2 Types of Calibration Actions

The two types of calibration actions discussed so far in this paper are preventive and reactive. However, it is now necessary to introduce a *quick check* calibration action. A quick check calibration action is used to determine if the machine is currently producing parts within tolerance. The motivation for introducing a quick check calibration action is that introducing a preventative only calibration plan introduces uncertainty of whether a reactive calibration action will still be needed to overcome unforeseen episodes of producing non-conforming parts. As quick check calibration actions incur little financial implications, they can frequently be scheduled to gain an understanding of the machine's capabilities. Information acquired from performing frequent quick check actions can then be utilised to adjust the maintenance strategy plan, maintaining both manufacturing capability and accuracy.

4.3 Strategy Suggestion

Once the total accuracy cost (Equation 1) has been calculated, the next stage is to calculate and provide the user with information that they can use to determine whether a calibration strategy is best suited to their organisation. As described earlier, the factors affecting the total machine accuracy cost ($CV_{total\ accuracy\ costs}$) are of interest in this paper. The costs of the reactive, regular, and quick check calibrations determine this overall cost. In addition to estimating the cost of each strategy, the remainder of this section presents a technique for reducing both cost and machine downtime through predicting a minimum number of preventative and reactive calibrations over a given period.

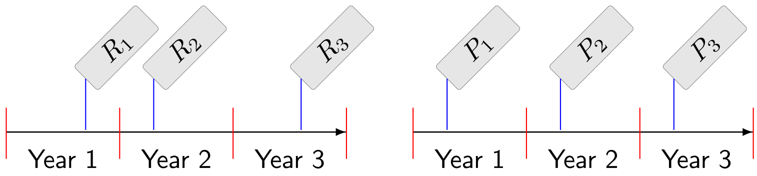
4.3.1 No Current Strategy or Switching to Preventative

In some situations, a manufacturer may want to know the estimated cost of optimising their preventative calibration to minimise the likelihood of reactive actions. This is because maintaining machine tool accuracy by scheduling more frequent preventative calibration actions can reduce the likelihood of the machine producing non-conforming parts. If the likelihood of the machine producing non-conforming parts is reduced, then so are the costs associated with reworking and scrapping out of tolerance parts.

If the manufacturer currently has no strategy, it is assumed that they are operating in a reactive mode and thus are aiming to identify a suitable preventative strategy. In this section it is also assumed that the manufacturer has historic information available detailing previous reactive calibration actions. However, if the manufacturer does not have any information available, the technique will simply output a yearly calibration schedule containing one preventative calibration action, leaving the manufacturer to make suitable adjustments as more data regarding the probability distribution becomes available.

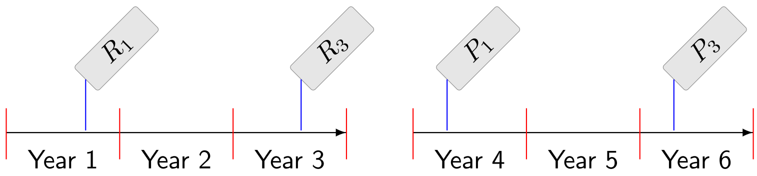
Estimating the potential cost of removing all occurrences of reactive calibration actions is challenging as the frequency of preventative actions will need to be scaled accordingly. In the case of switching to preventative calibration only, it is necessary to set the frequency of preventative calibration actions to minimise the likelihood of the occurrence of reactive actions. This is not a trivial task due to uncertainty surrounding when a reactive action may be needed. The solution presented in this paper is to identify a pattern of preventative calibration actions based on historic data, which would result in a preventative action scheduled before each historic reactive calibration action. However, as this is based on historical information, simply scheduling a predictive calibration action before the occurrence of a reactive action does not guarantee that it will no longer occur. To improve confidence, the optimisation objective of this process is to minimise the time distance between each predictive action and the historic reactive action. The technique presented in this paper has three stages which are descried in the following sections.

Stage 1: The first stage is to establish a loose pattern to determine a systematic frequency of preventative calibration actions. Here a loose pattern refers to the number of predictive and quick check calibrations actions required per year, as well as the recurrence of any pattern. In this section, the patterns concerned are those that are systematic, such as n number of calibrations per year, or one calibration per n years, etc. This technique is largely limited by the number of years of data available for analysis. For example, if only two years' worth of information is available, then the identified pattern may



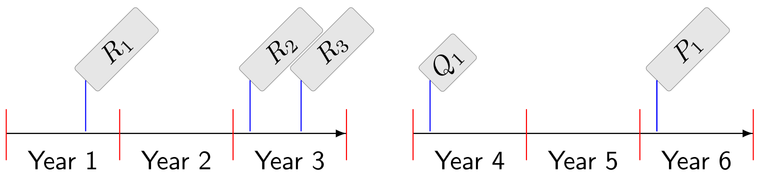
(a) Historic calibration actions (b) Produced calibration action plan

Figure 4: Derived predictive calibration pattern from a consistent frequency of total calibration actions



(a) Historic calibration actions (b) Produced calibration action plan

Figure 5: Derived predictive calibration pattern based on the pattern of historic calibration actions



(a) Historic calibration actions (b) Produced calibration action plan

Figure 6: Derived predictive calibration pattern based on the pattern of historic calibration actions

be based on too little information to accurately represent real-world performance. To overcome this limitation, and to improve calibration plan quality, the presented system includes an adaptive monitoring stage (stage 3) based upon the results of the quick check calibration actions. In order to maximise the impact of the pattern identification technique, the following three scenarios are considered and accounted for:

1. If the frequency of calibration actions, both predictive and reactive, is the same throughout the entire period, then the frequency will be used for the number of preventative actions. For example, Figure 4 shows a historic calibration plan (Figure 4(a)) and a proposed predictive calibration plan (Figure 4(b)). In this instance, it is less important whether the calibration actions in the historic plan

are preventative or reactive.

2. Any cyclic pattern occurring over a two year period or more will become the frequency of preventative actions. Figure 5 provides an illustration of a basic pattern where there is one reactive calibration action every two years (Figure 5(a)). This results in the production of a pattern where one preventative calibration occurs every two years (Figure 5(b)).

3. If the number of calibration actions is irregular and no identifiable pattern can be found, an average number calibration actions per year will become the pattern. For example, Figure 6 illustrate a scenario where over a three year period, the first year has one quick check action, the second year has nothing, followed by a third year with two reactive actions (Figure 6(a)). This would result in the production of a calibration plan with a quick check calibration action in the first year, followed by a preventative calibration action in final year (Figure 6(b)). However, should the quick check action demonstrate large machine error and poor machining capabilities, then another preventative calibration action will be considered.

The above three scenarios do have a large degree of uncertainty which increases with the number of historic reactive calibration actions. This is because there is no certainty that scheduling a preventative calibration action before the occurrence of a historic reactive calibration action would prevent it from occurring. It could happen that a reactive calibration action is required due to the failure of a part which is not examined during a routine preventative calibration. For example, an electronic component, such as the power supply, which has a finite life and may not often exhibit and precursor events indicating that it is likely to soon fail. The aim of the technique presented in this paper is to identify a suitable sequence of preventative calibration actions which would help to minimise the likelihood of reactive calibration actions. However, as they are likely to occur, the technique takes as input the volumetric error of the machine tool after each calibration action and compares it against previous readings as well the manufacturing tolerances.

Stage 2: Once the frequency of preventative calibration actions has been identified, it is then necessary to schedule the calibrations to be as closely as possible to any historic calibration action. The scheduling algorithm presented in Algorithm 1 will schedule a fixed frequency calibration plan based on any identified pattern. The aim of this algorithm is to minimise the average distance between a scheduled predictive calibration action and that of a historic calibration action. The algorithm takes as input the number of calibration actions per year and outputs a series of yearly calibration actions, including the day (0 to 365, or 366 in a leap year) where they are scheduled. The algorithm starts at day 0 and iteratively increases until the distance metric no longer decreases. Here the metric is the standard deviation between the proposed date of the calibration in question. At this stage, if more than one calibration action per year is planned, the algorithm would be executed again; however, during this execution, it would minimise the distance between the proposed day and that of the second calibration action.

Algorithm 1: Optimal scheduling algorithm for positioning each preventative calibration actions close to historic calibration actions, while maintaining a fixed duration between each.

Input: The historic sequence of calibration actions in yearly form, $Y = \{y_1, y_2, ..., y_n\}$, where y_n is consistent of each calibration event, $y_n\{c_1, c_2, ..., c_n\}$. Each calibration action contains a cost value, v, and the type of calibration, t

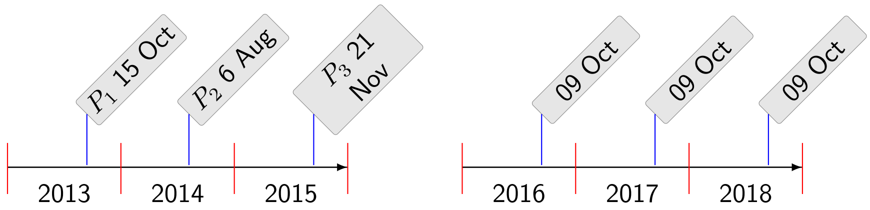
Input: The maximum number of calibration actions per year, $MaxFreq$.

Output: A set of tuples, $O = \{num, day\}$, which represents the yearly calibration number, num, and the number of days at which is will occur, day (0 to 365).

Algorithm `algo()`
    for $i \leftarrow 0$ **to** $MaxFreq$ **do**
        $d_1 \leftarrow 0$
        $d_2 \leftarrow 365$
        $day \leftarrow 0$
        while $d_1 \leq d_2$ **do**
            $d_2 \leftarrow d_1$
            $d_1 \leftarrow$ `proc(`day, i`)`
            $day++$
        end
        $O \leftarrow \{i, day\}$
    end
    return O

calculateDistance `proc(`day, $calNo$`)`
    $d \leftarrow 0$
    $qty \leftarrow 0$
    for $i \leftarrow 0$ **to** $|Y|$ **do**
        $v \leftarrow |y_i|$
        if $v > calNo$ **then**
            $dayAt \leftarrow y_{i,calNo}$
            $d \leftarrow (dayAt - day)^2$
            $qty++$
    end
    return $d = \sqrt{\frac{d}{qty}}$

An example is shown in Figure 7 where three calibration actions over a three year period (one per year) have resulted in the production and scheduling of a yearly preventative calibration plan. Figure 7(a) demonstrates the date of a calibration action. For the purposes of this example it is less important to know whether they are preven-



(a) Historic calibration actions (b) Produced calibration action plan

Figure 7: Derived predictive calibration patter from a consistent frequency of total calibration actions

tative or reactive actions; however, what is important is that the dates of the actions are not occurring at a fixed frequency. Processing this set of calibration actions with Algorithm 1 results in the production of the preventative calibration plan demonstrated in Figure 7. Here the the minimum average distance between the proposed calibration date and those selected converges with a metric value of 44 when the proposed date is the tenth of October.

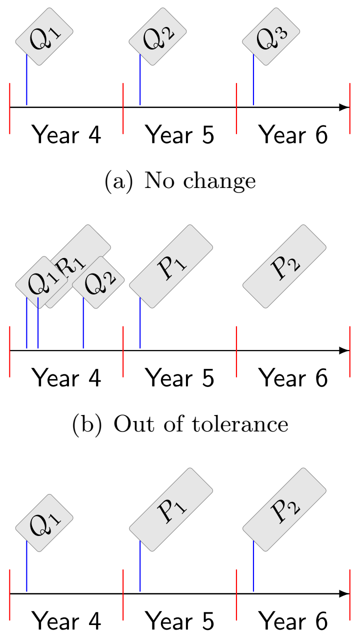
Stage 3: The previous stages result in a preventative only sequence of calibrations ($C = \{c_1, c_2, ..., c_n\}$) aimed at producing a simplified and systematic sequence of calibration actions to decrease cost and increase machining capabilities. However, considering the uncertainty surrounding whether a scheduled preventative action would keep the machine within tolerance and prevent a reactive calibration, it is necessary to monitor the output of each calibration action (preventative, reactive, and quick check) to establish whether the machine's error is worsening and whether more preventative actions need to be introduced to prevent machine failure and reactive calibration actions.

The process requires the manufacturer to specify the tolerance to impose on manufacturing capability (t) in terms of a micron error (µm/m). Each calibration action, c_i will result in a machine error value, e_i, also in µm/m. Each e_i value will be recorded to establish a rate of change, r using the following equation:

$$r = \frac{\Delta e}{\Delta d} \tag{2}$$

where $\Delta e = e_i - e_{i-1}$ and $\Delta d = d_i - d_{i-1}$. Here t is the number of days within the calibration plan that are between the current and previous calibration actions. The Decision Support System (DSS) then uses these values to determine if modification to the calibration plan is necessary and if so, to suggest the most suitable modification. The DSS contains a set of modification rules which have both preconditions and effects. The DSS is sufficiently flexible to allow the introduction of new rules based on a manufacturer's experience. The DSS presented in this paper has the following rules:

1. If the machine is within tolerance ($e_i \leq t$) and there has been no change or an improvement in error ($r = 0$), the next preventative calibration action is to be



(a) No change

(b) Out of tolerance

(c) Increasing

Figure 8: Updated calibration strategy due to the result of a calibration action

replaced with two quick check calibration actions. The first is to be scheduled half way between the current action and the one being removed. The second is to be scheduled half way between the removed calibration action and the next preventative action. The philosophy behind replacing one preventative action with two quick checks is that any potential deviation in the machine's error can be quickly detected and input to the DSS. A new strategy can then be generated to prevent a machine from producing non-conforming parts. An example is provided in Figure 8(a) where the calibration plan presented in Figure 6(b) is updated after the quick check action identifies that there has been no change in machine error.

2. If the machine is out of tolerance ($e_i \geq t$), then a reactive calibration action must be immediately initiated. In addition, the calibration sequence needs to be modified as the machine has gone out of tolerance without being noticed. Here the day at which the machine went out of tolerance is estimated through iteratively multiplying the machine error (e_i) by the rate of change (r) until $e_i \geq t$. At this point, n is the estimated number of days prior to the current calibration where the machine went out of tolerance. A new quick check calibration action will be inserted at d_{i+n} to check the machine's error. An example is provided in Figure 8(b) where the calibration plan presented in Figure 6(b) is updated after the quick check action identifies that the machine is out of tolerance. This initiates a reactive calibration action as well as scheduling more preventative actions.

Algorithm 2: Rules to update the calibration strategy

Input: Set of calibrations, c.
Input: Set of dates when each will be carried out, d.
Input: The current calibration action, i.
Result: updated set of calibration actions, c, and durations, d

if $(c_i \leq t)$ *&* $(r \geq 0)$ **then**
  for $i \leftarrow i$ **to** $|c|$ **do**
    $remove(c_i, d_i)$;
    $t = (d_{i+1} - d_i)/2$;
    $addQuickCheck(t)$;
    $addQuickCheck(d_{i+1} + t)$;
  end
end
if $e_i \geq t$ **then**
  $addReactive(d_i)$;
  $t = (d_{i+1} - d_i)/2$;
  $addQuickCheck(t)$;
end
if $(r \geq o)$ *&* $(r \times (d_{i+1} - d_i) \geq t)$ **then**
  $t = \max(r \times (d_{i+1} - d_i)), r \geq 0, r \leq t$;
  $addQuickCheck(t)$;
end

3. If the machine's error is increasing and the rate of change informs that it will be out of tolerance by before the next scheduled calibration action, it is necessary to adjust the schedule of the calibration actions, as well as consider introducing new actions. To calculate if the machine is likely to be out of tolerance before the next calibration action, the current error, e_i, is multiplied by the number of days until the next calibration, $c' = c_i + r \times (d_{i+1} - d_i)$. If the estimated error is greater than the tolerance, $c' > t$, then a new quick check calibration action is introduced before the machine goes out of tolerance. An example is provided in Figure 8(c) where the calibration plan presented in Figure 6(b) is updated after the quick check action identifies that the machine's error is increasing and the prediction identifies that the machine will be out of error by the next calibration action. This results in scheduling more preventative calibration actions.

The set of proposition rules contains a pre condition and an effect. Once the precondition is satisfied, the effect causes an update to the calibration strategy. Algorithm 2 describes the rules detailed above implemented in the DSS system presented in this paper.

4.3.2 Sensitivity

As historic and current cost data is used in the model to estimated the total predicted calibration cost, it is necessary to consider how sensitive the total calibration cost is to changing inputs. The purpose of performing sensitivity analysis it to make the manufacturer aware of possible change due to the fluctuation of uncontrollable costs. Although a complete sensitivity analysis of all input values is valuable, this paper is concerned with the potential impact of inputs which are either out of the manufacturer's control or are difficult to control. For example, the manufacturer may not know what their item costs are going to be for further components, nor can they be sure of future energy and raw material prices. In this section, a factorial approach (Hamby, 1994) is taken where the value of each input of interest is increased by a predetermined quantity within a predetermined range. The total cost is then calculated for each combination of inputs.

In this analysis, the aim is to determine the potential impact of these changes on the overall calibration strategy costs. The cost which are considered here are:

1. The change in raw material cost and its impact on the overall calibration schedule cost. This calculation uses the historic price raw material costs of aluminium, steel, titanium, etc.

2. The change in energy cost should be considered due to its volatility.

3. Influence on producing non-confirming parts on the calibration strategy. This involves changing the probability that parts will be reworked or scrapped.

5 Developed solution

The decision support solution presented in this paper has been programmed in Java, and both the code and case study data are available from the authors upon request. The software allows the user to input their current calibration plan in the form of a sequence of preventative and reactive calibration actions. Each action requires the input of all contributing costs, as well as the date of occurrence. Both the calibration strategy selection and sensitive analysis algorithms have been coded into the program. For all experiments used in this paper, an 3.60 GHz Intel core i7 CPU with 16GB of RAM.

5.1 Case Study

In this section, a case study is provided where a manufacturer has a currently calibration strategy consisting of a mixture of preventative and reactive calibration actions. This case study is based on data and validation from an industrial collaborator. It is demonstrated how the decision support system presented in this paper can be utilised to aid the manufacturer by (1) estimating the cost of their current strategy, (2) establishing a preventative only strategy, and (3) performing sensitivity analysis on the preventative only strategy, highlighting the influence of increasing input costs. The input costs for

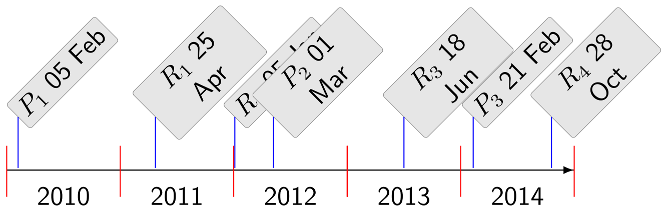


Figure 9: Five year historic calibration strategy using in the presented case study

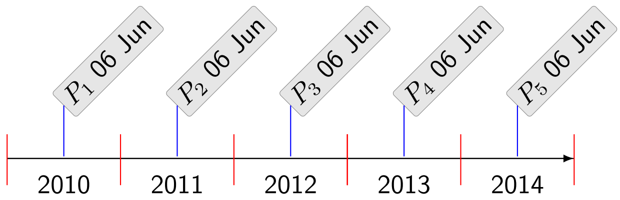


Figure 10: Five year historic calibration strategy using in the presented case study

the provided case study are based on the manufacturer's historical information and are provided in the Appendix (Section 8).

Figure 9 provides a graphical illustration of the company's historic calibrations strategy spanning a five year period. As seen in the figure, the calibration strategy contains three preventative calibrations which take place once per two year period. It can also be seen that there are three reactive calibration actions which take place in the third, fourth and fifth year. The time line presented in Figure 9 provides a good indication that the reactive calibration actions are occurring during and after the years where no preventative calibration actions are scheduled. The next stage is to use the presented decision support system to produce a preventative only calibration strategy.

5.1.1 Preventative Only

Using Algorithm 1 produces the preventative calibration strategy presented in Figure 10. The algorithm has established this pattern by first of all determining that there is no systematic or recurring pattern within calibration actions, and therefore an average approach is taken. The average is always rounded to the nearest whole number as only full preventative calibration actions are considered at this stage. In the case study presented in this paper, the total number of historic calibration actions was six over a five year period, therefore the average calibrations per year in the future plan is one. The next stage is to schedule the recurring date of the preventative calibration action to maintain a systematic schedule. This is performed by iteratively increasing the proposed date until the standard deviation between it and the previous calibration actions within that year is minimised. In the presented example, the algorithm converges at the sixth of June for each consecutive year.

Table 2 provides the financial cost of both the historic and the scheduled preventative calibration plan, showing an estimated financial saving of £13.9k resulting from switching

	Cost in £		
	Preventative	Reactive	Total
Historic	21.2k	28.3k	49.5k
Scheduled	35.4k	0	35.4k
		Difference	13.9k

Table 2: Cost comparison of both historic and proposed calibration strategy

to the provided preventative calibration schedule. Although the cost associated with the preventative calibration actions has increased, the financial saving has come from the estimated removal of reactive calibration actions. This financial saving informs the manufacturer that there is sufficient flexibility to accommodate a few reactive calibration actions.

5.1.2 Sensitivity Analysis

In this section, the potential effect that the following three factors have on the overall calibration strategy cost is examined. These factors are (1) part costs, (2) energy costs, (3) probability that parts will require reworking or scrapping, and (4) the occurrence of unpredicted reactive calibration actions. In this section, this is performed by incrementally increasing each cost for the proposed preventative only strategy. Here a base case cost is defined as the cost of both the historic and proposed preventative plan (those presented in Table 2). Each of the mentioned inputs will then be varied by a predetermined step size and within a predetermined range. The base-case values in this case study for the product cost, energy costs, and scrap and rework probabilities are £25, £0.12 per Kilo Watt, and 0.7% and 0.3%, respectively.

The component value is incremented by £25 starting from £25 to £5000. The cost of electricity will start at £0.1 per Kilo Watt, and iteratively increase by 1 pence until the price has doubled at £0.24. The likelihood of the electricity cost doubling or decreasing significantly throughout the calibration period should be relatively low; however, as energy prices are becoming increasingly volatile it is beneficial to make the manufacturer aware of the potential impact. The effects of an increasing probability of producing non-conforming parts (rework and scrap) is considered by iteratively by increasing the probability by 1 % from 0 % until 100 % is reached. To gain an understanding of the financial implications of reactive calibration actions occurring, reactive calibration actions, with a cost determined from the average of previous reactive calibration actions, are iteratively added from zero to the maximum number of historic calibrations per year times times the number of years. In cases where there were no historic calibration actions, the maximum for this sensitivity analysis is set to two per year; however, this can easily be changed based on the manufacturer's experience.

Performing this sensitivity analysis on this case study results in 20,020,000 iterations of the model with changing values and takes 33 minutes 15 seconds to complete. This factorial analysis allows for the identification of potential change if various input values

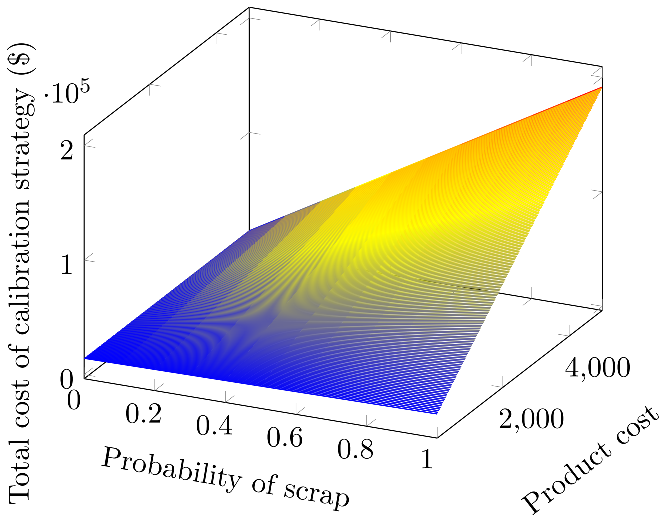


Figure 11: Difference between scrap probability and part cost for both the historic and proposed preventative calibration actions

which could significantly alter the total cost of the calibration strategy. In this section, the following two interesting relationships are discussed: the relationship between the probability of scrap and the part value, and changing energy costs and the part value. There are many other changing costs which affect the total cost of the calibration strategy; however, their impact is insignificant compared to the two that are discussed. For example, the total calibration cost will increase as the probability of rework also increases. However, as the rework cost estimation is not impacted by the change in part value, it has a low significance on the total cost.

The probability of parts being scrapped is an input which does have significant impact on the total cost. Figure 11 illustrates the difference between an increasing probability of scrap, increasing part costs, and the total cost of the calibration strategy for the current and historic sequence of calibration actions and the preventative only strategy. From this graph, it is noticeable that although the increasing part cost does increase the total cost, an increasing probability of scrap has more significant implications as the part cost increases. From this graph, the manufacturer can establish the caution should be taken to minimise the likelihood of producing scrap components. This informs the user about the importance of maintaining the accuracy of their machines, and organisations wanting to minimise the potential scrap costs may consider the introduction of additional preventative calibration actions.

The cost of energy is another input to the model which has uncertainty as to future price. This is largely due to volatility in the supply of energy and its effects needs to be considered. As the presented model considers energy costs when calculating the manufacturing cost of the part, Figure 12 illustrate the difference between both an increasing energy cost and an increasing input part cost on the total cost for both the current and preventative and historic calibration strategy. From the graph it is noticeable

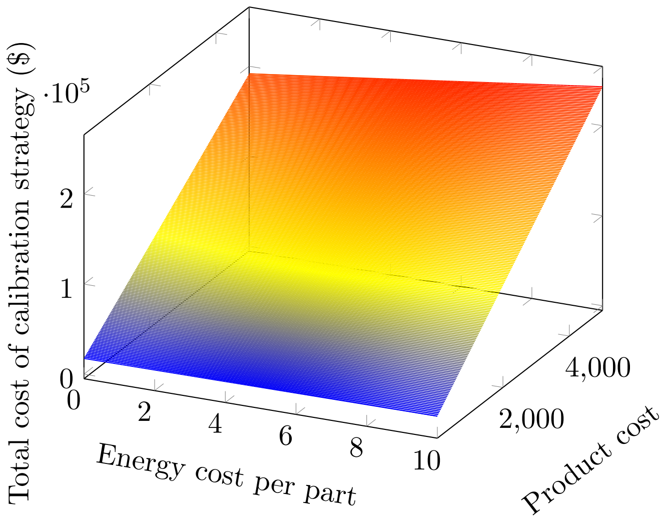


Figure 12: Difference between changing energy price and part cost for both the historic and proposed preventative calibration actions

that the energy cost does impact upon the total cost, and as expected, the significance of an increase energy cost increases as the product cost increases. Although there is little that the manufacturer can do about fluctuations in energy prices, this graph helps the manufacture know the potential impact on the total calibration schedule cost. This should help to make the manufacturer aware of the need to adhere to the proposed calibration plan, as the introduction of any new reactive calibration actions along with increasing costs could be costly.

Figure 13 illustrates the impact on cost should unforeseen preventative calibration actions occur. This graph clearly demonstrates the potential financial implications should additional reaction calibration actions occur. The figure is interesting as it demonstrates that two reactive calibration action can occur and the preventative only plan would still be below the cost of the historic plan. If a third reactive calibration action was to be performed, then the value would only be £3k higher than the historic calibration plan. Presenting this information to the user is significant as it allow them to make the informed decision of whether the uncertainty surrounding the likely occurrence of unforeseen reactive calibration actions can be offset against financial savings from the preventative only plan.

5.1.3 Monitoring

The previous section has illustrated the economic differences between the historic and proposed calibration sequence. Furthermore, it has identified that the financial saving creates the potential for unforeseen reactive calibration actions to be carried out if necessary. The proposed calibration plan is an initial schedule which will be updated after each subsequent calibration action. In this section, the update of the calibration plan

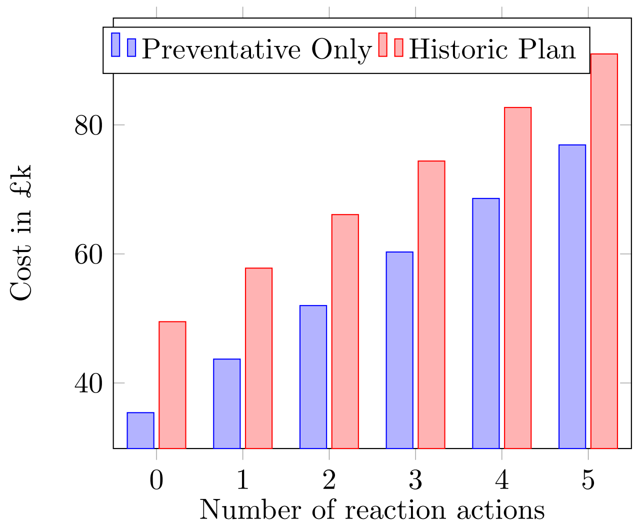


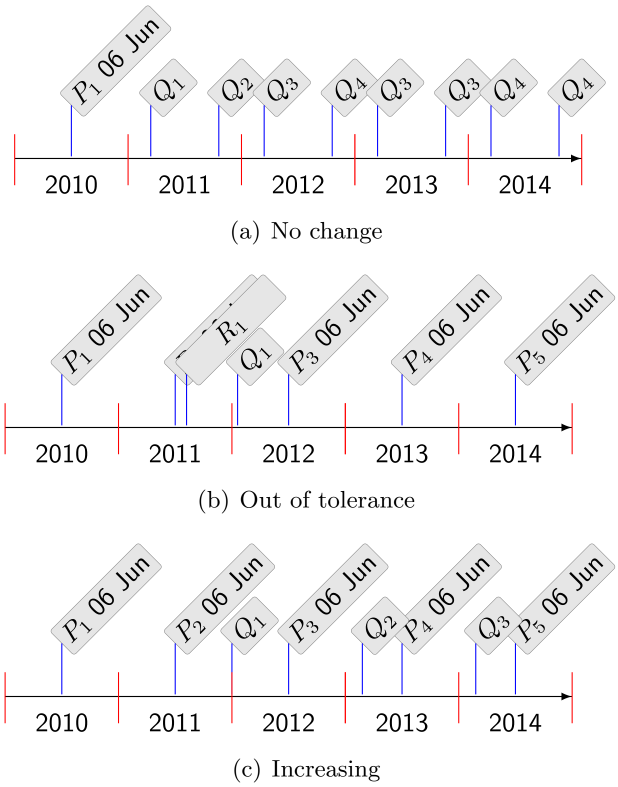
Figure 13: Graph demonstrating the increasing cost of incrementally adding reactive calibration instances to both the preventative and historic calibration plan

(Figure 10) is considered after the second preventative calibration action. An illustrative example is provided for each of the three scenarios where the (1) machine error is within tolerance and stabilised, (2) the machine error is found to be out of tolerance, and (3) the machine error is increasing and it is estimated to be out of tolerance before the next preventative calibration action.

Figure 14(a) illustrates the updated calibration sequence should there be no identified change in machine error. It is noticeable that in the updated calibration plan, that each preventative calibration action has been replaced with two quick check actions. This is because a quick check action does not require the machine to be out of operation for a long duration, nor does it require machine tool metrology experts or a diverse array of equipment. Two quick check actions have been scheduled to decrease the time to detect changing machine's accuracy. If the machine error is identified to be changing after a quick check action, then the DSS system will re-evaluate the calibration schedule and introduce preventative calibration actions.

Figure 14(b) illustrates that the machine has gone out of tolerance and a reactive calibration action is initiated. As a result of the reactive calibration action, an additional quick check action is scheduled before the next preventative calibration action. The role of this quick check action is to determine if the machine's error is increasing and whether there is a need to introduce more preventative calibration actions.

Figure 14(c) illustrates an increasing machine error where it is expected to go out of tolerance before the next preventative calibration action, P_3. In this situation, a quick check calibration action has been scheduled half way between the current calibration action and the next. The aim of this quick check action is to determine if the machine's error is further decreasing. If the error is due to be out of tolerance before the next preventive action, then the preventative action will be moved forwards to a date where



(a) No change

(b) Out of tolerance

(c) Increasing

Figure 14: Updated case study calibration sequence

the machine is still estimated to be within tolerance. A quick check action would then be scheduled half way between the current and subsequent calibration action to monitor machine error and perform further updates as necessary.

In addition to revising the structure of the calibration strategy, the DSS also provides an updated cost of the current calibration strategy. In the presented case study, the updated estimate costs are as follows: £7.4k for the updated strategy when there is no change, £43k when the machine is out of tolerance and a reactive action is necessary, and finally £36.1k when additional quick check actions to monitor the machine's error. The low value for the updated plan with no change is likely to increase when as the machine's error does start to change, potentially as the machine ages. The estimated costs from the latter two would start to decrease should the machine error start to stabilise.

6 Conclusion

This paper first presents a model capable of estimating the accuracy-related costs for a manufacturer based upon historic data. The model allows an accurate cost estimation of a manufacturer's accuracy-related costs based upon the parts that they are manufacturing, the frequency of preventive and reactive calibration actions, and additional costs such as electricity. A decision support system is then presented which optimises the number and schedule of preventive calibration actions based upon historical information. This system can suggest a pattern of preventative calibration action based on information provided on history calibration actions, both preventative and reactive. Sensitivity analysis is then performed on variables outside of the manufacturer's control (part value, energy cost, etc.) to inform them of the potential impact of changing costs. Finally, an example is provided to demonstrate the update of the calibration strategy based upon the measured machine error.

A case study is then provided where a manufacturer has a mix of both preventative and reactive calibration actions over a five year period. It is then demonstrated how using the presented decision support system can identify a schedule of preventative calibration actions to reduce the overall accuracy related costs. Sensitivity analysis is then performed to identify the potential impact on the total cost resulting from changing part value, energy cost, and the probability of parts requiring rework or to be scrapped. In the presented case study a saving of £13,877 over a five year period is presented. Although this financial saving might not appear significant, it is a 28 % reduction in total accuracy-related costs. In addition, the ability to actively monitor the output of a calibration and adjust the strategy has demonstrated that further financial savings are possible. This demonstrates the significance of the presented system and motivated further research in the area. Future work includes the continued empirical analysis and validation of the presented technique within an industrial setting. Future work is also been conducted into including further intelligence in the decision support system. For example, utilising information from different manufacturers with similar equipment to further improve the reliability of the proposed maintenance strategy.

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8 Appendix

Table 3 provides the input values used for the case study presented in this paper. Note that the full mathematical model is provided in Shagluf et al. (2015).

Symbol	Value
$CR_{i(adjust\ labour)}$	£20/hr
$CR_{i(adjust\ service)}$	£40/hr
$CR_{idle\ labourer}$	£30/hr
$CR_{i(m\ labour)}$	£50/hr
$CR_{management}$	£200/hr
$CR_{i(meas\ equip)}$	£50/hr
CR_{burden}	£15/hr
CR_{ppi}	£20/hr
CV_{fines}	£100
$CV_{penalties}$	£200
$CV_{shipping}$	£100
$CV_{i(input\ component)}$	£25
$QV_{i(adjust\ labour)}$	1
$QV_{i(adjust\ service)}$	1
$QV_{i(meas\ equip)}$	1
$QV_{i(input\ component)}$	1
$T_{investigation}$	4 hr
$T_{non\ production}$	1 hr
T_{ppi}	2 hr
T_{report}	3 hr
T_{rework}	1.5 hr
$T_{scheduling}$	24 hr
$T_{temp\ stabilisation}$	0.5 hr
$T_{transport\ qc}$	4 hr
$T_{warmup\ adjust}$	0.5 hr
$P_{conforming}$	0%
P_{scrap}	0.7%
P_{rework}	0.3%

Table 3: Nomenclature for quality control related equations