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Automated planning to minimise uncertainty of machine tool calibration

Automated Planning to Minimise Uncertainty of Machine Tool Calibration

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Abstract

When calibrating a machine tool, multiple measurement tasks will be performed, each of which has an associated uncertainty of measurement. International Standards and best-practice guides are available to aid with estimating uncertainty of measurement for individual tasks, but there is little consideration for the temporal influence on the uncertainty when considering interrelated measurements. Additionally, there is an absence of any intelligent method capable of optimising (reducing) the estimated uncertainty of the calibration plan as a whole. In this work, the uncertainty of measurement reduction problem is described and modelled in a suitable language to allow state-of-the-art artificial intelligence planning tools to produce optimal calibration plans. The paper describes how the continuous, non-linear temperature aspects are discretized and modelled to make them easier for the planner to solve. In addition, detail is provided as how the complex uncertainty equations are modelled in a restrictive language where its syntax heavily influences the encoding. An example is shown for a three-axis machine, where the produced plan exhibits intelligent behaviour in terms of scheduling measurements against temperature deviation and the propagation of error uncertainties. In this example, a reduction of 58% in the estimated uncertainty of measurement due to intelligently scheduling a calibration plan is observed. This reduction in the estimated uncertainty of measurement will result an increased conformance zone, thus reducing false acceptance and rejection of work-pieces.

Keywords: Machine Tool Calibration, Uncertainty of Measurement, Automated Planning, PDDL

Nomenclature

E_{C0Y} Squareness deviation of X-axis in Y-axis direction in micrometers per metre (µm/m)

E_{XY} Straightness deviation of Y-axis in X-axis direction in micrometers per metre (µm/m)

E_{YX} Straightness deviation of X-axis in Y-axis direction in micrometers per metre (µm/m)

k Coverage factor for $U_{CALIBRATION}$ according the calibration certificate

$U_{CALIBRATION}$ Uncertainty of the calibration according to the calibration certificate in micrometers per metre (µm/m) or parts per million (ppm)

u_c Uncertainty of uncorrelated contributor, in micrometers (µm)

$u_{DEVICE\,DTI}$ Uncertainty due to the Dial Test Indicator(DTI) in micrometers (µm)

$u_{DEVICE\,SQR}$ Uncertainty due to the mechanical square in micrometers (µm)

$u_{E,DEVICE\,POST}$ Uncertainty due to thermal expansion of the mounting post in micrometers (µm)

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$u_{E,MACHINE\,TOOL}$ Uncertainty due to thermal expansion coefficient of the machine tool, in micrometers(µm)

1. Introduction

Machine Tool calibration is the process to map the geometrical error of the machine tool in order to correct its systematic geometric errors (Schwenke et al., 2008). The significance of this process is dependent on application; manufacturers machining high value parts to tight tolerances, usually in the order of less than a few tens of micrometres, will require their machines to be calibrated regularly, whereas manufactures with broader tolerances may calibrate infrequently. There are many error components that collectively result in deviation of the machine tool from the nominal. For analytical and correction purposes, it is important to measure each error component. For example, a machine tool with three linear axes will have twenty one geometric errors. This is because each linear axis will have six-degrees-of-freedom and a squareness error with the nominally perpendicular axes (Mekid, 2009; Schwenke et al., 2008). Additionally, a rotary axis will have six motion errors and two location errors (Bohez et al., 2007; Seng Khim and Chin Keong, 2010; Srivastava et al., 1995).

Measuring an error component consists of selecting suitable instrumentation and test methods. The selection process is not as simplistic as it first appears. In order to make the best selection, many constraints need to be examined. Previous work in applying automated planning to machine tool calibration planning has shown that calibration plans can be optimised in terms of duration (Parkinson et al., 2011). This work involved modelling the process of machine tool calibration in the Planning Domain Definition Language (PDDL). This model can then be used alongside state-of-the-art planning tools to find the most efficient calibration plan, reducing the overall calibration time. Industrial case studies were then performed to validate the ability to produce complete and optimal calibration plans using this technique. This work resulted in the verification of the model's ability to automatically produce calibration plans with a duration saving of 10.6% over industrial and academic experts (Parkinson et al., 2012). This 10.6% equates to a £134 saving for a single machine tool, and a £2680 saving for a company with twenty machine tools. Optimising a calibration plan to minimise machine tool down-time is important from a production point-of-view. However, the effect on the measurement's quality is not currently taken into consideration and is important for high precision manufacturing. The main aim of the work presented in this paper is to expand the temporal model to be able to produce calibration plans that minimise uncertainty of measurement due to the schedule of the calibration plan.

Uncertainty of measurement is a parameter associated with the result of a measurement that characterises the dispersion of the values that could reasonable be attributed to the measurand (BIPM, 2008). Uncertainty of measurement is an essential part of metrology. Every measurement has uncertainty, the value of which must be reported along with the measurement. In the manufacturing industry, the uncertainties will be calculated to evaluate whether tolerances can be met. High accuracy and precision manufacturing such as the aerospace industry have tight tolerances, therefore reducing the estimated uncertainty of measurement will have an effect on tolerance evaluation, and can help reduce repeating tasks and false rejections.

Figure 1 illustrates the conformance (green) and non-conformance (red) zones based on the uncertainty value and the lower and upper tolerance limit (Forbes, 2006). The remainder is uncertain. From this illustration false acceptance and rejections can be visualised. False acceptance could occur if the measurement value is out-of-tolerance but the uncertainty of measurement brings it into tolerance. Conversely, false rejection could occur if the measured value is in tolerance but the uncertainty of the measurement makes it out-of-tolerance. Therefore, only measurement values that fall within the conformance zone are certain, within the given confidence level, to be within the tolerance. Minimising the uncertainty of measurement can increase the conformance zone reducing false acceptance and rejection.

It is possible to calculate the estimated uncertainty for each measurement individually either before or after the measurement has been performed. The estimated uncertainty is dependent on many temporal factors such as the prevailing environmental temperature and the duration for which an electronic instrument has been active. The existent environmental temperature will affect the thermal expansion and distortion

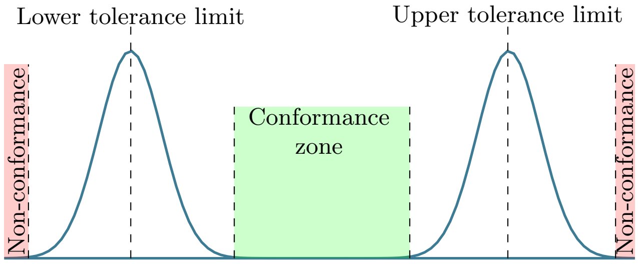


Figure 1: Conformance and non-conformance zones for two-sided tolerance.

of the machine tool and the measuring device. In this work, the environmental temperature profile for a machine tool is assumed to be repeatable; this is often referred to as the normal daily cycle.

Literature suggests that there are few tools available to aid with reducing the estimated uncertainty of measurement for machine tool calibration planning. Bringmann et al. (2008) correctly identified that there is little correlation between the selection of a measurement and the machine tool's configuration. However their work is concentrated on improving the selection of the best instrument and test method to use for geometric calibration (Bringmann, 2009). Muelaner et al. (2010) produced a piece of software that aids with the instrumentation selection based on the dimensional characteristics of a large artefact. Although this method is not aimed at optimising the sequence of measurements, it does help to optimise the selection of instrumentation for measuring each dimensional characteristic. The limitation of this tool is that is requires human intervention and does not guarantee completeness and optimality.

Co-ordinate measurement machines (CMM) are similar to a machine tool in physical design and movement, however they are used to accurately measure dimensional features of a work-piece. CMMs are designed to provide measurements to micrometre-level accuracy, and require regular calibrating. The geometric error components of a CMM are the same as a machine tool and the same measurement principles can be applied, albeit using more precise instrumentation. There is a wealth of literature on measurement techniques that can reduce the uncertainty of measurement when calibrating a CMM (Aggogeri et al., 2011; Beaman and Morse, 2010). However, there is an absence of any literature detailing methods of reducing the uncertainty of measurement for the entire calibration plan. This is most likely because CMMs often operate in temperature controlled environments, meaning that during calibration there should be minimal change in environmental temperature.

In summary, work has been carried out to reduce estimated uncertainties based on measurement criteria, such as instrumentation, temporal factors and measurement techniques. However, there is an absence of any literature indicating the uncertainty reduction of multiple, consecutive interrelated measurements, in this case machine tool calibration. In addition to the uncertainty reduction of calibration plans, there is an absence of literature indicating that work has been undertaken to intelligently produce calibrations plan that can help minimise uncertainty of measurement.

Automated planning and scheduling includes domain-independent planners that can solve large planning problems that contain continuous, non-linear effects (Klöpper et al., 2012). However, due to the complexity of the dynamics of such models, they are restricted to solving small scale problem instances with the implementation of a domain-specific heuristic (Fox et al., 2011).

COLIN (Coles et al., 2009) is a planner capable of handling continuous, linear numeric change through the use of linear programming. However, COLIN does not support PDDL+ process and events, instead it is limited to continuous change as expressed through the durative action (Coles et al., 2012).

UPMurphi (Della Penna et al., 2009) provides a "discretize and validate" approach to continuous planning and supports the full PDDL+ semantics. Although, this planner is both powerful and novel in its approach, it performs an exhaustive breadth-first search. This results in an exponential increase in the produced search space (Della Penna et al., 2012). This restricts the use of the planner to solve real-world application by implementing a strong, domain-specific heuristic function (Fox et al., 2011). This would provide a solution, but the loss of domain independence departs from the aim of the planning community.

$SHOP2_{PDDL+}$ (Molineaux et al., 2010) also supports the full systematics of PDDL+. It is different in its approach because it implements a hierarchical task network algorithm. Even though the published work suggests that this planner could out-perform the rest in terms of plan generation time, it is difficult to evaluate the scalability of the planner because it is currently not in the public domain.

In summary, due to the complex dynamics that are required to model the uncertainty of measurement minimization problem in PDDL+, and the current performance of the state-of-the-art planning tools, the non-linear aspects of the model are discretized and encoded in PDDL 2.1. With the discretized model, it is possible for state-of-the-art planners that do not handle continuous effects to solve the uncertainty problem. Section 3.1.5 describes the most suitable planner for our problem.

This paper provides a novel implementation for automatically producing machine tool calibration plans with a minimised uncertainty of measurement. First, a detailed description of uncertainty of measurement is provided. This explains the effect of temperature on the uncertainty of measurement and provides measuring squareness using a mechanical straight edge and a dial test indicator as an example. This section highlights the complexity of estimating uncertainty of measurement for multiple measurements with temporal, environmental and instrument dependencies. Next, modelling is provided where the use of automated planning and scheduling is used for estimated uncertainty of measurement reduction. This section describes how the problem reduced into a PDDL model that can be solved using current state-of-the-art domain-independent automated planning tools. In this work LPG-td (Gerevini et al., 2008) is used because of its extensive support of the PDDL syntax and its performance (Long and Fox, 2003). Experimental analysis is the provided where a case-study is performed for a three-axis machine tool. An excerpt of the produced plan is then presented and discussed. This examples shows measurements involving instrumentation other than a mechanical straight edge and dial test indicator. A brief conclusion is then provided, laying out scope for future work.

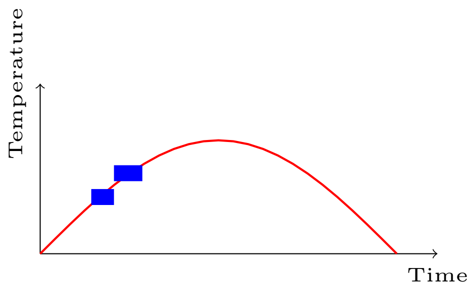
2. Uncertainty of Measurement

As stated in the introduction, uncertainty of measurement is a parameter associated with the result of a measurement that characterises the dispersion of the values that could reasonable be attributed to the measurand (BIPM, 2008). For example, a thermometer might have an uncertainty value of $\pm 0.1°$C. Therefore, for a given instrument it can be stated that when the thermometer is displaying 20°C, it is actually 20°C $\pm 0.1°$C with a confidence level of 95%. Quantifying and reducing uncertainty of measurement is an important task since the measurements are used for compensation purpose. It is important to determine whether the machine's tolerances are met. Tolerances in the machine's capabilities are particularly important because they are transferred directly to the achievable tolerance of the work-piece during machining. Therefore, the higher the uncertainty of measurement in calibration, the worse accuracy achieved during manufacturing.

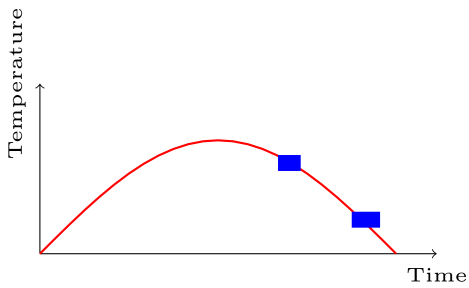
In a calibration laboratory, where conditions are predefined, estimation takes place in advance to ensure fitness-for-purpose. If too big, another method should be selected that can achieve the required uncertainty. In uncontrolled circumstances the worst case must be estimated, but can be modified based upon actual calibration conditions. The Procedure for Uncertainty MAnagement (PUMA) (ISO 1453-2, 2013) which provides a method for iteratively reducing the estimated uncertainty of measurement. However, this approach does not consider scheduling a sequence of measurements to reduce the overall estimated uncertainty of measurement due to the calibration schedule. In this section, the example of measurement squareness using a mechanical straight edge and dial test indicator is provided.

2.1. Temperature

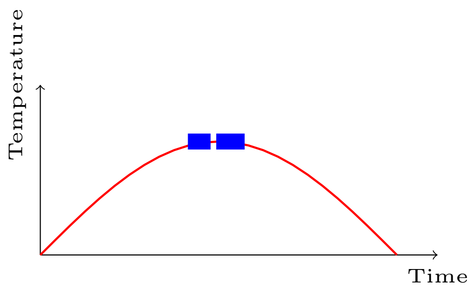
Environmental temperature is an important aspect of estimating the uncertainty of measurement, especially when estimating for interrelated measurements. Each machine tool has its own thermal inertia and larger machine tools will have a greater inertia. This inertia is typically much longer than it takes to perform a single measurement, and in most cases, continue to increase and decrease throughout multiple measurements. Figure 2 illustrates three potential scenarios that occur when planning for the effect of temperature



(a)



(b)



(c)

Figure 2: Three example temperature scenarios

on interrelated measurements. All three scenarios only consider two measurements for illustration purposes. A full calibration plan will consist of considerable more interrelated measurements. Figure 2(a) illustrate temperature rise during the measurement of two interrelated measurements. Conversely Figure 2(b) illustrates temperature decrease while taking two interrelated measurements. Figure 2(c) illustrates the ideal case when both interrelated measurements are taken where the temperature has stabilised.

2.2. Uncertainty Modelling

Taking into consideration the measurement method, measurement equipment and both their surroundings, it is possible to produce a method that can be used to estimate the uncertainty of measurement. This section provides an example relevant to this problem by showing how the uncertainty of the measurement is calculated when measuring the non-orthogonality (squareness) of two axes of linear motion when taking into consideration environmental temperature. The example shown in this paper is a reduced subset of the full model since providing a full estimate of the uncertainty of measurement is out of the scope of this paper.

2.2.1. Calculation

One known method, recommended by International Standards Organisation (ISO), involves combining the individual uncertainties using the root of the sum of squares to produce a combined uncertainty u_c. In this paper, Equation 1 is used for calculating u_c (ISO 230-9, 2005; BIPM, 2008).

$$u_c = \sqrt{\sum u_i^2} \tag{1}$$

Where u_c is the combined standard uncertainty in micrometers (µm), and u_i is the standard uncertainty of uncorrelated contributor, i, in micrometers (µm).

Once we have calculated u_c we can then calculate the expanded uncertainty U_c by multiplying by the coverage factor k, which in this case is $k = 2$ which provides a confidence level of 95 %.

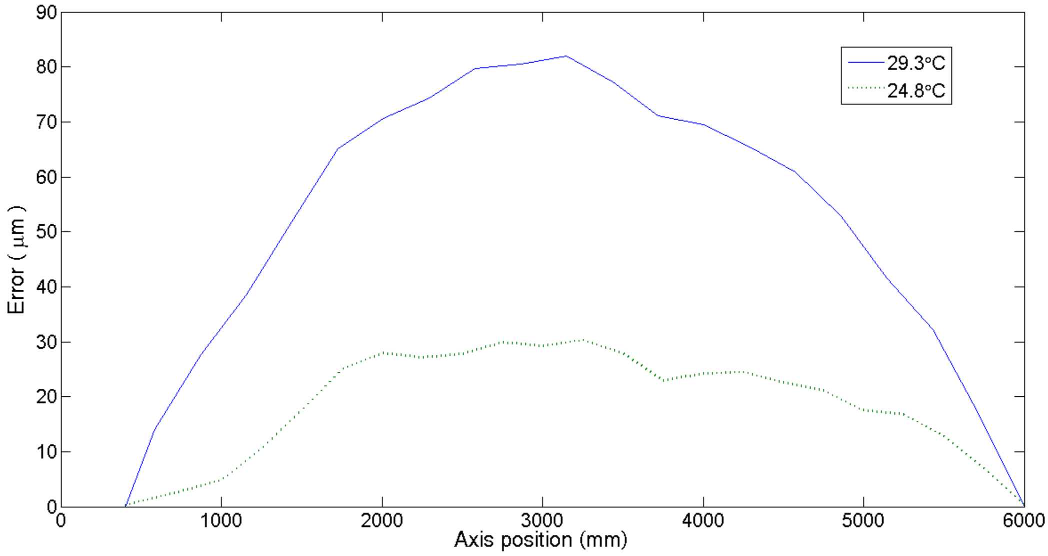


Figure 3: Y-axis straightness change (E_{XY}) due to temperature

2.3. Squareness

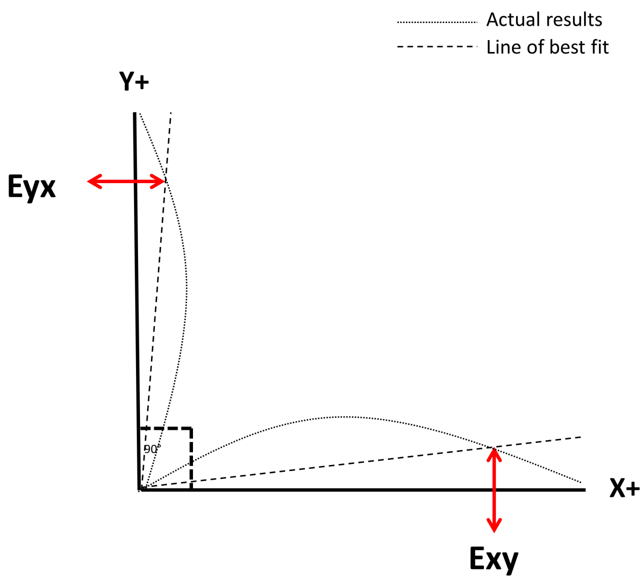
In this paper, the uncertainty of the squareness measurement is presented as an example of how uncertainty can propagate through influencing geometric errors. ISO 230-1 (2012) defines squareness as "the difference between the inclination of the reference straight line of the trajectory of the functional point of a linear moving component with respect to its corresponding principle axis of linear motion and (in relation to) the inclination of the reference straight line of the trajectory of the functional point of another linear moving component with respect to its corresponding principle axis of linear motion."

The squareness error can be measured using a variety of instrumentation and test methods. In this paper the method of measuring squareness considered is using a mechanical square and indicator. Squareness is contaminated by other geometric errors, in particular the straightness of each axis in the plane of measurement. When measuring squareness it is important to consider the uncertainty of measurement arising due to the change in the straightness of axes between measurements.

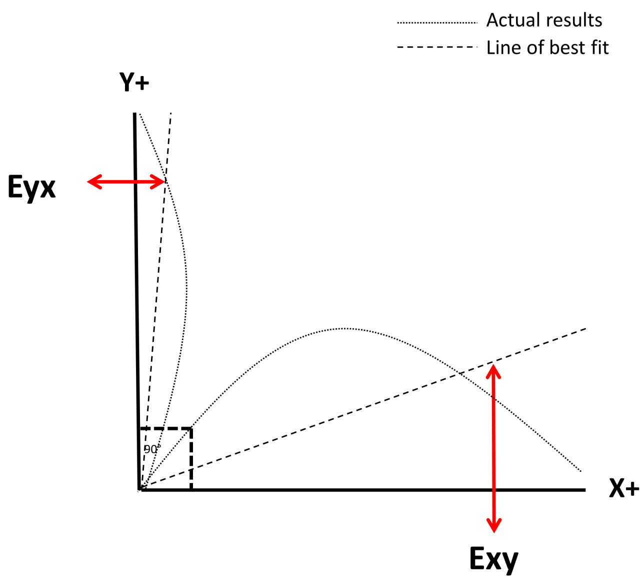
Figure 3 shows a real-world example of the Y-axis straightness in the X-axis direction measured on a gantry milling machine at two different temperatures. From this figure it is evident that the error quadruples with a 4.5 ^{o}C increase in temperature. Figure 4(a) and 4(b) show different squareness results for the same measurement taken in the two different temperature conditions. Figure 4(a) was performed during stable temperature, whereas Figure 4(b) was performed in conditions where the temperature is increasing, resulting in the E_{XY} straightness error increasing. The measuring order of the influential errors will affect the estimated uncertainty. For example, if the squareness measurement is taking place after the measurement of all the other errors, not only their uncertainties, but also any uncertainty in their change over the time period should be included when calculating the squareness uncertainty of measurement. If the squareness measurement is taking place without that of the other errors, the uncertainty calculation would have to either include the maximum permissible value for each error, or be calculated once these values and their uncertainties are known. This value can be acquired by monitoring the change in angular and straightness error with respect to temperature over a given time period.

2.3.1. Mechanical square and indicator

Squareness between two nominally perpendicular axes can be measured using a mechanical square and indicator. In this section a few of the contributing uncertainties are included to demonstrate possible sources



(a)



(b)

Figure 4: Influence of other geometric errors on the XY squareness error at different temperatures

that contribute to the uncertainty of measurement. The uncertainty of the dial indicator ($U_{Device\ DTI}$) can be calculated using the calibration certificate and Equation 2. The uncertainty of the mounting post ($U_{DTI\ POST}$) is calculated based on the known uncertainty of measurement due to the coefficient of thermal expansion.

$$U_{Device\ DTI} = \frac{U_{CALIBRATION}}{k} \tag{2}$$

Similarly, the uncertainty for the mechanical square ($U_{Device\ SQR}$) can be calculated using Equation 3 and the squares calibration certificate.

$$U_{Device\ SQR} = \frac{U_{CALIBRATION}}{k} \tag{3}$$

As illustrated in Figure 3, the effect that temperature has on the machine tool ($u_{E,MACHINETOOL}$) is acquired by monitoring the relationship between straightness movement and temperature The effect of temperature on this straightness can then be used when estimating the uncertainty of the squareness measurement. If empirical data is not available, values can be acquired from ISO 230-9 (2005) where it is recommended that the ISO tolerance for straightness deviation is taken as a first estimate. The combined standard uncertainty (u_c) can then be calculated using Equation 1.

To minimise the uncertainty of measurement, the change in machine temperature between straightness and squareness measurements should be minimal; this can be achieved by scheduling the tasks accordingly.

3. Automated Planning

Automated planning and scheduling is a branch of artificial intelligence that is concerned with the realisation of strategies or action sequences (Russell and Norvig, 2009). Automated planning is a useful tool for solving complex problems that require optimisation in multi-dimensional space. This makes automated planning particularly attractive for solving machine tool calibration planning problems, where the complexity is great enough to be cumbersome to manually plan. This work is currently concerned with offline planning, where the prevailing environment can be estimated using available models.

The work within this paper encodes the machine tool calibration uncertainty reduction problem in the Planning Domain Definition Language (PDDL2.1) (Fox and Long, 2003) The use of this language allows for many state-of-the-art planning tools to be used to solve the problem.

3.1. Modelling

The developed model is encoded in PDDL version 2.1. This is because we use quantification, numbers, time, durative actions (Fox and Long, 2003).

The previously developed temporal model (Parkinson et al., 2012) is extended to include the more complex uncertainty model described in Section 2.2. Figure 5 shows the functional flow between the PDDL actions within the temporal model. In the figure, durative actions are represented using a circle with a solid line, whereas the meta, non-durative action is represented with a dashed line. The following six actions are illustrated in the figure:

Set-up Setting up of an instrument to measure a specific error component on a specific axis.

Measure$_{no}$ The measurement procedure where no consideration is taken for any influencing errors.

Measure$_{in}$ The measurement procedure where consideration is taken for any influencing errors.

Remove Removing the instrument from the current set-up.

Adjust Adjusting the instrument to measure a different error.

Meta Zero cost meta action required to encode temperature information and uncertainty equations.

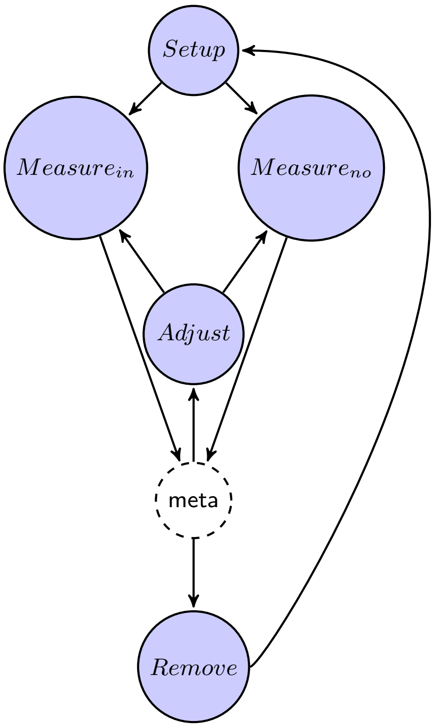


Figure 5: Illustration showing the PDDL actions within our domain and their functional flow.

In the temporal model, the cost of each action is the time taken to perform that specific task. Using this model will produce a calibration plan, indicating the ordering of the measurements and the time taken to perform each test.

In addition to these four actions, one zero-cost meta-action has been added after the measurement action to implement the temperature dependent uncertainty equations. The motivation behind the addition of the meta action is based upon the `at start`, `over all` and `at end` semantics of a PDDL durative action. This limits the implementation of the equations to being implemented as `at start` or `at end` effects. This can cause significant difficulty where equations use variables that also need to be processed instantaneously. For example, if the start temperature was recorded as an `at start` effect and the temperature change throughout the durative action was recorded as an `at end` effect, any uncertainty equations implemented as `at start` or `at end` effects would be unable to use the start or end temperature.

The following sections describe how the temporal optimisation model has been extended to encode the uncertainty optimisation model.

3.1.1. Uncertainty contributors

In PDDL2.1 (Fox and Long, 2003), numeric fluents were introduced to allow modelling of non-binary resources (e.g time). Numeric fluents are especially important for modelling uncertainty of measurement as they provide the contributors. For example, a device's uncertainty ($U_{DEVICE\ DTI}$) can be represented in PDDL as `(=(device-u ?i - instrument)0.001)` where the instrument object `?i` has the value of 0.001.

3.1.2. Temperature profile

As described in the Introduction, there are few planners capable of handing continuous non-linear, resources. Those that are require the representation through durative actions. This means that it is not possible to represent the continuous temperature change throughout the calibration process. This presents the challenge of how to optimise the sequence of measurements while considering temperature. The solution implemented in the model involves discretizing the continuous temperature change into sub-profiles of linear continuous change.

This can be achieved by using Algorithm 1 where we iterate over the temperature data looking for a difference in temperature greater than a given sensitivity. This allows the temperature profile to be discretized into a set of sub-profiles. An example can be seen in Figure 6 where the environmental temperature profile (difference from 20°C) for a forty eight hour period is shown (Monday and Tuesday), as well as the discritized profile when the sensitivity (s) of 0.1°C is used. In the provided example, the give sensitivity is a reflection of minimum sensitivity of the available instrumentation. The reason behind the second twenty-four hour cycle been greater than the first is due to the cooling effect of the weekend where no production is taking place still been evident throughout the Monday period.

Algorithm 1: The Discretized Temperature Data Function. This converts a continuous temperature profile into discrete, sub-profiles.

Input: Initial sensitivity s

Input: Ordered pair of timestamps and temperature data $T = (t_1, d_1), (t_2, d_2), (\ldots), (t_n, d_n)$ where t_n is the time stamp and d_n is the temperature data

Output: Set of ordered temperature profiles $P = (t_1, p_1), (t_2, p_2), (\ldots), (t_n, p_n)$ where p_n is the rate-of-change in °C per minute

$i \leftarrow 0$;
$td_p \leftarrow 0$;
while $i <= Size(T)$ **do**
    $td = |T(d_i) - T(d_{i+1})|$;
    if $(td > td_p) \& (td >= s)$ **then**
        $md = T(t_i) - T(t_{i+1})$;
        $rate = \frac{td}{md}$;
        $P \leftarrow (t_{i+1}, rate)$;
        $td_p = td$;
        $i + +$;
return P;

To model these sub-profiles in the PDDL model, we represet them as predetermined exogenous effects. To increase the range of planners that can be used to solve the problem, the model produced in this work is encoded in PDDL2.1 where there is no explicit mechanism to represent predetermined exogenous effects, unlike in PDDL2.2 where `timed-inital literals` are introduced (Edelkamp and Hoffman, 2004). The method used in this paper for representing predetermined exogenous effects is by clipping durative actions together (Fox et al., 2004). Given the predefined times $t_1, ..., t_n$ when the sub-profile $p_1, ...p_n$ will change, a collection of durative actions, $d_1, ...d_n$ are created that will occur for the durations $t_1, t_2 - t_1, ..., t_n - t_{n-1}$. An example durative action d_1 that represents a sub-profile p_1 can be seen in Figure 7 where the duration $t_1 = 42$.

3.1.3. Uncertainty equations

In the model, the addition of the meta action allows for the implementation of the uncertainty estimation equations, including the consideration of the change in environmental temperature over a measurement's duration. Incorporating the temperature requires the use of the measurement and meta action. As described earlier in Section 3.1.1, numeric fluents will be used to represent the uncertainty contributors. It is then possible, using the binary operators provided in the PDDL language (`+`,`-`,`/`,`*`) and the update functions for numeric fluents (`assign, increase, decrease, scale-up, scale-down`) to implement the uncertainty equations. Figure 9 provides the PDDL code which is used to increase the temperature based on the two rates-of-change which has been stored in a `temp` numeric fluent. In addition, Figure 10 shows the PDDL encoding for the estimation calculations used when performing a squareness measurement using a

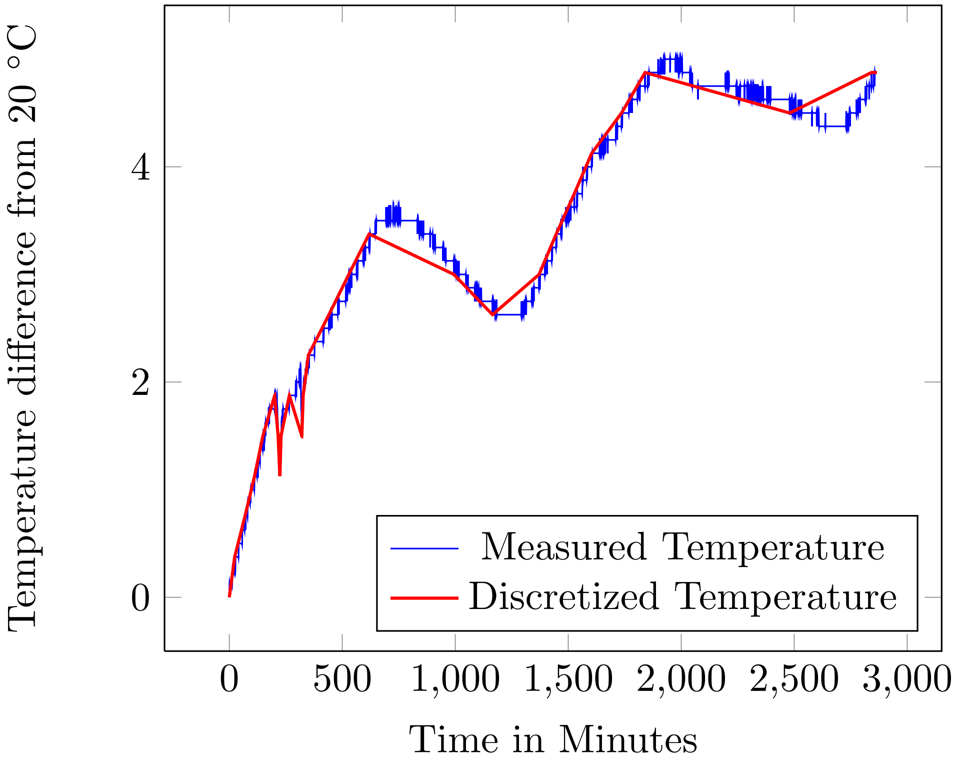


Figure 6: Graph showing both the original and discretized temperature profile.

```
(:durative-action temp-profile1
         :parameters ()
         :duration(= ?duration 42.0)
         :condition
            (and (at start (start1)))
         :effect
            (and (at start (assign (rate)0.00595))
            (at end (not(start1)))
            (at end (start2))
            (at start (clip-started)))
     )
)
```

Figure 7: Durative actions that represents the temperature sub-profile p_1 where the duration is $t_1 = 42$ and the rate-of-chage is 0.00595.

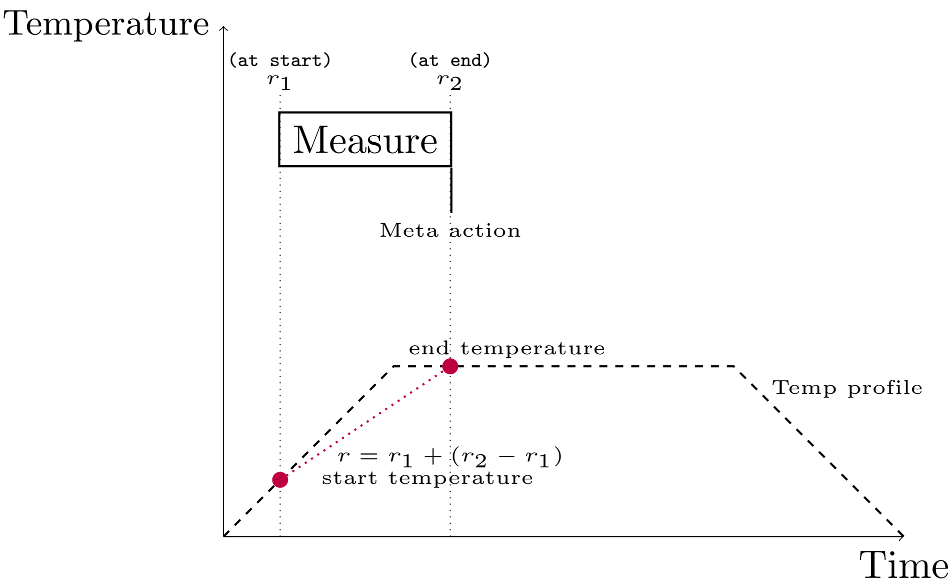


Figure 8: Illustrating how the meta action and the measure durative action interact to calculate the current environmental temperature.

```
(decrease (error-val ?ax ?er)(-(error-val ?ax ?er)
        (+(temp-u)
        ;calculate u_e_machine tool
             (+(*(*(u_t-e-c)(*(length-to-measure ?ax ?er)(temp)))
                  (*(u_t-e-c)(*(length-to-measure ?ax ?er)(temp))))
        ;calculate u_e_device
             (+(*(*(u_d-t-e-c ?in)(*(length-to-measure ?ax ?er)(temp)))
                  (*(u_d-t-e-c ?in)(*(length-to-measure ?ax ?er)(temp))))))
        )
    )
```

Figure 9: PDDL code showing the `temp-u` action where the temperature rate (`temp`) fluent based on the two rates-of-change is used.

```
(at start(assign(temp-u)
         ;calculate u_device using the length to measure.
              (+(*(/(k_value ?in)(*(u_calib ?in)(length-to-measure ?ax ?er)))
                   (/(k_value ?in)(*(u_calib ?in)(length-to-measure ?ax ?er))))
         ;calculate u_misalignment.
              (+(*(/(+(u_misalignment ?in)(u_misalignment ?in))(2sqr3))
                   (/(+(u_misalignment ?in)(u_misalignment ?in))(2sqr3)))
         ;calculate u_error contributors.
              (+(*(/(+(error-val ?ax ?e1)(error-val ?ax ?e2))(2sqr3))
                   (/(+(error-val ?ax ?e1)(error-val ?ax ?e2))(2sqr3)))
         ;calculate u_m_machine tool.
              (+(*(*(u_t-m-d)(*(length-to-measure ?ax ?er)(u_m-d)))
                   (*(u_t-m-d)(*(length-to-measure ?ax ?er)(u_m-d))))
         ;calculate u_m_device.
              (+(*(*(u_t-m-d)(*(length-to-measure ?ax ?er)(u_m-d)))
                   (*(u_t-m-d)(*(length-to-measure ?ax ?er)(u_m-d))))
         ;calculate u_eve.
              (*(/(u_eve)(2sqr3))(/(u_eve)(2sqr3)))))))
              )
         )
```

Figure 10: PDDL code showing the propagation of two errors (`error-val ?ax ?er1` and `error-val ?ax ?er2`) in the `measure-influence` action.

mechanical square and a dial test indicator (Section 2.3.1). From this PDDL encoding, it is noticeable that when performing the equation to estimated the errors contributing to the squareness uncertainty of measurement, the two `error-val ?ax ?er` numeric fluents are used.

Implementing equations where the result is influenced by other measurements is also encoded in the PDDL using fluents. For example, consider the calculation for the squareness error measurement using a granite square and a dial test indicator described in Section 2.3.1 where the uncertainty is influenced by the two straightness errors. In the model, this is encoded by assigning two fluents `(straightness1 ?ax - Axis)` and `(straightness2 ?ax - Axis)` the maximum permissible straightness error in the PDDL initial state description. This fluent will then be updated once the measurement estimation has been performed. The planner will then schedule the measurements to reduce the effect that the contributing uncertainty has.

Some planners are unable to handle non-linear effects. This means that calculations like $u^2_{DEVICE\ DTI}$ can not be encoded. Additionally, `PDDL` does not have any support for the square root function (Parkinson and Longstaff, 2012). The absence of both these functions requires either modifying the planning tool to support these features or implement a post-processor. The post-processor is the better of the two solutions as it still allows for domain-independence, increasing the range of planners than can solve the problem. Post-processing provides a solution to complete the estimated uncertainty equations, but it will result in a cumbersome solution. The approach adopted in this implementation is to use VAL (Howey et al., 2004) to validate the produced plans and provide a method to inspect the estimated uncertainty of each measurement. This is because the contribution from each measurement m_n towards the metric value m needs to be identified. If the planner could handle non-linear calculations like $u^2_{DEVICE\ DTI}$ it would only be necessary to calculate the square root of m. This would not affect the planner's ability to find an optimal solution as the square root function is a monotonic function, meaning that minimizing m would have the same affect as minimising $\sqrt{m}$.

3.1.4. Search metric

In the PDDL problem definition it is necessary to provide a search metric. The search metric is used by the planning tool's heuristic function to find the optimal solution. In the temporal model, the search metric `(:metric minimize (total-time))` was used to find the solution that took the least amount of time. The metric used to reduce the uncertainty of measurement is `(:metric minimize (u-c))`, where `u-c` is the fluent used to accumulate the result of estimated uncertainty for each measurement. Therefore, this measurement is the uncertainty due to the order of the plan.

3.1.5. Planner

As described earlier, the model presented in this work is encoded in a PDDL2.1 domain. Not only does this simplify the model, it also allows the use of state-of-the-art classical planners. Research in the area of classical planning is more established and significant improvements have been made, making it more more powerful for solving real-world problems when discretized (Tierney et al., 2012; Erdem and Tillier, 2005). The planner used in this work is the LPG-td planner (Gerevini et al., 2008) because it was a top performer in the International Planning Competition (Long and Fox, 2003) and the top performer involving domains with predictable exogenous events (Gerevini et al., 2006), and it can also handle non-linear effects. This means that equations such as $u^2_{DEVICE\ DTI}$ can easily be encoded in regular PDDL. For example, `(assign(u_c)(*(u_calib ?in)(u_calib ?in)))`.

4. Experimental Analysis

Initial validation of the PDDL model was performed by creating a test case problem to solve using the developed model. The produced solution can then be analysed to evaluate whether intelligent planning is exhibited.

4.1. Test Environment

All experiments were carried out on an Ubuntu 11.04 computer with a QuadCore AMD Phenom II X4 970 3.50GHz processor and 4GB RAM. The PDDL model was executed using the LPG-td planner. LPG-td was limited to ten minutes of CPU-time and 4GB of RAM. These constraints are imposed to represent the processing power and memory of a modern computer, and based on preliminary experiments a sufficient amount of time for the planner to identify an optimised plan.

4.2. Three-axis case-study

Due to the complexity of the model and the restriction on computing resources, at this stage only a small instance of the calibration problem can be solved in the allowed time. In this paper, we consider the calibration of a three-axis machine tool. The three-axis machine tool considered in this paper is a cantilever design with two horizontal linear axes (X- and Y-Axis) and a vertical axis (Z-axis). This machine tool has a total of twenty-four geometric errors that require measurement during calibration. This total is made up of six-degrees-of-freedom per linear axis, an accuracy and repeatability test, as well as a squareness error with the nominally perpendicular axes (Mekid, 2009; Schwenke et al., 2008). Figure 11 illustrates both the configuration of the machine tool in this example and its twenty-one pseudo-static geometric errors. The discretized temperature profile discussed in Section 3.1.2 is used in this case-study.

4.3. Produced plan

The produced calibration plan was found in 6 minutes 58 seconds with an uncertainty due to plan order metric of 28.15 µm In the remainder of this section, an extract taken from the three-axis calibration plan, showing the plan for calibrating the errors in the X-axis direction is discussed. Both the LPG-td planner and the PDDL syntax make it possible to maximise a search metric as well as minimising. Modifying the PDDL problem definition to include `(:metric maximize (u-c))` returns a plan with the metric of 47.93 µm. This shows that there is a significant difference of nearly 20 µm between the maximum and minimum.

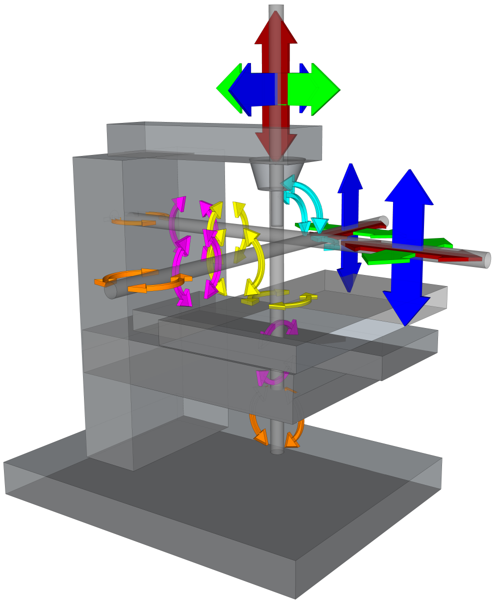
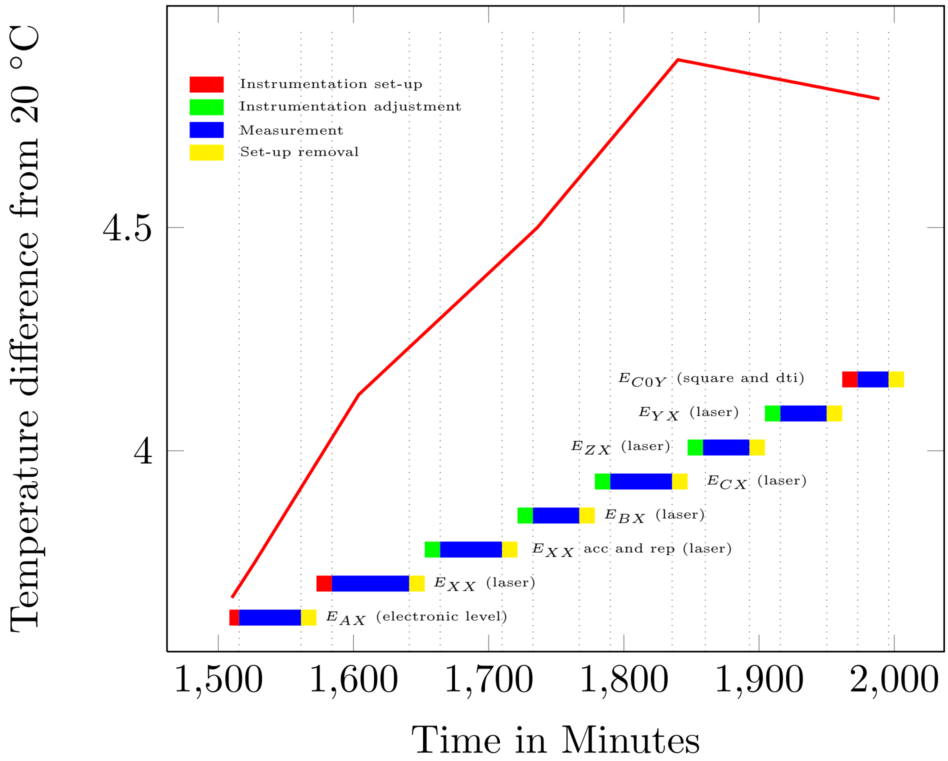


Figure 11: *Three axis machine tool with twenty-one pseudo static geometric errors.*

It is expected that the planning tool will schedule the measurement where the temperature difference will have the smallest effect on a measurement. Figure 12 shows the ordering or the measurements against the relevant section of the discretized temperature graph. The diagram illustrates the ordering of the measurements against time and the discretized temperature profiles. The red boxes indicate measurement setting up, green boxes for measurements where the instrumentation is adjusted, blue boxes represent the measurement, and yellow boxes represent removal of equipment. It is evident in this figure that interrelated measurements (E_{ZX}, E_{YX}, and E_{C0Y}) are scheduled where the temperature deviation throughout their measurement is at the lowest. Considering the squareness measurement seen in Section 2.3 where two straightness measurements influence the uncertainty of the squareness measurement. In the plan excerpt is can be seen that the two straightness measurements and the squareness measurement are scheduled adjacently at a point where the maximum temperature deviation is minimal. This has been achieved by encoding the method so that the maximum permissible error is included that is subsequently replaced by the actual measurement value plus any change as a result from a change in temperature. This illustrates that the planner can intelligently produce calibration plans to reduce the uncertainty of the calibration plan.

4.4. Limitations and future work

The provided case-study has shown how a sequence of measurements can be intelligently scheduled to minimise the estimated uncertainty of measurement. The main limitation of this approach is that the planning is to be performed once to construct the calibration plan, meaning that if any problems occur when performing the measurement, a new calibration plan will need to be generated. An alternative solution would be to use online planning techniques, where adaptive planning can take place if any deviation from the original plan is required. Another limitation is the time required to generate an optimal plan. In the case-study close to seven minutes was required, however, for large problem instances, search time will be significantly higher. However, due to the potential benefits of using automated planning, the authors believe that waiting for the generation of an optimal plan does not question the feasibility of the undertaken approach. Research into automated planning and scheduling is a fast moving discipline, and advancements in state-of-the-art automated planning tools can be utilised as the model is encoded in PDDL. The current model is restricted to LPG-td because it can handle the required PDDL features and can non-linear effects, but the authors anticipate a wider verity of planners being available in the not so distant future.



$\mathbf{E_{AX}}$: angular error around A-axis
$\mathbf{E_{BX}}$: angular error around B-axis
$\mathbf{E_{CX}}$: angular error around C-axis
$\mathbf{E_{YX}}$: straightness error in Z-axis
$\mathbf{E_{ZX}}$: straightness error in Z-axis
$\mathbf{E_{XX}}$: linear positioning error
$\mathbf{E_{C0Y}}$: squareness to X-axis

Figure 12: Graph showing an extract from the discretized temperature profile and an excerpt (errors in X-axis direction) from the produced calibration plan.

In future work the authors would like to integrate automated planning technology into a software tool for machine tool calibration. This would allow engineers to utilise this research, as currently interacting with a PDDL model is not feasible. This tool would retain the current methodology of using state-of-the-art automated planning tools so that advancements in the field can always been utilised. In addition, in this paper the ability to automatically construct calibration plans to reduce the uncertainty of measurement has been presented. However, in this paper the consideration to the temporal influence of uncertainty of measurement reduction has not been considered. Future work should continue to consider multi-objective temporal and uncertainty optimisation.

5. Conclusions

In this paper it has been identified that there is insufficient consideration for the uncertainty of measurement due to scheduling of the calibration plan for machine tool calibration. The effect of increased uncertainty of measurement on the conformance zone, resulting in an increased possibility of false acceptance and rejection has been discussed. It has also been identified that there are no methods that can reduce the uncertainty of measurement during calibration by considering the plan structure. In response, a novel approach to minimising the estimated uncertainty of measurement in automatically produced calibration plans is presented.

The challenges of implementing the model have been discussed in detail. Experimental analysis has confirmed that automated planning is a justifiable choice for producing calibration plans that are optimised based on the effect of temperature on the uncertainty of measurement. The significance being the ability to encode this expert knowledge in such a way that intelligent algorithms can reason with it and find an optimal solution to the presented problem.

The provided three-axis machine tool case-study has shown that using this novel technique can produce calibration plans where the uncertainty of measurement is minimised. The presented three-axis case-study shows a 58% reduction in the uncertainty of measurement due to the scheduling of the calibration plan where the maximum is 48 µm and the minimum is 20 µm. This is a significant achievement as it allows for the production of calibration plans that can reduce the estimated uncertainty of measurement. Therefore, improving the quality of the calibration and the accuracy of corrective action.

The work presented in this paper provides contributions to both the engineering community and the artificial intelligence planning community. In an engineering context, this work shows how the novel technique of automated planning can be used to produce optimal calibration plans that help to reduce the uncertainty of measurement. For the AI community, it presents a real-world planning problem that is perhaps at the capability limit of the current state-of-the-art planning tools and the expressibility of the PDDL language. Future work would be to develop planning tools that are better at solving planning problem with strong numeric and temporal properties, providing an optimal solution more quickly. This is an advantage of using the PDDL language since any advancement in AI planning technology can be utilised.

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