# Digital twin for tool wear monitoring and compensation in turning

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**Abstract**

In mass production of manufactured goods using conventional milling and turning, tool wear is reflected in the drift of quality control measurements. Methods have been developed to correct this drift and compensate the wear. With the possibilities offered by the digital twin concept, a new method of tool wear compensation was proposed including a digital twin of the tool and a digital twin of the lathe, based on the measurements of the parts. This digital twin solution provides useful functionalities such as a heritage process between the digital twin of old tools and the one of the tool being used.

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**Keywords**

digital twin, CNC, turning, tool-wear, compensation

## I. Introduction

In manufacturing, the importance of monitoring the tool wear has always been a focus of attention. It has long been known that the wear has an impact on the geometry and quality of the produced parts, as well as the risk of significant damage (for the part and the machine) if the tool reaches the end of its life.

As Manuele J. explained in 1945 already [1], the main effect on this wear on the geometries is a "gradual trend" in the dimensions throughout the production, while the manufacturing conditions remain constant. Unfortunately, this trend cannot be known accurately since it depends on many different parameters such as the manufacturing parameters (feed rate, cutting speed, depth of cut, etc.), the tool properties themselves, the material manufactured and the use of lubricant [1-2]. There are many scientific publications presenting studies on the influence of these parameters on tool wear (by looking at the evolution of the tool shape). In fact, knowing the influence of these parameters will help achieve optimal cost: the right choice is mainly based on the trade-off between the production time and material cost including the tools (maintenance, inspection, replacement, etc.). However, tool wear can only be limited but never suppressed, this is why there are methods to limit the effects of the tool wear on the production rates (by compensating or correcting these effects) [3].

On the other hand, digital twins, as part of the industry 4.0, have been in the spotlight in recent years for the new opportunities they can offer to the industry [4-5]. Digital twin is a concept involving a physical entity and its virtual representation that constantly mirror each other. The physical entity, called the physical twin, can either be an object (e.g., a part), a system (e.g., a lathe) or a process (e.g., a production line) and its virtual representation is called the digital twin. Thanks to continuous data flows between the twins, each twin always remains the exact copy of the other, which means that any event occurring on one twin happens also on the other twin (for instance, activity of the physical twin is reported on the digital twin or commands applied on the digital twin are also applied on the physical twin). This concept of digital twin has been made possible by the application of the Internet of Things (IoT or IIoT - industrial internet of things-) enabling the use of networked sensors and actuators, it is why it has become an important subject of research for the last decade.

Simple twins are interesting for simple applications such as monitoring or remote controlling for example, but a great property of digital twin is that it can be coupled to algorithms such as artificial intelligence: inside the digital twin, analysis and simulations can be executed and decisions can be made and, thus, applied on both twins. At that moment, the digital twin shows its full potential by becoming a “cognitive digital twin” or an “autonomous digital twin” [6]. In a certain way, the whole system can be considered as a cyber-physical system who self-regulate (and the data flux from the digital twin to the physical twin can be seen as a feedback loop). This property is very promising in the field of manufacturing (particularly for tool monitoring, as Qiao et al. also mentioned [5]), which is stimulating research in that field.

There are already studies on the application of the digital twin concept to the problematic of tool wear. They mainly focus on the analysis of the state of the tool through sensors on the lathe. Indeed, it has been shown that tool vibration, tool temperature or lathe power consumption are correlated with wear (among other parameters), and that this data can therefore be used to monitor its condition (as Siddhpura A. and Paurobally R. analysed in their work [7]). However, there are few that include the measurement of deviations in the dimensions produced as a parameter even though this is a simple and direct method of determining corrective actions.

In this article a simple digital twin for tool wear monitoring and compensation based mainly on part measurements is presented. After a presentation of the current research in section 2, there are a description of our work and discussions of the methods used and the possibilities for improvements or for new research topics in section 3. Before the conclusion, in section 4, the first results obtained with our simulations are presented as well.

## II. State of the art

In this section is presented recent work about digital twins applied specifically in the field of tool wear monitoring. Tool wear compensation methods applied in industry today and recent publications in this domain are also described.

### A. Digital twin for tool wear monitoring

As shown by Liu et al. in their review [8], manufacturing is the main subject of research on digital twin in the industrial domain since digital twins are a powerful concept to have an autonomous cyber-physical system able to reach production optima. This objective is one of the main concepts of Industry 4.0 or smart manufacturing which are important topics in research and objectives put forward for economic development. Therefore, scientific research mainly focuses on building digital twins of the machines to optimize their production time and anticipate maintenance.

On the other hand, concerning digital twins for tool wear monitoring, there is not so much research (Xie et al. [9] and Zhuang et al. [10] also mentioned that in 2021), and most of it focus on on-line indirect measurements: since there are correlations between parameters of the lathe working environment and the wear of the tool, it is possible to indirectly estimate the wear of the tool during the working time (on-line).

Qiao et al. [5] proposed in 2019 a digital twin to predict the tool condition by measuring the forces, the vibrations on the tool and its acoustic emission. Inside the digital twin the data are used by deep learning technics firstly to build a predictive multivariate function. This function, linking the observed data to a predicted tool wear condition, help to evaluate the tool wear during operations.

Later, Xie et al. [9] worked on a digital twin of tools that is linked to it all its life, from the first design and the production to the failure. The digital twin therefore collects data from different sources at different moments of its life. During manufacturing, the data collected are issued from the monitoring of the machine (feed rate, power consumption, force and vibrations, acoustic emission, etc.). As well, deep learning techniques are used to build models correlating these parameters to the wear of the tool which is measured off-line.

As a last example, Zhuang et al. [10] built a digital twin of the turning process, having all the information about the tool, the process (feed rate, etc.) and real-time monitoring (forces, vibrations, and temperature). A particular attention is given to the synchronisation of the twins, even for the geometry of the tool with a node updating process. As for the other articles, learning techniques are applied to select parameters and the type of wear, and build a model.

These more recent works mainly focus on a way to estimate the wear of the tool through the monitoring of the manufacturing process. Due to the complexity of wear mechanisms, this method requires learning algorithms and artificial intelligence to build and exploit models. However, there seems to be no publication on digital twins using the geometries of the parts produced to estimate wear, even though this is what is actually done in manufacturing. Also, these digital twins provide a state of the wear, but they do not provide corrective measures.

B. Tool wear compensation

Tool wear will incur increasing drift in the actual dimensions of manufactured parts. If the measurements are drawn (e.g., on a control chart [1,3,11]), a linear trend clearly appears, as presented in Figure 1. This trend depends on many different parameters due to the high complexity of the wear mechanisms: the tool and the lathe properties, the manufacturing parameters (environment and operations) and the material have direct or indirect impacts, which can be abrasive, adhesive, or diffusive.

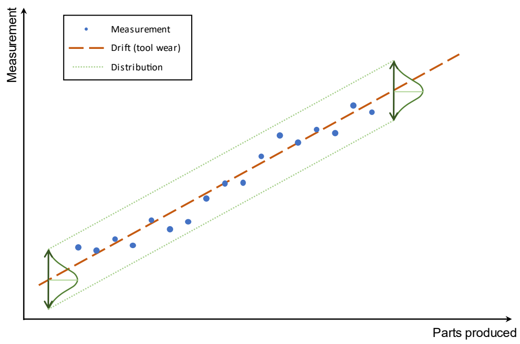


Figure 1: Typical profile of measurements for process subject to tool wear [11].

A common method in manufacturing to compensate the tool wear is applying a similar method as Sheikh described [3]: the tool parameters (mainly the tool offset) must be readjusted after a determined number of pieces have been produced, which is calculated from the drift and the distribution of the measurements (which both depends on the process, the tool, and the part). This number is a result of a compromise between keeping a low probability of producing scrap; and reducing downtime. When reaching the given number of parts, the operator measures the last part and applies a small correction to the lathe: usually, the offset is changed with the difference between the obtained measurement and the targeted measurement. The method and the distribution of the measurments are represented in Figure 2.

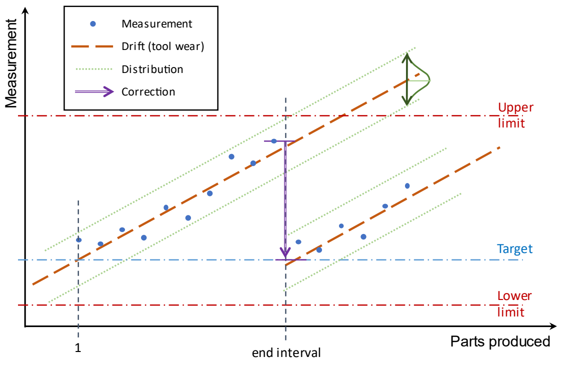


Figure 2: Common method for tool wear compensation.

The plot presented in Figure 2 is close to a control chart, which usually plot the average measurement depending on the number of the batch. Control chart can also be used for tool wear when the drift is so light (hence the tool wear is small) that many pieces are required to see it graphically. Control charts has existed for a century now and give an easy graphical way to set up a stable process with respect to the tolerances. It is normally combined with statistical process control which gives the mathematical relations between the tolerance interval and the measurement distribution [11,12], so it can be used to determine behaviours or to set the process for instance.

Gibson and Hoang worked in 1994 on a lathe computing by itself the required correction on the tool offset using statistical process control [13]: an inspection probe installed inside the lathe helps to collect measurements and the software computes with the statistical process control method if a correction or a tool change are required. The purpose of this system is mainly to correct automatically unexpected events but, based on the method implemented, it seems tool wear can be compensated. In this article, the position of the gauging system and the moment to use it with respect to the process are also discussed. The authors pointed out possible improvements which are subjects to research nowadays such as combining artificial intelligence to statistical process control, building smart manufacturing system which self controls, etc.

Few years later, Fraticelli [14] proposed sequential tolerance control with an application for tool wear. Sequential tolerance control consists in readjusting the targeted dimensions (i.e., the tool path) based on the measurements of the geometry realized by the previous operation of the process, to achieve the tolerances (i.e., it is a compensation applied on a dimension). It is close to the method employed by operators on manual lathe. In the application for tool wear, the compensation is computed based on the sequential tolerance control method but adjusted with the deviation due to the wear. This deviation is determined by the drift of the measurements using linear regression.

## III. Work and discussions

The purpose of this research is to find a digital twin solution for the tool wear monitoring and compensation, whose data source is mainly the controlled geometries of the parts that are produced. Our solution and discussions about it are presented in this section. Discussions concern the choice of the digital twin, but also what should be done at the end of life of the tool and its legacy. The results obtained with our simulations on our digital twin are presented in the next section.

### A. Digital twin solution definition

Since wear is a property of the tool, it seems logical that the digital twin must be that of the tool. The input would be the deviations of the geometries produced by the tool with respect to the target measurement, and the output will be the recommended corrections based on the drift determined. The drift due to the tool wear is computed from the deviation between the measurement of the geometry and the targeted measurement for two reasons: as explained in subsection II.B, the drift due to the wear is an error added on the target measurement, thus the difference helps to isolate the wear, and the deviation will not take into account corrections applied on the lathe (otherwise the axis shifts and linear regression cannot be applied). Also, the tool is not responsible for the target measurement as it is a parameter of the lathe (i.e., position of the tool imposed by the lathe based on commands) and the part. The fact that it is a relative value makes easier to compare tool wear between operations or parts too.

This version of the digital twin solution would however be limited, as explained in the next subsection concerning heritage. The digital twin solution proposed here is therefore an aggregate of the digital twin of the lathe and the digital twin of the current tool (following the definition of an aggregated digital twin provided by Schroeder G. et al. [15]), as illustrated in Figure 3.

As a mirror of the physical lathe, its digital twin can link the use of the tool to monitored manufacturing parameters, therefore the lathe builds a history of the "dead" digital twins of the former tools. This history is used as a database for new tools to function as a model and the selection criterium is the similarity of the manufacturing parameters. This process has been called "heritage", since the "new" digital twin of the current tool inherit information from an old digital twin. In this process, the digital twin of the lathe only helps to select a digital twin that was in similar process conditions as it is part of its working parameters and not one of the tool.

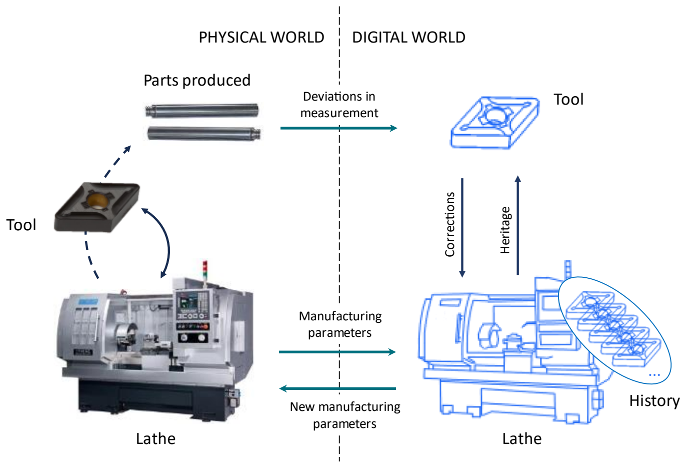


Figure 3: Schematic of the digital twin.

On the side of the digital twin of the tool, the measurements coming from the physical world and the information provided by the heritage will help the algorithm to determine the correction. This correction can either be based on the drift computed or on the model provided by the heritage depending on the decision taken. The digital twin of the lathe will use this correction to change the tool parameters in the manufacturing code and update it on its physical twin (as the manufacturing code is part of the synchronized data).

To get access to the manufacturing parameters, the digital lathe will have access to the CNC controller and a temperature sensor inside the physical lathe. It would then be possible to have the digital twin inside the controller (thus, it would be an embedded digital twin [15]), but external data storage might be necessary. However, the choice of the measuring device must be considered: if there is a gauging system inside the lathe (as in the work of Gibson and Hoang [13]) or if it is a coordinate-measuring machine, the digital twin might be better supported by an independent machine (computer on the industrial network or cloud).

Concerning this measuring device, we can think along the same lines as Gibson and Hoang [13]: the measuring system can be in-process (measuring at the same time as turning), in-cycle (measuring between turning operations) or post-process (measuring by another machine than the lathe). The first system has the less downtime but is the least precise method, and the third one induced no downtime and is very precise, but the measurement are delayed compared to the production. The second one might be a compromise between the two: it is precise enough, not delayed but it seriously increases the downtime.

B. Heritage for digital twin

Strictly applying the definition of a digital twin, it is assumed that every time a new tool is used by the lathe, a new digital copy must be generated. This means in other words that when the tool dies its digital twin also dies, and it would imply that all the information computed including the drift due to the tool wear would no more be used or would be deleted. Unfortunately, as Liu et al. [8] pointed out, there is very few research in this field, but Grives and Vickers [16] explained that the retiring digital twin should be at the disposal of the system for new digital twins to have access to past instances.

As a matter of fact, if the manufacturing parameters do not change significantly between two different tools, it can be assumed that the tool wear (thus the computed drift) will not change significantly as well. Starting from zero each time a new tool is installed will be a waste of time and resources. Furthermore, to obtain a stable and correct estimate of the drift by linear regression (as described in subsection II.C), a certain quantity of parts must be measured, which means that the correction will not be applied directly after the first part, whereas the estimated drift from previous digital twin could be used since the calculations are likely to give similar results if the manufacturing conditions are not changed from part to part, and tool to tool.

Our solution was to set up a system of inheritance between digital twins. The digital twins of tools should have access to the previous digital twins to use their results as a model: it allows them to use it as a substitute when the computations are unreliable, to anticipate behaviour such as the expected end-of-life, and to compare their results to detect abnormalities. We determined that the entity who should be responsible of that inheritance must be the digital twin of the lathe because the history of tools used is a property of the lathe (which is not in contradiction with the concept of digital twin concept). More importantly, the manufacturing parameters are linked to the use of the lathe, which means that if there is a digital twin of the lathe, this data can be monitored and correlated with the digital twin of the tool on an ongoing basis.

C. Model and computations

Since the drift in measurements due to the tool wear is supposed to be linear (see subsection II.B), the least square linear regression method should be enough to determine this drift (as Fraticelli [14] did for sequential tolerance control). Based on the principles of the least square method (as detailed by Duncan [11]), formulae for the drift and the distribution were determined.

The first part produced may have measurements outside the tolerance interval due to the difficulties to manually set the tool on the lathe correctly. This is why there is always a calibration after: the tool offset is changed in the controller to compensate. Thus, the following parts are produced by operations whose the reference system does not induce an offset geometric error, meaning that the measured deviation between the target measurement and the actual measurement is only induced by the process and the tool. Mathematically it means that, after the calibration, deviations will be directly measured and are referenced to the origin, therefore the

| | |
|---|---|
| Slope (drift due to tool wear) | $\mathrm{b} = \frac{\sum i \, \mathrm{d}_i}{\sum i^2}$ |
| Distribution (standard deviation along the slope) | $\hat{\sigma} = \sqrt{\frac{\sum \mathrm{d}_i^2 - \mathrm{b}^2 \sum i^2}{\mathrm{n} - 2}}$ |

Table 1: Formulae adapted from linear least square method for the digital twin.

interception of the linear regression at the origin is zero (as presented in Figure 4). The formulae for this special case are presented in Table 1.

This formulation is only valid after the calibration, otherwise the offset term of the linear regression is not zero. This also implies that any offset correction must never be considered in the deviation, otherwise these data are not referenced the same way. As a result, the points used for the regression do not have a linear behaviour since a correction applied acts as a reset of the origin (the plot of Figure 4 would have sawtooth shape) and the wear will be underestimated implying corrections increasing exponentially. Hence, the deviation measured between the target measurement and the actual measurement must be corrected with the cumulative correction before being added to the data for the regression computation.

The drift computed acts as an approximated wear law giving the deviation between measurements due to the tool wear. Therefore, by interpolating this law, the dimension of next part can be estimated, and a correction can be determined to avoid this drift. However, before applying directly the correction, the stability of the computations must be verified.

The stability of the computed slope is a way to check the convergence of the value. The more correct the slope is (because points are being added), the less the slope changes. Oscillations appear due to the process stability and the precision of the measuring device: the more scattered are the points, the more points are needed to differentiate the slope from the distribution around it. We can consider that the values are correctly approximated when the slope or the standard deviation converge. In other words, if the derivative of the slope relatively to the slope becomes small, the value of the slope becomes trustable. If this value is greater than the criterion (for

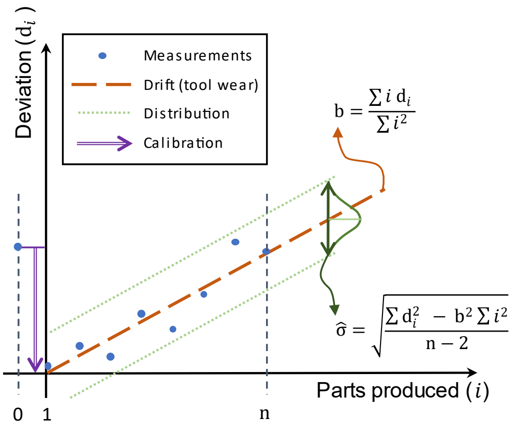


Figure 4: illustration of the linear regression method applied to the deviation measured.

our simulation, we obtained satisfactory results with a value of 5%), the slope calculated must not be used for the correction because of the risk of a too large correction, which could result in production of scraps. In that case, the digital twin can either decide to use his heritage as a temporary model for the correction or, in the case there is no heritage, to do nothing (the process is normally designed to be stable enough to allow the production of a few parts without controls).

The computation of the digital tool helps to have a glance at the end-of-life of the tool: if the slope begins to change faster and/or the standard deviation begins to increase, it might signify an advanced wear of the tool.

Simulations were conducted in order to evaluate this first version of the digital twin and the results are detailed in the next section.

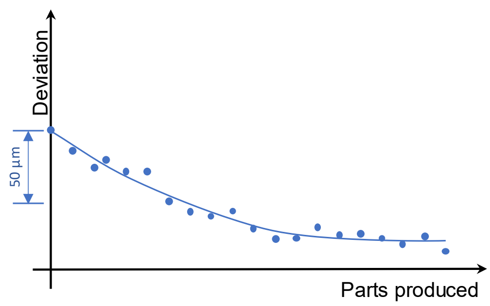


Figure 5: Deviation in the measurements due to the lathe started after a night without working in winter.

### D. Possible improvements

As it is a first version of a digital twin based on measurements, there are a few things that can be improved. In this section we present areas of possible improvement.

*Thermal effects*

The method presented in the previous subsection to determine the drift induced by the tool wear does not consider the temperature of the lathe. Unfortunately, if the temperature fluctuates between parts (which is the case when the lathe starts on a cold morning for instance), its impact on the measurements can be as important as the tool wear. Furthermore, the variations it induces on the measurements is not linear, which makes the previously detailed formulae unusable. An example of the deviation in these conditions is presented in Figure 5: the slope seems negative whereas it should be positive (since this point comes from the measurements on an external cylinder). We propose two suggestions. One would be to find or build a model with one parameter directly depending on the temperature monitored by the digital lathe, to compute the proportion of the deviation induced by the temperature. The other one would be that the measurements are grouped according to the temperature, so that the thermal variation between these data can be neglected, and the method presented in previous subsection can still be used but that will certainly require more data to reach the same precision (i.e., a complete set of data at each temperature).

*Moving linear regression*

Tool wear changes at two moments of the life of the tool: at the very beginning (usually not seen in the measurements because it happens on a short time) and at the end of life. In fact, an exponential increase of the tool wear can be interpreted as the beginning of the end of life of the tool. Unfortunately, if all the points used in the linear regression computation keep the same weight, the new points showing signs of an increase will not significantly influence the value of the slope, thus the increase will not be measured on time (which increases the risks of tool failure). A linear regression method with weights that change according to the number of parts measured may reduce this lack of sensitivity. However, attention must be given not to have the same problem of stability of the slope, as explained previously.

*Monitoring during process*

As presented in section II, most of the digital twin designed for tool wear monitoring uses indirect measurement such as the forces or vibrations. This can also be included in the digital twin to detect abnormal behaviour during process, as the measurements only provide information after the operations and not during it. It can give additional information for the determination of the end-of-life of the tool too (for instance the work of Bombinski et al. [17] about detection of accelerated tool wear).

*Pattern recognition*

One of the interests for control chart is the detection of phenomena in the process, by recognizing patterns. Since the deviation graph works similarly as control charts it might interesting to add pattern recognition features to correct other perturbations than tool wear.

*Sampling frequency adaptation*

Once the drift due to the wear is known, it is not necessary to keep measuring every part produced as it may not give additional information. Hence, it would be interesting to adapt the sampling rate to reduce downtime. This feature would determine the right interval based on probabilities of having an important variation.

| Parameter | Test 1 | Test 2 |
|---|---|---|
| Slope (µm/part) | 3 | |
| Standard deviation (µm) | 1 | |
| Dimension interval (mm) | 13.43 +0.07 - 0.03 | |
| Accuracy of the measurements (µm) | - | |
| Accuracy of the lathe (µm) | 5 | |
| Heritage | No | Yes |

Table 2: Parameters of the simulator for Test 1 & 2.

## IV. Results

To verify our method, simulations were executed with python scripts. A script generates the measurements for the simulation. This method only requires three parameters, which are the interval of dimensions, the drift due to the tool wear, and the standard deviation due to the process. It is also possible to set the (in)accuracies of the lathe and the measuring system, which will simulate the behaviour of the equipment by rounding the values.

The parameters set for the first simulation (called Test 1) are presented in Table 2 (the values are arbitrary chosen but within a range of plausible values). For this simulation, the real values of the measurements are used as an input of the digital twin, but the corrections applied (output) have an accuracy of 5 µm.

The measurements of the parts produced are represented in Figure 6a and the deviations deduced in Figure 6b. This first simulation already proves the efficiency of the digital twin as all the parts produced have a dimension close to the one targeted, except for the first parts due to the required amount of data necessary to have a trustable value of the slope. In fact, few measurements were required before having small variations in the derivative of the slope as shown in Figure 7 (for Test 1, it is after the $6^{th}$ part produced that the digital twin definitively applies the slope it computes). The remaining deviations appearing in Figure 6a (despite the application of corrections) are due to the standard deviation, which cannot be suppressed, as well as the limited action of the correction due to the precision of the lathe. In this case, the standard deviation estimated by the digital twin is not the one of our parameters due to the accuracy of the lathe. For instance, if the correction proposed by the digital twin is 2 µm, it will not be applied by the lathe since it only applies correction in multiples of 5 µm.

Simulation without taking into account inaccuracy of the lathe (on top of no inaccuracies of the measurements) would not be interesting because the system will apply corrections after each piece and the linear regression computation will converge very quickly. Of course, in reality, both the lathe and the measuring system have inaccuracies. The impact of the inaccuracies is discussed in the subsection C with the analysis of the limitations induced by the equipment.

### A. Heritage

The heritage can be evaluated by running a new simulation (called Test 2 whose parameters are detailed in).

New measurements are generated with this new simulation but, this time, the results from the previous simulation are known, thus a model exists for the digital tool. As presented in Figure 9, when the criterium of stability is not met, the slope is the one inherited (the last value obtained during Test 1) instead of zero (as it can be seen in Figure 7 for Test 1), which results in having all measurements close to the target as shown in Figure 8a.

For Test 1 and 2, the heritage process does not seem to be important because without heritage the efficiency of the digital twin is already sufficient (the maximum deviation without heritage is about 10 µm whereas the heritage provides deviations below 5 µm). However, when the precision of the equipment is worse, it impacts the measurement distribution, making the regression less stable (the linear regression requires more measurements), which can cause an important drift if the heritage is unavailable as it is explained in the next subsection.

B. Influence of the equipment

The heritage will be more useful when the system lacks accuracy. In order to prove it, four more tests were executed. Tests 3 and 4 show the impact of the accuracy of the measuring machine on the system, and the proof that heritage compensates it. Tests 5 and 6 show the sensibility of the digital twin to a highly perturbed system (simulated with a high standard deviation) and they once again show the interest of heritage. The parameters set for these four tests are detailed in Table 3.

*Influence of the accuracy of the measuring system (tests 3 & 4)*

The accuracy of the tool has an impact on the measurements sent to the digital

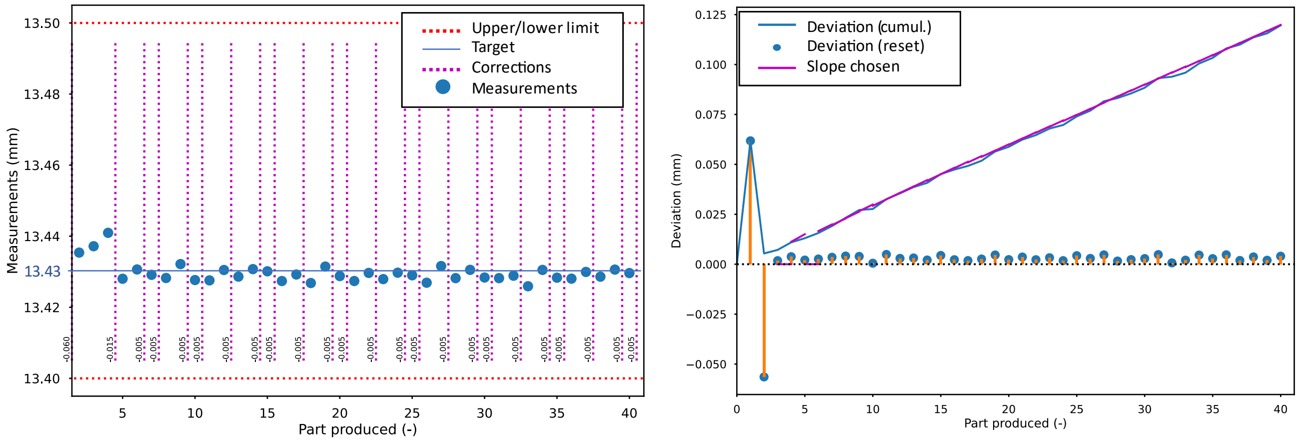

Figure 6: Test 1 - (a: left) Measurements of the geometry produced; (b: right) the deviation of the measurements.

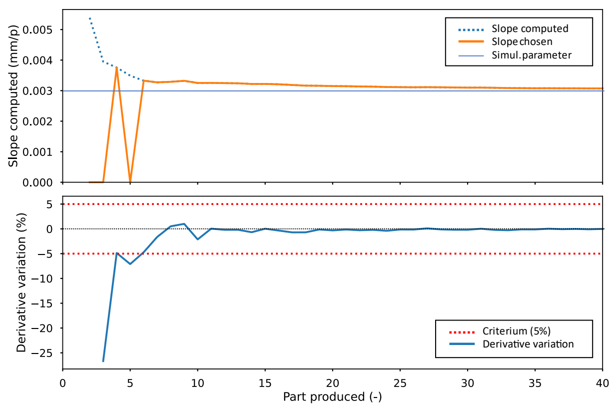

Figure 7: Slope and its variation computed by the digital twin for Test 1.

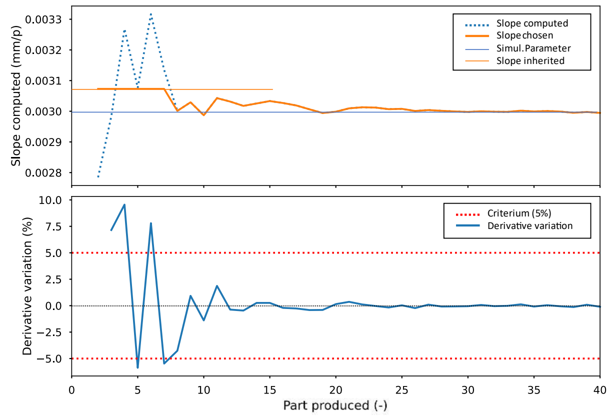

Figure 9: Slope and its variation computed by the digital twin for Test 2.

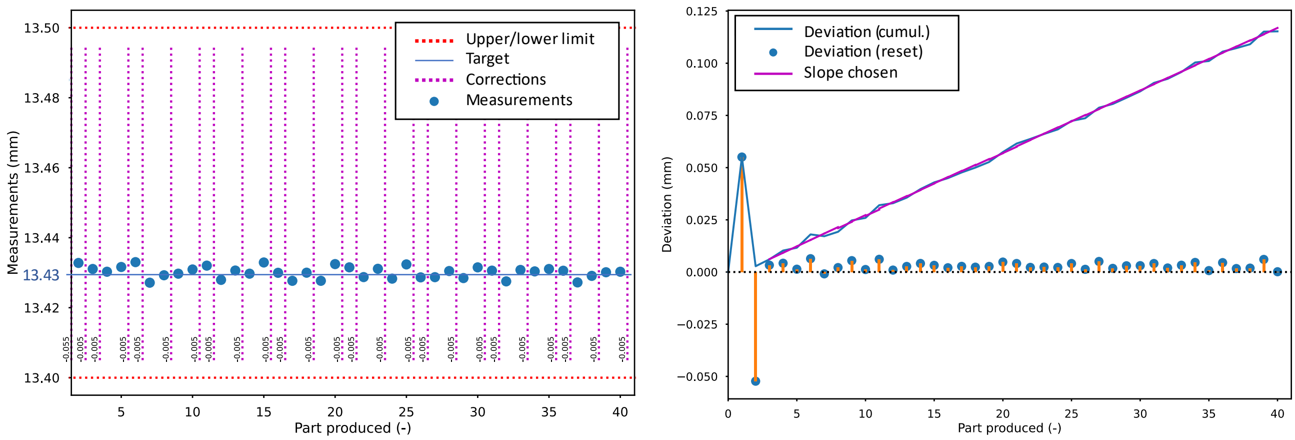

Figure 8: Test 2 - (a: left) Measurements of the geometry produced; (b: right) the deviation of the measurements.

twin. If this accuracy is greater or equal to the standard deviation of the process, the distribution will mainly be caused by the rounding of the measurement, and the standard deviation computed by the digital twin will be higher than the real one.

The "rounding" behaviour combined with normal distribution can be seen graphically as oscillations and implies a larger number of measurements to have a stable slope. As it can be seen in Figure 10 and Figure 12, the required number of parts before the digital twin trusts its slope is about two times more than in the first tests.

This test showed the impact of the accuracy of the data on the digital twin efficiency: decreasing the accuracy of the measures implies delays for the digital twin before starting to adjust, allowing a more important drift in the measurements for the first parts produced. Hence, the measuring system must be chosen with respect to the range of tolerance and the expected process parameters.

It is also important to point out that, once the digital twin has determined the drift due to the tool wear, the corrections are applied efficiently: as we can see in Figure 10a, some corrections seem invisible in the measurements (two consecutive parts have equal dimensions despite the fact that a correction was applied between the two process) due to the fact that these corrections were applied in advance to counteract the drift due to the tool wear.

| Parameter | Test 3 | Test 4 | Test 5 | Test 6 |
|---|---|---|---|---|
| Slope (µm/part) | 3 | | | |
| Standard deviation (µm) | 1 | | 5 | |
| Dimension interval (mm) | 13.43 +0.07 -0.03 | | 13.45 +0.05 -0.05 | |
| Accuracy of the measurements (µm) | 10 | | | |
| Accuracy of the lathe (µm) | 5 | | | |
| Heritage | No | Yes | No | Yes |

Table 3: Parameters of the simulator for tests 3 to 6.

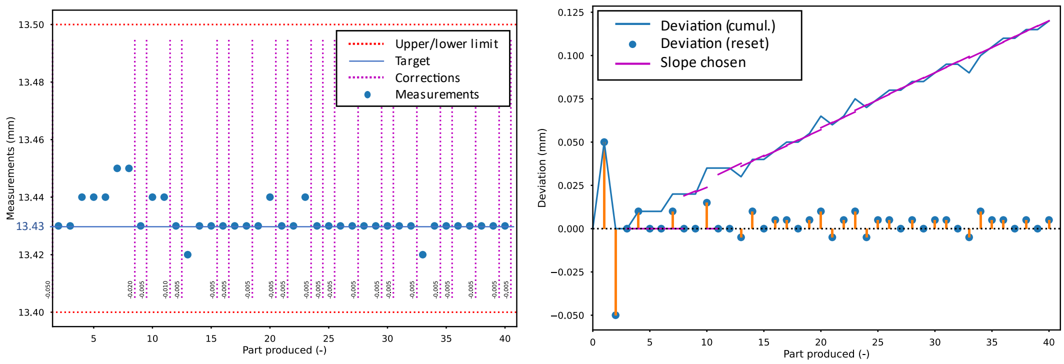


Figure 10: Test 3 - (a: left) Measurements of the geometry produced; (b: right) the deviation of the measurements.

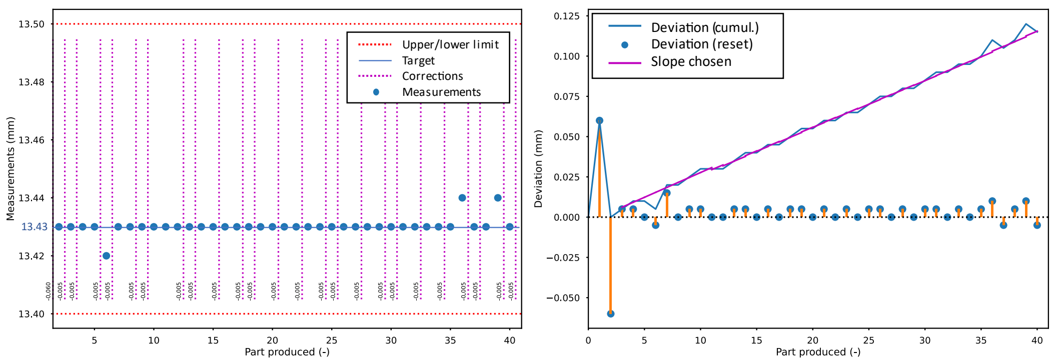


Figure 11: Test 4 - (a: left) Measurements of the geometry produced; (b: right) the deviation of the measurements.

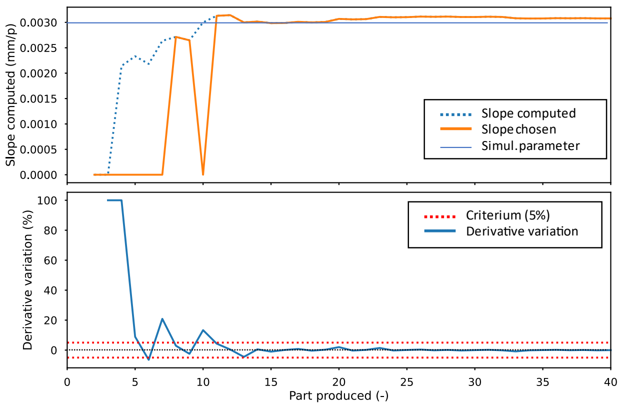


Figure 12: Slope and its variation computed by the digital twin for Test 3.

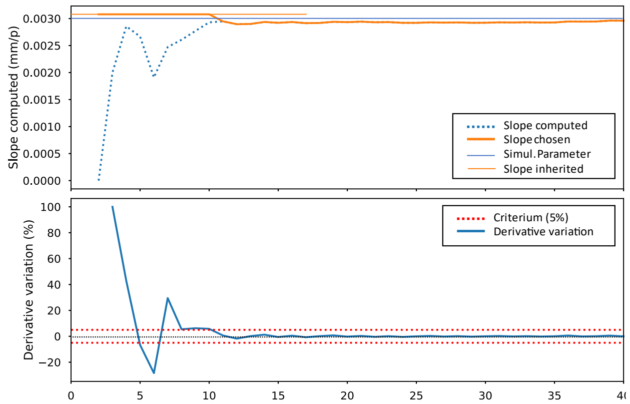


Figure 13: Slope and its variation computed by the digital twin for Test 4.

If the heritage process is available (as it is for Test 4), the delay for the estimated drift to converge cannot be deduced from the measurements. As shown in Figure 11a, almost every dimensions measured are on target, definitivetly prooving that inherited model is a good substitute to avoid large deviations for the first parts. However, if we look at the values of the slope determined by the digital twin (presented in Figure 13), the delay is visible and is obviously the same as without heritage.

In a way, it seems that heritage can compensate the bad accuracy of the measuring system, so the choice of this device might be not very critical. However, we need to keep in mind that heritage implies that “retired” digital twins of the tool managed to find a drift close to the real one, which means that the first tool would require particular attention as it cannot inherit.

*Behaviour of the digital twin in a process with a large distribution (tests 5 & 6)*

The special case where the range imposed by the tolerances is tight compared to the precision of the manufacturing process (which can be interpreted through the standard deviation) will be evaluated on the digital twin to see its limits. This kind of case does not usually happen in manufacturing, as we want to keep a low probability of scrap production: the process is selected to have a small distribution, or the tolerances are adapted to fit the capabilities of the machine, according to the statistical process control theory [11].

For the tests 5 and 6, the standard deviation set is 5 µm, which means that the measurements are mainly distributed on a range of ±15 µm (99.7% of probability). As we decided to set the middle of range as the target dimension, the process would have a significant probability to produce scraps after the 13th part produced (with a drift of 3 µm/part, there will be less than 2σ after the 13th part, meaning that the probability that the 14th part is scrap is more than 15%).

A more difficult case for the digital twin is when the first digital tool is created as the heritage is impossible. As it is shown in Figure 14, the digital tool managed to find a wear law before the dimensions reached the upper limit. For sure, if the accuracy of the measurements was smaller than the standard deviation, the digital twin would have corrected sooner as explained before. However, if the accuracy were worse, there would certainly be scraps produced.

The heritage process (Test 6) is once again interesting as it can be seen in Figure 15 : the only deviations seen in the measurements are due to the standard deviation which cannot be suppressed.

If the drift produced by the tool wear was completely compensated by the digital twin, the only detected deviations would be only due to the distribution of the process. If this scenario becomes possible it means that the whole process reaches a high level of precision, so it would be possible to have a range of tolerance as tight as the distribution. This allows to produce more precise parts, even if the process is highly perturbed. The opposite action, i.e. allowing the process to be less precise due to the range of the tolerance, is not possible since all the manufacturing parameters change and thus the wear, making the heritage obsolete.

## V. Conclusion

A new method of compensating for tool wear for lathes is presented, based on the concept of the digital twin, which offers new ways of achieving intelligent manufacturing systems. This digital twin solution is an aggregate of two digital twins: one for the lathe and one for the tool as they have different properties.

This digital twin has two data sources: the measurements of the geometries produced by the tool and the monitoring of the lathe. The digital tool uses the measurements to determine the deviation caused by the tool wear and calculates an approximated law to provide offset correction as compensation. The digital lathe will then use this correction to update its manufacturing code.

The greatest interest for using two different twins is what we called heritage: it is now possible to store data from old digital twins of the tool (as they supposed to disappear with their physical twin) in the digital twin of the lathe. The principle of heritage is that when a new digital tool is used in same conditions as an old digital tool this new digital tool can use the data from the old one as a model, which is useful when collected data are not

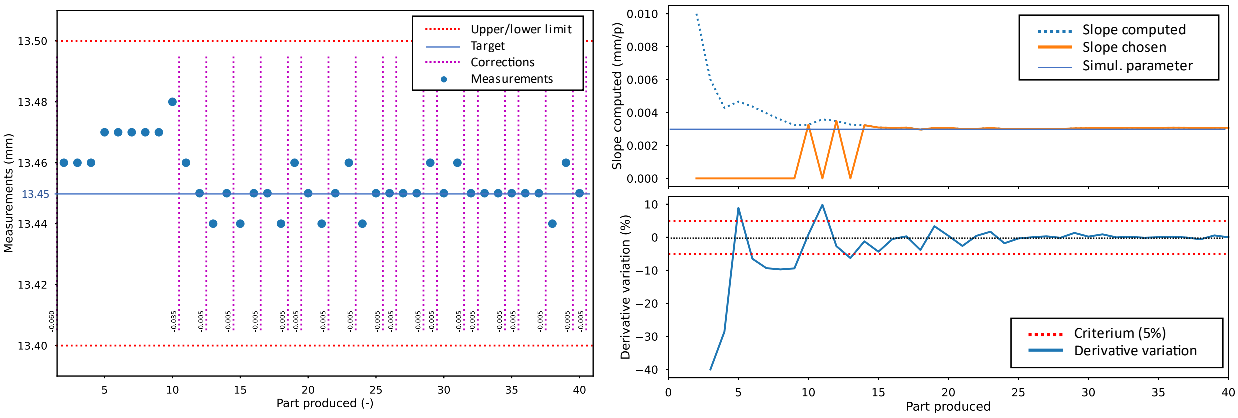


Figure 14: Test 5 - (a: left) Measurements of the geometry produced; (b: right) the slope and its variation computed by the digital twin.

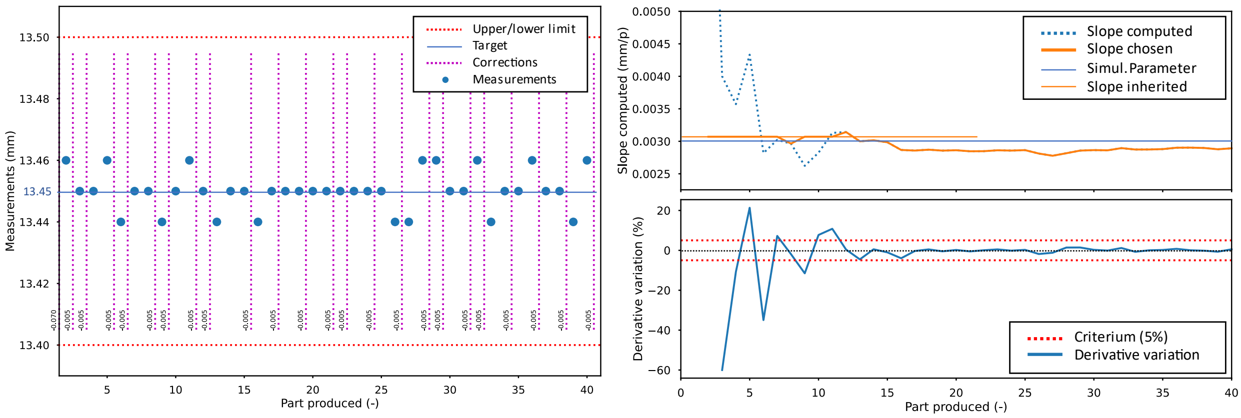


Figure 15: Test 6 - (a: left) Measurements of the geometry produced; (b: right) the slope and its variation computed by the digital twin.

sufficient to apply corrections. These manufacturing conditions are provided by the digital lathe.

Simulations were conducted to try and to evaluate the efficiency of such a system and the results are very promising: it allows the lathe to produce more precise parts and even more when the heritage process takes place. However, it is a first version of this kind of digital twin as there are very useful possible improvements such as adding compensation for the thermal effects or detection of abnormal behaviour.

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