Tool wear prediction and damage detection in milling using hidden Markov models

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Abstract
It is widely accepted that tool wear has a direct impact on a machining process, playing a key part in surface integrity, part quality and therefore, process efficiency. By establishing the state of a tool during a machining process, it is possible to estimate both the surface properties and the optimal process parameters, while allowing intelligent predictions about the future state of the process to be made; thus ultimately reducing unexpected component damage. This state estimate can be achieved by implementing a variety of in-process monitoring techniques and observing the development of selected data features as the wear state of the tool progresses. This paper explores the use of hidden Markov models (HMM) along with in-process recorded acoustic emission (AE) data, to probabilistically classify a tool's current wear state, its likely future state, and to detect potential damage during ball-nosed milling of Titanium-5Al-5Mo-5V-3Cr (Ti-5553).

1 Introduction

Over the past decade or so, acoustic emission (AE) has received, and continues to receive, a significant level of interest in the field of condition monitoring and process control. Acoustic emissions are caused by phenomena such as sliding friction at a flank-workpiece interface and the breaking of chips [1]; both of which are directly related to a cutting process and corresponding tool condition. AE therefore, has been used in a considerable amount of previous work for the monitoring of tool condition [2–7], surface roughness [8, 9], and event detection [1] to name but a few. AE based monitoring is also available from a number of commercial monitoring system suppliers [10]; however, it is often used alongside a range of different sensors in a data fusion approach [1]; the benefits of which include increased reliability, more robust decision making, and increased noise rejection. Such commercial systems are rarely successfully implemented, however, as they tend to target a wide range of processes with simple data processing methods and often fall short of the requirements set by industry; they also follow a diagnostic approach rather than prognosis of events before they happen [10].

In finish milling, the focus is largely on the surface of the part. Required roughness values are regularly given in product specifications, and maintenance of the surface finish within certain limits is considered crucial. As tool condition plays a significant role in surface generation, tools are therefore often replaced conservatively and rarely experience breakage. It is consequently desirable to determine surface properties and tool state in-process; made possible using measured AE signals and the correlation between tool condition and workpiece surface integrity. Making use of prior process knowledge and gathered data, it is possible to begin to predict the future state of the process based on its current and previous behavior, for instance, using hidden Markov models (HMM).

This paper will begin by outlining the theory behind the work presented, then detailing the machining trial used to obtain test datasets. It will then continue to present and discuss such datasets, finally drawing conclusions and stating the next steps in this work.

2 Theory

2.1 Tool wear

Tool wear is the change in physical state of a tool from its supplied condition to its condition after use. Depending upon both the tool and operation, this wear can consist of one or more different mechanisms which each result in various changes to observed signals. Flank wear is often considered the dominant and simplest to measure wear mechanism and is therefore investigated in detail in the previous literature [4, 11–14], often using a tool-maker microscope to obtain numerical values. Flank wear can also be predicted using Taylor's equation for tool life expectancy [15], another reason why it is commonly used in wear detection methods. This, however, is often not sufficient as it is typical for the dominant wear mechanism of a process to develop over time; from flank wear to crater wear for example. Flank and crater wear have been seen to mask the effects of one another in measured signals [16, 17], and thus any desired relationship between wear and monitoring signals is often difficult to establish for a longer process that experiences multiple wear types. By measuring 3D tool geometry, it is possible to gain more of an insight into a tool's wear state than has previously been possible.

The surface of a material following machining is a function of a number of factors including process parameters and tool condition [18]. It has been shown that flank wear of a tool has a direct impact on surface roughness [19] and considering that tool wear can be established from AE signals, it can be assumed that material surface properties can be inferred from those same AE signals [20]. Surface roughness is considered to be strongly related to the performance of a part in service [9].

2.2 Acoustic emission

AE has been widely used in the detection and monitoring of tool wear with successful results in both turning and milling operations [21–26] - partly due to the fact that the signal frequency of interest is much greater than that of the noise generated by the machine [6]. The previous work, however, appears divided when considering the signal processing strategy used. Both time and frequency domain analysis have their own benefits and drawbacks, often relating to the specific process of interest and which process parameters are expected to change. One of the most commonly-used features, the root mean square (RMS) value of the AE signal, is a measure of the power content of the signal that can be seen to increase with flank wear [6]. The downside of this, is that the RMS value is also associated with process parameters such as radial or axial depth of cut [27] and distinguishing the cause of an RMS change can be challenging; this often requires calibration on a per-process basis unless the process state remains constant. It has also been suggested that it is possible to isolate the effects of tool wear on the RMS value of the AE signal over a 10 second sample (AErms) by using a time domain averaging (TDA) technique [4]. This paper, as it focusses on a stable, repeated, periodic process, concentrates on time domain features including RMS, peak signal values, skewness, kurtosis, and mean values primarily. The time domain features are used as part of a principal component analysis (PCA) which, in turn, provides input data into a HMM.

2.3 Principal component analysis

Principal component analysis (PCA) has a number of different uses depending upon the desired outcome. Primarily, PCA is a tool for identifying patterns in data sets of high dimension where simply displaying the data in a graphical form is not possible. Once any significant patterns have been found in the data, redundant data can be discarded, enabling PCA to be used as a tool for dimensional reduction, data compression, variable selection, and data classification to name a few [28]. In this work, where a number of feature variables have been calculated, it is possible to perform a PCA to aid in both identification of the meaningful features, and creation of a single new feature which represents the aggregate effects of the input features. This feature of a single dimension can then be used as the observed variable for a HMM, with the associated states defined for training.

2.4 Hidden Markov models

A hidden Markov model (HMM) is a statistical model used to model a system that behaves as, or can be assumed to behave as a Markov process. A system can be considered a Markov process if its past and future states are independent of one-another given the current state of the process, or alternatively put, a system can be considered a Markov process if the probabilities of its future states can be calculated from its current state only, regardless of its previous history. HMMs have primarily been used for speech recognition in the past [29], however, a number of instances of machinery-based HMM applications can be found in previous works [30–34] with varying degrees of success.

This paper proposes HMMs to be well suited to the modelling of monitored and progressively wearing machining processes for a number of reasons. Primarily, as a cutting tool's wear state is an aggregate of its previous states and must progress in this manner, one can treat the mechanism of wear as a Markov process due to the ability to draw future state probabilities from the current state only, given predefined machining conditions are understood. Furthermore, when monitoring a cutting operation, tool wear is most commonly measured indirectly using a variety of sensor systems rather than measuring edge wear instantaneously [1]. This is well accommodated for in the operation of the HMM, where indications of the most likely underlying or 'hidden' state are inferred through the observation of related states or variables. In the case of tool wear monitoring, the hidden state can be considered as the level of wear present on the tool and its current wear mechanism, while the observed variables will be those data collected from related sensors based within proximity to the operation.

In order for a HMM to determine the state estimate with the highest chance of being correct, HMMs make use of known or learned probabilities for the transitions between states (transition matrix) and the hidden state given an observed dataset (emission matrix). This can be visualised in Figure 1.

Figure 1 contains a number of necessary elements needed to define a HMM, which, when using the same notation as in Ref. [34] are:

1. $\mathbf{S_N}$, the state of the model, consisting of N individual states.
2. **A**=$\{a_{ij}\}$, the set of transition probabilities, between states, of the system of interest.
3. **B**=$\{b_j(s)\}$, the probability distribution of the observed variables for each individual state.

In addition to these, the following shall be defined:

1. $\mathbf{O_T}$, an observation of the system as part of a sequence containing T elements.
2. **V**=$\{v_1, v_2, \ldots, v_M\}$, the set of possible observed values coming from the model, assuming a discrete system. (A,B,C,D,E,F in the example given in Figure 1). This can be defined as an infinite sequence if the underlying system provides a continuous output.

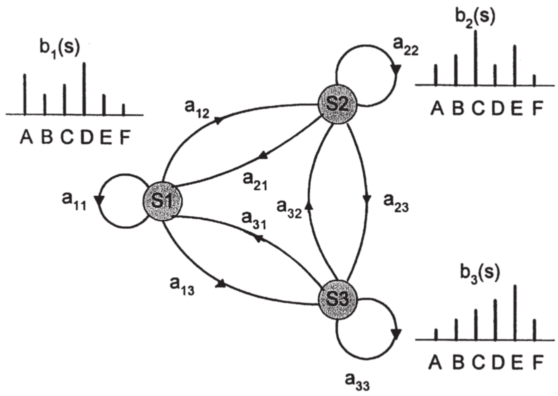

Figure 1: Example of a three-state hidden Markov model [34].

3. $\Pi = \{\pi_i\}$, the initial state distribution when the observation sequence begins. π_i being the probability of being in state S_i to begin with. In the case of tool wear, it is assumed that all tools will be sharp and un-worn at the start of observation.

The parameters $\{a_{ij}, b_j(s), \pi_i\}$ can be estimated and adjusted to maximise the likelihood of an observation sequence, $P(O|\lambda)$, given the model $\lambda = (A, B, \Pi)$ [34] via a training technique such as the Baum-Welch algorithm, providing data is available with previous knowledge of a sequence of states and corresponding observations. Once the parameters are refined, they can be used to decode the most probable sequence of states given a sequence of observations $\{O_1, O_2, \ldots, O_T\}$ using the Viterbi algorithm. Description of these algorithms is out of the scope of this paper but are well detailed in Refs. [32, 35]. Individual elements and the HMM model used for this system specifically are detailed further in Section 3.

3 Experimental methods

3.1 Process Parameters

The test parameters used in this paper are taken from an industrial process and are intended to be representative of the operation used in manufacture. Using these parameters allows any gathered data and developed models to be directly applied and validated in a typical industrial environment. The parameters used are an axial depth of cut (Ap) of 0.3mm, radial depth of cut (Ae) of 0.7mm, spindle speed of 5082rpm, and feed rate of 4.268m/min. The experimental tool paths are also designed to be representative of the industrial process.

The aviation industry is gradually seeing a move towards increased levels of titanium components [36], and consequently, there is a significant research interest in increasing the efficiency of the manufacture of these components. For that reason, Titanium-5Al-5Mo-5V-3Cr (Ti-5553) is the material that will be used and referred to throughout this paper; an alloy used heavily in the manufacture of landing gear components.

3.2 Data Collection

The experimental machining trial used to develop the desired tool states and corresponding AE data was split into two parts. Firstly, nine tools were used to machine a solid billet for predetermined time intervals, consequently generating a selection of tools in different wear states. These tools could then be measured using an Alicona 3D optical microscope system to classify the various levels of wear and explore how the wear characteristics develop with time. Once the state of the tools was confirmed, the second half of the experimental trial was conducted, using these tools to cut a material specimen while collecting monitoring signals from the process. This methodology provides information on the tool state, wear development with time, the effect tool state has on the signals generated during cutting, and the effect tool state has on the material surface. These correlations are explored further in Ref. [37].

Tool usage durations were chosen in half-hour increments, ranging from zero to three hours based on current usage data from the industrial process, and extended beyond the current limits to provide an overview of tool wear above and beyond that experienced during normal usage.

As previously mentioned, the tool paths were designed to accurately represent those found in manufacture, resulting in the full cutting radius of the tools being utilised and maximising tool life. To achieve this, the tool's lead angle is constantly changed, while machining rings around a circular billet. The second pseudo five-axis process machined a selection of test specimens taken from a Ti-5553 landing gear component, using the previously worn tools and collecting data from a number of different sources during the operation. An AE sensor was attached to the back of the workpiece fixture and the workpiece assembly was placed on a dynamometer, allowing both AE and force data to be collected simultaneously. It should be noted, however, that in an industrial environment, a dynamometer is not appropriate due to its intrusive nature and size limitations. This operation results in AE data relating to each of the tool usage durations, which in turn can be used as the observed sequence for state diagnosis using a HMM following a PCA. As close to 100% of the variance is accounted for in the first component, only this component will be used and treated as a dimensional reduction from the time-domain features originally calculated.

3.3 Data scaling

In order for such a system to be robust and applicable to an industrial environment, the model input data must be conditioned and verified reasonable by comparison with existing known training data. Any large signal deviation from within expected thresholds is an indication of tool damage, while slight deviations are expected due to varying environmental and process parameters. It can be expected that any new, unused tool will behave in a similar manner to other similar tools and thus signals from the initial usage duration can be compared and normalised to remove any environmental effects, ensuring that the AE signals obtained throughout each tool's life fit an appropriate scale for use with a pre-trained HMM. It should be noted, however, that this does not account for changing process parameters such as spindle speed and machining feed rate, as these variables not only affect wear rate, but also the signal features monitored. This fact will be touched on again in the following sections, as a knowledge of wear rate is needed for the model to accurately predict future states independently of machine parameters; the end goal for this project.

3.4 HMM training and topology

Training of the model used in this work was completed using the MATLAB statistics and machine learning toolbox as it contains an implementation of the Baum-Welch algorithm previously described in Section 2.4. Once provided with a sample observation dataset and corresponding process states, this algorithm provides maximum likelihood matrices of both transition and emission probabilities. The chosen training states were obtained through using a multi-class support vector machine to cluster the sample observation data, a detailed description of which can be found in Ref. [35]. The specific SVM and clusters used in this paper are explained fully in Ref. [38] due to space limitations here. Once training has been accomplished, the Viterbi algorithm can be used to solve the decoding problem, generating a sequence of the most probable states given an input observation sequence. Comparing this output sequence with the training state sequence provides an insight into the model accuracy for the specific training example and, therefore, a general case provided the process parameters remain consistent.

	New	Used	Worn	Damaged
New	> 0	> 0	0	> 0
Used	0	> 0	> 0	> 0
Worn	0	0	> 0	> 0
Damaged	0	0	0	1

Table 1: HMM topology shown through example transition matrix.

	Future new	Future used	Future worn	Future damaged
Current new	0.9798	0.0101	0	0.0101
Current used	0	0.9865	0.0068	0.0068
Current worn	0	0	0.9932	0.0068
Current damaged	0	0	0	1

Table 2: Transmission matrix estimate from Baum-Welch algorithm.

Another key feature to consider when designing a HMM, is the topology of the model given the possible underlying process state transitions. For example, given that tool wear must progress in an positive manner, it can be considered highly unlikely that a tool will revert back from a worn state to a fresh state, allowing a left-to-right model to be adopted. The model must also be capable of transitioning multiple states at once, ensuring that should a tool suffer damage during use (resulting in extremely accelerated wear), detection of this is as quick as possible. Table 1 describes the topology used when building and training the HMM in this work, consisting of 4 states, new, used, worn, and damaged respectively.

4 Results and discussion

The in-process AE data was sampled during each cut, with forty-nine cuts performed using each tool, therefore also providing forty-nine AE recordings per tool. The corresponding statistical time-domain features were calculated and mapped to the new PCA space, and as previously mentioned in Section 2.3, the first principal component scores were then taken as a new data set. Plotting each data-point with its corresponding time results in the plot shown in Figure 2. Similarly, Figure 3 shows the change in value between points plotted as opposed to the individual data-points themselves. In general, it can be seen from these plots that at low levels of tool wear, the signal variance increases gradually as wear progresses, however, at higher levels of wear, the sampled values become more erratic with a greater number of potential outliers. It is expected that this is due to progressive flank wear acting as the dominant mechanism in the early tool life, while crater wear is experienced as the tool tip becomes weaker after further use. Crater wear is often non-uniform across tool flutes due to manufacturing tolerances and tool holding inaccuracies, and as such, provides an explanation for the more irregular behavior as the tool is used further. The phenomenon of increasing variance is useful nonetheless, as it provides a convenient feature to group wear states by. There is also a noticeable drop in signals at the end of life, indicating tool breakage or chipping and, therefore, reduced contact with the workpiece.

Figure 4 shows how the initial trial's AE signals have been split into four states using the SVM described in Section 3.4, providing the input data for HMM training; each point having a corresponding state in a sequence from left to right. Training results in both estimated transition and emission matrices, as shown in Tables 2 and 3 respectively. It can be seen from Table 2 that states can only remain consistent or jump to the neighboring state, with the exception of the final state which is classed as damaged and can occur at any time. It should be noted that the values in Table 3 are rounded to three decimal places and the observed variable input is quantized to a set of ten values, resulting in four possible states and ten possible input values and, therefore, a 4x10 matrix of probabilities based on the current input.

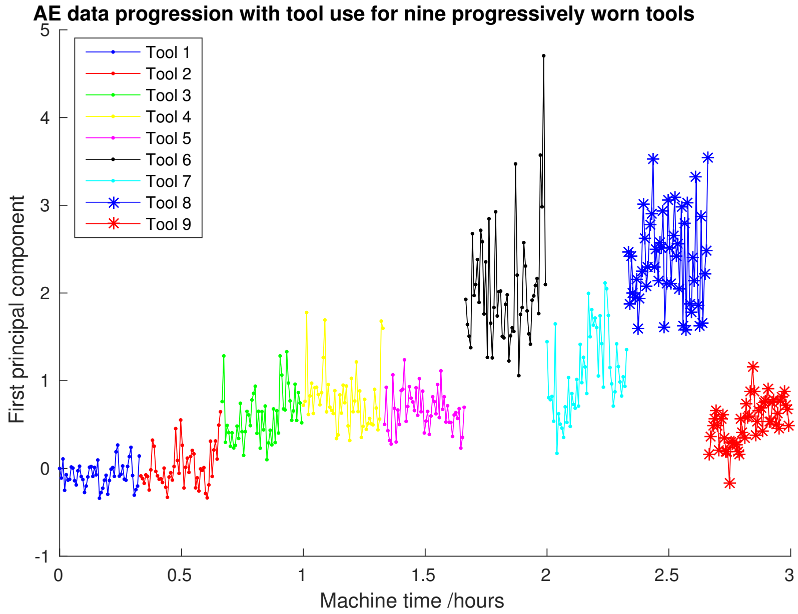

Figure 2: Plot of first principal component of AE data for all nine progressively-worn tools.

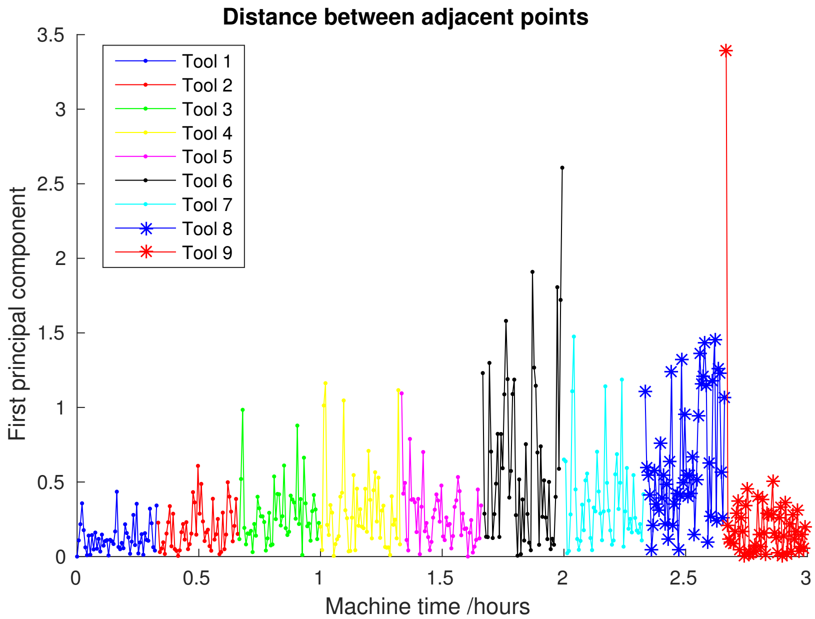

Figure 3: Plot of differences between first principal component values of the AE data.

Possible input values:	1	2	3	4	5	6	7	8	9	10
New	0.880	0.046	0.009	0.009	0.009	0.009	0.009	0.009	0.009	0.009
Used	0.146	0.611	0.172	0.032	0.006	0.006	0.006	0.006	0.006	0.006
Worn	0.019	0.121	0.127	0.261	0.210	0.134	0.076	0.032	0.006	0.013
Damaged	0.271	0.559	0.051	0.017	0.017	0.017	0.017	0.017	0.017	0.017

Table 3: Emission matrix estimate from Baum-Welch algorithm.

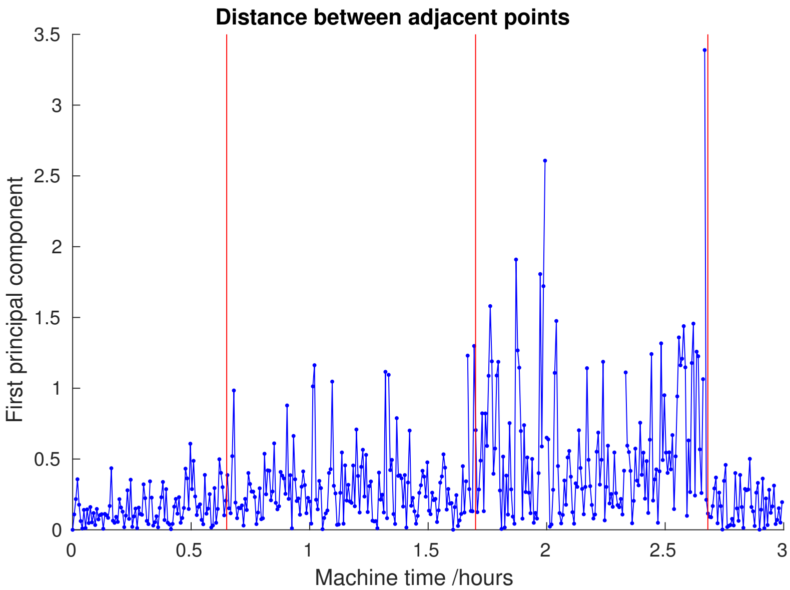

Figure 4: Plot showing states based on SVM classified clusters.

Using these estimated matrices, along with the Viterbi algorithm, the data sequence was then tested to estimate its possible states based upon the learned probabilities, and compared with those states the model was trained on. This resulted in an accuracy of 99.6% (439 out of 441 correct predictions) which can be seen in Figure 5. Figure 5 shows the observed data stream, quantised into ten possible values, with green and red markers showing correct and incorrect predictions respectively. Running the same state estimation on a sample observed dataset from a second trial (obtained in an identical manner to the first trial/ training data, and scaled to the same factor based upon new tool values) returns an accuracy of 98.0% using the same method and state clusters provided previously. Figure 6 shows the input sequence and correct/incorrect state estimates for this second dataset in the same way as Figure 5. This figure indicates that the second dataset is barely in state three before experiencing damage, shown by the drop around point four-hundred. As the data is scaled in the same way and the plot in Figure 6 barely climbs over a level of five, it can be assumed that the tool in this case experienced a different wear progression or rate, however, still experienced breakage at the same time. While the HMM has accurately diagnosed the state of the process based on the most probable state, at this stage, it is unable to give an insight into the potential future state. Figures 5 and 6 indicate that different tools can wear in distinct ways, and therefore, future state probability estimates based on a sample of points taken at a fixed sample rate, can become inaccurate as wear rate varies.

5 Conclusions and future work

It can be seen from the work presented above, that it is entirely possible to make informed, probabilistic estimates of machine state and tool wear levels based upon acquired AE data and a trained HMM, resulting in an accuracy of around 98% for a particular process. The inherent nature of a Markov model, however, means that all future state estimates are based on the current state only, and poses a potential problem when assessing a process with variable parameters and, therefore, varying wear rates. The model will still predict the state in this instance, although may not be as accurate if progressing through wear states more quickly for example. It is also limited in its ability to predict the future state with an associated time-frame and likelihood due to its time-independent nature, and lack of knowledge of previous state transitions. Thus, this model is capable of wear diagnosis more so than state prognosis.

One solution to this problem is to adapt the model so that input process parameters scale the learned matrices, yet this requires extensive testing and a vast knowledge of how wear varies with particular process parameters

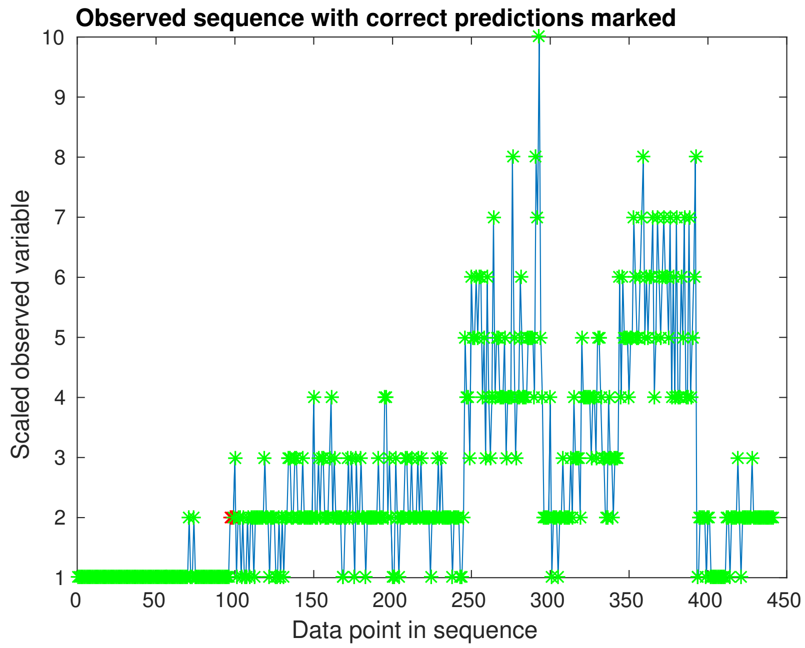

Figure 5: Plot showing PCA magnitude input sequence with correct state estimates marked.

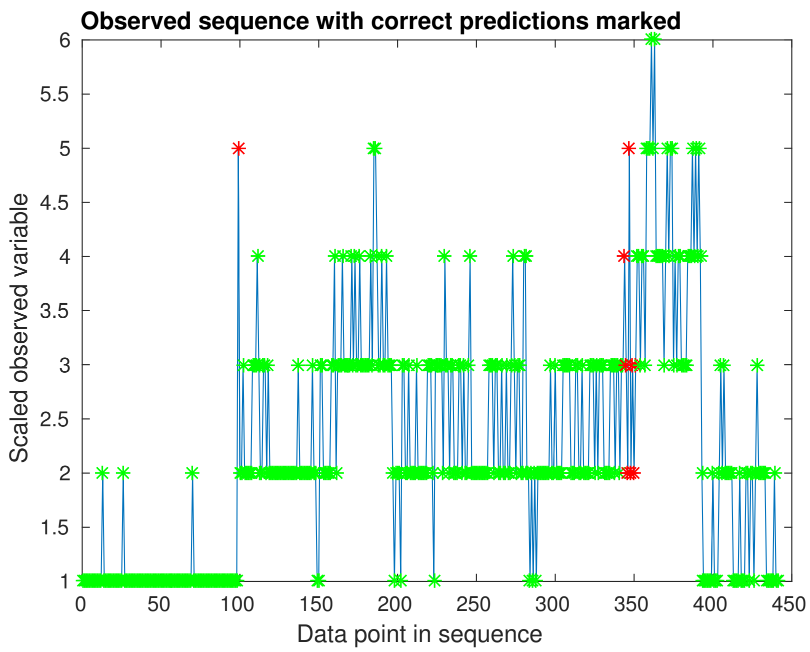

Figure 6: Plot showing PCA magnitude input sequence and state estimates for second trial dataset.

individually, and combined. This solution would effectively require a new set of matrices for each possible combination of input parameters, which could potentially grow in numbers very quickly for continuous input variables.

Another solution would be to use a second HMM to asses the current in-state time as an observed variable, and train this to provide wear rate information along with the diagnosis from the initial model. Combining the outputs would enable an educated prognosis of future states, yet this is not an ideal solution as a single more appropriate model would be beneficial and a more elegant solution. It is for this reason that future work will investigate Gaussian process (GP) NARX models as described in Ref [39].

6 Acknowledgements

This work was co-funded through the EPSRC Industrial Doctorate Centre in Machining Science (EP/I01800X/1) and by Messier-Bugatti-Dowty.

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