A Multi-State Diagnosis and Prognosis Framework with Feature Learning for Tool Condition Monitoring

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Abstract—In this paper, a multi-state diagnosis and prognosis (MDP) framework is proposed for tool condition monitoring via a deep belief network based multi-state approach (DBNMS). For fault diagnosis, a cost-sensitive deep belief network (namely ECS-DBN) is applied to deal with the imbalanced data problem for tool state estimation. An appropriate prognostic degradation model is then applied for tool wear estimation based on the different tool states. The proposed framework has the advantage of automatic feature representation learning and shows better performance in accuracy and robustness. The effectiveness of the proposed DBNMS is validated using a real-world dataset obtained from the gun drilling process. This dataset contains a large amount of measured signals involving different tool geometries under various operating conditions. The DBNMS is examined for both the tool state estimation and tool wear estimation tasks. In the experimental studies, the prediction results are evaluated and compared with popular machine learning approaches, which show the superior performance of the proposed DBNMS approach.

Index Terms—Tool Condition Monitoring (TCM), Diagnostics, Prognostics, Deep Belief Network, Multi-state.

I. INTRODUCTION

Tool condition monitoring (TCM) has become indispensable to smart manufacturing, automated machining, and other industrial processes nowadays. It not only reduces unnecessary machine downtime and maintenance costs, but also improves the quality and precision of the product. The TCM framework provides diagnostics and prognostics to estimate tool states (e.g., fresh, progressive wear, accelerated wear, worn, etc.) and predict tool wear.

The idea of TCM is to monitor the health condition of the tool continuously using data analytics. Signals such as force, torque, vibration and acoustic emission can be collected and monitored using various sensors mounted on the machinery systems. The data-driven approaches have become a mainstream solution to TCM. They make use of computational intelligence, machine learning or deep learning models that learn from run-to-failure historical data from the system. Such approach can learn the knowledge from data without domain knowledge. Since a perfectly defined physical model of tool wear is not available, data-driven approaches are appealing in practice.

Among the data-driven approaches to TCM, conventional machine learning methods such as neural networks (NNs) [1], Gaussian process regression [2], make use techniques that are common in pattern classification, such as feature extraction and feature selection. For instance, the selected features are further used as input to NNs for classification or regression tasks. While these conventional methods work in many tool condition monitoring applications, they suffer from two shortcomings. Firstly, the features are manually extracted highly relying on prior domain knowledge. Moreover, the hand-crafted features extracted from one application scenario may not be generalized to other scenarios. Secondly, due to their shallow architectures, conventional NNs have a limited ability of learning complex non-linear prediction in diagnostics and prognostics. We consider that deep belief networks (DBNs) [3], [4] have the potential to overcome the aforementioned shortcomings. DBNs with unsupervised generative feature learning could be able to mine the useful information from raw data and approximate complex non-linear mappings between raw data and the tasks.

There are two main tasks, namely diagnosis and prognosis, dichotomized the prediction process in TCM system. The previous studies have mostly focused on either diagnosis or prognosis in TCM [5], [6]. Diagnosis is to estimate what the current health state is. Prognosis is to predict what will happen next. Prognostics is the study as to show how the tool condition degrades and to estimate the remaining useful life (RUL) of the tool. With effective and reliable estimation of RUL, TCM can reduce overall downtime of the manufacturing processes. Although prognostics plays an important role in TCM, it still a lukewarm research area with few reported studies. In a TCM system, the tool wear estimation forms the basis of tool RUL estimation. In this paper, we would like to focus on tool state estimation as the main diagnostics task and tool wear estimation as the main prognostics task.

The performance of prognosis can be improved based on more accurate current health state estimation. Because the
degradation trends of the system/components may be different based on different current health states, the results of diagnostics and prognostics are tightly related with the overall performance of the TCM system. Since the distribution of data in different health states are naturally multifarious, any single model is quite hard to handle them. We consider that multi-state diagnosis and prognosis framework distinguishes health states in finer details, that allows us to apply different models according to the diagnostic data attributes. We have a good reason to believe that such multi-modal approach offers better performance. Therefore, this paper proposes a multi-state diagnosis and prognosis framework (MDP) based on tool state estimation by fault diagnosis to provide more reliable and accurate prognostic prediction in tool condition monitoring, namely tool state classification and tool wear estimation.

This paper is organized as follows. Section II reviews current related literature. Section III introduces the proposed multi-state diagnosis and prognosis framework and a deep belief network based multi-state approach. Section IV describes the details of the real-world gun drilling dataset in the aspects of experimental setup, data acquisition and data preprocessing. Section V presents the evaluation metrics of diagnostics and prognostics, respectively. Section VI presents and analyzes the experimental results of tool state estimation and tool wear estimation as well as the comparison with other methods on the real-world gun drilling dataset. Section VII concludes this paper and highlights some potential future research directions.

II. LITERATURE REVIEWS

Generally, TCM approaches are categorized into physical-based approaches, data-driven approaches and hybrid approaches. Physical-based approaches are highly depending on expert domain knowledge. However, in many complex systems, it is hard to establish well-defined mathematical models. Moreover, physical-based approaches are only suitable for certain operating conditions and lack of generalization capability to suit the model for different conditions. Data-driven approaches are based on historical data and require less domain knowledge. Data-driven approaches usually use artificial/computational intelligence techniques such as neural network, support vector machine, Gaussian process regression, fuzzy inference techniques, etc. Hybrid approaches attempt to combine physical-based approach and data-driven approach together.

In the early studies, many data-driven approaches made binary tool state (i.e., healthy and faulty) estimation. Li et al. proposed a TCM framework utilized neuro-fuzzy techniques to estimate the feed cutting force based on the measured feed motor current. Neural networks (NNs) are also popular used on TCM frameworks to generate non-linear mapping between inputs and outputs. Applied NN for fault diagnosis. Zhu et al. proposed an online TCM framework based on force waveform feature extraction.

Hidden Markov Model (HMM) based approaches are widely used in TCM. PS-HMCO is a temporal probabilistic physically segmented approach based on HMM for prognostics. This approach is effective by using multiple physically segmented HMM in parallel with each HMM focusing on a different tool wear regiment. VDHMM is an adaptive-Variable Duration Hidden Markov Model to adapt with different cutting conditions for prognostics. Recently, Zhu et al. proposed a hidden semi-Markov model (HSMM) with dependent durations for online tool wear monitoring with online tool wear estimation and RUL estimation. However, feature extraction and selection are needed for HSMM.

Based on the similar rationale, key feature based approaches probabilistic and neural networks approaches, linear discriminant analysis, switching Kalman filter, and genetic programming are applied to fault diagnosis and RUL estimation.

However, all of the aforementioned approaches require well-defined hand-crafted features and their performances are highly relying on the quality of the manually extracted features. Some approaches such as cannot accomplish multiclass tool state classifications to reach the high precision and quality requirements in manufacturing processes. In addition, the aforementioned approaches are only suitable for fixed operating conditions and they did not address flexibility and generalization problems.

III. MULTI-STATE DIAGNOSIS AND PROGNOSIS FRAMEWORK FOR TOOL CONDITION MONITORING

This paper proposes a novel multi-state diagnosis and prognosis framework (MDP). The schematic diagram of the MDP for TCM decision making is shown in Fig. 1.

There could be different ways to implement the MDP framework. We suggest a deep belief network based multi-state approach to the problem, that we call DBNMS. We formulate the DBNMS as a pipeline process. We first identify the tool states using evolutionary cost-sensitive deep belief network (ECS-DBN) which is suitable for imbalanced data classification, then based on different tool states choose appropriate DBN models for more accurate and robust tool wear estimation based on the tool states, finally we make reliable decisions based on the accurate estimates. DBNMS includes two main steps. In the first step, we carry out fault diagnosis where ECS-DBN is used to handle imbalanced data problem. In the second step, we carry out fault prognosis by using appropriate DBN models to learn feature representations automatically. In practice, the distribution of data samples obtained from different tool states may vary and skew, conventional classifiers often fail to classify minority classes due to imbalanced training data. In the DBNMS implementation, the raw data are taken to the system only with the standard time-windowing and normalization. Thus, DBNMS can be considered as an end-to-end deep learning solution to the TCM problem.

Fig. 2 compares different frameworks including physical-based framework, conventional data-driven based framework and deep learning based framework. Each round box in the figure denotes a data-driven process. Traditional physical-based framework requires strong domain knowledge to hand design physical models while data-driven based frameworks...
only require historical data with less domain knowledge. For some complex systems/components, it is quite hard to formulate precise physical models. In contrast, it is more feasible to obtain data such as sensor signals, operational conditions, event data which are related to the health conditions of the systems/components. Therefore, data-driven framework is applicable for such kind of applications. From Fig. 2, it is obvious that deep learning based framework is an end-to-end framework with automatic feature learning comparing with conventional data-driven based framework. Conventional data-driven framework needs extensive human labor for hand-crafted features and has several tedious individual modules which need to be trained step-by-step. Deep learning based framework has automatic feature representation learning without hand-crafted features. All of its parameters are trained jointly. It is suitable for large-scale data.

In this section, MDP framework for diagnostics and prognostics in TCM is proposed and presented in details. The proposed MDP framework incorporates with fault diagnosis and tool wear estimation tasks. Diagnosis is the task of estimating the health state of the system/component at the current time stamp given all historical data. Prognosis is the task of predicting the wear of the tool in future time stamp.

A. Fault Diagnosis: Tool State Estimation

Fault diagnosis is to estimate current health state of the tools based on current and historical data. It is essentially a classification problem. Many existing studies only assume binary tool states which are fresh and worn. However, such assumption does not allow for accurate and robust predictions. We consider that tool wear is a progressive process, thus, the state of tool wear is multiclass. We also note that the number of data sample obtained during faulty state of the tool is always far less than that of healthy state of the tool. The minority data are always more important because misclassifying them will cause fatal failure and highly costs. Thus there is a need to address imbalanced data problem. Unfortunately, the conventional algorithms such as neural network, DBN generally assume all misclassification costs are equal which is not suitable for such problem. We note that in many real-world applications, misclassification costs are usually unknown and hard to be decided. We suggest using ECS-DBN to address the imbalanced data problem in fault diagnosis. ECS-DBN proposed by Zhang et al. [43], [44] incorporating cost-sensitive function directly into its classification paradigm and utilizing adaptive differential evolution for misclassification costs optimization is shown good performance on handling imbalanced data problems on many popular benchmark datasets.

1) Multiclass Classification of Tool States: Each class in the multiclass classification corresponds to a tool state. We propose a multi-state description to provide more detailed representation of tool wear process. The health state of a tool is fresh and sharp in the initial wear stage, and the tool wear increases progressively with cutting time, then its flank wear rapidly reaches accelerated wear region, eventually it worn after the accelerated wear region. In contrast, the binary classification of tool states (i.e., fresh and worn tool states) may not be able to reflect this wearing process accurately. In addition, multiclass classification of the tool states can improve the final performance of the proposed framework by splitting tool states more precisely so as to avoid unnecessary tool replacement or workpiece damage.

In this paper, the number of classes or states are chosen based on domain knowledge in machinery. According to the size of flank wear, four classes are suggested as shown in Table I. When the average flank wear $V_B$ is less than or equal to 100$\mu$m, the tool is considered as fresh. The progressive wear region of the tool is between 100$\mu$m to 200$\mu$m. The accelerated wear region of the tool is between 200$\mu$m to 300$\mu$m. The tool is considered as worn when its flank wear is equal or more than 300$\mu$m. The tool should be replaced immediately when it is worn to avoid workpiece damage and ensure the product quality.

2) Evolutionary Cost-sensitive Deep Belief Network (ECS-DBN) [43]: Assume the total number of classes is $n$, given
TABLE I

| Class | Flank Wear ($V_B$) | Tool State |
|-------|-------------------|------------|
| 0     | $V_B \leq 100\mu m$ | Fresh      |
| 1     | $100\mu m \leq V_B \leq 200\mu m$ | Progressive Wear |
| 2     | $200\mu m \leq V_B \leq 300\mu m$ | Accelerated Wear |
| 3     | $V_B \geq 300\mu m$ | Worn       |

A sample data $x$, $C_{i,j}$ denotes the cost of misclassifying $x$ as class $j$ when $x$ actually belongs to class $i$. In addition, $C_{i,j} = 0$, when $i = j$, which indicates the cost for correct classification is 0. The meaning of the element $C_{i,j}$ is the misclassification costs of predicting class $i$ when the true class is $j$.

Given the misclassification costs, a data sample should be classified into the class that has the minimum expected cost. Based on decision theory [46], the decision rule minimizing the expected cost $R(i|x)$ of classifying an input vector $x$ into class $i$ can be expressed as:

$$R(i|x) = \sum_{j=1}^{n} P(j|x)C_{i,j}, \quad (1)$$

where $P(j|x)$ is the posterior probability estimation of classifying a data sample $x$ into class $j$. According to the Bayes decision theory, an ideal classifier will give a decision by computing the expected risk of classifying an input to each class and predicts the label that reaches the minimum expected risk. In the traditional learning algorithms, generally all costs are assumed to be equal. In cost-sensitive learning, all costs are non-negative.

However, in real-world applications, the misclassification costs are essentially unknown and nonidentical among various classes. The previous studies [47] usually attempt to determine misclassification costs through try-and-error, that generally does not lead to optimal misclassification costs. Some studies [48] have designed some mechanisms to update misclassification costs based on the number of samples in different classes. However, this kind of methods may not suitable for some cases where some classes are important but rare, such as some rare fatal diseases. To avoid hand tuning of misclassification costs and achieve optimal solution, adaptive differential evolution algorithm [49, 50] has been implemented in this paper. Adaptive differential evolution algorithm is a simple yet effective evolutionary algorithm which could obtain optimal solution by evolving and updating a population of individuals during several generations. It can adaptively self-update control parameters without prior knowledge.

Mathematically, the probability that a sample data $x \in S_{data}$ belongs to a class $j$, a value of a stochastic variable $y$, can be expressed as a softmax function:

$$P(j|x) = P(y = j|x) = \frac{\exp(b_j + \mathbf{W}_j \cdot x)}{\sum_i \exp(b_i + \mathbf{W}_i \cdot x)}, \quad (2)$$

where $b$ and $\mathbf{W}$ respectively are bias and weights within the network. Implement the misclassification costs $C$ on the obtained probability $P(y = j|C, W, b)$, then it can obtain the cost function:

$$P_{\xi} = \sum_{i=1}^{n} P(y = j|x) \cdot C. \quad (3)$$

The hypothesis prediction of the sample $\zeta$ is the member of the minimum probability of misclassification among classes, can be obtained by using the following equation:

$$\zeta = \arg \max_j P_{\xi}(y = j|x). \quad (4)$$

Note that the ECS-DBN only focuses on output layer. For the pre-training phase and fine-tuning phase, the method implemented in this paper is the original greedy layer-wised pre-training method proposed by Hinton [3].

The procedure of training ECS-DBN is presented as follows. Firstly, we randomly initialize a population of misclassification costs. Secondly, we use the training set to train a DBN. After applying misclassification costs on the outputs of the networks, we evaluate the training errors based on the performance of the corresponding cost-sensitive hypothesis prediction. Thirdly, according to the evaluation performance on training set, we select proper misclassification costs to generate the population of next generation. Fourthly, in the next generation, we use mutation and crossover operator to evolve a new population of misclassification costs. Adaptive DE algorithm [50, 51] will proceed to next generation and continue the mutation to selection until the maximum generation is reached. Eventually, we obtain the best misclassification costs and apply it on the output layer of DBN to form ECS-DBN. At run-time, we test the resulting cost-sensitive DBN with test dataset to report the performance.

In ECS-DBN, each chromosome represents misclassification costs for each class, and the final evolved best chromosome is chosen as the misclassification costs for ECS-DBN. The misclassification costs are used to encode into the chromosome with numerical type and value range of $[0, 1]$. G-mean of training set is chosen as the objective to be maximized for ECS-DBN on training dataset. A maximum number of generation is set as the termination condition of the algorithm. The algorithm is terminated to converge upon the optimal solution. At the end of the optimization process, the best individual is used as misclassification costs to form an ECS-DBN. Then test the performance of the generated ECS-DBN on test dataset.

B. Prognostics: Tool Wear Estimation

There are many existing algorithms which can be used as the degradation model such as linear or non-linear regression methods, neural networks [40, 52], support vector machine [53, 54], switching Kalman filter [39] and so on. However, those conventional methods are highly relying on hand-crafted features and cannot provide an effective feature representation learning. We consider that a DBN with the unsupervised feature learning techniques allows us to automatically learn features that could be more suitable to establish a framework with better feature representation learning. Here
Deep belief network (DBN) proposed by Hinton et al. contains multiple hidden layers and each hidden layer constructs non-linear transformation from the previous layer with minimum reconstruction errors. Typically, DBNs are trained with two main procedures, i.e., unsupervised pre-training and supervised fine-tuning. The fundamental building block of DBN is Restricted Boltzmann Machine (RBM) which consists of one visible layer and one hidden layer. To construct DBN, hidden layer of anterior RBM is regarded as the visible layer of its posterior RBM. DBN is stacked with several RBMs and its architecture allows to abstract higher level features through layer conformation.

In RBM, the joint probability distribution of \((v, h)\) of the visible and hidden units has an energy given by \(E(v, h)\):

\[
E(v, h) = - \sum_{i \in \text{visible}} a_i v_i - \sum_{j \in \text{hidden}} b_j h_j - \sum_{i,j} w_{ij} v_i h_j,
\]

where \(v_i, h_j\) denote the states of visible unit \(i\) and hidden unit \(j\), \(a_i, b_j\) are their biases and \(w_{ij}\) represent the weight between them. Probabilities have been allocated among connections pairs visible and hidden units via function:

\[
p(v, h) = \frac{e^{-E(v, h)}}{\sum_{v,h} e^{-E(v,h)}}.
\]

The possibility of the state of hidden vector \(h\) given by a randomly input visible vector \(v\) is as

\[
p(h_j = 1|v) = \text{sigmoid}(b_j + \sum_i v_i w_{ij}),
\]

where sigmoid function denotes \(f(x) = \frac{1}{1+e^{-x}}\). The possibility of the state of visible vector \(v\) given by the previous obtained hidden vector \(h\) is followed by

\[
p(v_i = 1|h) = \text{sigmoid}(a_i + \sum_j h_j w_{ij}).
\]

The widely used contrastive divergence \(56\) algorithm is used to update the weights and biases.

IV. DATASET

In this paper, a real-world gun drilling dataset is used as a case study under the proposed framework. The dataset was acquired with a UNISIG USK25-2000 gun drilling machine in the Advanced Manufacturing Lab at the National University of Singapore in collaboration with SIMTech-NUS joint lab.

A. Experimental Setup

In the experiments, an Inconel 718 workpiece with the size of \(1000\,mm \times 100\,mm \times 100\,mm\) is machined using gun drills. Inconel 718 is widely used in Jet engines. The tool diameter of gun drills is \(8\,mm\). The details of tool geometry can be found in Table \(\text{I}\). The experimental setup and layout are shown in Fig. \(\text{III}\) and Fig. \(\text{IV}\) respectively. Four vibration sensors (Kistler Type 8762A50) are mounted on the workpiece in order to measure the vibration signals in three directions (i.e., \(x\), \(y\), \(z\)) during the gun drilling process. The details about sensor types and measurements are summarized in Table \(\text{II}\).

To collect the data, we conduct experiments that are schematically shown in Fig. \(\text{V}\). The details of the gun drilling
cycle are as follows.

1) Start the machine.
2) Feed internal coolant via coolant hole of the gun drill.
3) Drill through the workpiece.
4) Finish drilling and pull the tool back.
5) Shutdown the machine.

The internally-fed coolant exhausts the heat generated during gun drilling process for improved accuracy and precision.

As described in the previous subsection, the data are sent through a DAQ device with various sampling rate for different kinds of sensors. We designed and programmed an automatic data collection and logging system with LabVIEW® (National Instruments, USA) for the purposes of data acquisition, storage and presentation. The sampled signals are acquired, logged and presented on a laptop via data collection and logging system.

C. Data Preprocessing

Data preprocessing includes data alignment, data normalization and time windowing process. The experimental data used in this paper is aligned by the same adaptive Bayesian change point detection (ABCPD) method proposed in [1]. There is no need to give a repetitive introduction of data alignment process in this paper. Therefore, only data normalization and time windowing process are introduced in this subsection.

1) Data Normalization: In order to handle different ranges of different sensor signals, data normalization is applied on the data to form the normalized inputs in the range of [0,1] prior to any train or test. The normalization is conducted on each sensor signals, this will ensure to treat all sensor signals across all kinds of conditions equally. In another word, the normalization is applied by each dimension of the input data.

2) Time Windowing Process: Time windowing process is to move a sliding window along the time axis of multiple sensor signals and map the original data samples into short-time frames. We then extract and select features over the short-time frames.

Suppose \( t \) is the total number of time series data and \( M \) is the dimension number of each data sample, the original time series data samples are \( X = (x_1, \cdots, x_t, \cdots) \), where the \( t^{th} \) data sample \( x_t \) is \( (x_1, \cdots, x_M)^T \). After time windowing process, we have a series of short-time frames \( X = (x_{t}, \cdots, x_{t+\tau-tw}) \). The \( t^{th} \) data sample \( x_t \) becomes \( (x_{t}, x_{t+1}, \cdots, x_{t+\tau-tw-1}) \), where \( tw \) denotes the short-time window size. An illustration of time windowing process is shown in Fig. 8.

In general, it is suggested to choose the size of time window equaling to integral multiple of the number of data samples acquired during a full rotation of the spindle or the drive of the machine. The time window size is \( tw = N \ast \frac{60}{S_n \ast f_s} \), where \( S_n \) represents the spindle speed (rpm) and \( f_s \) is the sampling frequency (Hz). \( N \) denotes the integral multiple. In this paper, the time window size \( tw \) is chosen as the number of data samples obtained during one full rotation of the spindle of gun drilling machine (i.e., \( N = 1 \)). Because the gun drilling process is a cyclic rotation process, as the spindle rotates 360 deg, the significant characteristics of the signals repeat.

V. PERFORMANCE EVALUATION METRICS

In this section, the common performance evaluation metrics \([1], [3], [10], [11], [23], [30], [39], [40], [43], [45], [57]–[60] \) for diagnostics and prognostics are reported.

A. Evaluation Metrics for Diagnostics

Considering an imbalance multiclass classification problem, assume \( y \) denotes the true target value and \( \hat{y} \) represents the estimated target value. \( \hat{y}_i \) is the predicted target value of \( i^{th} \) data sample \( x_i \) and \( y_i \) is the corresponding true target value. \( N \) is the total number of data samples. To evaluate the performance
Fig. 6. Illustration of an example of vibration raw data. There are a total of 4 vibration sensors placed on top of the workpiece. Each vibration sensor obtained 3-axis (i.e., x, y, z axes) vibration signals. These raw data cover a whole gun drilling cycle from machine startup to machine shutdown.

Fig. 7. The procedure of gun drilling experiments includes 5 steps, namely startup, coolant feeding, gun grilling, finish drilling & pull back the drill and finally shutdown the machine.

Fig. 8. Illustration of a time windowing process with windowing size of 2 (i.e. tw = 2). We obtain short-time frames by moving a sliding window along the time axis of data samples.

of a classifier, the most popular and straightforward evaluation metric is the overall accuracy. The accuracy is formulated as

\[ \text{Accuracy} = \frac{1}{N} \sum_{i=1}^{N} 1(y_i = y_i), \]  

where \( 1(\cdot) \) is the indicator function.

Unfortunately, in the case of imbalanced data distribution, this measurement does not well describe the performance at system level [61]. For example, it tends to dilute the actual performance on minority classes.

To provide a balanced view, many other performance metrics were proposed in this research area, such as precision, recall, F1-score and geometric mean (G-mean). In this paper, accuracy, G-mean, precision, recall and F1-score are used. They are formulated in (10) - (13). Note that the weighted average of the G-mean, precision, recall and F1-score of each class are used to evaluate the performance of multiclass classification.

\[ G\text{-mean} = \sqrt{\frac{TP}{TP + FN} \times \frac{TN}{TN + FP}}, \]  

\[ \text{Precision} = \frac{TP}{TP + FP}, \]  

\[ \text{Recall} = \frac{TP}{TP + FN}, \]  

\[ F1\text{-score} = 2 \cdot \frac{\text{precision} \times \text{recall}}{\text{precision} + \text{recall}}, \]  

where TP, FP, FN, TN represent true positive, false positive, false negative and true negative, respectively.

G-mean evaluates the degree of inductive bias which considers both positive and negative accuracy. The higher G-mean values represent the classifier could handle more balanced and better performance on all classes. G-mean is less sensitive to data distributions. Precision reflects the exactness while recall reflects the detection accuracy. Often times, a system of high precision may lead to low recall, and vice versa. F1-score
represents a balance view between precision and recall in real-world applications.

B. Evaluation Metrics for Prognostics

1) Root Mean Square Error: The most popular evaluation metric, i.e., the root mean square error (RMSE) of the estimated tool wear, is used as a performance metric.

\[
RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^{N} (y_i - \hat{y}_i)^2}
\]  
(14)

In this paper, the units of RMSE values are \(\mu m\).

2) R2Score: R2Score is the coefficient of determination of regression score function. The best possible R2Score is 1.0 and it can be negative. A constant model which always predicts the expected value of \(y_i\) disregarding the input features, would get a R2Score of 0.0. R2Score is an asymmetric function which is defined as \(15\).

\[
R2Score = 1 - \frac{\sum_{i=1}^{N} (y_i - \hat{y}_i)^2}{\sum_{i=1}^{N} (y_i - \bar{y})^2}
\]  
(15)

where \(\bar{y}\) is the mean of the observations, as \(\bar{y} = \frac{1}{N} \sum_{i=1}^{N} y_i\).

3) Mean Absolute Percentage Error (MAPE): Mean absolute percentage error (MAPE) is a statistical measurement of forecasting prediction accuracy.

\[
MAPE = \frac{1}{N} \sum_{i=1}^{N} \frac{|y_i - \hat{y}_i|}{y_i}
\]  
(16)

VI. DIAGNOSTICS AND PROGNOSTICS RESULTS

Note that the DBNMS approach consists of both diagnostic and prognostic steps. We would like to evaluate their performance respectively.

A. Implementation Details

In this paper, five-layered ECS-DBN and DBN have been implemented on the gun drilling dataset. The learning rates of both pre-training and fine-tuning are 0.01. The number of pre-training and fine-tuning iterations are 200 and 500 respectively. The range of hidden neuron number is \([5, 60]\). The hidden neuron number of the networks are randomly selected from the range of hidden neuron number. The dataset is randomly split into training and test datasets. The training ratio is 0.85 and the test ratio is 0.15. All algorithms are trained with 5-fold cross validation. All the simulations have been done for 10 trials.

B. Results of Tool State Estimation

Tool state estimation is also called fault diagnosis in the MDP framework as shown in Fig. 1. It is naturally an imbalanced classification problem. In real-world applications, the fatal faulty cases are always much fewer than healthy cases. Therefore, we form an imbalanced gun drilling dataset and apply ECS-DBN [43] on this dataset to investigate how well the ECS-DBN could handle with imbalanced data on fault diagnosis.

![Table IV: Details of the Gun Drilling Dataset](image)

| Number of Channels | 14 |
|--------------------|----|
| Total Number of Data Samples | 19,712,414 |
| Number of Training Samples | 13,798,690 |
| Number of Testing Samples | 5,913,724 |
| Imbalance Ratio of Class 0 to Class 3 | 1.64 : 1.50 : 1.27 : 1.00 |

Table IV summarizes the imbalanced gun drilling dataset. We select the dataset from the raw experimental data by discarding noise data samples. The total number of data samples in the gun drilling dataset is 19,712,414. The number of training data samples and test data samples are 13,798,690 and 5,913,724 respectively. The data are labeled into 4 classes according to Table I. The imbalance ratio (IR) between 4 classes is 1.64:1.50:1.27:1.00.

In the DBN, the number of hidden neurons are randomly chosen from the range of \([10, 50]\). The activation function of DBN is ReLU. Stochastic gradient descent has been utilized as the fine-tuning training algorithm. The number of pre-training epochs is 300 while the number of fine-tuning epochs is 1000. Training batch size is 500. The parameters of adaptive DE are the same with [43]. We adopt the conventional machine learning algorithms for comparison purpose from [62] with default parameters. In order to show the statistical significance of the performance of ECS-DBN, Wilcoxon paired signed-rank test has been implemented in this section.

The experimental results of imbalanced gun drilling dataset with evolutionary cost-sensitive deep belief network (ECS-DBN), gradient boosting (GB), K-nearest neighbor (KNN), DBN, MLP, linear regression (LR), support vector machine (SVM), AdaBoost, SGD and Lasso, on gun drilling imbalanced dataset in terms of accuracy, G-Mean, precision, recall and F1-score.
TABLE V
COMPARISON OF THE PERFORMANCE BETWEEN EVOLUTIONARY COST-SENSITIVE DEEP BELIEF NETWORK (ECS-DBN) AND DEEP BELIEF NETWORK (DBN), SUPPORT VECTOR MACHINE (SVM), MULTILAYER PERCEPTRON (MLP), K-NEAREST NEIGHBOR CLASSIFIER (KNN), GRADIENT BOOSTING (GB), LOGISTIC REGRESSION (LR), ADABoost CLASSIFIER, LASSO, AND SGD DIFFERENT MACHINE LEARNING ALGORITHMS ON GUN DRILLING IMBALANCED DATASET IN TERMS OF ACCURACY, G-MEAN, PRECISION, RECALL, F1-SCORE.

| Model Name | Accuracy | G-mean | Precision | Recall | F1-score |
|------------|----------|--------|-----------|--------|----------|
| ECS-DBN    | 0.9393 ± 0.0228 | 0.649 ± 0.1526 | 0.9027 ± 0.0542 | 0.8591 ± 0.1289 | 0.8776 ± 0.0950 |
| GB         | 0.8886 ± 0.0760 | 0.4913 ± 0.2227 | 0.8626 ± 0.1177 | 0.7568 ± 0.2368 | 0.7875 ± 0.1988† |
| KNN        | 0.8699 ± 0.0117 | 0.3468 ± 0.0378 | 0.7626 ± 0.1147 | 0.7150 ± 0.1751 | 0.7343 ± 0.1435† |
| DBN        | 0.8123 ± 0.0623 | 0.2581 ± 0.1892 | 0.6543 ± 0.2541† | 0.5933 ± 0.3422 | 0.6012 ± 0.2996† |
| MLP        | 0.7435 ± 0.1485 | 0.1660 ± 0.1177 | 0.5319 ± 0.1360 | 0.5213 ± 0.3499 * | 0.5184 ± 0.3249 † |
| LR         | 0.7322 ± 0.0130 | 0.0476 ± 0.0537 | 0.6465 ± 0.1286 | 0.4311 ± 0.3731 | 0.4436 ± 0.3093 † |
| SVM        | 0.7132 ± 0.1371 | 0.1530 ± 0.2037 | 0.4612 ± 0.3808 | 0.4433 ± 0.4201 | 0.4270 ± 0.3722 † |
| AdaBoost   | 0.6944 ± 0.0429 | 0.0017 ± 0.0023 | 0.3721 ± 0.3574† | 0.3690 ± 0.4100† | 0.3491 ± 0.3659† |
| SGD        | 0.6607 ± 0.0481† | 0.0107 ± 0.0163 | 0.5363 ± 0.3036† | 0.3390 ± 0.3802 | 0.3294 ± 0.3153† |
| Lasso      | 0.6503 ± 0.0885† | 0.0139 ± 0.0502 | 0.3422 ± 0.3406† | 0.3238 ± 0.4021† | 0.3049 ± 0.3373† |

† indicates that the difference between marked algorithm and the proposed algorithm is statistically significant using Wilcoxon rank sum test at the 5% significance level.

TABLE VI
COMPARISON OF THE AVERAGE COMPUTATIONAL TIME OF ECS-DBN AND DBN WITH 5-FOLD CROSS VALIDATION ON THE GUN DRILLING IMBALANCED DATASET OVER 10 TRIALS.

| Model Name | Average Computational Time(s) | Average Computational Time without DBN training time(s) |
|------------|-------------------------------|------------------------------------------------------|
| ECS-DBN    | 9977.39 ± 148.55              | 1280.28                                              |
| DBN        | 6907.11 ± 2308.22             | -                                                   |

1) Suitability: We report the accuracy via a 5-fold cross validation over 10 trials in Table V. ECS-DBN outperforms all other competing algorithms. The results suggest that ECS-DBN is more suitable for diagnostics than the other competing algorithms, therefore, potentially leads to better prognostics in the MDP framework.

2) Stability: To measure the stability of the diagnostics module, the performance variance are compared. It is noted in Table V that, ECS-DBN outperforms other competing algorithms with comparably lower variances. This suggests that ECS-DBN could provide lesser variance in predictions so as to enhance the stability of the diagnostic module.

3) Quality: For quality evaluation of the classification made by diagnostic module, F1-score is calculated [60]. F1-score represents the trade-off between precision and recall by interpreting a harmonic mean between precision and recall. Higher F1-score represents better quality of predictions. According to Table V, we observe that ECS-DBN achieves the best average F1-score over 10 trials of 0.8776 with a low variance of 0.0950 among other competing algorithms. The performance of the ECS-DBN suggests that it could provide quite good quality of diagnostic predictions.

4) Computational Time Analysis: Average computational time of ECS-DBN and DBN are presented in Table VI. Based on the computational time without DBN training time, it can be observed that comparing with the training time of DBN, the average time of adjusting proper misclassification costs by evolutionary algorithm is very small that can be ignored. Therefore, ECS-DBN with evolutionary algorithm to find the appropriate misclassification costs is quite efficient for imbalanced multiclass classification and thus makes ECS-DBN to be applicable in diagnostic module.

C. Results of Tool Wear Estimation

Tool wear estimation is the prognostic step in the MDP framework as shown in Fig. 1. In this section, the analysis of the results mainly consists of three parts. Firstly, we evaluate its performance under different signal states. Secondly, the performance of DBNMS approach is evaluated and compared with other single state approaches at algorithmic level. Finally, the comparison between MDP framework and other single state frameworks at system level is presented.

1) Comparison of Different Signal States: Sensor selection is an important part in numerous industry applications which is widely used to reduce costs and easy installation. To verify the effects of different signal states, the simulations of DBNMS with the signals from different kinds of sensors have been carried out in this section. In this real-world experiment two kinds of sensors have been used, namely dynamometer and accelerometer. The force and torque signals are taken from the same dynamometer while 12 vibration signals are obtained from 4 accelerometers. Therefore, totally 7 different combinations of sensor signals including single force signal, single torque signal, 12 vibration signals from accelerometers, force and torque signals (F-T), force and vibration signals (F-Vib), torque and vibration signals (T-Vib), all force, torque and vibration signals from both dynamometer and accelerometers (F-T-Vib) have been investigated in this section.

Table VII shows the test results of DBNMS with 7 different combinations of sensor signals, i.e., force, torque, vibration, force and torque (F-T), force and vibration (F-Vib), torque and vibration (T-Vib), all force, torque and vibration signals from both dynamometer and accelerometers (F-T-Vib) have been investigated in this section.
2) Comparison of Different Algorithms: In order to study the effects of multi-state approach and single state approach at algorithmic level, 12 different regression algorithms, i.e., DBNMS (smooth), DBNMS, DBN, MLP, extreme learning machine (ELM), support vector machine (SVM), ridge regression (RR), Lasso, AdaBoost, stochastic gradient descent regressor (SGD), elastic net (EN), least angle regression (LAR), are used as the inputs. According to the figures, it is clear that the combination of F-T-Vib obtained lower average RMSE values, lower average MAPE values and higher average R2Score values with small variance than other six combinations. The results also show that we benefit from the fusion of multiple sensing signals. Therefore, in the rest of the paper, all force, torque, vibration signals are used as the inputs.

3) Computational Time Analysis: Table IX reports the average computational time of 11 different regression algorithms, i.e., DBNMS, DBN, GB, ELM, SVM, RR, Lasso, AdaBoost, SGD, EN and LAR over 10 runs on gun drilling dataset with time windowing processing. It can be observed that LAR takes the least time compared to other algorithms.

### Table IX: Average Computational Time Analysis for Different Algorithms

| Algorithm        | Average Time (s) |
|------------------|------------------|
| DBNMS (smooth)   | 0.2              |
| DBNMS            | 0.3              |
| DBN              | 0.4              |
| MLP              | 0.5              |
| ELM              | 0.6              |
| SVM              | 0.7              |
| RR               | 0.8              |
| Lasso            | 0.9              |
| AdaBoost         | 1.0              |
| SGD              | 1.1              |
| EN               | 1.2              |
| LAR              | 1.3              |

The experimental results of these 12 different algorithms are obtained on test data. Their performances on test data with all sensor inputs over 10 trials are shown in Table VIII in terms of RMSE, R2Score and MAPE. From the observation in Table VIII, DBNMS has shown lower average RMSE values, lower average MAPE values and higher R2Score values than those of other competing algorithms. Thus, the results indicate that DBNMS has better average performance with low variance than many popular algorithms. To clearly illustrate the comparison results between different algorithms, the results are plotted into three boxplots in terms of RMSE, R2Score, MAPE respectively in Fig. 12. It is obvious that DBNMS outperforms other algorithms in terms of RMSE, R2Score and MAPE.
has the shortest average running time. DBNMS is still useful for TCM with more accurate performance in spite of longer training time. Our experimental platform is a desktop PC with Intel Core i7-3770 3.40GHz CPU, NVIDIA GeForce GTX 980 and 32GB RAM. All the simulations are done under Linux system.

4) Comparison of Different Frameworks: To evaluate the frameworks as shown in Fig. [1] at system level, namely, conventional data-driven based, deep learning based and MDP, we summarize the performance of these frameworks in Table. [X]

Since there is a lack of physical model for these specific gun drills, we do not compare MDP with physical-based framework in this paper. Here the MLP-PCC [1] is chosen to represent the conventional data-driven framework. A DBN based framework with automatic feature learning is a typical deep learning approach solution. To show the effect of multi-state modeling, we only implement the multi-state in MDP framework, and single state in both conventional and deep learning framework.

From Table. [X] it is observed that the proposed MDP outperforms conventional data-driven based framework as well as deep learning based framework in terms of RMSE and R2Score. With multi-state modeling, MDP can provide more accurate results than other single state frameworks.

VII. Conclusion

In this paper, a multi-state diagnosis and prognosis (MDP) framework has been proposed for tool condition monitoring using a deep belief network based multi-state approach (DBNMS). The proposed DBNMS is based on the multiple tool states identified by ECS-DBN that can switch to appropriate prognostic degradation models for prediction. The DBNMS has been applied to tool wear prediction on gun drilling and the experimental studies show that the DBNMS outperforms many popular machine learning algorithms in tool condition monitoring. It has also been shown that the DBNMS is able to generate more accurate and robust prognostic predictions and has good generalization ability over various operating conditions.

To elevate the overall performance of TCM, diagnosis and prognosis are tied in one framework. Due to different data attributes in different health states, a multi-state diagnosis and prognosis framework has been proposed. The proposed MDP framework is one step further towards an unified end-to-end diagnosis and prognosis framework for TCM.

We hope to extend the idea to other conventional data-driven frameworks. Our future work includes the application of multi-
objective deep belief networks ensemble (MODDBNE) as the degradation model to obtain optimal hyper-parameters for better performance. Other deep learning architectures will also be examined based on the gun drilling real-world experimental datasets to achieve better accuracy in TCM.

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