A Knowledge Transfer Platform for Fault Diagnosis of Industrial Gas Turbines

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***Abstract* — The aim of this paper is to introduce the bases of an intelligent fault diagnostic platform, which assists in detecting mechanical failures of Industrial Gas Turbines (IGTs). This comprises an integration of an expert system and its complementary signal processing techniques. The essential characteristic here is not to exclude humans (experts) from the diagnostic process, but rather to transfer their knowledge and experience to a computerized platform. The automated process executed by the computerized platform is to ensure the scalability and consistency in fault diagnosis; while the humans are required to corroborate the transparency and liability of the outcomes. In this paper, a Knowledge Transfer Platform (KTP) is proposed for fault diagnosis of industrial systems. It is then designed and tested for combustion fault diagnosis using field data of IGTs. The preliminary results have revealed the feasibility and efficacy of the proposed scheme, which has the potential to be further extended to a large industrial scale and to different engineering diagnostic applications.**

Keywords— knowledge transfer, fault diagnosis, industrial gas turbine, expert system, signal processing.

I. INTRODUCTION

For industrial applications, fault diagnostic tools are of great importance in ensuring the availability and productivity of machineries and plants throughout their lifecycle. Today, with the fast development of sensor and computing technologies, traditional "fail and fix" maintenance strategy has vastly transformed to a "predict and prevent" mechanism through the use of advanced computerized techniques [1].

Among these techniques, an early development is Expert System (ES). ESs are designed primarily as *if–then* rules, by reasoning using existing knowledge from the human experts. It worked well, however, ES by its nature could never be better than the human expert, since the knowledge base contains heuristics - rules of thumb used by human experts who work in the domain. Essentially, ESs have an information extraction bottleneck and knowledge extension drawbacks [2]. Moreover, with the increase in size and complexity of industrial processes, ordinary knowledge-based rules can often be incomplete, lack consistency and robustness to uncertainties.

Alternatively, more diagnostic tools tend to use techniques based on direct Signal Processing (SP), which provide improved accuracy and an increased degree of automation. These approaches do not rely on prior expert knowledge, but rely on the precision and richness of operational and historical data collected on the mechanical system. Latent features are then extracted from the sensor measurements to characterise the health and fault conditions of the system [3,4].

The fault diagnostic tools are used to provide automatic early warning of mechanical fault, so that premature component failure can be avoided. On the one hand, this requires reduced "missed alarms" (i.e. the component is faulty, but the diagnostic tool could not pick it up) to minimise the financial losses due to machinery component failures. On the other hand, it also requires reduced "false alarms" (i.e. the component is normal, but the diagnostic tool has identified it to be faulty). This requirement is because, for the Industrial Gas Turbine (IGT) systems considered here, even short periods of unscheduled outages can cause large financial losses as a result of downtime and reduced productivity. The same applies to similar equipment/plants from other emerging engineering sectors [5]. Thus, high levels of confidence (trust) in the predictive tools is of significant concern; and the only way to create trust is to make the process more transparent, so that the humans are able to understand what has led to the automated diagnostic outcome [6].

In terms of transparency, ESs, although often thought to be outdated, can be very valuable in providing insights of the system, as the *if–then* rules are normally implemented by using the existing knowledge from the human experts, which relies on a long-term accumulation of domain-specific experiences in the fault mechanisms, mechanical principles and other related expertise of the machine [7]. Taking these into consideration, this paper proposes a Knowledge Transfer Platform (KTP) for fault diagnosis, where the platform combines the strengths of both ES and SP techniques. In this way, the KTP will be able to deliver better efficiency and accountability in fault diagnosis, because it automates the diagnostic process with more consistency and robustness via the SP techniques, and it increases transparency in the process through the expert knowledge-based reasoning mechanisms. The key aspect here is not to replace humans, but instead to leverage computerised technologies to human experts. By retaining staff with valuable domain expertise, it makes their contributions even more vital in the subject area. In such manner, more work can be done quicker, since the computer performs the boring/tiring tasks, e.g. scanning and analysing large amount of data, while human experts review the outcomes, training the diagnostic agent to progress.

In the following sections, Section II describes the overall concept of the proposed KTP; Section III designs a KTP for fault diagnosis of a combustion system on IGTs; Section IV presents a case study and its results; and finally, Section V concludes the paper.

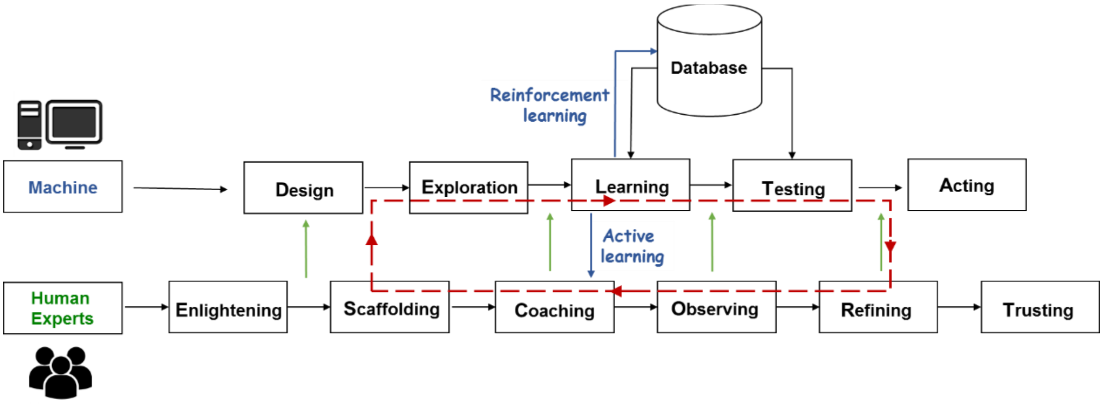


Fig. 1. The outline scheme of the KTP.

II. THE CONCEPT OF THE KTP

This paper proposes a new way to cooperate humans and machine (computer) for industrial fault diagnostics, in such a way that humans provide valuable experience and expertise in the subject area, whereas the machine assists them by dealing with complicated and repeated data analysis tasks. The outline scheme of the proposed KTP is demonstrated in Fig. 1.

A. *The Role of the Machine*

The machine will be evolving through a DELTA process:

1) **D**esign: the structure of the intelligent fault diagnostic platform will be designed;

2) **E**xploration: exploring the expert knowledge-based rules, i.e. the "symptom-problem" look-up table;

3) **L**earning: learning to classify the patterns (i.e. "symptoms") from field data using complementary SP techniques;

4) **T**esting: using independent datasets from various sources to test the diagnostic agent's robustness;

Repeat from Step 2), until the machine outcomes are acceptable by the human experts.

5) **A**cting: The last stage is of course when the machine can act in the absence of human experts in fault diagnostics of the subject area.

B. *The Role of the Humans*

In parallel, the human experts will be involved over an ESCORT process:

1) **E**nlightening: contributing insights and helping the programmer to gain a greater understanding in the subject area;

2) **S**caffolding: contributing expert knowledge and providing outline rules, with the maximum coverage of the existing "symptoms" and their corresponding "problem" types;

3) **C**oaching: setting tasks and giving feedbacks to the machine's performances, i.e. providing test cases and the corresponding fault (or normal) types from industrial practices;

4) **O**bserving: monitoring the machine's performance through a variety of tests, e.g. checking the outcomes on a regular basis;

5) **R**efining: examining the machine's performance and refining the expert rules if necessary, e.g. modifying existing rules or adding newly discovered rules.

Repeat from Step 2), until the machine outcomes are acceptable by the human experts.

6) **T**rusting: The ultimate goal is indubitably when the machine can be trusted to act in the absence of human experts for the fault diagnostic tasks.

C. *Machine Learning Paradigms*

During the learning phase of the machine, two learning paradigms will be applied.

1) Reinforcement Learning [8]: The diagnostic agent learns itself to achieve successes which lead to the highest long-term rewards, e.g. minimum errors from the observations/ field data.

2) Active Learning [9]: While SP techniques handle the routine cases, the edge cases/ difficult calls will be sent to the human experts for investigation, which will in return strengthen the learning abilities of the diagnostic agent.

III. A KTP DESIGN

As a proof of concept, the proposed KTP scheme is applied for fault diagnostics of a combustion system on IGTs here, although it can be readily transferrable to other industrial fault diagnostic applications. In this case, signals collected from the Pilot Burner Tip (PBT) thermocouples are studied, as shown in Fig. 2, which provide information of the temperature distribution in the combustion system [10]. The sampling rate is one sample per minute.

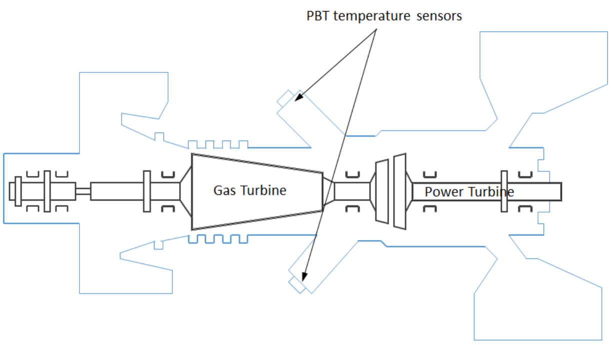


Fig. 2. The position of PBT sensors on an IGT.

A. *Signal Representations—"Symptoms"*

For an adequate description of the subsequent expert knowledge-based rules (the "symptom-problem" look-up table), the different "symptoms" (signal representations) for the case study are categorized as follows [11].

1) Normal Signal: It indicates that the machine is running at normal conditions, with the changes of signals' mean and variance remaining within a reasonable range.

2) Stuck Signal: It describes a condition where the sensor reading sticks to a particular value and remains unchanged despite changes in the operating point.

3) Spike Signal: It characterizes a sudden increase in the sensor reading to an extreme high value out of a typical sensor reading range.

4) Bias Signal: It constitutes a step change in the sensor reading from the mean baseline.

5) Drifting Signal: It represents gradual change of a drift-type which occurs over a long-time span.

6) Erratic Signal: It consists a change in the variance of the sensor readings, showing with consistent spiking noise.

Examples of the six types of signal representations are illustrated in Fig. 3.

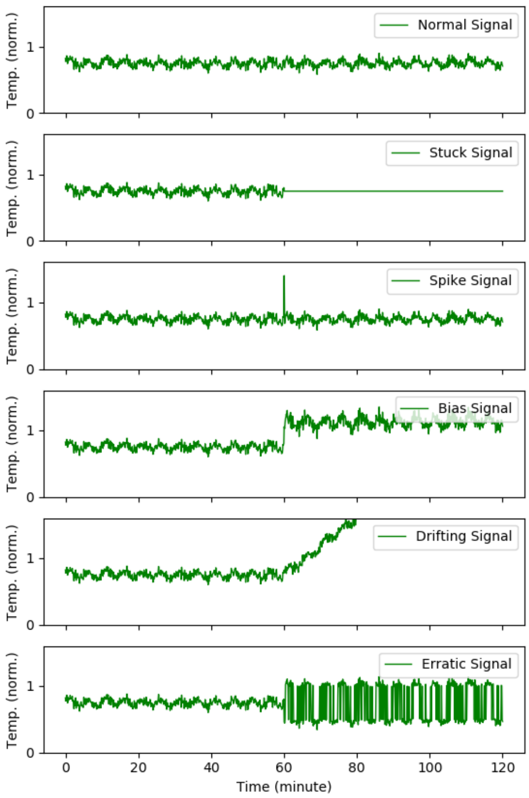


Fig. 3. Example signals: six types of signal representations (with normalised temperature readings).

B. *Expert Knowledge—"Problems"*

Experienced IGT service engineers have concluded that typical sensor faults appear to be "Stuck Signal" and "Spike Signal", due to the low sampling rate. As for combustion system component faults, through a number of field investigations, it can be summarized that,

1) When the PBT measurements represent a "Bias Signal", followed by "Drifting Signals" gradually over a long-time period, the case is usually caused by a leakage of main burner, where the flow is shown quicker, or a blockage of the main burner, where the flow is shown slower.

2) When the PBT measurements present "Erratic Signals" consistently, the case is normally caused by the presence of carryover/condensate within the gas fuel system, which can impinge on combustion hardware causing damage. [12]

C. *Expert Knowledge-based Rules*

Based on the subject-matter investigations by the human experts, the observed "symptoms" and their corresponding "problem" types are utilised to form the knowledge-based rules as follows.

1) If "Stuck Signal", *then* "Sensor Fault";

2) If "Spike Signal", *then* "Sensor Fault";

3) If "Normal Signal", *then* "Normal: Steady-state Condition";

4) If "Bias Signal", *then* "check all sensors in the group";

4.1) If "all sensors change", *then* "Normal: Operation Point Change";

4.2) If "not all sensors change", *then* "Component Fault";

5) If "Drifting Signal", *then* "check all sensors in the group";

5.1) If "all sensors change", *then* "Normal: Load Fluctuation";

5.2) If "not all sensors change", *then* "Component Fault";

6) If "Erratic Signal", *then* "Component Fault: Gas-fuel Issue";

7) If "None Above", *then* "Unknown Case: Consult with a Human Expert".

D. *Signal Processing Techniques*

With the built rules, the next step is to classify the input signals into different types of signal representations, including an "Unknown" type. This can be done through a number of SP techniques.

This paper applies an existing SP approach based on wavelet analysis and thresholding techniques, which contains three main steps:

1) *Decomposition of the signal by Maximal Overlap Discrete Wavelet Transform* (MODWT). The use of the wavelet techniques is to provide the time-frequency information of the signal, where usually the decomposed low-frequency components characterize the underlying trend of the signal, whereas the high-frequency components have the noise and/or fault signified. Furthermore, the application of circular convolution in MODWT allows the low-pass and high-pass filters of DWT to be applied on time-series of any length [13].

2) *Universal threshold estimation of the MODWT detail coefficients*. This universal thresholding method was first proposed in Donoho and Johnstone (1994) based on a Gaussian noise model [14], which is expressed as

$$\lambda_j = \hat{\sigma}_j \sqrt{2 \log n}, where\ \hat{\sigma}_j = 1.4828 \times MAD(D_j)$$

where λ_j is the threshold for decomposition level j, n is the length of the signal, D_j is the detail coefficients at level j, and *MAD* is the Median Absolute Deviation.

3) *Cross Validation* (CV) *to determine the optimal decomposition level for thresholding* [15]. The standard CV technique can be found from Nason (1994) [16]. However, here, a modified approach is used, which follows the work by Kozionov et al. (2011) [17]. The optimal level for thresholding is determined as the level with the lowest CV score, which is calculated from

$$F(k) = \sum_j \left(\hat{f}_k^{even} - \bar{z}_j^{odd}\right)^2 - \left(\hat{f}_k^{odd} - \bar{z}_j^{even}\right)^2$$

Firstly, the data set $\{x_1, \cdots, x_n\}$ is separated into odd and even indexed data sets. $\bar{z}_j^{odd}$ and $\bar{z}_j^{even}$ represent their corresponding interpolated data sets with original length *n*. $\hat{f}_k^{odd}$ and $\hat{f}_k^{even}$ are the wavelet regression estimates of the interpolated odd and even data sets reconstructed at level *k* calculated from

$$\hat{f}_k = a_k + \sum_{i=1}^{k} d_i$$

where a_k is the approximate coefficient at decomposition level 'k' from MODWT and d_i is the detail coefficient at an arbitrary decomposition level 'i' from MODWT.

Another modification is that, a value of 1 is added to the level obtained from the CV score. For example, while the standard approach would give Level 1 as the most relevant detail level, the modification may give Level 2 as the result. This was determined empirically, which gives a better compromise between precision and accuracy for the specific industrial application, or to suit the extracted expert rules, in order to catch mild transients which the original CV approach would miss [11].

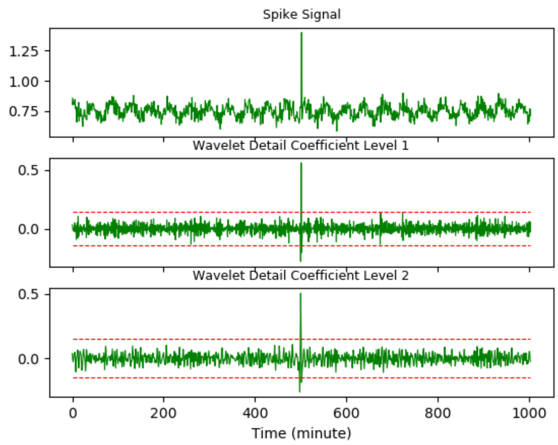
For demonstration, three diagnostic examples are shown in Fig. 4. It is shown that, all faulty signals can be detected by the applied techniques. With a simple logic table of the combined results from both decompositions, the type of the fault can also be identified. For instance, a single time step of exceeding thresholds at both decompositions indicates a Spike Signal; consistent results of exceeding both thresholds indicate an Erratic Signal; and one time step of exceeding Level 2, with some detected faults in Level 1, would indicate a Bias Signal.

IV. Case Study

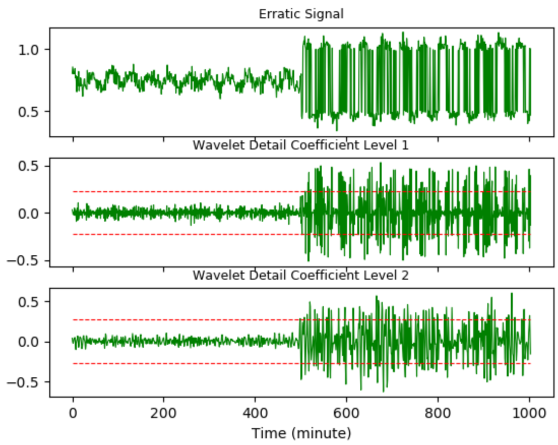
The proposed techniques are then applied to a real industrial case for fault diagnosis of combustion system on an IGT. This is a previous pre-chamber failure case, where a leak path resulted in extra gas in the pilot burner, which caused the step increase of temperature and eventually the burnout. The PBT measurements are shown in Fig. 5, and two example points are investigated as a feasibility study. There are six PBT signals, with each corresponding to one combustor can. The diagnostic results of the studied measurements are shown in Fig. 6 and Fig. 7 respectively, for the two example cases (points A and B).

Fig. 6(a) is specifically included to show that how the 2 levels are determined through the above-mentioned Cross Validation step (Step 3). As a compromise between accuracy and precision, it determines the most relevant or minimum detail level to consider and ignores the rest to minimize false alarms. For the data at case point A, the determined cross validation level is 2, so it ignores the rest of the levels as an approximation. This has explained that how the small transients in the PBT1 signal are disregarded to avoid false alarms. For the same reason, only the first two levels are considered for the thresholding scheme, shown in Fig. 6(b) - (f). For case point A, it is shown that the step changes in PBT2 have been identified, while the other five PBTs are in the normal state. This indicates a Component Fault in combustor can 2, based on the previously specified expert rules, which is in agreement with the real field investigation report.

Similarly, in Fig. 7, PBT2 has been identified for step changes again, whilst the other five sensors are within normal ranges. For simplicity, only the results for PBT2 are shown here for case point B.



(a)



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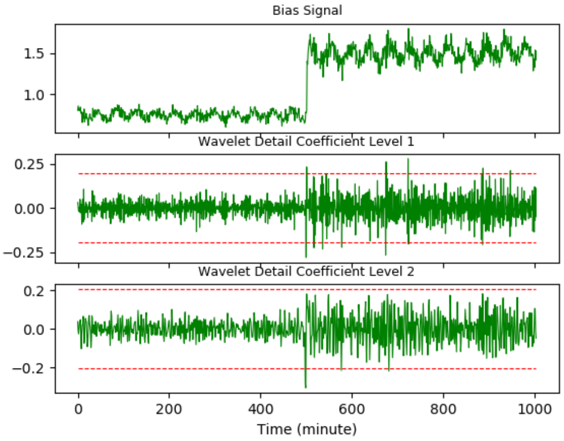


(c)

Fig. 4. MODWT and threshold setting of three example signals: (a) spike signal; (b) erratic signal; and (c) bias signal.

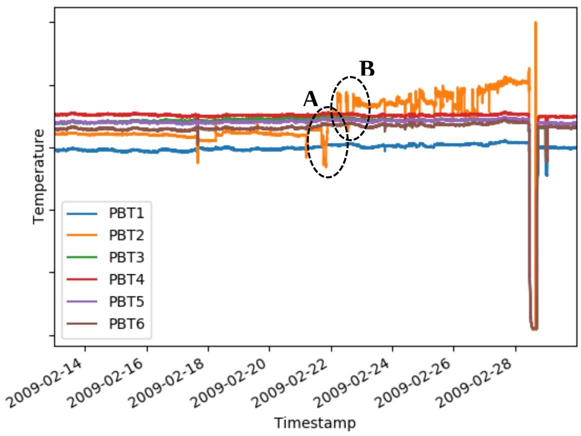
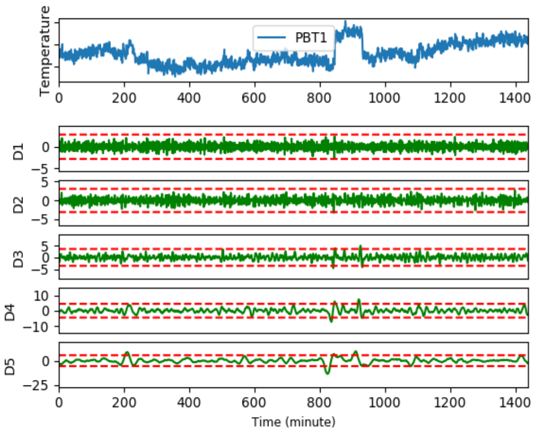
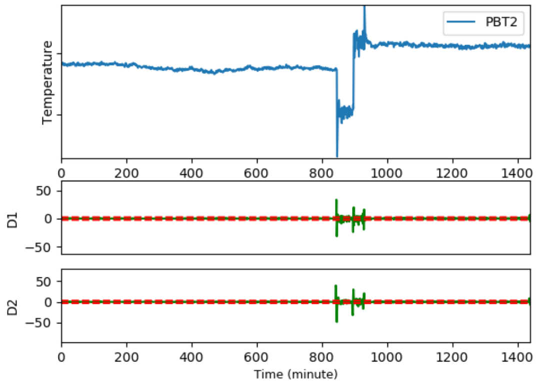


Fig. 5. Case study: PBT measurements on an IGT



(a)



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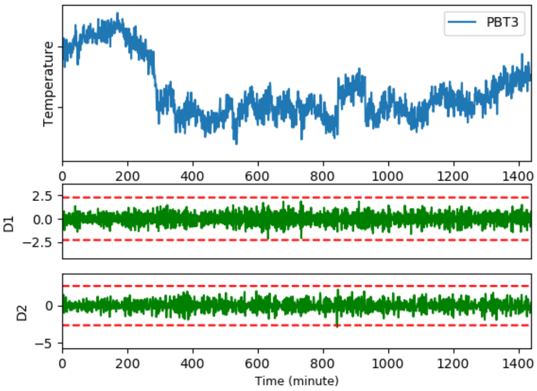

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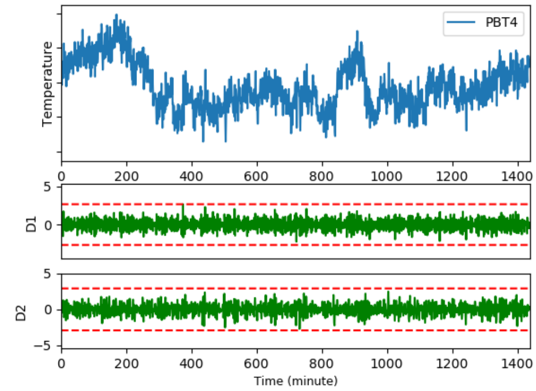
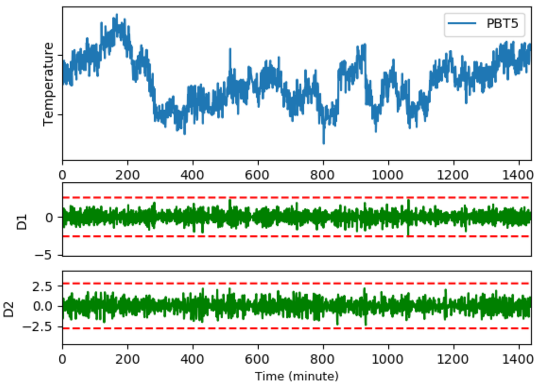
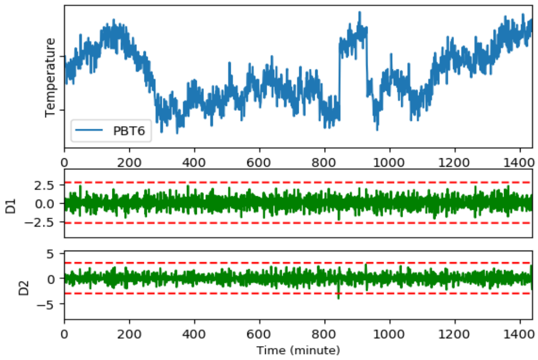


(d)



(e)



(f)

Fig. 6. Diagnostic results of the case study at point A for onset fault from PBT2 based on diagnostic results of the six PBT sensors.

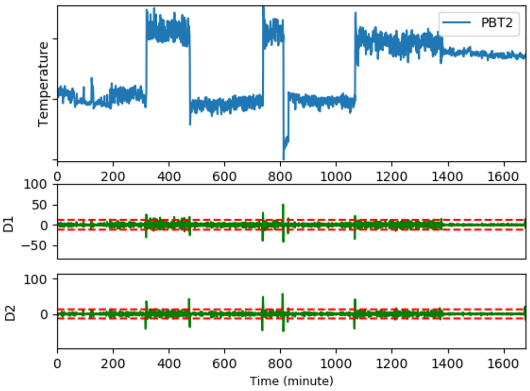


Fig. 7. Diagnostic results of the case study at point B for onset fault from PBT2.

V. CONCLUSION

This paper has introduced a Knowledge Transfer Platform for fault diagnosis of industrial systems. A scheme to combine Expert Knowledge and its corresponding Signal Processing techniques is presented. Then, a simple feasibility study is conducted for fault diagnosis of the combustion system on a gas turbine. The automated process by the SP techniques is to achieve immensely repeated data analysis and accuracy of the fault detection results, whereas industrial engineers are needed to contribute in building the expert knowledge-based rules, so as to categorize or interpret the automated fault detection results.

The ultimate aim of the KTP is to train the machine to be trustworthy in performing the fault diagnostic tasks. This will require the experienced engineers to scaffold the basic expert rules to start with. Then, the machine can learn the knowledge-based rules via reinforcement learning using online data. The patterns or rules that cannot be learned adequately by the machine will be sent to the human experts again via an active learning scheme. It is expected that the humans will be kept in the loop all the time, although the requirements of their inputs will be reduced more and more through time.

From the academic point of view, the direct SP tools may be readily available, but the contribution of industrial expert knowledge is invaluable. As for future work, for the proposed KTP scheme to work in a real industrial environment, not only is there a need to search for suitable SP and machine learning tools, but also human experts should not be held back to their knowledge contribution. It is paramount for the policy makers in industries to encourage their engineers to participate. For this end, a "Recognition and Reward" policy is recommended, so that the human experts' knowledge and their contributions will be acknowledged and paid for. Only in this manner can data scientists and industrial engineers work together in harmony to generate KTPs, and have them accepted and implemented for widespread industrial applications.

ACKNOWLEDGMENT

The authors would like to thank Siemens Industrial Turbomachinery Ltd., Lincoln, U.K., for providing access to the real-world gas turbine data to support the current research.

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