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RESEARCH ARTICLE

Keynote Summaries of the First International Symposium on Dynamics, Monitoring, and Diagnostics

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Abstract: The first International Symposium on Dynamics, Monitoring, and Diagnostics was held in Chongqing, China, in April 2022. The Symposium, which was attended both virtually and in person, had an audience of 2000 and was aimed at enhancing the intelligence of condition monitoring for engineering systems. During the Symposium, five keynote addresses were delivered by world leading experts, and this paper is comprised of summaries of these addresses to ensure that the important messages of these speakers are properly on record and readily able to be referenced.

Keywords: Eigen-structure assignment; gear wear; gear diagnostics; information theory; intelligent diagnosis; machinery; maintenance; passive vibration control; prognostics; structural modification

I. INTRODUCTION

This keynote summary reflects the important aspects in the field of dynamics, monitoring, and diagnostics. Current research and potential research trends in the future on these important topics are discussed. Section II on choosing the good signal model for vibration-based condition monitoring was completed by Professor Jérôme Antoni from the University of Lyon. Section III on the enhancement of vibration monitoring under noisy nonstationary conditions was written by Professor Stephan Heyns, Dr. Stephan Schmidt, and Dr. Daniel Wilke from the University of Pretoria. Section IV on machinery informatics: an interdisciplinary subject to enable intelligent maintenance was written by Professor Jing Lin from Beihang University. Section V on frequency and mode assignment via structural modifications: basic theory and applications was presented by Professor Huajiang Ouyang from the University of Liverpool. Section VI on gear wear: measurement, diagnosis, and prognosis was written by Dr Wade Smith from the University of New South Wales.

II. CHOOSING THE GOOD SIGNAL MODEL FOR VIBRATION-BASED CONDITION MONITORING

Vibration-based condition monitoring heavily relies on signal processing, for designing methods of detection, identification, and characterization of faults, or for preprocessing signals before they are fed to machine learning classifiers. A plethora of ad hoc methods have been proposed to achieve these tasks, sustained by an impressive diversity of heuristics and algorithmic variants, and leading to everlasting round-robin benchmarks. Although the quest for universal methods is hopeless, the point made by this presentation is that "optimal" indicators and signal processing methods can be designed, provided that they are guaranteed to capture the diagnostic information contained in a "good signal model."

Coming back to the basics, condition monitoring consists in assessing the health status of a machine from measurements, typically in the form of vibration, electric current, instantaneous speed of rotation, etc. [1]. A fundamental goal is to recognize possible symptoms of a fault—the so-called mechanical signature [2]—which usually manifest themselves as subtle changes in the signal properties [3]. This is where signal models are needed. A signal model is here understood as a way to describe the observed measurements, with capability to capture its symptomatic behavior; this is not to be confused with mechanical models, which are more concerned with the explanation of the physical phenomena that produce the signals.

The standard and historical signal model is to describe machine signals as a sum or periodic components, as generated by the steady-state response of a system to rotating forces. Condition monitoring then essentially consists in checking for the presence of characteristic fault frequencies, which can be calculated from the kinematical diagram of the machine. It is noted at this juncture that Fourier analysis offers an optimal tool in this endeavor. One refinement of this model is to recognize that machine signals are actually periodic with respect to the angle of rotation of the mechanical components, rather than to time;

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189

even very small speed fluctuation can make this difference palpable and jeopardize standard Fourier analysis if not properly considered. The good signal model under this perspective is that of angle-periodic signals. From the technological aspect, the angle-periodic model requires the additional measurement of a reference angle of rotation, either by a dedicated encoder or directly from the signal itself [4]; from the theoretical aspect, it has been showed how to perform Fourier analysis of angle-periodic signals directly from the time measurements [5,6], that is, without needing angular resampling [7,8].

Models based on sums of periodic components are good enough to represent "deterministic" signals but are unable to reflect signals with "random" behavior, as is often encountered when the bandwidth of the measurements is increased [9]. It is noted here that randomness is to be understood in its epistemic meaning, as a way to coarsely describe phenomena that are too complex to be modeled otherwise. When dealing with rotating machines, typical examples are provided by surface faults in bearings and gears. The theory of cyclostationarity perfectly covers these cases by extending the periodic model to random signals that still experience some hidden periodicity due to the rotation of the mechanical components. An illustrative example of a (second-order) cyclostationary (CS) signal is a stationary random noise that is amplitude modulated by a periodic function. The application of CS models to condition monitoring has been the object of several research works in the last two decades [10], recently revivified by the introduction of a fast algorithm to calculate the spectral correlation [11], a tool that generalizes Fourier analysis to jointly display the spectral and the modulation contents of a signal.

Just as for the periodic model, the CS model needs to be refined when applied to signals measured on machines that do not operate at perfectly constant speed. The issue is however more intricate, since the angular dependence essentially impacts the hidden periodicities (e.g. modulations) of the signal but barely its local correlation. Angle-time cyclostationarity is a new framework introduced by the author a decade ago to account for this situation [12,13]. An angle-time CS signal is one whose statistics depend on temporal time lags (in second) and are periodic in angle (in radian). This framework allows the generalization of the spectral correlation to its order-frequency counterpart, which can jointly display the spectral (in Herts) and the modulation (in 1/rad or in order) contents of a signal. Some examples of successful applications of this framework are the diagnosis of rolling element bearings [14,15], the detection of rattle noise in gearboxes [16], and blind deconvolution [17].

One of the definite outcomes of good signal models is to allow the design of optimal health indicators, in the sense that they maximally extract the diagnostic information contained in a signal [18]. (Angle-time) CS models have proven very rich in this respect; they have the quite unique capability to capture the diagnostic information conveyed in the form of nonstationarity, as is the case for the repetitive impacts or, more generally, by the modulations produced by faults. This draws a direct analogy with speech and music signals, where information is mainly communicated by nonstationary patterns. This reasoning is to be opposed to most other approaches, which mainly search for the diagnostic information in the departure from non-Gaussianity [19].

It is worth pointing that other signal models, not covered in this presentation, have proven successful in condition

monitoring. One exploits the sparsity characteristics of incipient faults. It consists of representing the fault signature by means of a decomposition basis that requires very few components and to search for the presence of these in the measurements. The periodic model actually falls in this category, where periodic components constitute the sparse representation. Perhaps less obvious is that a CS signal is also an instance of a sparse model; this is because its spectral correlation—a 2D distribution—is actually made of a sum of spectral lines indexed by discrete cyclic frequencies, that is, a 1D distribution. This fact was for instance exploited in [20].

In conclusion, signal models offer to condition monitoring the framework to develop optimal diagnosis tools and health indicators, where the notion of optimality takes a precise meaning in terms of the information that a model is able to capture. This is particularly needed nowadays, when facing the huge number of scientific publications in the field of condition monitoring, and attempting to benchmark their contributions.

III. ENHANCEMENT OF VIBRATION MONITORING UNDER NOISY NONSTATIONARY CONDITIONS

Vibration monitoring of rotating machinery under noisy nonstationary operating conditions remains difficult because of challenges such as amplitude and frequency modulation, as well as impulsive noise, that impede the application of conventional condition indicators.

To improve the performance of vibration monitoring under nonstationary conditions, various techniques that rely on traditional signal processing can be used. Learning-based methods provide a complementary perspective on the signal processing problem, by potentially alleviating some of the shortcomings of traditional condition monitoring methods.

This section highlights some concepts to enhance vibration monitoring under nonstationary conditions, from signal processing and learning-based perspectives, and also through the use of a complementary approach.

A. A MULTIFACETED CHALLENGE

Vibration monitoring of complex machinery often poses a multifaceted challenge. Not only does one deal with time-varying operating conditions as seen in Fig. 1 top right, but often we also deal with weak damage components that need to be separated from the effects of the nonstationary conditions, see the top left. Yet another problem is the vulnerability of some analysis tools, to the effects of extraneous impulsive signal components. This is highlighted at the bottom left. In the 4th industrial revolution, we also have to deal with progressively large amounts of data from multiple sensors, and fleets of assets, and may lead to us being overwhelmed by more and more data as shown at the bottom right.

Signal processing and learning-based techniques are both commonly applied in condition monitoring. But to deal with the problems outlined in Fig. 1, we propose the use of signal processing techniques combined with learning-based techniques: Increasingly using these two approaches in a complementary way. Both these approaches encompass methods, training, and evaluation as shown in Fig. 2.

However, these two approaches differ in focus: Signal processing predominantly focuses on the methods used and
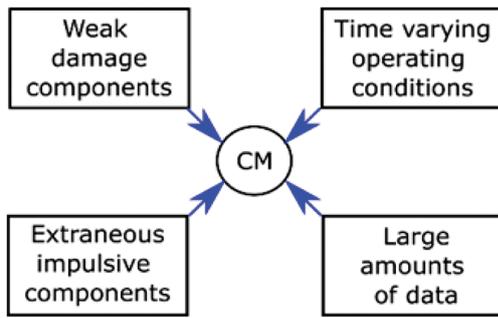
Fig. 1. Multifaceted challenges in vibration-based condition monitoring.
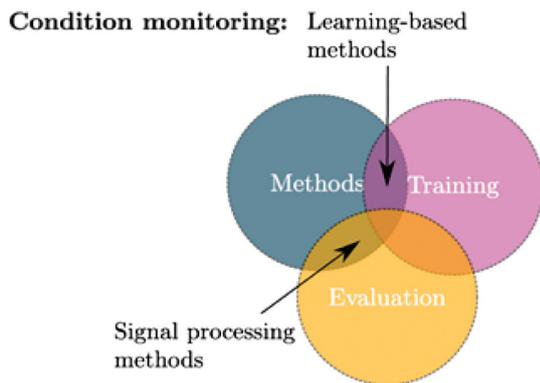
Fig. 2. A complementary approach.

how the time series data are evaluated. Training is defined through expert knowledge obtained through years of experience. Learning-based approaches focus on the methods used and the training required to maximize method performance. This may be viewed as the intersection between methods and evaluation which corresponds to signal processing and intersection of methods and training which corresponds to learning-based methods.

Through the complementary use of these two approaches, we endeavor to move in the direction of scalable solutions which benefit from the advantages of the present day focus on data-driven approaches and algorithms, while addressing the need for reduced human specialist expertise required for large-scale predictive analytics but not forfeiting the physical insights obtained from signal processing techniques.

B. SIGNAL PROCESSING

Various signal processing methods have been developed to deal with time-varying operating conditions, weak damage components, and extraneous impulsive components. Some of these techniques are documented in detail by [21,22], and [23]. Supplementing classical signal processing analysis methods with historical data can also be very useful [24,25]. Such an approach allows the detection of anomalous components over time, detects changes in these anomalies over time, and ultimately allows one to perform automatic fault detection. These methods however still require an engineer to decide which processing should be performed. This remains difficult for complex machinery with many rotating components and sources.

C. LEARNING-BASED METHODS

Learning-based methods provide complementary perspectives on the signal processing problem, by potentially addressing some of the shortcomings of traditional condition monitoring methods. In this regard, the use of generative learning as opposed to discriminative learning is becoming more important because of the focus on the unsupervised problem in condition monitoring, given the usual limitation of limited historical fault data to provide suitable labels. Such unsupervised models try to model the underlying patterns or distributions of data points. The success of these models can be assessed in terms of the reconstruction error, which represents the distance between the original data points and its projection onto a lower dimensional subspace represented by the model and an interpretation of the latent signals which capture the structure of the model [25,26].

In principle, one can use learning-based methods to relieve the workload of engineers, at least for part of the condition monitoring process, by automatically learning the underlying structure of the data, through a process of encoding and decoding the data.

Recent work emphasizes the value of untangling time in the learning process [27]. This is something that is not always realized when applying common machine learning methods in condition monitoring.

D. COMBINING SIGNAL PROCESSING AND LEARNING-BASED METHODS

Complementary use of signal processing methods together with learning-based methods has proven to provide significant advantages. In Fig. 3 on the left, one sees a health
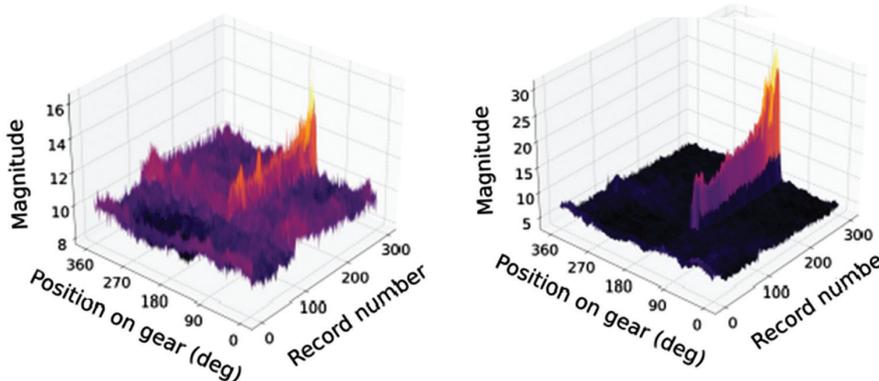
Fig. 3. Complementary use of signal processing and machine learning methods.

indicator as function of angular position on our damaged experimental gear, using a learning-based perspective only. The health indicator clearly shows the fault at 180 degrees.

But if one combines time synchronous averaging together with a learning-based approach as on the right, one gets a much crisper definition of the fault angle and fault progression as function of record number (or time).

E. CONCLUSION

There is still a plethora of challenging problems in vibration-based condition monitoring. These problems relate to issues such as nonstationary operational conditions, weak damage components, extraneous impulsive inputs, and large amounts of data. Fortunately, signal processing provides very useful ways to enhance our ability to extract diagnostic information from these signals.

At the same time, statistical and machine learning methods are becoming important in the context of vibration monitoring. This is due to lower levels of human experience required, and the scalability of these methods to process huge amounts of data.

The complementary use of these signal processing and learning-based techniques provides new and untapped potential for future research.

IV. MACHINERY INFORMATICS: AN INTERDISCIPLINARY SUBJECT TO ENABLE INTELLIGENT MAINTENANCE

A. BACKGROUND

During the past few decades, the techniques with respect to machinery diagnosis and prognosis are growing rapidly, especially with the development of instrumentation, internet, computer science, and other emerging information technologies, such as machine learning. The major reason is that machinery diagnosis or prognosis is an interdisciplinary subject mainly concerning machinery dynamics, computer science, instrumentation, and measurement. We can easily understand it by reviewing the evolution history of machinery diagnosis. For example, we do not have to rely on the personnel experience as long as the data acquisition system and signal analysis methods are available. Lots of remote condition monitoring and diagnosis systems were established during the past two decades, which benefits from the technical advance and cost reduction of internet and electronic products. Furthermore, based on these systems, tons of data are produced and transferred to remote sites in real time for the purpose of remote monitoring, diagnosis, or maintenance. The methods with respect to big data analysis, machine learning, and AI algorithms are consequently with a blowout type increase in the applications during the past 10 years.

However, on the other hand, whenever the manufacturers or the service providers are wondering how to integrate the methods and techniques efficiently so as to set up an optimal solution for maintenance. The key is to understand the health condition and the degradation trend thoroughly and deeply, which significantly depends on how much information obtained throughout the lifecycle of the machinery. Machinery informatics is a subject to investigate the origin, representation, evolution, and acquisition of the information on the health and performance throughout the machinery lifecycle.

B. RESEARCH CONTENT

In 2004, Qu [28] proposed the concept of informatization of mechanical products, which can be considered as the origin of machinery informatics. In this concept, the performance of traditional mechanical products could be improved significantly by proper utilizing all kinds of dynamic information on them, which comprises three steps, data acquisition, feature extraction, and performance improvement.

Machinery informatics can be understood from three aspects. First of all, the research subject is machinery and the main purpose is high efficiency and low cost, no matter what method or technique is employed. It concerns the total lifecycle of the machinery, including design, manufacturing, operating, and maintenance. Secondly, the information here is generalized, which contains not only dynamic information with respect to the structure, function, and performance of the machinery but also information technologies concerning data storage and communication, feature extraction and integration, decision, and prediction. To some extent, the research process is to reveal the mechanism and relationship between different dynamic behaviors or between the dynamic behavior and the signal representation by using information technologies, including the emerging big data and AI technologies. Finally, fusion of different disciplines is the breakthrough point to investigate machinery informatics. The fusion can be happened on different levels which include sensation, feature extraction and decision, or on different stages within the total lifecycle, or even across different levels and stages.

C. TECHNICAL ROUTE

The more information utilized, the more accurate or complete evaluation can be obtained about the condition of the machinery. Originally, dynamics and cybernetics were employed to model the failure and degradation process for parts and the total system. For more generality, hydraulic-electromechanical coupling was investigated for the design, fault diagnosis, and performance evaluation for complex electromechanical systems [29]. By using this way, the information flow, matter flow, and energy flow are taken into consideration simultaneously. Consequently, more correlative information among different subsystems is utilized to characterize the complex electromechanical system accurately. Particularly, for high-precision electronic equipment such as radar and radio astronomy telescope, the issue on electromechanical coupling has been studied intensively and applied successfully for system design and performance analysis [30].

Information extraction and fusion can be complemented by using model-based or data-driven method, or the combination of the two. Among data-driven methods, the emerging big data technology is considered as a promising way to obtain latent information or reveal unknown correlation mechanisms between the machinery performance and the signal representations. However, lack of interpretation is the prominent imperfection when machine learning methods are simply used. For this reason, how to integrate professional knowledge into the method is attracted high attentions up to now, which is also considered as key feature of the new generation of artificial intelligence.

D. CONCLUSIONS

Machinery informatics is an interdisciplinary subject to reveal the latent correlation mechanism between the performance and the signal representations, which helps to understand the health condition and degradation trend more clearly and accurately. Together with professional knowledge, the emerging information technology could be employed as an efficient way to investigate machinery informatics.

V. FREQUENCY AND MODE ASSIGNMENT VIA STRUCTURAL MODIFICATIONS: BASIC THEORY AND APPLICATIONS

Passive vibration control makes use of mass, stiffness, and damping to influence how a structure behaves when excited and requires no external power to operate. It is more reliable and inexpensive in general, in comparison with active and hybrid control.

A particularly interesting passive control methodology is to assign frequencies or modes or both by means of structural modifications, that is, changing the mass and stiffness (and much less often, damping) of a structure so that it acquires desirable frequencies and modes. The required structural modifications may be found through a trial-and-error process, which is tedious and does not guarantee an optimal solution. Inverse structural modifications aim to determine the required modifications in a systematic way.

Research into structural modifications for passive vibration control at Liverpool was initiated by Mottershead [31] in early 2000s and has been championed by Ouyang in recent years. The Liverpool approach is mostly a receptance-based methodology. Using a small number of receptances that can be measured fairly easily, a numerical model

of the structure to be controlled is not required. This means two big advantages: (1) absence of modeling errors and (2) realistic representation of real structural properties (e.g., nonproportional damping). This keynote speech gives a brief introduction of the theory behind the receptance-based approach and focuses on several successful examples of laboratory and practical implementations.

After introducing the concept of passive vibration control with two real examples—vibration absorbers used in Millennium Bridge in London and Taipei 101 Tower—the speaker defined frequency and mode assignment and briefly described the procedure of the receptance-based inverse structural modification approach. Forced vibration and based-excited vibration of a one-degree-of-freedom (DoF) mass-spring-damper system were used to demonstrate the vibration suppression principle of frequency assignment. The inherent mathematical challenges in frequency/mode assignment were highlighted using the equation of the linear eigenvalue problem. The concept of receptance was provided.

The speech then moved forward to the presentation of the examples of applying the receptance-based approach for frequency and mode assignment by means of structural modifications, conducted mostly in the Dynamics and Control Group at Liverpool, often in collaborations with international researchers.

The first example is about a five-DoF mass-spring structure shown in Figs. 4 and 5.

Among the five frequencies and modes, two frequencies and their associated modes are assigned different values. In particular, a node is assigned to each of the two modes, which is quite challenging. The determination of the required modifications is cast as a continuous-variable optimization problem with the five masses and five grounded springs being the design variables. These modifications are found to realize the desired modal properties very well when they are implemented in practice [32].

Fig. 4. A five-DoF mass-spring structure with a shaker.
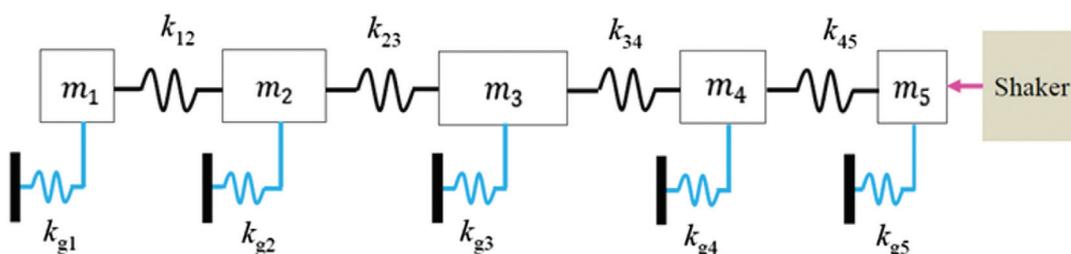
Fig. 5. Schematic of the structure in Figure 4.

Because the actual mass and stiffness modifications are respectively in the form of small blocks of identical mass and thin steel plates of nominally identical stiffness, determination of the required modifications is recast as an integer-variable optimization problem in multiple units of the mass blocks and steel plates, which leads to a very good yet very different solution from that of the continuous-variable optimization [33]. Structural modifications in terms of integer multiples of standard units are more realistic and thus more useful in practice.

Apart from the discrete structure shown in Fig. 4, a continuous structure of a Γ-shaped frame is modified to gain one or two frequencies of a Π-shaped frame, as shown in Fig. 6.

For this kind of flexible structures, not only translational receptance but also rotational receptance at the modification (connection) point are required, the latter of which is more difficult to acquire (when using a translational input such as a hammer impact and translational accelerometers). To overcome this difficulty, an indirect method for measuring a rotational receptance in a hammer test using (translational) accelerometers was developed [34]. The main idea is the introduction of a simple auxiliary structure, a T-shaped frame in this case, to the modification point, in order to "tease out" the rotational receptance there, via substructure-decoupling technique. One frequency, two frequencies, and one frequency and one antiresonant frequency were respectively assigned successfully [35].

The third example is a mass modification to a real dual-shaft system with two discs, a pair of gears, and five sets of bearings treated as linear springs, as shown below Fig. 7.

Each circular disc has 16 small circular threaded holes equally spaced around the disc. A hole allows a set of screw and nut to be attached to a disc so that its inertia is modified. Two frequencies were assigned separately or simultaneously [36].
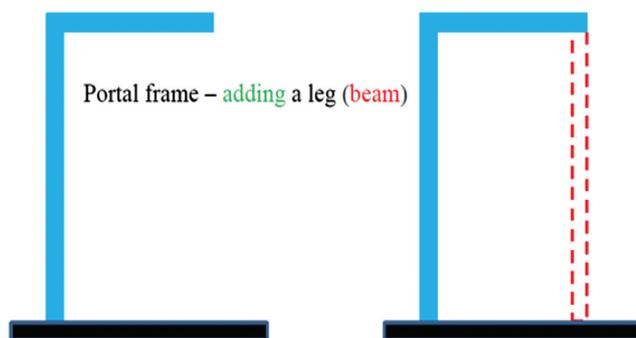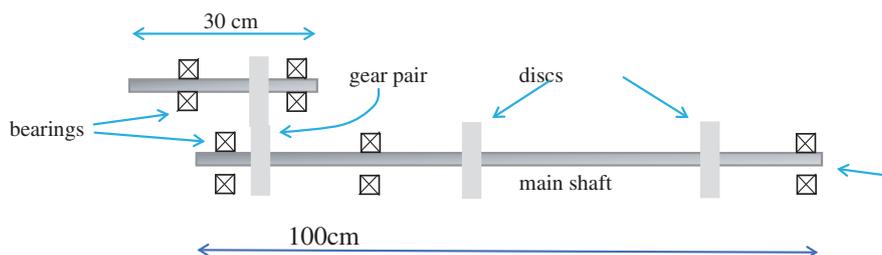
The fourth example was frequency assignment of a linear feeder conducted by Zanardo [37].

A brake-clutch in a Spanish company emitted loud squeal noise. The mass and stiffness modifications required to suppress it were determined and the latter was implemented on a laboratory brake-clutch which no longer squealed after a spring was connected to the stationary disc of a simplified brake-clutch system [38].

Assignment of one or two frequencies of a complicated ship-hull structure was briefly discussed in the speech. Since this work will be submitted to a journal, it is not covered here.

A U-shaped pipeline had five mass-spring supports as vibration isolators. Its internal fluid flow speed and the measurement noise were taken as interval-type uncertainty. Two antiresonant frequencies were assigned with high accuracy in the presence of the uncertainty [39]. This work brought application of frequency assignment closer to practical use.

The Liverpool approach relies on high-quality measured receptances. For this reason, research on how to measure receptances of complicated structures was carried out. This speech gave two such examples: receptance matrix of a point on the tail cone of a Lynx helicopter [40] and torsional receptance of a shaft [41], both through an auxiliary structure (an X-shaped frame and a T-shaped frame, respectively) and substructure decoupling.

Partial assignment [42,43] is more challenging and also more useful. Work on this topic is going on and several papers on this topic have been published.

It should be pointed out that eigenvalue (or pole) and eigenvector assignment may be made using the Liverpool approach in principle. It should be noted that the real part of a complex eigenvalue/pole is more sensitive to damping.

Fig. 6. The original (Γ-shaped frame) on the left and the modified (Π-shaped frame) on the right.

VI. GEAR WEAR: MEASUREMENT, DIAGNOSIS, AND PROGNOSIS

A. BACKGROUND AND INTRODUCTION

Geared transmission systems inevitably experience wear, which in its broadest definition includes any material removal process, of which the most relevant for gears are abrasive wear, based on the contact and breakage of

Fig. 7. A dual-shaft system with two discs, two gears, and five sets of bearings.

asperities in sliding contact, and fatigue pitting, based on repetitive loading.

Wear creates deviations from the ideal involute tooth profile, altering the load distribution at the meshing interface, and so the development of one wear mechanism can promote the initiation of another and can ultimately lead to gear failure, whether catastrophic or functional (machine no longer performs to requirements). This wear may be evenly distributed around the gear or localized to a small number of teeth, although in most applications it tends to be widely distributed, especially in moderate-severe stages. Because of this, its diagnosis has typically been based largely on changes in gear mesh (GM) harmonics. Abrasive wear is highly dependent on sliding velocity and so tends to generate a "double-scalloped' wear pattern, with minimal wear at the pitch line, where the sliding velocity dips momentarily to zero, and higher wear near the root and tip of the tooth [44]. This creates a distortion in the gear meshing pattern, affecting several harmonics of the GM frequency, with the second and higher harmonics considered the best indicators of wear in the early stages [44]; however, these have not been shown to give a clear indication of severity and their capability in tracking wear level remains unproven.

B. MEASUREMENT OF ABRASIVE WEAR USING TRANSMISSION ERROR

Transmission error (TE) is defined as the difference in the angular displacement of the driven gear with respect to that of the driving gear, taking into account the gear ratio [45,46]. TE occurs in healthy gears from factors such as the deformation of teeth under load or to profile modifications made in the manufacturing process (e.g., tip relief). Faults introduce their own additional TE signatures, with, for example, root cracks (stiffness reduction) exhibiting localized load-dependent symptoms and abrasive wear (profile changes) showing distributed load-independent effects.

The measurement of TE requires shaft encoders on the input and output shafts, ideally on an unloaded portion such as the free ends. TE is readily divided into three categories: geometric (GTE), measured at low speed and low load; static (STE), measured at low speed and operating load, including deflection of the teeth; and dynamic (DTE), measured at operating speed and load, thus including transfer function effects. While the concept of TE has been understood since at least the 1930s [47] and was used throughout the 20th century [48], its early use was rather as a design and quality control tool, and it was not employed for gear diagnostics until the early 2000s, with the seminal work of Endo *et al.* [49,50]. Yet even since then, in the author's opinion, it has been somewhat underused as a monitoring tool, perhaps owing to the perceived difficulty in measurement requirements.

Despite showing great potential for diagnostics, until recently one important aspect of TE was overlooked: that of the mean (or DC) TE component. TE is calculated by obtaining phase-time maps of the two shafts in question and subtracting one from the other (allowing for gear ratio). In this process, since the initial phase of both maps is arbitrary, it is usually set to zero, giving a resulting TE curve with zero mean. However, as illustrated in Fig. 8, in the event of moderate-severe abrasive wear, the primary effect on (geometric) TE would be a DC offset in the TE curve
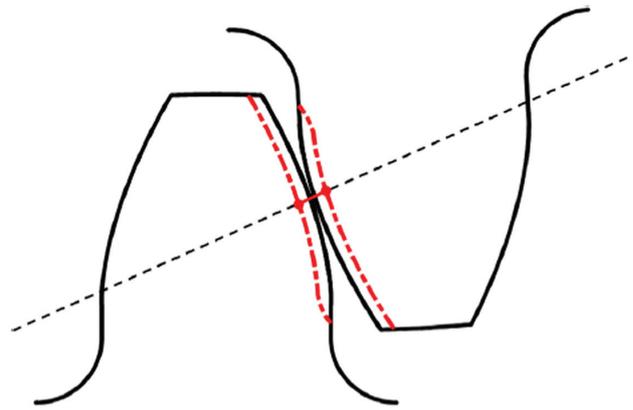
Fig. 8. Schematic showing how with extended wear the DC component of TE is primary, and not variations around the mean [51].

corresponding to the mean depth of material removed, with variations about that mean a secondary consideration, and diminishing in importance with the further progression of wear.

This realization—that wear is essentially captured by the DC component of TE, typically discarded—prompted the development in [51] of absolute TE (mean plus deviations). The key to the absolute TE concept is to establish, in a given TE measurement, a reference point (a certain tacho pulse from the input shaft, e.g.) in the hunting tooth cycle (HTC) of the gear pair. It is this that allows comparison of measurements at different wear stages, because the same HTC reference point can be used in all subsequent measurements. This is done by using a "rephasing" technique explained in [51], which rephases future measurements so they commence at the same HTC reference point, meaning the starting phase of the encoder phase maps is no longer arbitrary, giving a meaningful DC component of TE when one map is subtracted from the other. Once this reference point is decided, all subsequent measurements are to be rephased so as to commence at the same point in the HTC, allowing the generation of so-called "absolute TE" curves that evolve with the condition of the gear pair, all using the same (ideally unworn) initial reference condition.

To test this concept, an extended wear test was conducted on a single-stage spur gearbox rig at UNSW Sydney. The test employed soft gears and no lubrication, to generate high levels of abrasive wear. Further details can be found in [51]. Figure 9 shows the generated absolute TE curves and their evolution throughout the test. Test 0 served as the baseline and hence has zero absolute TE, with Test 14 the final test. A dominant periodicity can be seen in the TE curves (GM frequency), but after the first few measurements this variation about the mean is dwarfed by the mean TE itself, which approaches 800 μm by Test 14—very severe wear for module 2 gears.

To validate these figures, all wear particles from the gears were carefully collected throughout the test and weighed periodically, and the mass used to calculate the average wear depth using the known material density, geometry of the gears, and the assumption that the wear was uniform across the gear face width. The resulting calculated wear depth is plotted in Fig. 10, alongside the mean TE figure obtained using all three TE forms: GTE,
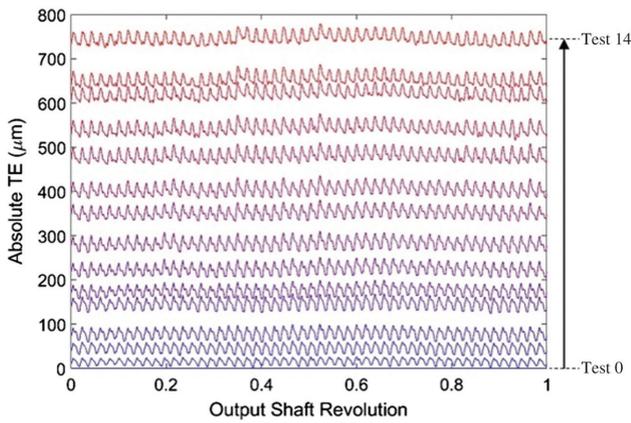
Fig. 9. Schematic showing how with extended wear the DC component of TE is primary, and not variations around the mean [51].
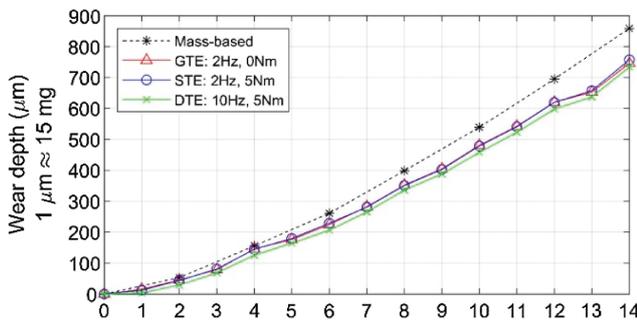
Fig. 10. Wear depth calculated using "absolute TE" concept and comparison with particle mass-based measurements [51].

STE, and DTE. It is clear that all TE forms give virtually identical results, and that the TE wear quantification is indeed very close to the mass-based calculation.

As shown in [51], the vibration signals recorded throughout the testing did not give a clear indication of wear severity. While this example shows the power of TE in gear diagnostics, it is interesting to note that a good approximation to the mean TE (and hence wear level) could be obtained using just once-per-rev tachometers on the input and output shafts. This would essentially give one point for each of the curves in Fig. 9—more than sufficient to diagnose wear severity in the moderate-severe stages.

C. A DIGITAL TWIN APPROACH FOR WEAR MONITORING AND PREDICTION

This section explains the development and use of simulation models to monitor and predict gear wear, the basic premise being that with regular updating of certain model parameters, good predictive capabilities can be achieved, even with very simple models. Figure 11 shows a 21-DOF lumped parameter representation of the same gearbox used in the absolute TE study. The model includes a term, e, for the profile changes (GTE) arising from wear.

Figure 12 gives a very basic schematic of the proposed wear prediction approach, first outlined in [52]. The scheme consists of the 21-DoF model ("dynamic model"), which feeds GM contact forces/pressures into the wear model, which in this case is simply Archard's abrasive wear model [53], requiring only contact force/pressure, sliding velocity, and a single wear model parameter K (to be updated based on measurements). Without any wear model updating, the model predicts future wear levels and resulting gear tooth profiles, which can be fed back into the dynamic model. However, with no self-correcting mechanism, these predictions would likely deviate from reality after some time, and so the updating loop on the right-hand side of Fig. 12 is introduced. This updating loop is based on a comparison between measured and simulated vibration responses, with Archard's wear parameter K adjusted to ensure a match between the two. Ideally, this would be based on a vibration
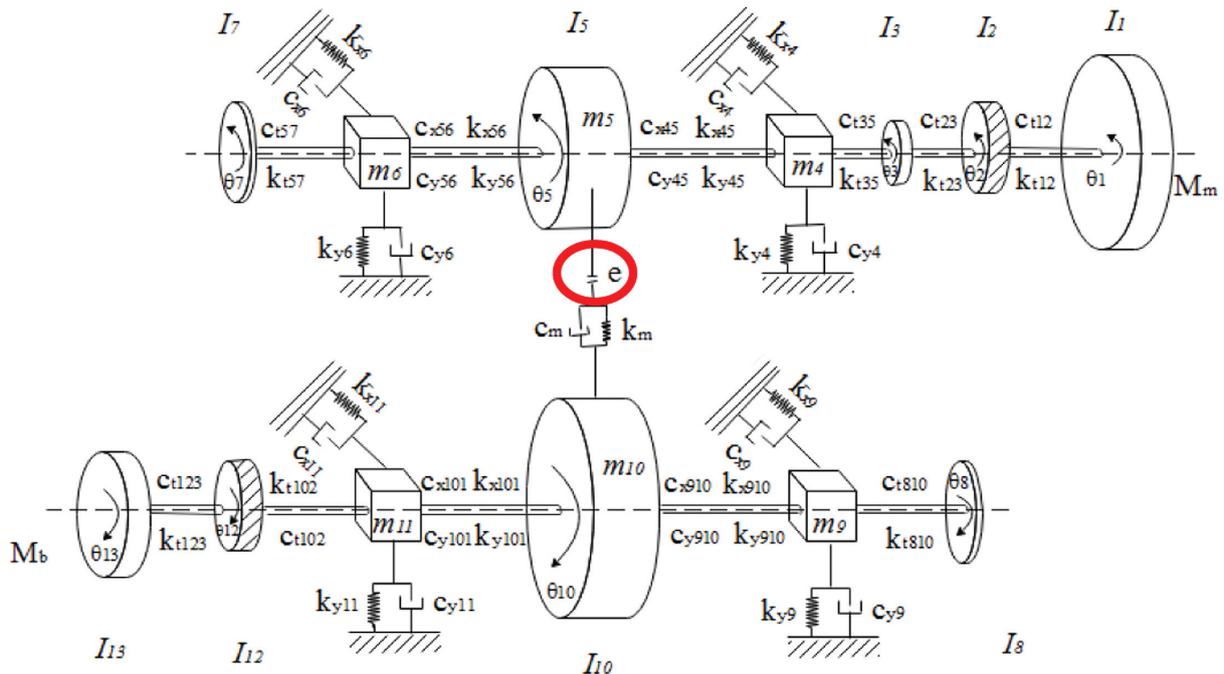
Fig. 11. 21-DOF lumped parameter model of UNSW gearbox test rig [52].
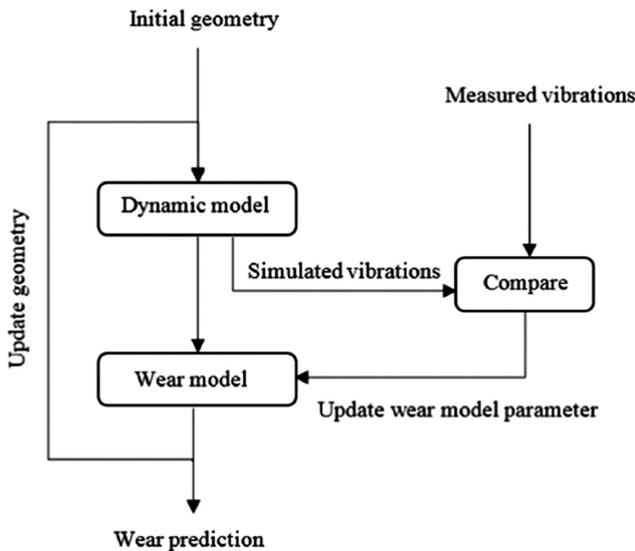
Fig. 12. Proposed vibration-based updating methodology for predicting gear wear [53].

indicator both sensitive and specific to tooth profile changes. In the results that follow, however, simple vibration RMS levels were employed, found to be acceptable in this case of a simple single-stage gearbox with no other developing faults.

Figure 13 shows the results of applying the gear wear monitoring approach to a dry test on the single-stage spur gearbox. The left plot shows a comparison between experimental and simulated vibration RMS levels throughout the test. In this case, wear parameter updating was only required on two occasions, undertaken whenever the two RMS values differed by more than 5%. The right plot shows the experimental and simulated wear depth evolution, where excellent agreement can be seen. Note that wear depths were not compared in the updating process, and the agreement between these two curves is a genuine indication that the (updated) model is tracking very well the true state of the gears. Ref. [54] gives further details, and in [55] a more comprehensive prediction process is outlined, in which the abrasive wear component of Fig. 12 is augmented with a fatigue pitting prediction loop so that the two common wear modes can be monitored and predicted simultaneously.
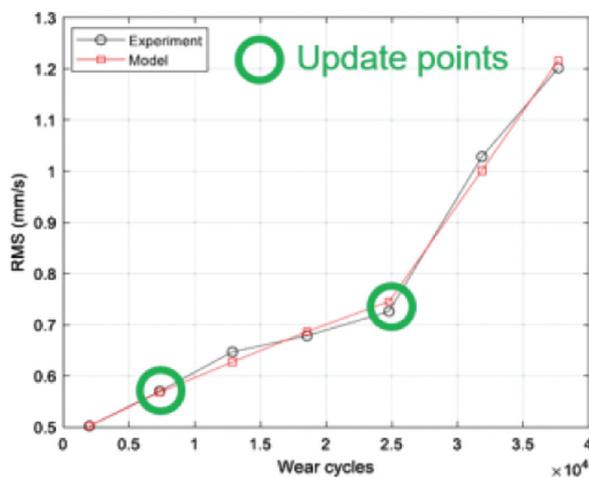
D. ADVANCED WEAR ANALYSIS USING CYCLOSTATIONARITY

Space limitations prevent a full discussion of work in this area, but brief mention must be made of the use of CS signal analysis in the detailed study of gear wear. This work commenced with studies [56,57], which explored the connection between the level of cyclostationarity in the vibration signal and the surface roughness of gears. The theory—supported, though not yet clearly "proven," by experimental evidence—is that gears with rougher surfaces will produce signals with stronger second-order CS content (at cyclic frequency equal to GM) due to the increase in asperity contacts associated with increased roughness. More recent and advanced developments of this concept include application of generalized Gaussian CS signal models to represent sliding contact conditions in gears using acoustic emission signals [58,59], and the discovered connection between carrier frequency CS signal content and gear tooth spatial frequency distribution [60]. The latter was proposed as a way of differentiating abrasive- and pitting-dominant wear cases in gears, since the two wear mechanisms produce surfaces of vastly different spatial composition (high frequency for abrasion and low for pitting).

E. CONCLUSIONS AND FUTURE DIRECTIONS

This paper briefly explained several key developments in gear wear measurement, diagnosis, and prognosis, based on research at UNSW Sydney over the last few years. This includes the use of TE as a powerful yet underused diagnostic tool, the prediction of gear wear using a simple digital twin approach, and the use of CS modeling to uncover the finer details of gear surface conditions.

Despite this progress, much remains to be done. Surely an area for further development involves TE analysis—a measurement likely to become more accessible under Industry 4.0 and Internet of Things paradigms, where shaft encoders and other embedded sensor technology will become increasingly commonplace. Prognostics is an obvious area for further work, yet improvements in robust fault severity assessment will be required to fully enable the potential in this domain. A last mention should be made of CS signal analysis. A fortuitous feature of gear signals is that even the
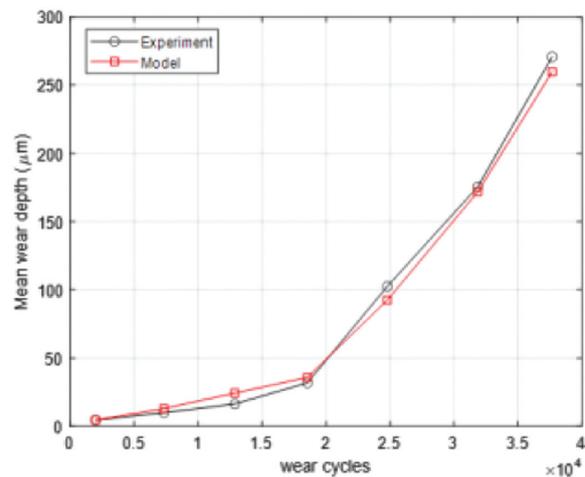
Fig. 13. Comparison between experiment and model after updating wear parameter *K*. Left: vibration RMS (used for updating); right: wear depth (not compared during simulation) [54].

random components tend to have a very deterministic statistical structure, with the cyclic frequency of random vibrations known precisely (GM frequency), and often unique in a given machine. This permits the separation of such content and the isolation of components related solely to the gear pair under analysis. This is a promising avenue for fault severity assessment and prognostic analysis.

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CONFLICT OF INTEREST STATEMENT

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