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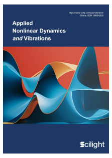

Review

Making Sense from Nonlinear Dynamic Signals—From Fault Detection to Prediction

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Abstract: Modern engineering systems are complex and sophisticated. Any minor issue can be escalated to total system failure. To resolve this issue, many researchers have contributed many diagnostic methods efforts using digital signal processing. However, two barriers have to be overcome. First, enormous amount of signal data is required from system processes. Recently Industry 4.0 paradigm promoting digital transformation of industry and societies resolves this issue partially, but what signals from the system can be used. Second, operational data from the dynamic system are nonlinear and often chaotic, how can the signals be interpreted to identify fault, assess reliability and decide remedial actions. This article reviews fault diagnosis and system health monitoring research efforts and outcomes in the last couple of decades. The ultimate goal is to develop fault-free systems. The best way to achieve this goal is to prevent faults from happening. Two approaches of nonlinear signal modelling, i.e., chaotic systems and frequency distribution analysis for fault detection have been researched. Lessons learned are summarized with discussions on, merits and drawbacks. These experiences are shared in this article to stimulate further research towards the ultimate goal of fault-free system operations and controls.

Keywords: nonlinear signals; chaotic systems; scalograms; distribution of frequencies; fault-free systems

1. Introduction

Modern engineering systems are complex and sophisticated. Any minor issue can be escalated to complete system failure. With Industry 4.0, enormous amount of information can be collected from system processes online—the commonly known health monitoring paradigm. The idea is to continuously monitor signals generated from the system so as to judge if it is running as expected. The aim is to be able to support proactive intervening decisions to stop the system before it goes bad. This concept has been researched for decades. A typical application is to monitor performance of aircraft engines [1]. In this case, system parameters including engine fan speeds, vibration, oil pressure, oil temperature, exhaust gas temperature were monitored during flight time. Statistical relationships between these parameters and the system's performance (the aircraft) such as safety, fuel consumption, maintenance costs were computed by multiple regression analysis.

Many system performance indicators can't be directly measured. Assessment of system health often depends on monitoring parameters that are not explicitly linked to performance indicators but can be measured conveniently. Furthermore, the signals (measurable parameters) are not always controllable and steady, hence, induce unexpected variations in system performance (the outcomes). How to analyze the signals correctly so that the system parameters affecting system performance can be identified for deciding on reliable remedial actions is the research goal of many researchers.

To monitor system health, a signal source from the system being monitored should be available. Large amount of digitized data over intervals that are comparable to system response time is required [2]. The usefulness of collected data depends on the sensing and communication technologies bringing relevant and efficacy data for processing. In an early research in which health of the foundation piles of a wharf was required to be diagnosed, a sinusoidal hydraulic vibrator was developed to generate excited vibration to instigate reflective signals from the structure (the signal source) so that modal vibration theory was applied to interpret where the problem could be [3]. This early work laid the ground for a series of research efforts to monitor and subsequently advancing to making sense of the signals so that appropriate actions can be taken to ensure the system is performing as expected. With Industry 4.0, which supports adequacy of data points required for system health monitoring paradigm, this barrier can be regarded as resolved [4].

One of the difficult issues in health monitoring is prevention of faults. Faults are deterioration of the machine's capabilities to a point when the machine could not perform as before leaving the machine operator almost no time to take remedial action preventing rejects or causing damage to the machine [5]. System health monitoring assumes that the system deteriorates over time (but still performing satisfactorily) so that continuous monitoring of certain operating parameters of the system will be able to detect problems before they occur [6]. Therefore, the ability to continuously measure and process signals from the system to check its status is pre-requisite to health monitoring.

Having continuous stream of signal data is the primary requirement for successful system health monitoring. However, signals from many engineering systems are complex and difficult to interpret. For example, fluid powered systems are inherently nonlinear. Small differential input (cause) to the mechanism can have unstable output responses (un-proportional consequential effect) [7–9]. They are essential components for aerospace systems, but their performance needs dynamically diagnosed by specialized data processing algorithms [10]. Enormous amount of engineering resources is required to fine tune the nonlinear signal processing algorithm so that the fault diagnosis system can identify if a fault has occurred.

This paper reviews a range of nonlinear signal analysis methods of fault prognosis and further development of these methods to computational processes to specific application in different industries. So long as sufficient data is available, these methods do not link to any application context information of the raw signal data stream hence making it context independent. More importantly, the trend that the system is going into faulty state can be monitored so that while the performance is deteriorating and the system is still working within acceptable conditions, preparation for providing the right repair can be made and the system can be stopped before producing bad outcomes.

The paper has 5 sections. Section 1 (this section) introduces the aim of this paper and the underlying research concepts. Section 2 reviews signal diagnosis methods based on chaos theory, both from literature and from experimental research outcomes. A short summary of learnings on the merits and drawbacks of these methods has been included. Section 3 focuses on research monitoring trend of system performance based on traditional approach using wavelet transforms and learnings from chaotic system approach. Section 4 discusses progress of signal diagnostic research so far and potential future direction of investigation. Section 5 concludes this paper.

2. System Performance Diagnosis

To support proactive intervening decisions that can stop a system to become unusable, it is necessary to understand how and why the system behaves under known parameters. Many different research approaches have been attempted with certain level of success. This section outlines these research attempts and reviews their merits and drawbacks so as to form the basis for exploring more effective and universal system performance diagnostic systems.

2.1. Necessity of Continuous Signal Analysis

In an early industry engagement, an original equipment manufacturer (OEM) in Northern Europe installed 4 paper pulp machines in Tasmania, Australia. In order to help the Australian company to operate the machines correctly, a dedicated high speed telecommunication line (Note: internet not available on-site) was setup to transfer machine parameter data (about 30 parameters including water temperature, fluidity, pressure, etc) back to the OEM for analysis [11]. After running a theoretical process model of the paper pulp machine, the OEM was able to advise the Australian operator changes required to achieve best production outcome. Due to the speed and cost to transmission, one set of parameters was sent every 5 min. The frequency was considered sufficient given the slow chemical reaction of the process.

In another industry research project with a household appliance manufacturer, sensors and data loggers were setup in several washing machines. Data was transmission every 5 s via the power line of the machine to the laboratory of the appliance manufacturer [12]. In this case, the appliance manufacturer was interested to know operating patterns of the machine in the customer's environment, such as frequency and type of washing cycles, load information, speed range, fault occurrence and so on. Subsequently, reliability models were used to analyse causes of failures, and some duty cycles were adjusted.

These early investigations indicate that systems have rhythms of operations, which could be converted by sensors, measured and recorded as "signals". Faults in the system change the system's rhythms. By comparing currently measured rhythms with previous, known to be good, rhythms, it is possible to assess discrepancy of the system. Some faults are tolerable from the system's perspective. Faults that are vulnerable to cause problems could be verified in a process model that was used to guide the customer managing the system's operations remotely [13].

2.2. Chaotic Systems Theory to Signal Diagnosis

Mechanical systems in operation often exhibit dynamic regular motion that can be detected as vibration signals that could be collected somewhere on the system [14]. Due to system rigidity, vibrations from mechanical systems are often thought of demonstrating regular, predictable performance. For example, in rotational machines, if an accelerometer is placed at an off-centre distance, the accelerometer signals capture over time will be a sinusoidal wave, a nonlinear dynamic signal. It is easy to interpret what the system is doing. However, slight non-uniform mass distribution or frictional disturbance, which are not measurable, could cause unidentified deviations in vibrations. These irregular vibration signals are often marked by engineers as chaotic signals, i.e., vibrations that are not periodic nor confirm to known patterns. Unfortunately, this assertion is not entirely true. Chaotic systems do exhibit periodic phenomena. Cvitanović characterized chaotic dynamics using periodic orbit theory and global averages [15]. Corrections could be made if an exact representation of the system was required. Due to complexity of nature, it is not possible for human systems to model all system's behaviour. This chaotic system concept aligns well with the requirements to understand what is causing faults to emerge but without deriving complicated mathematical models.

Chaotic systems have two dynamic nonlinear characteristics: (1) fractal structure; (2) unstable periodic. A parametric controller could be designed according to fractal bifurcation and stabilizing the periodic orbit [16]. This work demonstrated that chaotic systems do have recognizable patterns of behaviour. If the patterns are understood and modelled, chaotic systems could still be controlled or diagnosed. Furthermore, if external influence on the system remains unchanged, the periodic pattern will continue. However, continuous system activities will cause damage that will change the pattern such that the system will behave differently. For example, a loosened or unbalanced gear system due to wear and tear would cause crack, bilaterial impact and more severely, gear tooth falling off [17]. In addition to the system exhibiting periodic, or quasi-periodic motions, it also shows chaotic motion. Hence, one of the research directions in system fault diagnosis is to process nonlinear signals with chaotic system models and analysis methodologies

2.3. Phase Space Reconstruction Method

Modelling of chaotic systems is not always possible, especially if the system is a complex system with many components interacting in conjunction with external influences. The principal method to analyse chaotic systems is by phase space reconstruction [18]. The rationale behind the method can be illustrated in Figure 1.

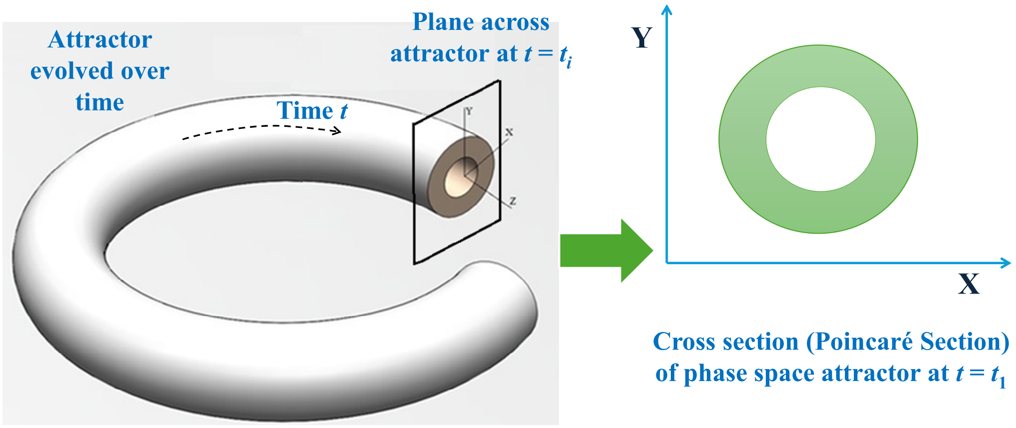


Figure 1. Relationship between phase space attractor and Poincaré section.

In Figure 1, performance of a simple chaotic system can be thought of as evolving 2 dimensional variables X and Y over time and is represented by a phase space attractor. For n dimensional chaotic system ($n > 2$), it is difficult, if not possible to represent with 3D diagram. As it is hard to visualize the phase space attractor, the Poincaré section is used to visualize the attractor [19]. A Poincaré section is essentially a sample of the signals from the system at time $t = t_i$. Poincaré section is the cross-section of the attractor recorded in 2D format. The x-axis is $x(t)$ while the y-axis is $x(t + \tau)$.

To illustrate how Poincaré section works, it is useful to start with a simple "non-chaotic" nonlinear system, a perfect sinusoidal motion system as shown in Equation (1). Physically, it can be the linear displacement (in mm) of an off-centre point on a rotational disc over time.

$$x = \sin(\omega t) \tag{1}$$

Figure 2 shows the shape of the Poincaré sections at different τ: 0.1, 0.3, 0.5, 0.7 and 0.9 of π.

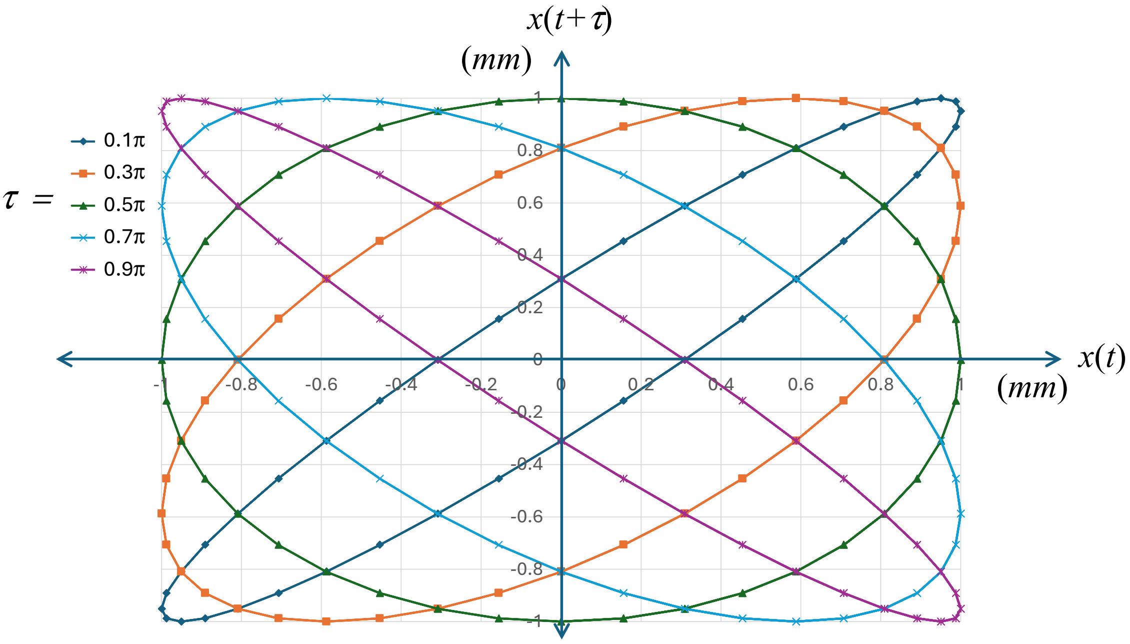


Figure 2. Poincaré section of sinusoidal motion at different delay values τ.

If a fault exists in the system, mathematically, this means some random signals are found in its motion. Figure 3 shows the Poincaré section of the same system at delay values 0.1τ. The deviations are shown as a dot (sample points spread around the "regular" path) on the graph.

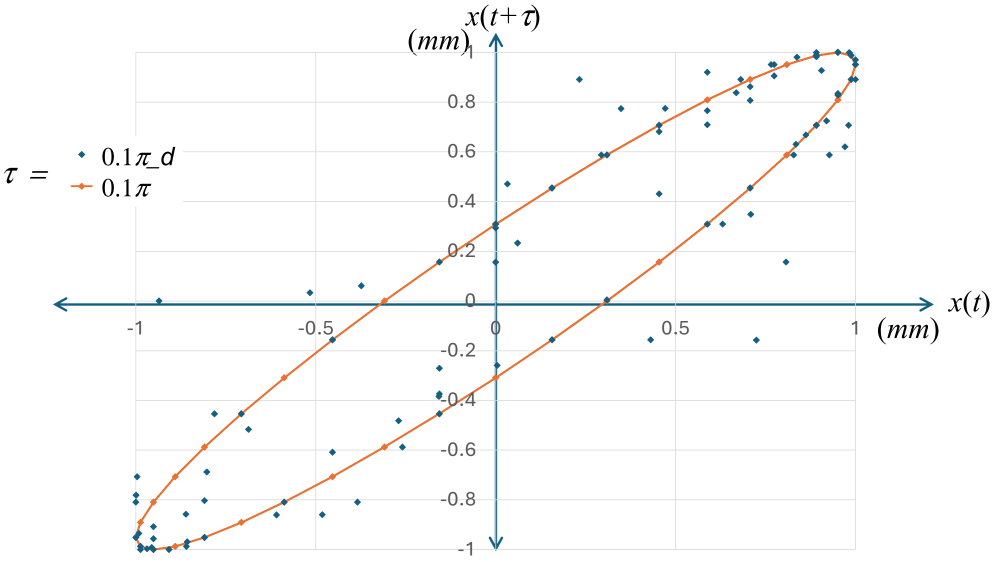


Figure 3. Poincaré section of sinusoidal motion at different delay values τ.

A more complicated chaotic (nonlinear) system will exhibit irregular form. The most studied chaotic system is the Hénon equations as shown in Equation (2).

$$\begin{aligned} x(t+1) &= \mathrm{y}(t) + 1 - ax(t)^2 \\ y(t+1) &= bx(t) \\ a = 1.4&, b = 0.3 \end{aligned} \tag{2}$$

Plotting *x*(*t*) in time domain shows irregular responses (Figure 4). It can be seen in Figure 4 that *x*(*t*) look irregular but some patterns do seem to repeat irregularly. The system is stable.

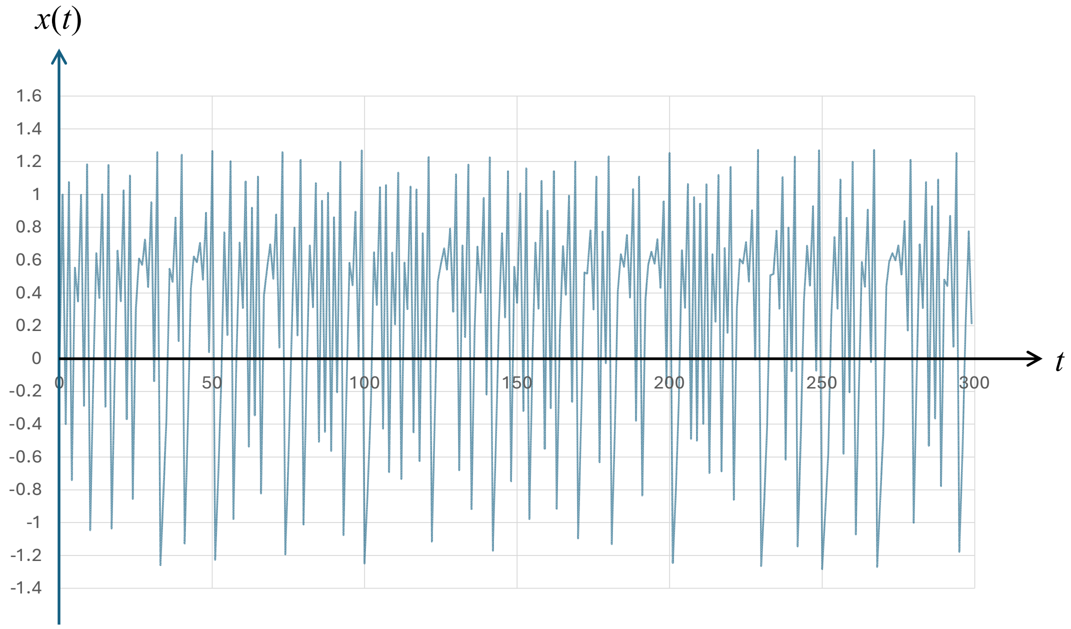


Figure 4. Hénon equation *x*(*t*) in time domain *t*.

The phase space reconstruction Hénon map for *x*(*t*) is shown in Figure 5.

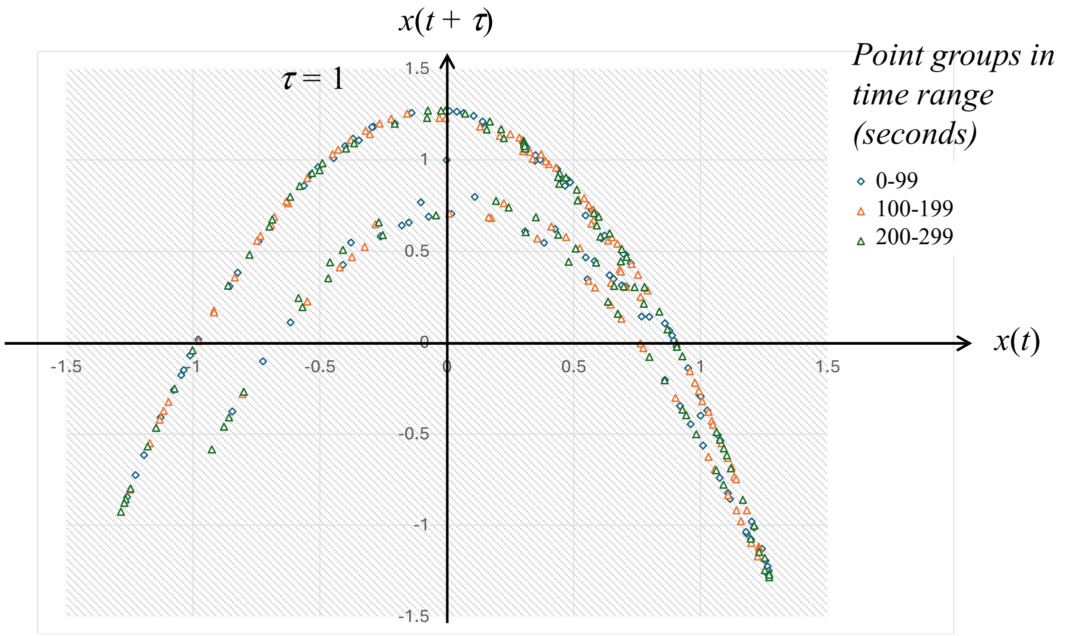
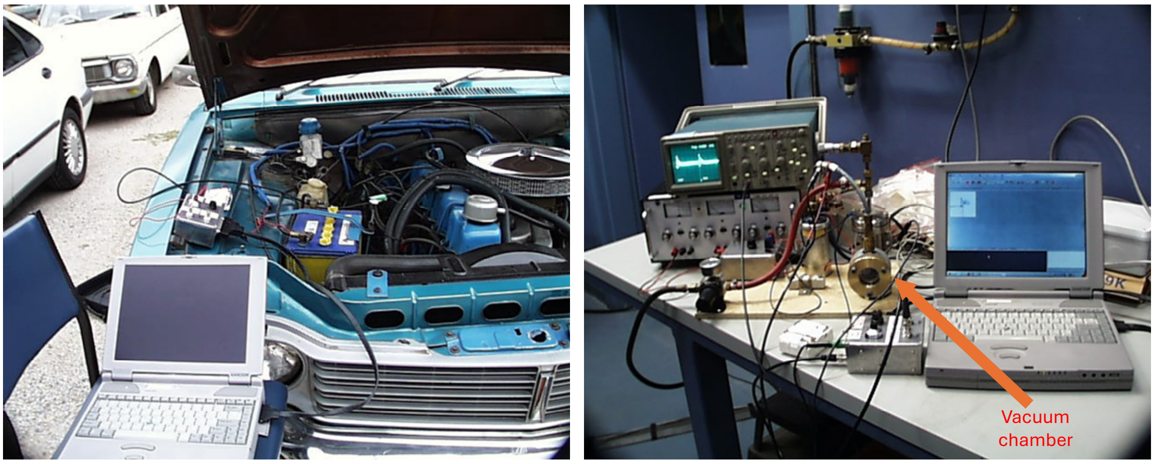


Figure 5. Hénon equation *x*(*t*) with one time unit delay.

The Hénon map is a simple chaotic system that most variations are constrained within a reasonable limit. The advantage of phase space reconstruction is to use the same signal that exhibits chaotic behaviour where underlying structure is displayed in a 2D format. No filtering of "noise" or "transient" information has occurred in this reconstruction, hence the Poincaré sections are still “noisy” but the underlying patterns could be exposed. Visual interpretation or comparison with other similar signals is then possible using pattern differentiations.

2.4. Applied Phase Space Reconstruction Method

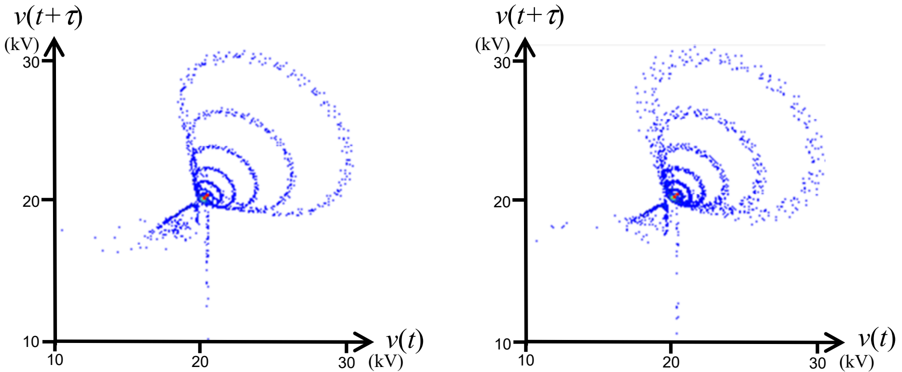
The theory of signal analysis using phase space reconstruction sounds good but how can it be applied to industrial cases? The immediate question encountered was “how much data is required to support a phase space reconstruction?”. Sparking conditions could affect engine efficiency. To examine the effect of sparking due to air pressure in car engines, an experimental vacuum chamber was setup (Figure 6).



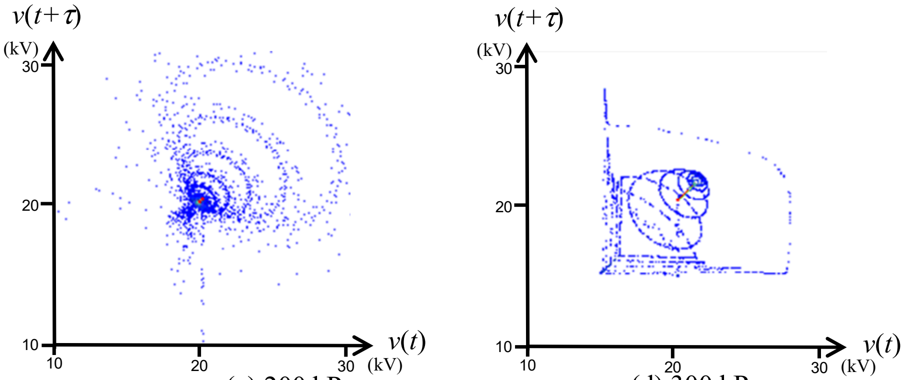
(a) Testing on vehicle (b) Experimental setup

Figure 6. Spark plug simulator experimenting effect of air pressure on sparking performance.

The voltage signal was captured and plotted against its time delay value. The second question encountered was “what is the appropriate time delay value τ to be used?”. It was observed that this value could be anything between 1 to hundreds of cycles [20]. The Poincaré sections for different air pressures are shown in Figure 7.



(a) 0 kPa (b) 100 kPa

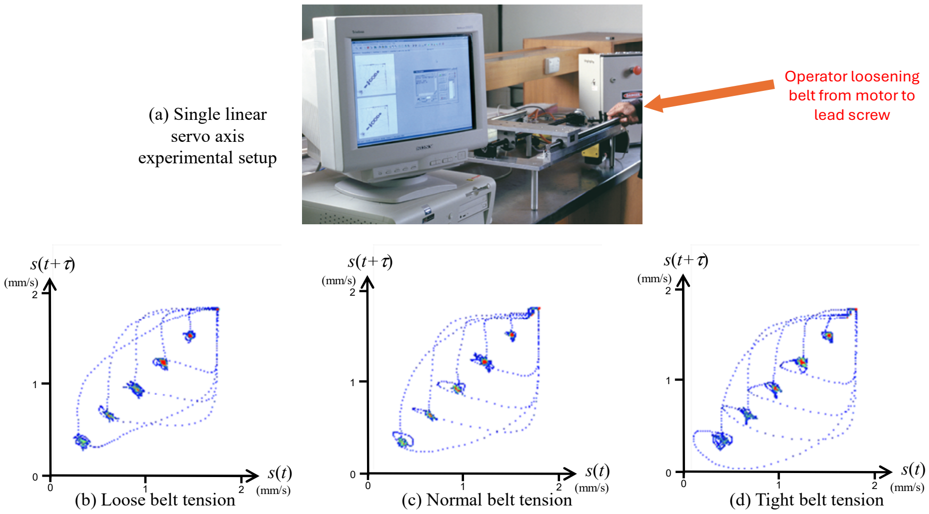


(c) 200 kPa (d) 300 kPa

Figure 7. Poincaré sections of spark plug voltages for different air pressures.

Some observations were valuable. Due to large time delay value, several thousands of sample points were required. Minimum six thousand points was found to be satisfactory in most cases producing consistent (looks complete) Poincaré sections. The perfect sparking condition was 0 kPa, but sparking could still be possible at higher pressures. However, there was a more abrupt transition between 200 kPa and 300 kPa. The pattern at 300 kPa was clearly different.

Mechanical systems such as linear axes had much slower responses. In Figure 8, the belt connecting the motor and lead screw was loosened and the motion dynamics (in terms of speed of the linear axis) were measured. Their Poincaré sections showed minor variation as shown [21].

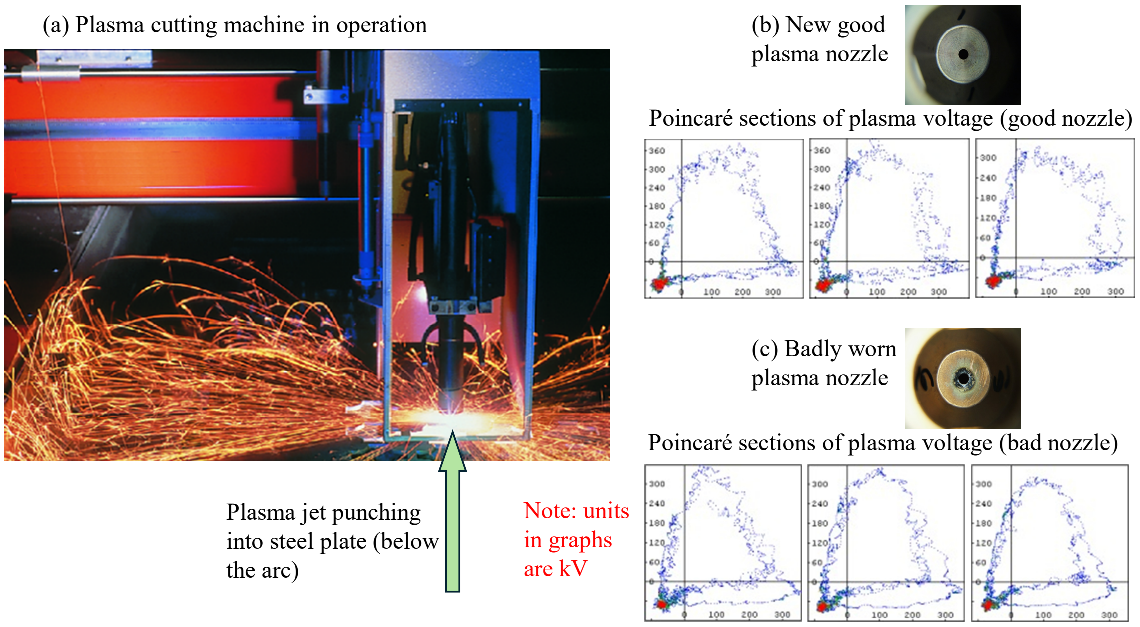

(a) Single linear servo axis experimental setup

Operator loosening belt from motor to lead screw

(b) Loose belt tension (c) Normal belt tension (d) Tight belt tension

Figure 8. Single linear axis experiment setup and its Poincaré sections.

So far the investigations were laboratory-based. All measurable system variables were monitored closely and controlled within acceptable range. Applications to industry cases have been successful on plasma cutting machines and die casting machines [22]. The plasma cutting machine case was particularly successful to prompt replacement of consumable plasma nozzle so as to reduce the chance of burning blow holes to workpiece (Figure 9). The Poincaré sections of the good and bad nozzles are shown. Note that there are 3 sets of nozzle data for each of the groups. The shape of Poincaré sections in the same group show similar patterns. The bad Poincaré sections differ from the good ones but how to judge the differences could vary between delay time settings and opinion of the analyst.


(a) Plasma cutting machine in operation

(b) New good plasma nozzle

Poincaré sections of plasma voltage (good nozzle)

(c) Badly worn plasma nozzle

Poincaré sections of plasma voltage (bad nozzle)

Plasma jet punching into steel plate (below the arc)

Note: units in graphs are kV

Figure 9. Monitoring condition of consumable nozzle in high temperature plasma cutting process.

Another example of industry application expanded the methodological concept to “family of machines”. This application extended from the single linear servo-axis investigation to computer numerically controlled (CNC) grinding machines [23]. The phase space reconstruction method was used to examine if the same pattern change was exhibited when the same fault appeared on CNC machines within the same model. A diagnostics software called MachineGP was developed and installed as part of the standard machine support suite. Figure 10 shows screen dump of the software on three machines with different machine models.

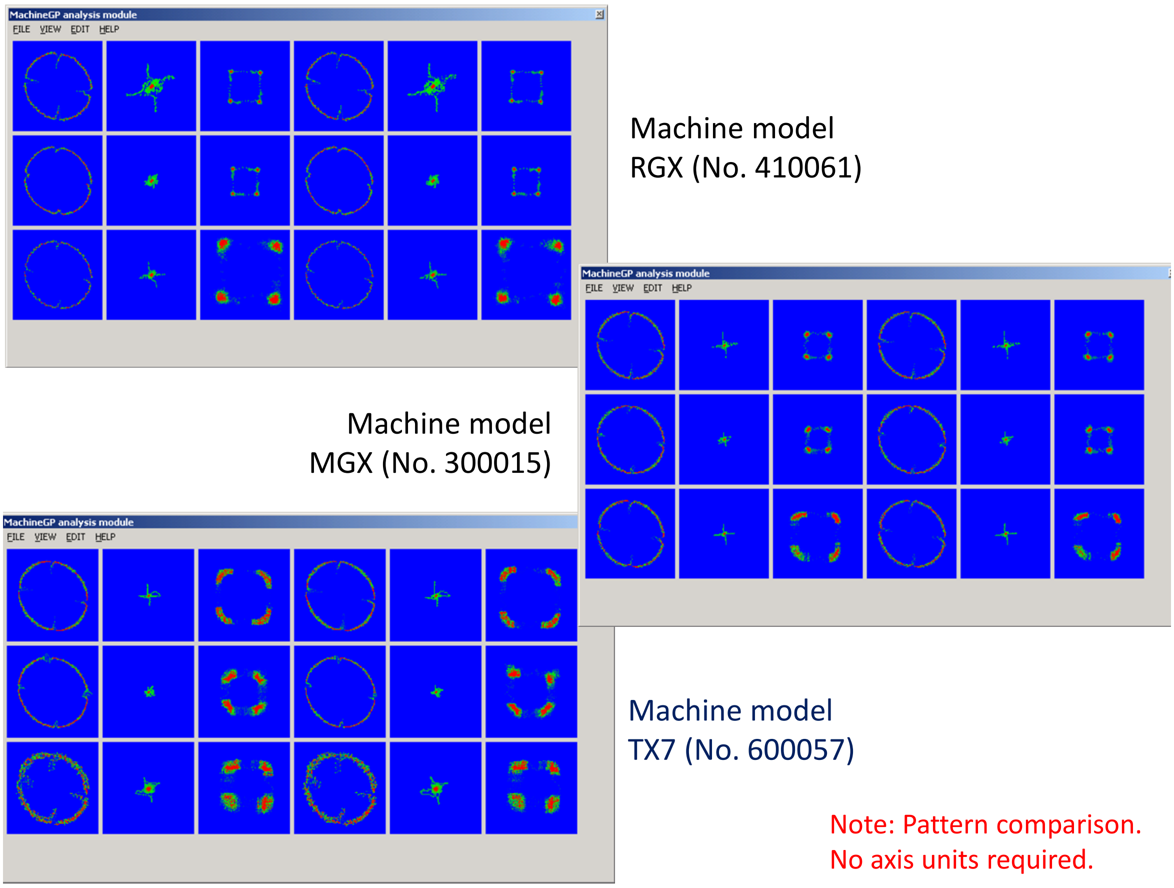


Figure 10. Screen dump of CNC machine diagnostics software.

It is clear from Figure 10 that there are pattern differences among the three models. The differences are not immediately obvious but certainly detectable and quantifiable.

2.5. Learning from Analysis of Systems Based on Chaos Theory

Some learnings from the above research investigations and literature reviews could be drawn. From the single linear servo-axis experiment and the CNC machine models, if these systems are regarded as chaotic systems, they behave in classes. Similar systems, especially systems with similar designs and vary in a few parameters, have similar Poincaré section pattern displays. This phenomenon greatly reduces the difficulty to create data baseline for the same model of machines. However, it is still not clear how much similarity could be drawn from the same “model”. The plasma cutter case example reflects the complexity of the patterns such that the “similarity” is not readily recognizable, although the overall shape can be vaguely identified. Setting up the baseline Poincaré section is time consuming due to the need for large amount of experimental data as well as tuning the analysis settings. If a new machine model is required, this work could take months. After all, successful recognition of faults depends on knowledge of possible fault patterns that are captured previously. An unknown fault can be highlighted but exactly what it is and how to handle it needs another investigative often with a new analysis system. The merits and drawbacks of signal analysis based on chaos theory can be summarized in Table 1.

Table 1. Summary of merits and drawbacks of chaos theory based signal analysis method.

Method Characteristics	Merits	Drawbacks
System can react chaotically	No first principle modelling	Every system needs experimental investigation (learning must be in experiments)
Identification of fault by recognition of 2D Poincaré section patterns	Simple, visual analysis allowing non-professional users	(1) Unknown patterns could be ignored (2) Faults are recognized AFTER they appear in the system—damage is done already
Many Poincaré section patterns have specific features and density distribution	Patterns can be analysed and recognized digitally	Computational time long affecting possibility of real-time diagnosis
Poincaré sections are constructed using simple time delay data from the same data stream	Data collection and subsequent transformation is straight forward	Difficult to find the optimal time delay value for particular system
Systems with similar design structure can be classified in classes of chaotic behaviour	Systems in the same class may not need repeated data collection to setup	No universal rule to define similarity of features—risk of over-confidence on class definition

3. System Performance Extrapolation

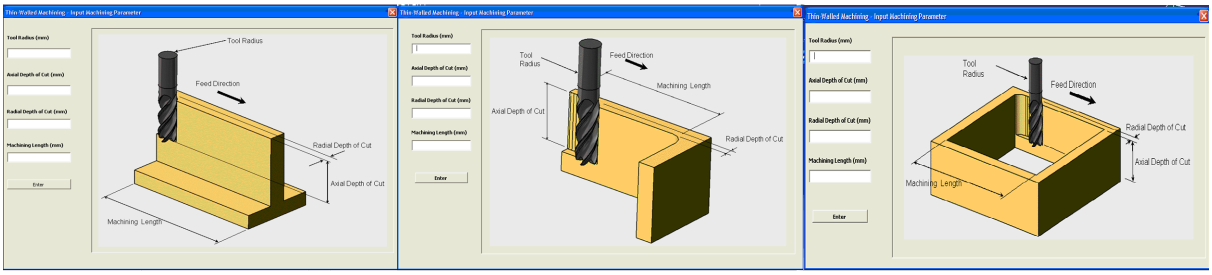
The purpose of signal analysis of nonlinear systems is to understand how the performance of the systems so changes can be detected. It is beyond just discovering what happens in the system and act on "it" (the failure). When failure occurs, it is already too late. Damage is done. If it is a manufacturing process, rejects are made. If it is a rescue mission, disaster could happen. Faults should not be allowed to eventuate. They should be stopped before loss materializes. To do this, we need to "feel" the system and predict beyond current time on how the system will behave.

3.1. Model-Based Fault Analysis

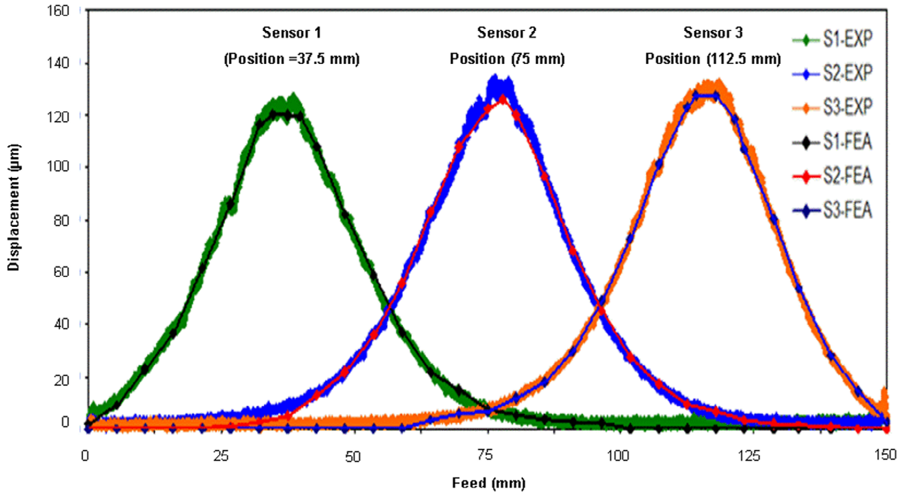
Thin wall machining has been known to cause issues due to deflection of thin wall. This type of faults can be predicted. The analysis involved detailed modelling of the workpiece design including planned manufacturing process parameters such as cutting path, depth of cut, federate, tool geometry and so on. Cutting forces are computed and input into a finite element deflection estimation process (Figure 11). Based on the computed deflections at different times, the cutter tool path is then offset by the estimated amount to compensate for the missed material in the cut path [24]. Experiments showed that the error of machining could be reduced to within micron scale. It is interesting to note that most severe deflection occurred when milling at the middle of the wall. Deflection was negligible at the two end ends of wall milling.

On the other hand, tool wear in machining operations is closely related to abrupt interactions between the tool and the workpiece. Predicting cutting forces during machining process was possible given specific operational information such as material properties and machining parameters [25]. Irrespective of how uniform the block of metal could be made, the modelling analysis demonstrated that irregular forces on the system was unavoidable. The nonlinear signals thus generated formed the basis to treat the system statistically, i.e., outcome variations could be estimated [26]. Based on this principle, occurrence of tool wear was associated with surface and material properties [27].

These researches provide deeper understanding of the nature of nonlinear signals in machining processes. The thin wall machining research unveils the relationship between signals generated by distorted geometry and the errors as the resulting outcomes. The tool wear research outlines possible approach to predict tool wear—a fault that is critical to manage in manufacturing. The nonlinear signal analyses highlight one important objective of the research, i.e., to correlate the symptoms with the causes so that mitigation and if possible, preventive actions can be taken. However, the resources required in this approach are enormous, both in terms of time to create the model as well as computing faults over the process period. It is also limited to well-defined processes instead of more general applications. The time to find solutions is too long.



(a) Milling rib (b) Milling bracket (c) Milling box

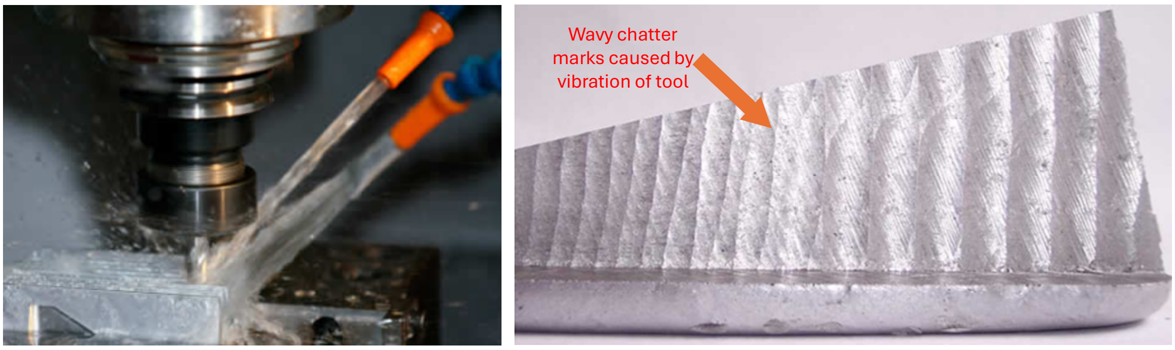


(d) Comparison of experimental and theoretical signals

Figure 11. Deflection prediction under continuous cutting forces.

3.2. Sampling Over Time

One of the most common problems in machining of metal workpieces is chatter. It is a phenomenon of self-excited vibration, which is produced by high cutting force between workpiece and cutting tool, especially working on “hard-to-cut” metal alloys [28]. Figure 12 shows the typical machining process and outcome.



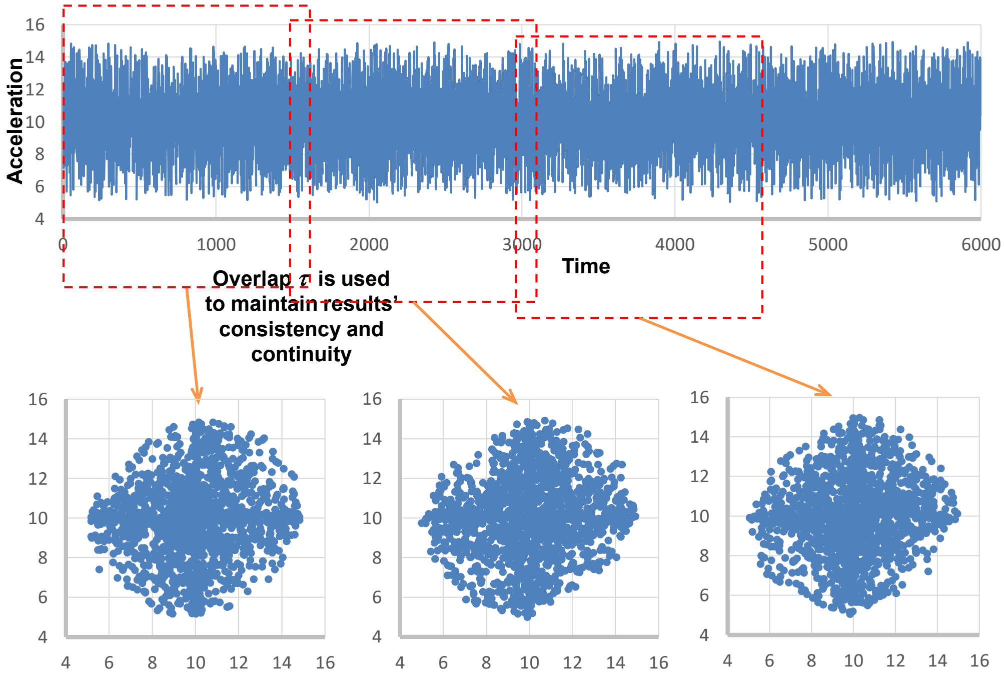
(a) End milling process (b) Workpiece surface due to chatter

Figure 12. Chatter phenomenon and its outcome.

Chatter does not always happen. It occurs when certain set of conditions during machining process is met, but what is in this set of conditions is not entirely clear. Ding et al. [29] hypothesized as a resonant phenomenon but experimental findings were not definitive. Different types of sensing mechanisms resulted in different signal characteristics and patterns [30]. Furthermore, chatter was not a phenomenon that existed and persisted in every milling process—cutting experiments could go on days without chattering being noticed. [31] Using phase space reconstruction method, some of the Poincaré sections showed strange patterns but not indicative enough for chatter detection [32].

Later in the research, a different approach to interpret the Poincaré sections was invented. First, instead of using the whole recorded time, signals were cut into segments so that trends could be identified from analysis of each of the time segments (Figure 13). The Poincaré section of each time segment was regarded as matrices which fitted into a polynomial [33]. Coefficients were calculated for the polynomial and the trend was observed. It was surprising to see that the first coefficient showed consistent trending behaviour and subsequently became the discriminator for onset of chatter. The idea is similar to statistical process charting method monitoring rejects in a manufacturing operation. This research broadened the methods of interpreting Poincaré sections to not limited to visual pattern recognition.

The algorithm for discriminating chatter onset is simple—just by value of the first coefficient. Hence, the computation process is straightforward and suitable for implementation in simple microcontrollers. The method of time signal segmentation extends the experimental data to an additional time dimension, which is important to subsequent researches.



Note: Units in phase space reconstruction are in mm/s². A dot in the represents a record at $x(t)$

Figure 13. Data segmentation in preparation for phase space reconstruction.

3.3. Learning from Signal

Several learnings could be summarized in the fault prediction research. Merits include:

(1) Faults are unavoidable. Both model-based (using cutting forces) and time-window (data sampling over time) analyses demonstrated feasibility of detecting occurrence of specific faults in the system. Subsequent remedial actions can be taken or even to the extent that preventive measures can be put into place.

(2) Faults do not occur suddenly. It is a micro-faults accumulation process. Only when sufficient amount of micro-fault is accumulated then the fault is recognized. This implies that in order to predict the fault, higher accuracy and frequency of data sampling is required to quantify and assess extent of micro-faults in the system.

(3) Drawbacks are:

    (a) The model-based fault prediction approach is limited by the preciseness of fault conditions and generation sources. As such, it is hard to determine if an alarm should be raised on some borderline symptoms.

    (b) Sequencing and priorities could be an issue since there is no further information on which issue is more important than others.

    (c) Limitation of this research is obvious. It is very specific to milling cutting. Other machining processes might need other methods to interpret system data to arrive at required decision.

4. System Dynamics and Trend Assessment

Manufacturing is a broad engineering discipline. Other than metal removal manufacturing, many other forms of manufacturing processes need automation. Trampoline manufacturing is a good example [34]. The automatic double threaded trampoline machine was designed to exercise webbing motion with microcontroller timing control instead of the old version mechanical cam-based activation. Weaving an Olympic scale full size trampoline matt could take a day. Missed threading could happen during the day and might not be noticed immediately by the operator—the operator had other machines to attend to as well. If the missed threading was found after post-inspection, the whole matt had to be destroyed. Some kind of continuous process health monitoring and fault prevention is necessary.

4.1. Analysis Using Scalograms

The weaving operation involved back-and-forth movement of a long metal bar known as the rapier, which carried a thread between pre-hanged cross threads of the yet-to-be-woven matt. This is the only fast moving dynamic part of the machine. Although whether the thread could be successfully weaved depended largely on the thread being hooked at the end of the stroke, speed and vibration of the rapier's stroke would have indirect effect, Since live signals were required from the working machine, wireless signal acquisition method similar to Sulistyawan et al. was adopted [35]. In order to monitor actions of the automatic trampoline machine, an acceleration sensor device with an Arduino microcontroller was mounted on the rapier. Acceleration signals were transmitted and captured to the server wirelessly. As in the chatter research, the data streams were segmented over the time period according to Equation (3) [36].

$$n = \frac{t_T - t_0 - 1}{t_S - t_0} \tag{3}$$

where

t_T = Total number of samples in the experimental run

t_0 = First signal sample in the experimental run to be used for analysis. Data before this count are discarded.

t_S = End of first segment signal sample in the experimental run to be used for analysis.

Note that all segments have the same number of signal samples, i.e., minimum 6000 data points. This research explored a different route of signal analysis. How long each segment should be depended on perception of when a fault might or might not occur. For every segment, the continuous wavelet can be computed using standard wavelet transform equations or software such as MATLAB [37]. Then the scalogram *SG* is the square of the wavelet.

Continuous wavelet transform scalogram reflects the energy density of signals. Abrupt transition in signals result in larger absolute value of the coefficient [38]. When it is plotted against time, abrupt transitions appear as brighter colours in the scalograms due to higher frequency clusters. Unfortunately, the scalograms were not clear. The transition frequencies were blurred with neighbouring frequencies. Instead synchro-squeezed scalograms had better discrimination properties [39]. Visualization of synchro-squeezed scalogram for the purpose of distinguishing transition state of the system is an important step to understand what to look for. To embed this perception into system control, further interpretation with an innovative concept is necessary.

4.3. Distribution of Frequencies Characteristics: Sum Standard Deviation Frequency

The scalogram is a distribution of frequencies of the system at a particular time. As a statistical frequency by itself, two basic parameters could be computed, i.e., mean frequency (*MF*) and standard deviation frequency *SDF* [40]. It was found that *MF* showed the shift of system performance and could be useful for recognizing existence of faults, whereas *SDF* represented variations in the system and were more relevant to trend of performance shift. Unfortunately, *SDF* values were unstable due to a lot of noise and external influences.

To find a stable condition indicator, Sum Standard Deviation Frequency (*SSDF*) is proposed—Equation (4). It borrows the concept of moving average. *SSDF v*alues are the sum of first m SDF in each dataset where *m* is a defined number for summing consecutive signal streams, then the *SSDF* for a dataset.

$$SSDF = \sum_{j=1}^{m} SDF_j \tag{4}$$

The first *m SDF*s are used because this is the period in which micro-faults start to accumulate but the total effect is still tolerable. Since the synchro-squeezed continuous wavelet scalogram is a signal frequency power distribution representing health condition of the system, the value of *SSDF* of a dataset represents the potential of developing fault within the remaining *SDF* time frame of the dataset.

4.4. What Pattern to Look for?

Further research using *SSDF* as the triggering indicator for system condition changes was conducted on 3D printing machine [41]. The method worked well on additive manufacturing process in which a loosened timing belt was introduced as the fault symptom. This work has included an introduction of fault pattern learning using deep peak clustering method. The outcome was satisfactory but research for generalization of the analytical process would need more future research.

4. Discussion

This article summarizes decades of research to find appropriate interpretation methods for different kinds of signals captured from different kinds of industrial machines. The form of signal analysis methods have changed a lot over the decades but the fundamental principles are still useful. Several general conclusions could be drawn from work so far.

First, to enable diagnosis of system health, some kind of signals is required. There is no universal type of signals that could be regarded as always applicable. It depends on availability, frequency, distinguishable variations and continuity. One thing for sure is that to detect emerging fault from a healthy system, a continuous stream over the whole operating cycle is necessary.

Second, the ability to detect fault is desirable but in the era of Industry 4.0, it is the new fully automated system that would need proactive fault diagnostics and remedial abilities. Feedback of performance should be immediate while the system is operating. In this sense, development of digital twin that incorporates both model-based prediction as well as real-time nonlinear signal analysis becomes an urgent requirement [42]. The new robotic system was designed with the erratic electric discharge machining tool that could generate variety of chaotic nonlinear signals for exploring different methods of interpretation.

Third, some systems might appear as unstable and sometimes labelled as chaotic. Irrespective of how the system behaves, it is always possible to use phase space reconstruction to visualize the trend. However, recognition of change to faulty conditions is only possible for very specific cases.

Fourth, in any signal diagnosis process, adequacy of data points is a fundamental requirement. From experience, thousands to millions of sample data points in a system run are captured. The continuous sample data stream are cut into segments so that trending could be observed from the computed performance indicator. Timing for fault appearance varies depending on nature of the system's operation.

Finally, there is still no definitive universal analysis method that can be used irrespective of application cases. More research to make sense of captured signals is required to broaden applicability of known methods to new applications. Furthermore, it is clear that the world is moving towards the era of artificial intelligence (AI). New system development requirements and operational paradigms are emerging that affect everyone's lives. Digital transformation has turned every engineering artefact into a data-rich, algorithm-mediated, cyber–physical system [43]. Research in nonlinear signal analysis will incorporate AI into the learning process.

5. Conclusions

Analytical methods to make sense from nonlinear dynamic signals captured from a system vary greatly among researchers. This article reviews a school of investigation using two approaches: chaotic systems modelling and frequency transformation. The foundation of either approaches is to detect changes over time. If a symptomatic indicator can be found, changes of the indicator from a known "normal" state will illustrate emerging issues that system control (automatic or manual) is put on alert. However, irrespective of which approach is adopted, two fundamental issues have to be resolved: (1) signal source that contains information about the system's dynamics; (2) interpretation that can extract hidden meanings from the signals. More research will be required as a universal solution is still far from being discovered.

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Use of AI and AI-Assisted Technologies

No AI tools were utilized for this paper.

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