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Diagnosing Intermittent Faults through Non-linear Analysis

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Abstract: To cope with certain exogenous stimuli, there have been inexorable advances of technology, with an increased focus and fascination with the accuracy of diagnostic equipment. This can become a difficult problem to solve as it warrants real-time monitoring whilst taking up unnecessary measures to improve overall system reliability and maintainability. Intermittent faults may be benign or malignant in nature and their overall impact on a system varies with mission objectives and operating conditions. Major failures can often be averted if these problems can be detected sufficiently in advance by observing them in dynamical behaviour. The phase space trajectory reconstructed from a time series is known to elucidate such behaviours however it is seldom applied for fault analysis. This article makes use of dynamic system theory and investigates its application for fault estimation by analysing non-stationarities which arise due to the changing dynamics under intermittent conditions. Intermittent fault detection presents a challenge for traditional fault diagnostic equipment as they do not manifest themselves all the time. The idea is to move away from the traditional approaches and investigate the use of non-linear analysis by building a reference trajectory using the phase space reconstruction. This is used as an objective measure for any deviations caused by intermittent phenomena. The method is validated using simulated data and shows promise. The implications of the study are to identify new fault isolation bounds necessary to improve diagnostic success rates and potentially lead to early diagnosis of intermittent faults in electrical equipment.

Keywords: Condition monitoring, fault detection, diagnostics, non-linear analysis, decision support.

1. INTRODUCTION

All systems are susceptible to faults during operation. Some of these problems can occur within acceptable operating tolerances and hence result in subsequent inherent diagnostic difficulties (Zhou et al. (2019)). This often leads to several unsuccessful fault diagnosis which negatively impacts critical system stakeholder requirements; including system safety, dependability and life-cycle costs. It is also the leading cause for No Fault Found problems (Khan et al. (2014)). Some authors have argued that it is essential to avoid such phenomena, or at the very least, reduce the level of impact that unsuccessful diagnosis can have on a business operation (De Kleer and Williams (1987)). However, any fault diagnostic method will have a limited capacity when dealing with the increasing complexities of modern systems. E.g., in electromechanical systems, many faults originate as intermittent occurrences rather than a sudden event. Intermittent faults can result from unsuccessful (or inefficient) troubleshooting regimes. But since these problems rarely lead to a loss of complete functionality of a system (even though their components may be out of specification), it becomes important to improve understanding of failures from a multidisciplinary perspective; including the development of condition monitoring with advanced diagnostic capabilities. Intermittent problems are often random in nature, but (sometimes) their behaviours can be recurrent (Bakhshi et al. (2014); Khan et al. (2018)).

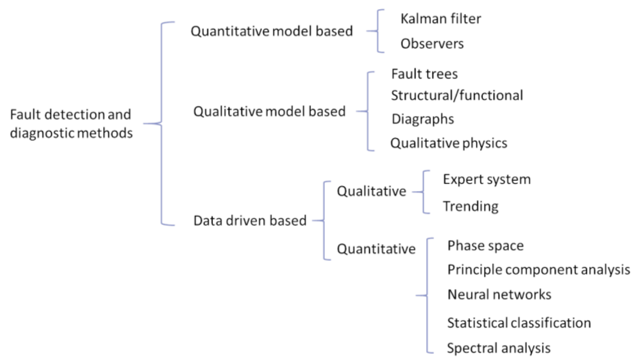


Fig. 1. Some prominent fault detection techniques

According to Khan et al. (2014), there are typically three causes of intermittent faults: (i) abrupt parameter changes, (ii) structural changes, and (iii) sensor malfunctions. As shown in Fig. 1, generic approaches can be used for their detection. However, these methods vary in their strengths in terms of their detection rates, diagnosability, robustness, adaptability, model/computational requirements, etc., to detect dynamic changes in the deterministic structure of a signal which may be instantaneous or relatively slow dynamic changes. Yet, most of these methods provide no quantitative evaluation of the conditions that will make the fault identifiable as an intermittent fault (Bondavalli et al. (2000)). In contrast to hard fault detection, intermittent faults do not have any particular characteristics. The authors have not come across any study which discusses this issue in detail; this presents a unique opportunity to contribute to the field. As a result, the following three activities are carried out:

- The ideal system behaviour is rearranged into phase space, based on some delayed embedding. The evolving state of the system is traced as a reference trajectory through this space;
- Future (predicted) operational trajectories are compared against the reference; predictions are made based on the k-nearest neighbours algorithm;
- The residual is subsequently computed to diagnose the fault.

The authors demonstrate the applicability of the technique with simple examples for developing deterministic qualitative (and quantitative) observations which can be used in detecting observable intermittent variations. This strategy differentiates from the majority of existing techniques by its peculiar theoretical perspective as it does not:

- Make any specific assumptions on the mathematical structure of data;
- Rely on assumptions of stationarity, i.e., statistical properties (such as mean, variance, etc.) do not have to be constant over time;
- Need to consider the data as the output of a linear dynamical system.

The remainder of the paper is organised as follows: Section 2 explains the theory behind non-linear analysis. Section 3 builds on these concepts using examples on how it can be used for intermittent fault detection. Finally, some conclusions are reached from the preceding analysis.

2. NON-LINEAR ANALYSIS

2.1 Phase space reconstruction

Elements within dynamical systems can be reconstructed by observing their output. As the system evolves with time, the state vector traces out a path in the phase space, known as the orbit of state trajectory, providing a phase portrait of the system at a given instant. It can map a time series to higher dimensional space so that all possible states of a system can be represented (with each possible state of the system corresponding to one unique point in the phase space). This shape (of the phase diagram) provides qualities of the system which may not have been apparent otherwise, such as hidden periodicities, non-stationary or the systems qualitative behaviour; indicating that higher complexities would require higher dimensions to describe the states of a given dynamical system completely. The criteria for reconstructing a phase space using a time delay method assumes a time series, $x_1, x_2, ..., x_N$, which is transformed into a phase space with vector $z_i = x_i, x_{i+\tau}, ..., x_{i+(d-1)\tau}$, where τ is the time

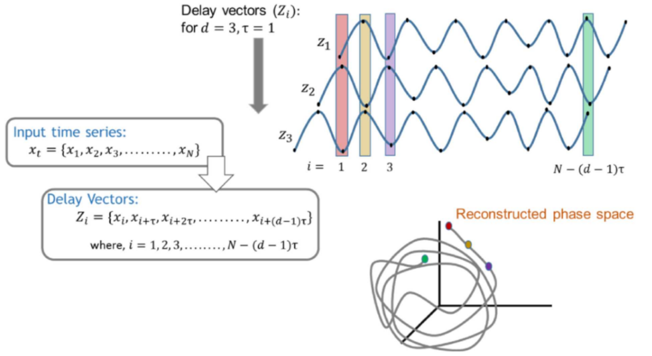


Fig. 2. Phase space reconstruction of a time series using the time-delay embedding theorem

delay and d is the embedded dimension. This process is illustrated in Fig. 2. A time series can be reconstructed accurately only if its embedding dimension and delay time values are correctly chosen.

2.2 Reducing singularities

Subsequent data points are connected to establish some relationship by structure and information. This relationship is highly dependent on the sequence of time as it reveals the typical dynamic behaviour of related variables. This is in contrast to random noise which will not exhibit any structure. If the delay and embedding dimension parameters are not optimal, the phase space trajectory will lead to ambiguities called singularities. A low number of singularities indicates that data points can be isolated across the trajectory and the system becomes highly predictable. A high number of singularities are not good and hence a lot of time is spent at reducing them as much as possible. As a result, the optimum parameters which have the maximum predictability can be calculated using Takens theorem and the False Nearest Neighbour algorithm.

2.3 Finding the optimal time-delay

According to Takens (1981), almost every value of time delay should work in achieving an attractor that closely follows the behaviour of a system. Yet, due to practical limitations (such as finite data length, finite precision and the presence of noise), choosing a time delay can become problematic. As each signal can contain new information within their successive measurements of time, the focus is placed on producing independent delayed coordinates in their reconstructed phase space. This is because, if the delay is too small (compared to the time scale of the system), it will produce highly correlated delayed vectors, restricting it to the diagonal of the reconstructed phase space. On the other hand, if the delay is too large, all the delayed vectors will become completely uncorrelated and the reconstructed phase space will not represent the true dynamics of the system. This makes the proper selection of the time delay of prime importance in using the time embedding technique as it preserves the essential dynamics required to reconstruct the trajectories. This paper makes use of the autocorrelation function for its calculation (Kim et al. (1999)):

$$c_T = \frac{\frac{1}{N}\sum_{i=1}^{N}(x_i - \hat{x})(x_{i+\tau} - \hat{x})}{\sigma^2} \quad (1)$$

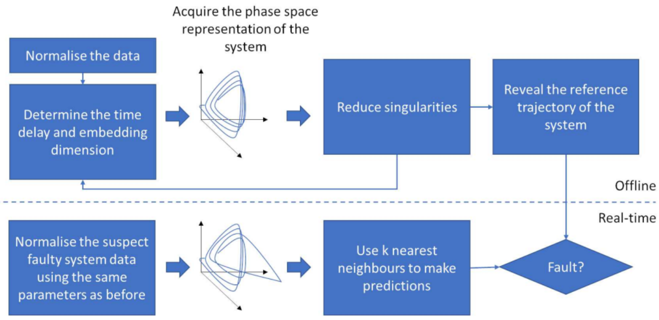


Fig. 3. Principle of the non-linear analysis method

where N is the number of data samples, $\hat{x} = \frac{1}{N}\sum_{i=1}^{N} x_i$ is the sample mean and $\sigma^2 = \frac{1}{N}\sum_{i=1}^{N}(x_i - \hat{x})^2$ is the sample variance. The time at which the autocorrelation function reaches its first zero-crossing indicates that the two coordinates are linearly uncorrelated and hence is taken as a good estimate to use as an embedding time delay.

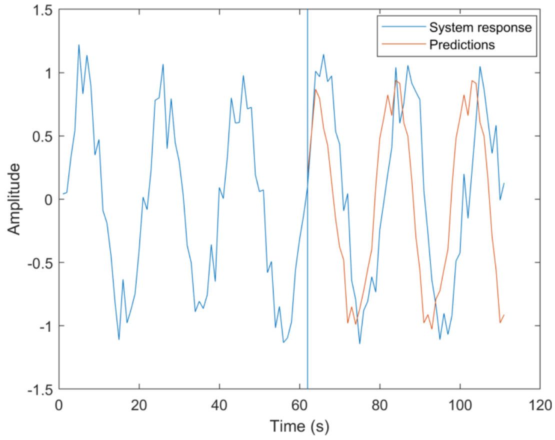
2.4 Determining the embedding dimension

It is known that the embedding dimension, d, has to be, at least, twice the dimension of the real-world solution, i.e., $d \geq (2D+1)$. Here, D is the original system dimension. If d is larger than it should, the dimension of the reconstructed system will contain redundant information. If d is smaller than it should, then the points near the space coordinates may be due to the folding effects of the projection and not the data in the original dynamic system. In this case, any predictions made using this phase space will not be good enough. In the simulations used in this paper, the False Nearest Neighbour (FNN) algorithm is used for estimating d. The main idea is to examine how the number of neighbours of a point along with a signal trajectory changes with increasing embedding dimension. Therefore, an appropriate selection for the embedding dimension is when the percentage of FNN approaches to zero (Rhodes and Morari (1997)).

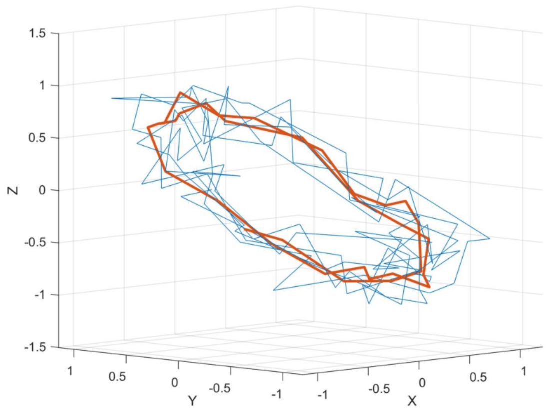
2.5 Prediction in phase space

After an appropriate trajectory is obtained, predictions of future sensor measurements must be made. KNN can be used to locate the data points that are closest to the value we want to predict. This is a non-parametric approach which relies on observes the future values of these neighbours and take their average from the past states of the system. This helps to predict the next value [1] . As a rule of thumb, K is chosen to be $d+1$. The principle is shown in Fig 3. Of course, these predictions assume that most of the state information is readily available in the past data. This places an emphasis on the importance of ensuring the quality of past data that can represent all possible future conditions, to obtain the state definitions and the number of nearest neighbours (Smith et al. (2002)). It should be noted that the predictions can be improved by making use of some weighting regime, e.g., assigning more weight to the most recent neighbour and so on. The authors made

[1] It should be noted that other approaches such as AR, ARIMA models often outperformed the average k-nearest neighbour method.



(a) Predicting the system response



(b) The behaviour in phase space; blue: system response, red: predictions

Fig. 4. The system response (unfiltered)

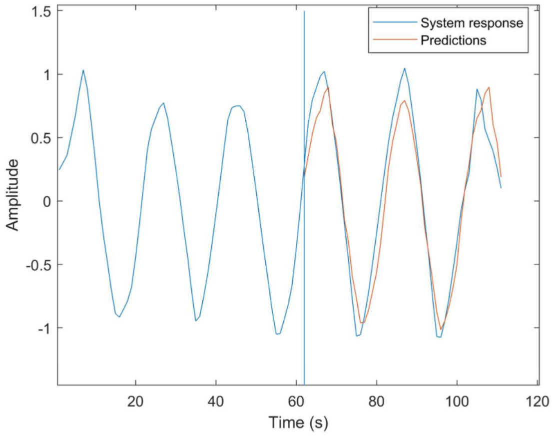
use of the Inverse Distance Weighting (IDW) interpolation method, which is a deterministic spatial interpolation approach often used to estimate an unknown value using known values with corresponding weighted values:

$$X = \frac{weight_1 x_1 + weight_2 x_2 + ... + weight_n x_n}{weight_1 weight_1 ... weight_n} \tag{2}$$

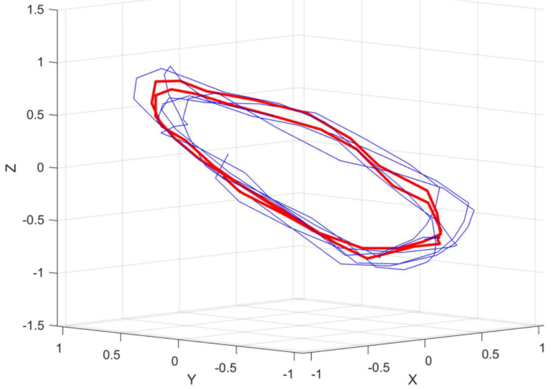
where $weight_n = \frac{1}{distance_n}$ is being used to calculate each respective weight.

3. SIMULATIONS

Example 1: Acquiring the phase space representation. Consider the noisy system response in Fig. 4a. The delay and embedding dimensions are estimated to be 5 and 3, with $k = 4$. The result in Fig. 4b emphasises the need to denoise the data in order to make cleaner predictions on the system responses in the phase space; figs. 5a and 5b reflect much better results after a filtering process. If a fault (or drift) is encountered, the model would be able to diagnose any deviations from the expected predictions; which are calculated by simply averaging 4 nearest neighbors of the data sample.



(a) Predicting the system response



(b) The behaviour in phase space (filtered); blue: system response, red: predictions

Fig. 5. The system response (filtered)

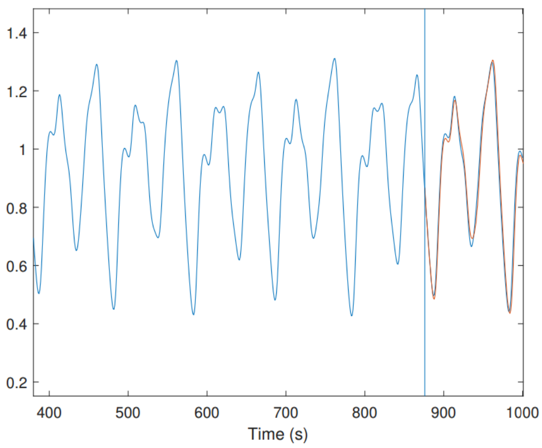


Fig. 6. Predicting a chaotic time-series (predictions in red)

Example 2: Making better predictions. Predicting a non-linear time delay differential equation - the Mackey-Glass equation, to generate complex dynamics [2]:

$$\dot{x} = \frac{0.2x(t-\tau)}{1+x^{10}(t-\tau)} - 0.1x(t) \quad (3)$$

[2] The time series is obtained by using the fourth-order Runge-Kutta method to find the numerical solution to the previous equation. It assumes that $x(0) = 1.2$, $\tau = 17$, and $x(t) = 0$ for $t < 0$.

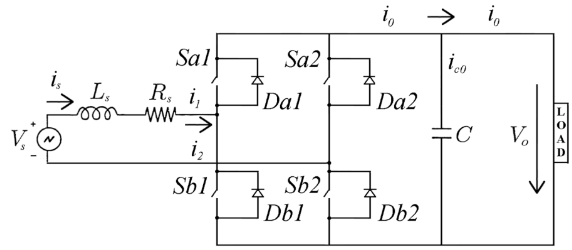


Fig. 7. Single-phase voltage source switch-mode rectifier

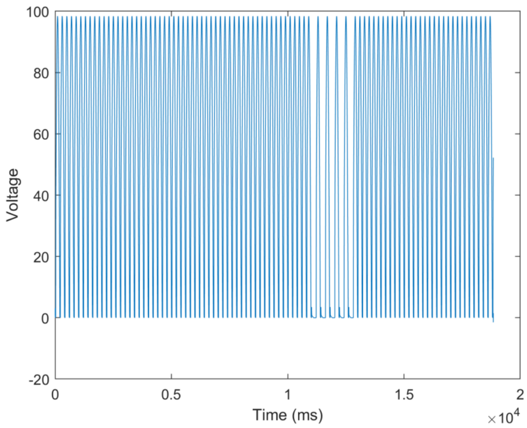
This trajectory is chaotic with no definitive time period. As the series does not converge or diverge, it is highly sensitive to initial conditions. The delay is set at 5, with an embedding dimension of 6. The result of the prediction is illustrated in Fig. 6. The initial 880 samples are used to map the signal trajectory in the phase space, while the rest of the 120 samples are used to validate the predictions. This example makes predictions by using Equ. 2.

Example 3: Calculating the fault likelihood. In order to demonstrate the use of the strategy for fault diagnostics, a model of an AC/DC single-phase converter is used as presented by Pires and Silva (2002), and depicted in Fig. 7. The system is simulated using the parameter values $R_0 = 100\Omega$, $C_0 = 10000\mu F$, $L_s = 10\mu H$, $R_s = 0.01\Omega$, $V_s = 220V$. The switching was designed to be in phase with the input voltage (50Hz sinusoid). The optimal parameters are determined to be a delay of 32, with an embedding dimension of 3. Two different conditions were trialled: *normal* which has no change and *intermittent fault* where $Sa1$ fails between $t = 1.1s - 1.3s$.

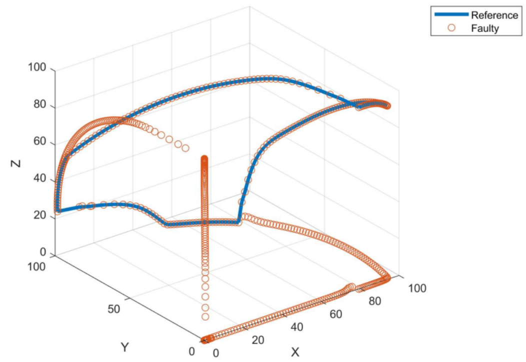
The intermittent fault is modelled as an impulse function and applied across $Sa1$ representing a damaged transistor. This impulse is applied during the systems steady-state operating phase and with the drop-in signal lasting 0.2 seconds as shown in Fig. 8. Using this method, it is also possible to identify hard faults, albeit enough information is available. This is because even though there is a fault and the phase space is expected to deviate from the healthy values; there might be no dynamic changes throughout the observed process period. This is in contrast to the intermittent case which will clearly identify a change. Furthermore, if there is a need to investigate the underlying implications of collective anomalies, a threshold can now be applied to the residual to indicate a fault. This will make it less sensitive and, depending on the application, reduce the number of false alarms. This is done by making use of a sliding window that calculates the moving mean μ, and variance σ^2, of the residual within that window. For fault detection purposes, this is followed by computing the fault likelihood, FL, as the complement of the Gaussian tail probability, Q (Khan et al. (2019)):

$$FL_t = 1 - Q(\frac{\hat{\mu} - \mu}{\sigma}) \quad (4)$$

where $\hat{\mu}$ is the median. By placing a threshold on FL_t, it can be used to report a fault incident. This equation serves as an estimate on how accurate the model is able to detect collective deviations, in context to the history within the assigned window. In most cases, it will (almost) always provide a distribution of results that will have smaller variances and be centred near 0. If any sudden jumps are

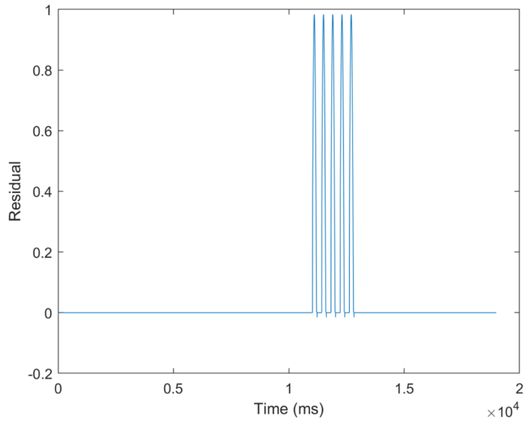


(a) Fault appearing in $Sa1$

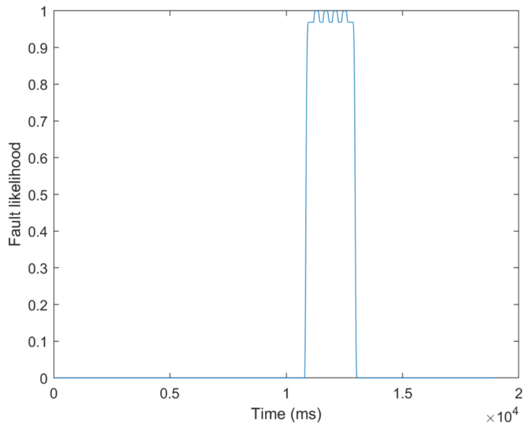


(b) The phase space representation with no fault and with an intermittent fault

Fig. 8. Circuit behaviour in phase space



(a) The residual of the system response



(b) Fault likelihood

Fig. 9. Probability of a (intermittent) fault

encountered in the residuals (as in fig. 9a), it can be used by the anomaly likelihood to generate an alarm each time a predefined threshold is crossed. Fig. 9b illustrates this concept for intermittent fault detection.

Example 4: Diagnosing intermittent faults in a DC motor. The authors have taken a simplified view of the system dynamics using a transfer function of a DC motor as illustrated in Fig. 10. Three intermittent faults are injected by interrupting the current supply to work at 50% at 90, 120 and 290 seconds. These interruptions last for 10 seconds each. The signal and its phase space reconstruction result is illustrated in Fig 11. It can be seen that although signal phase follows its typical path in Fig 11b, there are instances where it deviates from the expected trajectory. Across the time series, a 100 sample window is used to make predictions of the expected trajectory of the signal phase. This is used to generate the residual from the predicted vs actual response. A number of deviations can be identified in 12a, which are used to register the alarms in 12b. The anomaly likelihood is calculated over a moving mean of 10 samples; increasing this number can result in a much smoother outcome, but it will also reduce reaction time[3]. Therefore, a trade-off must be reached on accuracy vs speed.

[3] as it will have more samples to consider in the window.

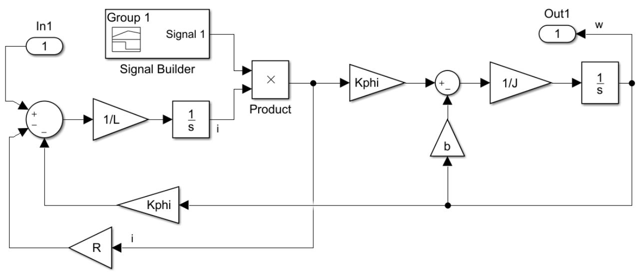
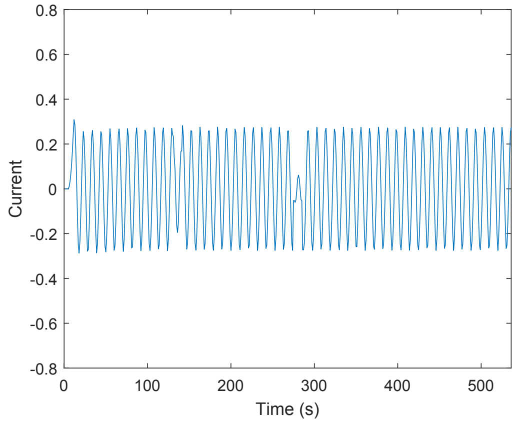


Fig. 10. Simulink diagram of DC motor: $L = 0.1H$, $K_\phi = 0.3$, $J = 0.1Kg/m^2$, $b = 0.01$, $R = 2\Omega$

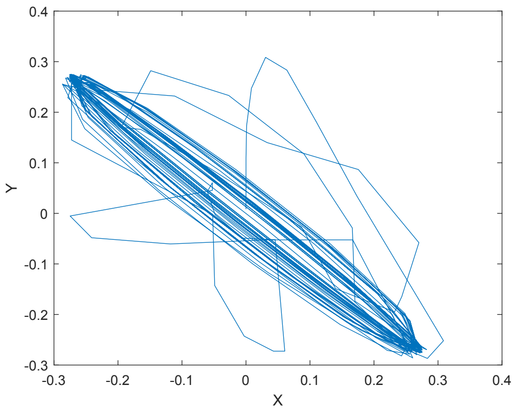
4. CONCLUSION

The paper proposed the use of non-linear analysis for fault diagnosis in electromechanical systems to address the problem of intermittent faults. These methods are well established in their application in mechanical systems with limited research found for the case of intermittent faults. The results here confirm that its use is applicable for electronic systems where the phase space can be used to study changes between normal and non-stationary occurrences. This also demonstrates the possibility of isolating where these problems occur in the time-series when analysing non-linearity.

The authors are further exploring the following research avenues:



(a) The motor current signal

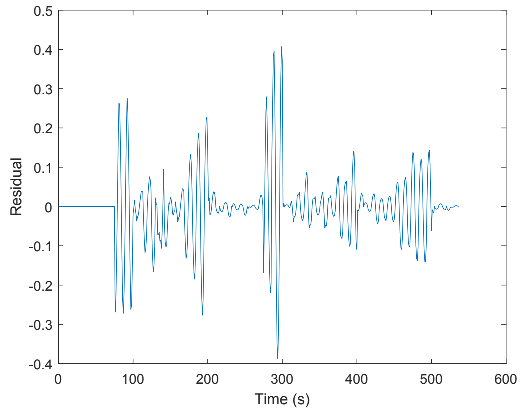


(b) Signal phase space with $d = 2$ and $\tau = 5$

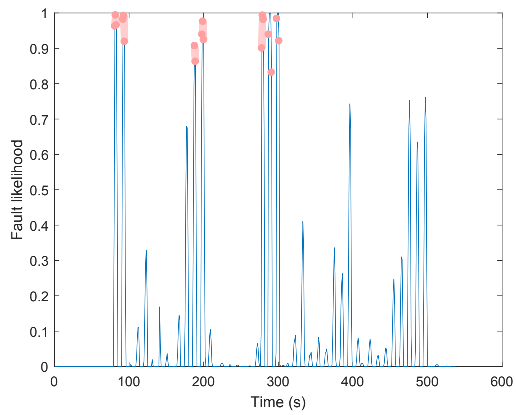
Fig. 11. The signal's behaviour with intermittent response deviations

- Investigating the impact of higher dimensions;
- Optimising the time windows to locate the intermittent occurrences accurately in time;
- Comparisons with conventional approaches.

Note: The Matlab codes and simulink models have been released on the lead author's Github page: https://github.com/drsamirkhan/nonlinear_prediction/



(a) The residual from the actual vs predicted output



(b) Fault likelihood with a threshold ≥ 0.8

Fig. 12. Diagnosing the intermittent fault

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