

Fault classification and diagnostic system for unmanned aerial vehicle electrical networks based on hidden Markov models

Rory Telford , Stuart Galloway

Institute for Energy and the Environment, University of Strathclyde, Glasgow, Scotland

✉ E-mail: rory.telford@strath.ac.uk

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Abstract: In recent years there has been an increase in the number of unmanned aerial vehicle (UAV) applications intended for various missions in a variety of environments. The adoption of the more-electric aircraft has led to a greater emphasis on electrical power systems (EPS) for safe flight through an increased number of critical loads being sourced with electrical power. Despite extensive literature detailing the development of systems to detect UAV failures and enhance overall system reliability, few have focussed directly on the increasingly complex and dynamic EPS. This study outlines the development of a novel UAV EPS fault classification and diagnostic (FCD) system based on hidden Markov models (HMM) that will assist and improve EPS health management and control. The ability of the proposed FCD system to autonomously detect, classify and diagnose the severity of diverse EPS faults is validated with development of the system for NASA's advanced diagnostic and prognostic testbed (ADAPT), a representative UAV EPS system. EPS data from the ADAPT network was used to develop the FCD system and results described within this study show that a high classification and diagnostic accuracy can be achieved using the proposed system.

1 Introduction

The increasing trend of unmanned aerial vehicle (UAV) deployment for a variety of missions can mainly be attributed to the promise of reduced costs and reduced risk to human operators [1]. However, eliminating the function of pilot from unmanned aircraft and replacing it with completely autonomous flight control complicates a number of issues, such as vehicle reliability. UAVs rely on a robust and intelligent control system that monitor and anticipate problems occurring in the flight dynamics, as well as compensating for communication time delays.

A UAV reliability investigation undertaken by the US Department of Defence [2] showed that the major sources of failure can mainly be divided into power/propulsion system flight control, communication and human/ground subsystems. Owing to the power system being integral to UAV reliability, the proper management of its health is imperative to UAV affordability, mission availability, operational efficiency and their acceptance into civil airspace.

Electrical systems are a critical aspect of UAV power systems, particularly with the advent of the more-electric aircraft [3]. On-board electrical loads include crucial subsystems such as avionics, propulsion, life support and environmental controls. UAV electrical power systems (EPS) operate in harsh environments and are characterised by physically compact topologies, where high-density generation provides energy to power electronics interfaced loads. Within the EPS, a diverse range of failure modes exist that have varying effect on network reliability; a major challenge is the design of fault tolerant control systems that can quickly detect and diagnose both critical and degraded faults to ensure robust health management and reliable operation. Previously, systems based on advanced diagnostic techniques [4–6] have been utilised for this purpose, although, generally, there has been limited focus on the EPS.

This research proposes the development of an EPS fault classification and diagnostic (FCD) system based on HMM that has the ability to accurately detect, classify and assess the impact of UAV network faults. The application of HMM to the EPS domain has previously been researched; Abdil-Galil *et al.* [7] investigated their implementation to the classification of power

quality disturbances and Suxiang *et al.* [8] utilised them for the diagnosis of power transformer faults. The main value identified in these applications included the inherent scalability and potential to simultaneously infer the probability of multiple system state hypotheses. The proposed FCD system evaluates their applicability to UAV EPS and how their use can supplement health management and fault tolerant control.

This paper outlines the development and operation of the FCD system, where the operation can be divided into two separate stages:

- Stage 1 – Classification of EPS network state.
- Stage 2 – Diagnosis of fault severity through parameter calculations.

This two stage system has the capacity to autonomously discriminate between a variety of potential system conditions and quantify the severity of any fault occurrence using EPS data. Both outputs of the system are vital elements in the control and monitoring of the network that provide key information regarding network behaviour. The application of the proposed system was verified with data collected from a subset of NASA's advanced diagnostic and prognostic testbed (ADAPT) network, the ADAPT-Lite (ADL) network [9].

The paper opens by presenting background information on; the ADL network and ADL data; the challenges associated with classifying EPS faults; related work, and an introduction to HMM. The following section outlines the proposed FCD system applied to the ADL network and Section 4 presents operational results of the system. Future work is explained in Section 5 and the paper is concluded in Section 6.

2 Background

2.1 ADAPT-lite system

The NASA ADAPT [9] is a unique facility that is designed to test, measure, evaluate and help mature diagnostic and prognostic health management technologies. The ADAPT system is representative of the topology of an EPS vehicle system in that it

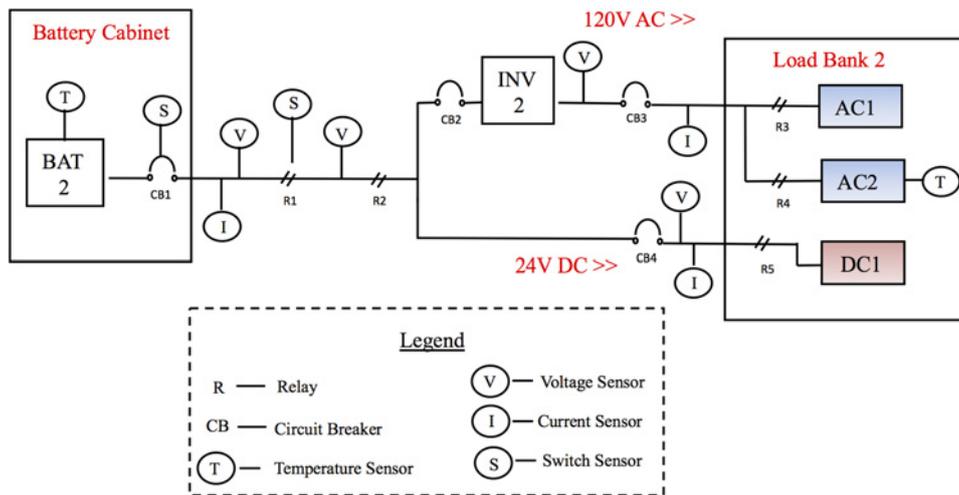


Fig. 1 Schematic of ADL Network on which the proposed FCD system is validated

provides energy generation/conversion, energy storage, power distribution and power management functions.

For the purpose of this paper, the FCD system is applied to a subset of the ADAPT system, the ADL network. A schematic of the ADL network is shown in Fig. 1. It includes a single battery, two AC loads and one DC load. An inverter converts DC power from the battery into AC to power the two AC loads. The single DC load is powered directly from the 24 V battery. Sensors throughout the network monitor voltage, current, temperature and switch positions. The circuit breakers (CBs) are nominally closed. The network has a non-redundant power configuration of the EPS that supports mission and vehicle critical loads.

The FCD system was designed and tested using data from the ADL network. The data was publicly available and distributed by

the Second International Diagnostic Competition (DXC'10) [9]. The data involved individual controlled experiments undertaken on the ADL network with each experiment detailing sensor readings for all sensors within the network. Each experiment covered roughly four minutes of time, with sensor readings detailed every 100 ms. Within a number of the experiments, failure scenarios were injected into the network. Only one failure was present during each experiment, meaning multiple failures within the network are not considered.

The injected failure scenarios are characterised by the location of the fault and the fault mode. Faults are injected to all components within the ADL network, including sensors. Fault modes include 'abrupt', 'intermittent' and 'incipient'. The severity of the injected fault was either network 'critical' or 'degraded'. ADL fault

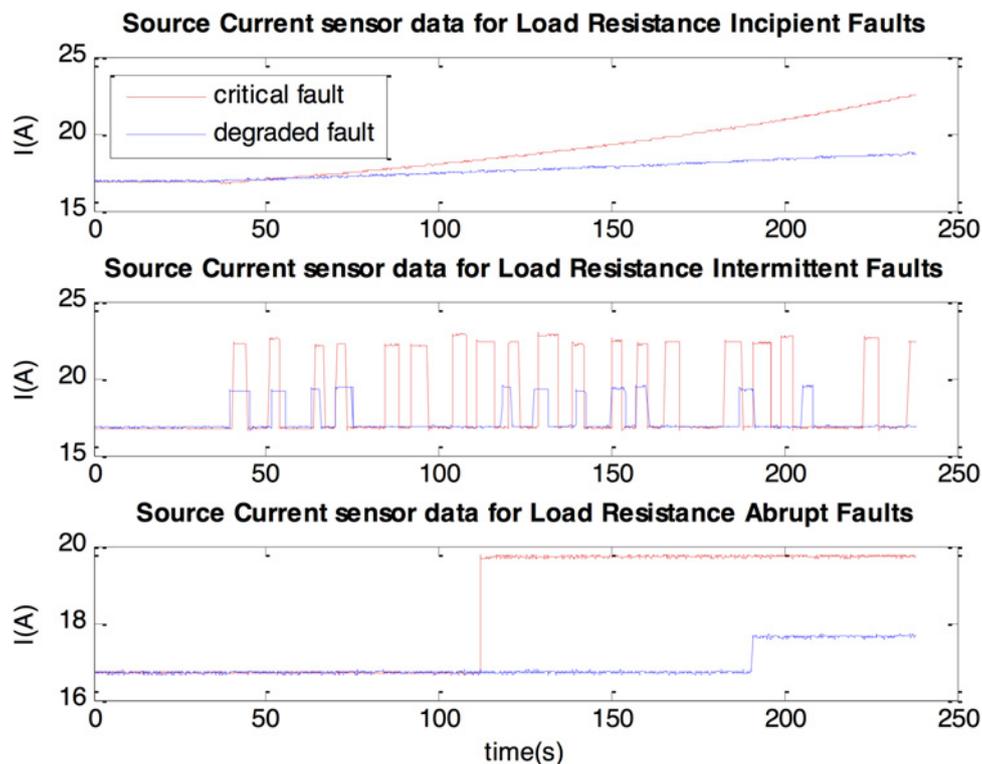


Fig. 2 Outline of faults injected into ADL network

Faults are characterised by their mode, location and severity. For brevity, only the power source current sensor data for various fault modes and severities occurring at an AC load are illustrated

characteristics are illustrated in Fig. 2. With the occurrence of critical faults, the UAV mission is no longer sustainable and abort recommendations should be provided; with degraded faults occurring, the network can still support critical loads and no abort recommendations need be provided. The data enabled the development and operation of the FCD system to include both network state classification and a diagnosis of fault severity.

2.2 Diagnostic challenges of EPS

The complex and dynamic nature of EPS leads to a number of challenges in attempting to accurately diagnose the occurrence of system faults and correctly initiate network recovery options to optimise reliable operation. The first of these challenges involves the number of mode inducing components such as relays, CB's and loads leads to a large range of network mode possibilities having to be considered [4]. Secondly, transients introduced into the system by mode inducing components throughout nominal switching periods, means the implementation of simple threshold based monitoring systems is an inadequate solution, because of the high false positive rates the transients would induce. In addition, the failure of system components and sensor noise distortion can lead to system state uncertainty. Furthermore, a diversity of EPS faults produces a range of fault onset periods, ranging from seconds for switch based faults, to days or weeks for source based faults. These challenges highlight the necessity to develop robust monitoring systems that can handle EPS state uncertainty as well as detect faults that manifest over differing time periods and have varying impact on network reliability.

2.3 Related work

The challenge of detecting and diagnosing EPS anomalies is a widely researched area [10, 11]. Generally, the techniques that are developed in an attempt to address this problem fall within two categories: non-model based and model based. Non-model based methods typically involve limit or trend checking [12], the installation of special sensors [13] and the development of expert systems [14] that implement the knowledge of diagnostic experts to determine the implication that observed symptoms have on network state.

The model based approach [15] usually concerns the development of models which capture nominal behaviour – these come in a number of different forms, including signal processing [16], statistical [17] and causal [18]. Fault detection and diagnosis is achieved through the generation of residuals, that is, differences between measurements and the expected normal behaviour. Within this paper, a statistical, multiple model based technique is employed – this approach involves the use of system data to develop separate state-space models that correspond to both nominal and fault conditions. Diagnosis then involves probabilities being assigned to each model, given observational data. Similar systems have been developed using interacting multiple models of Kalman filters [19, 20].

Regarding UAV's specifically, the majority of fault diagnosis is centred on assessing hardware faults in the flight control surfaces and sensors, and the failure of communication links to the control station; Cork *et al.* [21] and Bateman *et al.* [22] focussed efforts on identifying failures and implementing a reconfiguration of the control system to bring the aircraft to a normal state, or, in the worst case, abort the mission. Most of these techniques are based on parameter estimation for residual generation [23], data driven artificial neural networks [24] and mathematical models such as petri nets [25].

With respect to UAV EPS fault diagnosis, and the ADL in particular, Mengshoel *et al.* [4], used Bayesian networks, a form of causal model, to represent sensors which were compiled to arithmetic circuits to determine network diagnoses. Wilson *et al.* [5] used causal dependency graphs of fault causes and fault effect propagation paths to detect system faults and Narasimhan *et al.* [6] used a Hybrid Diagnostic Engine framework where behavioural

and transitional models formed a basis for diagnosing changes in the operating modes of ADL components. A number of these techniques are based on graphical representations of the networks being modelled and successful implementations of such systems depend upon proper selection of the type of network structure. The utilisation of diagnostic systems based on HMM, as proposed in this paper, could overcome this modelling issue as there is no requirement for network structures to be specified; instead, HMM use data to learn model parameters that statistically describe certain conditions.

Their ability to provide probabilistic reasoning under uncertainty and solve classification problems associated with time series input data under minimal computational burden makes them a potentially attractive solution for UAV EPS fault detection, classification and diagnosis.

Traditional applications of HMM are in areas such as speech, handwriting and gesture recognition [26–28]. Recently, HMMs have been applied to classifying patterns in process trend analysis [29], anomaly detection in nuclear reactor cores [30], machine condition monitoring [31, 32] and classifying electrical grid distribution network line disturbances [7, 33]. Rabiner [28] provides a comprehensive introduction to HMM.

2.4 Hidden Markov models

The ADL sensor data is an example of multivariate time series data where non-stationary periods define the presence of fault conditions. The ability to determine the latent physical state responsible for such changes in the data is the main goal of fault classification. Relating observational data to latent variables is a fundamental concept of HMM. This relationship involves non-stationary periods in the data representing transitions between latent states and, conversely, stationary periods in the data representing some form of latent state. It is therefore vital to have the capability to model data in a way that certain temporal aspects are explicit. Modelling the distribution of the ADL data and then detecting shifts in its characteristics would enable such changes to become explicit.

There are a number of distribution functions that can be used for modelling the probability distribution of observed variables. Typically, the simplest function applied for continuous density observations assume Gaussian distributions per latent state [34]. Considering the multidimensional nature of the ADL data, approximating the distribution with a single Gaussian function would provide an overgeneralised fit [35]. A solution to this is to approximate the unknown density with a mixture of simple density functions. The general form of a variable x of dimension d using M mixture components is given by

$$P(x) = \sum_{i=1}^M P(\theta_i)P_i(x|\theta_i) \quad (1)$$

where θ_i are the parameters of the i th simple density used as a mixture component. The most widely used mixture model is the Gaussian mixture model (GMM) [30], where each base distribution is a Gaussian with parameters $\theta_i = \{\mu_i, \Sigma_i\}$ comprising the mean vector μ_i and covariance Σ_i . The likelihood of an observation for each mixture component is given by

$$p(x|\theta_i) = \frac{1}{\sqrt{2\pi^d \det(\Sigma_i)}} \exp \left\{ -\frac{1}{2} (x - \mu_i)^T \Sigma_i^{-1} (x - \mu_i) \right\} \quad (2)$$

Changes in observation distribution can be detected by testing which base mixture component returns the highest likelihood for a given observation where each distribution comprising the GMM represents a latent class conditional density [34]. The relationship between latent states and observational data is illustrated in Fig. 3.

This example shows both the 'hidden' Markov temporal dynamics and the GMM representation of the observation space. A Markov model is a state based model that assumes the presently active

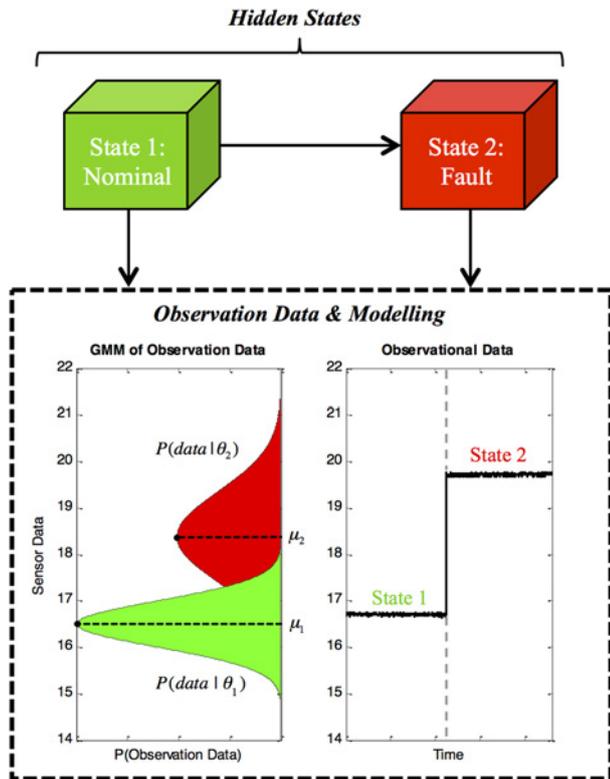


Fig. 3 Illustration of relationship between latent states and observational data that form HMM

Data (right-hand side) is modelled by a GMM (left-hand side). Shifts in dominant mixture distributions indicate hidden state transitions

state has been generated solely by the previous n states it has been in, where n is the model order. A HMM abstracts time series observation data into a state based form and uses a first order Markov chain to model the dynamics of the hidden state sequence [30].

The observations in Fig. 3 are current sensor data from a load resistance offset fault within the ADL network; the GMM has two base densities representing the distribution of the data. Regions in the data where the current remains constant can be modelled by a single mixture component which in turn can be mapped to certain states within the hidden sequence.

At fault onset, current magnitude increases; the increase in current corresponds to a change in the most likely mixture component represented by the increased current value, resulting in a change of state in the HMM.

Inference of the state evolution in a HMM for a given observation period can be undertaken using a number of different methods [34]. A maximum a posteriori (MAP) estimation infers the most probable state sequence in chain structured models; in the context of HMM, the MAP estimation is known as Viterbi decoding [36]. The Viterbi algorithm (VA) computes

$$s^* = \underset{s_{1:T}}{\operatorname{argmax}} p(s_{1:T}|x_{1:T}) \quad (3)$$

The VA enables the optimum underlying system state sequence, s^* , to be inferred across the observation period, $x_{1:T}$, where all possible state sequences, $s_{1:T}$, are considered. In Fig. 3, it can be inferred from the data that the ADL is in a nominal state until the point in time where the change in current magnitude enhances the likelihood of the network being in a faulted state.

An additional property of HMM concerns the probability of their statistical parameters yielded through training. These are a measure of how well a model has fitted the training examples presented to it through its parameters. A framework that contains multiple HMM permits the classification of candidate observation

sequences by inferring the probability of the sequence being generated by a given model. This measure can be used to select the model which returns the highest likelihood and in doing so allows it to be classified with a label associated with that model.

In this application, a series of HMM are trained based on different input data sets, each representing different system conditions. New data is classified by applying it to each of the models, with the model returning highest probability of generating the data assumed to be the closest match and therefore the most likely condition of the system.

3 FCD system outline

The operation of the FCD system proposed by the authors, and illustrated in Fig. 4, is split across two stages – Stage 1 classifies the network condition, and, once the network condition has been classified, Stage 2 diagnoses the severity of any fault that may have occurred. In this section, an overview of FCD operation and development is provided. This overview highlights the system's ability to differentiate between a number of EPS network conditions and identify both critical and degraded modes of ADL network operation.

3.1 System operation

3.1.1 Stage 1 – Fault classification: A framework of multiple trained HMM corresponding to separate conditions within the ADL network enables the classification of candidate system data. A total of 15 conditions, described in Table 1, are modelled within the framework. A decision on network state is made by primarily calculating the log-likelihood [28] of the input data, given each model's trained statistical parameters; classification then involves selecting the labelled model that returns the highest log-likelihood.

3.1.2 Stage 2 – Fault severity diagnosis: Stage 2 operates on the basis that a fault has been classified from Stage 1 of the system; hence, if a nominal state has been classified after Stage 1, there is no requirement for the implementation of severity diagnosis. However, in the event of a fault being classified, it is necessary to diagnose fault severity to determine the impact the presence of the classified fault has on the reliable operation of the UAV.

Calculating fault parameters enables the severity of any ADL fault to be quantified. Fault parameter calculation algorithms (FPA) were developed that use the models' optimal state sequence, calculated using the VA, to determine the parameters. The set of parameters required for the quantification of fault severity is dependent on the mode of fault that has been classified. Hence, three separate FPA's were developed corresponding to the three modes of fault (abrupt, intermittent and incipient) within the ADL network, as outlined in Table 1.

As an example of operation, if FC1 is classified after Stage 1, the optimal state path for the particular HMM of this fault condition will be calculated and then, considering FC1 relates to an abrupt fault mode, the FPA for calculating parameters for an abrupt fault would be initialised. The algorithms essentially utilise the optimal state path sequence to detect points in time where the state of the system changes. Deciphering points of state changes enables parameters to be calculated.

After fault parameters have been calculated, the severity of the fault can be determined. In the case of UAV operation, information on the criticality of EPS faults occurring is necessary to determine the impact the fault may have on vehicle and mission reliability.

3.2 System development

3.2.1 Data preparation: Machine learning is critically dependent on the quality and volume of training data and the selection of features that are presented to the learning algorithms [28]. Training a model on inappropriate data will result in an inadequate

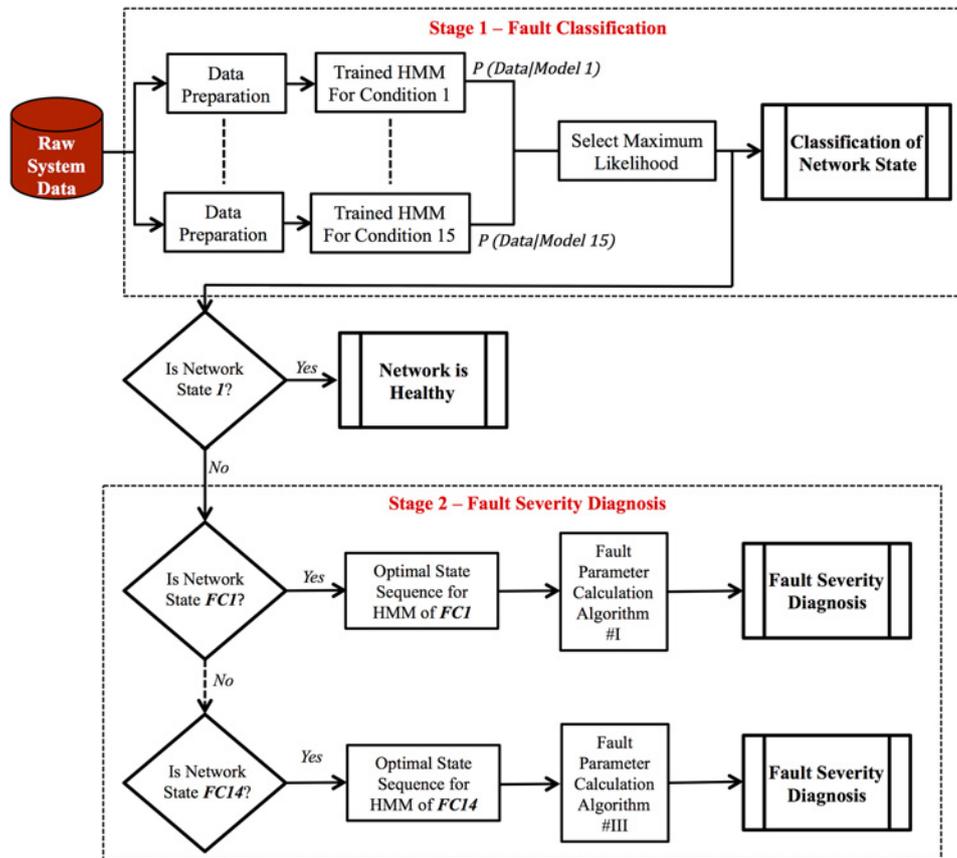


Fig. 4 Outline of two-stage FCD system applied to the ADL network

representation of the generalised behaviour of the modelled condition, and produce a model that will perform poorly at the inference stage. Extracting unique signatures for each condition is integral to FCD system development, especially when attempting to discriminate between a large set of network conditions. Consequently, to attempt to provide each HMM with the best data representation of condition behaviour, several processes were undertaken to prepare the data.

Firstly, capturing the dependencies that existed within the multivariate ADL data throughout certain conditions was

Table 1 Conditions modelled within the FCD system

There are 15 conditions in total – 1 nominal and 14 fault conditions. Note that Sensor Stuck and Failed Off faults are akin to abrupt faults. Also, the FPA utilised for each condition is detailed. For clarity, Abrupt fault mode FPA is titled #I, Intermittent fault mode FPA is titled #II and incipient mode FPA is titled #III.

Network conditions modelled	Condition #	FPA #
no fault	nominal	1
DC load faults	DC load abrupt resistance	FC1
	DC load intermittent resistance	FC2
	DC load incipient resistance	FC3
AC load faults	AC load abrupt resistance	FC4
	AC load intermittent resistance	FC5
	AC load incipient resistance	FC6
inverter faults	fan load failed off	FC7
	inverter failed	FC8
	voltage sensor stuck	FC9
current sensor faults	intermittent	FC10
	incipient	FC11
current sensor faults	stuck	FC12
	intermittent	FC13
	incipient	FC14

necessary to eliminate any redundant information being used during model training, and to reduce the dimension of the observation space. This can be achieved through a simple analysis, such as variable plotting, or through a more formalistic approach, such as principal component analysis [37].

Also, in order to align to a notionally common scale, the data for fault conditions was normalised. However, for nominal conditions, normalisation would convert the data to the common scale and any sensor noise would be undesirably magnified. Accordingly, the absolute deviation of the nominal data was extracted to maximise the constancy associated with nominal conditions. De-noising of the data was also undertaken using wavelet analysis [38]. These processes, being applied to a current sensor within the ADL network during an intermittent fault and under nominal conditions, are illustrated in Fig. 5.

As a result of the preparation, the data applied to each HMM for model training were feature vectors describing sensor data for a variety of sensors sensitive to the specific network condition being modelled.

3.2.2 Model selection: Modelling the observation space of HMM with a GMM captures non-stationary intervals through changes in dominant mixture distribution and thus changes in latent state. However, the degree to which non-stationary periods are measured depends upon the number of mixtures that represent the distribution because of the fact that some non-stationary behaviour is absorbed into changes within the dominant mixture component as opposed to changes between distributions.

Although increasing the number of states and mixture components will implicitly capture a finer degree of non-stationary behaviour, the computational complexity of the model will increase. This modelling flexibility poses the problem of determining the cardinality of parameters, for example, how many states to use and how many mixture components will be present in the observation model. The quantity of training data also has to be considered with respect to learning the parameters of the models and whether the set of

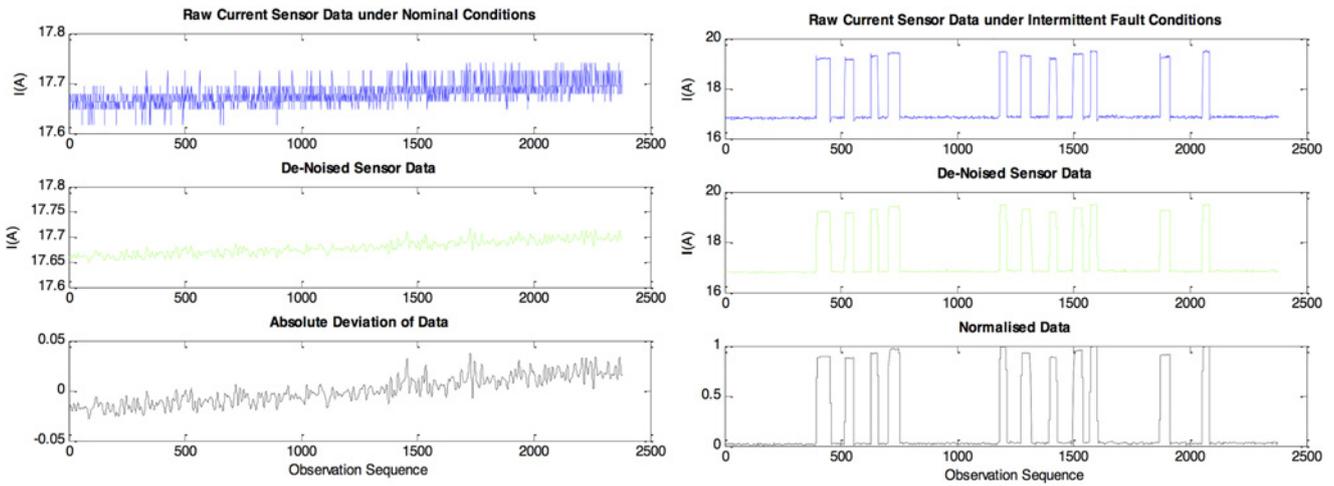


Fig. 5 Illustration of data preparation undertaken prior to model training

Raw data was de-noised using wavelet analysis. For data describing nominal conditions, preparation involved calculating the absolute deviation before model application; for fault condition data, a normalisation process was applied

training data is sufficient to specify a set of parameters that suitably model the condition.

When fitting HMM to data using the expectation maximisation (EM) learning algorithm [39], increasing the cardinality of states and mixture components will increase the likelihood of the trained parameters. The problems associated with increasing the likelihood of trained parameters are that models become over fitted to the training examples presented to them. Over fitting [35] is a phenomenon in which the models learn features pertinent only to the training set, and which will therefore perform poorly at inferring new, unseen data. A solution to overcome such problems is to introduce terms in the model selection criteria that punish model complexity, but still take into account the model fit.

One such technique that considers model likelihood but retains a term to punish model complexity is Bayesian information criterion (BIC), which is defined formally as

$$\text{BIC}(X, \theta) = \sum_{n=1}^N \log P(x_n | \theta) - \frac{N_m}{2} \log N \quad (4)$$

where X is the training data set, θ is the maximum likelihood estimate of the model, N is the dimension of the training set and N_m is the number of degrees of freedom (parameters) of the model. Minimising the BIC value will optimise the number of parameters in terms of both model fit and complexity. Consequently, for each of the 15 modelled conditions within the ADL network, BIC was used in determining model selection.

The relatively limited volumes of training data, particularly with regards to fault conditions, meant the number of model parameters considered was limited [28]. Accordingly, when developing the HMM, BIC ratings for each of the models were calculated by increasing the number of states from 2 through to 5 and training files, describing each condition, from 1 through to 5. Table 2 shows optimal models for selected conditions, chosen by minimising the model BIC. The log-likelihood details the degree to which the parameters of the HMM describe the training files presented, with a value closer to zero detailing a higher model fit. The BIC considers all model elements, and determines if there is

Table 2 Optimal HMM parametrisation

Network condition model #	Training examples	States	Log likelihood	BIC
1	5	3	-2732.3	5526
FC2	2	4	-3346.8	6804
FC4	2	2	-1815.6	5704
FC6	3	3	-2831.7	3646

the necessity to either increase or decrease cardinality. Table 2 highlights the state variability among selected models within the framework, where some modelled conditions require a greater number of states to achieve model optimality, compared with others.

3.2.3 Parameter calculation algorithm development:

Considering the FPAs are based around the determination of optimal state sequence within HMMs, and that each condition model has a variable number of states, there is a requirement to establish how these states should be interpreted. The workings of the FPAs assume that the initial state within the state sequence represents the nominal network state. The fault parameters are calculated on the basis that diversions from this initial state are changes from a nominal to a fault state. This is illustrated in Fig. 6, which shows current sensor data for an AC Load

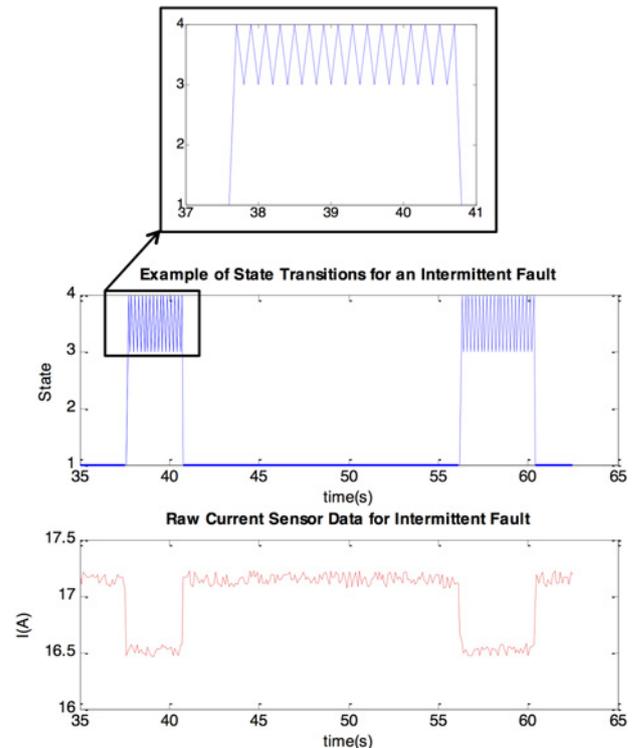


Fig. 6 Example of optimal state sequence when ADL intermittent fault data is applied to a four state intermittent fault HMM

Table 3 Fault parameters required for determination of fault severity

FPA I –Abrupt mode fault	FPA II-Intermittent mode fault	FPA III –Incipient mode fault
time of fault onset power offset	time of fault onset power offset average time in fault state average time not in fault state	time of fault onset drift gradient

intermittent resistance fault and the associated optimal sequence within the related four state HMM of that condition.

The state sequence begins in State 1, and, at fault onset, the state sequence changes. Whilst in a fault condition, the state sequence alters between States 3 and 4. However, when in a nominal condition, the state sequence returns to State 1. The algorithms utilise the times of state transitions to extract fault parameters from the system data. The severity of any fault occurring can be determined through the extraction of the parameters.

Table 3 outlines the parameters calculated by each of the three FPA's.

4 FCD system operational results

Operational testing validates the FCD systems ability to detect the occurrence of, classify and diagnose the severity of ADL faults. Testing was undertaken with the application of ADL data to the FCD system. 129 test cases, separate to the training cases, were applied – within each case, the types of fault present as well as fault severity was labelled, thus enabling the accuracy of the system to be measured.

4.1 Classification accuracy

The classification results of the system are outlined in Table 4. These results show that the classification system was 95.3% accurate at discriminating between the 15 network conditions. This equates to six misclassifications out of the 129 test cases presented to the system. Out of the six misclassifications, four of these are attributed to the misclassification of incipient faults. In all six test cases that were misclassified, the network was classified to be in a nominal condition.

4.2 Fault severity diagnosis accuracy

The diagnostic results of the system are also presented in Table 4. Severity diagnostic accuracy is based on the ability of the system to accurately calculate the fault parameters with these parameters determining the severity of the fault to the network – severity can be either network critical or network degraded. Table 4 highlights both the calculation accuracy of the fault parameters and the accuracy of the diagnostic decision.

Table 4 FCD operational testing results

Fault location	Fault mode	# Tests	Classification accuracy, %	Fault parameter calculation accuracy, %	Diagnostic decision accuracy, %
nominal	N/A	20	100	N/A	100
DC loads	abrupt	9	100	100	100
	intermittent	8	87.5	100	100
	incipient	7	85.7	71.4	85.7
AC loads	abrupt	9	100	100	100
	intermittent	8	100	91.6	100
	incipient	8	87.5	81.25	100
inverter	fan failed off	2	100	100	100
	failed off	2	100	100	100
voltage sensors	stuck	5	80	100	100
	intermittent	5	100	100	100
	incipient	4	75	50	100
current sensors	stuck	14	100	100	100
	intermittent	14	100	100	100
	incipient	14	92.8	64.28	100
	total	129	95.3	89.89	99

Fault Parameters were deemed accurate if they were within $\pm 5\%$ of the actual parameters. In the majority of fault test cases, the calculation of parameters was accurate. For abrupt and intermittent faults, the calculation accuracies were high. The main instance where accuracy was not sufficiently high was when calculating parameters for incipient faults, which, in some cases was as low as 64.28%. The relatively low value of 89.89% for parameter calculation accuracy can mainly be accredited to the inaccuracies of incipient parameter calculations.

The diagnostic decision accuracy in determining fault severity was 99%. Out of the 129 test cases, there was only one instance where the severity of the fault was misdiagnosed.

4.3 Discussion

The test results validate that the FCD system can utilise system data to classify and diagnose fault severity with high accuracy. During fault instances where data was misclassified, the system was classified into a nominal condition; hence, there was no requirement to diagnose fault severity and the FCD system concluded that no critical condition had manifested. Despite the fact that the system had misclassified six fault instances, in five cases, the faults that had developed were minimal, and the network could indeed maintain reliable operation.

The majority of misclassified faults and inaccurately calculated fault parameters were accredited to incipient fault conditions, with the majority of inaccuracies concerning the time of fault onset as opposed to the magnitude of drift gradient. This suggests that it is necessary to increase the number of hidden states when modelling incipient conditions because, particularly in cases where there is a marginal drift from nominal behaviour in sensor readings, HMM with higher state variances were not detecting shifts within the data and hence fault onset. Examination of state sequence evolution when fault data was applied to incipient fault models showed that there was a delay between network fault onset and the model inferring a change in network state. Increasing the number of states would enhance sensitivity to slight changes in data, albeit with a trade off with model complexity.

Consideration also has to be given to the volume of available training data. A drawback of data driven multiple model approaches is that, compared with cases involving nominal condition data, there is significantly less data available describing fault conditions. This lack of data can result in fault condition models being over fitted with poor performance when inferring new instances of the same condition. In the case study presented in this paper, the BIC was used to optimise each HMM based on various parameters, including the number of training cases available. Test results have shown that the abrupt and intermittent fault models accurately inferred test cases, even though some models were trained using only two separate examples. The incipient fault models however, were not as accurate despite being provided with similar numbers of training examples. The solution to improving the performance of incipient fault models by

increasing the number of hidden states is dependent on the number of training cases available. Without more training examples, increasing the number of hidden states will simply result in a model over fitted to the select training examples. Such issues highlight that, while increasing the volume of data will lead to a better generalisation within all fault models, certain fault conditions are more dependent on the quantity of training cases for accurate inference of unseen data.

Overall, results have shown that the FCD system can detect and classify a range of network faults as well as measure the impact such faults will have on network reliability. There is a wide range of distinct conditions within UAV EPS networks, and, it is imperative that system dynamics are monitored and evaluated throughout a mission cycle. The development of the proposed FCD system using ADL data has shown that it has the ability to determine and quantify complex system dynamics from network data and that it has the potential to aid system monitoring and reliability enhancement.

5 Future work

The work reported in this paper represents the initial steps towards developing the FCD system based on HMM for application to UAV EPS. Further development would comprise extending the system for online application to EPS data. This expansion would involve the appropriate partitioning, or windowing, of the EPS data; windowed data covering a certain period of time would be input to the FCD system. The system would classify the network condition and, if required, diagnose the severity of any fault present over the time period. Network status would be updated when data covering the next windowed time period is input.

The system could also be updated to handle multiple network faults. The inclusion of a threshold within the likelihood classification framework would enable the detection of multiple failures. Presently, there is significant discrepancy between the likelihood of one fault model and the rest because the ADL data only describes a single fault. In the event of multiple faults, theoretically, the likelihood of multiple models will be similarly high. A likelihood threshold would determine whether there is enough evidence to suggest the presence of multiple faults.

6 Conclusions

The purpose of this paper was to outline a two stage HMM based FCD system that would detect, classify and determine the impact of EPS faults within UAV. The ability of the system to aid health management through the detection of degraded and critical faults, the discrimination between a number of fault types and locations, and the determination of fault parameters and the risk their occurrence poses to system reliability has been validated with development of the system for NASA's ADL network. Tests using ADL data proved that the system can operate with high accuracy, even with limited volumes of training data used throughout development. Despite the relatively simple application described within this paper, the system can be used as a framework to progress and apply to increasingly elaborate networks and fault conditions. Operationally there would be a requirement for data acquisition, through multiple sensor deployment, within such networks that would facilitate the FCD system to aid the understanding of complex UAV EPS behavioural dynamics throughout mission cycle, and enable support in enhancing both vehicle and mission reliability.

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8 References

- 1 Tousi, M.M., Khorasani, K.: 'Fault diagnosis and recovery from structural failures (icing) in unmanned aerial vehicles'. Proc. Third IEEE Systems Conf., Vancouver, Canada, March 2009, pp. 302–307
- 2 United States Office of the Secretary of Defense: 'OSD UAV reliability study', February 2003
- 3 Rosero, J.A., Ortega, J.A., Aldabas, E., Romeral, L.: 'Moving towards a more electric aircraft', *IEEE Aerosp. Electron. Syst. Mag.*, 2007, **22**, (3), pp. 3–9
- 4 Mengshoel, O.J., Chavira, M., Cascio, K., Poll, S., Darwiche, A., Uckun, S.: 'Probabilistic model-based diagnosis: an electrical power system case study', *IEEE Trans. Syst. Man. Cybern., A: Syst. Humans*, 2010, **40**, (5), pp. 874–885
- 5 Wilson, M., Kurtolugu, T.: 'A model based algorithm for the second international diagnostic competition'. Proc. 21st Int. Workshop on Principles of Diagnosis, Portland, USA, October 2010
- 6 Narasimham, S., Brownston, L.: 'HyDE – A general framework for stochastic and hybrid model based diagnosis'. Proc. 18th Int. Workshop on Principles of Diagnosis, Nashville, USA, May 2007, pp. 162–169
- 7 Abdel-Galil, T., El-Saadany, E.F., Youssef, A.M., Salama, M.M.A.: 'Disturbance classification using Hidden Markov Models and vector quantization', *IEEE Trans. Power Deliv.*, 2005, **20**, (3), pp. 2129–2135
- 8 Suxiang, Q., Hongsheng, H., Jian, C., Gongbiao, Y.: 'Remote monitoring and fault diagnosis system for power transformer based on HMM'. Eighth Int. Conf. on Electronic Measurement and Instruments, Xian, China, 2007, pp. 571–575
- 9 Poll, S., Kleer, J., Feldman, A., Garcia, D., Kurtoglu, T., Narasimham, S.: 'Second international diagnostic competition – DXC'10'. Proc. 21st Int. Workshop on Principles of Diagnosis, Portland, USA, October 2010
- 10 Granados-Lieberman, D., Romero-Troncoso, R.J., Osorio-Rios, R., Garcia-Perez, A., Cabal-Yepez, E.: 'Techniques and methodologies for power quality analysis and disturbances classification in power systems: a review', *IET Gener. Transm. Distrib.*, 2011, **5**, (4), pp. 519–529
- 11 Fenton, W.G., McGinnity, T.M., Maguire, L.P.: 'Fault diagnosis of electronic systems using intelligent techniques: a review', *IEEE Trans. Syst. Man Cybern. C Appl. Rev.*, 2001, **31**, (3), pp. 269–281
- 12 Gertler, J.J.: 'Survey of model-based failure detection and isolation in complex plants', *IEEE Control Syst. Mag.*, 1988, **8**, (6), pp. 3–11
- 13 Liu, L., Logan, K.P., Cartes, D., Srivastava, S.K.: 'Fault detection, diagnostics, and prognostics: software agent solutions', *IEEE Trans. Veh. Technol.*, 2007, **56**, (4), pp. 1613–1622
- 14 Filippetti, F., Franceschini, G., Tassoni, C., Vas, P.: 'Recent developments of induction motor drives fault diagnosis using AI techniques', *IEEE Trans. Ind. Electron.*, 2000, **47**, (5), pp. 994–1004
- 15 Isermann, R.: 'Model-based fault-detection and diagnosis – status and applications', *Annu. Rev. Control.*, 2005, **29**, (1), pp. 71–85
- 16 Ferracuti, F., Giantomassi, A., Ippoliti, G., Longhi, S.: 'Multi-Scale PCA based fault diagnosis for rotating electrical machines'. Proc. of the Eighth ACD, Ferrara, Italy, November 2010, pp. 296–301
- 17 Sarlak, M., Shahrtash, S.M.: 'High impedance fault detection in distribution networks using support vector machines based on wavelet transform'. Proc. Electric Power Conf., Vancouver, Canada, July 2008, pp. 1–6
- 18 Barua, A., Sinha, P., Khorasani, K.: 'A diagnostic tree approach for fault cause identification in the attitude control subsystem of satellites', *IEEE Trans. Aerosp. Electron. Syst.*, 2009, **45**, (3), pp. 983–1002
- 19 Zhang, Y., Rong Li, X.: 'Detection and diagnosis of sensor and actuator failures using IMM estimator', *IEEE Trans. Aerosp. Electron. Syst.*, 1998, **34**, (4), pp. 1293–1313
- 20 Maybeck, P.S., Hanlon, P.D.: 'Performance enhancement of a multiple model adaptive estimator', *IEEE Trans. Aerosp. Electron. Syst.*, 1995, **31**, (4), pp. 1240–1254
- 21 Cork, L.R., Walker, R., Dunn, S.: 'Fault detection, identification and accommodation techniques for unmanned airborne vehicle'. Proc. of Australian Int. Aerospace Congress, Melbourne, Australia, March 2005
- 22 Bateman, F., Noura, H., Ouladsine, M.: 'Fault diagnosis and fault-tolerant control strategy for the aerosonde UAV', *IEEE Trans. Aerosp. Electron. Syst.*, 2011, **47**, (3), pp. 2119–2137
- 23 Samar, S., Gorinevskaya, D., Boyd, S.: 'Embedded estimation of fault parameters in an Unmanned Aerial Vehicle'. Proc. of IEEE Int. Conf. on Control Applications, Munich, Germany, October 2006, pp. 3265–3270
- 24 Qi, J., Jiang, Z., Zhao, X., Han, J.: 'Fault detection design for RUAV with an adaptive threshold neural-network scheme'. Proc. of IEEE Int. Conf. on Control and Automation, Guangzhou, China, May 2007, pp. 554–559
- 25 Trigos, M., Barrientos, A., del Cerro, J., Lopez, H.: 'Modelling and fault diagnosis by means of Petri nets. Unmanned aerial vehicle application'. Petri Nets Theory and Applications, InTech, 2009, pp. 353–378
- 26 Hu, J., Brown, M.K.: 'HMM based on-line handwriting recognition', *IEEE Trans. Pattern Anal. Mach. Intell.*, 1996, **18**, (10), pp. 1039–1045
- 27 Rashid, O., Al-Hamadi, A., Michaelis, B.: 'A framework for the integration of gesture and posture recognition using HMM and SVM'. Proc. IEEE Int. Conf. Intelligent Computing and Intelligent Syst., Shanghai, China, November 2009, pp. 572–577
- 28 Rabiner, L.R.: 'A tutorial on hidden Markov models and selected applications in speech recognition', *Proc. IEEE*, 1989, **77**, (2), pp. 257–286
- 29 Kwon, K.C., Kim, J.H.: 'Accident identification in nuclear power plants using hidden Markov models', *Eng. Appl. Artif. Intell.*, 1999, **12**, (4), pp. 491–501
- 30 Stephen, B., West, G.M., Galloway, S., McArthur, S.D.J., McDonald, J.R., Towle, D.: 'The use of hidden Markov models for anomaly detection in nuclear core condition monitoring', *IEEE Trans. Nucl. Sci.*, 2009, **56**, (2), pp. 453–461

- 31 Ertunc, H.M., Loparo, K.A., Ocak, H.: 'Tool wear condition monitoring in drilling operations using hidden Markov models (HMMs)', *Int. J. Mach. Tools Manuf.*, 2001, **41**, (9), pp. 1363–1384
- 32 Miao, Q., Makis, V.: 'Condition monitoring and classification of rotating machinery using wavelets and hidden Markov models', *Mechan. Syst. Signal Process.*, 2007, **21**, (2), pp. 840–855
- 33 Jaehak, C., Powers, E.J., Grady, W.M., Bhatt, S.C.: 'Power disturbance classifier using a rule-based method and wavelet packet-based hidden Markov model', *IEEE Trans. Power Deliv.*, 2002, **17**, (1), pp. 233–241
- 34 Murphy, K.P.: 'Machine learning: a probabilistic perspective' (MIT, 2012)
- 35 Bishop, C.M.: 'Pattern recognition and machine learning' (Springer, New York, 2006)
- 36 Forney, Jr., G.D.: 'The Viterbi algorithm', *Proc. IEEE*, 1973, **61**, (3), pp. 268–278
- 37 Minka, T.P.: 'Automatic choice of dimensionality for PCA'. Technical Report No. 514, MIT Media Laboratory Perceptual Computing Section, 2000
- 38 'De-noising in Action', <http://www.mathworks.co.uk/help/wavelet/ug/denoising.html#f8-22239>, accessed April 2014
- 39 Khreich, W., Granger, E., Ali Miri, A., Sabourin, R.: 'A survey of techniques for incremental learning of HMM parameters', *Inf. Sci.*, 2012, (197), pp. 105–130