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Glossary

Abbreviation/acronym	Description
ANN	Artificial Neural Network
DAMADICS	Development and Application of Methods for Actuator Diagnosis in Industrial Control Systems
DB	Deutsche Bahn
EFFBD	Enhanced Functional Flow Block Diagram
FDI	Fault Detection and Isolation
GMDH	Group Method of Data Handling (type of neural network)
NI	National Instruments
PCA	Principal Component Analysis
QTA	Qualitative Trend Analysis
RBF	Radial Basis Function (type of neural network)
SOFM	Self-Organising Feature Map (type of neural network)

1. Executive Summary

This document reports on the work carried out in task 3.3.5 of the Innotrack project, and elsewhere, to develop algorithms for the detection and diagnosis of incipient and abrupt faults in switch systems.

Data were gathered from DC and AC switch systems. Section 3 gives a description of the experiments carried out. A commentary is then given on the data, including the fault symptoms discovered.

A literature review is presented in section 4, consisting of a general introduction to the field of advanced condition monitoring, followed by a detailed examination of the more established methods. The algorithms currently in use on the railways are also reviewed. Some faults can be detected perfectly well with these simple methods. It is important not to over-complicate monitoring systems by using complex algorithms where simple ones are adequate.

Section 5 presents an algorithm which has been developed to increase the capability of current monitoring systems with the detection and diagnosis of incipient faults at an early stage of development. This is something which current algorithms have struggled to address. The algorithm uses qualitative and quantitative trend analysis to pick out changes to the shape of waveforms from measurements of the key parameters.

In a large set of switches, even if the actuators are all of the same type, there are some inevitable variations in the way each switch operates, and therefore some inevitable differences in the parameters measured, even if the switch is in perfect condition. The algorithm in this document addresses this problem by using relative, rather than absolute, values to form fuzzy performance rules which track the gradual development of incipient faults.

2. Introduction

2.1 Background

In deliverables D3.3.1 and D3.3.2, the results were presented of previous work into fault diagnosis for switches. The focus was on two main areas: the key parameters where most fault symptoms can be detected, and the fault conditions which can be simulated and detected using standard hardware.

These deliverables lay the groundwork for further work into the deep analysis of collected data, with a view to developing advanced algorithms for detecting incipient faults.

2.2 Outline

Automatic condition monitoring systems on the railways are in an early stage of development. There are many disparate pilot systems in operation throughout Europe, and some basic systems have been deployed on a large scale. The systems currently in use are quite limited in their functionality, and the opportunity exists to use the data measured by these systems, subject them to some intensive analysis, and produce some more meaningful results. In particular, advanced data analysis may provide the possibility to detect and diagnose incipient (slowly-developing) faults, which are not usually detectable with threshold-based detection algorithms (which form the basis of most commercial condition monitoring systems).

Advanced algorithms have been developed for condition monitoring in other industries, and some of the work done by the University of Birmingham in recent years has focused on transferring this technology, in a way that fulfils railway requirements, to the diagnosis of incipient faults in switches. The work has also encompassed the collection of data for verifying the algorithms developed.

3. Data collection

In order to demonstrate the use of innovative algorithms to detect incipient faults, a data set was collected from a Siemens S700K AC electric actuator installed on a switch at the DB training school near Berlin Ostbahnhof. Previously, in the work for deliverable 3.3.2, data were collected on a DC switch actuator (Alstom HW type). A similar process of experimentation has been followed here. The AC switch actuator is more common throughout Europe and therefore is a better example for the demonstration of fault diagnosis in this project.

3.1 Variables measured

The S700K is an electromechanical actuator. The key parameters from D3.3.1 which are relevant to this type of actuator are **drive force**, **displacement** and **motor current**.

3.1.1 Drive force

Force in the drive was measured using a bespoke measurement system loaned by DB and made by VTEC. This consists of a load pin and a data acquisition device. The load pin is designed to replace a bolt in the drive assembly, as shown in Figure 1. The VTEC measurement system operates at a sampling frequency of 100 Hz.



Figure 1 - installation of the load pin

3.1.2 Displacement

The horizontal displacement of the switch was measured at the actuator drive rod, using a Micro Epsilon WPS250-MK30 draw-string displacement sensor. This device has a draw-string which is connected to the spindle of a potentiometer, producing a voltage proportional to the amount of string drawn out off the spindle. The maximum draw was 250 mm, which was just enough (using a cable tie to slightly increase the distance) to cover the entire throw distance at the drive rod end. Figure 2 shows this sensor in place.



Figure 2 - installation of the displacement sensor

3.1.3 Current

The S700K actuator uses a 380 V three-phase AC motor. All three phases are in use at any one time, but the connection changes from star to delta during the operation of the actuator. It was therefore sufficient to measure the current in only one phase of the motor. This was done using a LEM PCM-30 transducer, capable of a range of -30 to +30 A. Figure 3 shows the sensor in place.



Figure 3 - installation of the current sensor

3.2 Data acquisition equipment and post-processing

The force data were captured by the VTEC module, sampling at 100 Hz. The current and displacement data were captured using a National Instruments NI-6259 data acquisition unit, operating at a sampling rate of 1 kHz.

The current data were converted to r.m.s. format after capture, because this is a more appropriate variable to consider in a fault diagnosis system.

A single set of data files was constructed during post-processing, bringing the force data from the VTEC unit together with the current and displacement data from the NI unit. The force data were upsampled, using linear interpolation, to 1 kHz so that they could be plotted against the same vector of time values as the current and displacement data.

Because two different acquisition systems were being used, there were time lags between the start of the significant parts of the force waveform and that of the current/displacement waveforms. The data were aligned manually by plotting them together and estimating the points in each waveform which were the start of the significant parts.

3.3 Fault simulations

The data collection session at Berlin Ostbahnhof focused on simulating incipient faults, i.e. faults which develop over a period of time and show their symptoms gradually.

The following faults were simulated:

- Misadjustment of the locking mechanism
 - Loosening of the left-hand side
 - o Tightening of the left-hand side
 - Loosening of the right-hand side
 - Tightening of the right-hand side
- Changing of the fulcrum point (obstruction inserted between switch and stock rails)
 - o Left-hand side
 - o Right-hand side



Figure 4 - adjustment of the locking mechanism

3.3.1 Locking mechanism adjustments

The *Klinkenverschluss* locking mechanism can be adjusted for more or less tightness in locking. An adjustable bolt is provided for these adjustments, shown in Figure 4. Adjustments were made in increments of 1/12 turn (half a bolt face). Tightening the lock was quite difficult and only one or two adjustments were possible. Loosening it was easier and had some interesting effects on the data.

3.3.2 Fulcrum point adjustment

An obstruction between the switch and stock rails was introduced at progressively shorter distances from the actuator. This brought the fulcrum point nearer to the actuator, shortening the amount of rail it was trying to switch and therefore increasing the force required to complete the throw (because more force is required to bend a shorter piece of rail).

3.4 Data collection results

For each simulation, the waveforms have been overlaid on the same graph. The green waveform is faultfree, and the plots get progressively redder as the fault is made worse. In most cases, we can see some consistent trends as fault severity increases.

Table 1 is an index to the graphs, which can be found in Appendix A. The direction of switch movement is indicated in brackets after the fault name.

Simulation	Figure
Fault free (right to left)	Figure 22
Fault free (left to right)	Figure 23
LH locking mechanism tightened (right to left)	Figure 24
LH locking mechanism tightened (left to right)	Figure 25
LH locking mechanism loosened (right to left)	Figure 26
LH locking mechanism loosened (left to right)	Figure 27
RH locking mechanism tightened (right to left)	Figure 28
RH locking mechanism tightened (left to right)	Figure 29
RH locking mechanism loosened (right to left)	Figure 30
RH locking mechanism loosened (left to right)	Figure 31
LH fulcrum point changed (right to left)	Figure 32
RH fulcrum point changed (left to right)	Figure 33

Table 1 - references to plots of collected data

4. Survey of fault detection and diagnosis algorithms

4.1 Background

Automated fault diagnosis has been an area of high research activity for several decades. Most of the effort in this field has been focussed on industrial processes, such as may be found in the chemical and manufacturing industries. Industrial processes usually have dozens or hundreds of variables and a large, expensive plant which is built as a one-off exercise. This means that investment in fault diagnosis has been higher, because it is a proportionally smaller cost to the operators and yet yields a high return in increased reliability.

The diagnosis of actuators, on the other hand, has not been the subject of as much research effort. Within a large process environment, the failure of a single actuator is unlikely to bring the process to a halt, because redundancy is built in to such a system. The plant diagnostic system identifies an actuator as causing a problem but does not seem to go into any further detail.

The nature of railways is such that failures of actuators can very often lead to a system halt whilst remedial action is carried out. Train door failures cause delays because of the safety procedures that are followed. For example, certain types of rail vehicle cannot be used if a single door is out of action, because they are passenger emergency exits and must always be available. Failed switch actuators cannot be used to throw switches; therefore they limit the control a signaller has over the routing of trains. If the switch also fails to reach an end position, then traffic cannot be signalled over the switch until it has been locked in place manually, causing even more disruption.

4.2 Diverse methods for fault diagnosis

Figure 5 shows a categorisation of methods for fault diagnosis. The diagram has been reproduced from a review paper (1), with the addition of automata to the class of qualitative causal models. There are three main categories of fault diagnosis methods: qualitative model-based, quantitative model-based, and process history-based.

4.2.1 Model-based fault diagnosis methods

The basic concept of these methods for fault diagnosis is to establish a mathematical model of the system (usually called the "plant") to be diagnosed. This model then predicts the values of the plant's measurable variables. Signals known as residuals are generated by comparing the predicted variables to those measured from the plant itself. These residuals can then be used to determine if any faults are present, and what they might be. The most common functions for residual generation are subtraction of the model signal from the measured signal (to detect additive faults) and division of the measured signal by the model signal (to detect multiplicative faults).

Many methods exist for modelling the performance of dynamic systems, but the dominant form of model in the field of fault diagnosis is the state-space input-output model (1), usually in discrete form because variables are measured on a sampled basis.

One advantage of such a model is that it quite often exists already in the controller of a large plant. Statespace models are used to estimate the state variables of a system when they cannot be readily measured directly. This model is known as an *observer* and is used to provide more insight into a system's operation and therefore enable it to be better controlled. Mathematical models of this type have been used for some time for various applications including servo motors (2) and jet engines (3; 4).



Figure 5 - Families of fault diagnosis methods (1)

Parity equations (or relations) are another widely-used method of obtaining residuals. These are essentially a rearrangement of the state-space input-output model which result in a parity vector whose values are ideally zero when no fault is present. The parity vector is then monitored for change which would indicate the presence of a fault. It is generated in such a way as to make it dependent only on faults introduced to the system and not on the system's state itself (5).



Figure 6 - Enhanced functional flow block diagram for a generic model-based fault diagnosis system

Höfling and Isermann (6) used parity equations to form a fault detection system which tracked the parameters of the monitored system. Parity equations can be used for parameter estimation. By tracking changes in parameters, faults can be detected and diagnosed.

Gertler and Monajemy (7) used dynamic parity relations to generate directional residuals, meaning that the introduction of a particular fault moves the residuals in a straight line through the parity space (the vector space made up of the residual signals). A desirable property of some such systems is that the movement of the residuals is orthogonal for each different fault, and therefore diagnosis is very simple. This method is similar in outcome to the use of observers or extended Kalman Filters tuned to each fault (8), but Gertler and Monajemy claim that their method makes the design process simpler.

Ballé and Füssel (9) proposed a solution to the problem of modelling non-linear systems by viewing them as piecewise linear and constructing a "LOcal LInear MOdel Tree" (LOLIMOT). This is a structure of linear models which are each valid for a certain part of the system's operation. This method was tested on a control valve actuator of the type used in chemical processes.

Another non-linear modelling solution was proposed by Demetriou and Polycarpou (10). This used online approximators to model the performance of non-linear systems from a precise mathematical model. When the output of an online approximator is non-zero then a fault is detected. This system can also diagnose the characteristics of faults and can be designed to be robust to modelling errors.

4.2.2 Qualitative model-based methods

There are three main reasons cited in published literature for pursuing the use of a qualitative model. The first is that modelling inaccuracies are not a problem because qualitative methods do not rely on exact numerical modelling. The second is that qualitative methods can be used where it is not possible to make

quantitative observations. The third is that qualitative models make it possible to incorporate empirical knowledge about a system in the operational model (11).



Figure 7 - Enhanced functional flow block diagram for a generic qualitative model-based fault diagnosis system

A number of papers concerned with qualitative modelling and its application in fault diagnosis have been published by Professor Jan Lunze of the Ruhr-Universität Bochum, Germany, and various associates. There has been particular focus on the use of non-deterministic (or stochastic) automata as a modelling medium for physical processes (12). Automata are also known as state machines. Stochastic automata were applied to the observation of qualitative states (13) and the diagnosis of transient faults (14). A study was also carried out into the conditions which must exist for a deterministic automaton model to be valid (15), and the use of a semi-Markov process model, as a timed description of quantised event sequences, was evaluated (16). State machines are also used as a qualitative model by Ramkumar *et al* (17).

These papers all deal with situations where variables cannot be directly measured and so a qualitative model must be used to process the qualitative variables which can be measured. The methods involve a partition or quantisation of the measurement space so that a discrete-event representation can be constructed.

Various probabilistic methods then model the transition between states and produce a diagnosis output. A probability level is calculated for each possible fault, which is a useful output because it allows a human

observer to see the increasing probability that a certain fault is present over a period of time, and also can show how one fault initially appears more likely, but then diminishes as time goes on.

These methods are effective but there is always a compromise when quantised data is used as an input to a model. The probabilistic diagnosis algorithms are in place to deal with the ambiguity introduced by the use of these data. Quantisation also means that small changes in measured variables are not always detected straight away. This means that incipient faults may not be detected quickly enough.

Digraphs, also known as cause-effect graphs or signed directed graphs (SDG), were proposed by Iri *et al* (18) as a means of qualitatively simulating the performance of a physical system. The differential equations which mathematically represent a system were transformed to qualitative graphs by considering only the sign of each value (positive, negative or zero).

Digraphs can be used to represent a qualitative causal model(11), as part of a system to predict faults in a gas turbine. Users of this system were able to view raw data, model behaviour using standard quantitative equations, and add further qualitative information from knowledge by editing the resulting digraphs. Tarifa and Scenna(19) applied digraphs to chemical processes, using a propane evaporator as an example. A fuzzy logic rule base was then used to diagnose faults according to a knowledge base established during simulation of faults.

Qualitative physics is intended as a means for artificial intelligence systems to make reasoned decisions about the real world, based not only on standard mathematical behaviour models but also human-style deductions. A basic qualitative physics was proposed by de Kleer and Brown for perturbation analysis (20). The limitations of this approach then led to the development by de Kleer and Brown of a more complete physics based on confluences (21) and also to the development of qualitative process theory by Forbus (20).



Figure 8 - Enhanced functional flow block diagram showing the process of fault tree analysis

Fault trees are knowledge-based models which relate symptoms to particular fault conditions. They are used to determine the likely behaviour of equipment under failure modes. Heuristic knowledge and human reasoning are used to link observable symptoms to fault conditions. Providing there are enough symptoms to observe and that each fault has a unique set of symptoms, it is possible to diagnose faults accurately.

Fault trees can be derived from digraph models to form a diagnosis system for chemical processes (22). This approach was designed to include operator actions and disturbances from outside the plant. Fault tree analysis has also been used in the railway industry for manual diagnosis of all kinds of equipment.

Abstraction hierarchies are schemes for fault diagnosis where the end result is an isolation of the component or function which is faulty (23). The decomposition of a system, according to the functions performed within it, has been proposed (24). This allows the system state to be deduced qualitatively, leading to the isolation of the faulty component or subsystem.

Hierarchical schemes are suitable for large monitored plants such as the chemical processes which were being considered in these papers. However, we are concerned here with the diagnosis of faults in a single actuator, and so the scale of these methods is not appropriate.

4.2.3 Process history-based methods



Figure 9 - Generic process history-based fault diagnosis algorithm

History-based methods are fundamentally different from model-based diagnosis methods because no prior knowledge about the monitored system is required. Previously measured data from the system is analysed to produce some knowledge from it which can be used to diagnose faults. This function is known as *feature extraction* (25). Methods for the *application* of the knowledge are much the same as those for model-based methods.

There are several categories of feature extraction methods. These are shown in the process history branch of Figure 5. Quantitative feature extraction can be statistical or non-statistical. Statistical methods are concerned with finding patterns in abstract mathematical representations of data.

Principal Component Analysis (PCA) is one of the most recent of these representations and has been applied to face recognition (26; 27) and non-destructive testing of metal objects for sub-surface cracks (28). PCA is a mathematical transformation of vector or matrix data which reduces the dimensionality of the data.

Wavelet transforms are mathematical representations of signals with components in both the frequency and time domains. They have been used for feature extraction in many different fields including fault prediction

for ball bearings (29), classification of geographical data (30; 31), classification of NMR¹ spectra (32), wear estimation for industrial turning processes (33) and vibration monitoring (34).

Wavelet transforms are a function of a signal, two scaling variables a and b, and a "mother wavelet" which is a mathematical function with zero mean and finite length. The scaling variables allow the wavelet transform to be carried out at various scales, which can produce a multi-resolution analysis of the signal.

Frequency-domain analysis has been used for some years to extract the features of signals for diagnosis. Fourier transforms in particular can be used to track components of certain frequencies.

All these statistical methods rely on complex mathematical functions and produce fairly abstract data which requires further interpretation before it can be of use. The complexity of the functions limits their use in this application, where there is a need for the methods used to be transparent and understandable to the technical staff who would be expected to use the system.

Some initial work was carried out into the possible use of wavelet transforms as a means of representing the waveforms from different actuators in some common domain, but it was found that the performance of each actuator produced results which could not be reliably linked in any qualitative way.



Figure 10 - An example of a diagnosis system using ANNs to model the monitored equipment, and to recognise faults through patterns in the residuals

Artificial neural networks (ANNs) are very popular computing methods which have applications throughout engineering. Their basic operation is modelled on that of neurons in the human body, which have input and output components and a vast amount of interconnection (35).

They are capable of learning from input data and performing functions such as modelling of data profiles (which can be used to replace conventional mathematical models) and the classification of patterns (which

¹ Nuclear Magnetic Resonance

can be the diagnosis of faults from an initial set of observed residuals generated by a model of any kind) (35).

Because of their versatility, ANNs of many different types have been employed in fault diagnosis research in recent times. A set of training data is all that is needed to program them to model systems and diagnose faults, and they have had considerable success. Some examples of previous applications are catalytic cracking processes (1), power transformers (36) and robotic arm manipulators (37).

ANNs have the advantage, from a practical point of view, of requiring no detailed analysis of the monitored systems, only a set of training data (although detailed analysis can be incorporated in their design to aid in the learning process). However, their very nature is "black-box", that is it is difficult to observe how a neural network arrives at a particular decision. It is very important that the decisions made by a fault diagnosis system can be traced right back to their origins so that technician users can interact fully with the system and draw their own conclusions from its output. This is possible with ANNs, but it may not be easy to logically trace the symptoms of a fault in the measured data to the diagnosis produced, so they may not be the best choice for a railway fault diagnosis system.

Qualitative process history-based methods attempt to solve the problem in non-numerical ways. Two diverse types of qualitative method based on process history are Qualitative Trend Analysis (QTA) and expert systems.

Qualitative Trend Analysis describes the process of qualitatively extracting relevant information from observations and using it to draw conclusions about the state of a monitored system. Cheung, Bakshi and Stephanopoulos (38; 39; 40; 41) developed a comprehensive scheme for the representation of trends in sensor data. The basic method was to filter the waveform to the scale required for analysis, which removed some of the higher frequency information, and to then represent the waveform as a series of standardised curves.

This enabled sensor data to be partitioned into a sequence of *episodes*, where each episode is a trend of a particular shape. The episodes are represented by an "alphabet" of curve shapes. The problem with the scheme as presented in the sequence of papers (38; 39; 40; 41) was that the representation of the data constituted a classification problem, for which the authors had no ready solution but referred to the use of neural networks and other complex methods of classification.

This appeared to make the process very complex, but the idea of using an alphabet of basic shapes to represent waveform data is one which appeals greatly. Some quantitative information can be stored along with the sequence of shape characters. The starting and ending values in each episode are one example of this. Therefore, these representations contain both qualitative and quantitative information, making the approach ideal for this application. If data were collected from many actuators of the same type and in the same condition, it should be possible to represent the data in such a way that the qualitative performance would be identical in all cases (42). This can be achieved by using QTA.

A variation on QTA was proposed, where fuzzy rules were established for particular episodes of behaviour identified in measured data (43). This approach was shown to be very successful in detecting and diagnosing faults in chemical processes. Given that it is possible to find a set of episodes in a qualitative representation which are common to all fault conditions for a given actuator, fuzzy rules established for particular episodes (those where the effects of faults are the greatest) could be used to great effect. The fuzzy sets developed in this paper were of uniform size, translating to heuristic categories such as "average", "large", or "very small" (43).

A useful development of this would be to establish episodic fuzzy rules based on the performance of an actuator under fault conditions. The faulty performance would be measured at the point where the fault is on the verge of preventing the actuator from moving. The fuzzy sets established would be constructed so as to provide a gradual increase in membership between the point of fault free operation and the point where the

fault performance is measured. Then, as operational performance moves away from fault free and towards the fault, the membership increases, showing increased confidence that the fault is present.

Expert systems are methodical representations of human knowledge which diagnose faults by reasoning with IF-THEN rules. This can be done manually or using one of several expert system building tools. Their chief advantages are the ease with which they can be developed and the transparency of their reasoning (25). Their chief drawbacks are that they are very specific to particular systems and are difficult to update (25).

The power distribution industry has focussed heavily on the use of expert systems for the diagnosis of faults in components such as transformers and insulators. Dissolved gas analysis from transformer oil has been used to establish a set of diagnosis rules for the detection of faults in transformers (44). This was found to be very successful, with detection rates for the tested faults in excess of 90%.



Figure 11 - 'Alphabet' for qualitative classification of trends

Butler (45) combined an expert system engine, built using the EXSYS automated tool, with a neural network model of the aging of power components to form a diagnosis system for large networks of power distribution equipment. This was then used to find the location, within the network, of equipment which was behaving abnormally due to aging. Neural networks and expert systems were also combined for the diagnosis of steady-state faults in chemical processes (46), and for the diagnosis of power transformers (47).



Figure 12 - Qualitative trend analysis of measured data

4.3 Fault diagnosis on the railways

Traditionally, the diagnosis of faults in railway equipment has been carried out, once a failure has occurred, by technicians called to the equipment's location. According to failure statistics from the Southern region of the British network (48), between 17% and 22% of failures on point actuators could not be traced to a particular fault when the technicians examined them, resulting in a record stating "Tested OK on arrival", despite the fact that the actuator had failed in service and therefore a fault was clearly present.

Clearly a human examination is not sufficient to detect all the possible faults in these actuators. More insight is required into the operation of the actuator, and so automated condition monitoring has emerged as a potential solution. Commercial solutions focus, in the main, on diagnosing abrupt faults using large arrays of sensors to detect faults in the positioning and locking mechanisms of the actuator being monitored (49). There are currently several pilot schemes operating around the UK.

Little academic research has been carried out to advance this technology, however a number of papers have been published which aim to gain a better insight into the dynamics of an actuator and thereby to try and detect incipient faults which would not be seen on standard condition monitoring equipment until a failure was absolutely imminent.

A neuro-fuzzy diagnosis approach has been proposed for the diagnosis of pneumatic point machines, where the variables measured were first partitioned into a small number of regions (50). This allowed a piecewise linear input-output model to be used. Partitioning the operational variables in the same way, it was possible to generate residuals which were sensitive to faults. Local nodes on each actuator were capable of distinguishing sensor faults from actuator faults. Measured data from actuator faults was forwarded over a network to a central processor which ran an Adaptive Neuro-Fuzzy Inference System (ANFIS) to diagnose the fault.

This system is interesting because it uses a simplified model in order to reduce complexity. However, it does not fully address the issue of tuning the rule base so that the rules apply equally to each instance of an actuator type. In practice, this system would have required the faults to be simulated on each actuator in order to correctly tune the model, something which would not be possible on the railways.

Neural networks have been used to model the performance of pneumatic train doors and to diagnose faults (51). An RBF neural network modelled the displacement profile of the door to a level of accuracy which could be predefined. Complexity of the network was reduced by filtering and removing corrupt values from the data set. Diagnosis was carried out with a Self-Organising Feature Map (SOFM) neural network. The results published in this paper indicated that the accuracy of the system was roughly 80%.

This system used the latest neural network technology but it is unclear how easy it would be to implement it on a practical scale.

4.4 The DAMADICS benchmark actuator project

4.4.1 Background

DAMADICS (Development and Application of Methods for Actuator Diagnosis in Industrial Control Systems) was a four-year project to establish a benchmark for the assessment of diverse fault detection and isolation (FDI) methods (52). It was a Research Training Network funded by the European Commission under Framework V between 2000 and 2003. The project developed from the Framework IV INCO-Copernicus project, concerned with the integration of qualitative and quantitative methods for industrial fault diagnosis (53).

The project was presented in a special edition of Control Engineering Practice. There was an introduction paper (52), several papers presenting methods for FDI based on the benchmark actuator, and several further papers on general fault diagnosis and soft computing. The benchmark FDI methods will be reviewed in this section.

The benchmark is an electro-pneumatic valve actuator used in the sugar production process at a factory in Poland. These actuators are used throughout industry in many different types of process. They are spring-and-diaphragm pneumatic control valves which regulate the flow of liquids through the factory. A diagram of the actuator is shown in Figure 13.



Figure 13 - The pneumatic control valve actuator used as a benchmark in the DAMADICS project (52)

Qualitative reasoning and neural network diagnosis

Calado *et al* (54) proposed a qualitative reasoning approach with fuzzy neural network diagnosis. The inputs to the FDI system were the rates of change of the measured variables, normalised over the range [-1,1]. The authors cited the inaccuracy of numerical models as the main reason for using a qualitative model. The model in this method simulates the process and predicts the outputs in terms of the rates of change of the variables, in the same format as the inputs. The real measured variables are converted to the same qualitative format and compared with the model's predictions in a discrepancy generator. This detects whether or not a fault is present.

The discrepancies are then fed to a hierarchical fuzzy neural network which diagnoses the fault. The use of the qualitative model appears to have limited the usefulness of this method, because it was not possible for the system to detect all the faults. A major reason for this was that the small effects of incipient faults were, in some cases, indistinguishable from the noise in the variables.

This method was interesting because the qualitative processing of the input and measured variables meant that it might be possible to process data from several different actuators in such a way that the same rules could be used for all instances. This is a major requirement for the diagnosis of multiple distributed assets such as switch actuators. However, the qualitative model appears not to have enough functionality. It is fair to conclude that a purely qualitative approach to diagnosis is not sufficient to detect the small effects of incipient faults, which are the main target of this investigation.

State machines

Timed automata (state machines) were used in the method devised by Supavatanakul *et al* (55). The actuator was modelled as a discrete event system, and the occurrence of faults was considered as a discrete phenomenon. The model was able to distinguish between fast and slow state transitions, so it could detect faults which affected the time taken for the actuator to perform its function. The discrete-event model was proposed as an alternative to standard quantitative models which was more robust to imprecision and uncertainty, and less complex.

The first function of this system was concerned with identifying the flow of states from measurements taken during simulations. A separate automaton was constructed for each fault. The input and output model values were then obtained. Sequences of extended states are determined, and then the possible active states were found. The automata which did not fit the possible state sequences were excluded from the candidate set. The remaining automata represented the faults which were possible.

The method was tested against the DAMADICS benchmark by applying it to data measured over about 100 seconds, where a particular fault occurred. The method was able to distinguish the fault which had occurred from three other actuator conditions, comprising the fault free conditions and two faulty conditions. However, it was not made clear whether the method was capable of distinguishing the other faults in the DAMADICS data set.

Interval observer model

A novel model-based method was used by Puig *et al* (56). It aimed to tackle model uncertainties, parameter differences and disturbances by making the diagnosis stage robust to such unwanted inputs. The model consists of observers which predict the outputs of the plant to be within certain intervals. These intervals allow uncertainty to "propagate into the residuals", so that the input to the fault detection function takes account of the uncertainty in the system. As with all model-based methods, there is the disadvantage of high mathematical complexity, making predictions less transparent.

The modelling of uncertainty as an interval means that faults with effects smaller than the interval are likely to be dismissed as uncertainty. This is, to a certain extent, mitigated by the use of non-linear observers, which allow the use of less conservative intervals than would be possible with linear observers. This system was aimed at fault detection; the paper mentions that fault isolation (diagnosis) is a subject for further work. Therefore this method has only limited relevance to this application.

Neural networks for both modelling and diagnosis

Witczak *et al* (57) used a new type of neural network to both model the system under observation (by performing system identification) and diagnose faults. This neural network is the Group Method of Data Handling network (GMDH). The bounded-error approach was used in the design of the neural network to try and minimise modelling uncertainty. The fault diagnosis network monitored the residuals generated from comparison of the model to the real system, and maintained an adaptive threshold around the residuals to increase the sensitivity to faults. However, the authors conceded that some faults could not be detected and diagnosed. Significantly this included incipient faults. It seems that incipient faults are often lost when modelling uncertainty is taken into account, especially if a qualitative model is used.

Neural networks take a large amount of calculations to establish. This was addressed to some extent by ensuring that the most time-consuming calculations were carried out off line before monitoring started (57), however with a large set of identical actuators, some system identification would need to take place every time the system is installed on a new instance of the actuator. It might be possible to achieve this with a minor retuning of the neural network, rather than a full learning process.

Frequency analysis

Model-free fault detection and diagnosis methods are relatively rare, but Previdi and Parisini (58) proposed such a method based on a spectral estimation tool called the Squared Coherency Function (SCF). This

function produces a frequency-based transform of the waveform. An envelope is established around the SCF of the fault-free waveform. Different envelopes are established for each type of fault.

Thus, the fault can be detected and partly diagnosed by checking which envelopes are violated by a faulty waveform. This method is not suitable for use in this application because it is only capable of picking up abrupt faults. Incipient faults would not be detected until they are severe enough to breach the threshold.

Fuzzy classifiers

Bocaniala and Sá da Costa (59) also proposed a model-free method which uses fuzzy classifiers to distinguish between faults by identifying regions within a multi-dimensional space (where each dimension corresponds to one measured variable) where there is correlation between variables measured during a particular fault simulation. Thus, if operational measurements fall within a particular region, a fuzzy membership function for that region becomes high in value, denoting that the actuator is in that particular state.

This method is very relevant to the topic of this report because it provides a direct link between the symptoms of a fault and the diagnosis. It was also designed with a view to diagnosing faults at different levels of severity, although it does not take account of the slow development of incipient faults. The methods used to tune the fuzzy classifier are computationally expensive and would not lend themselves to use on a large number of actuators.

Comments on the DAMADICS project

This set of papers was very useful because it showed the application of several very diverse methods to a common benchmark actuator. Thus it is possible to judge the comparative success of each method. The results from the application of a purely qualitative method (54) show that, although qualitative analysis can be useful in dealing with variations, it is not sufficient on its own to accurately detect the onset of incipient faults. In fact, most of the faults in the benchmark set for DAMADICS were abrupt faults. Despite this, it is clear that many of the methods were not suitable, for one reason or another, for fault diagnosis on switch actuators. The main disadvantages were that they would either be impractical to adapt so that rules would apply to more than one actuator of a certain type, or that they were incapable of detecting incipient faults.

4.5 Conclusions from literature

Both qualitative and quantitative fault diagnosis methods, be they model-based or not, have valuable properties. However, the problem here is to diagnose a large set of actuators of the same type, where the qualitative behaviour of each actuator is similar, but the quantitative behaviour is not. A new approach is required because neither a purely qualitative nor a purely quantitative approach is likely to succeed.

There are many problems with the use of quantitative models. The most obvious is that real world equipment can never be modelled with 100% accuracy. Model inaccuracies and uncertainties mean that residuals are unlikely to be solely dependent on faults, and this can lead to spurious detection of faults.

In previous years, the complexity of mathematical modelling has limited its use due to the physical limitations of computer equipment in carrying out the necessary calculations. Whilst modern computing power all but negates this disadvantage, the complexity of such methods makes them difficult for the layman to understand. A key requirement of a practical condition monitoring algorithm is that the method used must be understandable, at the overview level, to technical staff. This is so that they can engage more with the process and thereby gain more from its outputs.

Qualitative modelling is of particular interest because it has the potential to solve the problem of quantitative variation between instances of similar actuators. It is fair to assume that all instances of a particular actuator will share similar characteristics of performance when viewed qualitatively.

However, the results of the research carried out into qualitative modelling suggest that the ambiguity introduced may impair the ability of a diagnosis system to detect incipient faults at an early stage of detection. In many cases, qualitative models are no simpler or easier to understand than quantitative ones.

Qualitative methods alone cannot detect incipient faults with an acceptable level of accuracy, but quantitative methods will be difficult to implement across a set of actuators, each with slightly different characteristics. A method is required which uses a hybrid analysis to transform real-world measurements into a form where a single set of rules can be applied to data from multiple actuators.

The use of process history to establish rules for diagnosis is appealing, because the reasoning behind it is totally transparent to a technical user. Data from simulations of faults at maximum severity could be used to automatically establish rules which apply to episodes in the measurements from monitored equipment. These episodes could be established using qualitative trend analysis, which examines measured waveforms in a similar way to humans, looking for shapes and changes in those shapes. A combination of some of the methods discussed in this section, modified to the application in hand, seems like a better solution than simply choosing one method over all others.

A model-based approach does not tackle the problem in a similar way to a human, whereas several processhistory based methods are very intuitive. It is suggested that one possible solution would be to use a historybased method with a hybrid qualitative-quantitative analysis of the prior data. This could then be used to establish a set of rules which apply equally to the performance of any actuator of the correct type, providing that data measured from that actuator is also represented with the same hybrid analysis.

The resulting system analyses the shape and trends in measured waveforms in a similar way to a human, and decides, based on knowledge of the shapes and trends in faulty waveforms measured in the past, what faults appear to be present in the monitored data.

5. A detailed example of an advanced algorithm for detecting incipient faults in switch actuators

5.1 Meeting the requirements of the railway

Many of the established methods for fault diagnosis which have been described in section 4 are highly complex and require a large amount of effort, be that the collection of large data sets or the detailed modelling of electro-mechanical systems.

These methods are not well suited to railway application because they have requirements which conflict with those of the railway, namely:

- Ease of introduction: a FDI system for railway equipment must require only a small amount of effort and data from the asset to be monitored.
- Simplicity: the algorithm used must be intuitive to humans, because technical staff need to understand the way the system produces its output if they are to have confidence in it.

5.2 The minimal data set

Any system which is installed to monitor railway equipment must be capable of working without needing to perform fault simulations or complex modelling on the monitored assets. It is not practical to spend hours simulating faults on or modelling each actuator which needs to be monitored. Instead, the diagnosis algorithm needs to learn how to diagnose faults based on data measured offline (i.e. a history-based method), using an actuator at a lab or training school. This is perfectly feasible, since railway infrastructure companies keep examples of their track equipment for training purposes.

It is also permissible to allow a diagnosis system a short "running-in" period where it can measure the normal operation of an actuator being monitored. For a switch, this would mean moving it several times from normal to reverse and back again. Since this is quite often done following maintenance on a switch, this would cause no inconvenience to the infrastructure company.

The challenge is therefore to develop a system which can learn all it needs to know about faulty behaviour from one switch with a particular actuator, and then to apply those rules to an entire asset base, with only a fault-free data set from each monitored asset to acclimatise to that actuator's individual behaviour.

5.3 Dealing with variations in performance

The problem with the minimal data set is that it relies on the possibility that we can make rules from the single test actuator which are applicable out on the railway for a set of actuators which could number several thousand. It is inevitable that performance amongst these actuators will vary. Switch length, local climate, cant and the presence or absence of backdrives will all affect the performance of a switch actuator, not to mention the random variation which will also be present.

However, it is also true that we are considering a single type of actuator and therefore the intrinsic dynamics are likely to be similar, because the mechanical parts are the same in each case. The differences in performance are likely to be *quantitative*, that is, the differences are in the numbers measured, not in the shape of the dynamics. In fact, the shapes (the *qualitative* performance) are similar even on actuators which are driving very different loads.

This means that if we can track certain qualitative states in an actuator, ones which are always present despite variations, then we can watch these states for changes that might indicate a fault.

Qualitative Trend Analysis is a means by which this can be achieved. It is possible to express a sampled waveform in terms of the trends which make it up, as described previously in Figure 12. Because of variations, this representation may not always be exactly the same for each instance, but it is almost certain that there will be "common episodes" – qualitative states which are always present. If these change when a fault is present, then the values associated with the episode can be tracked and rules can be established to indicate whether the values are within a faulty range or a healthy range.

These values must be converted from their absolute form (which is subject to performance variations) to a form which is valid for all actuator instances. This can be done by expressing the value as a percentage change from the fault-free average, or as a simple difference from the fault-free average. These conversions are the weak point of such an algorithm, but the results suggest that they are sufficient to get quite a positive response from a diagnosis system.

5.4 The resulting system

The result of the considerations described in the previous sections is a functional design for a system which uses the minimal data set and the data from each monitored throw of an actuator to calculate a confidence level for the presence of each fault.

Figure 14 shows the first level functionality of this system. Function 1 is performed once, when all the fault simulations have been completed. It performs QTA on the data, finds the common episodes and establishes rules on the values connected with those episodes.

Function 2 is performed every time the diagnosis system is installed on an actuator. The data from the actuator's "running-in" are used to find a baseline for performance. QTA is performed on the data and the absolute values connected with the common episodes are stored. When the actuator is in operation, QTA is performed on the measured data by function 3, and the values are converted into relative quantities using the fault free absolute values found by function 2. A subtractive method (as specified in equation (1), where

 V_{rel} is the relative value for the current operation, V_{ff} is the fault-free absolute value and V_{op} is the absolute value measured during the current operation) was the most effective approach attempted.



Figure 14 - EFFBD showing level 1 of the proposed system

$$V_{rel} = V_{op} - V_{ff}$$

(1)

One important point to note is that the QTA method is sensitive to the scale of the trends it must analyse. Unfiltered data contains too many turning points to effectively isolate the trends of interest. For this reason, the data are filtered using an approximation of the Gaussian filter, implemented by successive applications of a local-averaging filter (a rectangular filtering function). This eliminates the high-frequency data, leaving a waveform which is a smooth set of curves which are consistent from one waveform to the next.

Figure 15 illustrates the effects of this filtering method. It may seem a little drastic, but the important trends will be affected in the same way by faults when viewed in the filtered waveform – but now, the system is not distracted by the smaller variations which mean less in terms of fault effects.



Figure 15 - Comparison of unfiltered and filtered waveforms

5.5 QTA and rule base construction in detail

Figure 14 shows the top level of the system's functionality. This section will now focus on the contents of function 1 in that diagram. The establishment of the rule base is carried out in two stages, the first being a QTA of the test data set, as already mentioned. Figure 16 shows the lower-level functional flow of the QTA process.

The differentiated values (gradients) of the waveform are used in the process of classifying partitions. By comparing the starting gradient with the ending gradient for a partition, it is possible to determine what shape the curve is, between the two points. The partitioning interval is chosen such that it is smaller than the dynamics of the waveform, thereby preventing the system from missing important trends.



Figure 16 - EFFBD illustrating the process of QTA for the establishment of rules



Figure 17 - EFFBD illustrating the formation of rules

The trend string consists of the qualitative states for each partition (i.e. the shape classification, written as a letter between A and I), the values of each filtered waveform at the start and end of the partition, and the time coordinates of the start and end of the partition.

When the trend string contains more than one partition which has the same shape, these are joined to form *episodes*. The episodes have the same format as the trends: containing qualitative state, start time, end time and the start and end values of the waveform. The episodes which make up a single waveform are called a *profile*.

The QTA is carried out separately for each variable measured.

Once a profile has been generated for each waveform in the test data set, the rules can be established. This process is illustrated in Figure 17. First, it is necessary to find the episodes which are common throughout the data set. This is important because the values in the episodes are compared to the values in the fault free set. This can only be done with episodes which are always present in the waveforms.

The values for each common episode are then converted from the absolute representation into a relative representation by taking the difference between the current value and the average value, for the same episode, under fault free conditions. A flag is added initially to each such value, signifying that it is suitable for rule formation.

Flags are then removed if the relative values are too small (i.e. too close to fault-free) and if they are too close to the relative value, for the same episode, from a different fault condition. These unflagging processes make the system stronger at diagnosing faults and at differentiating between them.

For each relative value which is still flagged, a fuzzy rule is created. Fuzzy rules represent the gradual transition from fault-free to faulty with a membership function which changes slowly from 0 to 1 as the fault becomes stronger.



Figure 18 – Π-shaped membership functions

Figure 18 shows an example rule set for one particular quantity. The *x*-axis here is the straight difference between the current measured value and the fault-free average. Each fault condition has a membership function whose peak is at the value which was measured during fault simulation. If each fault is simulated to a point where any further adjustments cause the monitored asset to fail, then we can impose a decline in the membership function, once the peak value has been reached: we know that if this fault were present, the actuator would be about to fail – so if the variation continues to get further from fault-free, we know that this fault is not to blame, because it would have stopped the actuator from working.

By forming a number of these rules, working with different episodes in the waveform and different measured variables, a very strong diagnosis system can be built, impervious to the variations between machines and able to tell the difference between a wide range of faults, based on the changes to individual episodes in the measured data.

5.6 Diagnosis of faults

When the monitored actuator is in service, the key parameters are measured each time it operates. This produces waveforms which are subject to the same QTA as previously described. Function 3, the diagnosis function, finds the common episodes each time, and uses their relative values to evaluate the membership functions for each rule. The average membership is taken for the rules pertaining to each fault, producing a confidence level for each fault, for that operation. Over time, an increase in a fault's confidence value indicates that the presence of that fault is becoming more likely.





Figure 19 shows the ideal output of the fault diagnosis system. Each row of graphs shows the confidence level for each possible fault, under the same simulated condition. The first row is the control. Subsequent rows show how the fault confidence level changes as a fault is introduced. Looking at row 2, the confidence level for the fault-free condition reduces as the fault increases in severity. Conversely, the confidence level for fault 1 increases. The confidence level for fault 2 remains very small, because that fault is not currently present in the actuator.



Figure 20 - Output of the fault diagnosis algorithm for right to left throws



Figure 20 and Figure 21 show the output of the fault diagnosis algorithm for the data gathered at Berlin Ostbahnhof. The directions of operation are right-to-left and left-to-right respectively. The format of these graphs is identical to that of Figure 19: the rows are the confidence graphs for a particular fault simulation. Table 2 provides a description for the numbered faults in the graphs.

Fault number	Description
1	Left-hand locking mechanism tightened
2	Left-hand locking mechanism loosened
3	Right-hand locking mechanism tightened
4	Right-hand locking mechanism loosened
5	Fulcrum point brought closer to actuator

Table 2 - Fault descriptions

As with the ideal graphs, these real results show a strong response by the system to a fault being introduced: all the graphs along the diagonal have a strong positive trend. In each case, the gradient of the trend for the fault being simulated is greater than the gradient of any other trend.

Faults 1 and 5 appear to correlate quite closely. This suggests that the symptoms of these faults are quite similar, although one is a different scale to the other. The use of variable gradients in the membership functions has allowed rules to be created for each of these faults separately, despite the effects being quite similar. The symptom of each of these faults is an increase in the force towards the end of the throw, so it is not surprising that they correlate well.

These results are promising but they do not tell the full story. In order to be completely satisfactory, more data would need to be obtained, from another S700K switch, so that the rules could be used in their full

capacity on an actuator which was not used for the fault simulations. This would prove that it is possible to establish rules on only one instance of an actuator, and apply them across a wide asset base of similar actuators, which could number in the thousands.



Figure 21 - Output of the fault diagnosis algorithm for left to right throws

5.7 Achieving a practical solution

It should be noted that this algorithm is not, in its present state, a practical solution for condition monitoring. There are certain problems which need to be overcome, not least of which is the weak point in the method: the use of differences between fault free and measured values to evaluate fault memberships. This method works best when the actuator used to create the rules is of a similar size and condition to the monitored actuator.

One solution to this might be to categorise switches of differing lengths as individual "actuator" types – establishing rules independently on each. Since switches of varying lengths exist in training schools, this is not an impossible solution. However, it does not address the problem completely.

The key, then, is to find a more effective way of achieving a value for "relative performance" which translates better between different instances of an actuator. However, the results presented here show that the qualitative trend analysis approach is effective as a framework for a more intelligent monitoring system.

Another point to note is that this algorithm ought to be used as one part of an integrated, larger system which takes advantage of the capabilities of monitoring approaches already in use. Some faults can be detected with very simple systems and there is no need to then overlay this algorithm on those faults, unless it can be demonstrated that it is more accurate or effective.

6. Conclusions

This report has presented the results of in-depth research into switch actuator condition monitoring. It is fair to conclude that there are dozens, if not hundreds, of perfectly valid advanced methods which can be used to diagnose the condition of a switch actuator, but most of them result in requirements such as large amounts of data, intensive mathematical modelling or a very advanced understanding on the part of the user. This does not mean that they cannot be used, however, and it is certain that elements of the complex methods reviewed in this report can and should be evaluated for further use. This is especially true of centralised condition monitoring systems, where data are collected at the switch site but then sent to a server to be analysed centrally. Here, complex algorithms and the attentions of highly-qualified staff are not impractical to implement.

However, this report also presents a possible solution which is based wholly on the requirements of the rail industry: for a system which requires minimal input data and analyses it in a similar fashion to how a human would – making it easier for technicians to understand the output.

There remains much work to be done in this field. So far, railway condition monitoring manufacturers have focused on providing simple, robust systems for field deployment. Effort now should be directed towards taking concepts such as the one presented here and developing them into practical solutions which can be implemented on the railway. This does not negate the work done towards providing the simple equipment – with some careful design, the complex analysis should be able to run as an extra layer to the capability which has already been provided.





Figure 23 - Fault free data, throwing left to right



Figure 24 - left hand locking mechanism tightened, throwing right to left



Figure 25 - left hand locking mechanism tightened, throwing left to right



Figure 26 - left hand locking mechanism loosened, throwing right to left



Figure 27 - left hand locking mechanism loosened, throwing left to right



Figure 28 - right hand locking mechanism tightened, throwing right to left



Figure 29 - right hand locking mechanism tightened, throwing left to right



Figure 30 - right hand locking mechanism loosened, throwing right to left



Figure 31 - right hand locking mechanism loosened, throwing left to right



Figure 32 - left hand fulcrum point changed, throwing right to left



Figure 33 - right hand fulcrum point changed, throwing left to right

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