Using a High Fidelity CCGT Simulator for building Prognostic Systems

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Abstract

Pressure to reduce maintenance costs in power utilities has resulted in growing interest in prognostic monitoring systems. Accurate prediction of the occurrence of faults and failures would result not only in improved system maintenance schedules but also in improved availability and system efficiency. The desire for such a system has driven research into the emerging field of prognostics for complex systems.

At the same time there is a general move towards implementing high fidelity simulators of complex systems especially within the power generation field, with the nuclear power industry taking the lead. Whilst the simulators mainly function in a training capacity, the high fidelity of the simulations can also allow representative data to be gathered. Using simulators in this way enables systems and components to be damaged, run to failure and reset all without cost or danger to personnel as well as allowing fault scenarios to be run faster than real time. Consequently, this allows failure data to be gathered which is normally otherwise unavailable or limited, enabling analysis and research of fault progression in critical and high value systems.

This paper presents a case study of utilising a high fidelity industrial Combined Cycle Gas Turbine (CCGT) simulator to generate fault data, and shows how this can be employed to build a prognostic system. Advantages and disadvantages of this approach are discussed.

Introduction

Electrical power utilities increasingly desire next generation condition monitoring systems, which can not only diagnose incipient faults, but also predict the time remaining until failure [1]. Such a prognostic system allows maintenance to be scheduled for a time that minimises disruption and impact while still operating safely [2, 3]. The field of prognostics has made advances in applications such as aerospace, electronics, and process control, but as yet has not been applied within the power domain, as the technology is not mature enough for industrial deployment of a prognostic system. This is largely because testing and validation of prognostic models remains a challenge as systems are rarely run to failure, preventing the possibility of gathering the data required for prognostic modelling [4, 5].

The field of prognostics is an emerging area of research [6] driven by the realisation that accurate prognostic systems would enable optimisation of both performance and maintenance of a system [7]. Prognostics is the process of predicting a system's remaining useful life (RUL). A system's RUL can itself be further clarified as either the failure of the system, or a certain performance threshold has been crossed. This RUL is considered equivalent to the time of failure (TOF) of a system or component: the remaining time, hours or duty cycles the system has before failure or a failure threshold is reached. The creation and implementation of an effective prognostic model would reduce maintenance and downtime of a system equipped with the model, allowing operators to implement predictive condition based maintenance in place of time based maintenance, thus substantially reducing costs of continuous maintenance and unplanned downtime [8]. The leading areas concerned with prognostics modelling are those which have high requirements for system control, monitoring and reliability such as aerospace engineering and the nuclear industry [8 - 12]. The aim of this research is to effectively expand the prognostic base into power generation.

The difficulty in creating a robust prognostic model within power generation arises from the lack of data available for power systems due to the high cost of creating a run-to-failure test of a large system. Also gathering, understanding and transforming data received from on-site industrial operators into a comprehensive and reliable model is a costly and difficult task [13].

Current maintenance policies and approaches

The current approach to maintenance and operation of plant health systems may be considered a responsive one, where actions are considered based upon the current condition of a component. In contrast, prognostics would fall under a predictive approach. Within this responsive approach there are three main methods. Firstly, there is a purely responsive approach where action is only taken upon failure of a component. Secondly, there is the time based maintenance approach where components and systems are replaced according to present schedules without regard to condition. Thirdly there is the diagnostic method. This diagnostic approach relies on scheduled or online diagnostics of key components or parameters of a system to determine what response should be undertaken, either replacement of the component or a continuation of use [6, 14]. With all three of these methods problems arise in the forms of sudden unplanned downtime, sudden failures resulting in safety concerns and extended downtime if replacement parts or maintenance is not available on hand [3, 8].

Simulation Suite

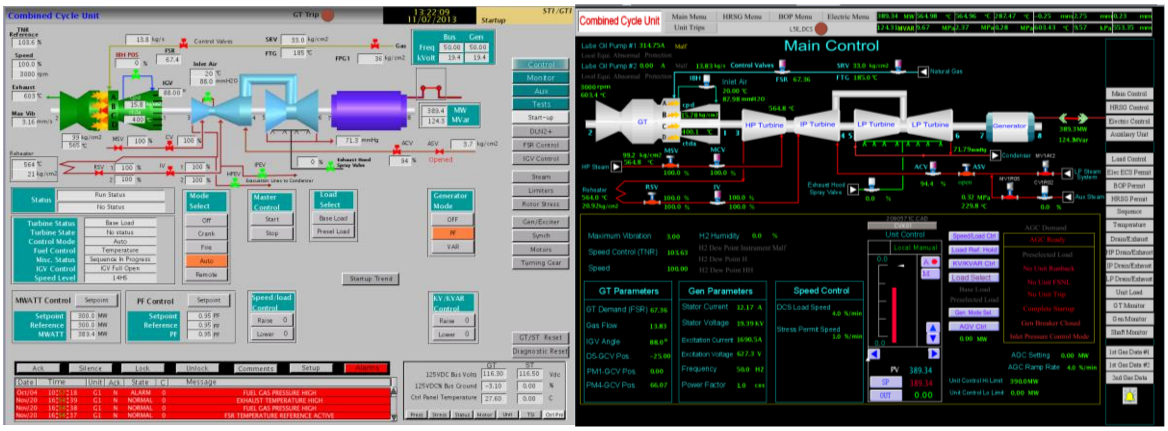

Figure 1. Real time plant operator displays

The simulation tools used for the plant and failure modelling are GSE Systems' Jade Simulation Tools. The Simulation Suite present at the University of Strathclyde facility comprises of several high fidelity plant simulators. The simulator currently used in this research is a high fidelity 400MW Combined Cycle Gas Turbine (CCGT) model. The Jade Tools used in the creation of the simulators are individual simulations of interlinked systems, with on-going interaction across all systems, and include flow simulation, electrical simulation and logic programs. This high fidelity modelling environment allows the introduction of failures and observation of how a plant system responds as a whole (shown in Figure 1). This also allows parameters of note to be logged as well as allowing the observation of the plant control system response.

A crucial benefit of the simulation environment is that it represents a fully controllable and reactive platform similar to the environment that plant operators engage with daily.

Simulators have already been established and deployed across a variety of industries, typically large scale complex systems with requirements on operational safety [15]. Therefore the time-intensive modelling work has already been achieved in these industries, simplifying the possibility of utilising simulators for prognostics.

Simulator methodology

This section presents a high level methodology for using the simulator environment for prognostic modelling. The methodology comprises six stages, as detailed below.

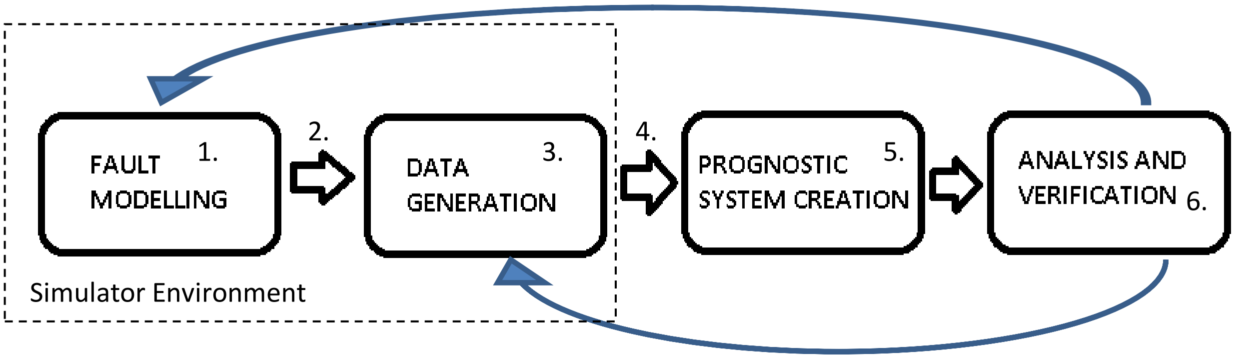

Figure 2. Methodology process using high fidelity simulators

1. Create and choose degradation and damage models

The first step undertaken is the creation of a deterioration or damage model. For useful prognostic models the time to failure of systems chosen are required to occur over extended periods of operation. This long-term fault development is required to maximise the usefulness of a prognostic system, by allowing operators time to assess the situation and scheduling maintenance. Also when choosing the damage model for research, consideration is also required of the parameters available. For example, creating the prognostic models within the Jade environment reduces the possibility of using vibrational data; as such parameters are not modelled with enough fidelity for effective use in prognostic models.

2. Integration with the simulator

When the degradation model is chosen and complete it will then be run alongside the high fidelity industrial model. This will enable the choice of model not only to be run and observed in an online and realistic condition but also allow the observation of overall impacts and possible secondary parameters within the plant model which may be affected. It also allows the observation of possible automatic control system alarms and responses.

3. Run simulator from base load to failure

The plant simulation is then run at base load (peak steady state operational output) whilst the degradation model is run until the failure threshold is reached. The benefits of computational simulation in any environment are twofold: the ability to model systems without the need of a physical implementation and the ability to instantly reset without any negative effects to nominal levels (or indeed any chosen condition or state). In the case of Power Generation in particular the benefits of simulation are clear. Firstly, with the scale, size and complexity of power generation systems, constructing full realistic experimental setups for research is prohibitively expensive. This is particularly the case for damage and deterioration modelling. For example, to generate a set of representative degradation data for research purposes, components must be run from nominal health to failure repeatedly. Any real component only has a single lifetime, so a physical experiment would result in high expense due to purchase of many components. Whereas with computational simulation, a fault can be incited in any component regardless of expense, run to failure, and then instantly returned not only to nominal health, but to any chosen health condition.

This leads onto three further points. Firstly, high fidelity simulation of components and faults means that critical systems such as turbines can be failed multiple times, gathering large banks of data not only on commonly-occurring faults, but also on possible rare failures. Secondly, the option to tune the starting health of a component allows not only for generic ideal system research, but more importantly it enables the simulations to reflect real plant health conditions and operation. Thus models can be tuned to account for maintenance and repair performed on a system. And finally, computational simulation alleviates safety concerns, enabling large scale catastrophic failures to be run without danger to personnel or public.

4. Gather output data

Within the GSE simulation tools there is the ability to monitor chosen parameters on a real-time graphical display. Once parameters have been chosen they can be logged through this display option, and most importantly captured and exported. The data running from base load through to fault inception and ending in component or system failure can then be exported easily via CSV file. As the system can be reset, multiple conditions surrounding the fault can be simulated, captured and exported together, making data handling and processing of the gathered data somewhat easier.

5. Create prognostic model

The methodology steps up to this point have generated a database of representative fault and failure data which can be used in the creation, test, and validation of a prognostic model. While there is no technique generally accepted as most appropriate for prognostic modelling, other industries have considered techniques like neural networks [16], Bayesian regression [17], and the General Path Model [18].

6. Return to simulator for additional validation

As further validation of the prognostic system, the simulator can be used to extract further degradation case study data. There is also potential for running the prognostic algorithm online, in tandem with the simulator.

Case Study

The following is an example of how faults can be created, implemented, recorded, and then exported from the 400MW CCGT model following steps 1 through to 4 of the research methodology discussed above.

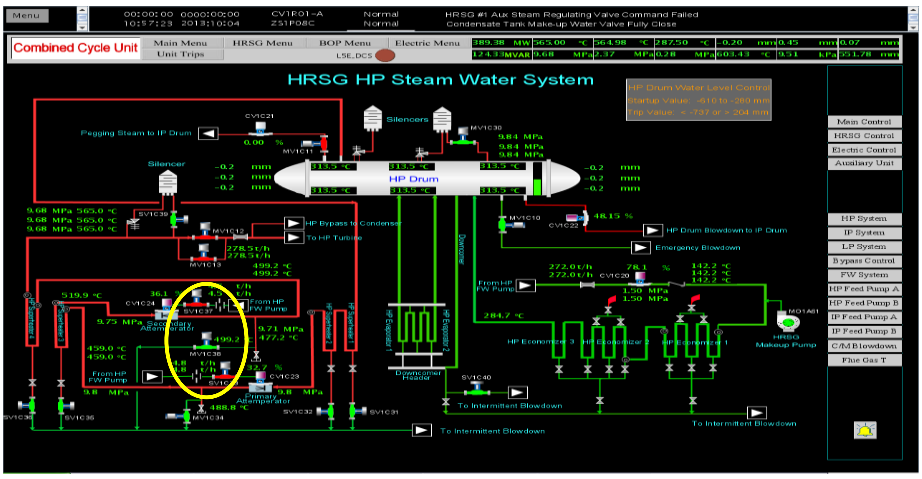

Figure 3. Operator Control screen with highlighted attemperator valve for fault inception

Step 1: The fault chosen is one from a library of pre-existing faults modelled within the 400MW CCGT simulation. It consists of the failure of an attemperator valve, Figure 3. An attemperator valve is used in the CCGT to pump additional water into the steam flow path to control the temperature and volume of the steam as it flows toward the turbines.

Step 2: The attemperator failure is initiated in the CCGT model by closing the valve manually on the operator control screen. This fault could occur in certain scenarios such as: operator error (accidentally closing the wrong valve), failure of the valve, or build-up of debris.

Step 3. The simulation is initialised at base load (391MW), and the fault is introduced by closing the valve on the operator screen. The fault inception can be seen occurring at point 01:00:30 of Figure 4. Very quickly the parameters can be seen to react to the valve failure and the CCGT plant goes into runback at 01:01:00. This is where the steam temperature and volume along the steam line decreases due to the lack of additional water provided by the attemperator valve whilst the control system tries to control the parameters of operation to reassert a safe and steady flow output condition. This can be seen in time period 01:01:00 to 01:02:00 of Figure 4.

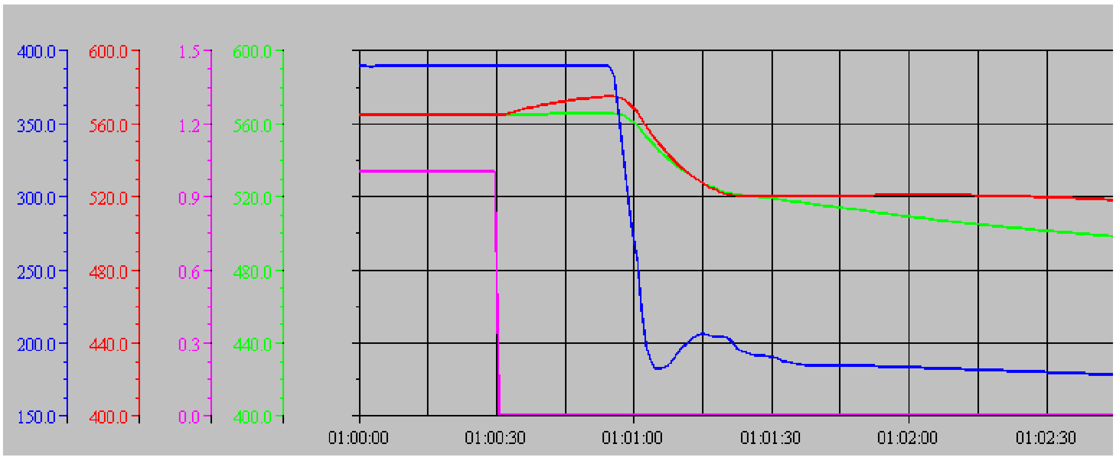

Figure 4. Parameters during fault: CCGT Power Output (MW: blue), Main Steam Temperature (^{O}C: red), Reheated Steam Temperature (^{O}C: green), Secondary Attemperator Valve Position (%: purple)

Step 4. Using the Jade Real Time Trending (JRTT) display, any parameters simulated through the CCGT plant simulator can be viewed, analysed by the operator, and extracted. The graphical display (shown in Figure 5) allows trends to be viewed and multiple relevant parameters to be exported to CSV file.

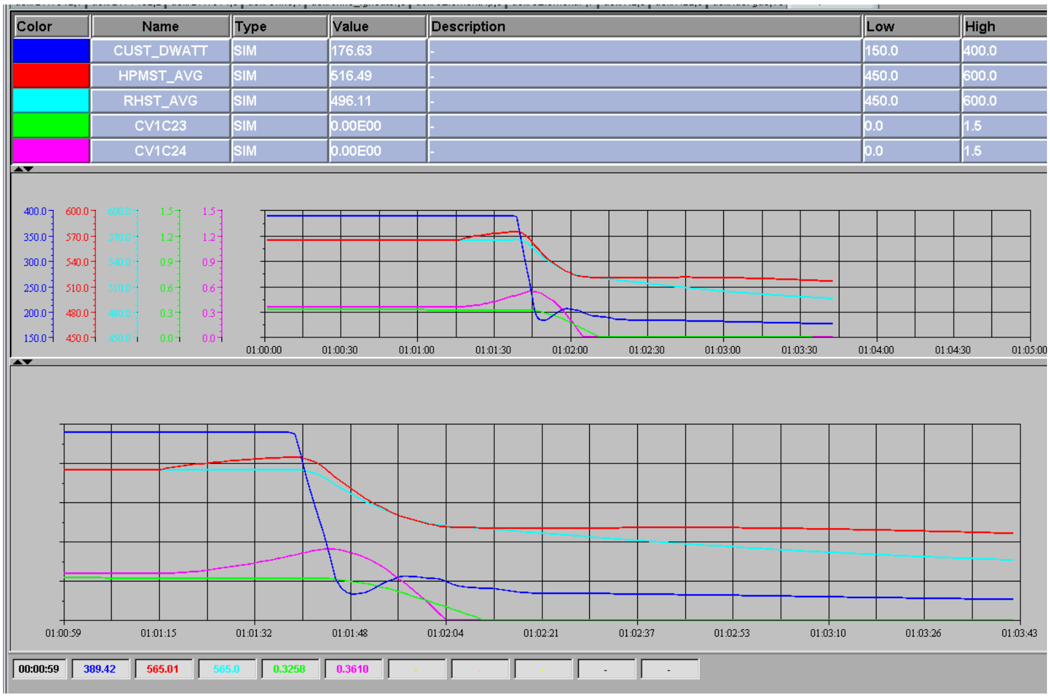

Figure 5. JRTT display. Selected parameters and monitored values

Conclusion

This paper presents the possible benefits of the use of large scale simulators for creating and gathering fault and degradation data. This approach of using high fidelity industrial simulators is a means of overcoming one of the main obstacles in prognostic modelling: the lack of access to failure data. Once fault and failure models have been integrated into the simulator environment, exporting failure data for prognostic modelling and validation is straightforward. The use of simulation provides a depth and range of data for possible fault and failure scenarios, which are more difficult to collect from in-service plant, since components are rarely allowed to fail.

The paper has described a methodology for using simulation to develop prognostic models, and demonstrated the generation of representative data using simulation of an attemperator valve failure. Future work will focus more on the creation, test, and validation of prognostic models.

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