

Prognostic Modeling of Valve Degradation within Power Stations

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ABSTRACT

Within the field of power generation, aging assets and a desire for improved maintenance decision-making tools have led to growing interest in asset prognostics. Valve failures can account for 7% or more of mechanical failures, and since a conventional power station will contain many hundreds of valves, this represents a significant asset base. This paper presents a prognostic approach for estimating the remaining useful life (RUL) of valves experiencing degradation, utilizing a similarity-based method. Case study data is generated through simulation of valves within a 400MW Combined Cycle Gas Turbine power station. High fidelity industrial simulators are often produced for operator training, to allow personnel to experience fault procedures and take corrective action in a safe, simulation environment, without endangering staff or equipment. This work repurposes such a high fidelity simulator to generate the type of condition monitoring data which would be produced in the presence of a fault. A first principles model of valve degradation was used to generate multiple run-to-failure events, at different degradation rates. The associated parameter data was collected to generate a library of failure cases. This set of cases was partitioned into training and test sets for prognostic modeling and the similarity based prognostic technique applied to calculate RUL. Results are presented of the technique's accuracy, and conclusions are drawn about the applicability of the technique to this domain.

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1. INTRODUCTION

Within electrical power utilities there is an increasing demand for condition monitoring methods capable of reliably predicting the RUL of assets (Sheppard & Kaufman 2009). This requirement is driven by the need to improve maintenance costs and scheduling, as well as safety considerations (Chen, Yang & Zheng 2012). The field of prognostics has made great advances in areas with high requirements on safety and dependability, such as aerospace and the nuclear industry. However within the power generation field, prognostic applications have not been implemented to the same degree. This is mainly due to the challenges of gathering sufficient data to enable robust testing and validation, as such systems are rarely allowed to run to failure (Heng, Tan, Mathew, Montgomery, Banjevic, & Jardine, 2009).

Within power generation, implementation of prognostic methods would enable operators to reduce maintenance and unplanned downtime by utilizing predictive maintenance policies in place of a time based maintenance approach (Vachtsevanos, Lewis, Roemer, Hess & Wu, 2006) (Sun, Zeng, Kang & Pecht 2012). However, there is a high cost associated with creating physical test systems from which to gather run-to-failure data. Additionally, gathering, understanding, and transforming data provided by on-site industrial facilities into a comprehensive and reliable model is a costly and difficult undertaking (Wenbin & Carr 2010), with operators often reluctant to provide commercially sensitive data.

One way to overcome this lack of failure data is to utilize simulation of assets to generate the data required. Following

this route, this paper proposes the simulation of degradation of valves within a power plant environment to create a similarity-based prognostic model. Within a plant environment, valves have been highlighted as a common source of faults, accounting for at least 7% of mechanical failures (Radu, Mladin & Prisecaru, 2013) (Latcovich, Åstrom, Frankhuizen, Fukushima, Hamberg & Keller, 2005), and with many hundreds of valves present in a typical generation plant (Westinghouse Nuclear, 2013), valves are a critical asset which could benefit from a prognostic system.

Within power generation, simulators have been widely deployed, particularly within the nuclear sector, for training purposes focused on improving operational safety (Harrison, 2013). Such simulators are used primarily for training and are certified as high fidelity tools and thereby the model and sensor data are within industrially accepted tolerances of actual plant values. Utilizing such high fidelity simulators negates the need for the creation of physical test beds, as well as providing an industrial acceptance and robustness to the simulated data generated (McGhee, Catterson, McArthur and Harrison, 2013).

The similarity-based prognostic method used here is based on an approach by Wang, Yu Siegel and Lee (2008). This similarity method has particular application benefits to the simulation approach proposed here. With simulation, the large number of run-to-failure cases needed for a similarity based approach can be generated easily. The use of simulation can also satisfy the requirements stated by Wang et al. (2008) for a successful implementation:

- 1) Multiple recordings of run-to-failure data are available,
- 2) The data recorded ends when the point of failure is reached, and
- 3) The data covers a representative set of components.

2. METHODOLOGY

This section discusses the creation of the valve failure model and the prognostic RUL model. A diagram of the process is shown in Figure 1.

2.1. Valve model simulation

The valve model was created from first principles, simulating fluid flow within a cylindrical pipe:

$$P_2 = P_1 + \frac{1}{2}\rho(V_1^2 - V_2^2) \quad (1)$$

$$A_1V_1 = A_2V_2 \quad (2)$$

Where P_1 , V_1 and A_1 correspond to the pressure, fluid flow and area of the pipe entering the valve, P_2 , V_2 and A_2 correspond to the pressure, fluid flow and area of the pipe at

the point of degradation and ρ describes the density of the fluid. Parameter values for the model are taken from an industrial Combined Cycle Gas Turbine (CCGT) plant simulator.

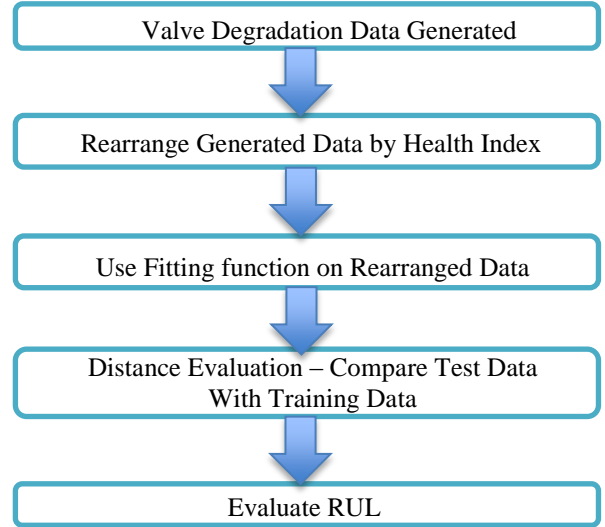


Figure 1. Procedure of RUL estimation

The degradation is represented by a decreasing area A_2 where the initial area of the pipe A_1 is constricted over time. This is represented by a degradation coefficient, δ , which is a numerical constant between 0 and 0.0001, drawn from a standard uniform distribution, describing the rate of decrease in the flow area.

$$A_2(t + 1) = A_1(0) - \delta A_1(t) \quad (3)$$

This degradation can represent debris build up along the area of flow, or “sticky valve failure” where the valve no longer fully closes or opens. A single run-to-failure event from initial healthy operating conditions to end of life can be seen in Figure 2, and a batch of 50 run-to-failure events can be seen in Figure 3. For this study, the end of life is considered to be $P_2 = 0$, i.e. completely blocked flow. However, in a power station deployment, maintenance intervention would be triggered significantly before this threshold is reached.

This modeling approach corresponds to the way components and faults are modeled in the industrial plant simulator used in the research. The plant simulator uses first principles equations based on pressure, fluid flow and flow area to model pipes and valves.

The modeling choices also need to be made with respect to the sensors and data readily available to station operators. Theoretically, measurement points could be placed at any point in the plant model, and the parameter value recorded

as if from instrumentation. However, for the prognostic model to translate directly from the plant simulator to the real plant environment, any measurements utilized by the prognostic model must be realistic points for instrumentation to be located. Therefore, only those parameters which would normally be recorded around a valve are considered.

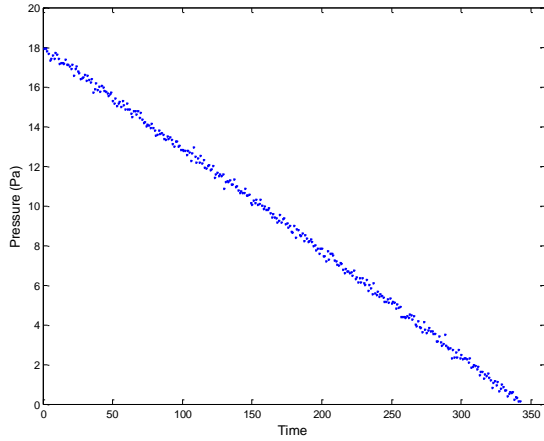


Figure 2. A single run-to-failure event

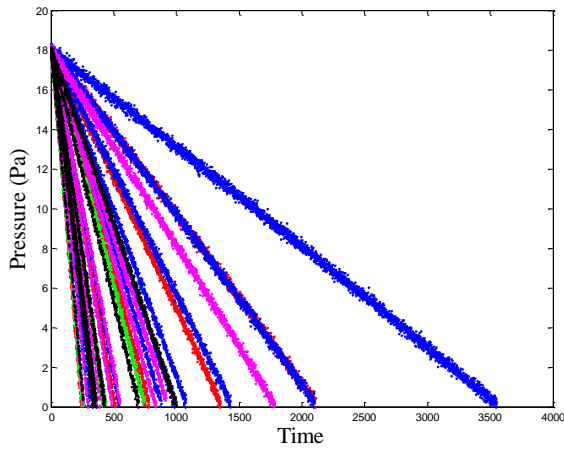


Figure 3. 50 run-to-failure events

For this study, the training data comprised 50 sets of time stamped pressure values, corresponding to P_2 in Eq. (1), from an initial value equal to P_1 down to 0. The simulated frequency of data capture is set at once per hour. For this case, the parameters taken from the CCGT were an initial pressure $P_1=18$ Pa, area $A_1=10$ cm² and flow $V_1=185$ kg/s. To represent measurement noise, each data point had a noise term added, drawn from a Gaussian distribution with mean 0 and standard deviation 0.0005.

2.2. Prognostic model

The procedure for creating the similarity-based prognostic model is split into three steps (Wang et al., 2008). The first two, described in sections 2.2.1 and 2.2.2, are data preparation steps applied to both training and test data. The third step compares the test data set against the training data. Of 55 run-to-failure events simulated, 50 were used as training data, with five for testing.

2.2.1. Arrangement by health index

The initial stage is to rearrange the data to create a Health Index (HI). The HI is used to describe the condition of the asset. Near the start of life the asset is assumed to be in a healthy condition and assigned the value 1, whilst the unhealthy or near end-of-life condition is assigned the value 0. This HI is then applied to every data run and the data rearranged according to the asset's time-to-failure (Figure 4). As shown in Figure 4, the start of life (healthy) and end of life (unhealthy) values correspond to $P=18$ and $P=0$ respectively.

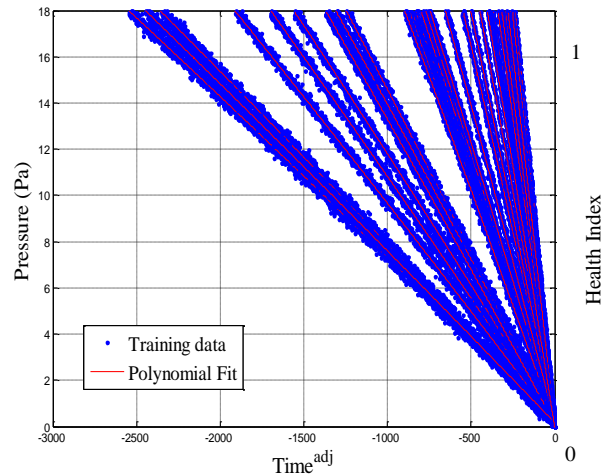


Figure 4. Training set comprising 50 run-to-failure events rearranged according to HI

Polynomial fitting

Having rearranged the data according to the HI, each run-to-failure event is then fitted using a polynomial function which best describes the event progress. In the specific case of this valve degradation example, the fault progression looks to approximate a linear fit. However, in other cases the best fit may be a higher order polynomial or other function. In this case the polynomial fit is:

$$f(x) = ax + b \quad (4)$$

where a and b are the model parameters. This polynomial curve is fitted to the HI for every run-to-failure event with the least squares fitting approach.

2.2.2. Distance Evaluation

To determine the RUL of the test runs, a sample of data from near the start of each test is selected. In the examples below, time steps 50–100 are chosen to represent the current and recent historic condition of the valve. This data is then compared against every 50 time step segment of each training data polynomial fit until the closest match to the test is found. The distance evaluation is determined by:

$$d(\tau, Y, i) = \sum_{j=1}^r \frac{(y_j - f_i(-\tau - r + j))^2}{\sigma_i^2} \quad (5)$$

where d is the distance of the test data from the training data sample, y is the position of the test data (time step number), f_i is the polynomial curve fitted to the i th training data sample, r is the length of the test data Y , τ is the number of time steps Y is shifted from 0 and σ is the RMS error from the polynomial fit.

Once the distance between the test run and all windows of all training runs is established, the estimated RUL is chosen by selecting the training run sample with the smallest distance d (i.e. the most similar run-to-failure event). The RUL from that point of the training run is the estimated RUL for the test run.

3. EXPERIMENTAL RESULTS

The five test runs are summarized in Table 1 and shown in Figures 5 – 9. As can be seen, the true RUL of each test run compares well with the predicted RUL value.

Table 1. Summary of Test run results with associated Estimated RUL and True RUL

<i>Test Run</i>	<i>Est RUL</i>	<i>True RUL</i>
1	230	239
2	898	889
3	631	624
4	673	638
5	1204	1195

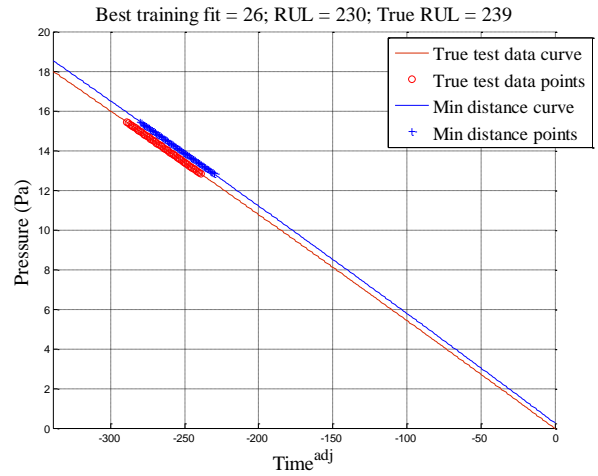


Figure 5. Test run 1: Estimated RUL = 230, True RUL = 239

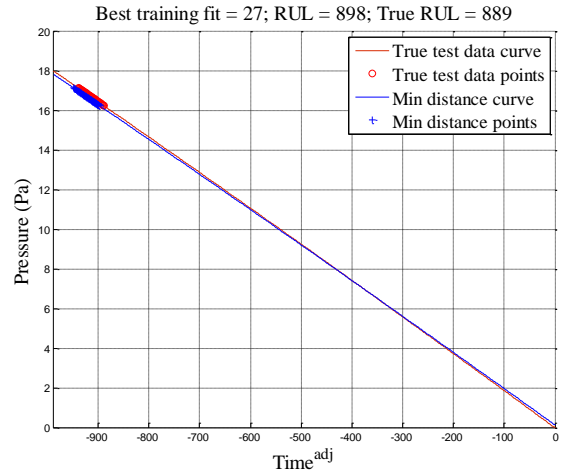


Figure 6. Test run 2: Estimated RUL = 898, True RUL = 889

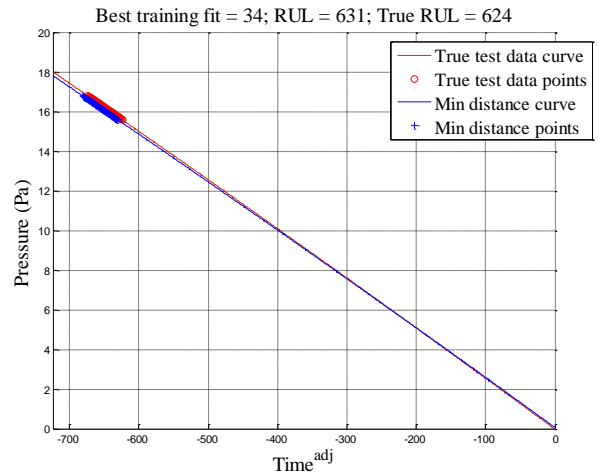


Figure 7. Test run 3: Estimated RUL = 631, True RUL = 624

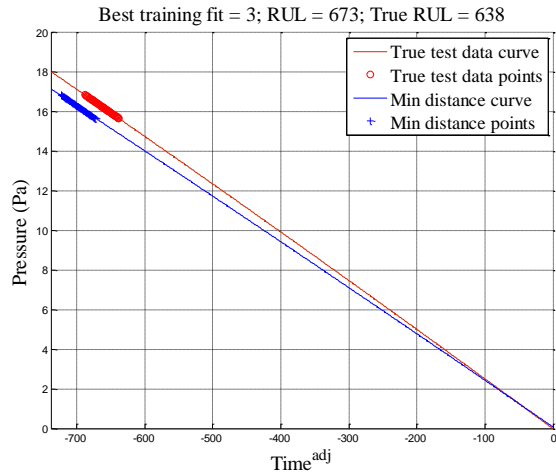


Figure 8. Test run 4: Estimated RUL = 673, True RUL = 638

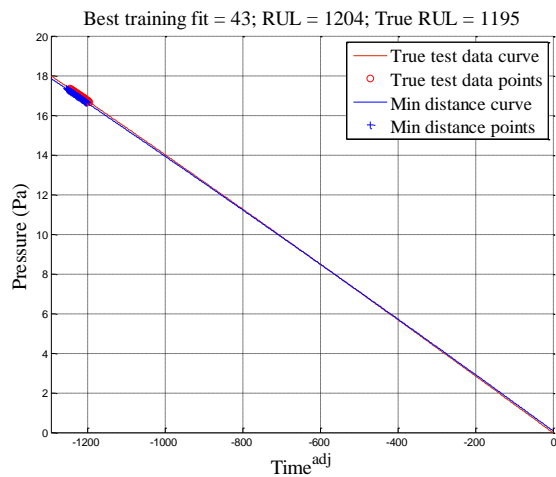


Figure 9. Test run 5: Estimated RUL = 1204, True RUL = 1195

These results are considered accurate enough for the application domain, being within 10 hours of the actual RUL in most cases, and 35 hours in the worst case. While this technique estimates the time to complete failure (zero flow), in a power station maintenance would be triggered by a reduction in flow, significantly before failure. The estimation of RUL gives an indicative window of time in which maintenance could or should be performed, thus providing support to maintenance planning. Future work will consider how far in advance of estimated failure a maintenance trigger should be set, bearing in mind uncertainties in the RUL prediction.

The high accuracy of the case study RUL predictions is due to the range of failures included in the training data set, which is due in turn to the use of simulation. With the high fidelity plant simulator, plant conditions can be varied and

reset for multiple fault runs, generating as many failure examples as desired.

There is potential for this similarity based prognostic method to be improved further, with a larger training data set containing a greater breadth of degradation and failure cases. Future work will consider how large the training set needs to be, and how to integrate actual valve failure data as it becomes available.

However, as more training data is added, RUL selection becomes more complex. Future extensions of this technique may need to consider implementing different methods of distance evaluation, to retain prediction accuracy. Also, as this method relies on training using run-to-failure data, it is limited to accurate prediction of previously seen fault types.

4. CONCLUSIONS

The similarity-based prognostic approach described in this paper provided accurate results when estimating RUL of valves within a power station. This research utilizes a high fidelity CCGT plant simulator to allow the creation of a large suite of failure cases, simulating a relatively low risk but high consequence failure mode for which there is limited in-service data. This paper demonstrates a method of first principles modeling of failure, in order to generate the data required for data-driven prognostic modeling. This is shown to accurately predict the remaining life of five test cases.

Having tested the method there are a number of possible routes now available for further research using this approach: testing the approach with real plant data, applying the prognostic method to different types of faults, and comparing this technique to other prognostic techniques for similar applications.

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REFERENCES

- Chen, Z.S., Yang, Y.M. & Zheng Hu, (2012) A Technical Framework and Roadmap of Embedded Diagnostics and Prognostics for Complex Mechanical Systems in Prognostics and Health Management Systems, *IEEE Transactions on Reliability*, Vol. 61, (Issue: 2), Pages: 314 – 322, doi: 10.1109/TR.2012.2196171
- Harrison, S. (2013), The Case for Simulation and Visualisation Based Training, *Marine Electrical and Control Systems Safety Conference, (MECSS 2013)*, October 2-3, Amsterdam
- Heng, A., Tan, A. C. C., Mathew, J., Montgomery, N, Banjevic, D. & Jardine, A. K. S., (2009), Intelligent Condition-Based Prediction of Machinery Reliability,

- Mechanical Systems and Signal Processing*, Vol. 23, (Issue 5), Pages: 1600 – 1614, doi: 10.1016/j.ymsp.2008.12.006
- Latcovich J., Åstrom T., Frankhuizen P., Fukushima, S., Hamberg H., & Keller, S., (2005), Maintenance and Overhaul of Steam Turbines, *International Association of Engineering Insurers 38th Annual Conference*, September, Moscow
- McGhee M. J., Catterson V.M., McArthur S.D.J. & Harrison E. (2013), Using a High Fidelity CCGT Simulator for building Prognostic Systems, *European Technology Conference 2013. EuroTechCon 2013*, November 19-21, Glasgow, UK
- Radu G., Mladin D. & Prisecaru I. (2013) Analysis of potential common cause failure events for Romania-TRIGA 14 MW reactor, *Nuclear Engineering and Design*, Vol. 265, Pages: 164-173, doi: 10.1016/j.nucengdes.2013.06.027
- Sheppard, J.W., Kaufman, M.A. & Wilmer, T.J. (2009), IEEE Standards for Prognostics and Health Management, *IEEE Aerospace and Electronic Systems Magazine*, Vol. 24, (Issue: 9), Pages: 34 – 41, doi: 10.1109/MAES.2009.5282287
- Sun, B., Zeng, S., Kang, R. & Pecht, M.G. (2012) Benefits and Challenges of System Prognostics, *IEEE Transactions on Reliability*, Vol. 61, (Issue: 2), Pages: 323 – 335, doi: 10.1109/TR.2012.2194173
- Vachtsevanos, G., Lewis, F. L., Roemer, M., Hess, A., & Wu, B. (2006). *Intelligent fault diagnosis and prognosis for engineering system*. Hoboken, NJ: John Wiley & Sons, Inc
- Wang, T., Yu J., Siegel D. & Lee J. (2008). A Similarity Based Prognostics Approach for Remaining Useful Life Estimation of Engineered Systems, *International Conference on Prognostics and Health Management, 2008. PHM 2008*, October 6-9, Denver, CO, 10.1109/PHM.2008.4711421
- Wenbin Wang & Carr, M.,(2010), A Stochastic Filtering Based Data Driven Approach for Residual Life prediction and Condition Based Maintenance Decision Making Support, *Prognostics and Health Management Conference, 2010. PHM '10*, Jan 12-14, Macao, 10.1109/PHM.2010.5413485
- Westinghouse Nuclear, (2013), AP1000 PWR Nuclear Reactor Brochure

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