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NONLINEAR MODEL BASED DIAGNOSTIC OF GAS TURBINE FAULTS: A CASE STUDY

Yongwen Liu
Key Lab for Power Machinery and Engineering of Ministry of Education
School of Mechanical Engineering
Shanghai Jiao Tong University
200240 Shanghai, China
Email: ywliu@sjtu.edu.cn

Ming Su
Key Lab for Power Machinery and Engineering of Ministry of Education
School of Mechanical Engineering
Shanghai Jiao Tong University
200240 Shanghai, China
Email: msu@sjtu.edu.cn

ABSTRACT

During the lifetime of a gas turbine, its gas path components deteriorate gradually and sometimes serious problems happened. Direct physical and indirect model based methods can be used in health monitoring systems for gas turbines.

The gas turbine under study is run as part of a combined cycle generation unit, sited in the BAO Steel Power Plant. The basic health monitoring system is based on vibration signal. After the vibration monitoring system failed to detect foreign object damage (FOD) fault, a health monitoring system based thermodynamic model is tried to explain quantitatively why the performance degradation happened, with the foreseeable usage as part of the online health monitoring system.

The present work is based upon component level nonlinear gas turbine model, so errors caused by linearization can be avoided. The component level model of gas turbine is built as dynamic model, and the off-design performance of gas turbine is evaluated as the steady-state solution of the dynamic model. A dynamic tracking filter, which tracking field measurements with PI control loops, is incorporated into the gas turbine dynamic model. Output of the dynamic tracking filter is called correction factors, which are used as multiplicative corrective values of component performance parameters (i.e., flow or efficiency) in the gas turbine model.

With dynamic tracking filter and aero-thermal dynamic model, the model based fault diagnosing of gas turbine is implemented as a three step process. As a case study, several measurement data sets are tried to detect and isolate FOD fault happened. The result demonstrates that a model based gas path analysis can detect and isolate fault even when no vibration level alarm is reported.

INTRODUCTION

During the lifetime of gas turbines, various gradual and abrupt performance degradations may happen. By health monitoring and fault diagnosis system, the working status of gas turbines can be deduced from field measurements, and proper countermeasures can be taken. Direct physical and indirect model based methods can be used in health monitoring systems. Mathematical modeling of the normal and faulty operations facilitates the detection of performance degradation.

Research and development of gas path analysis (GPA) methods is initiated by Urban in the late 1960's [1]. From the linear GPA developed by Urban, various GPA methods are developed, including nonlinear GPA, optimal estimation based on linear model, nonlinear model based methods, neural networks, rule based expert system, and rule based fuzzy expert system [2]. Some popular soft-computing methods are also tried in the related works [3] [4].

The common feature of neural network methods and rule based methods is the absence of gas turbine model, only the relations between symptoms and fault are needed. But the accumulation of knowledge by experience and field data is not an easy job. It is interesting to note that sometimes mathematical models of faulty engine are used to explore the symptom-fault relations [4].

The fault detection and diagnosis method presented in this paper is a kind of nonlinear model based method. The nonlinear model based methods in the literature tend to utilize various optimization processes to match field measurements with model results [2] [5]. By incorporating dynamic tracking filter into a component level gas turbine model, the present work shows that matched performance parameters can be found by simulating the dynamic model. This can greatly reduce the time and effort to develop a health monitoring system of gas turbines.

The gas turbine under study is part of a combined cycle generation unit, sited in the BAO Steel Power Plant. The basic health monitoring system is based on vibration signal. After the vibration monitoring failed to detect foreign object damage (FOD) fault, a health monitoring system based thermodynamic model is sought to explain quantitatively where and how the performance degradation happened, with the foreseeable usage as part of the online health monitoring system.

NOMENCLATURE

BFG	blast furnace gas
F	function
FOD	foreign object damage
HRSG	heat recovery steam generator
LHV	low heating value
P	pressure, Pa
SE	correction factor of efficiency, --
SW	correction factor of flow, --
T	temperature, K
u	control variable
W	mass flow rate, kg/s
X	performance parameters
Z	measurement parameters

Greek

α	empirical coefficient for pressure drop

Subscript

0	reference value
1	inlet
2	outlet
f	field measurement

PROBLEM DESCRIPTION

The gas turbine under study is part of combined cycle power generation unit. It is of model GT11N2-LBTU, retrofitted from GT11N2 by ABB and KASAKI for burning blast furnace gas (BFG). The gas turbine is connected to steam turbine with a 3611:3000 ratio gear box. The steam turbine is connected to power generator through flexible coupling. The heat recovery steam generator (HRSG) is triple-pressured without reheat, natural-circulated.

The BFG is a kind of low BTU fuel, with low heating value (LHV) ranging from 3100 kJ/Nm3 to 3500 kJ/Nm3. The BFG from blast furnaces is turbocharged after cleaning to spray into the gas turbine's combustor. The turbocharger is composed by low-pressure axial compressor with all stators variable, high-pressure centrifugal compressor and intercooler. The gas turbine has a 16-stage axial compressor; the first three stages have variable stator. The combustor has a single can burner. The turbine has four axial stages. At design point, the output power of the gas turbine is 144 MW with 3611 RPM rotating speed.

More than ten years have passed since the generation unit came into commercial operation in 1997. Gradual and abrupt performance deteriorates are observed.

In May 2009 the gas turbine was rebalanced due to increased vibration levels on both bearing pedestals. On June 02, 2009, a sudden increase of the vibration level on both bearings was observed. Since the amplitude of the vibration was well below the alarm level, the unit could be operated without any limitations. The scheduled A-Inspection started on Sep. 15, 2009. The damages in the turbine were detected during a borescope inspection on Sep. 18, 2009. Open engine inspection is conducted per the power plant's request, the root cause of damage is foreign object damage caused by screw bolt of BFG strainer entered the turbine through combustor.

Before the vibration signal abnormality was detected, the thermal efficiency of the generation unit is about 2% lower than normal. The authors are invited to analyze the reason of the performance degradation. A qualitative analysis, which is much simpler than that presented in this paper, was performed. The conclusion that fault may happen in gas turbine was feedback, but the power plant was not convinced. While pressured by the requirement of continuous consumption of BFG to prevent environmental pollution, decision was made to keep the generation unit operating. The damage was unavoidably increasing until shutdown inspection. A more convincing diagnosing study is initiated with focus on model based diagnosing method. The ultimate goal is a new online health monitoring system.

MODEL BASED FAULT DIAGNOSING METHOD

Direct observation of measurement parameters of gas turbine compared with some reference values may disclose the condition of gas turbine. However, a change of the gas turbine condition generally involves a drift on nearly all of the measurements at the same time; so the identification of the underlying component fault turns out to be difficult. Moreover, the measurements are corrupted by random errors for which the amplitude is comparable with the drifts induced by the faults of interest [6].

To tackle with these problems, gas path analysis assumes that if some physical problems happened in gas path components, the performance parameters, such as compressor flow capacity, compressor efficiency, combustor efficiency, are affected at first. Then the measurement parameters, such as rotation speed, compressor exit temperature, turbine exit temperature, are affected [1] [2]. So the health conditions of components can be evaluated by the changes of performance parameters, not the direct observation of measurement parameters.

Aero-thermal simulation models of gas turbines are used to build the functions between measurement parameters and performance parameters. Generally the independents of the function are performance parameters, so inverse functions are needed with known field measurements to get the performance parameters.

A convenient and often used way of characterize the condition of each component of gas turbine is embedding correction factors of flow (SW) and correction factors of efficiency (SE) into the simulation model [7][8]. The correction factors of flow and the correction factors of efficiency are defined as multiplicative corrective factor as followed:

$$(W\sqrt{T}/P) = SW \cdot (W\sqrt{T}/P)_0 \tag{1}$$

$$\eta = SE \cdot \eta_0 \tag{2}$$

Linear and nonlinear simulation models can be used to estimate these correction factors. It is shown in [8] that use of linear methods may lead to substantial inaccuracies of significant parameters. Nonlinear model of gas turbine is used in the present work, partly because a nonlinear dynamic model is available from related works.

The nonlinear dynamic model represents functional relationship between measurement parameters and performance parameters, correction factors and inputs

$$\mathbf{Z} = F(\mathbf{X}, \mathbf{u}, \mathbf{SW}, \mathbf{SE}, t) \tag{3}$$

The solution of SW and SE in Equation set 3 can found by optimization algorithm. Besides conventional optimization algorithms, genetic algorithm and other newly developed algorithms can be used. Usually Euclidean norm of all measurement parameters under consideration is taken as the optimization target to consistently control the errors [2].

To be consistent with the dynamic gas turbine model, dynamic tracking filter is selected to compute the correction factors SW and SE in time domain. As circled by the red dashed line in Figure 1, the dynamic tracking filter is driven by errors of simulation results with regard to field measurements. The PI controllers continuously change the values of the correction factors until the errors are small enough [9].

For the present study, only steady-state solutions of the correction factors are needed. The correction factors can be solved in a pseudo-dynamic ways, which means the dynamic process to approach the steady-state is not important if the final steady solution is assured.

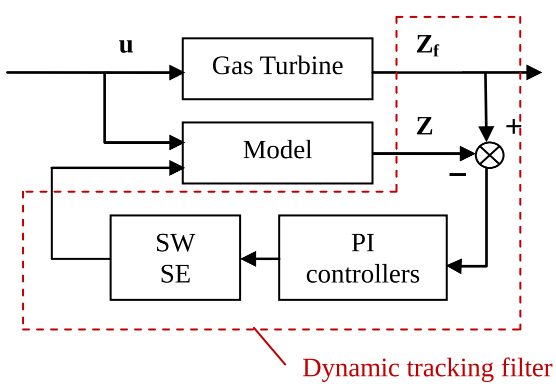

Figure 1. Operating principle of dynamic tracking filter

The steady-state values of the correction factors can also solved in an iterative way. When all derivatives of state variables are equal to zero, the Equation set 3 is degenerated into nonlinear algebraic equation set. The resulting nonlinear algebraic equation set is solved numerically with Newton-Raphson algorithm, but sometimes matrix singularity problem may cause trouble.

The dynamic tracking filter shown in [9] is generally a MIMO control system. It is decentralized into standalone PI control loops for this case study, and the pairing problem of standalone PI control loops is dealt with intuitively. For each PI control loop, the measurement parameter directly related in physics to the correction factor is selected as the feedback variable. For example, the thermal efficiency of compressor has direct impact on its exit temperature, while the flow capability has direct effect on its exit pressure through volume effect. The nonlinear dynamic model will spread out the effect of any correction factor changes.

The dynamic tracking filter can be design as a MIMO control system. That means combined error of measurement parameters may be used to drive the PI control loop. Two PI control loops may also be driven by single error. The only limit is stability of the model with these control loops. This could eliminate the under-determined problem or over-determined problem in matrix inversion operation involved method, such as linear gas path analysis.

MODELING WITH LIMITED DATA

The nonlinear model used in the fault diagnosing is a component level model, which means the system model of gas turbine is composed of modules representing components like compressor, combustor and turbine. Each module is composed of general thermodynamic equations, conservative laws, and performance maps peculiar to a specific engine. The so called “volume method” is used to build the dynamic model [10]. The volume method facilitates non-iterative algorithm of simulation, making it more suitable for online usage.

The effect of flue gas flow in HRSG on turbine back pressure is discussed briefly. The flow of flue gas in HRSG is modeled as ordinary channel flow, and the pressure drop characteristic is modeled as

$$\frac{P_1 - P_2}{P_1} = \alpha \cdot (W\sqrt{T_1}/P_1)^2 \tag{4}$$

Where α express the empirical coefficient.

A measurement data set under normal operating condition is selected as reference, which is shown in Table 1.

Due to various reasons, the component performance maps are unavailable with only a few exceptions. A well known fact is that performance maps are similar in shape; their differences can be described by linear transformation, such as translation and scaling [11][12]. The well-known GasTurb software provides tools for preprocessing of compressor maps and turbine maps [13].

Table 1. Measurements at reference day (Sep/13/2008)

Parameter	Unit	Value
Ambient temperature	^{0}C	29.65
Power demand of unit	MW	120.00
BFG flow rate	kNm^{3}/h	368.00
BFG LHV	MJ/Nm^{3}	3.20
BFG temperature into combustor	^{0}C	289.00
BFG pressure into combustor	MPa	1.31
Compressor inlet pressure (absolute pressure)	kPa	100.35
Compressor inlet temperature	^{0}C	28.80
Compressor exit pressure	MPa	1.22
Compressor exit temperature	^{0}C	409.00
Turbine exit pressure	kPa	1.00
Turbine exit temperature	^{0}C	533.50

The nonlinear dynamic model is built on MSC.EASY5, which is a commercial general purpose modeling and simulation software package. The compressor map and turbine map needed are generated by scaling the data files publicly available.

Fine tuning of performance maps are through simulating the dynamic model with dynamic tracking filter. The correction factors of flow and efficiency as part of simulation result are used to further scale the compressor map and turbine map. The finely scaled performance maps are input into the model, with all flow and efficiency correction factors are reset to one. The referred mass flow rate and efficiency interpolated from the performance maps and correction factors are listed in Table 2. Now, the dynamic model with all flow and efficiency correction factors being set to one represents the gas turbine under reference condition. This finishes the first step of model based diagnosing process.

For the single spool gas turbine under studying, the measurement parameter and correction factor pairs listed in Table 3 is selected in the way stated in last section. The PI control loops are added to the dynamic model one by one in trial-and-error way. The proportional gain and integral gain are selected to insure that negative feedbacks are imposed on the dynamic model.

Until now, the compressor and turbine performance map is only validated at reference condition. For other working conditions, the compressor and turbine performance map assumed may drift from the real ones. When gas turbine is run as part of combined cycle power plant, the variable inlet guided vane (VIGV) and variable stator vane (VSV) of compressor are adjusted to keep the temperature of flue gas within specified range, with the aim to operate the whole power generation unit more efficiently and safely. The operation of VSV and VIGV will change the compressor performance map, as shown in Figure 2 [10].

Instead of point-by-point correcting the performance maps, the modification to performance maps are lumped to the correction factors. That means the combined effect of performance map drift and VIGV/VSV manipulation is represented by the correction factors. Simple correction factor analytical functions are sought to represent these effect.

Because the VIGV/VSV manipulation is scheduled linearly with regard to ambient temperature and power demand, it should be reasonable assumption that normally correction factors are linear functions of ambient temperature and power demand.

Table 2. Performance parameter at reference day (Sep/13/2008)

Performance parameter		
Compressor referred mass flow rate	Value [kg/s]	288.75
	Correction factor	1.00
Compressor efficiency	Value	0.80
	Correction factor	1.00
Turbine referred mass flow rate	Value [kg/s]	519.75
	Correction factor	1.00
Turbine efficiency	Value	0.92
	Correction factor	1.00

Table 3. Pairs of measurement parameter and correction factor used in PI control loops

Measurement parameter	Correction factor
Compressor exit pressure	Compressor referred mass flow rate
Compressor exit temperature	Compressor efficiency
Turbine exit pressure	Turbine referred mass flow rate
Turbine exit temperature	Turbine efficiency

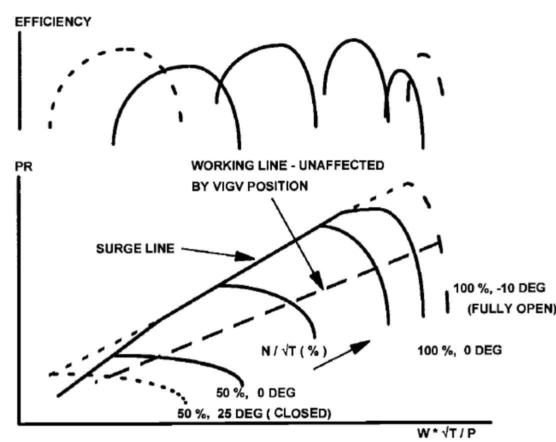

Figure 2. Effect of VIGV angle [10]

The measurement data set obtained at another normal day is listed in Table 4, the performance parameters and corrections factors obtained from model simulation are list in Table 5.

It can be seen from Table 4 and Table 5 that when the day becomes cold (the ambient temperature is 3.8^{0}C), the compressor flow capacity is decreased intentionally to maintain relatively high temperature of flue gas entering the HRSG. The compressor efficiency is lower due to partially closed VIGV/VSV. However, the increment of steam turbine efficiency should surpass the decrement of gas turbine efficiency, so the overall efficiency of combined cycle would be better. The effects of VIGV/VSV manipulation on turbine flow capacity and efficiency are minor; this seems due to the fact that the turbine is most probably choked.

For the two measurement data sets available, the power demand of the generation unit is the same, so the normal correction factors can only be estimated as the linear regression function of ambient temperature for the time being. For example, the normal correction factor function of compressor efficiency is defined as

$$SE = \frac{T_{amb} - 3.8}{29.65 - 3.8} \times (1.0 - 0.7549) + 0.7549 \quad (5)$$

Table 4. Measurements at another normal day (Jan/13/2009)

Parameter	Unit	Value
Ambient temperature	^{0}C	3.80
Power demand of unit	MW	120.00
BFG flow rate	kNm^3/h	358.50
BFG LHV	MJ/Nm^3	3.15
BFG temperature into combustor	^{0}C	282.00
BFG pressure into combustor	MPa	1.29
Compressor inlet pressure (absolute pressure)	kPa	103.10
Compressor inlet temperature	^{0}C	3.35
Compressor exit pressure	MPa	1.21
Compressor exit temperature	^{0}C	369.50
Turbine exit pressure	kPa	1.00
Turbine exit temperature	^{0}C	524.00

Table 5. Performance parameter for another normal day (Jan/13/2009)

Performance parameter		
Compressor referred mass flow rate	Value	274.41
	Correction factor	0.83
Compressor efficiency	Value	0.61
	Correction factor	0.75
Turbine referred mass flow rate	Value	524.52
	Correction factor	1.00
Turbine efficiency	Value	0.92
	Correction factor	1.00

FAULT DIAGNOSING

Measurement data set at abnormal day (thermal efficiency of the whole generation unit is about 2% lower than normal) are listed in Table 6. The power demand is unchanged, so the effect of power demand on normal correction factors is neglected. The correction factors obtained from simulation of the dynamic model is listed in Table 7, compared with values calculated by the normal correction factor functions.

The health parameters in Table 7 is simply defined as

$$H = \frac{SE}{SE_{normal}} \quad (6)$$

This means that the deviation of H from 1.0 signs something wrong.

As can be seen from Table 7, the simulated correction factor of compressor SE matched very well with normal values, but simulated turbine SE is obviously lower than normal value. This is a clear indication of a faulty turbine. This finishes the last step of model based diagnosing process.

So if the model based gas path analysis were available, the FOD fault could have been detected and isolated when thermal parameters showed abnormality (March/25/2009), before vibration level abnormality could be observed (June/02/2009).

Table 6. Measurements at abnormal day (March/25/2009)

Parameter	Unit	Value
Ambient temperature	^{0}C	12.31
Power demand of unit	MW	120.00
BFG flow rate	kNm^3/h	381.87
BFG LHV	MJ/Nm^3	3.22
BFG temperature into combustor	^{0}C	286.33
BFG pressure into combustor	MPa	1.32
Compressor inlet pressure (absolute pressure)	kPa	101.70
Compressor inlet temperature	^{0}C	12.30
Compressor exit pressure	MPa	1.21
Compressor exit temperature	^{0}C	379.49
Turbine exit pressure	kPa	1.34
Turbine exit temperature	^{0}C	522.60

Table 7. Health parameters at abnormal day (March/25/2009)

Performance parameter	Correction factor		Health parameter
	Simulated	Normal	
Compressor referred mass flow rate	1.04	0.89	
Compressor efficiency	0.94	0.93	1.00
Turbine referred mass flow rate	1.13	1.00	
Turbine efficiency	0.92	1.00	0.93

It is obvious from Table 7 that both the simulated correction factor of compressor SW and turbine SW are larger than normal values. This is because the turbine exit pressure in Table 6 is much larger than that in Table 1 and Table 2. This means larger pressure drop in Equation 4, and then a larger mass flow rate passing through turbine. The conservation of mass flow applied in the dynamic model would ask for more mass flow from upstream of turbine. The increase of BFG fuel flow rate partly make up for it, but most increased mass flow comes from compressor. So larger values of compressor SW and turbine SW is the direct result of exceptionally large turbine exit pressure. This is why the SWs are not taken into consideration as health parameters in Table 7. If output power of gas turbine is known, the SWs can be solved much precisely. But for combined cycle unit, total output power of unit is measured instead of that of gas turbine.

DISCUSSION

For this case study, robustness of the decentralized PI control loops is validated by simulation runs. To make sure the above diagnosing process works reliably, the stability of the dynamic model with dynamic tracking filter is analyzed. The variation of measurement parameters are assumed small, so the whole model is properly approximated as linear control system. The proportional gain and integral gain of all PI control loops are selected so that all eigenvalues of the linear control system have negative real part. The resulting absolute values of the proportional gain are all around 0.01, and absolute values of the integral gain are all around 0.001.The stability of the four measurement parameters listed in Table 3 are evaluated by Bode plot with MSC.EASY5 software package. The stability margin is defined as:

$$Stability\_margin = \frac{Upper\,/\,Lower\_limit}{Nominal\_value} \qquad (6)$$

Where the upper/lower limits are the limit values keeping the linear control system stable.

The large stability margin shown in Table 8 is probably the result of small value of proportional gain and integral gain. Similar results are obtained for the other two measurement data sets, so scheduling of PI loop gains is not necessary for this case.

For offline diagnosing, only steady-state solutions are required, so tracking performance of PI control loops is not important. For online diagnosing, trade-off between tracking performance and stability margin may need.

The sensitivity of health parameters to changes in measurement parameters is examined. The results are showed in Table 9. Here the sensitivity is defined as the ratio of fractional change in health parameter to fractional change in measurement parameter. It can be seen from Table 9 that the efficiency health parameters are sensitive mostly to component exit temperature, but the compressor flow capability is mostly sensitive to turbine exit pressure, and vice versa. Switching pair correspondence has been tried, however stability problem appears. There is some trade-off work to be done here.

The impact of measurement noise on diagnosing capability is examined though simulation. The measurement noise is assumed to be Gaussian random noise added to nominal values listed in Table 6. A Gaussian random number generator is used to produce a time series representing the ratio of noise magnitude to nominal value. The Gaussian distribution has a zero mean and 0.05 standard deviation. As an example, the noise component is add to turbine exit temperature, whose nominal values is 522.60 ^{0}C, with other inputs keeping constant as listed in Table 6. The turbine exit temperature input and the two health parameter outputs are shown in Figure 3. It can be seen from the figure that when turbine exit temperature varies within range ±3^{0}C, the turbine health follows with variation range ±0.03. The quality of the turbine health output is enough for visual check, proper filtering of the output is appropriate for computer programs. For the compressor health, high frequency variation is smoothed out by inertias in model. This and other dynamic simulations also verify the potentiality of online monitoring with the dynamic model.

Compared with other model based diagnosing methods with tracking filters, the dynamic tracking filter has the advantage of easy to understand and implement.

Table 8. Stability margin of measurement parameters at abnormal day (March/25/2009)

	Lower margin	**Lower freq.**	**Upper margin**	**Upper freq.**
Compressor exit pressure	0.00	None	15.59	0.00
Compressor exit temperature	0.00	None	2.28	0.03
Turbine exit pressure	0.00	None	None	None
Turbine exit temperature	0.00	None	None	None

Table 9. Sensitivity of health parameters at abnormal day (March/25/2009)

	Comp. exit pressure	**Comp. exit temp.**	**Turb. exit pressure**	**Turb. exit temp.**
Compressor SW	0.22	0.00	0.71	-0.46
Compressor SE	0.61	-1.07	0.00	0.00
Turbine SW	-1.00	0.10	0.39	-0.25
Turbine SE	-0.28	0.36	-0.46	-0.79

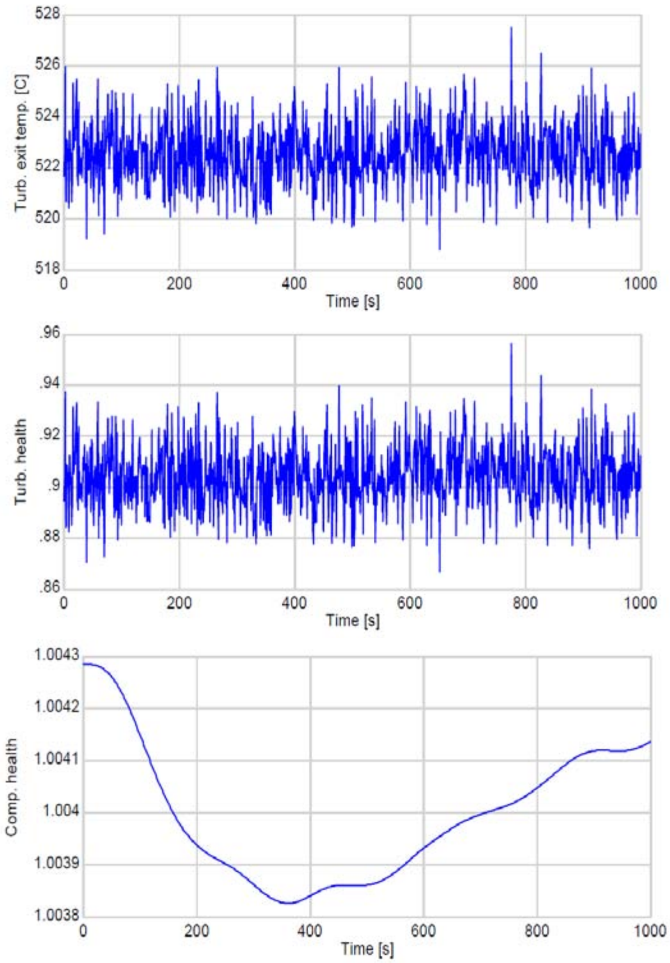

Figure 3. Effect of measurement noise on health parameters

The aero-thermal models based method shows some advantage over vibration analysis in this present work, but an ideal health monitoring system should combine the aero-thermal models based method and the vibration signal based ones. For example, in the case of FOD to turbine, the vibration signal from rear bearing pedestals together with gas path analysis would give more robust conclusion.

CONCLUSION

The present work shows how a nonlinear dynamic model with dynamic tracking filter could be used to diagnosing a gas turbine, which is a part of combined cycle power generation unit.

By incorporating dynamic tracking filter into component level gas turbine dynamic model, the model based fault diagnosing is implemented as a three steps process. The first step is to match the field measurements with the simulation results of the gas turbine at one normal working condition by dynamic tracking filter. The correction factors represent multiplicative errors between assumed component performance maps (i.e. flow and efficiency) and the real ones. After the component performance maps are scaled properly, the correction factors are reset to one, which represent reference condition of gas turbine. At the second step, the deviations of component performance characteristics caused by compressor VSV and VIGV manipulations with regard to ambient temperature and power demand are represented by the correction factors, also solved by simulation of the dynamic model controlled with dynamic tracking filter. In this way, the normal off-design performances are represented by normal correction factors functions, of which the independent variable is ambient temperature and power demand. The third step is the fault diagnosing step. The measurement data set in doubt is fed to the gas turbine dynamic model with dynamic tracking filter. The correction factors simulated are compared with the value of normal correction factor functions. The deviation of the correcting factors of turbine efficiency from normal value suggests that some problems happened in the turbine in the case studied.

Although the measurement data sets available is very limited, the initial result is encouraging. More data sets and simulations are needed to validate the method statistically before it can be applied on site as part of online health monitoring system.

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