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SHORT-TERM AND MULTI-STATE RELIABILITY MODEL FOR AN INDUSTRIAL GAS TURBINE

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ABSTRACT

This paper presents a short-term, multi-state reliability model for an industrial gas turbine. A new method is introduced to define the state boundaries. The transition intensities between any two states are determined from actual operation data and a Markov chain embedded in the operation data. The Chapman Kolomogorov equation corresponding to N-states is given. The equation can be applied to any gas turbine system. In the current paper, it is applied to a power plant having two identical 5.2 MW (nominal capacity at ISO condition) Siemens Taurus 60S gas turbines. The specific model included droop and isochronous modes of operation. The results show that the forced outage rates for the two gas turbines converge to 0.513 and 0.2661, respectively, when $t \rightarrow \infty$. Such a model will be applicable for short term planning of the operation of gas turbines hence contributing to a saving in life-cycle or maintenance cost.

Keywords: gas turbine, multi-state reliability, short-term reliability, multi-state markov model.

INTRODUCTION

Gas turbines are in general considered as fast starting machines and ideal to reduce carbon footprint. With current technology, powers as high as 340MW can be generated by a single gas turbine. Reports show that efficiencies up to 40% in open cycle and more than 60% in combined cycle configuration is possible (Boyc 2012). A cross-section of a single shaft gas turbine with the basic control and actuator blocks is shown in Figure-1. Main thermodynamic and turbomachinary components include multistage axial compressor, divergent duct, combustion chamber, expander or turbine, and exhaust system. The bleed system is also very important in controlling pressure surge or choke.

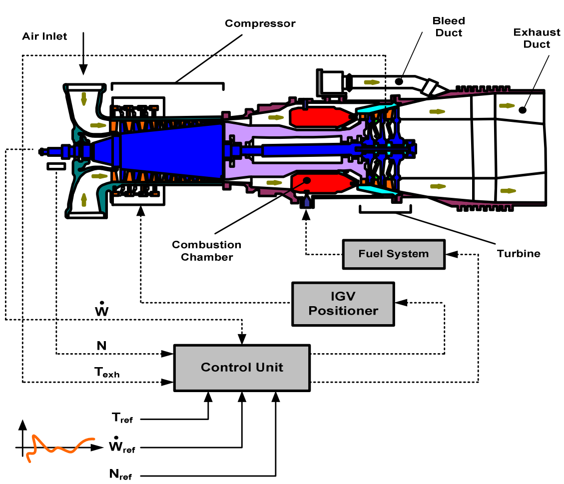

Figure-1. Single-shaft gas turbine generators (Tamiru, Hashim *et al*. 2011).

Gas turbines are highly specialized machines and therefore they often require skilled personnel to carry out condition monitoring and reliability predictions. Since high reliability is a priority, the maintenance cost for such machines makes up major portion of the annual maintenance budget. Main objectives of the maintenance strategy are to reduce downtime and increase availability and reliability of the machines.

Gas turbines experience high outage rate and extended downtime due to problems in the instrumentation, control system or gas path components (compressor, combustion chamber and turbine). Excessive vibration is a common problem. To combat any problem on real-time basis, a health prognostic is considered an important part of a proactive maintenance activity. It involves online fault detection, fault isolation or diagnostics, and prediction of remaining time before the system reaches unacceptable level. In line with prognostics, it is a regular practice to evaluate reliability of the machines for the days, months or years to come. This is especially very important in offshore operation where getting spare parts on time is commonly a challenge.

The current paper concentrates on reliability prediction. Traditionally, a two state model – fully functional state and failed state – is used to form reliability and availability models. However, since actual operations are featured by part load operation and modes like droop and isochronous, the two state idealization is considered inaccurate. As will be presented later, industrial gas turbines in fact experience multiple operating points due to reasons linked to actual performance deterioration and changes due to load demand as well as change in environmental conditions. The tendency of all these cases to exist simultaneously is also high.

A brief historical review on Multi-State Reliability (MSR) is available in (Lisnianski and Levitin 2003). This covered the years between 1970's and 2003. In (Fazekas and Nagy 2010), multi-state system (MSS) models were introduced for a power plant having extraction condensing and back pressure turbines. The states were defined based on the data for ambient temperature. Recently, Hagifam and Manbachi (Haghifam

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ARPN Journal of Engineering and Applied Sciences

and Manbachi 2011) showed a MSS model constructed for a CHP plant. Their work included the subsystems for electricity generation, fuel distribution and heat generation. Data quantization is an important step of multi-state reliability modeling. In the work of (Lisnianski, Elmakias *et al*. 2012), the operating range is equally divided into N regions, each defined by average value. In the work of (Billinton and Weng 2004), however, the apportioning method was used to create steady-state multi-state models.

The objective of the current paper is to extend (Lisnianski, Elmakias *et al*. 2012) work by considering performance indicator based approach to discern the main states. In addition to that the effects of droop and isochronous operations will be accounted for.

MODEL DEVELOPMENT

Any gas turbine is featured by three main operating regions: start-up, loaded or steady state, and shut-down. When a gas turbine is in steady state region, it changes the operating point in response to the load and change in environmental conditions. If it is part of a cogeneration or a combined heat and power plant, the exhaust gas from the gas turbine is used in a heat recovery steam generator (HRSG) to generate process steam. Synchronization of the gas turbine and HRSG is realized by the running the gas turbine in SoLoNOx mode. The name SoLoNOx is due to the use of lean premix combustion to reduce the formation of greenhouse gases. Siemens Taurus 60S gas turbines are known by this kind of design. For a load lower than about 50% of the rated capacity, the gas turbine is mostly in load control and the air flow rate through the system does not vary much but is at maximum capacity. At this state, temperature of the exhaust gas from the gas turbine is not high enough to run the HRSG. By virtue of the facts, it was therefore necessary to formulate operating region based model structures. Accordingly, we have approached identification of the states in the following manner.

Identification of dominant states based on non-dimensional plots

To establish the method, first it is assumed that there are N_{op} number of operating regions. Secondly, a choice is made on two non-dimensional parameters ψ_1 and ψ_2, both considered to be suitable for identifying the expected stated. For instance, ψ_1 and ψ_2, can be selected to be fuel flow rate and rated power since both parameters could reflect change in operating point of a gas turbine. For the general case, we prefer to keep these parameters generic. Given ψ_1 and ψ_2, our proposed strategy is to apply fuzzy sets on the two parameters so that the whole operating trajectory is classified into N_{op} regions. An example, assuming two fuzzy sets for ψ_1 and three fuzzy sets for ψ_2, is illustrated in Figure-2. The number of fuzzy sets is a function of the number of distinguishable regions.

Now, referring to the case represented by Figure-2, each region will be identified as $\mathbf{S}^{(j)}\left(j = 1,2,..., N_{op}\right)$. Using $\mathbf{\Lambda}^{(j)}$ to refer to set of all models required to characterize region j, we define $\mathbf{S}^{(j)}$ as

$$\mathbf{S}^{(j)} = \left\{\mathbf{\Psi}, \mathbf{V}^{(j)}, \mathbf{\Lambda}^{(j)}\right\} \tag{1}$$

Where, $\mathbf{\Psi} = \{\psi_1, \psi_2\}$; $\mathbf{\Lambda}^{(j)}$ and $\mathbf{V}^{(j)}$ are set of models and fuzzy sets, respectively, corresponding to region j. For a gas turbine $\mathbf{\Lambda}^{(j)}$ could be the superset containing models for the gas path, generator coils, lubrication system, and start-up system. For the gas path only,

$$\mathbf{\Lambda}^{(j)} = \left\{P_2^{(j)}, T_5^{(j)}, \dot{W}_{ele}^{(j)}\right\} \tag{2}$$

Where, $P_2^{(j)}$, $T_5^{(j)}$ and $\dot{W}_{ele}^{(j)}$ are compressor discharge pressure, turbine inlet temperature and electric power output, respectively. For a perfect identification of discernable states, the clustering has to be done in a high dimensional region defined by the number of measurable parameters. In the current paper, we prefer to limit the analysis to gas path signals only.

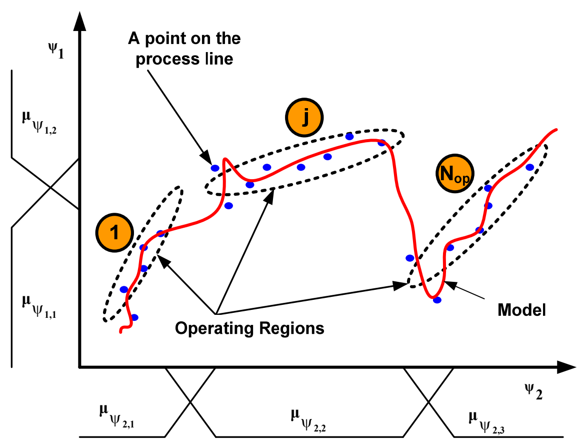

Figure-2. Multiple operating regions for a hypothetical system (Tamiru 2012).

Data quantization

The process experienced by a gas turbine is a continuous state and continuous time stochastic process (Lisnianski, Elmakias *et al*. 2012). However, handling a continuous-state model is a horrendous task. Hence, to use the multi-state model, the continuous signal is replaced by the discrete state continuous time model as represented by Figure-3. The corresponding multi-state Markov model is shown in Figure-4. Once the states are determined by the proposed approach, the idea shown in Figure-3 will be used to calculate for state transition intensities.

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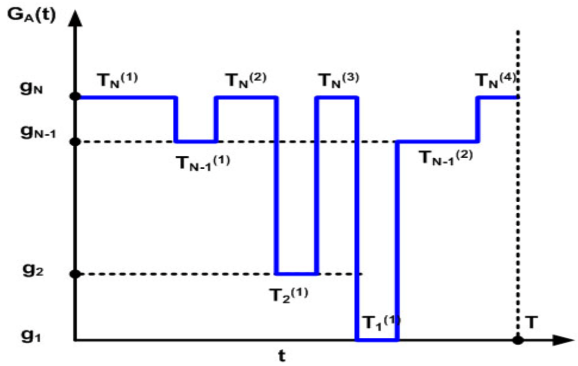

Figure-3. Operating trend idealized as stochastic process $G_A(t)$ (Lisnianski, Elmakias *et al*. 2012).

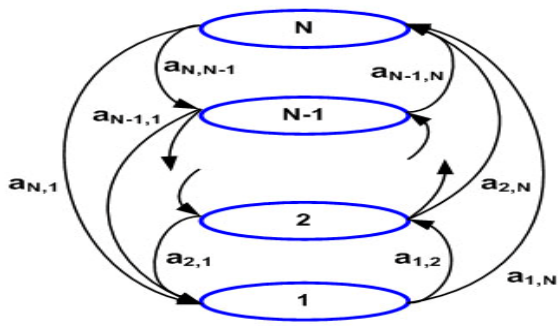

Figure-4. Multi-state markov model for a generic system.

General multi-state markov model

The general Chapman Kolomogrov equation for a Markov model corresponding to a system having N number of discernable states can be stated in matrix form as:

$$\frac{d\mathbf{p}}{dt} = \mathbf{A}\mathbf{p} \tag{3}$$

Where: $\mathbf{p} = \begin{bmatrix} p_1(t) & p_2(t) & p_3(t) & \cdots & p_N(t) \end{bmatrix}^T$ and

$$\mathbf{A} = \begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1N} \\ a_{21} & a_{22} & \cdots & a_{2N} \\ \vdots & \vdots & \ddots & \vdots \\ a_{N1} & a_{N2} & \cdots & a_{NN} \end{bmatrix}.$$

The transition intensities in the state matrix $\mathbf{A}$ are functions of accumulated time for each state $T_{\Sigma\, i}$ and accumulated number of transitions k_{ij} from state i to state j. As such,

$$a_{ij} = \begin{cases} \dfrac{k_{ij}}{T_{\Sigma i}}, \; i \neq j \\ -\sum\limits_{\substack{i=1 \\ i \neq j}}^{N} a_{ij}, \; i = j \end{cases}, \text{ where } T_{\Sigma i} = \sum_{m}^{k_i} T_i^{(m)} \tag{4}$$

Performance indices

Performance of the system can be explained by considering steady state probabilities, $p_{ss,i}(t) = \lim_{t\to\infty} p_i(t)$, and Forced Outage Rate (FOR). FOR has been used in (Lisnianski, Elmakias *et al*. 2012) to measure reliability of a power generating unit. It is defined as the probability that the gas turbine stays at state 1 (failed state) at time t with the gas turbine initially at state i. That is,

$$FOR_i(t) = p_1(t) \tag{5}$$

where $p_i(0)=1$, and $p_j(0)=0$ ($j \neq i$, $j=1,2,\ldots,N$)

Solution method

The Markov model in Equation-3 can be solved applying Universal Generating Functions (UGF). In the present paper, however, fourth order Runge-Kutta method from MATLAB is used to numerically solve the equation for a given initial condition.

RESULT AND DISCUSSION

System description

The models introduced in the previous sections are applied to a system having two identical gas turbine generators (named as GTG-1 and GTG-2) of aeroderivative type. The turbines may be set to work in droop or isochronous modes, the selection of which dependent on management decision. Nominal capacity of one gas turbine is about 5.2 MW. When the gas turbines are set to droop and isochronous mode, the one with the droop setting is allowed to work with small variation in shaft speed (usually a maximum of 5% change from nominal) while the shaft speed of the isochronous turbine remains constant. With this combination of control, the droop turbine delivers the base load while the isochronous assumes the responsibility of picking any extra load. However, the difference in the powers produced by the two turbines may be limited to 500 kW due to a concern related to power trip. In a situation where the power demand goes beyond 500 kW, the load setting for the droop turbine needs to be readjusted. For analysis purpose, both conditions need to be considered even though more load variation is experienced by the isochronous turbine. Known and estimated design point data of the turbines is as reported in Table-1.

Table-1. Calculated design point data for taurus 60s-7301 engine.

Parameter		Unit	Value
Speed		rpm	14944
Electric Power,		kW	5200
Heat Rate		kJ/kW.hr	11730
Compressor (12-stage axial)			
	*Inlet air flow,	kg/sec	21.364
	*Pressure ratio	-	11
Turbine (3-stage)			
	*Inlet Temperature,	°C	1035
	*Exit Temperature,	°C	505
	*Pressure Ratio	-	10.053

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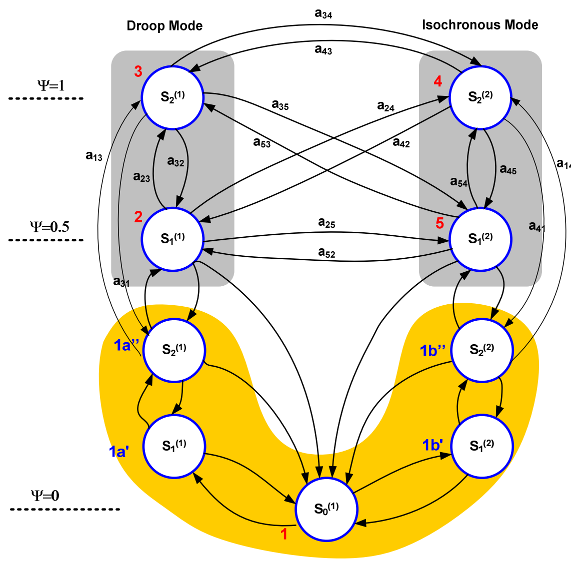

Figure-5. Actual operation trend for single-shaft gas turbine generators.

Calculation of k_{ij} and $T_{\Sigma i}$

The calculated values for state transitions and sojourn times for each state and corresponding to GTG-1 and GTG-2 are shown in Table-2 and Table-3, respectively. As compared to GTG-1, GTG-2 has stayed at one state relatively longer. This is well verified by the fact that this particular turbine has been supplying the base load by operating in isochronous mode.

Important aspect of the gas turbines that is worth mentioning is the input-output parameter scheduling. Each of the gas turbines is featured by variable geometry compressors. For a power demand less than 50% from the nominal, Variable Inlet Guide Vanes (VIGVs) and first three stages of the Variable Stator Vanes (VSVs) are held fully open while the fuel flow rate is manipulated to meet the load demand. For higher loads, both the VIGV and fuel flow rate are controlled to meet the required power. In this region, the turbine is on temperature control. Hence, on the basis of these and considering normalized power and normalized fuel flow rate to apply the concept proposed in the methodology, a five state model including the droop and isochronous mode of operations has been identified, Figure-5. The values reported in Table-2 and Table-3 are the results of applying the models presented as Equations (1) and (2), and Figure-2.

Table-2. Number of state transitions and cumulated time at each state for GTG-1.

States	1	2	3	4	5	Accumulated Time (hrs)
1	-	23	1	77	12	341.23
2	20	-	794	0	6	67.76
3	2	795	-	9	0	432.45
4	80	1	11	-	1120	372.86
5	11	1	0	1127	-	70.81

Table-3. Number of state transitions and cumulated time at each state for GTG-2.

States	1	2	3	4	5	Accumulated Time(hrs)
1	-	3	45	16	32	657.60
2	4	-	418	0	0	26.55
3	46	417	-	1	0	80.59
4	17	0	1	-	906	448.60
5	30	1	0	907	-	71.78

Calculation of probabilities and forced outage rates

The probabilities and FORs calculated using equation (3) and data from Table-2 and Table-3 are shown in Figure-6 to Figure-12. Even though the gas turbines are identical in design, the results are different for they experienced different operating conditions. For initial condition $p_1(0)=p_2(0)=p_4(0)=p_5(0)=0$ and $p_3(0)=1$, the probability of staying at maximum capacity for GTG-2 drops fast as compared to the result for GTG-1.

The graphs for $FOR_3(t)$, $FOR_4(t)$, $FOR_2(t)$, $FOR_5(t)$, and $FOR_1(t)$ are shown in Figure-8 to Figure-12. All values for GTG-1 converge to 0.513. In case of GTG-2, the convergence is rather at 0.266, which is by comparison lower by 51.87%.

For GTG-2, the maximum for $FOR_3(t)$ ($\max\{FOR_3(t)\}$) and $FOR_4(t)$ ($\max\{FOR_4(t)\}$) are 0.6591 and 0.513, respectively. GTG-1, on the other hand, experienced a corresponding value of 0.2661 and 0.3289, respectively. For intermediate states 2 and 5, GTG-2 features $\max\{FOR_2(t)\} = 0.6591$ and $\max\{FOR_5(t)\} = 0.513$ while GTG-1 is having $\max\{FOR_2(t)\} = 0.2661$ and $\max\{FOR_5(t)\} = 0.3289$.

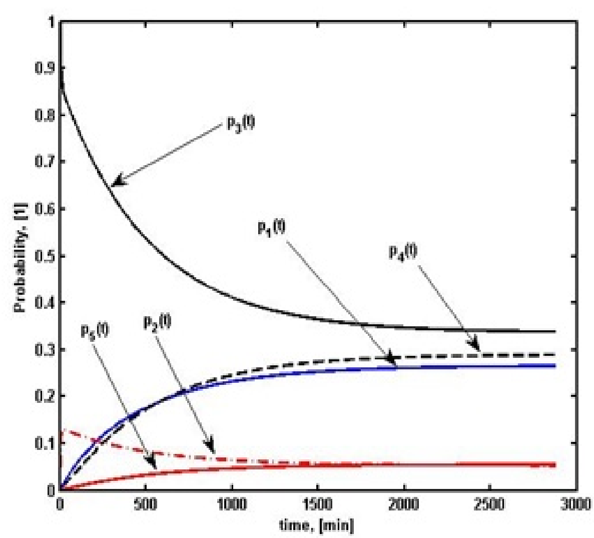

Figure-6. State transition probabilities for GTG-1. Initial conditions $p_1(0)=p_2(0)=p_4(0)=p_5(0)=0$, and $p_3(0)=1$.

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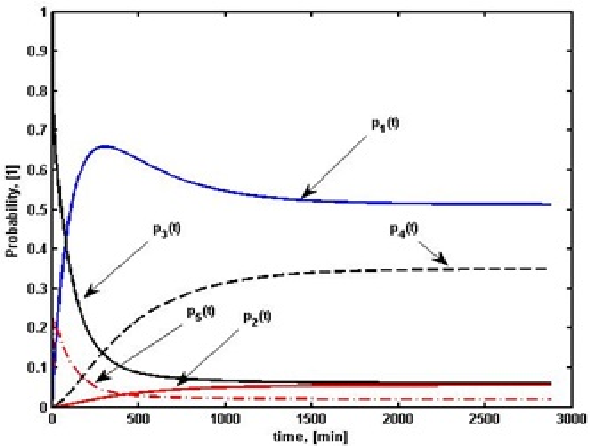

Figure-7. State transition probabilities for GTG-2. Initial conditions $p_1(0)=p_2(0)=p_4(0)=p_5(0)=0$, and $p_3(0)=1$.

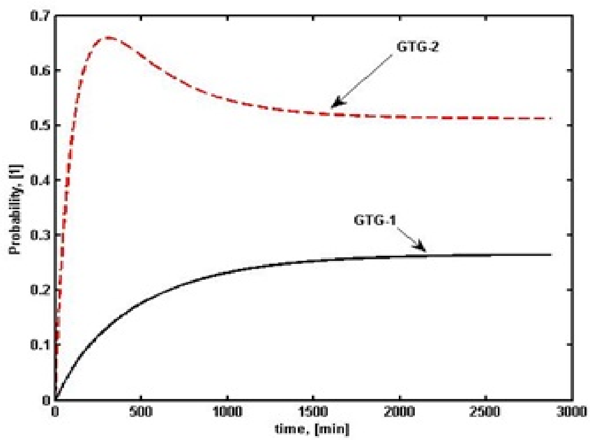

Figure-8. $FOR_3(t)$ as a function of time. Initial conditions $p_1(0)=p_2(0)=p_4(0)=p_5(0)=0$, and $p_3(0)=1$.

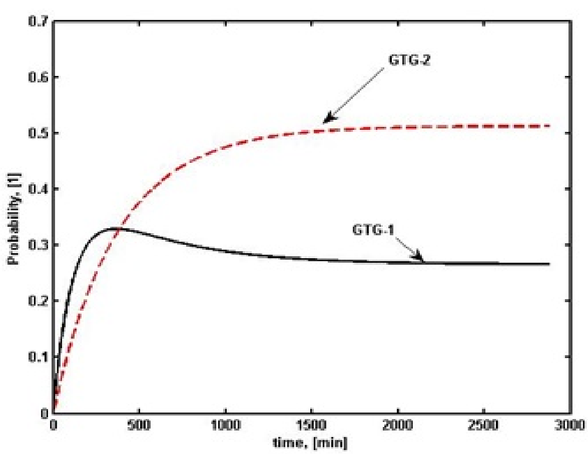

Figure-9. $FOR_4(t)$ as a function of time. Initial conditions $p_1(0)=p_2(0)=p_3(0)=p_5(0)=0$, and $p_4(0)=1$.

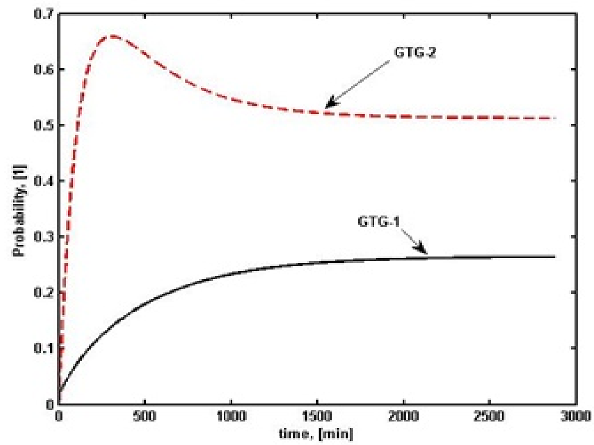

Figure-10. $FOR_2(t)$ as a function of time. Initial conditions $p_1(0)=p_3(0)=p_4(0)=p_5(0)=0$, and $p_2(0)=1$.

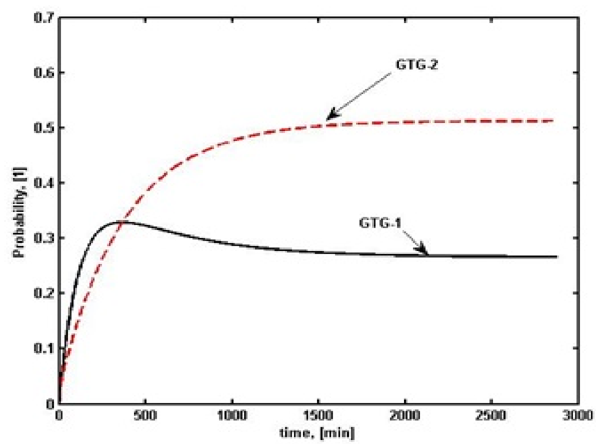

Figure-11. $FOR_5(t)$ as a function of time. Initial conditions $p_1(0)=p_2(0)=p_3(0)=p_4(0)=0$, $p_5(0)=1$.

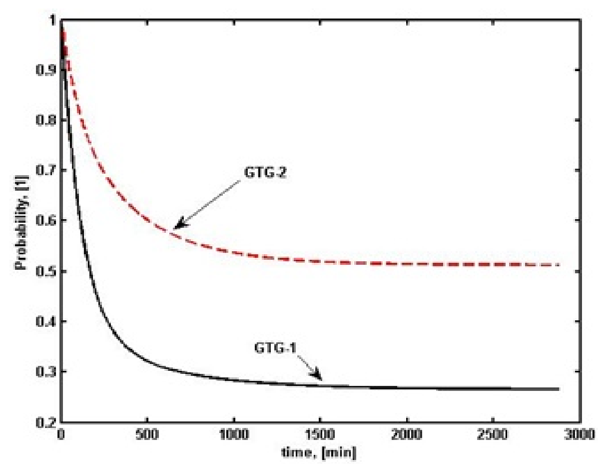

Figure-12. $FOR_1(t)$ as a function of time. Initial conditions $p_2(0)=p_3(0)=p_4(0)=p_5(0)=0$, $p_1(0)=1$.

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CONCLUSIONS

The purpose of this paper has been to introduce a short-term multi-state reliability model developed for industrial gas turbines. A new method for identifying dominant states is reported. A power plant having two identical gas turbines was considered to demonstrate applicability of the proposed method. It can be concluded that

- A multi-state reliability model can be developed from actual operation data. To make the model more meaningful, it would be better if the states are defined on the bases of two or more key performance indicators and some kind of clustering method.
- Even though the gas turbines are identical in design, they have demonstrated different probability trends for they operated in different extent of droop and isochronous modes.
- Forced outage rate happen to converge to a single value regardless of where the system was at initial time *t*.
- For $t \to \infty$, the forced outage rates for the two gas turbines converge to 0.513 and 0.2661, respectively.

The developed model is applicable for short term maintenance planning. Nonetheless, enhancement of the proposed method through case studies and high dimensional clustering methods is recommended in order to further validate the model and boost end users' confidence. Another area worth considering in connection with the current study is the idea of integrating short-term reliability and diagnostic methods. The future work will concentrate on the latter case.

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