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Prognostics of gas turbine: A condition-based maintenance approach based on multi-environmental time similarity

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ABSTRACT

The maintenance cost of a gas turbine is significantly higher than its original purchase cost. This study presents a novel prognostic condition-based maintenance (CBM) approach based on the theory of multi-environmental time similarity (METS). In this approach, gas turbine of the same type is regarded as the reference system, and two influential factors - the running hours and number of start-ups are selected as the main degradation indicators. The similarities are calculated based on the values of the degradation indicators under service environment and benchmark environment. Equivalent life (EL) of the object system under the benchmark environment is calculated on the basis of the similarities and historical data of the object system under the service environment. Remaining life (RL) of the object system is obtained by comparing EL and theoretical life. Real-time RL, historical RL and their calculating algorithms are proposed for acquiring more accurate historical degradation data that can be employed for decision making. Factored service factor is proposed as a key indicator in decision making of CBM, and four optional CBM scenarios are constructed based on different values of the factored service factor. This approach is applied in a thermal power plant in Hangzhou, China, and its effectiveness is proved as an extra power generation of 302,640 MW·h can be achieved due to re-scheduled maintenance.

1. Introduction

Enormous maintenance cost becomes a major concern for the users of gas turbines, and thereby hinders the adoption of this equipment [1,2]. Typically, the maintenance of gas turbines is carried out in a pre-scheduled manner, and the arrangement is usually determined by the manufacturer regardless to actual conditions [3]. Consequently, overhauls may take places when gas turbines are still in perfect condition or in state of fail [1], the maintenance cost could be thereby greatly increased due to these unnecessary maintenance activities. Nowadays, the maintenance cost consists a significant part of the

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Nomenclature

Abbreviations

A	assumption
ANN	artificial neural network
CBM	condition-based maintenance
EL	equivalent life
ETTF	estimated time to failure
FL	fuzzy logic
METS	multi-environmental time similarity
RL	remaining life
RLP	remaining life prediction
SbRLP	similarity-based remaining life prediction
TL	theoretical life

Symbols

A	service environments
$\alpha_a, \alpha_2, \ldots, \alpha_k$	influential factors during the operation of gas turbines
α_1	annual base load running hours using natural gas; Annual number of start-ups under part load
α_2	annual base load running hours using light oil; Annual number of start-ups under base load
α_3	annual base load running hours using heavy oil; Annual number of start-ups under peak load
α_4	annual peak running hours; Annual number of urgent start-ups
α_5	annual number of fast lifting load start-ups
α_6	annual number of trips
α_{T_i}	severity factor of trip of the *i*th type
B	benchmark environments
EE	extra electric generation attributed to maintenance postpone
F	equivalent influential factor under the benchmark environments
FAH	forecasted actual running hours
FAS	forecasted actual number of start-ups
FSF	factored service factor
f	time-varying function of the degradation indicator
H	running hours
I	percentage of water/steam injection volume in inlet air flow
IF	ideal maintenance interval
K	injection factor of steam
M	injection factor of water
MF	maintenance factor
n	number of trip types
O	object systems
PH	full runtime
PH_1	elapsed runtime
PH_2	runtime for prediction or maintenance interval
R	reference systems
S	number of start-ups
SF	service factor
T	number of trips
t	time point
t_1	starting point in running hours
t_2	current point in running hours
t_3	maintenance point running hours
t_1^*	starting point in number of start-ups
t_2^*	current point in number of start-ups
t_3^*	maintenance point number of start-ups
y	value of the degradation indicator
λ	similarities of the degradation indicators

Superscripts

A	service environments
B	benchmark environments