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START UP AND SHUT DOWN SIMULATION OF MICRO GAS TURBINE BASED ON REINFORCEMENT LEARNING

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ABSTRACT

The startup and shutdown simulation of a micro gas turbine (MGT) is concerned. In order to build an accurate dynamic model, the general models of core components are presented first. Then, two dynamic parameters that influence rotating speed and temperature dynamics are put forward for further identification. The identification is accomplished by a reinforcement learning algorithm. The comparison between the simulation and experimental data show that this learning method leads to high-accuracy MGT startup and shutdown simulation.

Keywords: micro gas turbine, reinforcement learning, dynamic modeling, startup and shutdown simulation, distributed energy generation

NONMENCLATURE

Abbreviations	
MGT	Micro gas turbine
TET	Turbine exit temperature (℃)
Symbols	
T	Temperature (K)
G	Mass flow rate (kg/s)
W	Power (kW)
H	Enthalpy (kJ/kg)
n	Rotating speed (rad/s)
c_p	Specific heat (kJ/(kg*K))
Subscripts	
g	gas
a	air
f	fuel
c	compressor
cc	combustion chamber
t	turbine

1. INTRODUCTION

Micro gas turbine (MGT) has been gaining research interest in recent years due to the worldwide demand on distributed energy generation. MGT has the advantages of compact size, high operation flexibility and low maintenance cost, which increase its application in commercial buildings and small industrial sectors.

In the distributed energy generation system, MGT is usually integrated with other energy conversion devices. Dynamic modelling and simulation of the distributed energy generation system are foundation for further system tasks, such as optimization, control and diagnosis. Accurate MGT modelling influences the whole system performance because the MGT outputs are inputs for the secondary energy conversion and storage devices, such as absorption chiller, electrical and thermal storage device.

MGT Startup and shutdown are one of the important processes that show strong dynamic characteristics. However, there are few literatures focus on the startup and shut down simulations. The challenge is to determine unknown MGT parameters that dominate transient behaviors, that is, dynamic parameters.

In this study, a modular-based modelling approach is applied for MGT model. The identification of dynamic parameters from experimental MGT running data is accomplished through reinforcement learning. The results of the identification and validation indicates that the reinforcement learning is an efficient method for accurate MGT startup and shutdown simulation.

2. DYNAMIC MODELNG OF MICRO GAS TURBINE

2.1 Configuration of MGT

In order to simulate the startup and shut down process of a micro gas turbine, a mathematical MGT model that reflects both steady and transient states is necessary in this study. The configuration of MGT is shown in Fig. 1. The core parts of a micro gas turbine are: compressor, combustion chamber, turbine, rotor and recuperator. Recuperator is one of the distinguish parts that differentiates MGT from large gas turbines. It aims at increasing the MGT efficiency by heating the compressed air using the heat of exhaust gas.

$$G_g H_{g,out,cc} = G_a H_{a,in,cc} + G_f \bullet LHV \bullet \eta_{cc} \tag{4}$$

LHV represents the low heat value of fuel gas, and η_{cc} stands for combustion efficiency.

2.2.3 Turbine

Similar to compressor, the performance of turbine can be represented by turbine maps. The expansion π_t ration and turbine efficiency η_t are determined by turbine maps [1]. The general compressor and turbine

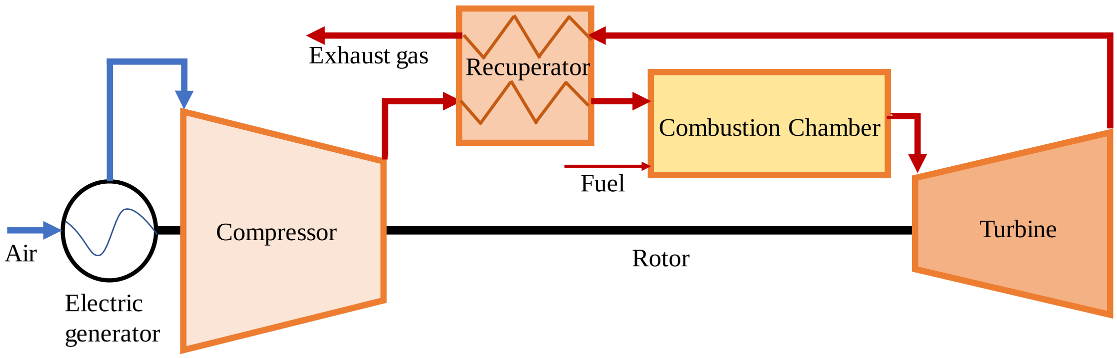

Fig 1 Configuration of MGT

The relative independent characteristics of MGT part makes it suitable for modular-based modeling. General models for each component will be established first. These modules can be then specified with detailed MGT parameters and in some cases modifications on characteristic maps are needed to build a high-accuracy MGT model.

2.2 Component models of MGT

2.2.1 Compressor

The output states and performance of the compressor are mainly decided by a compressor maps. The compressor maps [1] decide the compression ratio π_c and compressor efficiency η_c , so the outlet temperature and work consumed by compressor can be calculated.

$$T_{a,out,c} = T_{a,in,c} \times \left[1 + \left(\pi_c^{\frac{\kappa_a - 1}{\kappa_a}} - 1 \right) \Big/ \eta_c \right] \tag{1}$$

$$W_c = G_a \times \left(H_{a,out,c} - H_{a,in,c} \right) \tag{2}$$

where κ_a is the specific heat ratio of air.

2.2.2 Combustion Chamber

Combustion chamber is the place fuel and air mixed and reacted. Mass and energy balance equations apply here.

$$G_g = G_a + G_f \tag{3}$$

maps reflect the nonlinear performance change under different working condition. Then, the outlet temperature and work generated can be calculated as:

$$T_{g,out,t} = T_{g,in,t} \times \left[1 - \left(1 - \pi_t^{-\frac{\kappa_g - 1}{\kappa_g}} \right) \eta_t \right] \tag{5}$$

$$W_t = G_g \left(H_{g,out,t} - H_{g,in,t} \right) \eta_m \tag{6}$$

where κ_g is the specific heat ratio of gas and η_m is the mechanical efficiency.

2.2.4 Rotor

Rotating speed is one of the controlled states in in MGT, thus the modeling of rotor must be dynamic for further control and diagnosis study. The rotor momentum equation governs the variation of rotating speed n .

$$J \frac{dn}{dt} = \frac{900}{\pi^2 n} \left(W_t - W_c - W_L - W_f \right), \tag{7}$$

where W_L , W_f are the load input and the work consumed by auxiliary devices. J is the momentum of inertia of rotor.

2.2.5 Recuperator

Recuperator is also one of the crucial parts that are responsible for dynamic response of MGT. A precise recuperator model is important to simulate the temperature dynamics. Since the recuperator temperature is a distributed parameter system, in this modeling study, the recuperator is divided into N segments along one direction. For each segment i, the temperature dynamics can be describe as following:

$$\begin{cases} G_g c_{p,g,i}\dfrac{dT_{g,out,i}}{dt} = G_g c_{p,g,in,i}T_{g,in,i} - G_g c_{p,g,out,i}T_{g,out,i} - \dot{Q}_{g,i} \\ G_a c_{p,a,i}\dfrac{dT_{a,out,i}}{dt} = G_a c_{p,a,in,i}T_{a,in,i} - G_a c_{p,out,i}T_{a,out,i} + \dot{Q}_{a,i} \\ \dfrac{Mc_{p,w}}{N}\dfrac{dT_{w,i}}{dt} = \dot{Q}_{g,i} - \dot{Q}_{a,i} \end{cases} \tag{8}$$

where $\dot{Q}_{g,i}$, $\dot{Q}_{a,i}$ are the gas heat flow and air heat flow in segment i and it can be decided according to the counter-flow pattern. $Mc_{p,w}$ denotes the thermal capacity of recuperator mental wall.

2.3 MGT parameters for dynamic simulation

Most of the MGT parameters can be obtained from the manufacturer data sheet, published papers or technical reports, while some parameters are not easy to determine, especially the dynamic parameters.

Momentum of inertia of rotor J and thermal capacity of recuperator wall $Mc_{p,w}$ are the most important parameters that greatly influence the MGT dynamic behaviors in the rotating speed and temperature. However, those two parameters are unknown and cannot be obtained directly.

In this study, reinforcement learning is used to identify dynamic parameters J and $Mc_{p,w}$. The shutdown simulation is conducted to identify those dynamic parameters, and the startup simulation is also performed to validate the identified parameters.

3. REINFORCEMENT LEARNING FOR MGT DYNAMIC PARAMETERS

The basic idea of reinforcement learning is to search actions to maximize the reward that are feedbacks from the environment. The principle diagram of reinforcement learning for MGT dynamic parameters identification process is shown in Fig. 2.

Since the action of this task is the to decide MGT parameters, the action set is continuous, so a continuous action reinforcement learning algorithm [2] is chosen in this study. The details of this algorithm are described as follow.

Let $X = \left[J \ Mc_{p,w}\right] = \left[x_1 \ x_2\right]$ be the action set. For each parameter x_i that need to be learned, the range is

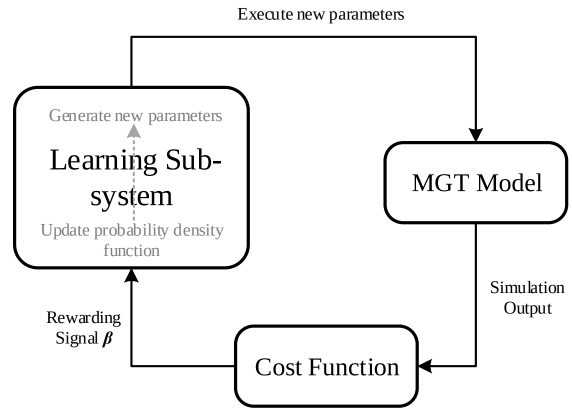

Fig 2 The principle diagram of reinforcement learning for MGT parameters identification

$X_i = \left[x_{i\min} \ x_{i\max}\right]$. In the $k-th$ learning, the new parameter $x_i(k)$ will be generated by a probability distribution within the range X_i, and the probability density function is $f_k(x_i)$. The initial distribution is assumed as uniform distribution.

$$f_1(x_i) = \begin{cases} 1/\left(x_{i\max} - x_{i\min}\right) & x_i \in X_i \\ 0 & x_i \notin X_i \end{cases} \tag{9}$$

After the $k-th$ learning, parameters $x_i(k)$ are applied in the MGT model. The MGT simulation output is compared with experimental data, so a cost function value $C(k)$ is calculated. In this task, the cost function involves integrated absolute error between the simulation output and experimental data in rotating speed and turbine exit temperature (TET). Then, a reward value $\beta(k)$ is calculated according to the cost function value $C(k)$.

$$\beta(k) = \min\left\{\max\left\{0, \frac{C_{mean} - C(k)}{C_{mean} - C_{\min}}\right\}, 1\right\} \tag{10}$$

where C_{mean} and $C_{\min}$ are the mean and minimum value of the cost function among the k times learning.

In the $k+1-th$ learning, the probability density function $f_{k+1}(x_i)$ is updated according to the following rules.

$$f_{k+1}(x_i) = \begin{cases} \alpha(k)\left[f_k(x_i) + \beta(k)H(x_i, r)\right], & x_i \in X_i \\ 0 & x_i \notin X_i \end{cases} \tag{11}$$

where $H(x_i, r)$ is the Gaussian probability density function with a mean value of $r = x_i(k)$ and a variance value of $g_w\left(x_{\max} - x_{\min}\right)$. g_w is a tuning parameter for reinforcement learning algorithm. Besides, $\alpha(k)$ is a normalized factor to make sure the accumulated probability is 1.

$$1/\alpha(k)=\int_{xi_{\min}}^{x_{i\max}} f_i(x_i,k+1)dx_i \tag{12}$$

It is suggested in Equations. (10) and (11) that when a set of parameters results in better consistency with data than any or average previous performance, the reward signal $\beta(k)>0$ and in the next update, the probability of last set of parameters is increased. In this way of strengthening positive feedbacks, accurate MGT dynamic parameters could be learned.

4. REINFORCEMENT LEARNING AND VALIDATION FOR MGT STARTUP AND SHUTDOWN

4.1 Reinforcement learning of MGT dynamic parameters with shutdown simulation

In this study, a popular MGT, Capstone C30 is modelled and simulated. The technical specification of C30 can be found on the official website [3]. Since the dynamic behaviors of the shutdown process are mainly governed the thermal capacity $Mc_{p,w}$, the shutdown data will be used for the parameter identification.

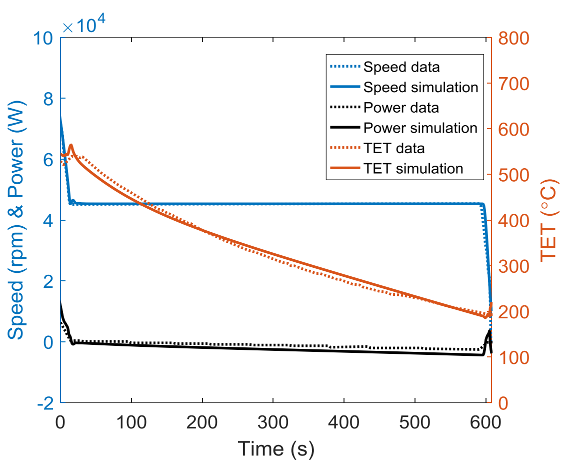

Fig 3 Shutdown simulation compared with experimental data of MGT Capstone C30

The shutdown procedures of C30 are described here. When the shutdown demand is given, the MGT starts power ramp down, then the fuel is off and the MGT stays at idle speed to wait the MGT cool down. After the cool down, the AC/DC link is disconnected and the shutdown process is finished.

The learning results for the dynamic parameters are J=0.09 kg*m^3 and $Mc_{p,w}$=0.19 kJ/K The comparison between the simulation and experimental data of rotating speed, TET and electric power are shown in Fig. 3. It should be noted that only rotating speed and TET data are evaluated during the reinforcement learning. The average errors for the rotating speed and TET 0.57% and 2.67%.

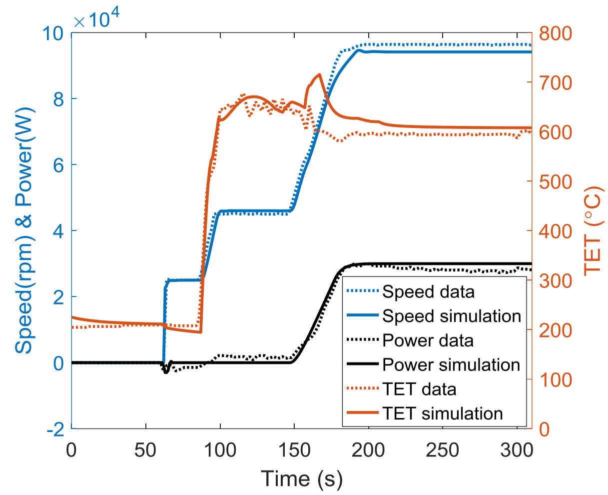

Fig 3 Warm Startup simulation compared with experimental data of MGT Capstone C30

4.2 Validation of Reinforcement learning results under MGT shutdown simulation

The startup experimental data are used for validation. The startup procedures are: when the start demand is given, the MGT links to AC/DC and the speed is spun up to 25000rpm. Wait for the MGT to stabilize and then add the fuel to spin up to 45000rpm. Stay at the idle speed to wait the MGT to warm up. Then the power ramps up to full power and the startup is finished.

The learned parameters are applied in the startup simulation. The simulation outputs compared to the startup experimental data are shown in Fig. 4. The error of rotating speed and TET are 1.69% and 3.30%, which indicates a high MGT model accuracy.

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