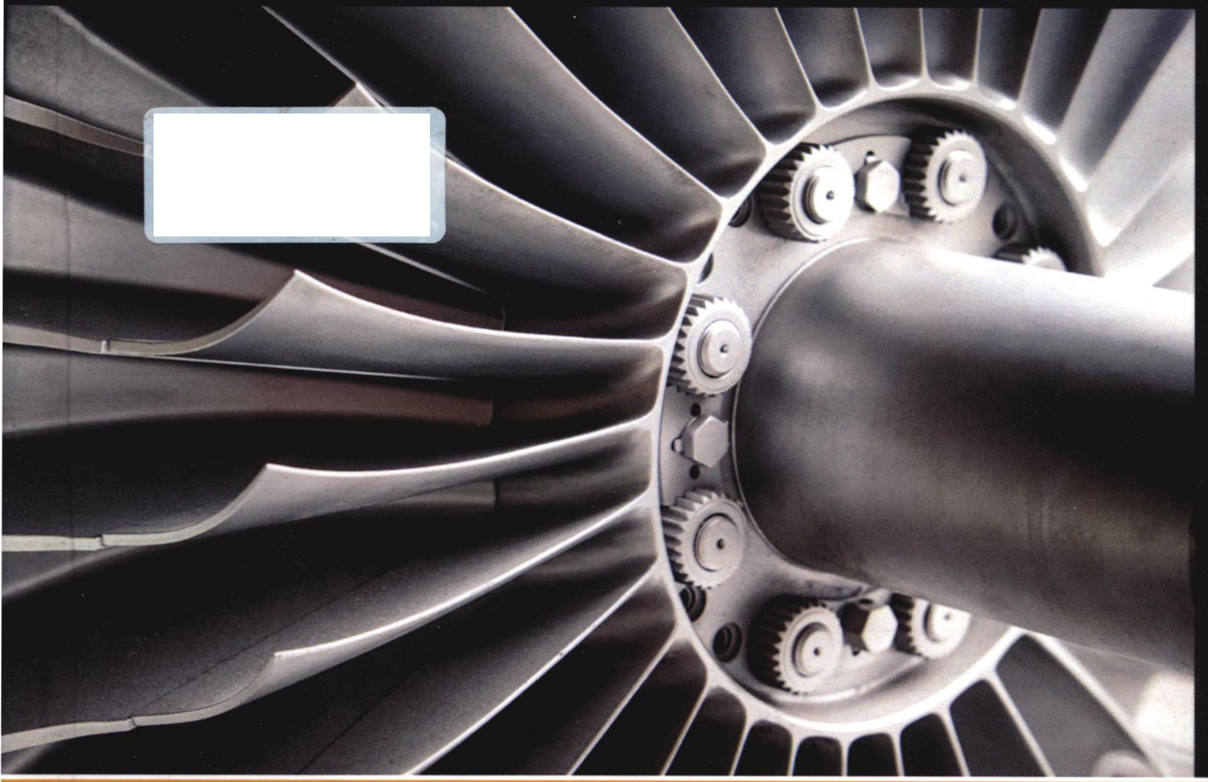

Gas Turbines Modeling, Simulation, and Control

Using Artificial Neural Networks

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CRC Press
Taylor & Francis Group

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CRC Press
Taylor & Francis Group
Boca Raton London New York

CRC Press is an imprint of the
Taylor & Francis Group, an **informa** business

CRC Press
Taylor & Francis Group
6000 Broken Sound Parkway NW, Suite 300
Boca Raton, FL 33487-2742

Printed on acid-free paper
Version Date: 20150723

International Standard Book Number-13: 978-1-4987-2661-0 (Hardback)

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Preface

Gas turbines (GT) are one of the significant parts of modern industry. They play a key role in the aeronautical industry, power generation, and main mechanical drivers for large pumps and compressors. Modeling and simulation of GTs has always been a powerful tool for the performance optimization of this kind of equipment. Remarkable activities have been carried out in this field and a number of analytical and experimental models have been built so far to get in-depth understanding of the nonlinear behavior and complex dynamics of these systems. However, the need to develop accurate and reliable models of GTs for different objectives and applications has been a strong motivation for researchers to continue to work in this fascinating area. The study in this field includes white-box- and black-box-based models and their applications in control systems. Artificial neural networks (ANNs) as a black-box methodology have been regarded as suitable and powerful tools for data processing, modeling, and control of highly nonlinear systems such as GTs. Besides, because of the high demand of the electricity market, the power producers are eager to continuously investigate new methods of optimization for design, manufacturing, control, and maintenance of GTs. In recent decades, ANNs have shown a high and strong potential to be considered as a reliable alternative to the conventional modeling, simulation, and control methodologies.

This book presents novel methodologies for modeling, simulation, and control of GTs using ANNs. In the field of modeling and simulation, two different types of GTs are modeled and simulated using both Simulink® and neural network-based models. Simulated and operational data sets are employed to demonstrate the capability of neural networks in capturing complex nonlinear dynamics of GTs. For ANN-based modeling, the applications of both static (MLP) and dynamic (NARX) networks are explored. Simulink and NARX models are set up to explore both steady-state and transient behaviors. The models developed in this book can be used offline for design and manufacturing purposes or online on sites for condition monitoring, fault detection, and troubleshooting of GTs. This book provides new approaches and novel solutions to modeling, simulation, and control of GTs. It is structured as follows:

Chapter 1 discusses the motivations, necessity, and goal of modeling and control of GTs. A classification of GTs is provided and main considerations in GT modeling are presented. The chapter briefly explains the most important criteria and considerations at the beginning of the GT modeling process including GT types and configurations, modeling methods, control system types and configurations, as well as modeling objectives and approaches. The chapter also defines the current problems in the area of modeling, simulation, and control of GTs. Finally, it briefly provides the scope and main objectives of current and future activities in the area of GT modeling and simulation.

Chapter 2 presents a comprehensive overview of the research activities in the field of white-box modeling, simulation, and control of GTs based on the classification of GTs. The most relevant scientific sources for different kinds of GTs including low-power, industrial power plant, and aero GTs are explored in this chapter.

Chapter 3 gives a comprehensive overview of the most significant studies in the field of black-box modeling, simulation, and control of GTs based on the classification of GTs. It covers models of low-power GTs, industrial power plant gas turbine (IPGT), and aero GTs.

Chapter 4 briefly discusses the structure of ANNs and ANN-based model building processes, including system analysis, data acquisition and preparation, network architecture, as well as network training and validation. It explores different challenges in using ANN-based models for industrial systems and describes the advantages and limitations of this approach.

Chapter 5 introduces a novel ANN-based methodology for offline system identification of a low-power single-shaft GT. The processed data is obtained from a SIMULINK model of a GT in MATLAB® environment. A comprehensive computer program code is generated and run in MATLAB for creating and training different ANN models with feedforward multilayer perceptron (MLP) structure. The code consists of 18,720 different ANN structures including various training functions, different number of neurons, as well as a variety of transfer (activation) functions for hidden and output layers of the network.

Chapter 6 presents modeling of the transient behavior of GTs. Simulink and NARX models are created and validated using experimental data sets to explore transient behavior of a heavy-duty IPGT. The results show that both Simulink and NARX models successfully capture the dynamics of the system. However, a NARX approach can model GT behavior with a higher accuracy compared to a Simulink approach. Besides, a separate complex model of the start-up operation of the same IPGT is built and verified by using NARX models. The models are set up and verified on the basis of measured time-series data sets. It is observed that NARX models have the potential to simulate start-up operation and to predict dynamic behavior of GTs.

Chapter 7 gives a model of the start-up operation of a heavy-duty IPGT by using NARX models by using the data taken experimentally during the start-up procedure. The NARX model is set up on the basis of three measured time-series data sets for two different maneuvers. To verify the resulting models, they are applied to three other available data sets and comparisons are made among significant outputs of the models and the values of the corresponding measured data.

Chapter 8 elucidates a neural network approach for controller design of GTs. A conventional proportional-integral-derivative (PID) controller and neural network-based controllers consisting of ANN-based model predictive (MPC) and feedback linearization (NARMA-L2) controllers are designed and employed to control rotational speed of a GT. The related parameters for all controllers are tuned and set up according to the requirements of the controllers design. It is demonstrated that neural network-based controllers (in this case NARMA-L2) can perform even better than conventional controllers. The settling time, rise time, and maximum overshoot for the response of NARMA-L2 is less than the corresponding factors for the conventional PID controller. It also follows the input changes more accurately than the PID.

This book can be an invaluable source of research for graduate and postgraduate students, researchers, mechanical, mechatronics, and control engineers, as well as GT manufacturers and professionals who deal with artificial intelligence, neural network, GTs, and industrial equipment. Readers can learn how artificial intelligence can be used to solve complicated industrial problems specifically in the area of GTs. This book can also be used as a rich source of information about research activities in the field of modeling, simulation, and control of GTs.

Acknowledgments

The authors would like to express their sincere appreciation to Dr. Raazesh Sainudiin in the Department of Mathematics and Statistics at the University of Canterbury (UC) and Professor Mohammad Bagher Menhaj in the Electrical Engineering Department of the Amir Kabir University of Technology (AUT) in Iran who have greatly assisted in the research resulting in the writing this book. We would also like to express our gratitude to Dr. Mark Jermy and Dr. Sid Becker, the postgraduate coordinators in the Mechanical Engineering Department, Professor Milo Kral, the head of the Mechanical Engineering Department, and Professor Lucy Johnston, the dean of Postgraduate Research at UC, for their help and support.

Our appreciation also goes to Professor Pier Ruggero Spina, Professor Mauro Venturini, Professor Michele Pinelli, and Dr. Mirko Morini in "Dipartimento di Ingegneria" at "Università degli Studi di Ferrara" in Italy for providing experimental data and their close collaboration in development of Simulink and ANN models. We also warmly thank Assistant Professor Mohsen Fathi Jegarkandi at the Aerospace Department of Sharif University of Technology and Dr. Naser Rahbar at Malek-Ashtar University of Technology (MUT) who have greatly helped the authors for development of the control system of GTs. We would like to express our sincere gratitude to the staff at Iranian Offshore Oil Company (IOOC) for their technical support and close cooperation during site visit and data acquisition.

It is our great pleasure to acknowledge the help and support of the UC staff in Admission and Enrolment, ICT Services, Recreation Centre, Student Services, and UC libraries. We are also very grateful to all technicians, administrative staff, fellow postgraduates, students, and friends at UC whom we had the pleasure of working and cooperating with.

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Nomenclature

Abbreviations

AMPC	Approximate model predictive control
ANFIS	Adaptive network-based fuzzy inference system
ANN	Artificial neural network
ARX	Autoregressive with exogenous input
ASME	American Society of Mechanical Engineers
BPNN	Backpropagation neural network
CCGT	Combined cycle gas turbine
CCPP	Combined cycle power plant
CO	Carbon monoxide
CSGT	Control system of gas turbine
CT	Compressor turbine
CUSMUS	Cumulative sum (technique)
DC	Direct current
DCS	Distributed control system
DLE	Dry low emission
DLN	Dry low nitrogen oxide
DNN	Dynamic neural network
FDI	Fault detection and isolation
FFNN	Feedforward neural network
GA	Genetic algorithm
GAST	Gas turbine governor model
GG	Gas generator
GPC	Generalized predictive control
GT	Gas turbine
HDGT	Heavy-duty gas turbine
HP	High pressure (gas turbine)
IGV	Inlet guide vane
IPGT	Industrial power plant gas turbine
LP	Low pressure (gas turbine)
MGT	Microgas turbine

MIMO	Multiple-input and multiple-output
MLP	Multilayer perceptron
MP	Minimum phase
MPC	Model predictive control
MSE	Mean square error
NARMA	Nonlinear autoregressive moving average
NARMA-L2	Feedback linearization control
NARMAX	Nonlinear autoregressive moving average with exogenous inputs
NARX	Nonlinear autoregressive with exogenous inputs
NMP	Nonminimum phase
NMPC	Nonlinear model predictive control
NN	Neural network
NO	Nitrogen oxide
OEM	Original equipment manufacturer
PD	Proportional-derivative (controller)
PI	Proportional-integral (controller)
PID	Proportional-integral-derivative (controller)
PR	Pressure ratio
PT	Power turbine
RBF	Radial basis function
RBFNN	Radial basis function neural network
RL	Reinforcement learning
RMSE	Root mean square error
RNN	Recurrent neural network
SIMO	Single-input and multiple-output
SISO	Single-input and single-output
TDL	Time delay
TIT	Turbine inlet temperature
TOT	Turbine outlet temperature
UPFC	Unified power flow controller
VSV	Variable stator vane

Variables

C_p	Specific heat in constant pressure (J/kg K)
C_v	Specific heat in constant volume (J/kg K)
HR	Heat rate (kJ/kWh)
I	Moment of inertia (kg · m^2)
J	Cost function
LHV	Lower heating value of fuel (J/kg)
m	Mass (kg)
$\dot{m}$	Mass flow rate (kg/s)
M	Momentum (N m)

N	Rotational speed (rpm, or 1/s)
P	Stagnation pressure (Pa)
q	Lower thermal value (J/kg)
Q	Heat power (W)
R	Specific gas constant (J/kg K)
S	Entropy (J/K)
SFC	Specific fuel consumption (kg/kWh)
t	Time (s)
T	Temperature (K)
U	Externally determined variable (system input)
u'	Tentative control signal
V	Volume (m^3)
W	Work (J)
$\dot{W}$	Power (W)
Y	Variable of interest (system output)

Constants

C	Pressure constant
D	Delay
F	Fuel to air mass flow rates ratio
J	A natural number
K	A natural number
N	A natural number
$N_1, N_2, N_3, \ldots, Nu$	Horizons (MPC factors)
PR_C	Compressor pressure ratio

Subscripts

00	Ambient
01	Compressor inlet
02	Compressor outlet
03	Turbine inlet
04	Turbine outlet
A	Average value (for compression process in compressor)
C	Compressor
Cc	Combustion chamber
D	Data set
F	Fuel
G	Average value (for expansion process in turbine)
Gt	Gas turbine
In	Inlet
M	Measured
Mech	Mechanical

Med	Medium
Out	Outlet
R	Reference (desired)
T	Turbine
U	System input
Y	System output

General symbols

D	Derivative (controller)
E	Error
F	Function
I	Integral (controller)
M	Maneuver
N	Number
P	Proportional (controller)
Trainbfg	BFGS Quasi-Newton training algorithm
Trainbr	Bayesian regularization training algorithm
Traincgb	Conjugate gradient with Powell/Beale restarts training algorithm
Traincgf	Fletcher-Powell conjugate gradient training algorithm
Traincgp	Polak-Ribiére conjugate gradient training algorithm
Traingdx	Variable learning rate gradient descent training algorithm
Trainlm	Levenberg-Marquardt training algorithm
Trainoss	One step secant training algorithm
Trainrp	Resilient backpropagation training algorithm
Trainscg	Scaled conjugate gradient training algorithm

Greek symbols

γ	Ratio of specific heats
η	Efficiency
ξ	Pressure loss coefficient
ρ	Contribution