

Contents

- 1 Introduction** 1
 - 1.1 Prognostics and Health Management 1
 - 1.2 Historical Background 5
 - 1.3 PHM Applications 8
 - 1.4 Review of Prognostics Algorithms 10
 - 1.5 Benefits and Challenges for Prognostics 14
 - 1.5.1 Benefits in Life-Cycle Cost 14
 - 1.5.2 Benefits in System Design and Development 15
 - 1.5.3 Benefits in Production 16
 - 1.5.4 Benefits in System Operation 16
 - 1.5.5 Benefits in Logistics Support and Maintenance 17
 - 1.5.6 Challenges in Prognostics 18
 - References 21
- 2 Tutorials for Prognostics** 25
 - 2.1 Introduction 25
 - 2.2 Prediction of Degradation Behavior 28
 - 2.2.1 Least Squares Method 28
 - 2.2.2 When a Degradation Model Is Available
(Physics-Based Approaches) 31
 - 2.2.3 When a Degradation Model Is NOT Available
(Data-Driven Approaches) 38
 - 2.3 RUL Prediction 44
 - 2.3.1 RUL 44
 - 2.3.2 Prognostics Metrics 49
 - 2.4 Uncertainty 53
 - 2.5 Issues in Practical Prognostics 68
 - 2.6 Exercises 69
 - References 70

3	Bayesian Statistics for Prognostics	73
3.1	Introduction to Bayesian Theory	73
3.2	Aleatory Uncertainty versus Epistemic Uncertainty	76
3.2.1	Aleatory Uncertainty	76
3.2.2	Epistemic Uncertainty	78
3.2.3	Sampling Uncertainty in Coupon Tests	80
3.3	Conditional Probability and Total Probability	86
3.3.1	Conditional Probability	86
3.3.2	Total Probability	92
3.4	Bayes' Theorem	93
3.4.1	Bayes' Theorem in Probability Form	93
3.4.2	Bayes' Theorem in Probability Density Form	95
3.4.3	Bayes' Theorem with Multiple Data	99
3.4.4	Bayes' Theorem for Parameter Estimation	102
3.5	Bayesian Updating	104
3.5.1	Recursive Bayesian Update	104
3.5.2	Overall Bayesian Update	108
3.6	Bayesian Parameter Estimation	110
3.7	Generating Samples from Posterior Distribution	114
3.7.1	Inverse CDF Method	114
3.7.2	Grid Approximation Method: One Parameter	116
3.7.3	Grid Approximation: Two Parameters	119
3.8	Exercises	122
	References	124
4	Physics-Based Prognostics	127
4.1	Introduction to Physics-Based Prognostics	127
4.1.1	Demonstration Problem: Battery Degradation	130
4.2	Nonlinear Least Squares (NLS)	131
4.2.1	MATLAB Implementation of Battery Degradation Prognostics Using Nonlinear Least Squares	133
4.3	Bayesian Method (BM)	140
4.3.1	Markov Chain Monte Carlo (MCMC) Sampling Method	140
4.3.2	MATLAB Implementation of Bayesian Method for Battery Prognostics	147
4.4	Particle Filter (PF)	152
4.4.1	SIR Process	154
4.4.2	MATLAB Implementation of Battery Prognostics	160
4.5	Practical Application of Physics-Based Prognostics	165
4.5.1	Problem Definition	165
4.5.2	Modifying the Codes for the Crack Growth Example	167
4.5.3	Results	170

4.6	Issues in Physics-Based Prognostics	172
4.6.1	Model Adequacy	173
4.6.2	Parameter Estimation	174
4.6.3	Quality of Degradation Data	175
4.7	Exercise	176
	References	177
5	Data-Driven Prognostics	179
5.1	Introduction to Data-Driven Prognostics	179
5.2	Gaussian Process (GP) Regression	181
5.2.1	Surrogate Model and Extrapolation	181
5.2.2	Gaussian Process Simulation	183
5.2.3	GP Simulation	187
5.2.4	MATLAB Implementation of Battery Prognostics Using Gaussian Process	201
5.3	Neural Network (NN)	207
5.3.1	Feedforward Neural Network Model	208
5.3.2	MATLAB Implementation of Battery Prognostics Using Neural Network	221
5.4	Practical Use of Data-Driven Approaches	226
5.4.1	Problem Definition	226
5.4.2	MATLAB Codes for the Crack Growth Example	228
5.4.3	Results	230
5.5	Issues in Data-Driven Prognostics	232
5.5.1	Model-Form Adequacy	232
5.5.2	Optimal Parameters Estimation	233
5.5.3	Quality of Degradation Data	235
5.6	Exercise	236
	References	238
6	Study on Attributes of Prognostics Methods	243
6.1	Introduction	243
6.2	Problem Definition	245
6.2.1	Paris Model for Fatigue Crack Growth	245
6.2.2	Huang's Model for Fatigue Crack Growth	247
6.2.3	Health Monitoring Data and Loading Conditions	250
6.3	Physics-Based Prognostics	252
6.3.1	Correlation in Model Parameters	253
6.3.2	Comparison of NLS, BM, and PF	263
6.4	Data-Driven Prognostics	269
6.4.1	Comparison Between GP and NN	270
6.5	Comparison Between Physics-Based and Data-Driven Prognostics	274
6.6	Results Summary	275

6.7	Exercise	276
	References.	279
7	Applications of Prognostics.	281
7.1	Introduction	281
7.2	In Situ Monitoring and Prediction of Joint Wear	282
7.2.1	Motivation and Background	282
7.2.2	Wear Model and Wear Coefficient	283
7.2.3	In Situ Measurement of Joint Wear for a Slider-Crank Mechanism	285
7.2.4	Bayesian Inference for Predicting Progressive Joint Wear.	288
7.2.5	Identification of Wear Coefficient and Prediction of Wear Volume	292
7.2.6	Discussion and Conclusions	296
7.3	Identification of Correlated Damage Parameters Under Noise and Bias Using Bayesian Inference	298
7.3.1	Motivation and Background	298
7.3.2	Damage Growth and Measurement Uncertainty Models	299
7.3.3	Bayesian Inference for Characterization of Damage Properties	301
7.3.4	Conclusions.	309
7.4	Usage of Accelerated Test Data for Predicting Remaining Useful Life at Field Operating Conditions	309
7.4.1	Motivation and Background	310
7.4.2	Problem Definition	311
7.4.3	Utilizing Accelerated Life Test Data.	312
7.4.4	Conclusions.	321
7.5	Bearing Prognostics Method Based on Entropy Decrease at Specific Frequencies	321
7.5.1	Motivation and Background	321
7.5.2	Degradation Feature Extraction	324
7.5.3	Prognostics	331
7.5.4	Discussions on Generality of the Proposed Method	336
7.5.5	Conclusions and Future Works	338
7.6	Other Applications	339
	References.	342
	Index	345

<http://www.springer.com/978-3-319-44740-7>

Prognostics and Health Management of Engineering
Systems

An Introduction

Kim, N.-H.; An, D.; Choi, J.-H.

2017, XIV, 347 p. 166 illus., 155 illus. in color.,

Hardcover

ISBN: 978-3-319-44740-7