Contents

1. Introduction **1**

1.1. Motivation . . . 1

1.2. Objectives . . . 2

1.2.1. Main objective . . . 2

1.2.2. Specific objectives . . . 2

1.3. Hypotheses . . . 3

1.4. Structure . . . 3

2. Background and Literature Review **5**

2.1. Failure Prognostics . . . 5

2.1.1. Particle-filtering-based failure prognostics . . . 7

2.1.2. Markov chain-based failure prognostics . . . 10

3. Markov Chain Representation for Failure Prognostics **11**

3.1. Characterization of $\tau^L(\omega)$ in Eq. (3.7) . . . 15

3.2. Characterizing the transition probabilities of $\{\Theta_k^L(\omega)\}_{k\geq 0}$ . . . 16

4. Fast-Running Markov Chain-based Prognostic Algorithm **18**

4.1. Offline learning stage . . . 19

4.2. Online evaluation stage . . . 21

5. Synthetic Example **24**

5.1. Obtaining the transition probabilities of $\{\Theta_k(\omega)\}$ [FRMC-PA steps A1-A5] . . . 25

5.2. Training φ [FRMC-PA steps A6-A7] . . . 26

6. Experimental Validation **31**

6.1. Offline stage . . . 33

6.1.1. Learning the degradation dynamics . . . 33

6.1.2. Obtaining the transition probabilities of $\{\Theta_k(\omega)\}$ [FRMC-PA steps A1-A5] . . . 35

6.1.3. Training φ [FRMC-PA steps A6-A7] 37
6.1.4. Analysis of the offline stage computational burden 39
6.2. Online stage 39
6.2.1. Analysis of the online stage computational burden 40

7. Conclusions **45**
7.1. Future Work 45

Bibliography **47**

A. Discrete-time Markov Chains **53**

B. Proof of Propositions **56**
B.1. Proof of Proposition 1 56
B.2. Proof of Proposition 2 58
B.3. Proof of Proposition 4 59

C. Algorithmic Solutions to Compute Probability Distributions **60**