Prognosis of Electrical Faults in Permanent Magnet AC Machines using the Hidden Markov Model

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Syed Sajjad Haider Zaidi, Wesley G. Zanardelli, Selin Aviyente, Elias G. Strangas

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Wesley Zanardelli; Selin Aviyente; Elias Strangas; Syed Sajjad Haider Zaidi

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-Failure prognosis and prediction of future state of operation is important to ensure continued operation and to exercise condition base maintenance. -Most of the work in machines is focused on the diagnosis instead of prognosis. But time to failure, or remaining useful life is important. -Generally prognosis needs large historic data sets to extract fault progression trends, which are not available in most of the cases.

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Overview

Introduction

- Failure prognosis and prediction of future state of operation is important to ensure continued operation and to exercise condition base maintenance.
- Most of the work in machines is focused on the diagnosis instead of prognosis. But time to failure, or remaining useful life is important.
- Generally prognosis needs large historic data sets to extract fault progression trends, which are not available in most of the cases.

The problem under study

- A method for prognosis of electrical failures in a PM synchronous motor is presented.
- Transient increased contact resistance faults are investigated. Similar results for turn-turn and turn to frame faults.
- Objective: Determine the probability of failure at the next step.

Introduction

Methodology

- Fault prognosis is the next step of diagnosis and diagnosis information forms the basis of prognosis techniques
- the $q-$ axis current is used to extract information about faults
- Features of fault characteristics are extracted from Time Frequency distributions
- Diagnosis - Linear Discriminant Classifier (LDC)
  - Training of classifier for discrete fault states
  - Classification of test samples
- Prognosis - Hidden Markov Model (HMM)
  - Training/defining of HMM model parameters
    - Calculating State dependent observation probability (B)
    - Calculation of State Transition probabilities (A)
    - Defining the initial state probabilities (π)
  - Prediction of failure state probability

Type of fault and experimental setup

- Samples were time frequency features of the current i_q,
- Artificial faults were imposed. These are transient faults representing increased contact resistance, of fixed value and of fixed duration.
- A fault is identified by recognizing both inception and clearing, but only the inception transient is used to determine fault severity.

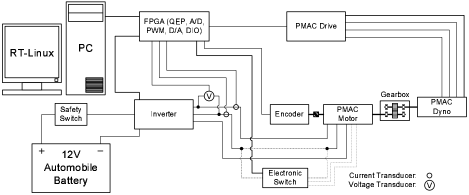

Figure: Experimental Setup

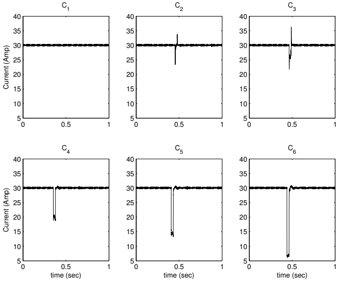

Figure: Sampled I_q Current

Machine and fault characteristics

- Specification of the test machine:

No of poles	6
Construction type	Surface mounted PMAC machine
Rated voltage	12V
Usage	Automotive application
Rated power	1HP
No load speed	3000rpm

- A custom FPGA-based I/O board was used as the drive controller. Its response was much slower than the fault dynamics
- The sampling frequency was 16.67kHz.

Application of Proposed Method

- The fault studied was an intermittently increased contact resistance, a transient electrical fault in the winding of the PMSM machine.
- The fault was created in the lab by inserting a resistor in series with a terminal in the winding to simulate a momentary breaking of the contact.
- The severity of the fault was primarily defined by the value of the inserted resistance.
- Resistances of $2.14pu$, $2.80pu$, $4.03pu$, $6.33pu$, and $15.84pu$ were inserted to mimic a progressively worsening fault.
- The transient faults have two stages, inception and removal. Both can be classified as separate events by the analysis of the time frequency features.
- In this work, the fault features were extracted from the inception event.

Feature Extraction - Three methods

Un-decimated Wavelet Transform (UDWT)

- UDWT has greater flexibility compared to STFT
- Different base functions can be used
- Good time resolution and high frequency resolution
- Tiling is variable

Wigner Ville Distribution

Defined as

$$W(t,\omega) = \int s(t+\frac{\tau}{2})s^*(t-\frac{\tau}{2})e^{-j\omega\tau}d\tau.$$

where s is input signal, t is the time, ω is the frequency

- High time-frequency resolution
- No tradeoff problem between time and frequency
- The major shortcoming is of multi-component signals in terms of the cross-terms

Choi Williams Transform

Defined as

$$C(t,\omega) = \int\int\int \varphi(\theta,\tau)\, s(u+\frac{\tau}{2})\, s^*(u-\frac{\tau}{2})e^{j(\theta u-\theta t-\tau\omega)}du d\theta d\tau, \quad \varphi(\theta,\tau) = \exp\left(-\frac{(\theta\tau)^2}{\sigma}\right)$$

where s is input signal, t is the time, ω is the frequency, σ is the smoothing parameter

- Filtered/smoothed version of the Wigner distribution
- Amount of smoothing is controlled by σ
- Smoothing comes with a tradeoff of reduced resolution

Classification

- Linear Discriminant Classifier (LDC) is used
- The discriminant function is defined as:

$$D_k(x) = x_1\alpha_{1k} + x_2\alpha_{2k} + ... + x_N\alpha_{Nk} + x_{1+N}\alpha_{1+Nk}$$

  where α_{ik} are the trained coefficients for k_{th} class, x is the features vector used for training.
- A sample vector of coefficients belongs to a particular class if the discriminant function is greater for that class than for any other class i.e. x belongs to class C_j if

$$D_j(x) > D_k(x) \quad , for \quad k \neq j$$

Prognosticator - Hidden Markov Model

- A statistical modeling method which assumes states to be Markovian.
- States here correspond to discrete levels of fault severity.
- Finds the hidden variables from the observable parameters.
  - Observable Parameters - Features extracted form sampled signals.
  - Hidden Parameters - Machine States
- The model parameters
  - State transition probability matrix ($a_{ij} = p(x_{t+1} = j | x_t = i)$)
  - State-dependent observation density ($b_j(y_t) = p(y_t | x_t = j)$)
  - Initial state probability ($\pi_i = p(x_1 = i)$)
- Problem to be solved
  - Given the observation sequence $y = (y_1, \cdots, y_k)$ and set of model parameters, choose corresponding state sequence $x = (x_1, \cdots, x_k)$ which is optimal to have generated the observation sequence.

Prediction Algorithm

- The normalized forward probability, $\delta_t(i)$, at time t for each state S_i, and the state transition probabilities, a_{ij} are used to predict the probabilities of states at time $t+1$. The transition probability to state S_j at the time instance t+1 is given by

$$\mathrm{P[q_{t+1}= S_j|\lambda] = \sum_{i=1}^{j} P[q_t= S_i|\lambda]a_{ij} = \sum_{i=1}^{j} \delta_t(i)a_{ij}}$$

  where λ is the set of model parameters.

- The most probable state at time $t+1$ is one which has the highest probability
- The predicted state probabilities are updated using state dependent observation $b_t(j)$ at each time step. The algorithm works as follows:

Prediction Algorithm

- Initialize

$$\delta_1(i) = \pi_i b_i(O_1) \;\; 1 \leq i \leq N$$
$$q_1(i) = 0 \;\; 1 \leq i \leq N$$

- Recursion

$$q_t(j) = \arg\max \sum_{1 \leq i \leq N} [\delta_{t-1}(i) a_{ij}] \quad 2 \leq t \leq T, \quad 1 \leq j \leq N$$

$$\delta_t(j) = \sum_{1 \leq i \leq N} [\delta_{t-1}(i) a_{ij}] b_j(O_t) \quad 2 \leq t \leq T, \quad 1 \leq j \leq N$$

State Dependent Observation Distribution **B**

Experimental method to obtain the distributions:

- The distributions of the projections of the observations are assumed to be Gaussian

$$P(O/S_i) = \frac{1}{\sqrt{2\pi\sigma_i^2}} \exp\left(-\frac{(O-\mu_{O/S_i})^2}{2\sigma_{O/S_i}^2}\right)$$

- Training phase gives a set of LDC coefficients corresponding to each class (called LDC plane)
- Training samples are projected on all LDC planes
- Mean and variances of projections are used to define the state dependent observation distribution

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State Transition ($\mathbf{A}$) and Initial State (π) Probabilities

Both should result from extensive testing and aging/fatigue models.

- The state transition probabilities are computed using a heuristic method
- The probabilities are computed from matching pursuit decomposition of the sampled data

- The initial state probabilities should be
  - From the manufacturer
  - Repair facilities
  - Large scale sample analysis
- Assumed values are used for the demonstration
- Prognosis algorithm was tested with an assumption that the machine already has traces of fault
- The initial probability of class 2 is set high as compared to others.

State Dependent Observation Density Statistics - UDWT

- Means of the projection on each plane

	P_1	P_2	P_3	P_4	P_5	P_6
1	**0.6263**	0.8329	1.6662	1.9190	3.0788	4.43410
2	-0.0668	**14.2365**	17.0266	20.4563	28.99.79	43.0349
3	-0.0177	14.0670	**17.3373**	20.5170	29.3376	43.7851
4	-0.0268	13.2008	16.0605	**22.1399**	32.5496	48.0109
5	-0.0034	12.5658	15.4205	21.8770	**32.9591**	48.6149
6	-0.0110	12.5841	15.5384	21.8047	32.8978	**48.6836**

- Variances of the projections on LDC planes

	P_1	P_2	P_3	P_4	P_5	P_6
1	0.2188	0.3748	0.6602	0.2251	0.1785	0.2058
2	0.0031	0.0241	0.0176	0.1725	0.0470	0.0425
3	0.0072	0.0812	0.0228	0.4906	0.0600	0.0500
4	0.0066	0.0299	0.0251	0.0873	0.0269	0.0583
5	0.0094	0.0168	0.0328	0.2754	0.0238	0.0626
6	0.0086	0.0302	0.0278	0.4548	0.0201	0.0584

  - C is the class, P is the LDC plane

A State Dependent Observation Density Statistics- WVD

- Means of the projection on each plane

	P_1	P_2	P_3	P_4	P_5	P_6
1	**6.8544**	5.8337	5.0972	3.6628	2.3158	1.1945
2	6.8033	**5.8776**	5.1430	3.7109	2.3900	1.3013
3	6.7765	5.8629	**5.1559**	3.7687	2.4843	1.4219
4	6.5098	5.6555	5.0384	**3.8567**	2.7262	1.7653
5	5.5336	4.8971	4.4652	3.6653	**2.8685**	2.1619
6	3.4635	3.2352	3.1011	2.8799	2.6232	**2.3641**

- Variances of the projections on LDC planes

	P_1	P_2	P_3	P_4	P_5	P_6
1	0.0286	0.0458	0.2820	4.7961	0.2259	0.0182
2	0.0284	0.0521	0.3000	4.6780	0.2371	0.0162
3	0.0268	0.0515	0.2849	4.5926	0.2294	0.0152
4	0.0233	0.1134	0.2013	4.7297	0.1701	0.0120
5	0.0137	0.2317	0.0988	3.5576	0.0948	0.0069
6	0.0033	0.2408	0.0153	1.2946	0.0203	0.0039

  - C is the class, P is the LDC plane

State Dependent Observation Density Statistics- CWD

- Means of the projection on each plane

	P_1	P_2	P_3	P_4	P_5	P_6
1	**6.8545**	5.9820	5.2338	3.8745	2.6148	1.5756
2	6.8426	**5.9924**	5.2388	3.8752	2.6176	1.5820
3	6.8364	5.9823	**5.2477**	3.9147	2.6789	1.6580
4	6.7027	5.8607	5.1847	**3.9623**	2.8096	1.8467
5	6.2210	5.4443	4.8794	3.8640	**2.8811**	2.0450
6	5.0197	4.4060	4.0439	3.4009	2.7384	**2.1516**

- Variances of the projections on LDC planes

	P_1	P_2	P_3	P_4	P_5	P_6
1	0.0218	0.0554	0.2132	3.5857	0.1953	0.0143
2	0.0215	0.0584	0.2179	3.5532	0.1981	0.0140
3	0.0212	0.0522	0.2066	3.5301	0.1898	0.0136
4	0.0197	0.0427	0.1680	3.4105	0.1592	0.0120
5	0.0160	0.0502	0.1116	2.9207	0.1113	0.0089
6	0.0096	0.0891	0.0426	1.9052	0.0464	0.0046

  - C is the class, P is the LDC plane

Plots of the State Dependent Observation Density Satistics

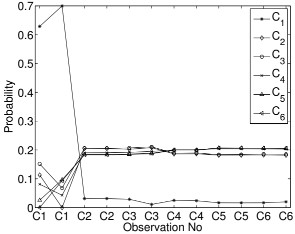

Figure: UDWT

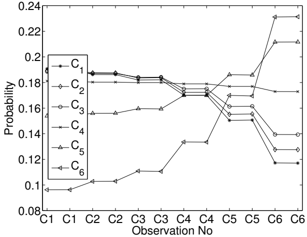

Figure: Wigner

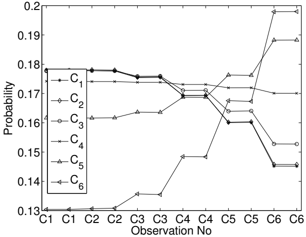

Figure: Choi-Williams

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HMM Parameter Values - State Transition Probability Matrix

- Sample mean of each class was calculated
- MP decomposition was performed
  - A greedy adaptive algorithm
  - Chooses the atom of the dictionary that best represents the signal
  - Decomposition was performed by Gabor dictionary
  - Uses Gaussian window for atom generation $g(t) = e^{-\frac{1}{2}t^2}$
  - 3905 normalized atoms were generated by time shifting, scaling, and modulation

$$g_\gamma(t) = (k_\gamma/\sqrt{s})g(t - \tau/s)cos(\xi t + \phi)$$

where s is scaling constant, τ is time shift, k is normalizing coefficient

- From the decomposed samples the state transition probabilities are calculated
- Only forward path probabilities were allowed as the fault analyzed is non reversible

Class	1	2	3	4	5	6
1	0.5063	0.2435	0.1481	0.0800	0.0200	0.0021
2	0	0.4935	0.2127	0.1651	0.0967	0.0320
3	0	0	0.4542	0.2709	0.1535	0.1214
4	0	0	0	0.4529	0.2900	0.2571
5	0	0	0	0	0.5800	0.4200
6	0	0	0	0	0	1.0000

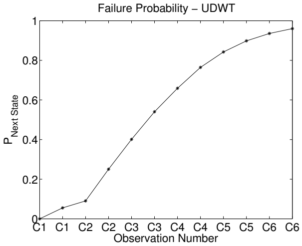
HMM Parameter Values - Assumed Initial State Probabilities (π)

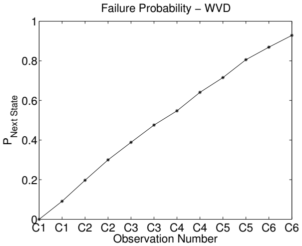
- Historic data, or manufacturer input was not available
- Assumed values were used to demonstrate the developed method

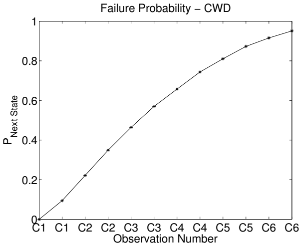
Class	1	2	3	4	5	6
Probability	0.07	0.60	0.15	0.1	0.08	0

Probability of the Failure State (C_6)

An artificial sequence of observations was constructed to test the method. These observations were actual sampled signals arranged in order of severity to mimic a natural fault progression.







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Results

- State Dependent Observation probabilities are higher if the projection are made on the corresponding plane
- The values of b_i were computed using UDWT have less discriminative value, except for the healthy class (C_1), in comparison with the the b_i obtained using the Wigner or Choi-Williams distributions
- Although for Wigner and Choi-Williams distributions the probabilities are close for the early fault severities, these are adequately discriminative for the high fault severities.
- The values of b_i computed using features extracted from Choi-Williams distribution are slightly more discriminative then the Wigner distribution, due to the smoothness provided by Choi-Williams distributions.
- The probability of failure, class 6, increases as the current state of fault severity increases, which is in accordance with the expected results.

Conclusions

- A fault prognosis method was developed and demonstrated based on the Hidden Markov Model
- Parameters of the HMM were calculated through a mixture of experiments and heuristic methods
- The HMM is used to estimate the most probable next state at every time step, as well as the probability of failure
- The prognosis algorithm produces similar failure probabilities for all three distributions used