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Prof. Prabhat Kumar Singh Dikshit

(Supervisor & Chairman)

HOD, Department of Civil Engineering

Indian Institute of Technology (Banaras Hindu University)

Varanasi-221005

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(Ahin Banerjee)

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It is certified that the above statement made by the student is correct to the best of my/our knowledge.

Prof. Prabhat Kumar Singh Dikshit
(Supervisor)
Department of Civil Engineering
IIT (BHU), Varanasi- 221005

Prof. Prabhat Kumar Singh Dikshit
(Head of Department)
Department of Civil Engineering
IIT (BHU), Varanasi- 221005

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DEDICATED TO MY LOVING FAMILY
&
FRIENDS

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Date:

Place: Varanasi

(Ahin Banerjee)

ABSTRACT

The extensive use of high-end automated assets in an automotive sector is the current paradigm shift as a prerequisite of Industry 4.0. In tandem, the life cycle assessment is the prerequisite for such automated systems to optimize the return on this significant investment. Today's market places increasing emphasis on quality efficiency and environmental performance. Scientific understanding of the degradation process and its phenomena is essential for designing and achieving optimal performance. Even before designing high-performance, environmentally friendly gadgets, a product's life cycle optimization is critical. Machine downtime due to maintainability and system component replacement is quite often associated with elevated expenses. Present work is motivated towards developing a computationally efficient system health prognostics methodology directed towards enhanced performance within optimized cost and safety standards. System's health assessment under actual operating conditions and its future state prediction very often helps in developing an effective maintenance plan. Data-driven models are employed to take advantage of condition based maintenance (CBM), which provides an optimized maintenance strategy for estimating the system's remaining useful life (RUL).

The proposed work utilizes data driven models to predict the RUL of a clutch actuator motor in an electric automated manual transmission (*e*-AMT) application. In an *e*-AMT car, the electromechanical actuator works in tandem with a permanent magnet direct current (PMDC) motor to facilitate automated clutch operation, and any failure or decrease in performance of this motor potentially cause the vehicle to stall. Motor degradation is characterized by a deviation in their performance parameters from their initial values. The change in parameters in turn will cause degradation in performance of the clutch along with the motor which is a part of the clutch assembly, eventually leading to function failure of the system. Current methods for forecasting failures triggered by electronic component faults rely on defining monotonically deviating parameters and modeling their evolution over time. This dissertation establishes a prognostics approach that uses machine learning features derived for an electrical motor response to solve this issue. Exponential degradation modeling and the three variants of particle filter (PF) are applied in the development of an efficient reliability methodology for predicting automotive motor failure. Subsequently, the robust and reliable techniques for motor RUL prediction will support scheduling an optimal maintenance plan.

First, the degradation model to exhibit the state of health of the clutch was developed. The initial step has been in the selection of an appropriate prognostic parameter. Unusual patterns in the sensor data set collected from experiments indicated that current (I_a) is one such prognostic parameter to indicate the state of the health of the clutch. A novel condition indicator (CI) and a threshold for a conditionally independent noisy signal from the motor subjected to cumulative degradation were established. A dominating feature characterizing the motor health was discerned amongst time, frequency and time-frequency domain and identified while analyzing the time-series signal composed of an agglomeration of different frequencies that produce higher octaves. Tests for monotonicity and trendability metrics affirmed a distinguishing CI. Principal component analysis (PCA) allowed the fusion of features for the selection of the best-performing CI. The proposed CI was used in an exponential degradation model to predict the RUL of the motor accurately.

The second part of the thesis involves the application of three variants of particle filter (PF) with various resampling techniques to account for heavy-tailed observations and non-Gaussian characteristic of noise to improve the accuracy of RUL estimation. The prediction of the motor's RUL is pursued by a model-based filtering method that relies on an empirical model and a stochastic filtering technique. The empirical model describes the degradation in clutch health with the progression of the fault in a motor component. The stochastic filtering technique on the other hand was used to first solve the 'motor health state' estimation problem, followed by a prediction problem in which the estimated motor health state is extrapolated forward in time to predict RUL. A comparative analysis of the results showed major enhancement in the prediction accuracy respectively and in the efficacy of RUL estimation due to traditional PF, unscented particle filter (UPF), and improved unscented particle filters (i -UPF) vis-a-vis the ordinarily fitted exponential degradation model.

Further, the verification and validation of the prognostic models have been performed utilizing the benchmark Li-ion battery data from the repository of NASA, Prognostics Centre of Excellence (PCoE). The resulting accuracy within the existing 10% results itself validates the superiority of the proposed scheme. This work shows the effectiveness of adaptive filtering techniques towards efficient predictive maintenance (PdM) by employing analytics, which are methods and techniques that use asset data, such as condition and loading data, or experience, to detect or predict changes in the physical condition of the equipment. By integrating PdM in current industrial practices, the use of these analytics contributes to a larger shift towards Industry 4.0.

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NOMENCLATURE

The principal abbreviations used in this thesis are presented for easy reference. Additionally, most symbols are identified where they are used, or first used if use is different than given below.

List of Abbreviations	Description
RUL	remaining useful life
<i>e</i> -AMT	electric automated manual transmission
HIL	hardware-in-loop
ECU	electronic control unit
CBM	condition based maintenance
OEM	original equipment manufacturer
PdM	predictive maintenance
PHM	prognostics and health management
CPS	cyber physical systems
PMSM	permanent magnet synchronous motor
PMDC	permanent magnet direct current motor
CLR	cumulative loss ratio
PID	proportional integral derivative
SHM	structural health monitoring
FMEA	failure mode effect and analysis
CI	condition indicator
PF	particle filter
UPF	unscented particle filter
<i>i</i> -UPF	improved unscented particle filter
UT	unscented transform
NN	neural network
MLP	multi layered perceptron
GA	genetic algorithm
FFT	fast Fourier transform
MCSA	motor current signature analysis
PCA	principal component analysis
GMM	Gaussian mixture models

HMM	hidden Markov model
EKF	extended Kalman filter
UKF	unscented Kalman filter
EPF	extended particle filter
ESS	effective sample size
SPC	sequential Monte Carlo
TTF	time-to-failure
SOH/ SOC	state-of-health/ state-of-charge
EOL/ EOD	end-of-life/ end-of-discharge
ECM	electronic control modules
TCU	transmission control unit
PWM	pulse width modulation
ADAS	advanced driver assistance systems
ALCT	accelerated life cycle test
MIDC	modified Indian drive cycle
ESA	electrical signature analysis
FIR	feature importance ranking