Chapter 1

Introduction and Literature Review

Automated manual transmission (AMT) is widely used in automobiles. Using a data-driven approach, the current effort aims to contribute to the enhancement of plant model advances in AMT for hardware-in-loop (HIL) simulations. The clutch alongside the various transmission components like multispeed gearbox is equipped with rank and shift actuators that is controlled by an electronic control unit (ECU), which assists in enhanced driving comfort. For a vehicle starting through a range of gear ratios, the AMT technology enables superior and quick acceleration by integrating the electromechanical actuators. For a city drive cycle the actuator motors are subjected to harsh operating conditions that results in a higher transient response. This work involves data-driven modelling of transient responses to predict failure in a motor and motor controller system. Further, the work is directed towards developing a prognostics methodology to study the clutch motor failure including the remaining useful life (RUL) computation. The RUL as an additional source of information helps in minimizing the ineffective maintenance costs via implementation of an effective condition based maintenance (CBM) strategy.

The term prognostics is coined as the art of early prediction in the process of real-time monitoring. Tsui et al. (2015) narrated the required changes in prognostic methodologies over the tailored models obtained using historical data. The rising maintenance costs alongside the safety hazards aimed towards the need for newer models concerning the “no fault found” problems in case of a complex engineering system. The present work incorporates two different data driven schemes in the absence of historical data to trade-off the robustness in prediction results along with the computational complexity, accuracy and reduced uncertainty.

With the present theme of the thesis, this chapter emphasizes a detailed review on the recent works relating to the data driven maintenance philosophy and a shift towards CBM. The various CBM approaches in an auto industry in context to the data-driven modeling and RUL estimation is focused. Commonly used data-driven modeling procedures for diverse engineering applications are introduced, which helps us in framing the multiple objectives in the present work. An introduction to the electric automated manual transmission (*e*-AMT) technology is presented in the subsequent section which is followed by the motivation and problem statement. Rest of the chapter will emphasize on the past literature works. In the end the detailed outline of the thesis along with the authors contributions can be found.

1.1 Introduction to Electric Automated Manual Transmission (*e*-AMT) Technology

In today's world, automobiles have become essential utilities. Vehicle designs have progressed from simple transportation utilities to sophisticated modern automobiles that can meet society's growing demands for safety, driving convenience, high energy consumption, low cost, lower carbon emissions and high-power capability, among other things. A transmission mechanism is one of the main components in a vehicle and is responsible for meeting the above specifications. The term "transmission mechanism" refers to a device that transfers power from the engine to the wheels through the axles. The Fig. 1.1 provides a schematic of the *e*-AMT drive train. The *e*-AMT is a semi-automatic type transmission system in which electric motors offers all the mechanical actuations.

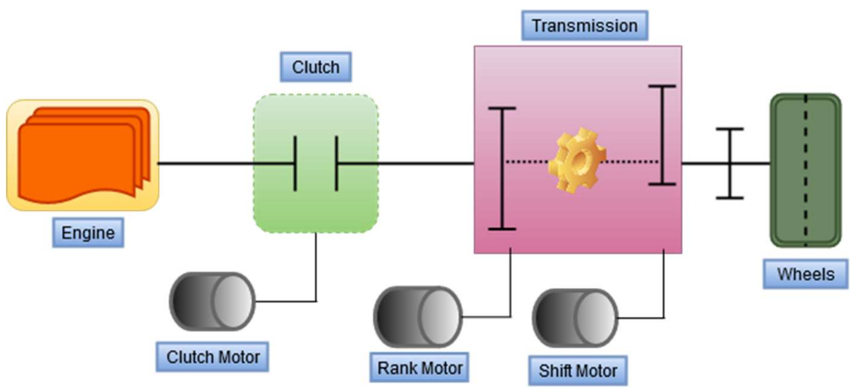

Figure 1. 1 e-AMT vehicle drive train

Modern cars are becoming more sophisticated, and the transmission systems are becoming more complicated. Original equipment manufacturers (OEMs) have introduced various types of transmissions to the automobile market in recent years, which can be divided into two groups: (i) manual systems and (ii) semi- or fully automatic systems. An automatic transmission, as the name implies, changes power or speed on its own, while a manual transmission requires the driver to do so. According to industry figures, automatic transmissions have been installed in 17.3 percent of all passenger vehicles sold in India since the year 2020. Looking into the sales figures in 2011, the percentage was just 1.4 percent. Unexpected faults of such electronically aided devices in the field may have disastrous consequences. If an effective prognostic approach is used to predict the onset of failure and minimize system risk, failures and unintended system downtime can be avoided. To avert risk and increase asset reliability, adaptive maintenance is therefore performed upon a real-time data set. Traditional maintenance actions till date are often practiced based on total kilometers travelled or calendar time, which results in comparatively much earlier time before the end of service life. The succeeding step in the process implies a preventive maintenance strategy which has been found to be less economical when compared to predictive maintenance (PdM).

1.2 Motivation and Problem Statement

Present study relates to AMT system in which the clutch pedal has been removed to enhance driving assistance, thereby increasing the level of comfort. The Fig. 1.1 schematically explains the necessity of the clutch. A clutch disables the power transmission from the engine to the wheels, thus aiding in gear shifting. The electrical motor assists in clutch mechanism by means of the logical commands from the control unit. The feedback signal from the motor to the ECU further informs about the current and voltage requirements, thus, satisfying the demand for smoother clutch operation. During the field operations the motor is subjected to harsh conditions by varying the inputs (i.e., the duty cycle) from the ECU, which results in harsh implications such as motor and the respective controller to fail.

The proposed study is directed towards the life prediction of the motor in transient operation for an automotive system using machine intelligence techniques (Gustafsson 2000). The existence of ample literature in support of the steady state fault prediction has been found. An ample literature supports as evidence of state fault prediction required for the present study. However, due to the unavailability of substantial work pertaining to the transient faults for this type of automotive application, provides the motivation to the present study.

In an *e*-AMT car, the motor for automatic clutch operation has been identified as a critical component and any defect or degradation in its functionality will cause the vehicle to stall. As a result, precise plans must be formulated in order to predict the motor's life and schedule maintenance strategies. The aim of this research is to develop a strategy for estimating the clutch motor's RUL in *e*-AMT applications. The Fig. 1.2 below discusses the idea in carrying out '***prognostics of a degraded motor***' via condition monitoring.

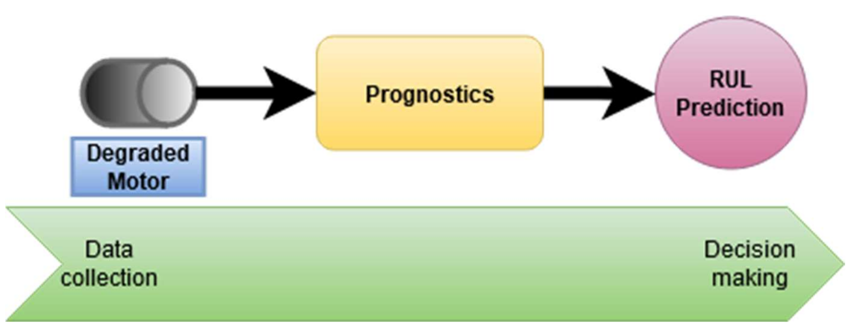

Figure 1. 2 e-AMT motor prognostics

Motor degradation is typically accompanied by a deviation in the feasible performance parameters from their initial values. The deviation in parametric drifts in turn cause degradation in performance of the clutch along with the motor which is a part of the clutch assembly, eventually leading to functional failure of the system. Current methods for forecasting the possible failures triggered by electrical component faults rely on defining monotonically deviating parameters and modelling their evolution over time. However, controlling component-level parameters has not been usually practiced in functional implementations where the components are embedded into a complex product or system. This dissertation establishes a '***prognostics approach***' that uses features derived from responses of clutch assembly comprising of an electrical motor component with parametric faults to solve this issue.

Understanding the deterioration mechanism and the accompanying phenomena is essential for designing and achieving optimal efficiency. Product life optimization as a critical factor needs to be recalled for designing high-performance environmentally sustainable applications. Machine downtime due to maintainability and system part replacement is often associated with high costs. Identifying ageing processes aids in determining a motor RUL and enhancing performance during its service life. Prognostics and health management (PHM) often refers to approaches that enable a professional to assess a system's current health/damage problems using CBM methodology, to anticipate the onset of failure, and reduce the risks associated with unhealthy system behavior.

1.3 Literature Review

Human employees are said to bring significant costs to the organization due to training and task memorization. Prognostics-aware platforms are becoming more common across many technologies, and they are crucial for maintaining autonomy. All engineering systems have shortcomings. The perfect system is one that has no failures in a certain period of time, which is essentially impossible to attain. One must endeavor to foresee or minimize/prevent system failures in all engineering projects. Even though system failures are often unknown, prediction of these failures and the system's reliability is accomplished through a prediction process (Pecht and Jaai 2010). Reliability analysis is critical for enhancing system performance, spanning system lifetime, and other reasons. Unexpected failures and faults can stifle operations or result in output deficits. Reliability, predictive fault detection/isolation, enhanced diagnostics/prognostics, component lifetime monitoring, health monitoring, and information management are all examples of PHM. The literature review section has been architectured into subsections as.

i. Maintenance philosophy
ii. Condition based maintenance in auto industry. For selection of the prognostic parameter subsequently the signal processing techniques are well formalized.
    a. Time-domain analysis
    b. Frequency domain analysis
    c. Time-Frequency domain analysis

Finally, after the signal processing and data characteristics are found, the review is narrowed down by the two data-driven modeling approaches which are characterized as:

1. Stochastic modeling approach
2. Adaptive approach

1.3.1 Maintenance Philosophy

The adaptive role of machine learning into the area of industrial manufacturing requires little human intervention while ensuring reliable operability. The increase in technological dependency within the industrial machines makes them excellent decision makers besides assisting technically, thereby increasing transparency. To maximize the work efficiency along with human safety the robust maintenance methodology needs to be adopted. Rather than repairing equipment immediately with parts that are ready to break, condition monitoring is a means to maximize equipment use and lower maintenance expenses. A list in Table 1.1 epitomizes the different maintenance types that has been adopted on the basis of the component type, component's failure phenomenon, advantages and the technology expenses in implementing them towards achieving sustainable operational standards.

Table 1.1 Industrial Maintenance Practices

Maintenance Types	Reactive Maintenance	Preventive Maintenance	Predictive Maintenance
Component Types	Non-critical components subjected to failure	Critical components subjected to wear-out	Critical components subjected to condition
Advantages & Disadvantages	Requires shutdown	Redundant breakdowns	Eliminates breakdown

	Requires human involvement	Requires human involvement	Requires no human involvement
Technology cost	Economical	Relatively Costlier	Expensive

The paradigm shifts in industrial revolutions in order to gain asset reliability, led to the adoption of the changing maintenance roles. The increasing shutdowns and redundant breakdowns affects the overall revenue for the industry. Predicting early failures can eliminate the unwanted costs, thereby enhancing productivity.

The research work highlights PdM strategy, that has proved to be more effective in avoiding unforeseen failures and reducing leverage. PdM employs these methods or analytics to provide users with information about the current and, ideally, future state of their physical assets. PdM accomplishes this 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 equipment. By integrating PdM in current industrial practices, the use of these analytics contributes to a larger shift towards Industry 4.0. Implementation of the cyber physical systems (CPS) in the smart industry provides the following benefits: real-time data acquisition by means of feedback control advanced modules and intelligent analytics (Lee et al. 2015). The shift towards the smart industry therefore provides with the concept of self-aware, self-configure, self-predict, and self-maintain. The increasing role of cognitive models where the expert knowledge base is created by transferring the same into the learning models alongside the feedback loop prioritize the optimized decision making. The Fig. 1.3 pictorially explains the increased asset reliability, decreasing maintenance and repair costs with the adoption of PdM. The maintenance is carried out by means of condition monitoring, hence our next section will address the CBM works in context to an automobile industry.

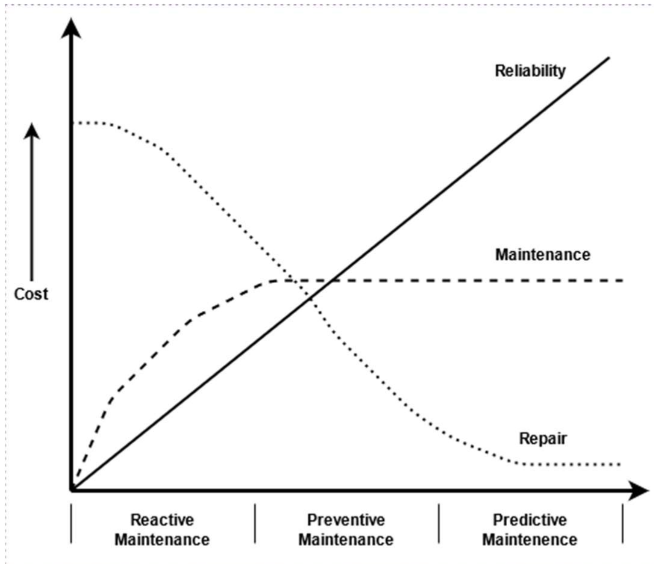

Figure 1. 3 Increase in asset reliability in using PdM

1.3.2 Condition based Maintenance in Auto Industry

CBM is an optimum maintenance strategy that is based on actual conditions obtained from in-situ, non-invasive tests, and operational measurement, whereas PHM is a framework that provides comprehensive yet individualized solutions for managing system health. CBM also known as predictive maintenance, is by far the most popular maintenance strategy in case of complex and difficult technologies wherein components have little or no failure characteristics. The trend in CBM is toward advanced technologies such as PHM. Diagnostic and prognostic technologies are included in PHM. Fig. 1.4 below provides a schematic to the sequence of steps in a prognostics workflow during a CBM approach. The CBM approach follows with the in-situ experiments for a critical system which is made to work under the different operating conditions. Sensors are fused at different junctions which assists in the acquisition of data. The next three steps follow the feature pre-processing, post-processing along with model development. The product development team in an industry moves ahead with model deployment, which assists in RUL prediction for the system.

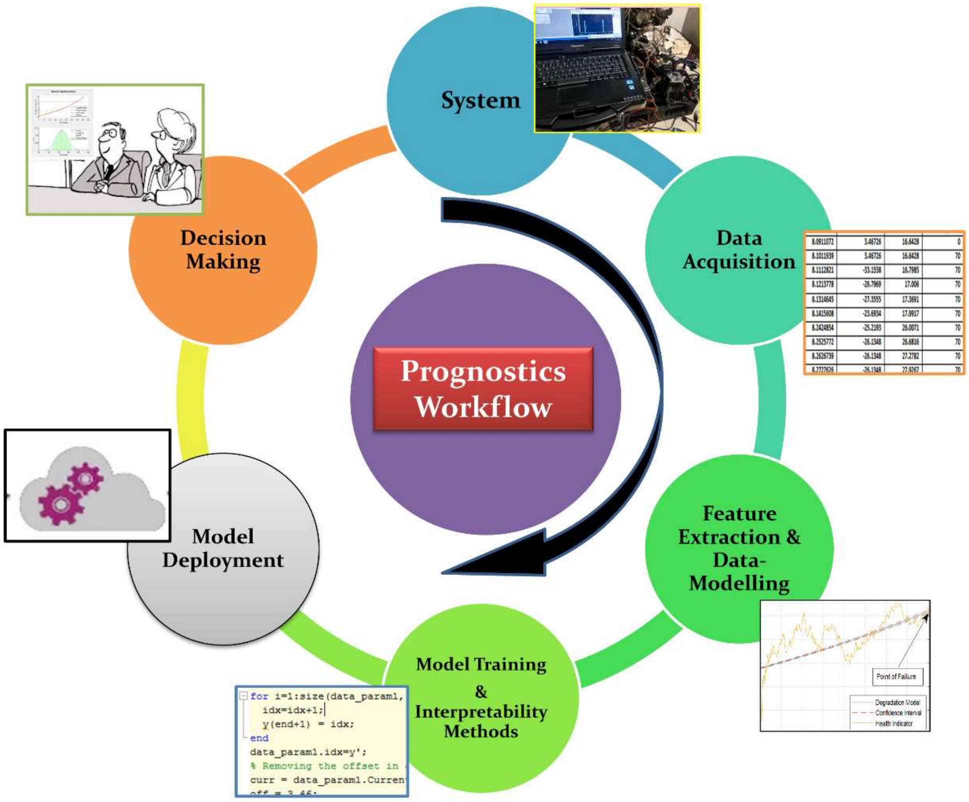

Figure 1. 4 (Moving clockwise) Visualizing the prognostics workflow to RUL as a decision making

In the case of prognostic technology, whenever an acceptable performance degradation range has been determined, we can quantify the RUL to failure by assuming that the measurement can always be harnessed to check the performance degradation. GM Global Technology, General Electric, Honeywell International, Robert Bosch, and IBM are among the Fortune 500 businesses with the most PHM patents from 2000 to 2015 (Liu et al. 2018). The firms listed above provide PHM services for a variety of applications, including airplanes, space shuttles, driverless automobiles, wind turbines, offshore oilrigs, and a variety of medical uses. According to their findings, electrical motors account for 18 percent of all PHM patents in electrical systems. Grounding faults, stator winding faults, short-circuit faults, overcurrent, and overvoltage problems were reported to be the most common motor defects (Liu et al. 2018). The present work is motivated considering one such application with direct current motor that assists in mechanical actuation. The idea lies in predicting the failure of the motor under the transient loading conditions.

A paradigm shifts from the conventional to the hybrid transmission types in case of automotive vehicles necessitates the usage of electric traction motors. These traction motors unlike industrial motors are subjected to dynamic loading conditions to fulfill the demand for dynamic torque and speeds across the different drive cycles. The unpredictable acceleration and deceleration mechanisms makes the motor to undergo frequent transient loading conditions resulting in an early degradation, thereby leading to failure. Nonlinear model predictive control (Samaranayake and Longo 2015) utilizing the voltage and current signals were developed in order to minimize degradation of permanent magnet synchronous motor (PMSM) used in case of both passenger and commercial vehicles (Samaranayake and Longo 2018). The cumulative loss ratio (CLR) was further calculated to find the RUL of the motor. In all the similar works estimation of the RUL was performed considering the transient responses from the motor while the methodology was to resolve the faulty signal via controller design. By means of speed control in a dc motor the overvoltage fault is taken care of by a Proportional Integral Derivative (PID) controller. Further down the line, Abraham and T.Nguyen (2018) found that in case of the motors dynamic loading conditions, the conventional controllers were heavily dependent towards the correct outcome of the neural network models in order to obtain correct voltage values that needs to be applied. The increasing inability of the controllers to handle transient fluctuations, amplified the motor failures. The time frame of the motor's degeneration toward failure is seen in Fig. 1.5.

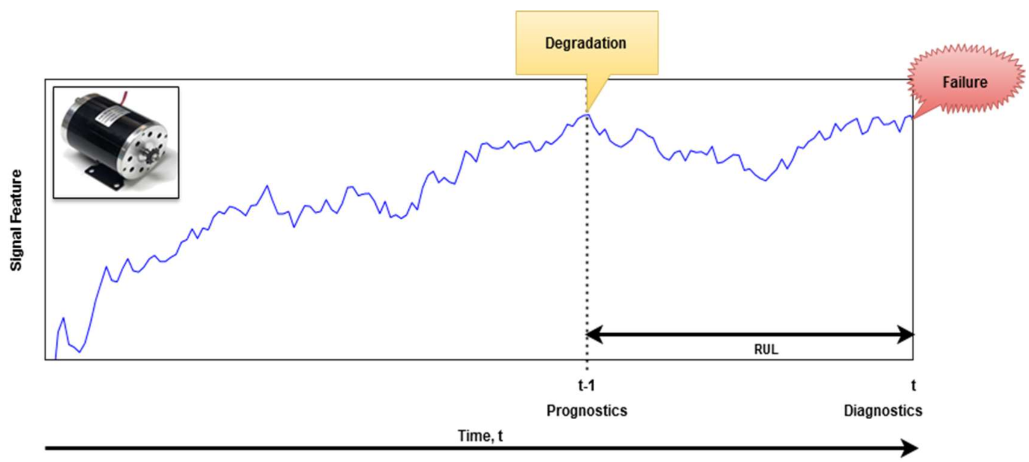

Figure 1. 5 Diagram featuring Prognostics and Diagnostics

The current diagnostic tools have proven to be inefficient to detect the onset of system degradation or Prognostics. However, our approach (motor Prognostics) deals with preventing the motor system from failure using the current (I_a) as a prime variable to providing an accurate estimate of the RUL.

CBM technologies are increasingly being applied to structures as a Structural Health Monitoring (SHM) and moving vehicles as an Integrated Vehicle Health Monitoring (IVHM)

(Elattar et al. 2016). In case of commercial vehicles (Abraham and T.Nguyen 2018), the PHM assists in eliminating the idle time during which breakdown occurs. However, while PHM technology has been extensively used in aviation and the military, it is also true that it has never been effectively implemented in the automotive sector (Chang and Park 2019) due to several constraints. Further, the use of failure mode effect and analysis (FMEA) helps ascertaining the critical component, on the basis of selection of the failure modes and its countermeasures. For an automobile industry consisting of several systems, finding the critical component leads to superior design changes and averting serious consequences. Presently, the PHM applications to moving vehicles is not only restricted to an aircraft industry, rather it extends the use to automobile applications also. The present work extends its use to one such application involving *e*-AMT cutch actuation.

CBM for a data-driven approach utilizes the sensor logged data by extracting the required information into a vector of data features for the clutch motor system. The collected raw signal comprising of a larger variety of useful information along with noise assist in system's degradation characterization. It is this useful part of the signal that needs to be processed using advanced signal processing techniques. Three well known signal processing approaches are seen in the data preprocessing works, namely the time domain, the frequency domain and the time-frequency domain. Robustness, wider range, and sensitivity are few characteristics of the preprocessed feature that helps in evaluating the performance of the system. In case of a transient working conditions, the observable change in the features can be perceived with the variations in case of a temporal and spectral representation. Engineering applications rely on time varying behaviors. Rapidly degrading systems unlike electronic systems and electric motors are considered time invariant. In order to model the dynamic behavior for a nonlinear and transient operating condition, the stability of the system is attained by means of time varying parameters response (Guo et al. 2014).

Nearly every single mechanical system requires an array of sensors to convert mechanical information like a shaft's rotation speed to electrical parameters like voltage or current that must be examined and analyzed. Because current (I_a) measurement is so directly related to the operation state of electric motors, nearly all PHM patents for electric motors are based on it (Liu et al. 2018). Voltage based measurement is also disclosed for the identification of fault conditions. The first signal procedure to classify fault modes is the order analysis of the current change over time for an electro-mechanical actuators involving flight control (Chang and Park 2019; De Martin et al.

2016). This is because identifying the change in current in one cycle is the easiest way to classify the fault mode.

For a large variety of electrical components, there is a most likely chance of constant rate of failure that may requires focus to shift on predictive methodologies over the much-appreciated preventive measures. Multiple applications of prognosis are seen in the literature using vibration signal (Coble and Wesley Hines 2009; Wang and Mamo 2019), temperature data (Barbieri et al. 2015; Guo et al. 2019) and crack length (Eker et al. 2014; Saidi et al. 2017). The availability of number of prognosis models with consequential dependency thereupon, raises a greater concern for alleviating degree of uncertainty. In the case of prognostic technology, whenever an acceptable performance degradation range has been determined, we can quantify the RUL by assuming that the measurement can always be harnessed to check the performance degradation.

CBM eliminates unexpected downtimes while also improving an engineering system's RUL. Present day diagnostics and prognostics utilizes CBM for increasing reliability. The qualitative criteria of fault diagnosis include fault identification, isolation, and assessment of fault extent. On the other side, prognosis is the process of forecasting when a system will approach the end of its useful life, regardless of whether or not an undesirable condition occurs. Mounting the sensors in various places allows for the identification of failure mode as well as cost savings. PHM might be used to a single vehicle, such as an aircraft or a military vehicle, utilizing just data collection. A diagnostic and prognostic model was built using a hybrid model (Chang and Park 2019) that took into account the analytical model and data processing. Finally, utilizing a thorough analysis model of noise vibration and harshness, temperature, and strength, the researchers introduced the progress of a soft sensor that can capture the condition of a specific weak spot.

Almost every mechanical system requires a set of sensors to convert mechanical data, such as the rotation speed of a shaft, into electrical parameters, such as voltage or current, that must be studied and analyzed. Because current sensing is so closely related to electric motor functioning, it is the topic of nearly all PHM patents for electric motors (Liu et al. 2018). It is also claimed that voltage-based measuring can be used to discover faults. The difficulty of current diagnostics to effectively monitor the motor's worsening behavior prompted the development of prognostics. The proposed study utilizes a degradation signal from the PMDC clutch motor to conduct a prognosis.

A recent study predicts an increase in demand for electromechanical actuators in order to provide flight control (De Martin et al. 2016), providing a data-driven strategy based on observed metrics such as fault frequency (F), severity (S), and testability (T). Due to increasing structural resistance favored by harmonic forces, an actuator develops a variety of mechanical and electrical problems. Increased mechanical impedance produced by unsynchronized linear drive for a linear ball screw (Huang et al. 2012), losses owing to gear tooth wear (Kundu et al. 2020), fractured rotor bar (Soualhi et al. 2013) producing rotor axis misalignment, and rolling element bearing faults (Gao et al. 2010) caused by inner race and outer race damage have all been common searches.

Fault dynamics emerging from the diverse nature of activity in an industrial system have been divided into four categories: transitory, permanent, intermittent, and incipient (Abid et al. 2021). Transient faults are caused by an impulsive shift that lasts for a short period of time before diminishing, whereas persistent faults result in system failure. During the active-inactive periods, the characteristic variable showed a cyclic pattern of intermittent faults, but the incipient failure had a slow rate of deterioration pattern. A particle filter (PF) framework was used to predict anomaly detection for an electric motor's winding degradation. In previous investigations using electric motors, failure mode categorization was observed to be accomplished through order analysis of current change over time (Chang and Park 2019; De Martin et al. 2016). One of the simplest ways to characterize the fault mode, according to the study, is to determine the change in current in one cycle.

The electrical problems in the actuator are caused by open and short circuit faults in the field and armature windings. An intelligent diagnostic system that detects multiple class faults was created using a machine learning method with multiclass NN (Murphey et al. 2006). Yuan et al. (2008) have demonstrated the magnetic field winding degradation that fits under the category of the stator winding fault very well.

Challenge in PdM approach lies in data sparsity (Chen et al. 2020a), therefore development of condition indicator (CI) becomes a critical aspect in the development of prognostic model. The subsequent section will elaborate the collected research study on data pre-processing works for the time domain, frequency domain and the time-frequency domain analysis. The health estimation methods involving prognostics strategies for a data-driven approach are divided into two categories: stochastic modelling approach and adaptive techniques.

1.3.2.1 Time domain analysis

Time domain analysis is one of the most widely used techniques due to its simple pre-processing, speed independency, and ease of use. Another primary concern is that it uses a relatively lesser memory requirement. The authors performed temporal analysis and extracted various statistical moments, i.e., mean, root mean square (RMS) (Suh et al. 1999), skewness, kurtosis, crest factor, peak value, peak-to-peak amplitude, shape factor, form factor and many more have been successfully employed in various investigations for motors. Even though the findings proposed that kurtosis (Saidi et al. 2017) offers additional information about the system much of the extracted temporal features are relevant indicators.

Amongst the time domain features, the simplest of all the features developed is the peak value of the extracted raw signal. It is the absolute of the max value of an ensemble of observations. Mean value aims towards smoothening the noisy signal present. The root mean square calculates the square of all observations of a signal and then estimates the average of these values under the square root. The crest factor is used to identify the impulse amplitudes of a signal by comparing these impulses to a defined threshold. To evaluate the dispersion, standard deviation is computed. The third moment, a.k.a., skewness is the cubic ratio between the distance of each observation and the standard deviation. The kurtosis calculates the peakedness of a signal.

The comparison of the dissimilar trends has been performed using statistical methods. In time domain analysis the use of lesser sophisticated signal processing techniques in shop floor can make use of the time domain analysis, the agility towards machine learning and other approaches of statistical techniques. Classification using a multi layered perceptron (MLP) neural networks provided higher classification efficiency with time domain based features as compared to frequency domain features (Sarcevic et al. 2017). Research works relating to the fault signals of bearing (Loutas et al. 2013; Saidi et al. 2017) and gear (Ben Ali et al. 2018a; Suh et al. 1999) were further processed to carry out the intelligent diagnosis and prognostics of the modern computer integrated manufacturing systems. The prognosis has been carried out using vibration data collected during experiments in a controlled environment and under accelerated loading conditions. Motors assists most of the works of heavy machinery in industrial applications, so condition monitoring of the motors becomes a priority.

Obtaining a single conditionally degraded parameter has been targeted towards accurate RUL prediction of an electric motor(Barbieri et al. 2015). Bearing faults for a series of motors were reported during its operation, thereby assisting in the development of the generalized path model or Type III prognostics. The method was validated further using a steady-state data obtained from accelerated degradation testing electric motor. Ordinary least squares method and genetic algorithm (GA) was used to find the efficacy of the algorithm ahead of using the time domain features (Barbieri et al. 2015).

1.3.2.2 Frequency Domain Analysis

The process monitoring for robotic application using frequency domain analysis was considered in order to solve the problem of big data management (Pappachan et al. 2017). The use of higher sampling rate in real-time monitoring of engineering applications was also discussed where the frequency of events occurring is insufficient. The use of power spectral density from the acoustic emission sensor data was used to classify the vibration signal of the spindle during an advanced machining to obtain better surface quality (Pappachan et al. 2017). A summary of works for monitoring fault conditions were seen to perform using fast Fourier transform (FFT)(Barbieri et al. 2015), wavelet analysis, image analysis and statistical analysis.

In identifying the performance of degradation and the faulty state of the rotating machinery, the authors made use of few frequency domain factors such as mean frequency, standard deviation frequency, coefficient of variability, frequency skewness, frequency domain kurtosis, RMS (Tse et al. 2019), etc. that had a novel contribution in evaluating the fault diagnosis. Further, the emergence of wavelets (continuous and discrete) has aided to the techniques of equipment diagnosis and prognosis (Suh et al. 1999). The requirement of lesser amount of data and the computational time adds to the benefit of the approach in characterizing the fault frequencies. The process helps in identifying several underlying fault frequencies along with the origin of the fault. The time to frequency data transformation gives rise to an information loss, which has been one of the major disadvantages in handling the nonstationary data obtained from rotating machines under dynamic working conditions.

1.3.2.3 Time-Frequency Analysis

The challenges faced during time and frequency domain analysis has been lessened with the time-frequency implementation. The continuous change in the temporal values leads to a non-stationary signal, thus making it almost unpredictable in nature. The time-frequency (*t-f*) approach serves in evaluating the characteristics of non-stationary stochastic signal through detection, estimation and classification (Sayeed et al. 2016). For a low signal-to-noise ratio, the time-frequency domain analysis can be performed basically in three ways as; Wavelet Analysis (WA), Short Time Fourier Transform (STFT), and Wigner-Ville distribution (WVD). The advantages in the process of time-frequency representations is that it encompasses optimal detection for a real-time system operating under a noisy environment.

In the research works of Sayeed et al. (2016) for estimating fault severity, the performed characteristics of the signal are matched with the *t-f* kernels and the nuisance parameters (i.e., the time and frequency shifts) by exploiting the corresponding covariance. Empirical mode decomposition (EMD) method as an advanced non-linear tool has been used to extract the hidden information in case of an electrocardiogram signal (Maji et al. 2020). The central tendency of the energy evolution (EE)(Wang and Tse 2015) using the higher harmonics, has been evaluated by means of moving average wear degradation index (MAWDI) for tracking the health of a slurry pump. In order to address abnormality detection in biomedical signals, and source localization in wireless communications for a multichannel non-stationary signals the multisensor time–frequency signal processing (MTFSP) as a tool in MATLAB has been preferred (Boashash et al. 2018). The coiflet wavelet transform along with *K*-nearest neighbor has been employed for finding DC motor faults of different types by making use of the acoustic signals (Glowacz 2015). The coiflet acts as a basis function in the decomposition of signal. The wavelets model the functions in the form of a localized time and frequency format by uniformly distributing the window size. To qualify as an efficient fault analysis approach, wavelets have been made use of in feature extraction of the non-stationary signal. The work (Glowacz 2015) discusses the role of motors in contrast to different industrial perspectives along with the material quality and the type of data processed in CBM of DC motors. Targeting towards the sensitivity during fault analysis of industrial motors, a more robust approach by means of combining different information from different sensors has been deciphered (Antonino-Daviu 2020). The motor current signature analysis (MCSA) was unable to restrict towards false positive indications while working with transient operating regimes, thus compromising towards motor's health integrity. The use of *t-f* domain therefore allowed:

i. Reliable and efficient diagnosis
ii. Avoidance of false alarms, and
iii. Uninterrupted operating conditions

The increasing adaptability towards the different domains in data preprocessing techniques facilitated in proper selection of CI employing feature fusion. The integration of partial and dependent information from multiple sensors of an aircraft gas turbine has been fused using kernel function in the construction of a health index (Song et al. 2018). The works of Xu et al. (2014) ascertained in developing a com-entropy based fusion prognostics framework for accurate forecasting of the failure state in case of an aircraft turbine. The idea of com-entropy considers the relative prediction error sequence and their respective weights while computing the entropy. The following steps are involved in the construction of the CI that can be summarized as (Xu et al. 2014):

i. Identification of the parameter
ii. Preprocessing of the extracted features
iii. Identifying the failure threshold
iv. Parameter isolation and failure definition

A joint prognostic method where a mixed-effects model for degradation modeling and the neural network (NN) model for data fusion and RUL prediction has been seen to be established (Gao et al. 2020). Non-linear model based fusion prognostics for lithium ion battery dataset have been found performed in purview of the accurate prognostics. For a large scale network data, classification of the anomaly detection based on the Dempster-Shafer theory of evidence and principal component analysis (PCA) has been found. Their work also introduced to the cognitive based data fusion algorithms like fuzzy set theory and expert systems (Chatzigiannakis et al. 2007).

Besides, for prognostics, the constructed condition indicators represent the system's degradation trend over time. These indicators are an ensemble of observations that represent the system behavior from its nominal condition (healthy state) to its critical state (failure) (Kai Goebel, Bhaskar Saha 2008). The subsequent section discusses the past works of the researchers in the field of data-driven modeling. The research works are categorized under two domains, namely, the stochastic and the adaptive approach.

1.3.3 Modelling Approaches

In the previous section, literature review concerning the three different types of signal processing techniques for a raw signal have been discussed. Based on the applications one amongst the three approaches have been found to yield a correct feature that reflects the signal characteristic. The present section will render the recent works on data-driven modeling based on the obtained feature while conducting prognosis. CBM (Camci and Chinnam 2010; Do et al. 2015; Eker et al. 2014; Kunst et al. 2009; Lei et al. 2018; Li et al. 2012a; Shin and Jun 2015), also known as predictive maintenance, is by far the most popular maintenance strategy in complex and difficult technologies wherein components have little or no failure characteristics. The trend in CBM is toward advanced technologies such as PHM(Coble 2010; Coble and Hines 2011; Johns et al. 2008; Mosallam et al. 2016; Xu et al. 2014). Diagnostics is said to perform after the failure has been encountered while prognosis deals with finding the RUL before failure.

Two classifications in context to data-driven CBM approach has been adopted namely, the first, is the stochastic approach or the machine intelligence based approaches while, the second is the adaptive approach. Prognosis establishes the bridge between the two data-driven approaches.

For a larger number of batteries (Chen et al. 2020b; Jiao et al. 2020; Li et al. 2014; Saha et al. 2009; Si et al. 2011), rotating machines (electromechanical actuators, gas turbines, wind turbines, large oil trucks, slurry pumps, and motors) (Ben Ali et al. 2018b; Brown et al. 2009; Byington et al. 2003; Celaya et al. 2012; Cheon et al. 2015; Nandi et al. 2005; Pagitsch et al. 2020; Saidi et al. 2017; Si et al. 2011; Tse et al. 2019; Wang and Tse 2015) and, for an array of data (likewise, the current, voltage, pressure, vibration, crack length and temperature) collected by means of sensors, have been made in use while implementing CBM. Thus, by means of intelligent sensors and with the involvement of the non-intrusive techniques, the CBM helps to strive towards industry 4.0 standards. The following section will elaborate the past literary works in explaining the recent research and developments in CBM with special emphasis on data-driven methodologies.

1.3.3.1 Stochastic Modelling Approach

The stochastic approach relies on the availability of the features (covariates) obtained from the stages of preprocessing. Presently an enormous impact towards degradation-based failure time prediction has been sought. For a large category of similar machines, the degradation behavior varies under different working conditions. The initial approach to estimation of RUL follows the well-known Weibull model in which the data needs to follow a distribution(Xie and Lai 1996). The accurate distribution gives rise to accurate parameters, which then regulates the algorithms performance through an accurate useful life estimation. For the deteriorating systems, their use has been found to be appropriate for a class of systems operating under stable and dynamic loading conditions (Do Van et al. 2012). For a class of deteriorating systems, Gamma distribution seems to fit perfectly well to the increasingly monotonic signal. Moreover, the paths are discontinuous so it can be distinguished as a cumulative sum of infinite small shocks (Do Van et al. 2012). Lei et al. (2018) and An et al. (2015) reviewed the CBM methods that rely on data-driven and physics based approaches, which involve Gaussian process and NN. The foregoing challenge lies in identifying the global degradation pattern. To avert failure, a combined exponential regression and parametric empirical Bayesian approach have been seen to be formulated. Initial prior has been provided by the exponential distribution which had been further used to estimate the posterior for Bayesian empirical approach, thus assisting in the prediction of a global degradation pattern (Wang et al. 2015).

Bio-inspired techniques sufficed NN, and neuro-fuzzy (Fagang et al. 2009; Özel and Karpat 2005) applications for life prediction of components. Deep learning algorithms (Berghout et al. 2020) for the development of nonlinear models (Guo et al. 2019)were another such approach as a tool to carry out machine learning. It had an advantage over a conventional neural network with the use of more hidden layers and neurons, thus, contributing to improved learning performance. Application areas began to rise with the use of techniques like pattern recognition and classification problems. Supervised algorithms such as support vector machines (SVM) have been used to predict the engine reliability (Hong and Pai 2006). Its prediction accuracy was also compared with the autoregressive integrated moving average and general regression neural networks (GRNN). SVM was also applied for fault detection in induction motors using vibration signals (Silva et al. 2009). It required relatively lesser user knowledge as compared to the fuzzy logic and artificial neural network (ANN). Four necessary steps of analysis in PHM involved reliability centered maintenance (RCM) analysis, sensors, detection algorithms, and prognostics (Silva et al. 2009). In order to propagate the combined idea of deep learning and reliability analysis the Cox proportional hazard deep learning model has been used to identify the time-to-failure via a LSTM network. Autoencoders have been recommended to achieve robust prediction (Chen et al. 2020a). Prognostics refers to the estimation of time-to-failure from the onset of fault whereas, fault diagnosis uses detection, isolation and estimation.

In order to implement PdM techniques manufacturing sector needs to be automated. The US-based McKinsey & Company in its reports in 2017 ranked the manufacturing sector as second, which can automate almost up to 73% (Manyika et al. 2017). The predictive maintenance requires the CBM system to be implemented that deploys embedded diagnosis and prognosis to determine the functional state of the equipment. Health and usage monitoring system was already been implemented for helicopter rotor blades using vibration signals (Uckun et al. 2008). Similarly, corrosion induced cracks of ship's hull are monitored for structural safety and reliability. Using maintenance data from an automobile fleet, training has been performed using long-short-term memory (LSTM) deep learning network in order to predict the time between failure (Chen et al. 2020a). Fault prognostics of DC motor was investigated by L. Wang et al. (2012) using nonlinear degradation data. Steady state constant current (Chang et al. 2010) was used for prognosis of a preloaded ball screw in a computerized numerical control machine. These predictive maintenance policies utilize contemporary degradation models for predicting residual life distribution using particular signals. Stochastic processes are found to be much appropriate to model the degradation process. The use of Weiner's theory to extend the useful life of the asset involving non-stationary degradation process (Letot et al. 2017). Forecasting technique has also been applied in prediction of the service life. While monitoring a machine under dynamic loading conditions there occurs an increase in the expenses, thereby lending the approach to be computationally expensive. However, the adaptive approach has been found to perform well in terms of cost effectiveness. This limits the application of the approach in our study.

1.3.3.2 Adaptive Approach

Statistical regression and Bayesian methods are also applied for RUL prediction (Bouzidi et al. 2018). The application of expectation maximization algorithm, hidden Markov model (HMM) (Zhu et al. 2020) and Gaussian mixture models (GMM) were the early developments in the area of control systems. With the rise in the complex nature of the systems and the transient states, the nonlinearity in system behavior came into effect. The ability of GMM seemed to have a severe shortcoming in their statistical efficiency for the development of nonlinear models using their observed datasets. The advancement of Kalman filters to track changes in features is one of the early steps taken by researchers in prognostics (Swanson 2001). Kalman filters identify impending failure and assesses probability of survival and RUL.

For the creation of a robust model, conditional probability has indeed been made use of in Bayesian approaches for modelling continuous and discrete variables using discrete Bayesian and GMM (Hu and Mahadevan 2018). The work reflects the interdependence of data alongside the mathematical models, in the design and development of optimized engineering systems. The optimal univariate Gaussian Mixture (OUGM) and the multivariate Gaussian Mixture (MGM) has been utilized for Bayesian networks learning, thereby improving the accuracy in case of conditional probability data. The constant variance in case of conditional probability values from GMM restricted its use any further. Thereby, the OUGM led to topology learning and parameter learning. The trained model has been further used for quantifying the uncertainty and model calibration (Hu and Mahadevan 2017). Gebraeel et al. (2005) in their works with bearing condition monitored data, introduced the idea of Bayesian updating of the stochastic parameters in case of degradation models. A physics-based model involving particle filters (PF) was described by Jouin et al. (2016) wherein the posterior distribution was expressed as the number of particles. The use of different combinations in the earlier works include the size of data, the allowed level of noise with bias in data, the actual loading conditions, and the complexity of degradation that identifies the degradation behavior to predict future health. The applications of NN, PF, Gaussian processes and Bayesian methods were also elaborated. With the use of PF, the authors differentiate two approaches towards handling nonlinearity and noise processing. Resampling takes care of nonlinearity while noise has been treated by ignoring the fewer weighted particles. However, less periodic data from previous works (Jouin et al. 2016) has been found in context to the motor state estimation and analysis using PF that provides an additional space for motor prognosis. Solutions to the nonlinear state estimation problems have been found using extended Kalman filters (EKF), standard Kalman filter and unscented Kalman filter (UKF) (György et al. 2014).

Aim towards recursive filtering (Hidaka et al. 2016) has been targeted in the previous studies involving nonparametric Bayesian filter a.k.a., particle filter. The performance however, depended on the choice of the proposal distribution. For nonlinear systems, EKF, UKF (Van Der Merwe et al. 2001; Zheng and Zhang 2005) alongside the linearization approach have been used to obtain the proposal distribution. Comparison of the results have been further observed using extended particle filter (EPF) (Shariati et al. 2019) in the works of autonomous underwater vehicle. The EPF is an integration of extended Kalman filter (EKF) with PF for some unmeasured states for parameters and state estimation. The problem of particle degeneracy have been overcome by means of using second order EPF for a family of exponentially modeled (Zhang and Yan 2020) observations. For the same computational complexity an increased accuracy up to second order (Van Der Merwe et al. 2001) has been achieved by means of using UKF. In case of a standard PF approach which results in higher variance, UKF assists in selecting the prior. The inherent complexity in the particle generating steps of UKF is thereby passed on to UPF (Fasheng and Yuejin 2009). The resulting second-order accuracy of UKF helps in obtaining the proposal distribution for unscented particle filter (UPF). For an unsteady likelihood, the UPF has been found advantageous to sample the particles. In contrast to PF, the presence of a significant number of particles reduces the statistical complexity of the UPF.

The main objective of sequential Monte Carlo (SMC) otherwise called PF is to represent the required probability density function by a set of particles with the associated weights. The state variables are then predicted using these particles and weights. The accuracy and infinitesimally small computation time in case of residual systematic resampling technique have been found to be the best. Comparative results (Walker et al. 2015) in favor of PF have proven to be better in accuracy than the nonlinear least squares and UKF methods. Randomized selection of the particles in the process of state estimation was found throughout the works seeking convergence (Elvira et al. 2017)(Pitt et al. 2012). For a high dimensional nonlinear system, the clustered PF (Lee and Majda 2016) capture non-Gaussian features of the true signal and uses fewer particles than the standard approach. Here, the neighbor state variable is affected by each observation at a spatial location by clustering the state variables that implements the coarse grained localization. Filter performance has been checked based on comparison for ensemble adjustment Kalman filter and clustered-PF applied to the Lorenz 96 model. The implementation of hidden Markov models (HMM) aided in the automated detection of the faulty state. The inclusion of uncorrelated information regarding degradation behavior and noise added to the discrepancy in the RUL prediction. To add further, experimental findings on bearings concluded that the fault occurrence time is another major shortcoming while estimating RUL involving a data-driven method (Li et al. 2012a; Zhu et al. 2020).

In this framework, one of the more deeply investigated subjects has been, and still is, the replacement of the traditional hydraulic/electro-hydraulic technology with the electromechanical ones. The 4th Industrial revolution has highlighted the necessity for smart factories in particular. As the operation and maintenance management is improved by placing internet of things (IoT) on real functioning equipment, the use of PHM is increasing. The work by Gencturk et al. (2020) involves using robot's configuration data, and the necessary hazard rate information for model development and predicting failure. PHM extends its use to enhance the reliability of the robot system by target tracking up to completion of the task followed by the RUL estimation. Some additional sources of sensory information were load, temperature, pressure and the humidity, that helped towards a model based prognostics. A data-driven prognostics as a means of knowing the status using sensor data and reporting the RUL is scope of the present study.

The original contributions of this work lead to a systematic approach for developing data-driven (empirical) models and methods aimed at performing the tasks constituting the CBM framework. PHM has risen to prominence as a viable alternative to conventional reliability predictions. CBM assists in achieving the predictive capabilities that would let the maintainer obtain a very beneficial maintenance strategy. A motor health assessment step is accompanied by a degradation modelling and RUL prediction step in the established prognostic process. The important contributions of the thesis are summarized in Figure 1.6.

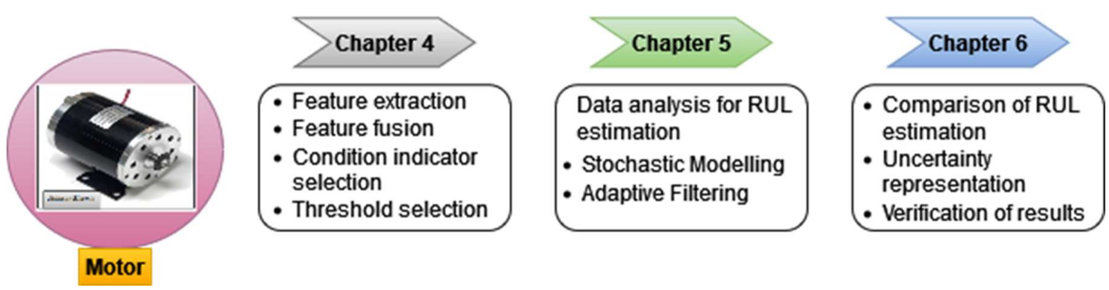

Figure 1. 6 Schematic of the major contributions

1.4 Objectives of the Work

A bulk literature on CBM studies relating to data-driven RUL estimation for rotating machines operating under steady state is available but studies relating to transient and non-linear operating conditions are yet insufficient for solving problems of electromechanical actuators. The present work involves the following objectives:

1. Identification of a critical motor parameter in order to design an efficient, reliable and robust predictive maintenance schedule.
2. Development of a novel condition indicator using the data features derived from pre-processing and PCA based feature fusion technique.
3. Data-driven RUL estimation of an electromechanical clutch actuator using an unlabeled data.
4. Development of an improved prognostic methodology for motor prognosis by means of adaptive filtering techniques.
5. Development of a computationally efficient RUL estimation methodology by comparing different resampling approaches for the three particle filter variants.
6. Validation and verification of the model using a benchmark data.

1.5 Organized Structure of the Thesis

The thesis has been organized into seven chapters. They are entitled as: Introduction and Literature Review; Remaining Useful Life methodology; Experimental Set-up and Data Acquisition; Data Characteristics and RUL Estimation Techniques; Data Analysis for RUL Estimation; Comparison of Two Different Approaches to RUL Estimation; and Conclusions and Future Scope of Work. The last chapter is followed by the relevant references cited in the thesis, publications that came out of the present work and the resume of the author.

The chapter 1 lays a foundation of the present work. A brief introduction to the *e*-AMT technology is offered. It then elaborates the motivation towards the present study. The work reports the application of DC motor in an *e*-AMT clutch operation under dynamic loading conditions. This summary emphasized the limitations in the application of CBM elements and the allied techniques aiming towards prognostics when dealing with complex and dynamic engineered systems. It then summarizes a condensed overview of the past literature works relating to data-driven CBM and PHM works. PdM approach has been introduced as a key process for enabling maintenance activities in the present-day applications. The literature review revealed the available gap in the knowledge base and the objectives of the present study has been drawn out.

Chapter 2 presents the state-of-the-art along with the different data-driven RUL methodologies which have already been implemented over the years in different domains of engineering. Aiming towards computationally efficiency and accurate prognostic solution, a detailed description is presented.

Chapter 3 discusses the first step towards identifying the critical component for an automobile system in an OEM industry. For building a PHM process in particular the experimental setup along with data acquisition is also explained. Summary of the sensors used to monitor the degradation parameters has been presented along with given motor specifications. The experiment extends to three different loading conditions in a motor, and thereafter three sets of data were collected.

Chapter 4 presents an overview of data characteristics for extracting information about the degradation behavior, such as feature selection, feature extraction and dimensionality reduction. Novelty in the work has been directed in CI construction by means of feature fusion technique and threshold selection. CI can be used to assess the health status of the monitored component and predict the RUL using two different data-driven approach. A detailed description along with the mathematical expressions in elaborating the stochastic and adaptive filtering approach, for estimating the RUL were featured.

Chapter 5 presents a data-driven prognostics method for health assessment and RUL estimation of automobile component. The effectiveness in the construction of a reliable CI and its dependency to classify and detect the diverse state-of-health of various systems has been realized. Based on the machine learning and adaptive modelling approach, this CI might be utilized to improve the performance of data driven fault detection methods. The method uses exponential degradation modelling and adaptive filtering methods, namely PF, UPF, *i*-UPF to map the relation between sensor data and degradation behavior, thereafter, RUL is estimated. Finally, the results of applying the proposed method on a real-life application, namely clutch motor under three different loading conditions has been carried out in the present chapter.

Chapter 6 elaborates the comparison in the RUL prediction results of the three PF variants. Superiority of the approach and its dependency on the resampling techniques is discussed on the basis of RUL prediction error and other accuracy metrics. The optimal choice of the proposed PF variant helped in achieving robust results.

Validation and verification of the model was conducted using the benchmark Lithium ion battery data from Prognostics Centre of Excellence, NASA Ames Research Centre.

Chapter 7 concludes the research work developed in this thesis and discusses the perspectives and future work.