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Review of Health Prognostics and Condition Monitoring of Electronic Components

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ABSTRACT To meet the specifications of low cost, highly reliable electronic devices, fault diagnosis techniques play an essential role. It is vital to find flaws at an early stage in design, components, material, or manufacturing during the initial phase. This review paper attempts to summarize past development and recent advances in the areas about green manufacturing, maintenance, remaining useful life (RUL) prediction, and like. The current state of the art in reliability research for electronic components, mainly includes failure mechanisms, condition monitoring, and residual lifetime evaluation is explored. A critical analysis of reliability studies to identify their relative merits and usefulness of the outcome of these studies' vis-a-vis green manufacturing is presented. The wide array of statistical, empirical, and intelligent tools and techniques used in the literature are then identified and mapped. Finally, the findings are summarized, and the central research gap is highlighted.

INDEX TERMS Reliability methods, condition monitoring, faults and failures, prognostics, diagnostics.

I. INTRODUCTION

As the technology is advancing at an exponential rate, the design of electronic products and systems also trend towards miniaturization, integration, multi-function, and low cost. An early-stage failure prediction is vital for the reliable, successful, and long-lasting operation of electronic components and devices [1]. In the era of integration, millions of components are combined on a small-sized chip; the failure of one component can initiate the failure of the complete device, which leads to escalating the global problem of e-waste. The research study suggests that by the end of 2020, the amount of worldwide e-waste generation is expected to exceed 50 million tons, including 17.5 million metric tons of small devices, lamps, and components; 9.1 million metric tons of big gadgets or devices. The freezing and cooling equipment contribute 7.6 million metric tons, whereas computers and connected IT components are responsible for 10.5 million metric tons of screens [2]. The various electrical parameters and environmental factors influence the operating parameters of electronic components and devices, cause faults or failures before the prescribed lifetime, as mentioned in the datasheet. The literature suggests that various factors affect the performance and life of electronic components, i.e., temperature, humidity, vibration, dust, stress, etc. Fig. 1. shows the various influential parameters.

The problem of e-waste is accelerating globally, at the rate of 4% to 5% annually. Out of waste and discarded material, numerous electronic components tend reusability.

Failure prediction depicts the time to failure, which helps the user to estimate the reusable potential of the component. In such a manner, electronic waste will be reduced, which will

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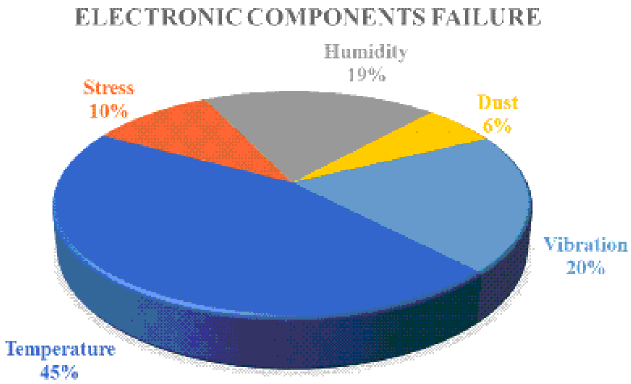

FIGURE 1. Influential factors for electronic components.

lead to green manufacturing. The various failure prognostics techniques and reviewed their performance indices and design trade-off. It has been further explored that voting techniques are having a higher rate of parallel hardware redundancy. Although, this technique is feasible to detect hard failures, while subtle detection degradation in components behaviour, it faces many difficulties. The innovation-based detection system can be changed to employ the residuals of an existing filter for better use and ease.

This paper is further organized into three sub-sections. The first section relates to the condition monitoring of the electronic components that analyze the root cause of faults and failure. In the subsequent section, the health monitoring of various active and passive electronic components is discussed. The diagnostics, prognostics, and maintenance of electronic components are explored in this section. The techniques for estimating the remaining useful lifetime (RUL) are reviewed in the third section. The experimental, empirical, and data-driven techniques are explored and discussed in this section.

II. CONDITION MONITORING OF ELECTRONIC COMPONENTS

The electronic components are widely used in almost every design and manufacturing industry. The failure of electronic components may lead to a complete breakdown or shutdown of the system. The various researchers have studied the failure of various electronic components and their failure detection techniques. The condition monitoring is a technique that assesses the health and condition of components or equipment using different diagnosis and prognosis techniques. The appropriate remedy is suggested based on the outcome of condition assessment so that any kind of failure or fault can be prevented. The process of condition monitoring is shown in Fig. 2.

A. CONDITION MONITORING OF CAPACITORS

Due to low cost and space effectiveness, an electrolytic capacitor is extensively used in control applications and power systems [3]. As per military handbook MILHDBK-217-F, electrolytic capacitor is considered as one of the most expensive passive components in control systems and power electronics [4]–[6]. Fig. 3 shows the fishbone diagram for an electrolytic capacitor. They discussed the electrolytic capacitor as the most critical component, which is majorly responsible for most of the breakdowns, and it can fail even at a temperature of 25°C. But, the internal temperature is considered as a limiting factor for unexpected derating or destruction of the electrolytic capacitor. As suggested by Evox Rifa [7] (a) in the technical note, heat is the most significant factor which affects the operational life. As heat enhances, the internal temperature of the electrolytic capacitor tends to increase, which can cause capacitors to fail. Researchers have reviewed the failure mechanism of the non-solid category of electrolytic capacitors [3], [6], [8], [9].

The cause and effect diagram for an electrolytic capacitor is depicted as in Fig. 3. As the electrolyte evaporates, the total volume of electrolytes reduces, which causes the capacitance to decrease and equivalent series resistance to increase. ESR has a growing effect on temperature, i.e., as the ESR increases, the temperature also increases, which further tends to evaporate the electrolyte, and the process will go on [10]. So, as the end of life is considered, ESR is regarded as the most influential factor, as compared to other factors. An old rule of thumb that the failure of an electrolytic capacitor depends on the loss of electrolyte [9], [11]. The failure of the electrolytic capacitor is noticed when its 40% of the electrolyte lost, which consequently increases the value of ESR. Whereas Evok Rifa (a) has stated a condition to detect the life-end of an electrolytic capacitor is, when the equivalent series resistance has increased by two times its initial value, then the capacitor is said to be failed [7]. As per (Parler,b), EIA standard IS-749 has been used by Cornell Dubilier, which specifies that when ten per cent of electrolytic capacitors are failed due to parametric failure and ten per cent are failed due to open or short circuit and when the ESR final value is 200% of its initial value, that period is considered as lifetime of electrolytic capacitors [12]. The variation of temperature and ESR with frequency [13], stated that as the frequency level reaches too few kHz levels, the equivalent series resistance becomes the major factor which decides the capacitance [5]. Considered capacitor as the most critical component in the electronic industry, which needs special care and attention to be paid for condition monitoring and health prognostics, by specifying several examples [14]–[16]. Various methods have monitored the health of the electrolytic capacitor. Observed the life of electrolytic capacitors by considering ESR as a critical factor [5], [8], [13]. The real-time diagnostic method based on the evaluation of electrolyte evaporation and the value of ESR to estimate the derating or deterioration status of an electrolytic capacitor. The predicting method using the least mean square algorithm based on adaptive filter modeling [17]. The condition monitoring and failure identification methodology of electrolytic capacitors consider ESR as a critical factor. They have proposed the methods so that the faulty component can be replaced

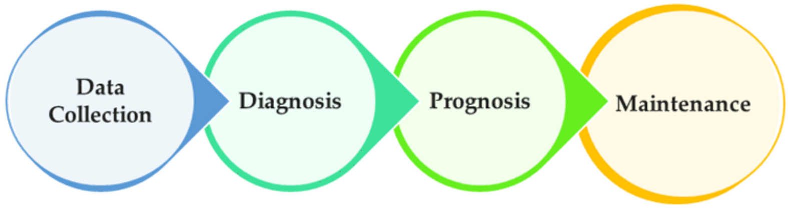

FIGURE 2. Condition monitoring process.

before the actual failure occurs. The methodology to identify faults and failures is based on Kalman filters, gradients, and recursive LMS algorithms as well as continuous-time models so that necessary preventive and maintenance action can be taken against faulty components [18]. While choosing the capacitors, the correct rating of temperature, frequency, and voltage must be selected. For X7R and C0G ceramic capacitors, presented time-based failure models at various applications [19]. Rashmi *et al.* use an accelerated life testing method to explore the failure of electrolytic capacitors. The main concern is to follow the weight of the electrolytic capacitor. When the capacitor is put under thermal stress, the heat starts increasing, and electrolyte starts evaporating. The reduction in weight of the electrolytic capacitor is the crucial parameter of reduction in the electrolyte, which leads to failure of the electrolytic capacitor—further, the method to find critical time using accelerated testing methods. The period at which ESR has been reduced to 200%, the corresponding lifetime is noted for the respective component. In such a way, it saves the experimental time to estimate the overall lifetime of the component [20].

B. CONDITION MONITORING OF OPERATIONAL AMPLIFIER

The effect of pulsed ionizing radiation on an operational amplifier and complementary BJT [21]. At the intermediate stages, the failure induced by ionization has been identified. Around complementary bipolar junction transistors, follower mode has been constructed and investigated the effect of emitter photocurrents of both configuration p-np as well as np-n. It has been found that photocurrents flow in the opposite direction [21]. In this manner, both facts are conflicting with each other. In the case of the operational amplifier, the probabilistic safety assessment (PSA) technique is used for evaluating the safety of a nuclear power plant. New technology is proposed, which predicts the failure rate. By considering the effect of diagnosis function in PLC, the calculated failure rate is better than the conventional failure rate [22]. The failure of solder joints is analyzed under the influence of temperature, vibration, and other stress parameters [23]. Condition monitoring of solder joints for the reliability of SnAgCu lead-free products, solder joints are the critical parameter to be observed. Investigate the influence of simulation methodology on the growth of joint cracks of solder parts [24]. They have used ANSYS 5.6 simulator and crack growth previous record to ascertain the correlation between growth and crack initiation. Life prediction and assessment of lead-free solder joint have been investigated. To verify the thermal fatigue, the life of the PBGA assembly, which has to lead to free solder joints with stress has been placed on the design of the reliability concept [25]. The review of two different state-of-art simulation approaches based on degradation [26].

C. CONDITION MONITORING OF FIELD-EFFECT TRANSISTORS

For MOSFET, a novel SPICE based simulation technique is proposed, which targets the drawbacks of previous technologies. Although these two degradation-based techniques are based on the same physics of failure model, reliability has been addressed from dissimilar viewpoints [26]. So, both models are equally valuable for designing and manufacturing phase as well as for the end-users. Health monitoring of electronic components is presented using a continuous-time Markov chain with Cox's proportional hazard model. The degradation analysis of power MOSFET is performed using accelerated life testing, and a model for parameter estimation is proposed [27]. While designing a chip, the designer uses the degradation-based model to analyze the presence of design-susceptible components in the chip. All the designers and users assume that failures are random and ascendable so that failure rate-based technique can be imposed. The silicon carbide power MOSFET is analyzed under short circuit stress, and its degradation behaviour is explored using trap analysis [28] It is further understood that design does not dominate any of the failure modes of the circuit. Otherwise, the manufacturers and designers need to explore advanced methods to locate a more critical failure mechanism.

D. CONDITION MONITORING OF DIODES

The reliability of photonic devices continues to be a challenging issue. For early reliability predictions, a sublinear model based on experimental data for 500–1000-his proposed. The accuracy of early model predictions is assured by minimizing measurement errors [29]. The failure analysis of Schottky diodes is studied using derating rules. Experimental validation is proposed for the reversed polarized Schottky diodes; results are compared with derating rules published by the European Space Agency [30]. A comprehensive review of Light Emitting Diode (LED) failure modes and mechanisms is presented. The mechanical stability of an LED is

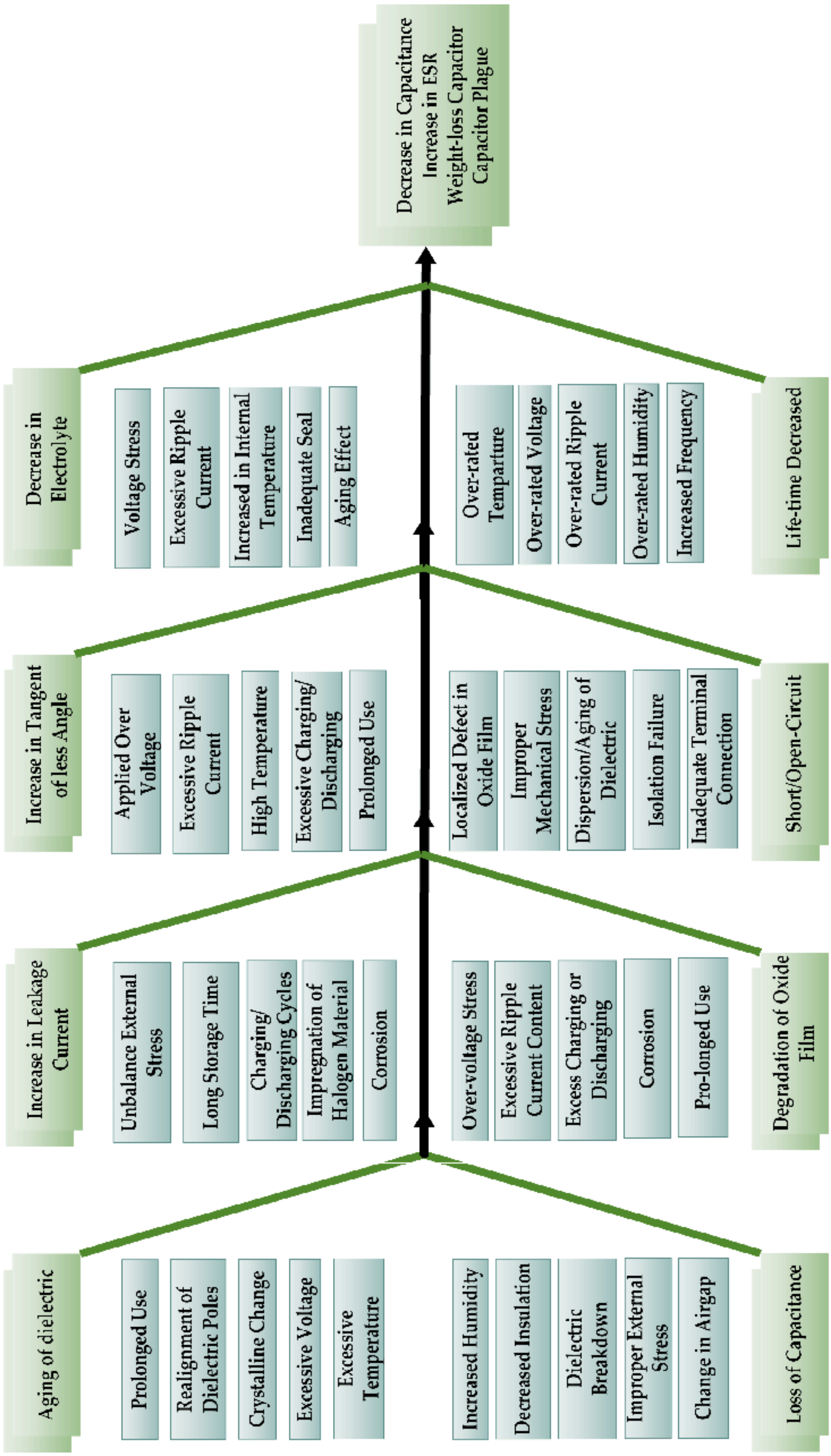

FIGURE 3. Fishbone diagram of electrolytic capacitor.

explored by a solder heat resistance test as well as temperature cycle tests [31]. The military handbook empirical method and Markov reliability models are employed for reliability analysis of diodes and concluded that diodes are more sensitive to temperature cycling [32].

E. CONDITION MONITORING OF INSULATED GATE BIPOLAR TRANSISTOR (IGBT)

In an inverter, incorrect wiring or mounting of an IGBT could cause module destruction. Based on the wire bond and solder joint, a reliability prediction model is proposed to compute the system reliability of the electronic power model. It is further explored that during power cycling, temperature amplitude, and inhomogeneous component structure, degradation of IGBT accelerates [33]. Under extreme operating conditions, a systematic methodology is developed for Trench Insulated Gate Bipolar Transistor (T-IGBT) failure mechanisms and identifies the cause of failure [34]. The reliability assessment of IGBT is presented through a case study of IGBT based power inverter module, and the degradation behaviour of IGBT is analyzed through a machine learning approach. The failure of IGBT is explored at accelerated environmental parameters and mechanical stress [35]. A failure model for IGBT based photovoltaic (PV) systems based on the ageing effect is discussed. It is also concluded that bond wire fatigue is the critical parameter, which leads to shortening the remaining useful lifetime of IGBT [36]. The residual lifetime of insulated gate bipolar transistors (IGBT) is explored using mathematical indices, and its performance is analyzed at various critical parameters [37].

F. CONDITION MONITORING OF THYRISTOR

The thyristors are having a wide range of applications, from dimmer to high voltage power transmission. The failure mechanism of silicon carbide super-gate turn-off thyristors(GTO) is analyzed, during extremely high current density pulsed operation, using the experimental approach and computer-aided simulation [38]. For accessing the reliability and temperature life model of thyristors, in the HVDC converter system, HALT testing at extreme stress levels is conducted, and feasibility is studied [39]. Accelerated life testing based experimental approach is used for analyzing failure in thyristor. An intelligent system is designed for the reliability model of the thyristor. Artificial intelligence techniques, i.e., artificial neural networks, fuzzy logic, and adaptive neuro-fuzzy inference system, are explored, and a graphical user design interface is framed for users. Accuracy of all the techniques is accessed and compared [40].

G. CONDITION MONITORING OF SENSORS

Highly reliable assured sensors need in-depth knowledge of its failure modes and analysis. Reference [41] used neural network-based analysis for fault diagnosis and identification of sensors. Reference [42] used principal component-based fault detection for sensors. They proposed a fault diagnosis scheme based on squared interval form of residual vectors, and the proposed system was validated using Monte-Carlo simulation. The reliability of ceramic sensors was assessed by [43]. A test protocol was established by [44] to evaluate the reliability of commercially available hydrogen sensors. Reference [45] estimated real-time identification of sensor failure. Life analysis of the temperature sensor was done by [46]. They further explored the free replacement warranty policy for temperature sensors.

H. CONDITION MONITORING OF NANO-ELECTRONICS

Nanoelectronics has emerged as a revolutionary change in the electronics industry, but its reliability assessment has become a challenging issue. Reference [47] explored the product quality of nanoelectronics components using a system dynamics approach. Reliability of nano and micro filled conductive adhesives were assessed by [48] by IR reflow, thermal cycling, and pressure cooker test. Very less research has been conducted in Nanoelectronics and associated parts. The various failure modes of electronic components and devices are enlisted in Table 1.

III. HEALTH MONITORING OF ELECTRONICS COMPONENTS

Prognostic and diagnostic techniques assess the current health of electronic components, which further determines the residual life of the component. Fig. 4 summarizes the process of health monitoring, starting from data collection to maintenance of electronic component, as per decision given by diagnostic and prognostic process. The method initiates with the data collected from various sensors and systems, and it grows towards fault detection, root cause diagnosis, and optimization of the system. Life estimation is decided by the prognosis method, and necessary repair/maintenance is scheduled as per the decision.

A. DIAGNOSTIC OF ELECTRONIC COMPONENTS

The diagnostic is a process to determine the problem or fault in a machine, system, or component and evaluating the reason(s) of fault. Also, failure may have processed within the system or device and appraising the condition or susceptibility of such a system or device either during working conditions, off-shelf, or under development stage. Table 2 depicts the comparative analysis of various failure techniques.

To support globally integrated manufacturing activities, propose the remote prognostic, diagnosis, and maintenance system [49]. They also introduce remote diagnosis techniques to be developed for their globally integrated system. The single fault, as well as multiple faults, and study both gear fault and bearing fault in the drive-line [50]. Wavelet transforms to process the real-time domain vibration signals, and then these preprocessed signals are used in the drive-line. Neural networks are used to investigate the fault and identify the specification of a fault occurring in the model drive-line.

Furthermore, it is explored that, by using multilayer artificial neural networks, single faults, as well as multiple faults, are successfully classified into distinct groups. Using a

TABLE 1. Device types and failure modes.

Device type	Failure mode	Device type	Failure mode
Capacitor, aluminium, electrolytic, foil	-Short -Open -Electrolyte leak -Capacitance reduced	Capacitor, paper	-Short -Open
Capacitor, ceramic	-Short -Change in value -Open	Capacitor, mica/glass	-Short -Change in value -Open
Capacitor, plastic	-Open -Short -Change in value	Capacitor, tantalum	-Short -Open -Change in value
Capacitor, tantalum, electrolytic	-Short -Open -Change in value	Capacitor, variable, piston	-Change in value -Short -Open
Diode, general	-Short -Open -Parameter change	Diode, rectifier	-Short -Open -Parameter change
Diode, silicon control rectifier (SCR)	-Short -Open	Diode, small-signal	-Parameter changes -Open -Short
Diode, TRIAC	-Failed off -Failed on	Diode, thyristor	-Failed off/on -Short -Open

TABLE 2. Comparative analysis of failure techniques.

Techniques	Application Stage	Overview
FHA (Fault Hazard Analysis)	Development stage	An individual component; whose failure can affect the entire system.
FMA (Failure Mode Analysis)	Design Phase	It identifies how failure could occur and preventive measures for safety.
FEA (Failure Effect Analysis)	Under fault and failure	Fault analyzing for every component, comprising of a complete system.
FMEA (Failure Mode and Effect Analysis)	Manufacturing and Assembly	Detection, Diagnosis, and Correction.
FMECA (Failure Mode, Effect and Criticality Analysis)	Design and Manufacturing	Identify critical failure modes and safety hazards. They were used for maintenance planning.
FTA (Fault Tree Analysis)	Under fault and failure	top-down approach with deductive failure analysis
ETA (Event Tree Analysis)	Design and Manufacturing	Risk assessment tool using probability. Stops the fault to accelerate further.

multivariate state estimation technique using the Bayesian network, explain the response of feasibility study and provide both faults diagnostic as well as fault estimation competencies for the Space Shuttle Main Engines (SSME) [51]. In their research, they simulate various single sensor failure and five-component failure models for correct prognostic and diagnosis. The output of simulation shows that it is a feasible technique for fault estimation and fault diagnosis. Using artificial neural networks ANN, suggest a method for fault diagnosis and prognostics of rolling element bearings [52]. Time-varying failure rate and weather conditions are used to analyze the failure of PV systems, in contrast to the conventional failure model [53]. To select the diagnostic methods and techniques decision-making model, mostly used in predictive maintenance programs [54]. The suggested model uses the integration of tools such as factor analysis (FA) and analytic hierarchy process (AHP). This model is validated in screw compressors, where a combination of lubricant and vibration analysis is used. For condition monitoring applications, A fuzzy logic-based expert system precisely, prognosis, and diagnosis of the diesel engine through oil analysis [55]. A fault diagnosis method based on neural networks has been developed by [56]. In normal healthy operating conditions, a robust observer is designed to check and diagnose

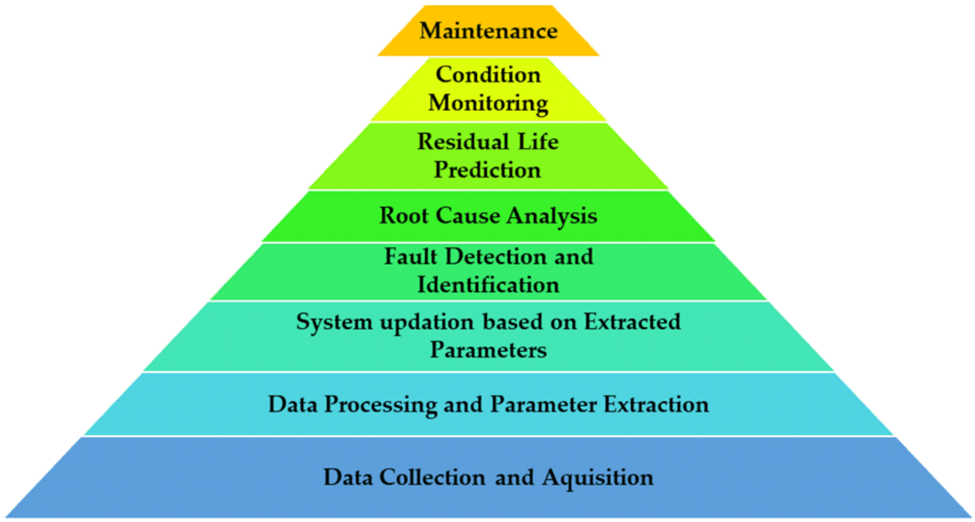

FIGURE 4. Health monitoring process of electronic components.

the faults and failures. Incorporating Neural Networks, various states have been analyzed and compared, which helps for fault prognosis. It also presents the implementation technique for fault estimation and fault diagnosis [57]. After checking their real-time availability for measurements, the proposed method considers two independent and self- directed modules, which are the survival of fault indicators (for monitoring purposes). In Fault Detection and Diagnosis (FDD) of gas turbine engines use a synergistic approach [58]. The methodology employs soft computing, statistics, and signal processing in a complementary behaviour to target fault estimation at transient conditions. Traditional failure detection and diagnosis methods use engine signatures acquired at steady-state conditions. However, using steady-state engine signatures, it is difficult to diagnosis emerging faults. Herein, only moderate faults are developed and detected. Using a fuzzy logic-based model and artificial neural networks, The review of various vehicle fault prediction techniques [59]. To model a fault estimation service, different variables have been studies. This method helps estimate and predict faults as well as useful as a precautionary measure to avoid tangible and intangible losses.

Vibration signal based condition monitoring, and the forecasting system to improve the specific critical equipment in an industrial plant are discussed [60]. To detect and diagnose faults and failures of heavy-duty diesel engines, Information modeling, and established databases for lubrication samples [61]. They propose a new methodology based Spectrometric Oil Analysis Programme (SOAP) of lubrication samples. The proposed technique is validated and analyzed for both the mean time between failure as well as accuracy in detecting the faults. As compare to prognostics, the fault diagnostics is widely researched. It includes the detection and classification of faults. Previously, the prognostic element has not been given much attention. This research attempts to review and study the prognosis element of condition-based maintenance (CBM) and its use in the manufacturing and design industry to prevent and identify the faults and failures. The Health monitoring paradigm of electronics components is shown in Fig. 5.

B. PROGNOSTICS OF ELECTRONIC COMPONENTS

The prognosis is a technique that makes use of the acquired condition monitoring data to predict a variety of useful information relating to the condition of the machine or equipment under study. It is an estimation technique for residual life of a component/ equipment or device, probable condition of the device after the specified time, and the probabilities of reliable operations henceforth. The advantages of the prognostic technique, as the prediction of faults and failures, reduce repairing cost and reduce unforeseen failures [62].

Pijnenburg *et al.* survey the pitfalls of existing probabilistic models. They use statistical analysis using regression type, with explanatory variables acting additively on the hazard function [63]. Siddiqui *et al.* treat the remaining useful life as a random variable that represents the residual life of a unit or entity [64]. Lim *et al.* consider the variable mean residual life (MRL) as a life distribution parameter [65]. Tang *et al.* review the remaining life as a random variable and using various distribution functions; its reliability function is represented its asymptotic behaviour [66]. Hong Suh *et al.* specify continuous and discrete wavelets for equipment prognosis and diagnosis [67]. For gear fault diagnosis and prognosis, they explain the wavelet-based techniques. Using plant operating data, Bom *et al.* explore the Weibull statistics as a useful tool in estimating the residual life of a component [68].

Weibull distribution is used to analyze the reliability of electronic devices using the rule of power law. This study also summarized the sensitivity of hyperparameters under different voltages [69]. Expose the multi-layer perceptron neural networks in condition monitoring [70]. To determine the residual life of a component, present a life consumption

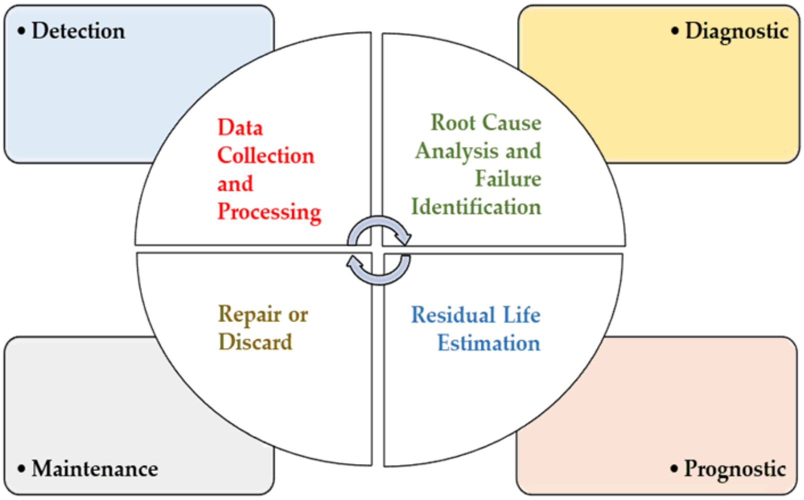

FIGURE 5. Health monitoring paradigm of electronics components.

monitoring methodology [71]. Due to vibration and temperature, damage accumulation is measured using the physics of failure in combination with recorded data. The damage data information obtained from the test board measures the remaining life of the solder joints. Here, two different methods, namely, direct method and iterative method, are applied to predict the residual useful life of a system. Attempt to forecast reliability by using neural network techniques using the history of failures [72]. The reliability study of surface-mounted on printed circuit boards (PCBs) is conducted using cycling thermal loading, and lifetime is explored [73]. The review the existing residual life analyzing and estimation techniques that are employed in gadgets and electronic systems [74]. A health monitoring technique is proposed, which estimates the remaining useful life of electronic appliances and components and employs this technique in spacecraft applications. For assessing the remaining useful life (RUL) of washing machine components, propose a complete two-step methodology for assessing residual life [75]. In the first step, using Weibull analysis, they utilize the mean time between failure data to assess the average life of the component. In the second step, they develop artificial neural networks and analyze condition monitoring and prognostic health data. At last, the residual life of the component is explored by integrating ANN analysis with Weibull analysis. In drilling operations, hybrid modeling technique for on-line assessment performance and prediction of residual life using vibration signals [76]. Using the wavelet packet decomposition (WPD) technique, features have been extracted from vibration signals. For analyze the health assessment of tool wear, a hybrid Logistic regression (LR) analysis with maximum likelihood technique is used. For estimate the RUL (remaining useful life), the Auto-regressive moving average (ARMA) model is then deployed. The proposed model is validated using drilling operations, and the same can also be implemented in other manufacturing processes.

Demonstrate an experimental methodology to assess the component's life [77]. They summarize that progression is directly related to acoustic emission. So, acoustic emission has become a strong tool for the health prognosis of gears. For reuse evaluation, investigate a new technique, based on the determination of a threshold value [78]. Review the various health prognostic techniques from different viewpoints such as tools, concepts, and approaches to figure out the realistic challenges of this methodology [79]. Assuming that based on this estimation, repairing and maintenance and the minimizing of prediction errors is meaningful. Here, they demonstrate a hybrid predictor based on the neuro-fuzzy ANFIS technique for prognostic health studies. The hybrid prediction technique estimates the residual life of electronic devices [80]. The benefits of moth the techniques are fused into this proposed methodology. Demonstrate the technique to estimate residual lifetime as well as reuse the capability of used electronic components [81]. The power semiconductor and capacitor are explored using physics of failure, under ageing effect, and feasibility of the multistate degraded system is analyzed [82]. For NIMH battery cells, The methodology to analyze remaining useful life for reuse purposes, so that battery can be reused, in case they are disposed of before the end of their life [83]. Artificial Neural Network technique is used for the prediction of residual life of machines [84]. For the life estimation of the washing machine's components, the vibration method [85]. Accelerated life testing is conducted, vibration signals are measured on electric motors. When the degradation state of equipment is not observable, suggest a methodology to analyze the reliability, and the mean residual life [86]. Use the latest developed models for predicting the residual useful life [87]. Explore the strengths and weaknesses of the different prognostic models and identify the relative efficacy of these models in different prognostic situations [88]. During the implementation of the process model, the advantages and necessity of Proportional Hazards Model (PHM) are discussed [89]. They propose an updating practice, where samples are generated during model implementation, and previous samples are updated. A simulation-based observation is carried out on a component degradation model. By this method of updating sample values, it is analyzed that more accurate reliability of remaining useful life is calculated. The generalized likeness prognostic technique for a similarity-based residual life estimation model [90]. Applications of the Gaussian model is discussed for time-based health monitoring of gear [91]. Gaussian model is used to explore the critical value of harmonic components. Gaussian model is a nonparametric model with the capability of flexibility and uncertainty estimation. Due to its enormous advantages, it is used for time series modeling and dynamic systems estimations.

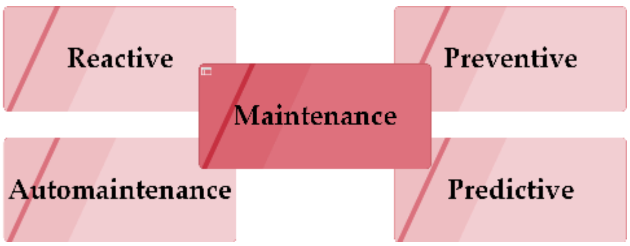

FIGURE 6. Types of reliability centered maintenance.

C. MAINTENANCE AND REMEDY FOR FAULTY ELECTRONIC COMPONENTS

Maintenance is a recurring and regular technique to keep specific equipment or component healthy in a reasonable operating condition so that component or equipment will produce the expected outcome without the degradation of service or derating of component life. There are four types of reliability centered maintenance in practice, namely reactive or condition-based breakdown maintenance (CBM), preventive maintenance, predictive maintenance, and auto maintenance [92], as shown in Fig. 6. In reactive or breakdown maintenance, the equipment and machines are repaired after failures occur. In preventive maintenance, equipment and tools are maintained before breakdowns arise to reduce the recurrence of collapse. Predictive maintenance determines the condition of the on-shelf component to predict when maintenance is required. Auto maintenance means periodically analyzing, cleaning, and maintaining equipment after a regular interval. The latest research studies have presented the fact that ageing-related failures can be supported using preventive maintenance. But, condition-based maintenance indicates the health condition of the device, it generates an alarm when the device or component fails to produce a specific result, and derating condition has been monitored. Nowadays, the manufacturing and design industry attracts more to condition-based maintenance (CBM). The main motive of condition-based monitoring is to achieve reliable, extended life and cost-effective operation of critical electronic equipment such as aircraft, spacecraft satellite, or hydropower plants. The researchers have utilized condition-based maintenance for health prognostics of components [93], [94]. In condition-based maintenance, collected health data of equipment using vibration analysis, acoustic analysis, or oil analysis, and then data has been analyzed and processed [17], [95]–[97].

By condition-based maintenance approach, health monitoring of device or component has been explored, and residual life or mean time between failures has been estimated. In CBM, health prognostics and condition monitoring of device or component are two main issues to be identified. An overview of the use of maintenance optimization models has been given by Liao *et al.* [98] and Dekker [99]. For single unit and multi-unit systems, review various maintenance policies, and compare all the existing plans [100]. They have put more emphasis on the single-unit system rather than a multi-unit operation. A relationship between various maintenance policies has also studied. To continuously deteriorating and derating a single unit system, investigate the analytical modeling of a condition-based inspection/replacement policy [101]. Considering the inspection schedule, and replacement threshold value as decision parameters, a new maintenance policy for multi-level systems has been proposed for gradually deteriorating single-unit systems. From the viewpoint of life cycle management, review the adaptive role of maintenance. They suggest a maintenance framework containing maintenance activities during the product life cycle [102]. To set up an industrial plant, an analytical model to select the most appropriate prediction technique [103]. The new technique by integrating the condition-based maintenance policy with sequential imperfect maintenance policy with Condition-Based Predictive Maintenance (CBPM) [104]. Due to improper maintenance, a new maintenance policy is proposed, which is concentrated towards higher reliability and based upon the degradation analysis. In the implementation of total productive maintenance (TPM), focus on the systematic identification of obstacles [105]. Propose a predictive maintenance technique based on sensory updated degradation and derating method [106]. This proposed policy explores contemporaneous degradation models. In cumbersome process industries, for critically examine the components or assemblies, a summarized review of the optimization models so that preventive steps for repair or replacement of faulty components/assemblies can be grasped [107].

IV. REMAINING USEFUL LIFE (RUL) PREDICTION TECHNIQUE

The residual life of the component instructs the user to replace or reuse the component as per the current health status of the component. Fig. 7 shows the various techniques for RUL prediction and assessment. Remaining useful life (RUL) is a metric of component's life that guides the user to reuse the component again. Fig. 7 demonstrates the various techniques which help predict the remaining useful life [108]. The knowledge-based or human experience predicts the upcoming failure or fault. The prediction

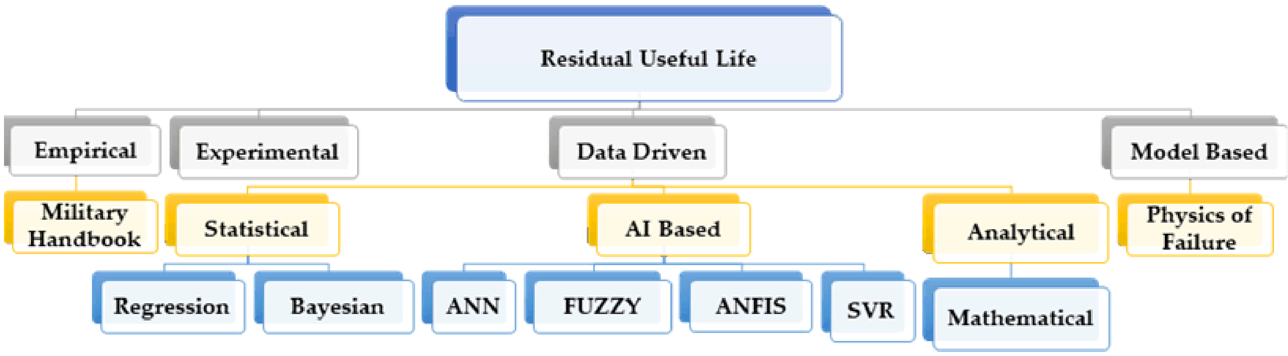

FIGURE 7. RUL prediction techniques.

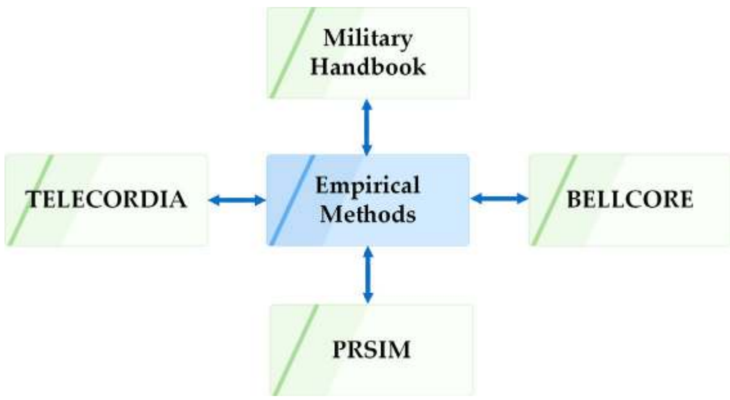

FIGURE 8. Empirical methods for RUL prediction.

based on historical field data or human experience is not always accurate. So, statistical, analytical, or model-based techniques are more successful than experience-based techniques. Reviewed all existing methods and models of failure prediction[109].

A. EMPIRICAL METHODS FOR RUL PREDICTION

Empirical standards are failure data collection resources which are accepted by recognized industries and government organization. Military handbook, Bellcore, Telecordia, RIAC, etc. are the primary sources of empirical standards. Military handbook is one of the empirical models that is based on experience and survey-based data. The MIL-HDBK-217F and MILHDBK-217-revised are two widely used versions of the military handbook. The failure data is mostly from US army maintenance data, test results, public information, or field data. A topology is proposed for high gain dc-dc converter reliability analysis using the military handbook, and simulator n15 are opted to prove the theoretical results [110].

Similarly, other empirical standards like Bellcore, TELECORDIA, RIAC, etc. explore components and have collected their failure data. The empirical methods are shown in Fig. 8. The different standards are useful in various applications, e.g., for military applications. MILHDBK-217F is used, and for telecommunication applications, the use of TELECORDIA is famous. Table 2 compares the properties of the military handbook and TELECORDIA, analyzed topologies and performances of five types of converters using military handbook [111]. Reliability analysis of the digital processor module using part stress method, incorporating military handbook data (MILHDBK-217F) for reliability prediction of nuclear power plant [112]. In such a way, the military handbook has used as a powerful tool for the reliability prediction of critical components and devices. Web-based commercial software for failure prediction because rapidity to produce the response also matters along with the accuracy [113]. Then, the comparison has been made of military handbook and Bellcore method with commercially available web-based software PRISM. Failure rate calculations have been validated. Although it is easy to use pre-collected data, as the technology advances and due to change in environmental parameters, most of the data in such standard books are not up to date. The various reliability models are compared in Table 3.

B. EXPERIMENTAL TECHNIQUES FOR RUL PREDICTION

Experimental methods are although time-consuming, but the data is realistic. The respective component or device is kept on the different stress conditions, and the behaviour of the component or device is assessed. The accelerated life testing

TABLE 3. Comparison between various reliability prediction models.

Parameters	Reliability Prediction Models		
	MILHDBK-217F	**Telcordia SR-332/Bellcore**	**NSWC-98/LE1**
Application of Reliability Models	Military Applications	Telecommunication Industry	Mechanical Industry
Failure Calculation	Failure in Time (FIT) per million hours	Failure in Time (FIT) per billion hours	Use FIT along with material properties and operating environment modes.
Environment Classification	Fourteen environment classifications (Three ground, eight air, one space, two seas)	six environment classifications (Four ground, one air, one space)	Three environment classification (two naval and one ground) along with material properties.
Device Model	SMT is available	SMT is not available	SMT is not available
Component level	lesser number of gate count IC	larger gate count IC	Mechanical components
Useful Life Analysis Technique	the steady-state useful life failure rate	Infant mortality rate and steady-state useful operating life failure rate	Part count and part stress
Manufacturer	Military handbook	Bell Communications Research	Naval Surface Warfare Center

method is the best method to explore the response of the component or device in a particular set of conditions in less time. The statistical techniques to analyze the accelerated life testing method using step-stress tests [114]. For step-stress accelerated life testing, develop a Bayes model [115]. The accelerated life testing processes on a different set of capacitors and analyze the most stable and reliable set of capacitors by calculating the final capacitive and ESR failure time [116]. The experimented on electrolytic capacitors to find out its life time [117]. This method proves to be a practical predictive method. He has exposed the capacitors on accelerated thermal and voltage environment and noted the survival time of all the capacitors and estimated the total lie time of the component. The thermal stress test of electrolytic capacitors and ensured the weight of capacitors. Declination in weight represents the evaporation of electrolyte, which in turn increases the capacitance and decreases ESR [118]. Such a way, accelerated life testing has proved as an effective way to obtain the residual useful life, so that necessary action can be taken before permanent failure[20]. Using accelerated life testing and DOE approach explored the component's reliability incorporating the physics of failure [119, 120]. Accelerated thermal electric testing is conducted for the development of electronic products, at elevated temperature and electrical load[121].

C. DATA-DRIVEN METHODS FOR RUL PREDICTION

The data-driven reliability technique is about analyzing the data and estimate the reliability of components through statistical as well as intelligence techniques.

1) STATISTICAL METHODS

Statistical methods are describing or summarizing a collection of data. There are different techniques. Regression and Bayesian techniques are the widely used statistical methods for RUL prediction.

2) REGRESSION METHOD

The regression line describes the relationship between the predictor variable and response. explore a technique to analyze the equipment performance and to estimate the residual life of the electronic equipment [122]. It follows proactive maintenance practices. In the first stage, by considering the logistic regression concept with maximum-likelihood technique, a performance model is established. They discuss the practical situation using historical data or the non-availability of sufficient empirical data. In the proposed logistic model, using features of online data, Real-time performance is then analyzed. For fault and failure detection of actuators, The technique based on a data-driven approach [123]. Using Gaussian based regression method, for remaining useful life estimation of milling cutter, use an experimental approach, using a small set of data [124]. Based on regression models and time-series estimation methodologies, discuss a method for the condition monitoring of machines The case of metal cutting tools, the health prognostics, and condition monitoring is done by using Hidden Markov Models (HMM) [125]. They claim that using HMM, estimation of remaining useful life with higher accuracy is possible. The residual helpful life of bearings is predicted using a logistic regression model in combination with a hazard model [98]. Analytical expression using regression analysis for tool life, with decision parameters such as temperature, cutting speed, feed, and depth of cut [126]. The case of complex systems when it is challenging to measure internal variables or sensors are unable to access internal state variables, then how the residual useful life can be predicted[127]. The residual life estimation of the machine based on vibration analysis [128]. They suggest the hybridization of two models Generalized Auto-Regressive Conditional Heteroscedasticity (GARCH) and autoregressive moving average (ARMA) model. Propose a hybrid technique that integrates Logistic Regression (LR) with Relevance Vector Machine (RVM) to evaluate the actual degradation and

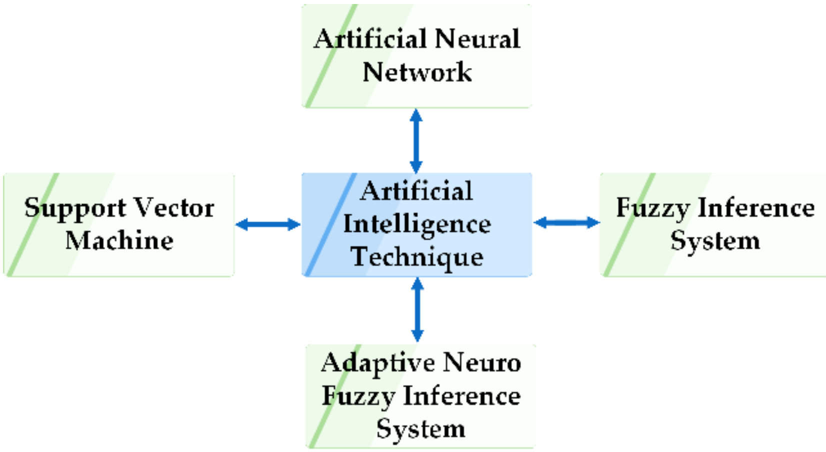

FIGURE 9. Artificial Intelligence techniques for RUL prediction.

estimate emerging failure until real failure takes place [129]. RVM analyzes the probability of failure after completion of the training process. The proposed technique is validated by applying the experimental data and simulated response to this machine. The result interprets the effectiveness of the proposed model. The similarity-based model is discussed for health prognostics and to estimate the residual useful life of the equipment [130]. The condition monitoring technique for drill bit [131]. They combine logistic regression with autoregressive moving average model and assess the residual useful life. The need and advantages of updating a proportional hazard model (PHM) [89]. New samples are extracted by the process of model implementation and estimate the remaining useful life of a system—the existing techniques for predicting failure before it occurs [87].

3) BAYESIAN METHOD

In inferential statistics and decision making, Bayesian logic plays a vital role. Here, the prior knowledge of historical events is used to estimate the upcoming events Construct an assistant for on-line shopping, which helps an e-shopper to choose the desired product from various on-line shops based on user personal choice and preference [106]. This proposed shopping assistant is developed based on value networks that extend Bayesian networks with user preference. This technique is validated by taking an example of on-line shopping for bicycles. This made the system more convenient and cost-effective. They review various methods for condition monitoring of the system. The practical applicability of Bayesian decision networks to review the effect of design decisions on the life cycle performance [107]. Apprising of Bayesian methods where real-time data of condition monitoring updates the stochastic parameters of exponential degradation models [108]. For monitored devices, they discuss a closed-form remaining useful life prediction model, using degradation models updated data. At last, accelerating life testing of bearings are conducted, degradation signals are extracted. The degradation data model and residual life model are applied to these degradation signals and estimated the residual life. The new methodology for the root cause analysis and review of the case study of workplace accidents such as floor-level falls [109]. This proposed methodology is based on the machine learning concept, such as the Bayesian decision network, which is trained using various algorithms such as support vector machines and fault tree approaches. Then responses obtained from various techniques are compared. The Bayesian network proves to be the best methodology for this research. The evaluation process of the residual useful life of complex systems, where accessibility of internal state variables is a problem [102].

4) ARTIFICIAL INTELLIGENCE (AI) METHODS

Artificial intelligence is concerned with programming computers to perform specific tasks more efficiently and that too at a higher pace, which in toto could be substantially better than what could have been achieved by humans.

The various artificial intelligence techniques are shown in Fig. 9.

5) ARTIFICIAL NEURAL NETWORK (ANN) METHOD

Artificial neural networks are one of the algorithms used in machine learning. The neural network technique is a technique where computational methods stimulate the behaviour of neurons. It explores the effect on computation time when the dataset is increased or decreased. Artificial neural networks help to predict, which is the best-suited model. Backpropagation neural network suggested back propagation neural network technique as a widely used technique in major industries as well as real-time applications, such as grading of fruits maturity [132].Radial basis function (RBF): using RBF and ANN, the remaining useful life of bearings were estimated by Gebraeel *et al.* [133]. For achieving more accurate RUL prediction in case of pump bearings, Zhigang *et al.* suggest an artificial neural network (ANN) based method subject to condition monitoring. Mazhar *et al.* integrated Weibull analysis with artificial neural networks model to predict the useful residual lifetime of components for reuse purpose [75]. Using historical data of condition monitoring [134], Zhigang Tian *et al.* discuss an artificial neural network approach [135]. Jihong Yan *et al.* suggest a useful technique for estimating the residual life of components by utilizing artificial neural networks approach and reliability method [136]. Genetic algorithm and Particle swarm optimization (PSO): Ozel *et al.* use neural network modeling for prediction of surface roughness and tool flank wear of various cutting conditions in turning [137]. Jesuthanam *et al.* discuss the case of surface roughness estimation, where a novel hybrid approach of Neural Network (NN) trained with GA and PSO is incorporated [138].

6) FUZZY INFERENCE SYSTEM (FIS) METHOD

In condition monitoring and health prognostics, knowledge from expert systems is mostly inaccurate. Therefore, measures of the uncertainties in expertise are required for an expert system to produce robust outcomes. In fuzzy logic theory, Uncertainty measures that are commonly used are probability and fuzzy member functions. In tool wear detection and end of life prediction, fuzzy logic and fuzzy set theory are extensively used. Using a fuzzy-based Bayesian technique, Yadav *et al.* propose a structured model for estimating reliability improvement during product development [139]. In turning operations, Jiao *et al.* develop a fuzzy adaptive network (FAN) to model surface roughness [140]. The fuzzy adaptive network has the capability of linguistic representation of complex and indistinct data set as well as the learning ability of the neural network. A model is established to validate the methodology, which represents the effects of machining parameters on surface roughness. Afterwards, this proposed model is validated by using the results from pilot surveys. Daniel *et al.* suggest the use of surface roughness prediction techniques using fuzzy-nets [141]. The main objective of this technique is to establish a hybrid fuzzy net- surface roughness prediction model that uses vibration data and predicts surface roughness of turned workpiece. Peter *et al.* develop a graphic user interface based on fuzzy logic, which monitors the life prediction of laser machines [142]. Sivarao *et al.* compare machine performance using neural networks and fuzzy logic [143]. Attarzadeh *et al.* suggest a fuzzy logic-based realistic model attain higher accuracy in software cost prediction. Sikorska *et al.* investigate the cons and pros of the primary prognostic model to deduce the real-time applications for prognostic models and review their utility in engineering prognostics and diagnosis areas [88]. For the tractive performance of the intelligent air cushion system estimation, Hossain *et al.* adopt an adaptive approach using fuzzy logic [144]. Wang *et al.* explore an experimental model having a small set of data, using Markov chain Monte Carlo simulation [145]. For failure prediction of the component, they utilize the fuzzy logic technique.

7) ADAPTIVE NEURO-FUZZY INFERENCE SYSTEM (ANFIS) METHOD

Lee *et al.* propose a method using an adaptive neuro-fuzzy inference system(ANFIS), that co-relates texture features of the surface image with actual roughness of surface [146]. Antony *et al.* use the design of the experimental approach using the Taguchi method in integration with the neuro-fuzzy model and provide deep insight for solving a multi-response optimization problem [147]. For nonlinear dynamic systems modeling, Golob *et al.* propose a decomposed neuro-fuzzy model and its evolutionary learning model that uses an optimized FIS technique [148]. To explore and estimate system performance with more accuracy, transparency, and efficiency, Xiao-Sheng *et al.* identify the forecasting problems with a Belief Rule Base (BRB) [149]. Chen *et al.* suggest a new prognostic method using a hybrid technique of adaptive neuro-fuzzy inference system (ANFIS) and high-order particle filtering [150]. The ANFIS is trained via machine historical and empirical failure data. Based on Neuro-fuzzy System (NFS) and Bayesian algorithms, Chen *et al.* suggest a novel approach for machine health conditions [151]. After training with machine data, the Neuro-fuzzy System (NFS), is used as a health prognostic model to predict the propagation of the time-based machine fault condition. From the comparison of actual and predicted data, the probability density function is created using a neuro-fuzzy system, and an online model update scheme is developed. By taking predicted data of model as prior information, Bayesian estimation algorithms updated the degree of belief, in combination with online measurements. The outcome of the experiment interprets that the proposed approach can predict machine conditions more accurately and efficiently.

8) SUPPORT VECTOR MACHINE (SVM) AND SUPPORT VECTOR REGRESSION (SVR) METHODS

Based on the statistical learning concept, Support Vector Machine (SVM) is a powerful reliability analysis technique, based on the learning system. It is one of the supervised learning algorithms, in which the learning machine is given a set of features (or inputs) with the output values. A support vector machine is an implicit tool for exploring nonlinear classification and function prediction. Chun-Hsin Wu *et al.* reviews the practical application of support vector regression (SVM). They predict travel times and analyses the traffic data [152]. To predict engine reliability, Chiang Hong *et al.* attempt to apply the support vector machine [153]. The result interprets that this support vector regression model has better performance than the conventional models. A new health prognostic technique is proposed by Zhao *et al.*, which is based on LS-SVM as well as wavelet packet transform [154]. Using an artificial neural network and support vector regression, Reddy *et al.*, trade with the development of accurate warpage estimation model for plastic injection moulded parts [155]. To predict surface roughness in end milling based on machining parameters. Wang *et al.* introduce the least square support vector regression (LS-SVR) method [156]. Tomar *et al.* propose a novel methodology that estimates the pretext operating margin by applying the support vector machine and compared different kernel functions with weight [157]. The suggest a hybrid technique, containing a probability approach and support vector machine approach (SVM) to estimate degradation [158]. It is summarized that the remaining useful life prediction using regression analysis, artificial neural networks, and Fuzzy logics are widely used. Moreover, it is found from the literature survey that Neuro-Fuzzy and support vector regression techniques are not extensively used for modeling tool life prediction problems. This lacuna seen is one of the factors motivating the author to take up aforesaid techniques for failure prediction of electronic components.

D. MATHEMATICAL MODEL FOR RUL PREDICTION

The mathematical model establishes a numerical relation between influential variables and their output response. Various researchers have been used mathematical tools and techniques for research problem identification and formulation, for example, linear and dynamic programming, linear and non-linear optimization, formulation and validation, etc. Most of the mathematical models are complex and non-linear, where heuristic methods have been used to find the optimal solution. In [159] addressed the reliability assessment of assembly parts in the remanufacturing context. A hybrid linear column-creator technique was used to solve problems, which consumed milliseconds. The disassembly issue was addressed by [160]. They assessed cost and time taken by the end of life products by graph-based linear programming with a decision-making approach. The quality and value of disassembly and reassembly concepts were targeted in this paper. Reference [161] performed a cost-benefit function using fuzzy logic for reverse logistics and closed-loop supply chain. Reference [162] used the stochastic model and reliability theory for the assessment of degradation products. For the refurbishment of obsolete electronic components [163] suggested decision-making software. They have tried to ensure the replacement of end of life products using testing and conduction of case study. For reliability assessment of cell phones, [164] discussed quality based tests using the simulation environment, for replacement or refurbishment process. A linear programming based decision-making technique was formulated by [165]. They used the Markov chain model and mathematical mapping using simulation-based environment. Reference [166] discussed general reliability prediction for stochastic models. Reference [167] used the Taguchi approach for the design of experiments and analyzed the reliability of cutting tools. For-profit maximization [168] used particle swarm optimization. Consumer behaviour was investigated by [169] using utility theory. Quadratic programming with a sequential approach was used by [170]. They used a sequential model for optimizing non-linear models. Reference [70] used Brownian motion for the reuse concept of faulty products.

E. THE MODEL-BASED TECHNIQUE FOR RUL PREDICTION

The reliability prediction using empirical models are not accurate and do not identify the root causes. With the evolution of the latest technologies and devices, the need for physics of failure technique becomes high. This type of reliability technique considers failure modes and analysis to identify the time to failure and cause behind the failure. For exploring the reliability of semiconductor devices, Various physics of failure techniques [171]. The wear-out mechanism is deeply investigated using the physics of failure, and the life of components is estimated with higher accuracy. It identifies and models the dominant failure mechanism. The products are exposed to an accelerated level of stress to explore the minimum and maximum limit of operation. Using acceleration factors has reviewed the effect of environmental factors and electrical parameters, i.e., temperature and voltage, on the performance of capacitors [172]. They have calculated actual life by considering acceleration factors of voltage and temperature. The reliability prediction approach is employed for power electronic converters within a useful life and wear-out period, using converters modeling the random hardware failures [173]. Table 4 shows the comparison between PoF and MILHDBK.

Monte Carlo simulation: proposed a FORM and physics-of-failure based approach using Monte-Carlo simulations [174]. Incorporated Monte-Carlo and physics-of-failure with history standards in qualification testing for prognostics health management [175]. Graphical failure analysis: For medium scale industries, proposed a hybrid model combining empirical methods with graphical failure analysis by POF of failed parts [176]. Statistical and deterministic approach: explored statistical and deterministic approaches simultaneously to obtain accurate life expectancy information and to create a reliable product [177]. FEM based PoF: combined the design of experiments with FEM based physics-of-failure models to define response surface methods for plastic IC packages and make recommendations on increasing reliability. Arrhenius model: discussed the challenges in the estimation of reliability based on warranty data and proposed a method for estimating component reliability using an accelerated life test model [178]. Stochastic based model: accelerated life testing is incorporated to determine the momentum of a wheel with physics of failure [179].

V. CRITICAL ANALYSIS

This paper is bifurcated in three significant subsections. The documents related to the reliability prediction of electronic components are enlisted in one section. Most articles deal with root cause analysis of capacitors, operation amplifiers, bipolar junction transistors, field-effect transistors, etc. Still, a lot of research is necessary for the reliability exploration of advanced devices like memristors, FinFET, MEMS, etc. The multicomponent failure analysis is missing in this area of study. The reuse potential is least covered along with physical testing. Future extensions should investigate how the failure of one component affects the reliability of others and

TABLE 4. Comparison between physics-of-failure (PoF) and military handbook (MILHDBK).

Problem	Physics of Failure	Military Handbook
Model development	The models based on PoF supports probabilistic and deterministic applications	It cannot provide accurate design or reliability estimation, as data is outdated and assumption-based.
Root cause analysis	The root cause is identified.	The root cause is not identified. Wear-out issues are not targeted.
Accuracy	The accuracy level is higher than the military handbook.	As the military handbook is based on assumptions of constant failure rate data, so the accuracy level is low.
Device coverage	POF models are available for advanced and latest devices. Various computer tools are available for the reliability analysis of microelectronics devices.	Data is generally not updated. It does not cover new devices.
Arrhenius Model	Arrhenius model indicates the relationship between steady-state temperature and MTBF. It applies to POF.	The military handbook doesn't recognize explicit temperature variations.
Operating temperature	Failures based on temperature are explicitly considered.	Steady-state temperature effect analysis is not accurate, as it doesn't identify root cause and MTBF.
Data requirement	POF gives insight information on materials, stress levels, architecture, and predicts MTBF and identifies root cause analysis.	The military handbook doesn't explore material structure and architecture, failure modes, and root cause. Field reliability is not predicted.

what is the scope of recover the faulty component. The next section discusses the prognostic health approaches, which are further divided into three parts: (a) diagnostic (b) prognostic (c) maintenance of electronic components.

The papers discussed in this section is concentrated on root cause analysis and its remedial effects. It covers a wide range of issues like basic health assessment of components, cause and effect, damage and failure models, and corrective measures for faulty components. However, several other defects are not covered, including burn-in and warranty policies for refurbished components, condition-based reliability evaluation, multistage evaluation for reuse potential, etc. The last section of this paper targets the various techniques involved in remaining useful life prediction. This section deals with three themes: (a) empirical (b) data-driven (c) model-based methods. The papers presented in this section cover a variety of statistical, intelligent, and empirical models for reliability and residual life prediction. But, RFID based data acquisition, benchmarking, policies related to the degradation model based on time, and usage are highly ignored. The experimental method is mostly dealing with accelerated life test model, whereas other modes of testing should also be included.

VI. FUTURE RESEARCH

Most of the papers discussed component degradation, but very few articles proposed the refurbishment or reuse options after maintenance. Health assessment and real-time condition monitoring of end of life components so that refurbishment can be possible. Quality as well reliability should be tested for the refurbished or reused components. Rigorous condition monitoring should be done for the case, where multi-components are deployed along with a refurbished component. Various other experimental techniques should be addressed apart from accelerated life testing. Reliability related to different topics should also be investigated, i.e., data collection through RFID and experimental methods, validation and verification of collected data, real-time field survey data, frequency of faults or failures, the inclusion of expert opinion to modify the essential characteristics of components.

The reliability prediction of VLSI circuits and systems, memristors, OLEDs, FinFETs, smart sensors are highly ignored. Future work can be done to analyze its reliability. The optimized number and placements of components should be explored, which will save power, time, and cost as the Nano-electronics is growing with the accelerating rate. Reliability should be investigated for nanocomposite based fabricated LEDs, sensors, and devices. The manufacturers should provide different warranty models for a different mode of application. Users should give the flexibility to choose the model as per their application area. The papers addressing such problems are very less.

Researchers should focus on the risk and safety issues of users. Papers addressing GUI models for real-time interfacing between user and device are very few. It would be helpful for the user for real-time monitoring of used devices or components. Replacement/ dis-assembly perspective should be addressed. Warranty models, re-certifications should be designed for reused components. Accelerated life testing, maintenance, and diagnosis strategies should be maintained for second-hand products.

VII. CONCLUSION

This paper provides an overview of the studies hitherto conducted in the area of component reuse, maintenance, diagnostics, prognostics, and residual useful life prediction using different techniques. Most of the maintenance techniques address the maintenance-free life prediction of large plants and equipment only.

The existing maintenance practices mainly aim at repairing or replacing the failed components. These procedures ignore the potential of reuse capability of these components/parts.

The prudent approach effectively utilizing the reuse potential of these otherwise discarded components would go a long way in making a substantial saving in production and labour cost as also in achieving the objectives of reliable electronic industry.

Therefore, there is a strong need for developing simple methods to identify the reuse potential (RUL) of used components and parts. The failure prediction of one component can save the entire system and warns the user to replace the component with the operating one immediately.

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