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Review

A review on lubricant condition monitoring information analysis for maintenance decision support

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ABSTRACT

Lubrication Condition monitoring (LCM) is not only utilized as an early warning system in machinery but also, for fault diagnosis and prognosis under condition-based maintenance (CBM). LCM is considered as an important condition monitoring technique, due to the ample information derived from lubricant testing, which demonstrates an introspective reflection on the condition and state of the machinery and the lubricant. Central to the entire LCM program is the application concept, where information from lubricant analysis is evaluated (for knowledge extraction) and analyzed with a view of generating an output which is interpretable and applicable for maintenance decision support (knowledge application). For robust LCM, varying techniques and approaches are used for extracting, processing and analyzing information for decision support. For this reason, a comprehensive overview of applicative approaches for LCM is necessary, which would aid practitioners to address gaps as far as LCM is concerned in the context of maintenance decision support. However, such an overview, is to the best of our knowledge, lacking in the literature, hence the objective of this review article. This paper systematically reviews recent research trends and development of LCM based approaches applied for maintenance decision support, and specifically, applications in equipment diagnosis and prognosis. To contextualize this concern, an initial review of base oils, additives, sampling and testing as applied for LCM and maintenance decision support is discussed. Moreover, LCM tests and parameters are reviewed and classified under varying categories which include, physiochemical, elemental, contamination and additive analysis. Approaches applicable for analyzing data derived from LCM, here, lubricant analysis for maintenance decision support are also classified into four categories: statistical, model-based, artificial intelligence and hybrid approaches. Possible improvement to enhance the reliability of the judgement derived from the approaches towards maintenance decision support are further discussed. This paper concludes with a brief discussion of plausible future trends of LCM in the context of maintenance decision making. This present study, not only highlights gaps in existing

Abbreviations: LCM, lubricant condition monitoring; CBM, condition based maintenance; RUL, remaining useful life; CdM, condition monitoring; AI, artificial intelligence; ISO, international standards organization; API, American Petroleum Institute; OEM, Original Equipment Manufacturer; SAE, Society of Automotive Engineers; PAO, polyalfaolefin; UOA, used oil analysis; ASTM, American society for testing and materials; TBN, total base number; TAN, total acid number; mgKOH, milligrams of potassium hydroxide; EP, extreme pressure; MANOVA, multivariate analysis of variance; PCR, principal component regression; PLS, partial least squares; CLS, classical least squares; PHM, proportional hazard model; GMM, Grey Markov model; HMM, Hidden Markov model; ML, machine learning; DT, decision trees; LR, logistic regression; NN, neural network; SVM, support vector machine; RF, random forest; DL, deep learning; RB, rule-based; RL, representation learning; PCA, principal component analysis; SOM, self-organizing maps; CA, cluster analysis; FT-IR, fourier transform infra-red; GA, genetic algorithm; GRN, general regression neural network; ES, expert systems; IR, infra-red; KB, knowledge-based; KF, Kalman filtering; FL, fuzzy logic; ANN, artificial neural network; OCdM, other condition monitoring; FHT, First hitting time.

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literature, by reviewing approaches applicable for extracting knowledge from LCM data for maintenance decision support, it also reviews the functional and technical aspects of lubrication. This is expected to address gaps in both theory and practice as far as LCM and maintenance decision support are concerned.

Contents

1. Introduction

Condition-based maintenance (CBM), is a maintenance strategy that uses the information obtained while monitoring the condition of a physical asset to recommend maintenance actions for it. As Jardine et al. [1] argue, CBM enables maintenance actions to be taken only when there is corroboration of deviation of the behavior or condition of the asset. The process of monitoring the condition in the machinery is condition monitoring, also defined as a management technique utilizing regular evaluation of the actual equipment operating condition with a view of maximizing the total equipment operations based on equipment health condition data, where often such data is utilized for revealing deviations or faults in the equipment [2].

Different condition monitoring approaches are used where the International Standards Organization (ISO) classifies as seen in Table 1.

Tribology and lubricant are classified into two variants, where tribology deals with the science of wear, while lubricant analysis, also known as lubricant condition monitoring, deals with the analyzing the condition of the lubricant through which, the health of the equipment is inferred. Lubricant Condition Monitoring (LCM) compliments predictive and proactive maintenance strategies, and often applied as the first-line defense for mitigating early equipment deterioration, hence avert potential catastrophic equipment failures. Effective maintenance decisions have a considerable impact on the equipment operability, moreover since, poor decisions often bear adverse economic and environmental consequences. For successful maintenance decision-making, technical knowledge about the equipment is required along with information on the business and operational context. Hence, timely, accurate and reliable decisions should be made considering knowledge on the equipment state based on information derived from condition monitoring. This is essential for decision support systems aimed at aligning operational and business objectives of the organization and design of maintenance strategies aimed at attaining such objectives.

To design such robust maintenance decision support systems, recent years evince increasing interest in LCM, especially from academic researchers and industrial practitioners. A search from the web of science using search terms such as "lubricant condition monitoring", "lubricant monitoring", "oil condition monitoring", "oil analysis" and "oil monitoring" depicts

Table 1
ISO standard condition monitoring techniques [3].

Condition monitoring technique	ISO reference
Vibration	ISO 13373-1:2002; 13373-2:2005; 16587; 18436-2
Thermography	ISO 18434-1:2008; 18436-7
Acoustic emission and ultrasound	ISO 22906:2007; 29821-1:2011; 18436-6
Tribology and lubricant	ISO 14830-1; 18436-5

this increasing trend. There has been a marked increasing trend with the total number of publications over the last 5 years (2013–2017) being 419, which constitutes 35% of the total publications cumulatively over the last 20 years (1997–2017) of which, the search generated a total of 1216 articles. The subject publications incorporate the tribological aspects like chemistry, friction and design not dealt with in this review, while their decision application includes material design, medical, lubricant additives design and machinery. This current review focuses on publications leading to maintenance application. This emphasizes the interest on LCM as a concept for decision support.

Despite the interest towards LCM, there is seemingly few review articles that look at the state of the art applicative techniques of LCM for maintenance decision support, furthermore, the reviews are not directly linked to LCM. On LCM literature, and more specifically review articles, several authors consider models, approaches and techniques which are related to Condition Based Maintenance, for instance, Jardine et al. [1] who reviews algorithms applied for analyzing condition monitoring data with a view of extracting useful information for maintenance decision support, where such information remain core to implementing CBM. Their study classified techniques for deriving maintenance decision support into principal methods, for instance, for diagnosis, categorized into statistical methods, and approaches for artificial intelligence. Under methods applicable for prognostic decision support, they distinguish approaches for quantifying the remaining useful life (RUL), condition monitoring (CdM) intervals and designing optimal maintenance policies. However, in their study, methods that directly may be applicable for knowledge extraction or aiding decision support in the context of LCM are not reviewed or distinguished. Shin et al. [4] reviewed techniques for decision support for condition-based maintenance, where they classify the techniques under three main categories; model-driven methods, data-riven and knowledge-based approaches. Likewise, in the mentioned study, the applicability of the reviewed methods for LCM is not clear. Ying et al. [5], reviewed prognostic models applicable for CBM, where the models are classified under categories which incorporate physical models applicable where mathematical models can be constructed, knowledge-based that are configured with knowledge and reasoning aspects, data-driven methods based on statistical and machine learning techniques and combination models. Sikorska et al. [6] reviewed prognostic models for quantifying the RUL, where they not only highlight their strengths and weaknesses, but also business concerns which need to be considered prior to selecting appropriate models. Lee et al. [7] reviewed approaches commonly used in prognostics and health management for rotary machinery system, which the study categorized as model-based, data-driven and hybrid approaches. The study did not directly review their applicability in LCM. Kan et al. [8], while reviewing prognostic techniques applicable for non-stationary and non-linear rotating systems, enumerates a comprehensive list of statistical and Artificial intelligence (AI) based techniques, while detailing their advantages and disadvantages. The review, classified the techniques as model-based methods, data-driven models, and combination models. El-Thalji et al. [9], while reviewing prognostic monitoring tools for rolling bearing elements, classifies the techniques under statistical methods, artificial intelligence (AI) and physics-based approaches. However, the applicability of the enumerated approaches for decision support in LCM is not clearly discussed by [8,9].

Hence, a common flaw with the reviews is, although methods applicable for deriving decision support from condition monitoring data are discussed under CBM context, applicability for such approaches on Lubricant based data information is undiscussed. This gap is the concern of this review paper where the applicability of statistical, artificial intelligence and other approaches for analyzing Lubricant data and deriving maintenance decision support are reviewed. To the best of the author's knowledge, the aspect of LCM as espoused in CBM has seldom been reviewed in the context of maintenance decision support approaches.

This paper is structured as follows: Section 2 briefly describes the LCM concept and its integral aspects such as lubricant and its functions, LCM program constituting sampling, testing, interpretation of results and finally maintenance decision support. Section 3 reviews the applicative aspects of LCM in maintenance. Section 4 reviews the state of art approaches for extracting and application of knowledge from LCM in maintenance along with their advantages and derived judgement reliability constraints, while Section 5 briefly discusses aspects of possible improvements to overcome constraints that impede the reliability of LCM based decisions derived from the approaches, and general application trend in the maintenance field from the author's perspective. Section 6 lays out the plausible future trend of LCM in maintenance with Section 7 concluding the paper.

2. Lubricant condition monitoring

LCM, commonly known as used oil analysis program (UOA), is applied while analyzing the lubricant properties and often reveals possible contamination within the lubricant and changes in its properties. In this section, we first review lubricants and its functions, which are integral to the LCM program, and finally the concepts and steps involved in the LCM program.

2.1. Lubricant and its functions

The primary functions of lubricants include reducing wear and friction, protection against corrosion and rust, cleaning the system and removing contaminants from the system being lubricated. The term lubricant generally represents lubricating oil (mostly viscous fluid oil in nature) and lubricating grease (Semi-solid to semi-fluid in nature with the additional ingredient called thickener) [10]. A lubricant is made through the blending of one or more base oils and additives. An example of a typical blend of an engine oil lubricant is given in [11]. Base oils, which is oil refined from crude oil (mineral base oil) or through chemical synthesis (synthetic base oil) are classified based on its composition by the American Petroleum Institute (API) as shown in Table 2. Additives are chemicals used to enhance and modify the functionalities of the lubricants. Due to the diverse types and application of lubricants, classification becomes important for easy identification, quality level establishments and more persuasive communication between the stakeholders including the maintenance team. The blended lubricants can be classified in distinctive ways, for instance, classification by application and viscosity. Applications include automotive, industrial, aviation, marine, etc., whereas classification by viscosity utilizes the International Standards Organization (ISO) and Society of Automotive Engineers (SAE). A comprehensive discussion on the classification of lubricants by ISO and SAE can be found in [12].

The knowledge on base oil and additives used in a lubricant aide in important maintenance decisions while selecting lubricants, for instance, some additives may be incompatible to certain specific seals in a machine, while classification enables harmonized global specification easing lubricant selection decisions. However, while the lubricant is in use, degradation may set in due to intrinsic and/ or external factors which affects the machinery performance e.g. wear occurrence due to lubricant dilution also studied by [14]. To address these limitations, lubricant condition monitoring programs are designed which not only guarantees the lubricant condition to fulfill its function, but also indicate equipment states and identify failure risks.

2.2. Lubricant condition monitoring program

The LCM program entails analysis of lubricants that highlights its changes and/or deterioration which influences the lubrication properties [15]. Moreover, this information is used in maintenance decision making to abate any failure of the system, increase the system availability, reduce unnecessary lubricant replenishment costs, moderate environmental effects and enhance the diagnosis process. A comprehensive discussion on the importance and types of tests is addressed in [16]. Concerning specific LCM field, Zhu et al. [17], reviewed existing LCM hardware solution techniques, mainly sensors used for the lubrication tests. The study classified the monitoring sensors under electrical, physical, chemical and optical techniques. The review was limited to lubricant degradation caused by contamination and did not review the approaches used for analyzing LCM data for maintenance decision support as the case in our current review. Other review studies reviewing on-line monitoring approaches for LCM includes, a review of sensors for measuring viscosity [18], on-line oil dilution measurement methods [19], and lubricant condition monitoring using on-line monitors [20]. Other reviews in LCM include the study of interaction between anti-wear and extreme-pressure additives [21] and techniques applicable for measuring the degree of lubricant oxidation [22]. The aforementioned reviews were limited in a more considerable extent, to a particular aspect of the LCM program for instance sampling [18], additives [21] and oxidation [22], which do not advance comprehensive state of art review that could assist in maintenance decision support due to partiality. In this study, we intend to review the wholesome LCM program and how it can be used by practitioners in maintenance decision support, hence this section divulges the LCM program.

A lubrication condition monitoring program is composed of three key steps (see Fig. 1), discussed further in the upcoming paragraphs:

Table 2
American Petroleum Institute Base oil classification [13].

Group	Sulphur, wt. %	Saturates, wt. %	Viscosity Index
I	>0.03	<90	80–119
II	≤0.03	≥90	80–119
III	≤0.03	≥90	≥120
IV	All poly-alpha-olefins (PAOs)		
V	All other not included in Groups I, II, II or IV		

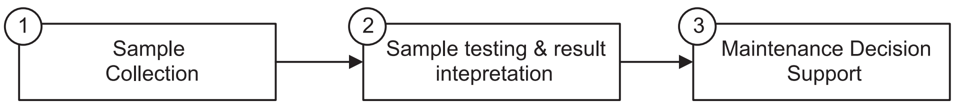

Fig. 1. Lubricant condition monitoring steps.

a) Lubricant sampling (sample scheduling and collection).
b) Lubricant sample testing and results (sample testing, processing and handling).
c) Maintenance decision support (results analysis, interpretation and decision-making).

2.2.1. Lubricant sampling (sample collection)

Lubricant sampling can be classified as dynamic or static, where static involves a discrete sampling event characterized by a fixed state or condition. In this case, a sample is drawn for testing while the equipment is either running or not operational. Dynamic sampling is characterized by constant changes in state or conditions, for instance, use of on-line and in-line sampling and analysis for testing the lubricant. In the in-line technique, the oil is analyzed while passing between the lubricant pump and the component to be lubricated, whereas on-line technique involves bypassing the oil to the analyzer. In static sampling, often referred to as off-line analysis, the lubricant sample is drawn out from the machine and analyzed in the laboratory which can be on-site or out of the site. Recent reviews on the sampling methods are given in [17,23–25]. For accurate maintenance decision making, the integrity of the lubricant sample which is a legitimate representative must be guaranteed. The applicability of the different sampling types may be adopted depending on different dynamics the machinery is running in e.g. for uninterrupted running, on-line sampling may be suitable, though other aspects such as cost and easy usability should be considered. Acceptable methods and frequency of lubricant sampling are essential for integrity and representation of LCM. For successful sampling and oil analysis results, three facets are discussed as important which include supporting hardware (e.g. [26]), sampling procedure (e.g. [27–33]) and sampling location (e.g. [27]). In dynamic sampling and monitoring using on-line monitoring, common sensor detection methods encompassing the wear category include optical, inductive, resistive capacitance and acoustic concurred by [34,10], while for physio-chemical properties include acoustic, vibrational and displacement [35,18]. Wear features such as debri concentration could be detected using acoustic [36], inductive detection type [34,37] optical or imaging [38], debri morphology could use optical [38] and resistive capacitance [39], while debri size could use inductive, acoustic or capacitance. Some authors have reviewed the detection types for physiochemical properties [38], water contamination [40], and soot contamination [41], while a comprehensive review of on-line lubricating oil sensors has been advanced by [10].

2.2.2. Lubricant tests and results

Used oil analysis (UOA) program, derives the test results from testing various lubricant parameters that highlight the condition and state of the lubricant. The test results form a vital source of information used while detecting early equipment failure or faults, because the lubricant condition considers the health or state of both the lubricant and equipment [17]. Four classes of the UOA test results are distinguished, that is physiochemical properties, elemental (wear) analysis, additive analysis and contamination analysis, also corroborated by [42]. In this section, we limit the discussion to some of the commonly analyzed parameters affiliated to the four classes as highlighted. A review with more comprehensive discussions and references indicating respective American Society for Testing and Materials (ASTM) test methods for analysis of lubricants is found in [43].

In-depth reflection on ***Physical and chemical (physiochemical) properties*** has been done by [44]. ***Elemental (wear) analysis*** occasions analysis of elements that constitute the metallurgy of components found in the lubricated equipment for example, iron, aluminum, lead, copper, chromium, silver and tin. A summary of elements tested with their respective viable source(s) can be found in [45], while several examples of the metallic elements and various testing techniques are illustrated by [46]. ***Additive analysis*** involves chemicals that impart specific new properties, improve existing base oil properties such as viscosity, as well as widen the range of applications of the lubricant [47] and potentially may infer the condition of the equipment [48]. A comprehensive study on lubricating oil additives is done by Ahmed and Nassar [47]. ***Contamination analysis*** is carried out when lubricant becomes adulterated with liquid or solid materials rendering it impure thus compromising its performance, which may involve contamination from water [49], fuel and soot [50], glycol or antifreeze [49] and insoluble-solid [51]. Direct or indirect test techniques are employed, for instance, fuel dilution can be tested directly (Gas chromatography or fuel dilution meter) or implied (flash point, viscosity or FT-IR spectroscopy) by traces of particles accepted in the fuel's composition such as vanadium or nickel [52,51]. An implication of this is the possibility that correlating the parameters potentially will assist in a more informed proactive maintenance decision.

Table 3 illustrates a summary of commonly tested and reported properties in lubricant condition monitoring. Notable is some properties classified in more than one category such as boron, silicon, vanadium also corroborated by Langfitt and Haselbach [53].

Table 3
Commonly tested lubricant parameters classified.

Classification	Common parameters	Articles
Physical & chemical	Viscosity @ 40oC, Viscosity @ 100oC, Total Base Number (TBN), Total Acid Number (TAN), Flash point,	[54–56]
Additives	Boron, Barium, Calcium, Magnesium, Molybdenum, Phosphorus, Sodium, Silicon, Zinc	[57–59]
Contamination	Water, Coolant, Vanadium, Soot/carbon, Potassium, Silicon, Sodium, Boron	[60–62]
Elemental (wear)	Chromium, Iron, Tin, Aluminum, Copper, Lead, Nickel, Vanadium, Titanium, Silver	[63–66]

Table 4
The spread of articles reviewed under lubricant categories.

Classification	Elemental(wear)	Additive	Physio-chemical	Contamination	Mix
Statistical	30%	17%	18%	63%	38%
Artificial intelligence	30%	33%	45%	38%	45%
Model based	15%	33%	21%	0%	3%
Hybrid	25%	17%	15%	0%	13%
Total	50%	3%	15%	4%	28%

The tested parameters, however, are processed and data is consequently analyzed for decision support. During offline and on-line condition monitoring, various data types are employed depending on the machine or condition of interest in the LCM program. Oil analysis data includes value type, spectroscopic or waveform and raw media such as images, videos, and text. It is important to note, that the data acquired by online sensors in different forms as depicted by their respective detection modes, require to be analyzed and interpreted to extract information that can offer maintenance support or will further be processed (feature extraction) to extract important information from the raw signals for various monitoring purposes. This process known as signal processing is mainly performed on the waveform and multidimensional type of data. Several methods are employed for signal processing, among them includes limit checking, spectral and statistical analysis [67]. The aspects of signal acquisition and processing are beyond the scope of this paper hence will not be discussed in detail. Value type data include raw data (acquired via data acquisition) and feature values (via signal processing) such as measured/processed values of different features (physio-chemical, wear in ppm, contamination in percentages or quantified particles). Event data is also a significant data type which includes the information related to maintenance actions and practices, breakdowns and other maintenance action such as overhauls observed on the machine.

In this review, elemental analysis-based papers constitute 50%, physio-chemical properties 15%, contamination 4%, additives 3% and a hybrid/mix 28% of the total reviewed publications (See Table 4). Several studies have reviewed the lubricants parameters, for instance, review of physiochemical, contamination and wear analysis in [38], while a review of elemental (wear) analysis and physiochemical properties was done by Salgueiro et al. [68]. A comprehensive review of oil analysis incorporating all the above categories has been done by several articles [15,29,69], however, they dwell on the lubricant tests and do not review the techniques used to extract knowledge, analyze and assist in decision making as the current review intends. As alluded to earlier, to assist the maintenance practitioners in decision making, incorporating lubricant test results evaluation and interpretation is important as discussed in the next section.

2.2.3. Maintenance decision support information

For robust maintenance decision making, relating technical apprehension of degradation process with data collection and analysis to appraise the state of equipment is essential [70]. A maintenance decision support system, is therefore necessary to aid the technical, maintenance and operational teams to analyze LCM information, generate output and knowledge to be used in maintenance decision making. Central to the success of a decision support system is the knowledge of the areas of application and the suitable approaches, specific to the maintenance need and available analysis data, which should cautiously be selected and used to ensure a sound maintenance decision is reached. For such, the areas of application then followed by the approaches used during extraction and application of the knowledge contained in lubricant analysis are reviewed in the next sections of this study.

3. Application of LCM in maintenance

The application of LCM program in maintenance decision making can be treated under three complimenting categories, which are: detection, diagnosis, and prognosis [71]. Prognosis deals with predicting the future performance of a system by analyzing either its degradation or deviation from expected state or condition in its routine operations. Prognosis involves both confirming whether a fault exists and determination of the remaining useful life (RUL) to ascertain time for maintenance intervention for instance, increase wear element count could be used to predict useful life of a machine [6]. In prognosis, an LCM program using historical data to derive patterns indicative of equipment faults and predicting the RUL of the lubricant or the equipment may be developed. This may leverage on a predictive model for forecasting critical failures before they occur, which ultimately enables better maintenance planning, scheduling and or intervention. The condition of lubrication oil and its circulation system reflect the health status of the machinery, and components being lubricated, for instance, sodium contamination has a resultant effect of a filter clogging [60]. Accordingly, early detection of deviation of the lubricant parameters will enable prompt and timely intervention to correct the condition or state. Further, diagnosis for instance, using wear metals analysis can be done to locate a faulty component, if immediate action is not possible or level of deterioration is higher than one allowing intervention. Similar to other fields, knowledge extraction can be achieved by associating or extracting patterns in the parameters of the oil samples either following a univariate or multivariate technique [42]. The patterns extracted can be applied in several ways with potential benefits such as maintenance cost reduction, waste reduction, and timely and accurate maintenance intervention. Some examples of the application of this knowledge among others include determining and predicting current and future health status of the machinery and lubricant, as well as predicting the remaining useful life (RUL) of machinery and lubricant.

4. LCM approaches in maintenance decision support

The use of LCM in maintenance has gained high academic and maintenance interest in the recent past. Recently, a considerable literature has grown up around the theme of LCM application in maintenance, not only as an early warning signal, but also for failure diagnosis and investigation (root cause analysis). A search of the literature revealed few studies which have reviewed some sections of LCM (see Section 2.2) and seldom review all approaches applied in maintenance decision support. This section reviews the diverse approaches used while applying LCM in maintenance towards the three application regimes of detection, diagnosis, and prognosis. Fig. 2 illustrates the proposed classification of approaches in this review that is, statistical, model-based, artificial intelligence and hybrid as reviewed in the next section.

4.1. Statistical approaches

This approach utilizes a statistical model, which interpret the form of relationship between variables. To define statistical models, we would review the work of McCullagh [72], who alludes that such models are linked with the statistical analysis of data, and hence the model and the analysis are regarded as inextricably intertwined concepts. Some examples of multivariate statistics applied in LCM are outlined by Sharma [73] which include cluster analysis, principal component analysis, multivariate analysis of variance (MANOVA), factor analysis, regression and so on.

Trend analysis has a number of functions such as, showing changes of a parameter with change of another parameter such as time, comparing lubricant features against limits, assessing magnitudes of changes between consecutive samples and tests [74], enabling early detection of feature deviation hence maintenance intervention is made such as inspection of components wear or ingression of a contaminant like water. Some LCM based studies that used trend analysis include [75–81]. Trending possesses various limitations such as single parameter analysis which may not offer meaningful diagnosis, moreover, a vast amount of vital information may go unnoticed. Nevertheless, some remedies given imply the use of trend analysis with level limits or threshold, monitoring rate of advance and using more than one property in the plot [82].

Correlation analysis, which overcomes the limitation of the univariate trending approach, demonstrates the strength of the relationship between two different variables using the correlation coefficient [83]. The high correlation of two lubricant parameters signifies a predictive association applicable in practice [42]. Conventional methods include Pearson and Spearman for normal and non-normally distributed data where normality tests are used to ascertain method to employ [84,85]. Correlation was used to evaluate the general relationship among the used oil parameters, for instance, chronicling the physiochemical and tribological parameters of the engine oil [83], while in other studies [93,87,88]. Most of the studies reviewed, seldom justify the correlation method used, only [42], carried out normality tests to justify use of Spearman's correlation method. Nonetheless, correlation analysis is limited to two-dimensional view which does not demonstrate flexibility for a multivariate view, therefore cannot show the cause and effect of equipment wear and further assumes a linear relationship. Hence, the need of multivariate analysis such as regression analysis discussed in the following section.

Regression analysis is a method of estimating the functional relationships among variables which are expressed in the form of an equation, where the value of the independent variable is used to estimate the value of the dependent variable. Linear regression evaluates the effect of predictor variables and variables that are significant predictors of the dependent variable offering maintenance support by exposing significant features influencing the dependent LCM feature. Linear regression was used in the exploration and analysis of lubricants in various studies [89–91]. Some grave challenges for regression analysis involve the utilization of mean values, the possibility of multicollinearity, overfitting and sensitivity to outliers, which could be addressed using principal component regression (PCR), classical least squares (CLS) and partial least squares (PLS). PCR is an extension of regression using qualitative variables for dimension reduction. PCR output is

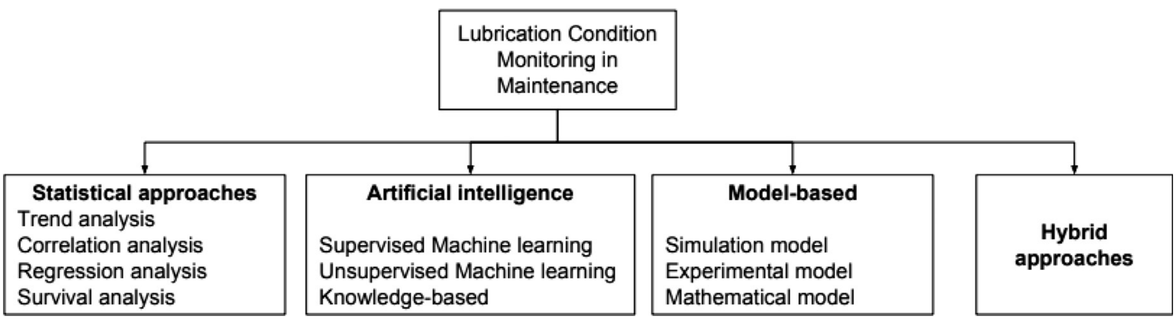

Fig. 2. Lubricant condition monitoring approaches in maintenance decision support.

subsequently modeled using PLS which incorporates a multivariate calibration, as used by [58,92,93]. PLS was used for prediction of oil properties using infra-red spectroscopy [94] and prediction of viscosity [92].

Some studies, however, have used a hybrid approach to gain the synergies of each technique for instance, combining correlation and trending [62], correlation and regression were combined by [95], while Al-Ghouti et al. [96] suggest PLS outperforms CLS and PCR while predicting TBN and Viscosity Index in their study.

Survival analysis models are valuable statistical tools that are used in the estimation of remaining useful life (RUL), a core aspect of predictive maintenance. The models also derive degradation models, but in most cases, they are used in combination with a model used to generate the faults [1,97]. RUL estimation has two algorithms commonly used, the first one focusses on the statistical nature of failures of equipment, while the second algorithm, models the individual failure modes based on wear prediction. Fig. 3 illustrates several statistical-based approaches employed for RUL estimation also corroborated by [98]. One category of RUL estimation is where the condition monitoring trail can be modeled to estimate RUL using LCM data, without failure event data, inferring it is based on the state processes observed directly. This model can follow the state process evolution in a continuous or discrete process. The continuous approach includes regression-based, Brownian with drift/Wiener process and gamma process. The models with a discrete process are Markov which can either take continuous or discrete time space.

Brownian motion with drift or Wiener continuous process are constructed as one-dimensional stochastic process following a Gaussian distribution. It was used to establish the appropriate juncture to carry out preventive maintenance by modeling the occurrence of wear particles in oil [99]. Other studies that have used this approach include [100,101]. Despite reducing noise, Wiener process contains limitations like reduction of details and being time intensive.

The Markov process acquires the Markov property that the effects of an action taken in a state depend on the current state only and not on the prior history, this means the current state characterizes the process hence termed as "memoryless." The Markov process has been used for sequential decision making under uncertainty. Discrete-time Markov depicts changes to a system happening at discrete time values while in the continuous-time Markov chain, changes in the system can happen at any time using continuous interval and decision Markov process [102]. This approach is employed to depict for instance, the deterioration process and state of a lubricant or equipment offering maintenance decision support, has been used in various LCM-based studies [103–105]. An extended Markov model is the Grey-Markov model (GMM), which incorporates the time series trend towards forecasting. GMM was utilized in several LCM aspects [64,106]. Markov processes have advantages of speed and results accuracy because of using a formula. On the contrary, it requires considerable care during building while implicit assumptions of memoryless characteristics and use of exponential distribution to represent times to failure and repair render additional constraints.

Another category commonly used in RUL estimation is based on indirectly observed states processes which incorporates the hidden Markov, filtering and proportional hazard models. *Hidden Markov model (HMM),* utilizes both the CdM and event data, incorporates two stochastic processes that is, Markov process and an observation process on the hidden states thus depends on an underlying and unobserved Markov process. HMM was utilized in different studies such as [105,97,107]. Despite HMM possessing more flexibility in fitting the data better, it's training is time intensive, requires extensive data and does not guarantee accurate prediction due to the intrinsic nature of the model [9]. *Proportional Hazard Model (PHM),* which models failure phenomena in a similar way to regression, instead of observations for the dependent variable (also known as hazard rate), covariates or observations are available as event data. PHM models the life of an individual that is influenced by covariates whose effect is multiplicative on the hazard rate, which is a function of a baseline hazard function in the parametric or non-parametric form [108]. For instance, modeling the level of iron wear particles influence to the failure of an engine would offer insights on expected failure hence intervention to abate failure depending on the computed rate. PHM was used in several LCM related studies [109,110]. Weibull PHM which uses a Weibull baseline hazard function was applied in several studies [111,112]. Despite advantages like using maximum information and preserving the actual form of variables, PHM is limited to censoring mechanism and model generalization.

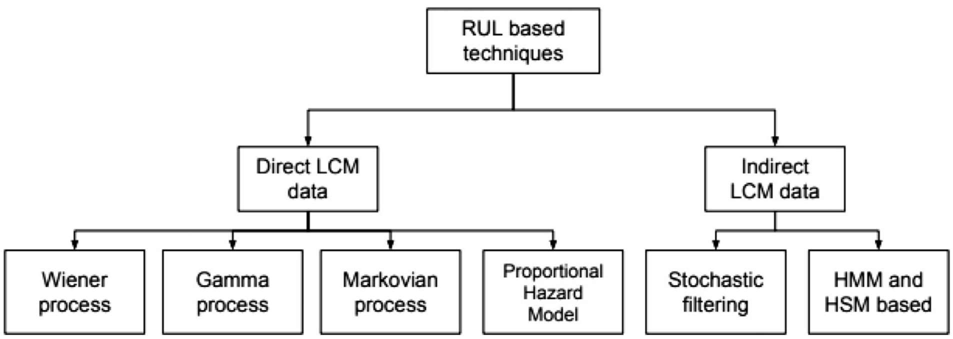

Fig. 3. Statistical approaches for RUL estimation.

Stochastic filtering, a recursive Bayesian algorithm used in predicting the remaining lifetime of a component by incorporating new condition monitored information into the estimation process [108,109], and was used in various LCM studies [113,115]. When using multiple simultaneous sources input, most approaches resort to feature reduction and approximations. *Kalman filter*, which is used as a state estimation technique, overcomes these challenges. An extended Kalman filtering was used to develop an approximate methodology to establish the conditional failure time distribution recursively [116] and state estimation in failure prediction using preventive maintenance [117]. Kalman filter process is limited being a non-linear method, hence growth in linearity for example statistically will influence its performance, and furthermore, it requires many assumptions. Particle filtering is a filtering technique which can handle statistic prediction data, unlike Kalman technique. This approach was used for predicting RUL [25].

The use of a hybrid approach has been advanced, for instance PHM and HMM, were used in conjunction to estimate parameters whose failure rate follow the Cox's time-dependent Proportional Hazards Model in [107], while a comparison using Weibull PHM and stochastic filtering process is given by [114]. A review of RUL estimation models categorized as experimental, data-driven, physics-based and hybrid is given by [118], while that of statistical data-driven RUL models that depend on directly observed state data of the equipment and those that do not, is done by [98].

Basic statistical approaches such as trend and regression analysis have been widely used in the LCM field, which can be attributed to the ease in analysis and interpretation, moreover, non-requirement of complex software to carry out the exercise makes it accessible. However, due to the requirement of incorporating other variables that may influence the analysis such as event data, the basic approaches which utilize continuous variables only are challenged, hence, other methods such as survival analysis come in handy. Table 5 illustrates a summary of the approaches highlighting their input, output and constraints that affect the reliability of the output in maintenance decision making support.

4.2. Artificial intelligence approaches

Artificial intelligence is computer science approach geared to the creation of intelligent machines that work and react following a pattern like the human, towards activities such as recognition, problem solving and so on. It incorporates two parts namely the knowledge base (knowledge used to make inferences) and inference engine (reasoning section which in some instances include machine learning algorithms), hence includes machine learning and knowledge-based approaches [1,123]. AI approaches exhibit intelligence, perceive their environment and make decision or actions to maximize the chance of success at a goal. Machine learning and knowledge-based approaches as shown in Fig. 4 are the approaches under the AI category as discussed in the following section.

Table 5
Comparative summary of statistical approaches.

Approach	Input	Output	Analysis approach	Validity constraints	Ref
Trend analysis	Oil features value type	Trend deviation from limits/thresholds	Single parameter trend plot	Focus on Single feature Loss of information (unnoticed)	[53]
Correlation analysis	Oil features	Linear relationship (correlation coefficient)	Two parameters correlation	Cannot pick patterns Heuristic output	[42,119]
Linear regression	Number and continuous feature data	Linear relationship between mean values of dependent and independent variables	Linear best fit relationship between the input and output features	Utilization of mean values	[120]
Wiener/Brownian approach	Degradation value type data and degradation parameters	Degradation of system depicted by confident interval of limits, failure occurrences and degradation prediction (FHT)	Continuous time stochastic process	Unable to model monotonic degradation	[121]
Markov model	State change probabilities	Output from states	Probability sequence with regression and maximum likelihood	Require manual process and cannot observe states themselves	[104,92]
Hidden Markov model	LCM and event data	Estimated model parameters classifying faults using visible observations (event) from the machine	Probability sequence with regression	Erroneous distinguishing state of machine due observability of some LCM aspects	[122,8]
Proportional Hazard Model	LCM and event data	Hazard ratio (instantaneous failure at a certain time)	Partial likelihood	Multiplicative (combinatorial) effect of model parameters	[98]
Kalman Filtering	Actual residual values of the current state	Trend trajectory to fault development to predict RUL	Joint probability distribution estimation	Limited to linear and high dimension data	[8]

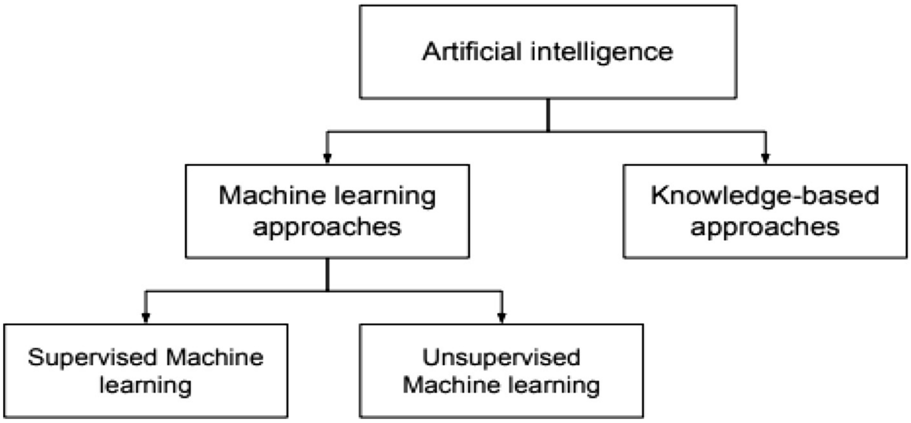

Fig. 4. Artificial intelligence categorization of approaches in maintenance decision support.

4.2.1. Machine learning approaches

Machine learning advanced from the study of pattern recognition, and focusses on recognition of patterns and regularities in data, exposing pattern or relationship structure referred to as a model [124]. There are two techniques used in this approach, supervised and unsupervised machine learning techniques as respectively reviewed in the next part of this section.

Rokach and Maimom [124] define ***supervised machine learning*** techniques, as methods where the relationship between a dependent(response) and independent variables(predictor) is observed from a set of training example. It is worthwhile to differentiate two main supervised models, classification models which predict group membership for data by allocating items in a collection to target class for each case in the data while regression models map the relationship between the target or response and predictor variables, which form the input data.

Logistics regression (LR) is a predictive analysis used to analyze data and disclose the relationship between one dichotomous variable and one or more nominal, ordinal or ratio-level independent variables [125]. The evaluation of coefficients and odds ration of the model offers maintenance decision support on the features contributing significantly to the prediction such as oil failure classification. It has been used in the determination of maintenance inspection interval lengths on aircraft maintenance data [126], fault diagnosis of transformer oil dissolved with gases [127] and other LCM studies [128,125,129]. LR models are flexible, and handle nonlinear effects, are not limited to the homogeneity of variance, but on the downside, are prone to overfitting, cannot predict continuous outcomes and require extensive data to attain stable results.

Decision trees (DT), models the consequences of possible decisions in relation to an outcome or event. Maintenance support is derived from interpretable rules with the option of a tree-based graphical representation that exposes significant features and their influence on the outcome modeled. Moreover it can be used in both classification and regression perspective, contributing to a hierarchical model of decisions and their consequences [124]. DT classification was used in LCM to generate the model predicting wear conditions of the equipment's using UOA wear particles data and failure events data [130] and further utilized to classify oil samples [131]. Despite DT offering flexibility and an in-depth interpretable output which need minimal knowledge to use, it is sensitive to outliers and missing values.

The *Neural network (NN)* algorithm considered here is supervised NN and is based on a series of standard features to establish the condition of a system. Preprocessing method such as transformation(creating a single input to a net from raw data) and normalization(distribute data and make it scalable) are carried out, where classification outcome is used in decision support. An extension of NN include genetic neural networks, where the genetic algorithm is used to optimize neural network parameters and fuzzy neural networks which tend to memorize standard patterns utilizing association for diagnosis [132]. NN was used to classify different lubricant grades by feedstock, differentiate between low and high temperature viscosity [133]. Other studies where NN is discussed for LCM include, e.g. [55,129,135–138,134]. Despite the applicability of NN for complex systems, some of the primary limitations of NN include, difficult trained model interpretability, sufficient computational resources requirement and extra effort involved in the training process. In an attempt to overcome the limitations, general regression neural network (GRNN) offers nonlinear mapping and higher approximation, was used for picking the relation of copper in lubricant with engine load and cylinder clearances [139].

Support Vector Machine (SVM) is a linear classifier that seeks to find the best hyperplane which classifies new observations according to the response variables, while variable importance reveals features influence on the classification response, both aspects invoke maintenance decision support. SVM was used to differentiate between new and used engine lubricant [140] and classifying used oil samples in [129,141]. Similar to DT, SVM can be used in both classification and regression models and can perform well using limited training samples which may be non-linear in structure or may be used in real time analysis and it is less prone to overfitting. Like NN limitation, SVM trained model interpretability is difficult, lacks probabilistic classification, hard to incorporate domain knowledge and is affected by noise.

Random forest (RF) resembles DT, except that a collection of un-pruned decision trees is combined to give a better classification accuracy, mode of the class's output by individual trees. Classification outcome reveals the sample prediction which prompts maintenance intervention as deemed necessary, whereas variable importance would guide the maintenance engineer to know the critical variables or features contributing to the output, for example, a feature like viscosity can be depicted to significantly influence the classification of a lubricant requiring to be changed/drained. RF is also used in feature selection due to its capability of providing variable importance measures [142]. RF has been used in determining Total Acid Number (TAN) from infra-red (IR) data of aviation lubricants [141] and used to determine important parameters [131]. Like NN and SVM, RF has results interpretation challenge, categorical data results may not be reliable, but achieves adequately in terms of classification accuracy, can process large datasets with many variables and able to estimate missing data.

Deep learning (DL) approach employs labelled or unlabeled data, raw media (unstructured e.g. vision imaging, speech recognition, natural language processing, text and audio recordings) data and performs automatic feature extraction by clustering without human intervention. The approach uses a logistic or softmax classifier while assigning likelihood to a particular outcome or label. For example, using color images of in-service lubricant wear debri as input data, DL may indicate that the input is 90% likely to represent copper debris. Maintenance support is obtained from the output that identifies associations, entity resolution and feature classification. DL has been proved to yield more accurate results than human beings but limited by factors such as overfitting, big data requirement and difficult to work with reasoning for instance application of scientific methods and programming. It was used in texture entropy detection of transformer oil [143], wear particle analysis and classification by various authors [128,144–147]. Deep learning is fast, usually more accurate and capable of building the features without supervision from either unlabeled or unstructured data. Notwithstanding, it is data intensive, rarely change with changing condition while the careful selection of classifiers offering accurate prediction is a limitation, hence [147] suggests linear discriminant analysis, quadratic discriminant analysis, naïve Bayesian method, and classification and regression tree method could potentially be effective.

Rule-based (RB) machine learning is based on the use of a set of relational rules representing knowledge captured by a system, and incorporates methods such as association rule mining, related algorithms and learning classifier systems and was used for developing a fault detection expert system [148]. The automated inference engine is used for maintenance problem solving using reasoning. RB is expressive and easy to write but requires additional techniques to deal with complex problems and can experience combinatorial challenge while being computationally and memory intensive.

Representation learning (RL) uniquely can be used in mapping from an image or item to output or to self. RL was used in reliability analysis of engine oil using polygraph [149]. Despite RL's advantage of showing data in a same and natural format, it has possibilities of contradictions and infinite looping.

The methods discussed above are categorized as supervised, while the next section deals with unsupervised machine learning techniques. ***Unsupervised machine learning*** techniques are used without a pre-specified dependent attribute, in other words, deductions are drawn from data sets with only input data without labeled responses.

Principal component analysis (PCA), generates new principal components (linearly uncorrelated) that establishes patterns in data and depicts them in a way to expose the similarities and differences. The generated components reveal patterns(fault groups) which a maintenance practitioner using his expertise can decode signifying for instance, fuel dilution, additive dilution and drive maintenance intervention. It is also a dimension reduction tool that can be used to reduce the number of variables under evaluation by obtaining a set of principal components. PCA has been used for dimension reduction in diverse areas for instance; it was used to reduce the number of variables in UOA prediction models [150–154]. PCA possesses several limitations for instance, limited to continuous data, offers limited interpretability, while it is used in linear data with low to medium deviation, challenges that self-organizing maps (SOM) overcome. SOM is based on unsupervised learning which can be used to visualize general space states like degradation. SOM can be used as an appropriate degradation indicator in LCM as used in wear particle classification analysis process [155] and clasifying wear particles to worn surfaces [156]. Capone et al. [157] used PCA and SOM to differentiate among the different diesel fuel diluted lubricating oils. Despite its advantages like ease interpretation and capability dealing with complex data, SOM has limitations in the determination of input weights to use and mapping which can lead to divided clusters.

Cluster analysis (CA) aims to classify several correlated observations (attributes or features) into some clusters (fault groups) according to similarities between them, such that each cluster is as homogeneous as possible with respect to the clustering variables. Incorporating this pattern recognition, image analysis and information (attributes) retrieval generated, while picking effects and interactions which require to be addressed, offer maintenance decision making support. Cluster analysis has been used in several LCM related studies in the recent past such as [158–160]. CA experiences some limitations that influence the subsequent results such as sampling errors and biasness towards setting the optimal number of clusters due to its heuristic nature as well. To address the uncertainty characteristic of classical CA, statistical methods like pv-clust and discriminant analysis are fronted. Pv-clust evaluates the probability values (p-values) for each cluster multiscale bootstrap resampling, was utilized while verifying cluster formation representing fuel dilution by [50]. A comprehensive review of this technique is found here [161]. Discriminant analysis assesses the adequacy of a classification was used by [162].

Other unsupervised techniques include the unsupervised ANN, which mimics the human brain structure, was utilized in identifying morphological features that enable classification of wear particles in relation to the wear processes [163] and other LCM related studies [86,55,164]. Deep learning also has unsupervised characteristics linked with deep neural network that involves algorithms for classification, regression, and enhanced learning.

While developing regression or classification models employing the supervised learning methods, most researches have used unsupervised learning techniques for selecting the input variables. This is done by discovering hidden patterns or selecting admissible parameters and thus accounts for Hybrid approaches. Several machine learning hybrid approaches were reviewed, for instance using principal component analysis and neural network, genetic algorithm(GA) and neural network [134], deep learning and clustering [38], deep learning and genetic algorithm [165], support vector machine and neural network [140], principal component analysis and cluster analysis [166]. Due to the need for synergy from different machine learning techniques, some authors have used a hybrid approach by utilizing more than one technique for instance [129,99]. Table 6 illustrates several machine learning approaches and constraint(s) viewed to impair the judgment/application in LCM based maintenance decision making support.

One notable aspect that is used to improve the performance of machine learning algorithms is the hyper-parameters optimization(HPO) also known as parameter tuning. Hyper-parameter define higher level concept about the model such as complexity or capacity to learn. The optimization can be performed manually, using grid search, random search or employing Bayesian optimization. A summary of sample hyperparameters for classification modeling is given in Table A1 found in Appendix A. The selection of supervised ML techniques for maintenance decision making, would require a tradeoff selection criterion, for instance low training effort and high prediction accuracy inherent with RF means lack of visual interpretability and vice versa considering DT and LR approaches which require moderate training effort. Similarly use of NN due to high training speed and robustness compared to SVM would limit a practitioner to having a large dataset despite both having a "black box" effect [167]. However, despite widespread academic use of both unsupervised and supervised approaches, limited application in the maintenance decision support in practice is witnessed due to their low infiltration rate in the LCM field.

4.2.2. Knowledge-based approaches (KB)

Knowledge based systems exhibit a form of intelligent behavior by utilizing symbolic representation of knowledge of observed situations and rules defined to infer maintenance related aspects from the previous events [6]. Frequently used knowledge-based approaches include expert systems (ES) and Fuzzy logic also corroborated by [123,175,176].

Table 6
Comparative summary of machine learning approaches.

Category	Approach	Input	Output	Analysis approach	Validity constraints	Refs.
Unsupervised-Machine learning	Cluster analysis	Numerical data or features extracted from signals as raw data	Correlated features in the cluster (fault groups) Information (attributes) retrieval	Linear correlation of features	Heuristic and biased output Validation of revealed (clusters) pattern	[159]
	Principal component analysis	Continuous data independent	Generate linearly uncorrelated components and feature reduction	Variance maximization on the uncorrelated set of features	Limited interpretability. Limited to continuous data	[168]
Supervised-Machine learning	Decision trees	Labeled feature data (Heterogeneous)	Interpretable rules for features effect to classification	Hierarchical representation on Linear decision rules,	Sensitive to outliers. Controllability of tree size	[169]
	Logistics Regression	Labeled and unlabeled LCM feature data	Response probability model coefficient and odds ratio	Binary response probability of features	Focus on the main effects of features.	[127,170]
	Neural Network	Labeled, unlabeled features (numerical, categorical, raw media)	Classification outcome	Weight modification approach	Limited interpretability and requirement big data	[171,140,8]
	Support Vector Machine	Labeled LCM data (could include images and text data)	Optimal hyperplane/ boundaries classifying new observations, variable importance	Non-probabilistic binary linear classification	Performance affected by noise. Lack probabilistic classification	[172,8]
	Random Forest	Labeled feature data (Heterogeneous)	Classification outcome and variable importance	Both regression and classification	Interpretability and theoretical analysis	[169,173]
	Deep Learning	Labeled, unlabeled, high dimensional raw media e.g. images, videos- feature vectors	Classification outcome and feature likelihood to a particular outcome	Feature extraction by clustering and classification	Data-intensive. Lack automation to changing conditions	[174,165]
	Rule-based	Features with associative rules	Classified fault detection	Association of rules/features	Combinatorial challenge	[148]

ES utilize domain expert knowledge employing to emulate decision making ability of a human, perform and exhibit reasoning for problem solving, hence advancing maintenance support. ES has been used for LCM data interpretation as developed by [145,177], to automate intelligently the classification process of wear particle [155], estimate the quality of oil [178], to evolve EXCARE system for maintenance of lubricants in service [74] and in a lubricant monitoring and diagnostics case study using computer-aided wear particle analysis software [179]. In a study in conjunction with a different condition monitoring technique, ES was applied using data from wear debris from oil and vibrational analysis by [180]. ES speeds up work, enhances the decision-making quality, and preserves expertise while the output can be used to test other system conditions. Furthermore, the rules required can either be heuristic or specific. On the contrary, ES contain limitations such us reliance on expert knowledge, inability to offer exact solutions, complexity in development, and lack of flexibility once built to accommodate new conditions.

In real-life applications, availability of exact information to build expert systems can be challenging, hence where vague or imprecise information is available fuzzy logic models can be built. The Fuzzy logic offers reasoning mechanism with interpolation properties using a syntax language with local semantics and membership functions, an inference based on a set of rules is made translating qualitative knowledge about the problem to be solved, thus offering decision support. Fuzzy logic model was used in predicting system operation and dependencies of iron particles [181], for predicting lubricant quality development [120], and other LCM related [182,183]. FL models render simpler and intuitive models from vague conditions while managing uncertainty to provide robust predictions. Nonetheless, all rules have an influence on the output, thus rule segregation is difficult hence may compromise model accuracy [7], moreover, increased features in FL could lead to a combinatorial challenge. The fuzzy logic technique can be incorporated in other approaches like Artificial Neural Network (ANN), Expert systems and Kalman filtering process to model logic systems that can take values in between for instance [184]. A comprehensive introduction to Fuzzy logic can be found in [185].

These approaches in LCM, have been used generally in maintenance decision support application but in a limited way, attributable to the strenuous and cost characteristics while requiring domain experts (both LCM and AI domains) to assemble the models. On the other hand, despite their versatility, limitations such as slow knowledge acquisition, codification, large knowledge infrastructure representation and combinatorial challenges makes them less developed in the LCM field as depicted in Table 7.

4.3. Model-based approaches

This approach uses physics related and mathematical models to solve problems [1]. In many instances, these models are used while analyzing both event data and LCM which is part of condition monitoring (CdM) data, where the approach uses mathematical equations to model the behavior and relationships in the system, while the degradation phenomenon is included [186]. Model-based approaches commonly used can be categorized into three types. First, simulation models, where computerized representations are built to understand and predict how changes and certain variables influence the system. The model estimates parameters designed as output measurements, which the practitioner utilizes in making decisions by employing both structural (logical features and the relationship amongst them) and quantitative(numerical inputs or distributions describing the features) features. Second, experimental models, where simplified physical representation of an occurrence being investigated is developed by experts in the field of study using a prototype test model. Investigations are carried out incorporating conditions that represent real life operations such as temperature and flow, the effects along with the experimental output offer support to maintenance decision making. Third, a mathematical model which uses time and frequency domain data extracted from real systems signals which is blended with expert, theoretical and technical knowledge of the machine or system. Different output modeled for instance failure lifetimes, additive depletion, RUL estimations, oil drain interval are optimized to inform maintenance decisions. They utilize mathematical models derived from first principles while statistically derived thresholds can also be used.

A simulation model was used in the study estimating failure modes using particle concentration and distribution for the gear lubricant [187], detecting metallic debris in lubrication oil [188], 3-dimensional system-level modeling of engine lubrication system [189] and modeling an unsteady lubrication circuit of a hydraulic system [190]. Other simulation models using LCM include [191,192]. Simulation models facilitate the behavioral study of a system without actually developing the real system, further exhibiting accurate results and ease to run the analysis. It is also beneficial in situations where uncertainty

Table 7
Comparative summary of knowledge-based approaches.

Approach	Input	Output	Analysis approach	Validity constraints	Ref
Expert systems	Rules in terms of features and feature values and knowledge base	Number and variety of features	Reasoning through a knowledge base via rules	Relies on expert knowledge Not feasible to provide exact output	[155]
Fuzzy Logic	Multi-valued logic with intermediate values	Membership value at the truth level of the argument in the scalar form	Non-linear mapping input in membership functions	Multiparameter influence and combinatorial challenge	[185]

Table 8
Comparative summary of model-based approaches.

Approach	Input	Output	Analysis approach	Validity constraints	Ref
Simulation models	Structural and quantitative data measured from the real system or approximated	Model parameter estimates highlighting cause and effects	A computer program –formulae and rules	Difficult to build an explicit model, Functions used do not adequately describe the system.	[209,189]
Mathematical models	Time and frequency domain data		A computer program-mathematical formulae and rules	Unable to model a complex system, integrate environmental effects	[1,210]
Experimental models	Structural and quantitative data measured from the real system or approximated		Bench-test /Lab-test approach	Unable to model a complex system.	[210,118]

Table 9
Hybrid approach sample papers.

Hybrid Techniques	Sample articles
Statistical + Artificial intelligence	[101,119,137,139,220,221]
Statistical + Model-based	[184,201,222–231]
Model-based + Artificial intelligence	[111,117,121,150,203,232,233]
Model based + Artificial intelligence + Statistical	[99]
Model based + OCdM	[36,213,214,218,234-237]

is high due to sparse data and offers experimentation at low cost and risks. Nonetheless, the approach entails intense computational effort, while results can be difficult to interpret, and further efforts to fully mimic real life (such as operational and environmental aspects) could make the model complex for analysis.

The experimental approach was utilized to model grease flow dynamics to predict wear and contaminant particles migration [193], validating a prototype lubricating oil pump [194], while it was further used in articles [195–205]. These models determine probable outcomes without having to set up large and costly experiments, while can be used without the need for data collection [5]. Furthermore, they are repeatable for validation and bear lower risk compared to real-life testing. Despite these advantages, the approach experiences, several limitations, for instance, specificity, hence they cannot be applied in other situations, moreover, not all parts in real life can be modeled to scale, they are problematic to build and unable to comprehensively integrate operational conditions of the system under study.

A mathematical model utilizes physics-related equations such as mass balance equations, was used in modeling the alkalinity changes in lubricating oil [206] and the thermodynamic behavior of thin lubricant film [207]. A hybrid approach is used, with a review of mixed lubrication performance that incorporates simulations, and experimental models are given by [208]. Table 8 illustrates a summary of model-based approaches highlighting constraints that may affect their reliability of LCM based decisions while being employed for maintenance decision support.

Use of simulation and experimental approaches interestingly is viewed to have increased in maintenance application despite cost, effort and sophistication characteristics [8]. This could be due to the versatility and synergetic characteristics while integrating various techniques like vibration, ultrasound, and LCM. There is a marked widespread use in tribological aspects such as friction and wear in conjunction with lubricant properties like film thickness which offers more intuition in machinery element and lubrication design and maintenance for instance [211,212,204]. Further, this is advanced as more developers are being integrated in the maintenance field directly or indirectly to offer near exact and "real" solutions.

4.4. Hybrid approaches

Hybrid approaches have been applied in several studies, where a combination of two or more approaches is used. Another significant growing hybrid approach utilizes two or more CdM techniques such as [213] where lubricant viscosity along with vibration analysis was used in a simulation model to suggest turbocharger bearing design parameters, while wear debris along with vibration analysis was used in [214]. Other studies integrate LCM with vibration analysis, for instance, discussed in [87,140,181,192,193,201,210,215–217] and with ultrasonic analysis, e.g. discussed in [36,218,219]. This approach offers synergy and each technique compliments the other, hence improved condition detection and determination leading to more fitting decision making. Table 9 illustrates several of the studies.

5. Discussion

This study set out to review the Lubricant condition monitoring approaches use in enhancing maintenance decision support in machinery. The study was based on recent developments and research with 43% of reviewed papers published in the last 5 years (Since 2013), 25% (2008–2012), 17% (2003–2007) and 13% before 2003, which shows growing trend in research of the subject.

Classical off-line sampling and monitoring as reviewed in Section 2.2 in the three-step LCM program, is in high use where old technology equipment are prevalent, furthermore high purchase and installation cost of the on-line system may be prohibitive. However, critical equipment such as in the military, health sector, airlines and marine offer unique operational characteristics which indisputably require automated LCM program for instance, online sensors and real-time monitoring. An important maintenance decision to make while reviewing technical and cost aspects in this context include, procurement of machines pre-installed with the system by the manufacturer, installation on existing machines, use of on-site or off-line sampling and testing. Offline sampling and testing remain important when comprehensive analysis such as particle shape classification and root cause analysis due to catastrophic failures which are time intensive may be necessary. The review in Section 2.2.2 highlights the use of selective test results deemed important for decision-making like viscosity, TBN, water and some wear particles, potentially limit and generate biased maintenance decisions. High reliance on elemental or wear particles usage in most approaches with 50% of reviewed articles considering the subject (See Table 4), attributable to direct link with machinery wear characteristics is notable. The heightened interest and growth using multiple parameter (mix) categories is characteristically visible constituting 28% of the reviewed articles. However, several lubricant analysis parameters seldom used in maintenance decision making may have significant value, such as nitration, oxidation and nitro-oxidation, which possess the potential to identify interactive effects additives and nitrous oxides may have on the performance of inhibitors leading to lubricant degradation, an aspect that conforms to our futuristic development needs in LCM. Despite limited applicative research (3% of reviewed articles), additive analysis has huge potential such as revealing the composition of a lubricant which could facilitate root cause analysis of machinery failures among other applications. Interestingly, current researches point towards developments of new additives that will reduce or eliminate causes of wear such as sulphated ash generation.

From the review of techniques in Section 4.1, *trend analysis* is pointed out as relying on single feature which may not comprehensibly offer reliable solutions, and can likewise miss important information because deviations from a single parameter threshold often gives partial information. By contrast, however, patterns are recognized as important for maintenance decision support. For instance, in LCM, it would be important for decision support, to integrate multiple trend plots such as for viscosity, vanadium, and carbon, as opposed to relying on single feature trends. In this case, one can diagnose, for instance, fuel dilution with higher certainty while employing multiple trends with expert assessment compared to analyzing a single parameter trend. For this reason, the use of pair-wise analytical techniques, such as the *correlation* analysis approach may yield better insights as compared to single parameter analytical approaches. However, it is notable that correlation analysis may likewise be unable to comprehensively assist decision-makers to pick patterns from LCM data, while on the other hand, associations derived from correlation analysis may not functionally be feasible. For instance, an analysis may indicate a correlation between flash point and aluminum based on LCM data, which may not be the case from the functional perspective of the lubricant. To address the aforementioned flaw while purely relying on correlation analysis, it is important to incorporate probability values to reveal significant correlations, while on the other hand, integrating expert knowledge and information from the literature. This integration will assist decision-makers to derive and validate feature patterns embedded in LCM data, and as a consequence, yield useful maintenance decision support. This approach further considers a linear relationship, yet we would ideally expect non-linearity while considering LCM variables, hence complementing correlation analysis with regression modeling would address the non-linearity flaws by the inclusion of polynomial model. Nonetheless, correlation could be used as a first line approach for decision support that offer initial direction towards picking fault patterns in the LCM data.

As regards employing *linear regression* in LCM, one important flaw of the approach is interpreting its output which is largely derived and depicted as linear relationships between LCM variables. The approach which utilizes mean values of both dependent and independent variables, may not be realistic considering the LCM field. For instance, investigating the relationship between iron and zinc assuming the parameters as either independent and dependent variables respectively, linear regression tends to compare the average values of Fe and Zn respectively in this case. Hence, if one would wish to compare the extremities of the dependent variables important decisions on, for instance, depletion of anti-wear additives due to low quantities of zinc may be omitted. Thus, to enhance the decision-making accuracy, quantile regression may be applied to address the aforementioned flaw. The quantile approach would yield better estimates of the effects of Zn on Fe for cases of both low and high levels instance (for the Zn parameter). As such, this would yield more comprehensive and realistic insights into decision support.

Looking at the review in Section 4.2, despite the expectations of better results for highly correlated data, the fact that the generated principal components may not be directly associated with the original variables limits PCA interpretability. This limitation could be addressed by using different rotation methods [168], where, in the case of LCM data with numerous features, principal components may yield better traceable correlated features (variable). For instance, between Calcium and TBN, where rotation will indicate their respective significance or contribution to the derived principal component, which, here could represent alkalinity of the lubricant, hence enabling easier interpretation and gaining more insights of possible maintenance areas to investigate under LCM. For other types of non-continuous LCM data, such as categorical data which may emanate from different sources, use of the independent principal component analysis (IPCA) approach would be ideal for separating mixed signals, which could yield better insights as opposed to the traditional PCA approach where such signals are not immediately apparent. Moreover, PCA uses gaussianity while ICA uses non-gaussianity for tracing source signals, which makes the IPCA more versatile for analyzing sensor signals of a non-gaussian nature. On the other hand, the dynamic principal component analysis (DPCA) is more useful for decision support for data which exhibits cross and autocorrelation characteristics [232]. This is owing to its more robust dimensional features reduction method.

For instances where cluster analysis is applied for evaluating patterns embedded in LCM data, one notable flaw is the element of biasness and heuristicity of the approach. For example, a cluster formed with TAN, Ni, viscosity would infer either oxidation or oil dilution by an acidic product such as fuel. Selecting one inference over the other would lead to a biased result, while vagueness would arise due to more than one feasible outcome. This challenge may be overcome by applying cluster verification techniques and incorporating expert assessment through an iterative knowledge discovery process. This process would extend to better pre-processing of the LCM input data prior to clustering correlated variables. For instance, in LCM, while investigating oxidation, integrating probability values to the clusters formed while applying correlation analysis for validating associations between variables such as viscosity and the total acid number, which experts may perceive as influencing oxidation, would ideally assist decision makers further validate similar LCM variables grouped via the cluster analysis approach. Similar to PCA, the robustness of cluster analysis depends on meticulous LCM data pre-processing to enhance the feature extraction process. The pre-processing here will ideally focus on detecting and analyzing outliers, for instance, introduced by sampling procedural errors where elements such as silicon may exhibit high values due to dirt ingression during offline sampling. From the analysis here, silicon may be presented as a critical feature in a principal component which is erroneous since the influence of dirt ingression on silicon during sampling influenced feature extraction, hence the decision-making process.

Evaluating *Logisitcs regression (LR),* which is pointed out as useful for effectively tracking and deriving the main effects of features of LCM output, however, has a limitation when interaction effects are not considered. This limitation may be seen where, for instance, iron (Fe) with a significant odds ratio of 0.8 (an increase in 1 ppm decreases odds of failure by 20%) is considered independently for decision making. In the same context, the probable outcome of a sample failure where both Fe and Water has an interaction odds ratio of 0.7, would imply that an increase of both water and Fe decreases the odds of sample failure by 30%. This interactive effect offers a more comprehensive decision support compared to instances where the combined effects of Fe and water are not considered as influencing sample failure. The use of multinomial logistics regression where more than two dependent variables are modelled, offers a wider modeling scope, where binary outcomes are not expected. This may influence outcomes such as lubricant sample results classified as either failed, caution (requiring action) and normal (fit for continued use). Evaluating *Decision trees (DT)* which is seen to have a similar limitation as PCA in dealing with outliers and non-continuous data such as categorical (for instance offering different aspects such as time intervals) would require some pre-processing. Nonetheless, we see the potential of exploiting *DT* benefits in image mining or classification, for example, wear debris classification or color classification for on-line oxidation diagnosis. The Interactive characteristics, interpretability and hyper-parameter tuning (See Table A.1 and Section 4.2.1) offer controllability that could cause more future interest over the other algorithms. The *SVM* discussed in the review is also mentioned as associated with challenges of analyzing data with noise and lacking aspects of probabilistic classification. Moreover, these challenges can be addressed by additional feature extraction methods such as PCA to establish important features that could influence the response variables such as contamination level, viscosity change and failure of equipment, while probabilistic interpretation of the output preferably could be attained by using relevance vector machine (RVM), also corroborated by [170]. The limitations of neural networks (*NN)* could be countered by addressing the provision of sufficient LCM training data and tuning. The NN capability of using noisy and missing variables data could be harnessed to improve the overall performance by not only using the technical data but also the rudimentary data such as wear particle morphological aspects in LCM wear analysis. However, interpretability challenges may be apparent due to its "black box" nature, where the relationship between input and output variable is not easily interpretable (e.g. how water and silicon content influences wear by evaluating the wear particle count). This flaw may be addressed by using techniques such as Neuro-Fuzzy systems to extract decision rules from the trained networks, where domain knowledge can be included in the Neuro-Fuzzy system in form of linguistic variables and fuzzy rules such as, "if wear particles greater than 50 ppm, wear is due to silicon". This approach would yield more robust fuzzy IF-THEN rules, which would improve interpretability and transparency for maintenance decision support. Evaluating *Random forest* (*RF),* is seen to have the limitation of interpretability and lacking a strong theoretical foundation. However, the feature variable of importance influencing a prediction and classification outcome would reasonably offer significant decision support. Furthermore, analysis of various generated decision trees, and exploitation of variable interactions, an aspect RF avails, could be harnessed to validate knowledge patterns utilized in LCM decision making. Data-intensive characteristics of *Deep learning* (DL) offers a challenge in LCM application, however increasing the amount of training data needed to improve the reliability of the approach will lead to better learning and feature extraction by the model, hence improvement in accuracy of the decision-making outcomes. Due to the versatility of DL, 'design to adopt' on-line feature learning, taking cognizance of dynamic lubricant system characteristics, will form a huge leap in the advancement of lubricant online condition monitoring, especially for either lubricant condition diagnosis or detection. For example, using on-line color images of in-service lubricant as input data, DL may indicate that the input is 90% likely to represent oxidation and automatically provide decision support in terms of maintenance intervention leading to actions such as reducing lubricant flow velocity or temperature. Hence, effective for real-time diagnosis and maintenance intervention. The main limitation of *rule-based* approaches is the explosion of the number of decision rules as the number of variables increase. When new features are introduced, for instance, adding a feature such as oxidation to rules describing fuel dilution to rules linked to variables such as Vn, Ni, viscosity, and carbon, would yield an additional generation of multiplicative rules in the LCM case. This would limit the ability to maintain consistency and performance of the decision rules. Possible linkage to a rules data-base semantically organized while developing the model may offer more robust rules for the model to learn from, and may demonstrate higher accuracy in maintenance support when new features are introduced in the modeling construct.

The limitation of the *Expert system(ES)* as far as reliance on the experts is concerned, can be overcome by incorporating more experts while validating decision rules. For instance, antecedent rules that are developed to depict a consequence of fuel dilution in high-speed engines may include limits of Vn, Pb, C and viscosity. If the ES is applied to medium or slow speed engines, the output will be erroneous due to the difference in fuel used in the different applications. Hence, incorporating experts with divergent experience and applying a dynamic review of both the rules and knowledge base to ensure the ES is always scalable, current and valid, would address this challenge. A challenge with Fuzzy logic systems is that it retains stagnant rules, which cause combinatorial challenges since any changes in the LCM variables, necessitates a change in the decision logic. For instance, rules governing change of decision rules for viscosity, while considering parameters such as Vn, water, carbon, and oxidation, may not offer reliable judgment in LCM if temperature, which was not part of the data set previously used to generate the decision rule, is now considered to affect viscosity. In such cases, multi-criteria fuzzy logic aspects advocated by authors, for instance, by [120] would enhance maintenance support by integrating divergent aspects of the LCM program such as oil and fault states, feature values and wear (size, morphology), which influences directly or indirectly the machine fault. We envision the dynamic fuzzy system, where real-time LCM and fault prevention rules are automatically updated and revised as system changes and noted online, to be an important direction for future research in this area.

A limitation of the simulation modeling approach discussed in Section 4.3, is deriving robust input distributions, especially for LCM data with multimodal distribution patterns. This is especially the case for noisy input data, with outliers. Such noise would lead to erroneous simulation output since it may not validly represent the underlying condition of the lubricant. This necessitates the need to improve data integrity for optimal model output, which could require accurate data collection procedures and systems. In addition, since the results derived from simulation models only mimic the 'real lubricant system', the need for expert validation is important in order to improve the results reliability. Considering the use of the *mathematical model,* for predicting optimized failure lifetimes, RUL estimations and oil drain interval, is viewed as important for enhancing maintenance decision support. However, mathematical models are limited as far as realistic lubricant systems may be modeled, especially modeling many real-life complex systems configurations. Hence, there is the need to Integrate several modeling constructs (simulation, experimental and mathematical) in LCM from which, simulation models may be used to derive mathematical relationship, for instance between calcium and alkalinity depletion derived from experimental/lab model (mathematical model), or comparing the total base number with the dielectric constant sensor outputs. Such integration

Table 10
Summary of articles classified by approaches used.

Classification		No. of articles	Approaches	No. of articles
Statistical approaches (SA)		67 (31%)	Trend analysis	13%
			Correlation analysis	15%
			Regression analysis	15%
			PLS & PCR	9%
			Stochastic and Kalman Filtering	9%
			Survival analysis	25%
			Hybrid Statistical approaches	13%
Artificial Intelligence approaches (AI)	Unsupervised Machine Learning Techniques	79 (37%)	Principal component analysis	9%
			Cluster analysis	9%
			Unsupervised Neural Network	8%
			Self-organizing maps	4%
	Supervised machine learning techniques		Decision trees	4%
			Logistics regression	8%
			Neural network	10%
			Support vector machine	5%
			Random forest	6%
			Deep learning	8%
			Rule based	1%
			Representation learning	1%
	Knowledge-based approaches		Expert systems	10%
			Fuzzy logic	6%
			Hybrid AI approaches	11%
Model-based approaches (MB)		27 (13%)	Simulation models	30%
			Experimental models	44%
			Mathematical models	11%
			Hybrid MB approaches	15%
Hybrid approaches		40 (19%)	SA + AI	10%
			SA + MB	28%
			MB + AI	15%
			MB + ML + SA	3%
			SA + AI	3%
			MB + OCdM	43%

Note: No. of articles is based on the proportions of articles reviewed under each of the five classifications while the proportion of articles depict proportion of articles reviewed covering a specific approach based on the respective classification.

between mathematical and simulation modeling approaches could offer robust seamless validation over the entire modeling process. Creating an interface between the model and real system potentially will in future be advanced where algorithms such as deep learning can pick information about on-line lubricant (system) changes, for instance, color images of oil and send signals to the model indicating changes in oxidation level thereby adjusting the simulation parameters accordingly. This we see will significantly reduce reliability challenges.

Table 10 and Section 4 depict a relatively higher utilization of artificial intelligence (37%) and statistical (31%) approaches on a comparative basis. The widespread usage can be attributed to acceptability, flexibility, and ease of use. There is marked fair distribution of approaches in these two categories as shown in Table 10. Survival analysis approach accounts for 25% of the statistical approaches which could be attributed to its characteristics adoption to the relevancy of researches of RUL estimation and failure events, a fundamental theme in maintenance. Hybrid approaches have a moderate usage (28% of all articles reviewed), where collaborative effect, validation, feature extraction are some reasons attributed to using more than one approach and or including other condition monitoring techniques which were the highest in the class (43% of the hybrid articles). This as alluded in literature improves detection and decision-making capabilities.

Additional decisions towards better performance and RUL optimization (an important maintenance objective while applying LCM programs), could be reached using base oils from group II and above, such as synthetic base oils which show marked performance over conventional group I in aspects such as longer drain interval, better equipment protection and lower degradation rates offering another variant in maintenance decision support. Carrying out the total cost of ownership for assets, LCM further introduces aspects rarely considered such as environmentally friendly, food safety, energy conservation and health issues that lead to adjusting LCM programs appropriately by maintenance practitioners.

The approaches reviewed have been available in the literature, however, the rate of implementation in maintenance decision support using LCM is not commensurate to the extracted knowledge base. Among the reasons for such could be lower influx of the technology, costly installation especially during operation, coupled with high software cost. Additional reasons for low application include moderately low utilization of LCM in maintenance and lack of knowledge exchange between the developers and practitioners as seen in Section 4. The missing direct link between failure event and LCM data leading to over-reliance of the former in maintenance also seen in Section 4. Lack of data infrastructure in terms of actual data collection or size of data required (Section 4.2) and lastly, historical ideologies that LCM is used for root cause analysis (diagnosis) despite its ability to also be used for detection and prognosis as seen in the maintenance practice.

6. Future trends of LCM in maintenance decision support

LCM, as reviewed, is not only developing in a quick pace and widening its potential in maintenance applications, but also growing in terms of being a condition monitoring technique embraced and used as a first line defense of early warning in maintenance. Moreover, the non-intrusive characteristics as well as the value of knowledge extracted from the mechanical systems using LCM, may be attributable to the increase in attention. Despite the subject, in view of maintenance decision support becoming an important issue for future research, there is abundant room for future progress towards more technical and the expert-driven maintenance support approaches. Expected fast developments of lubricants and greases are expected to drive the development of LCM approaches to be able to offer decision support on the nature and type of lubricant to be used, but also, decision making aspects such as replacement intervals. Importantly, such decision would ideally be dynamically linked to the expected economic lifecycle of the lubricant or equipment. Additional decision-making aspects may consider the need for lower environmental impact (lubricant disposal and biodegradability), the need for improved energy efficiency, or development of innovative sensor technology. These new developments will, therefore, necessitate versatile decision support systems lubricants with highly varying parametric properties.

Therefore, with the technological development, further research and development of on-line signal processing and diagnostics tools that are cost-effective and easy to install under LCM, offering robust algorithms towards designing of intelligent systems will unquestionably in our view, stimulate growth in the LCM field while addressing these developing challenges. Research in advancing 3-D printing of sensors will possibly be an essential next step in developing robust and cost-effective sensors. A greater focus on integrating detection modes in a single sensor, further offering data fusion and separation characteristics could produce interesting findings that account more for the potential growth. This is especially important for techniques such as neural networks and deep learning where availability of large LCM data sets is essential. It is inevitable that Expert systems will have a significant role in the future development where we envision improvement in creativity, response, interaction and flexibility is key. This is because of the current and future drive in maintenance automation which exhibit less human interference and reliance. This will also be enhanced through the pre-installations by equipment manufacturers with tagged requirements for manufacturer on-line support and warranty extension counter-requirements. Development of a system that will be able to adjust decision rules especially when changes not envisioned in the knowledge base take place (for instance, fuel dilution reacting to a solvent dilution which is not an easily adaptable decision rule for machine learning), is seen as an important area of future research. Future increased focus on deep learning approaches such as computer vision recognition and image classification, remains a field with the possible potential to expand and revolutionize LCM programs. Widening the scope of models remain a factor expected to be advanced, where approaches will not be limited to elemental particles, but will also draw information from other lubricant properties such as additives, physio-chemical and dilution properties which are explored to a lesser extent. Hybrid utilization of more than two different approaches in our view is expected to yield useful approaches for decision support in LCM, where optimization of the unique synergies will be harnessed. Another area potentially expected to enhance decision support, is the use of integrated approaches for instance lubricant condition monitoring alongside with vibration analysis as seen in the review. This finding provides some support for the conceptual premise that integration of LCM with the other CdM techniques such as ultrasound, thermography would provide robust, reliable complementing decision support, an important issue for future research. Acoustic lubrication design for bearings has been on the rise and we foresee the development towards other applications alongside full LCM being an area that will grow in a fast pace due to its ability to detect problems earlier than other CdM techniques such as vibration. However, the complimenting characteristics of the techniques should undoubtedly extend benefits to the industry. The authors concur with Jardine et al. [1] synopsis of the future directions for CBM which most are similarly applicable to LCM.

7. Conclusion

The primary goal of the current study was to review the approaches utilized in lubricant condition monitoring while providing maintenance decision support for machinery maintenance. The study classified and reviewed the different lubricant tests and the approaches that incorporate methods and techniques used to process, evaluate and analyze lubricant condition data for maintenance application. This followed the three LCM program steps namely sampling, testing, and maintenance decision support, with emphasis on the last step where knowledge is extracted and applied. The study systematically classified the approaches while utilizing definitions that can potentially assist maintenance fraternity in developing more knowledge and insights in the LCM field. An implication of this is the possibility many organizations will embrace LCM programs and the technology thereof to harness the maintenance benefits while using other strategies concurrently. The current findings also add to a growing body of literature on lubricant condition monitoring and maintenance decision support.

Declarations of interest

None.

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Appendix A

See Table A1.

Table A1
A sample of hyper-parameters for model tuning.

Approach	Hyper- parameters	Ref
RF	# of classification trees	[238]
	# of variables	[173,169]
	Maximum depth of the individual tree	
SVM	Penalty parameter (C)	[238]
	Gamma parameter (γ)	[172]
	Kernels(sigmoid, radial bf, polynomial)	
LR	# of classification trees	[238]
	Maximum depth of individual trees	
Learning rate	[127]	
	# of variables	
	Penalty parameter (C)	
DT	Complexity parameter (cp)	[239,169]
	# of minimum split	
NN	# of hidden layer and units	[132]
	# of features	
	# of iterations	
RB	Merging threshold	[240]
	Estimated proportion of sentence-distance range. The shape and scalar factors for distribution	
RL	# of perceptron layers	[241]
	Learning rate for latent representation	
	Learning rate for the parameter in perceptron layer	
	Momentum term	
DL	Learning rate	[242]
	Architectures for deep neural networks	
	Activation functions	
	# of connected layers an neurons	

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