Mechanical Systems and Signal Processing 118 (2019) 108–132

Contents lists available at ScienceDirect

Mechanical Systems and Signal Processing

journal homepage: www.elsevier.com/locate/ymssp

Review

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

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ARTICLE INFO

Article history:
Received 6 February 2018
Received in revised form 31 May 2018
Accepted 14 August 2018

Keywords:
Lubricant condition monitoring
Condition-based maintenance
Maintenance decision support
Prognosis
Diagnosis

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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https://doi.org/10.1016/j.ymssp.2018.08.039

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