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RELIABILITY PAPER

A comparative analysis of maintenance strategies and data application in asset performance management for both developed and developing countries

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Abstract

Purpose – The present study empirically compares maintenance practices under asset performance management (APM), employed by firms in developed and developing countries (Belgium and Kenya, respectively).
Design/methodology/approach – Empirical observations and theoretical interpretations on maintenance practices under APM are delineated. A comparative cross-sectional survey study is conducted through an online questionnaire with 151 respondents (101 Kenya, 50 Belgium). Descriptive statistics and inferential statistics like independent *t*-test and phi coefficient were used for analyzing the data.
Findings – In both countries, reduction of maintenance and operational budget, return on assets, asset ageing and compliance aspects were established as critical factors influencing the implementation of asset maintenance and performance management (AMPM). A significant difference in staff competence in managing vibration, ultrasound and others like predictive algorithms was found to exist between the firms of the two countries. The majority of firms across the divide utilize manual and computer-based tools to integrate and analyse various maintenance data sets, while standardization and maintenance knowledge loss were found to adversely affect maintenance data management.
Research limitations/implications – The study findings are based on the limited number of returned responses of the survey questionnaire and focused on only two countries representing developed and developing economies. This study not only provides practitioners with the practical guidelines for benchmarking, but also induces the need to improve the asset maintenance strategies and data application practices for asset performance management.
Practical implications – The paper provides insights to researchers and practitioners in the articulation of imperative effective maintenance strategies, benchmarking and challenges in their implementation, considering the different operational context.
Originality/value – The paper contributes to theory and practice within the field of AMPM where no empirical research comparing developed and developing countries exist.

Keywords Kenya, Belgium, Maintenance data, Asset performance, Survey, Developing countries
Paper type Research paper

1. Introduction

Asset performance management (APM) is a multi-disciplinary management process that optimizes the asset performance over its life cycle by safe operation and minimizing downtime (Parida *et al.*, 2015). The availability of any plant depends on measures such as reliability, maintainability and spare parts availability of the equipment or components (Choudhary *et al.*, 2019). Asset maintenance and performance management system (AMPMS)

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is designed to derive knowledge from the various types of maintenance data to improve the overall reliability and availability of a facility. Ultimately, AMPMS converts available maintenance and reliability data into knowledge for maintenance decision support. In this case, a substantial amount of these data can be acquired through asset maintenance, condition assessment and monitoring, where organizations acquire precise information about the assets (Antomarioni *et al.*, 2019). Many organizations attach various objectives to the maintenance data collected like for root cause analysis, optimization programs, reliability analysis and maintenance planning. However, a considerable number of organizations lack user-based focus, thus collect data out of a procedural requirement (Tretten and Karim, 2014). This is because they face challenges such as lack of clear maintenance objectives and suboptimal maintenance data management strategies. These challenges underscore the need to establish clear maintenance objectives, strategies and maintenance data management practices. Consequently, organizations can articulately generate knowledge from maintenance data for use in decision support as also corroborated by (Xiao *et al.*, 2019). Therefore, maintenance strategies (e.g. predictive) and maintenance objectives (e.g. reliability and maintenance inventory) should be derived while considering their dependencies (Wakiru *et al.*, 2019a).

Maintenance data management is viewed as a crucial factor driving an organization's objective of attaining an optimal APMS. Most maintenance-intensive industrial installations generate various types of data while employing various maintenance strategies. This includes failure event and condition monitoring data collected during corrective, condition-based, preventive and predictive maintenance (Fraser *et al.*, 2015). However, deriving maintenance decision support using individual types of data does not offer robust solutions. Hence, there is a need to amalgamate or integrate the different data sets for a concurred solution in a data management system. The data management system encompassing data collection, storage, analysis (knowledge discovery) and subsequent application (knowledge application) varies from one installation to another (Wu *et al.*, 2014).

Considering knowledge discovery, there are numerous techniques for maintenance data collection, integration and analysis. These techniques range from traditional modes like manual recording to modern practices like those found in enterprise resource planning (ERP) systems. However, the data structure inevitably should allow uncomplicated analysis to enhance efficient derivation of maintenance knowledge and final application. To achieve these appropriate characteristics, the data system and staff handling the process require to demonstrate consistency in data management, while countering challenges like knowledge loss and technological changes (Ghahfarokhi and Zakaria, 2009).

On the other side, to achieve knowledge application, the maintenance staff who utilize these data should be competent to interpret results, derive decision support and implement the same (Wang *et al.*, 2019). Therefore, the aspect of maintenance staff's level of interpretation competence is vital, especially while involved in sophisticated strategies included in condition monitoring.

It is perceived that firms in developed countries exhibit different APM practices compared to those in developing countries, which are still in the early stages of industrial development. The perceived differences may be attributed to the advancement of skills, technology and techniques for maintenance data collection, integration, analysis and interpretation. However, these perceptions have not been validated empirically as also corroborated by (Muchiri *et al.*, 2017). Consequently, a comparative study will enhance our understanding of the APM practices of countries representing the two divides and seek to validate the perception empirically. We select Belgium and Kenya, where the World Economic Situation and Prospects (WESP) categorizes them as developed and developing economies, respectively (WESP, 2019). Our choice of both types of countries considers several reasons.

To begin with, our choice is in conformance with the overarching objective of this research. In this case, it is to determine the differences and similarities between firms in different economic, political, social and institutional conditions. Second, our choice is informed by the results of maintenance-based surveys made separately by (Muchiri *et al.*, 2010) and (Muchiri *et al.*, 2017) for Belgium and Kenya, respectively. The study in Kenya demonstrated a low application of automated knowledge discovery techniques like ERPs and suggested the need to invest in predictive and condition-based maintenance (CBM) maintenance strategies. In Belgium, training of operators and preventive and predictive maintenance were preferred strategies in maintenance optimization. In both studies, proactive maintenance practices that include preventive and predictive maintenance were emphasized as an essential requirement. Predictive maintenance is characterized by exploitation of CBM and improving personnel competence while retaining appropriate maintenance objectives. As also alluded by (Fraser *et al.*, 2015), there is a lack of research that examines these characteristics of predictive maintenance. Moreover, it subsumes the use of automated or semi-automated maintenance data management tools like ERPs and computerized maintenance management systems (CMMs), aspects we view as essential in asset performance management (APM). The studies do not provide any comparative analysis, which would not only act as a benchmark, but also reveal the maintenance practices that are undertaken similarly or differently. Comparative analysis heightens awareness of other systems, thereby casting a fresh light that enables critical contrasting with prevalent aspects, enhancing understanding. It provides access to alternative options and problem solutions and contributes to generalization by allowing for the evaluation of the scope and significance of certain phenomena, hence providing a good representation of the industry. Hence, there is motivation to use a comparative survey approach while incorporating maintenance data management practices as additional critical underlying dimension. Third, our choice stems from the relevance and impact of this topic in the maintenance field. This study contributes by furthering previous theoretical considerations regarding maintenance practices, particularly by elucidating the practices under maintenance data management context in developed and developing countries.

In this study, we seek to investigate how maintenance strategies and data application practices for asset performance management are employed by maintenance-intensive companies in developed and developing countries (Belgium and Kenya, respectively). Among the sub-objectives include establishing the critical drivers for implementation of asset maintenance and performance management (AMPM) and the maintenance strategies exploited. Further, we quantify the relationships and dependencies between maintenance objectives selected by the firms. Next, we consider the maintenance data management practices by first exploring the various types of condition monitoring techniques employed and staff competence in handling and interpreting individual results. Hence, we address the hypotheses; "There is a significant difference between Kenyan and Belgian maintenance staff's competence and capability level of handling and interpreting different condition monitoring results". Besides, to recognize the various heterogeneous maintenance data the organizations collect, we seek to establish the techniques employed and the challenges organizations face while integrating the heterogeneous data (condition monitoring, event and other data) for maintenance decision support.

The remaining part of the paper proceeds as follows: Section 2 presents a brief literature review of relevant studies, while Section 3 describes the methodology utilized for this study. Section 4 presents the results and discussion, and Section 5 offers an implicative summary. Finally, Section 6 entails conclusion and proposed future work.

2. Relevant literature review

APM encompasses activities and processes undertaken to monitor an asset condition and manage the maintenance and performance processes. These overarching activities and processes in APM can be categorized as maintenance strategies and objectives, and maintenance data (condition monitoring and failure event) management, which encompasses data collection, integration and application.

2.1 Maintenance strategies and objectives applied in asset maintenance and performance management

Various maintenance strategies are employed widely to enhance APM by addressing and preventing failures, hence enhancing the productivity and profitability of a production system (Xiao *et al.*, 2019). Common and widely implemented maintenance strategies include corrective maintenance and preventive maintenance which subsumes time-based (predetermined interval) and CBM. CBM subsumes several approaches employed to derive maintenance decision support. They include predictive condition-based maintenance which predicts the deterioration condition in the future for maintenance decision-making (Lu *et al.*, 2007), while predictive condition and model-based maintenance involves monitoring, modelling and predicting a system's deterioration. Processes supporting the various maintenance strategies include data collection, data application through predictive models and decision-making frameworks encompassing both technical and financial aspects (Antomarioni *et al.*, 2019). These processes are subsumed in maintenance data management, discussed in Section 2.2. However, to meticulously address decision support aspects, including equipment life cycle (Ghosh *et al.*, 2018), maintenance cost management (Endharta and Yun, 2017) and asset performance, and further articulate the overarching strategy of the maintenance function in the organization, deriving and application of maintenance objectives is essential (Wakiru *et al.*, 2019a). Hence, it is of utmost importance that such goals are aligned and linked to the organizational maintenance strategies at the operational, tactical and strategic levels. The maintenance team undertaking optimization of maintenance programmes additionally uses these objectives.

2.2 Maintenance data management in asset maintenance and performance management

During asset maintenance, data that describe characteristics of the various maintenance intervention (e.g., condition monitoring data, failure events logs/data and process control data) are is generated and are frequently recorded in separate databases. However, organizations that utilize the data for decision support should consider the objectives and challenges engrained as well as the management of the data (Ungermann *et al.*, 2019). This is discussed in the following parts of this section; in Section 2.2.1 we review condition monitoring, in Section 2.2.2 failure event data and in Section 2.2.3 maintenance data integration.

2.2.1 Condition monitoring data. CBM strategy is undertaken to detect and identify potential failures for accurate intervention before their occurrence. Moreover, condition monitoring techniques are utilized to point the existence of the problem, its severity, failure mode occurrence in specific components and root cause analysis of the problem (Xiao *et al.*, 2019). Various condition monitoring techniques are employed under CBM like vibration analysis, tribology and oil analysis, thermography, acoustic and ultrasound analysis (Wakiru *et al.*, 2019b). Ultimately, these techniques demonstrate significant gains in the asset's availability, performance and, consequently, productivity. This type of maintenance, compared to the others, presents the need to reinforce the diagnostic capacity to be able to carefully follow the state of the "health" of the assets (Wakiru *et al.*, 2019b). Hence, for the organization to derive optimal solutions, the proficiency of analyzing, interpreting and employing the results obtained from the different techniques is essential (Wang *et al.*, 2019). However, the implementation and application of the condition monitoring strategy face various challenges in asset-intensive organizations. Such problems include lack of consistency in undertaking the programme, long interpretation lead times, misinterpretation and multiple handling requirement (de Azevedo *et al.*, 2016). We explore the condition monitoring techniques used along with the analysis and interpretation capabilities of maintenance staff and, ultimately, the challenges organization face while using the methods.

2.3 Event or failure data

Event or failure data are collected and recorded following several downtime-related events like equipment failure, repairs, spare management and other incidental stoppages to the plant (Tambe and Kulkarni, 2016; Wakiru *et al.*, 2019). At higher system abstractions, event data on maintenance planning and spare parts management are collected and stored using maintenance information systems. Examples of these systems include ERP and the CMMS, now also referred to as enterprise asset management (EAM). Additionally, the collection of failure event data routinely requires manual data entry to the information systems (Fraser *et al.*, 2015). The data collected address various objectives as espoused by the maintenance requirements, which may include root cause analysis, procedural requirements and inventory management. However, despite the importance of event data, organizations experience various challenges such as data non-standardization, data independence and inconsistency in data collection (Galar *et al.*, 2012). We explore the objectives and challenges experienced by the organizations while working with the event data.

2.4 Integration of data in maintenance decision support

The application of maintenance knowledge derived from maintenance data represents the goal for maintenance data management. The use of one data type for maintenance decision support is limited to domain information the data represent and may not reveal conclusive insights. Hence, the use of heterogeneous data is proposed in the literature and may yield hybrid or integrated techniques, which some authors argue would offer more robust and intuitive decision support (Antomarioni *et al.*, 2019; Galar *et al.*, 2012). This underpins the significance of deriving decision support by linking various condition monitoring data set like vibration or oil analysis data with failure data, where some studies (e.g., (Wakiru *et al.*, 2019b)) cite a lack of linkage between them. Data integration is defined by (Niu *et al.*, 2010) "as the process of combining data and knowledge from multiple sources, to maximize the useful information content, for increased reliability or discriminant capability".

However, plants experience the challenge of integrating and managing data ready for maintenance analysis. This aspect could reduce data preparation time and ensure short turnaround times in data analysis and evaluation. Therefore, various methods are employed for data collection, storage, integration and evaluation. The methods range from simple conventional (e.g. manual, PC-based tools like Excel), to modern tools such as ERP like SAP, computerized maintenance management system (CMMS), cloud and big data management systems with business intelligence software ingrained (Tretten and Karim, 2014). These efforts face several challenges like the lack of standardization of data sets, maintenance knowledge loss and technological changes challenges (Ghahfarokhi and Zakaria, 2009). The lack of standardization of the data sets constitutes a critical threat that ultimately affects the reliability and maintainability of the maintenance data. Moreover, this standardization challenge is aggravated when an organization maintains unstructured data, employs disparate systems and lacks a standard taxonomy to follow while aggregating data (Wakiru *et al.*, 2019b).

We explore the maintenance data usage, relating to the practised mode of integration of both condition monitoring and event data, and challenges faced while integrating the desired improvement the participants expect to enhance the maintenance data application and usage.

3. Method

We describe the research methodology adopted in the study in the following section. We review the participants, the data collection tool and the procedure followed.

3.1 Survey approach

The objective of this paper is to explore and compare the application of maintenance strategies, objectives and data management in AMPM. The survey research strategy was selected as an optimal means to derive insights in practice while comparing Kenya and Belgian firms. Due to its flexibility, adaptability and objectivity, both literature and interview/survey are employed to investigate for a better understanding and provide unique insights on the phenomenon (Saunders *et al.*, 2016). The study employs an online survey approach because it remains rapid and effective while dealing with a broad spread population. Widespread use of online surveys is attributed to lower administration costs, efficient data collection, convenience and the ability to branch questions based on prior responses (Bhatia and Awasthi, 2018).

3.2 Data collection tool

The questionnaire used in this study consisted of 5 sections and 19 main questions. Structured easy-to-understand and relevant questions, with a list of possible answers for the respondents, ensured respondents interpreted the questions as intended. Footnotes were used to offer definitions of various words and terms that were suspected could be misunderstood. Despite this format being recommended for mail surveys, an open-ended option was additionally employed to enhance the respondent's interpretation. This enhancement improved the validity and reliability of the instrument.

The questionnaire was based on the relevant literature and domain-based theory and knowledge, hence guaranteeing a high degree of constructs and content validity. Furthermore, the questionnaire was reviewed and pre-tested by academic peers (PhD scholars) and practising engineers (from a large chemical production plant and a maintenance engineer's association) to ensure adequate coverage of the questions. This phase of review required the respondents to evaluate the questions clarity, technical soundness, ease of interpretation and consistency. Following an analysis considering the suggestions and comments, the questionnaire was pre-tested using five companies in Kenya and two companies in Belgium representing varied industries: mining and manufacturing, chemical and pharmaceutical manufacturers, aviation, drilling, cement grinding and power generating. In this case, the respondents pre-testing the questionnaire were required to write their reflections on adequacy, clarity and ease of responding to the questions.

3.3 Procedure

After the final revision by the authors and experts, the designed questionnaire was produced in the online platform, as shown here (https://forms.gle/WDYM56hQhRM9X4Rj7). At this point, the final review and dummy participation was carried out before it was ultimately sent out to the respondents. The survey incorporated an actual collection of the primary data using structured self-completed web (access through a web browser using a hyperlink) and mobile (access via QR-quick response code) questionnaires depending on the mode of distribution or access to the respondents. The access platforms were embedded in an email that contained a brief explanation of the reason for the survey, clarification on what the data will be utilized for and confirming the confidentiality of the data and contacts of the respondents.

Short, personalized invitations, email reminders and telephone reminders of respondents that were known were employed to enhance the response rate. Moreover, respondents were promised an incentive that retains a summary report on the critical results after data analysis.

3.4 Survey participants

The focus of the survey was on maintenance and planning managers, maintenance and reliability engineers, and other senior professionals within the maintenance and operations functions. The classification of the respondent's type of industry was undertaken using the standard European industrial classification code (NACE, 2008). The empirical study was conducted implementing a cross-sectional survey of the Belgian (developed country) and Kenyan (developing country) firms that directly or indirectly maintain their assets or equipment. The population considered in Kenya was selected from the Kenya Association of Manufacturers (KAM) directory with 1,043 addresses (importers and manufacturers). Out of the population, 358 were qualified to participate in the survey as manufacturing companies retaining maintenance-intensive equipment. On the other hand, Belgium Maintenance Association (BEMAS, 2019) with networks for maintenance-intensive Belgian firms was used to identify 440 companies. By the end of the survey period, the response rate in Kenya was 28% (101 respondents) and in Belgium was 11.13% (49 respondents). However, further analysis of the responses identified one respondent with over 60% of the survey unanswered. The authors agreed to strike out to prevent any infliction of errors in the analysis. Altogether, a response rate of 18.80% (150 responses) was attained. The respondents' profiles are presented in Table 1.

Based on the respondent's profile, in Kenya, the respondents were dominated by other manufacturing, while in Belgium, companies manufacturing chemical and pharmaceutical products dominated. These results seem to be consistent with other research which found general sectors depicted as others dominated the distribution (e.g., Alsyouf, 2009), while that of Muchiri *et al.* (2010) represented lower response from firms manufacturing pulp and paper products in Belgium.

The survey adopts the classification as employed by (Ukko *et al.*, 2019), which defines companies with less than 49 employees as small-sized, 50 to 249 medium-sized and more than 250 employees as large-sized. It is demonstrated that Belgian respondents had no small-sized company, while most of the firms had over 25 contracted employees. In contrast, 17% of respondents were in small-sized companies, and most of the Kenyan companies had less than ten contracted employees. These maintenance staff distribution results show firstly that Belgian firms are more extensive than Kenyan in terms of size. Moreover, most of the companies in the two countries were sizable and retained a hybrid distribution incorporating own and contracted employees, which further indicates, to some extent, considerable outsourcing of maintenance-related services.

3.5 Tests for potential bias in the survey data

To evaluate the threats of potential bias that may be inherent in survey data, we initially assessed the potential non-response bias by comparing early and late responses. We applied the results of the 17 maintenance objectives and 7 condition monitoring techniques based on the responses in Kenya. In our research, data collection was spread over three month. We, therefore, define early responses as those received in the first 75 days and late responses as those that are received in the last 15 days of the survey period. The late responses, characterized by a significant period between the previous responses were obtained, indicating reminders using the telephone and emails. The *t*-test was carried out between the early (85) respondents and late (15) respondents on specific items. The results did not indicate any significant difference between the two groups at a 5% level of significance; hence, the data were free from non-response bias.

We tested the issue of common method bias employing Harmon's single-factor approach. Based on Harman's one-factor test, no factor in the unrotated factor solution demonstrated to

		Kenya, N (%)	Belgium, N (%)
Industry sector of respondents			
Manufacture of food products		15(15%)	5(10%)
Manufacture of pulp and paper products		8(8%)	0(0%)
Manufacture of coke and refined petroleum products		5(5%)	3(6%)
Manufacture of chemical and pharmaceutical products		4(4%)	20(41%)
Manufacture of basic metal and fabricating metal products		12(12%)	4(8%)
Manufacture of machinery and equipment		3(3%)	3(6%)
Transportation and storage		12(12%)	4(8%)
Other manufacturing, repair, installation of machinery and equipment		19(19%)	9(18%)
Mining and quarrying		4(4%)	1(2%)
Electricity, gas, steam and air-conditioning supply		12(12%)	1(2%)
Construction		7(7%)	1(2%)
Respondent company number of employees			
<49 employees	Small	17(17%)	0(0%)
50–249 employees	Medium	36(36%)	15(31%)
>250 employees	Large	47(47%)	34(69%)
Contracted maintenance staff size of respondents			
<10 employees		63(63%)	15(31%)
<250 employees		34(34%)	24(49%)
>250 employees		3(3%)	10(20%)

Table 1.
Respondent companies' profile

account for greater than 50% of the variance in the data set. In this study, the maximum variance explained by any single factor was 19.195% in the case of maintenance objectives. Condition monitoring techniques retained 32.668%, evidently suggesting the absence of common method bias (Harman, 1967).

4. Results and discussion

In the following section, the principal results and findings obtained are presented. Descriptive statistics and factor analysis were employed while processing the collected data.

4.1 Maintenance strategies in asset maintenance and performance management (AMPM)

The respondents were invited to indicate key drivers of AMPM implementation from a set of factors, and the results are presented in Figure 1. It is demonstrated that in both Kenya and Belgium, reduction of maintenance and operational budgets and optimizing return on assets (ROA) are identified to retain the substantial influence. In Belgium, regulatory compliance and ageing assets are more critical compared to Kenya. These results support previous research into this domain area by (Parida *et al.*, 2015) which links maintenance costs, operational costs and return on the investment to asset maintenance management. Surprisingly, only a minority of respondents in both Belgium and Kenya are driven by process and demand changes to implement AMPM. This may suggest smaller investment in dynamic related tools and systems that track such changes in the performance of the assets.

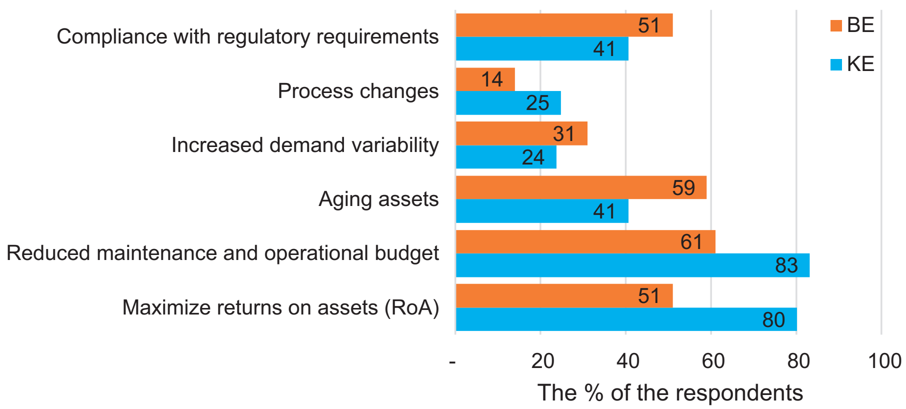

Figure 1.
Factors driving the implementation of asset maintenance and performance management in Kenyan and Belgian firms

The respondents were asked which maintenance strategies they employed from a set: corrective, preventive, predictive condition-based, proactive, predictive condition-based and model maintenance (also called prognostic maintenance). In Kenya, (91%) of respondents indicated utilizing preventive maintenance, while 76% use corrective maintenance. In Belgium, 98% of the respondents use preventive maintenance and 96% corrective maintenance. This result may be explained by the fact that the heightened use of preventive maintenance compared to corrective maintenance often improves the performance of an asset. This is achieved by addressing failures before materializing and ultimately enhancing the reliability of system. A significant difference is noted in the use of predictive CBM with 71% and 44% in Belgium and Kenya, respectively. This result may suggest a higher utilization of modern equipment and technology that incorporates sensor measurements and algorithms for future-based maintenance analysis in Belgium, compared to Kenyan firms. However, 33% of respondents in Kenya insinuated using proactive maintenance, and 15% indicated predictive condition-based models, while in Belgium, 48% and 35%, respectively. The finding also accords with our previous observations, which showed a significant number of firms did not invest in the management of dynamic maintenance aspects. These dynamic aspects are primarily employed for proactive and predictive maintenance.

The respondents were invited to indicate the essential maintenance objectives employed in maintenance optimization programs, and the results are illustrated in Figure 2. As expected, firms in both countries consider maintenance cost, availability, reliability, environment, health and safety as paramount. This could be explained based on the earlier finding that financial-based factors are predominantly driving the implementation of APM. However, production or operational throughput in Belgian firms' exhibits significant importance compared to Kenyan firms. This underscores the significance of throughput in Belgian firms. In this case, a firm seeks to eliminate throughput bottlenecks, reduce product rejects, enhance plant automation and improve safety. This aspect increases profitability, hence can be linked to the key drivers of APM earlier found to be cost and profitability optimization. Managing various times, the team engaged in the mentioned aspects possesses the potential to increase profitability through cost reduction and improved production.

To quantify the relationships and dependencies between the maintenance objectives selected by the diverse organizations, we employed measures of association that establish the

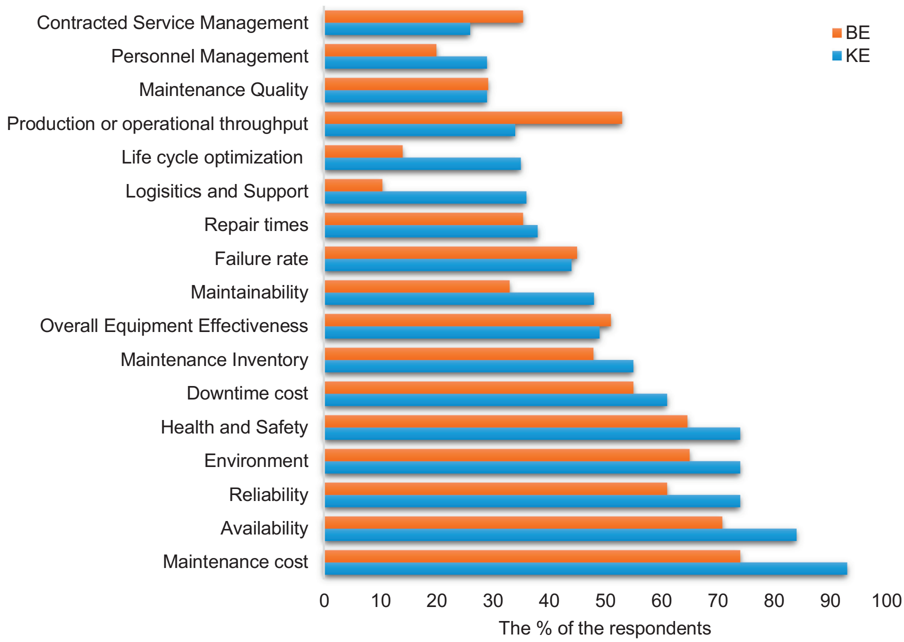

Figure 2. Maintenance objectives priorities among Kenyan and Belgian firms

existence, direction, strength and statistical significance of a relationship. Phi coefficient, evaluating the association between the variables in pairs (2×2), was employed. We adopt the suggested interpretations of measures of association offered by (Davis, 1971), where values below 0.3 (low relationship), 0.3–0.49 (moderate) and over 0.5 indicate strong relationships. For brevity, we sample a few derived relationships illustrated in Table A1 (Kenya) and Table A2 (Belgium) in the Appendix. The results depict a strong relationship between maintenance inventory and contract service management both in Kenya ($\varphi = 0.500$, $p =< 0.001$) and Belgium ($\varphi = 0.6348$, $p = 0.0062$). This implies that companies engaged in maintenance inventory management are concerned in contract service management, possibly linking the inventory management to outsourced partners like vendor-managed inventory with consignment stocking. On the flipside, there is a strong relationship between production throughput and contract service management in Belgium ($\varphi = 0.6569$, $p = 0.0042$) and low relationship in Kenya ($\varphi = 0.1400$, $p = 0.1610$). This indicates that companies keen on production throughput in Belgium are also keen on contract service management. This underscores the importance of contracted maintenance services in ensuring significant production, especially where maintenance of hi-technology equipment renders the in-house maintenance staff inadequate. This correlates with the respondent's characteristics where 69% of the respondents in Belgium retain over 25 contract employees.

These results taken collectively further support the expected idea of organizations prioritizing profitability by minimizing costs, improving availability and enhancing equipment reliability, which are core deliverables of AMPM programmes. However, it is crucial to note equally evolving critical objectives like reliability, environment safety and health and maintenance inventory, which suggest organizations in both countries are likewise considering the maintenance processes along with maintenance results in AMPM. However, from the results, it is revealed that maintenance objectives like production or operational throughput and contracted service management have a significant difference between the respondent's rates of both countries. This may infer the use of contracted maintenance service providers and heightened demand for maximizing production in the competitive European environment.

4.2 Maintenance data management in asset performance management

The respondents were asked to specify the leading applications of maintenance data in their organization's maintenance decision support framework; results are shown in Figure 3. It was discovered that most of the organizations in Kenya and Belgium utilize maintenance data for maintenance planning and scheduling and root cause analysis. Interesting to note among these results, significant respondents in Kenya intimated procedural requirements as a dominant use of maintenance data, while other purposes denoted to a lesser extent. This specific finding corroborates the suggestions and argument by (Tretten and Karim, 2014) that some organizations collect data without a user-based focus, and this becomes procedural.

On the other hand, the low-scale application of maintenance data for reliability, technological optimization and predictive purposes in Kenya is contrary to the earlier finding. This is in the premise of reliability being a vital maintenance objective and the general expectation. In this case, historical and/or sensor data are analysed for knowledge discovery to enhance equipment availability and reliability by employing predictive techniques. On the contrary, Belgian companies significantly apply maintenance data for risk and reliability management, which corroborates the earlier finding of Belgian companies using predictive condition-based maintenance significantly.

We consider condition monitoring data in Section 4.2.1, failure event maintenance data in Section 4.2.2 and maintenance data integration in Section 4.2.3.

4.2.1 Condition monitoring maintenance data. The participants were asked, among other equipment, which condition monitoring techniques they employed; the results are shown in Table 2. It is unveiled that in both Kenya and Belgium, lubricant analysis is predominantly used on engines, compressors, gear and hydraulic systems. This result is as expected because oil is consumed in these systems in sizeable quantity and offers insight on the equipment condition in a more convenient and more straightforward approach. However, the results show a significant usage of thermography in engines and vibration analysis in both engines

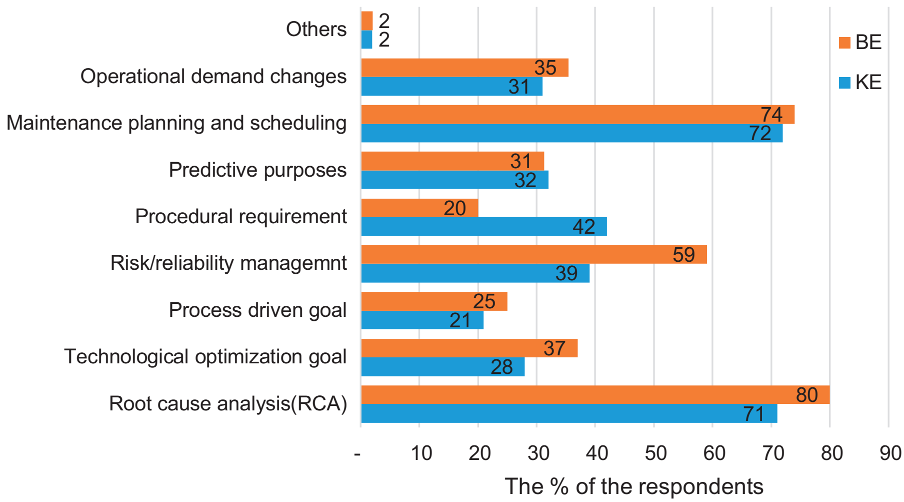

Figure 3.
Applicative purposes of maintenance data among Kenyan and Belgian firms

Table 2.
Types of condition monitoring techniques utilized in Belgian and Kenyan firms (% respondents)

	Engines		Gear		Hydraulic		Compressor		Pumps		Motors		Electricals	
Condition monitoring technique	BE	KE	BE	KE	BE	KE	BE	KE	BE	KE	BE	KE	BE	KE
Oil analysis	92	89	94	44	83	54	78	45	37	28	30	5	9	7
Vibration analysis	72	38	70	37	25	11	81	29	97	42	85	42	3	5
Thermography	52	41	27	34	25	16	44	29	33	25	42	44	97	52
Acoustic/Ultrasound	24	10	12	7	4	7	26	7	40	11	30	12	6	11
Predictive algorithm	16	20		9	8	9	15	15	7	17	18	10	22	20

Note(s): Key: BE- Belgium; KE-Kenya

and gear systems in Belgium. This result further correlates with more prior findings inferring incorporation of modern technology and techniques in asset maintenance.

On the other hand, the results relating to pumps, motors and electrical systems in Belgium indicate significant use of vibration analysis (pumps and motors) and thermograph (electrical), while relatively low in Kenya. A possible explanation for this phenomenon might relate to the inherent extensive manufacturing facilities in Belgium, as can be inferred from the results in Table 1 (69% of respondents in large-scale company). Moreover, large-scale facilities in Belgium can operate a large number of motors and pumps, as corroborated by (Muchiri *et al.*, 2010).

The most surprising aspect of the data analysis in Table 2 is that Kenyan firms had low utilization of vibration and ultrasound compared to Belgian firms. On the other side, both countries had low usage of different techniques like predictive algorithms. This may be attributed to slow popularity gain of the techniques in the engineering maintenance field (Antomarioni *et al.*, 2019), as opposed to other areas like healthcare, where they are widely employed.

A key aspect we sought to investigate was the maintenance staff's competence in handling and interpreting various condition monitoring-based results. To this end, the respondents were asked to rate the interpretation level of condition monitoring results by their technical staff using a Likert scale of 1 (extremely low) to 5 (extremely high). We utilized the independent sample *t*-test to establish the difference in the interpretation level between companies in Kenya and Belgium.

To test the hypothesis that the maintenance staff's competency in interpreting condition monitoring results in Kenyan and Belgian companies was associated with a statistically significant difference, an independent sample *t*-test was performed, as shown in Table 3. The assumption of homogeneity of variances was tested and satisfied via Levene's F test for all the condition monitoring techniques. For brevity, we highlight the results for the condition monitoring techniques that retained a statistically significant difference between the two countries. The independent samples *t*-test that associated with a statistically significant effect (significant *p*-values in italics) included ultrasound, vibration analysis and other techniques, whose confidence intervals also did not cross zero. As demonstrated, the Belgian companies were associated with a statistically more significant mean number of employees with a higher capability level than the Kenyan companies were.

	Levene's test for equality of variances		*t*-test for equality of means		
	F	*p*-value	*t*	df	*p*-value
Infrared thermography	1.048	0.308	0.773	147	0.996
			0.736	82.208	0.996
Ultrasound	18.147	0.000	−3.170	147	0.002
			−2.783	70.049	*0.007*
Vibration monitoring	6.0675	0.015	−2.435	147	0.016
			−2.239	77.609	*0.028*
Pressure, velocity	0.105	0.747	0.329	147	0.742
			0.318	87.450	0.751
Electrical discharge	0.032	0.858	0.371	147	0.711
			0.361	88.941	0.719
Others	0.075	0.784	3.955	147	*0.000*
			3.846	88.833	0.000
Lubricant condition monitoring	0.787	0.376	0.773	147	0.441
			0.736	84.332	0.464

Table 3. Independent sample *t*-test results for interpretation capability level

From the analysis in Table 3, ultrasound, vibration and the others (e.g., predictive algorithms) demonstrate to retain a significant difference in the level of interpretation between Kenya and Belgium. Several possibilities could be attributed to this finding: the difference in technological advancements level corroborated by earlier findings in Table 2, and non-compatibility of these "modern" techniques to equipment retained by organizations in Kenya. Lack of technical support due to obsolete technology or remotely located plants, lower maintenance staff skills and competence, are additional possibilities.

Another essential maintenance data type, different from condition monitoring, is the event data which are frequently proactively (schedule-based) and reactively generated following failure or events in the maintenance of equipment as investigated in the next section.

4.2.2 Failure event maintenance data management. This section of the survey required respondents to give information on the failure event data management regarding objectives attached and various challenges faced.

The respondents were asked which applications their organizations attached to the failure event data towards driving maintenance strategies, and the results are shown in Figure 4. It was pinpointed that most of the respondents in Kenya utilize the data for adjudging maintenance needs and the root cause analysis and for investigating the equipment availability and reliability. The low utilization of the process and technological aspects in Kenya represents a rather significant finding that will doubtless be much scrutinized, but there are some immediately reliable conclusions; firstly, as depicted in Section 4.1, process-related changes and life cycle aspects were shown not to influence the maintenance objectives application in the Kenyan companies significantly. Moreover, this indicates low utilization of process optimization in the Kenyan firms. However, in Belgium, results show meaningful use of the data for investigating equipment availability and reliability and for equipment replacement studies. This finding can be correlated with the ageing assets, a highly popular drive towards APM in Belgian firms, as illustrated earlier in Section 4.1. In the same way, firms from both countries insinuate lower utilization of the event data for process studies and technological optimization. This finding correlates to earlier outcome in Section 4.1 that process and technology-driven aspects seldom influence the application of asset performance management.

4.2.3 Maintenance data integration and management for decision support. In this section of the survey, insights were sought on dominant techniques exploited and challenges faced in

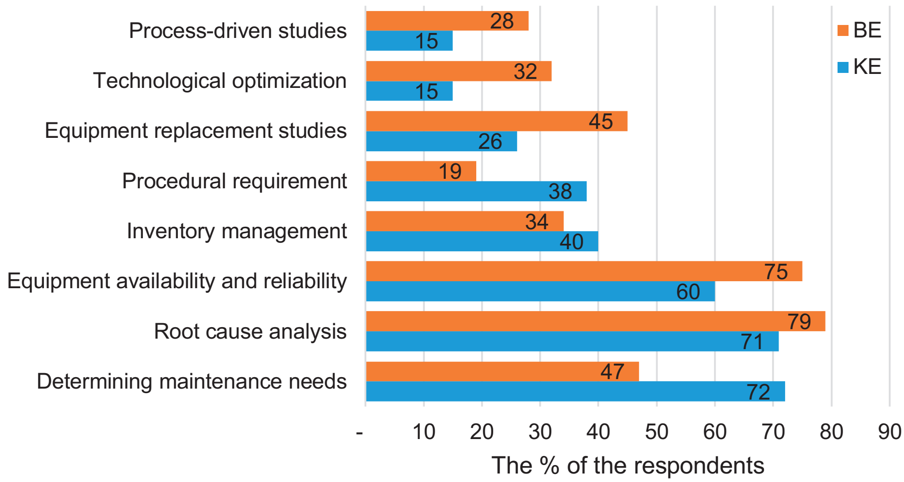

Figure 4.
Various applications linked to failure event data by Kenyan and Belgian firms

maintenance data integration. Finally, the desired improvements regarding the combination of both condition monitoring and failure event data are discussed.

The participants were invited to indicate methods or techniques they employed while integrating condition monitoring and failure event data in maintenance decision-making, and the results are shown in Figure 5. It is exhibited that over three-quarter of the participants in Kenya compared to a third in Belgium indicated they employ manual methods or techniques. On the other side, significant respondents in Belgium compared to Kenya operate company systems/ERPS. Applying PC-based tools like Excel and Access demonstrated a similarity between the two countries. These results confirm the popularity of manual intensive tools or systems to integrate the different data sets in the Kenyan firms. This popularity may imply low application of advanced maintenance technology and operations. The results related to Belgium confirm the advanced maintenance operationalization and reputation of modern technology that requires minimal human intervention to ensure quality analysis and ultimate decision support. Moreover, the higher utilization of other modern techniques in Belgian firms, compared to Kenyan, possibly indicates the difference in technology and automation between the two countries.

Another key objective of the study was to establish the key challenges or threats organizations face concerning maintenance data management. The respondents were asked to indicate which threats their organizations faced from a set of challenges; the results are illustrated in Figure 6. Comparing both countries, there is a concurrence of standardization and maintenance knowledge loss as critical challenges.

From these results, it is therefore likely that such connections of data heterogeneity, lack of skills and a standard means for integration exist across both countries. Thus, standardization and maintenance data management system could be significant factors, although not the sole factors related to the challenges. However, there is a marked difference in the other system to system integration, with Belgian companies depicting this as a vital challenge. This result seems to be consistent with the earlier finding that Belgian companies popularly utilized company-based tools like ERPs which attempt to handle different data sets from different domains. This derives the challenge where various departments may be running distinct ERP modules due to the domain differences and could be trying to integrate the modules/systems, which is challenging. On the contrary, the low significance of challenges like system-to-system integration and technological changes in Kenya compared to Belgian companies could be related to the manual techniques of data management popularly employed.

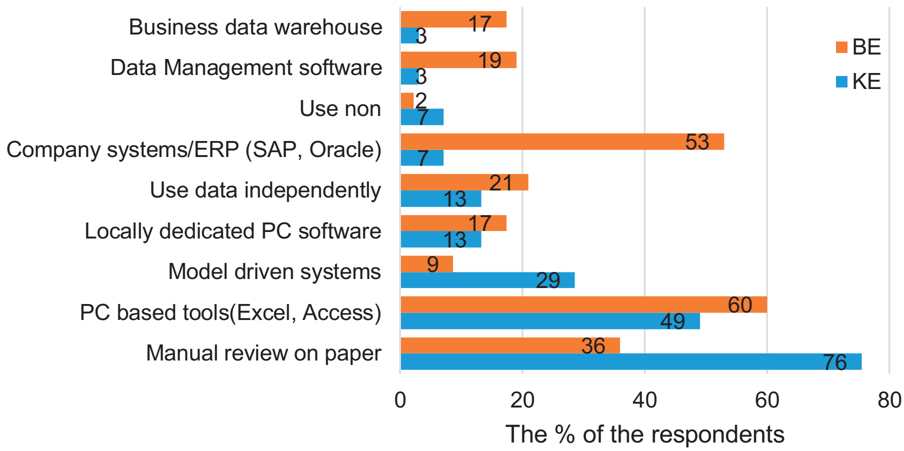

Figure 5.
Techniques employed for integrating both condition monitoring and failure event data by Kenyan and Belgian firms

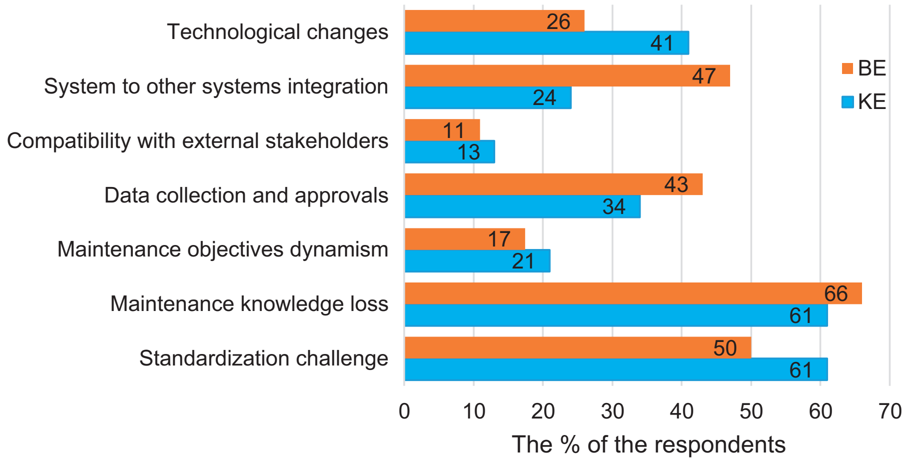

Figure 6.
Threats to maintenance data management in Kenyan and Belgian firms

Moreover, this infers the low utilization of data analysis and management software capable of integrating different datasets. Taken collectively, these results underline the concurrence of the respondents from both Kenya and Belgium on the need to incorporate various maintenance data towards enhancing maintenance decision support.

5. Managerial implications and theoretical implications

Our main aim in this study was to investigate and compare how asset maintenance strategies and data application practices for performance management are employed by maintenance-intensive companies in developed and developing countries (Belgium and Kenya, respectively). We have done so by a comparative analysis of responses from various stakeholders representing 150 firms. This section entails a discussion addressing the managerial and academic implications of the study.

5.1 Managerial implications

The implications of these findings will be of great interest to the main stakeholders (practitioners) involved in the implementation of maintenance management for asset performance management, such as managers in the maintenance, reliability, process and operational functions.

This comparative survey brought out critical aspects concerning the application and benefits of maintenance in enhancing asset performance management. Hence, maintenance is shown to improve the reliability and availability of physical assets while minimizing risk and operating costs, as underlined by APM. First, the various maintenance strategies guaranty optimal running and performance of the assets to increase availability and reduce maintenance and operational costs. Secondly, the implementation of various maintenance strategies provides data which can be analysed to derive decision support and hence enhance asset performance. Management could leverage this insight to enhance APM by exploiting the maintenance practices judiciously.

Another implication stems from the finding that asset ageing, among other factors like maintenance costs, return on assets and compliance with regulatory requirements, is a key driver compelling the implementation of asset maintenance and performance management. The ageing of assets is characterized by effects like increased consumption and failure rate of the equipment, whereas unexpected and involuntary spare obsolescence may be introduced due to time-dependent technological and logistical challenges. The results suggest that the modelling conventions could leverage the compliance with regulatory requirements, for instance, environmental regulations, and develop ageing mitigation options like replacement or extension of service life strategies to offer sustainable maintenance, reduce failure rates and optimize costs. Incorporating maintenance and specific equipment life extension strategies (e.g., remanufacturing) simultaneously could offer more practical decision support to extend asset life. For operationalization, management of change, in operational and compatibility aspects of the strategies to the asset's functional and operational characteristics, should be considered. For instance, product assemblies, whose core components can be replaced or restored to the original standard, may be proposed for remanufacturing to address both repair and replacement. Besides, this approach would also mitigate challenges like spare obsolescence and extended spare sourcing lead-times. However, these aspects should be evaluated carefully, as they change from one industry to the other and depend not exclusively on the compatibility with technology but also on the corporate strategies. Such ingrained strategies include the budget allocated and expected reliable operations to meet customers' and companies' expectations.

Another notable theme exposed is the delink of the envisioned maintenance objectives and respective maintenance strategies employed. This deficiency may be attributed to two possible causes: (1) incoherent selection of maintenance objectives while disregarding the various changes an organization has or is undergoing in the management, technical and environmental context, and (2) the survey results possibly reveal the lack of alignment of robust maintenance objectives to the maintenance strategy formulation process. Therefore, opportunities exist towards the selection of appropriate maintenance objectives for the specific organization considering several vital facets. To begin with, the process should retain and track historical objectives to ensure that tacit knowledge is reused and maintained. Our results highlight the importance of incorporating the stakeholders in the selection process. This can be achieved by interviewing the stakeholders and incorporating the historical objectives as possible candidates. Secondly, the process should consider the anticipated changes in the maintenance organization that may relate to processes, regulatory aspects and technology. This consideration will guarantee the derived objectives can proactively mitigate the substantial challenges encountered, at present and in future. Lastly, the process possibly should employ a multi-criteria decision model like the analytic network process (ANP) to derive appropriate objectives. Ultimately, the goals will be aligned with the organization's expectations, for instance, decision support towards optimizing maintenance strategies.

Additional implication of our study derives from our finding on the marked low utilization of other condition monitoring techniques like predictive algorithms and predictive condition and model-based maintenance approaches. The low utilization may be attributed to the slow popularity gain of the methods in the engineering maintenance field, as opposed to other areas like healthcare where they are widely employed. Exploitation of these approaches could provide consensual benefits like optimization of product quality, cost, operational efficiency and increased flexibility. For example, the use of predictive condition and model-based techniques could model the impact of maintenance strategies on the product quality, which is not explicitly investigated in literature (Wakiru *et al.*, 2020). However, to achieve the benefits, the management should collect and record various types of data to be exploited in the modelling and analysis.

Another important implication of our study derives from our finding that majority of the respondents acknowledged;(1) existence of diverse maintenance data sets generated from maintenance and operational activities, and (2) the need for easier integration of different data for comprehensive decision support as the most favoured desired improvements. However, high utilization of manual techniques compared to model-driven and data management tools to integrate various data sets (e.g., condition monitoring, operational and event data) was reported. In contrast, data standardization challenge was highlighted as a critical threat to maintenance data management. The study therefore highlights the necessity for a framework that would pre-process, standardize and integrate heterogeneous data to the analysis-ready state, and ultimately derive and integrate decision support. The framework will enable managers to employ data mining techniques to pre-process often unstructured data and merge heterogeneous data sets. Moreover, a data management software embedded with machine learning algorithms (e.g., classification models) could be developed to derive decision support. Notwithstanding, in-house skills will require to be upgraded, and outsourcing may offer an alternative if in-house skills are inadequate. However, for the success of this exercise, challenges revealed such as the perceived cost of infrastructure would necessitate a thorough evaluation of the infrastructure needed by the management. This will depend on the technical, economic and operational context and the type of data to be collected and analysed. For instance, installing sensors with algorithms for real-time data collection and analysis in ageing equipment approaching the end of life maybe uneconomical. This can be true if the infrastructure cost, equipment age and retirement strategies are considered. On the contrary, in such a case, employment of machine learning techniques to analyse offline data may offer significant decision support at a lower cost and requiring minimal infrastructural investment.

The handling and interpretation of condition monitoring maintenance programme remain a critical aspect for any benefits to be realized in the APM field. Firms in Kenya were associated with lower competence in handling and interpreting condition monitoring data and results (vibration, ultrasound and others like predictive algorithms). An antidote to these remains the training of maintenance personnel and implementing such vital techniques. An implication of this finding could mean that the management may require addressing challenges like cost of infrastructure and lack of skills. Thus, the use of consultants and original equipment manufacturers or their agents forms a reliable option. This option would offer desired results in both the evaluation and implementation phases of maintenance programmes. An unusual option to management here would remain integrating aspects of product service system (PSS) into their business model. In this case, a plant may opt to purchase “performance or use” instead of the physical equipment.

5.2 Academic implications

To date, a considerable body of research has sought to understand the maintenance practices under APM in developed countries (e.g., (Alsyouf, 2009; Muchiri *et al.*, 2010; Pinjala *et al.*, 2006) and developing countries (Muchiri *et al.*, 2017). Peculiarly, research comparing the maintenance strategies, objectives and data management systems between firms or application of two or more different settings (economies, technology, and others) and environment is lacking. Academic research towards several directions potentially could be undertaken based on this study’s results. (1) development of predictive algorithm-based models for condition monitoring decision support, (2) development of an architecture or framework to enhance data processing, standardization and integration at a fast pace with minimal manual adjudications and (3) research towards integrating various maintenance and equipment life extension strategies like remanufacturing simultaneously to derive asset performance optimization while considering ageing assets.

The present research contributes to the APM field on the need for maintenance data-derived decision support to optimize asset performance. Linking various, often heterogeneous data (in this case, condition monitoring, failure event, production and operational), equally known as data fusion (Diez-Olivan *et al.*, 2019) is revealed as missing in literature and practice. To achieve this integration, open data sharing, monitoring and collaborative practices are distinct concepts that organizations should exploit. Such concepts will ensure asset management attains a world-class level as enshrined in the Industry 4.0.

Industrial big data analytics, simulations and digital twin concepts (under Industry 4.0) offer robust antidote in the push for digitalization and collaboration. However, the challenge of ageing assets requires a research rethink on how to align maintenance decision-making, with core pillars of the Industry 4.0 concept. For instance, considering equipment in their mid or end of life, the utilization of some technologies like digital twins may not be cost-effective and efficient, compared to data analytics and simulation.

6. Conclusions, limitations and suggestions for future research

The proposed descriptive research reflects the empirical results comparing maintenance practices (maintenance strategies and data application) employed for APM by firms in developed and developing countries (Belgium and Kenya respectively), more specifically, motivations underpinning the consideration of maintenance data collection, analysis, knowledge discovery and integration in APM. The analysis used survey responses from 150 professionals working within maintenance, planning and operation functions. This descriptive comparative research revealed ageing assets, maintenance costs, return on assets and compliance with regulatory requirements as the key drivers towards implementation of APM. In both the divides, the use of preventive and corrective maintenance was shown to be significant compared to CBM approaches like predictive CBM. The analysis results of maintenance objectives exposed a strong relationship between maintenance inventory and contract service management objectives in both countries, while a lower relationship between production throughput and contract service management in Kenya compared to Belgium. Among the condition monitoring techniques, the study showed Kenyan firms had low utilization of vibration and ultrasound compared to Belgian firms. The study included a hypothesis which was tested, where condition monitoring techniques like ultrasound, vibration and the others (e.g., predictive algorithms) were established to retain a significant difference in the level of staff competence and results interpretation between Kenya and Belgium. The analysis results show that organizations in both divides employ manual methods for data integration and analysis, while more Belgian firms utilize company systems like ERPs compared to their counterparts in Kenya. The study identified non-standardized data and data collection inconsistencies as the critical challenges for organizations in both countries while handling various types of maintenance data.

The present study is, to the best of our knowledge, the first study to compare the maintenance practices between companies of a developing and developed country. However, the study experienced some limitations. In the first place, the study involved all the industrial sectors and tried to draw generalized findings based on the sector's responses represented. This does not erode the validity of the results concerning the Kenyan and Belgian industry; however, future studies can focus on a specific industrial sector whose results can be compared with this study. Secondly, the distribution of responses from small companies (Kenya with 17% and Belgium 0%) may have influenced the results. Despite compensatory mitigation (Kenya had a higher response rate compared to Belgium), future studies could vary the contextual variables like the number of countries, specific response group or size of industry (e.g., large companies). Lastly, this present survey represents a cross-sectional study that is limited to analyzing data from the population at a specific point in time. Upcoming work potentially includes quantitative case studies to validate this qualitative survey study.

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Appendix

Table A1. Maintenance objective relationship matrix for Kenyan companies

	A	*R*	*M*	LCO	*E*	HS	FR	DC	OEE	PT	MQ	MC	MI	CSM	LS	PM	RT
A	1.000																
R	0.3490**	1.000															
M	0.4610**	0.0500	1.000														
LCO	0.3120**	0.1410	0.4460**	1.000													
E	0.3010	0.1684	0.237	0.1960	1.000												
HS	0.3010**	0.1840	0.0332	0.1675	0.9902**	1.000											
FR	0.2200	00.2360*	0.3150**	0.3330**	0.2610**	0.2606**	1.000										
DC	0.0430	0.0960	0.0210	0.1110	0.1730	0.1935	0.6236**	1.000									
OEE	0.0630	0.3810**	0.0140	0.0650	0.0120	0.1200	0.1062	0.1100	1.000								
PT	0.2560*	0.0730	0.0850	0.1120	0.0560	0.5600	0.0172	0.0990	0.1830	1.000							
MQ	0.2227	0.0275	0.4413**	0.2568**	0.7446	0.7446	0.2632	0.2344	0.3022**	0.3189**	1.000						
MC	0.0130	0.2040*	0.1040	0.2240*	0.0160	0.0161	0.0160	0.2020*	0.1120	0.1140	0.1440	1.000					
MI	0.0510	0.1490	0.1270	0.3150*	0.1054	0.1310	0.2713	0.1110	0.1150	0.0850	0.1231	0.3160**	1.000				
CSM	0.0990	0.0120	0.3270**	0.3690**	0.2474*	0.1054	0.3282**	0.0340	0.0820	0.1400	0.2141	0.3030**	0.5000**	1.000			
LS	0.0410	0.3510**	0.0630	0.1160	0.0171	0.1349	0.1572	0.1320	0.3010**	0.1160	0.1106	0.0750	0.1060	0.0370	1.000		
PM	0.1070	0.2270*	0.1220	0.1780	0.2890*	0.2885**	0.3118**	0.1270	0.2750**	0.3130**	0.4229**	0.0090	0.1680	0.2850**	0.6370**	1.000	
RT	0.0040	0.1670	0.1400	0.0930	0.0410	0.0413	0.3448**	0.2440*	0.3450**	0.3950**	0.7486**	0.1340	0.1400	0.1280	0.5440**	0.6110**	1.000

Table A2. Maintenance objective relationship matrix for Belgian companies

A	1.0000																
R	0.5956*	1.0000															
M	0.3824	0.4142	1.0000														
LCO	0.1127	0.1005	0.5025*	1.0000													
E	0.4706	0.0147	0.0564	0.299	1.0000												
HS	0.3725	0.1789	0.00074	0.3701	0.9534**	1.0000											
FR	0.049	0.4118	0.4608	0.3627	0.5196*	0.5956*	1.0000										
DC	0.4118	0.0784	0.6078**	0.4387	0.1691	0.1373	0.3799	1.0000									
OEE	0.1569	0.3064	0.5245*	0.6471**	0.4853*	0.4485	0.6324**	0.3382	1.0000								
PT	0.4314	0.7083**	0.7034**	0.4093	0.2328	0.2917	0.6863**	0.5123	0.7059**	1.0000							
MQ	0.1925	0.2986	0.6078	0.5147**	0.5441*	0.5735*	0.7206**	0.326	0.7819**	0.6024*	1.0000						
MC	0.6912**	0.0368	0.0515	0.1887	0.598*	0.6446	0.4338	0.1667	0.3431	0.0711	0.5245*	1.0000					
MI	0.4167	0.4314	0.5245*	0.3799	0.0735	0.1945	0.7353**	0.5368*	0.3799	0.6667**	0.4461	0.0637	1.0000				
CSM	0.5858*	0.6397**	0.6789**	0.0809	0.0662	0.1618	0.6544**	0.4583	0.277	0.6569	0.4951	0.1127	0.6348	1.0000			
LS	0.58338	0.1495	0.0368	0.4118	0.7721**	0.6765**	0.5319*	1.0760	0.6838**	0.2402	0.5294*	0.5417*	0.1961	0.1152	1.0000		
PM	0.6373	0.5711*	0.7475	0.2561	0.2451	0.2083	0.3284	0.5515	0.3897	0.7917**	0.2892	0.2848	0.6495	0.6029*	0.544**	1.0000	
RT	0.0429	0.3311	0.2477	0.4611	0.4631	0.4733	0.737**	0.2968	0.6585**	0.6217**	0.5371*	0.1619	0.7566*	0.3948	0.5947*	0.4218	1.0000
	A	*R*	*M*	LCO	*E*	HS	FR	DC	OEE	PT	MQ	MC	MI	CSM	LS	PM	RT

Note(s): Sign. ** ≤ 0.01, *$0.01 < p \leq 0.05$. *A*: availability; *R*: reliability; *M*: maintainability; LCO; life cycle optimization; *E*: environment; HS: health and safety; FR: failure rate; DC: downtime cost; OEE: overall equipment effectiveness; PT: production throughput; MQ: maintenance quality; MC: maintenance cost; MI: maintenance inventory; CSM: contract service management; LS: logistics and support; PM: personnel management; RT: repair times