A systems approach to managing complex engineering assets: exploring shifts in equipment management and reliability enhancement paradigms

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Abstract: Engineering asset management is a complex socio-technical system, and there has been a surge in efforts to optimise the capacity utilisation of these assets in the wake of conflicting economic and performance objectives. The major challenge is in determining which assortment of approaches (tools, strategies, techniques, methodologies and philosophies) to apply in order to get optimal trade-offs of cost, risk and performance or reliability. This paper critically reviews the literature to examine shifts in physical asset management paradigms over the past few decades and to determine the best combination of approaches; and it shows that none of these approaches are able, individually, to optimise the trade-offs, but as a cluster. It proposes a Systems-thinking model-based integration approach. Pilot studies have shown that using the model proposed can yield savings in maintenance costs of 15–40% and in avoided costs of up to 15%.

Keywords: equipment management paradigms; multi-criteria risk-modelling; power-asset management; reliability; systems-thinking-approach; transdisciplinary approach.

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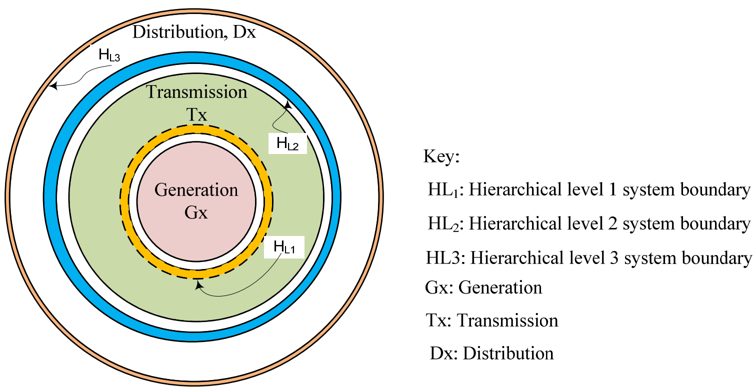
1 Introduction

This study addresses challenges in management of engineering systems by examining the equipment management paradigm shifts (evolutions), with emphasis on power infrastructure assets, over the past few decades; and then proposing a model that integrates a number of best strategies, techniques and models to effectively manage physical asset risks and to enhance reliability. It is a review paper with some case study content towards the end, which is aimed at informing the systems-thinking discourse for clarity. Management of physical assets is a complex process, because problems arise from not only the technology but also from complex social-economic systems; and as such, it requires a transdisciplinary and multi-criteria approach to adequately address these problems (Mkandawire et al., 2011a, pp.322–323; Papathanassioua et al., 2013;

Wognum et al., 2019, pp.78–79). The emergent nature of decision making process is eclipsed by ill-structured messes which cannot be solved by analysis only, but by a systems-approach (White, 1995; Mkandawire, 2015). The complexity of power asset management gets aggravated by the vastness and spatial nature of the infrastructure so much that in most cases it becomes too difficult to provide services and to locate faults to remotely located assets; thus, model-based approaches must be developed to cater for such isolated areas. Model based approaches are an emerging paradigm that must be leveraged on for such spatial and remote systems (Mo and Richardson, 2017). Giese and Hogräfer (2002) cited in Schneider et al. (2006, p.1411), advocates for an integrated model-based approach in terms of integrating enterprise resource planning (ERP), equipment database, geographical information system (GIS) and supervisory control and data acquisition (SCADA), but a gap still exists in model-based approaches that focus on maintenance strategies, philosophies, techniques, and socio-technical aspects.

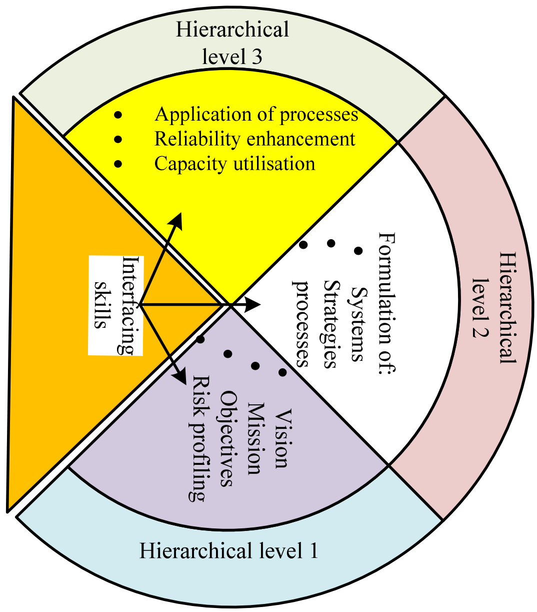
Figure 1 Hierarchical levels of power infrastructure assets (see online version for colours)



A set of physical assets usually consists of hierarchies or levels, mostly aggregated into zones with defined system boundaries that, among other things, can help in modelling of risk profiles and in improving decision making processes (Mkandawire et al., 2015a). For example, in power infrastructure asset management, three levels exist, namely: hierarchical level one (H_{L1}), two (H_{L2}) and three (H_{L3}); respectively, the generation (Gx), transmission (Tx) and distribution (Dx) systems (Figure 1). In terms of risk analysis and mitigation, the H_{L3} is the most critical as it represents risks that cascade from the Gx through the Tx to the Dx systems due to a domino effect that it creates (Billinton and Allan, 1992). Water utility, road infrastructure assets and complex process plants present a behaviour similar to power assets in terms of the domino effect. The physical asset management (AM) system is also a hierarchical one, and the objectives that can address the missions' gaps should be established in the corporate strategy (Figure 2, Level 1) so as to provide direction for the firm (British Standard, 2008; Woodhouse, 2004; Mkandawire, Ijumba and Whitehead, 2011a, pp.321–322). The corporate strategy comes at the top and consists of strategic (≥5-year time frame), tactical (2 ≤ 3-year time frame) and operational (≤1-year time horizon) plans (Schneider et al., 2006; Mkandawire, Ijumba and Whitehead, 2011b, pp.263, 271). Risk profiling (Figure 2, Level 1) is a performance measurement to ensure that the asset strategies are aligned with the objectives (Moubray, 1997; Schneider et al., 2006).

The risk profile must be reviewed regularly to retain relevance; and this is where skills, aided by user friendly models, must be interfaced at all levels of the AM process (Figure 2, middle-left). However, the task of rating the various tools and strategies is a very complex one and as such, physical asset managers usually seek for models that can help them to integrate the best tools so that they get optimum returns on assets that are being managed (Woodhouse, 2001; Mkandawire et al., 2011b, pp.264–266); and this study elucidates that approach.

Figure 2 Hierarchical levels of the asset management system (see online version for colours)



2 Overview of a shift in physical asset management paradigms

There have been four domains or paradigms of equipment management in the past half century or so, and each of them impacts the asset life cycle either adversely or positively (Mkandawire et al., 2011b, p.265; Moubray, 1997). The first paradigm or generation (Figure 3(a)) is the reactive domain, which helps to realise short term cost savings but subjects firms to surprises and catastrophic failures (Mitchell, 2006). The second one, (Figure 3(b)) was fashioned in such a way as to prevent the weakness of the first one, to safeguard the asset integrity and increase the bottom-line (Moubray, 1997; Mkandawire et al., 2011a). The third one (Figure 4(a)), developed progressively as a result of failure of approaches in the second domain to increase plant reliability; where about half of tasks carried out were found not to add any value (Mitchell, 2006).

Finally, the proactive generation (Figure 4(b)) evolved (Mkandawire et al., 2011a). It applies probabilistic, stochastic and computer aided models and concepts aimed at determining optimum maintenance decision processes (Chen and Trivedi, 2005; Chan and Asgarpoor, 2006); improving probabilistic capabilities of reliability centred maintenance (RCM) (Mkandawire et al., 2015a); and optimising spare parts holding levels for physical assets (Chowdhury and Koval, 2005, pp.1493–1498). Probabilistic techniques for modelling repairable systems have not received much attention for a long time yet they form the bulk of physical assets (Rigdon and Basu, 2000). They contain an assortment of non-invasive, proactive approaches from the third domain as well as computer models (Mkandawire et al., 2011b); with root cause analysis (RCA) employed, and the selection of such a mix of approaches is being dictated by empirical inferences rather than gut-feel (Woodhouse, 2004). Some philosophies, e.g., total productive maintenance (TPM) and risk based inspection (RBI) have also been integrated in the paradigms (Mkandawire et al., 2011b; Woodhouse, 2001; Mitchell, 2006).

Figure 3 (a) First paradigm and (b) second paradigm (see online version for colours)

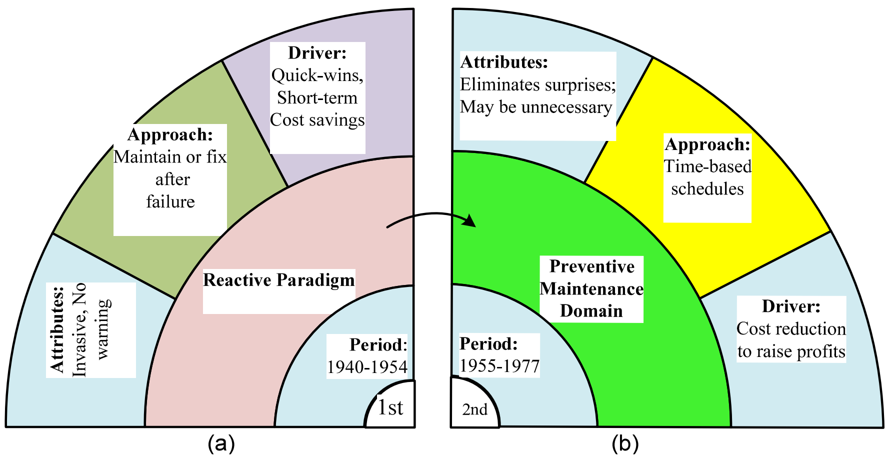
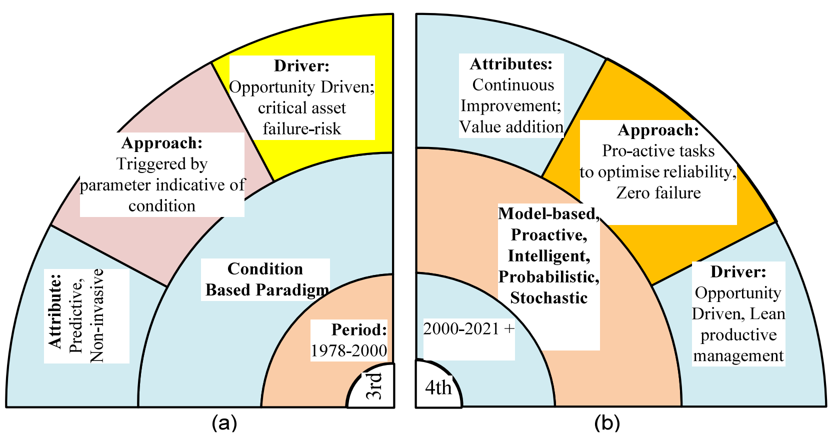


Figure 4 (a) Third paradigm and (b) fourth paradigm (see online version for colours)



In recent years, it is common practice to integrate the second, third and fourth generation strategies with, for example, power flow management techniques in aging assets so as to de-rate them and prevent overloading (Endo et al., 2009), to determine their age (Bajracharya et al., 2009), and to extend their life spans (Pothisarn et al., 2020). Ultimately, there has been a quantum leap into a new and ever evolving paradigm, i.e., the artificial intelligence (AI). Wavelet Transformation techniques, which offer better capability to depict sudden disturbances than Fourier Transforms, have also been blended with AI in five special applications in power systems diagnostics, protection, load forecasting; and power measurement and quality management (Ren et al., 2000). First, in power system protection, for improving performance of relays during transient earth faults (Janicek et al., 2007). Second, in power quality management, e.g., using discrete wavelet transforms (DWT) (Pothisarn et al., 2020), and to detect and locate disturbances based on the rate at which a fault wave travels to the control relay (Zheng and Makram, 1998; Zheng et al., 1999). Additional power quality management applications include the wavelet-multiresolution signal decomposition approach (Gaouda et al., 1999), as well as the wavelet series expansion and reconstruction to detect filter bank switching transients (Abu-Elanien and Salama, 2009; Zheng and Makram, 1998). Third, to detect partial discharges in transformers, cables, and gas insulated substations using ultra high frequency (UHF) signals; which offers more advantages than the standardised IEC 60270 method (Sinaga, 2012). Fourth, in load forecasting, by combining Wavelet transforms and artificial neural networks (ANN) for load forecasting (Li and Fang, 2003). Fifth, in power system measurements, applying algorithms to discrete wave transforms (DWT) for root mean square (RMS) value and phasor measurement (Liang and Jeyasurya, 2004; Mallat, 1989). A newer type of Wavelet Transform called direct quadrature Wavelet Packet (dqWPT)-based hybrid technique provides digital differential protection of transformers to augment ANN, wavelets and fuzzy logic techniques (Aktaibi, 2015). The major concern with the AI is that its accuracy and success depends on selection of the right technique for the application; some of which depend heavily on expert interaction during classification and training hence are prone to bias, are unable to accurately model expert behaviour, judgement, and other human factors (White, 1995). Lack of field specialists and case-specificity of AI tends to hinder its penetration and acceptance in industry. AI techniques such as reinforcement learning, deep learning and their combination-deep reinforcement learning usually do not involve expert interaction, hence they fill this gap; but their major disadvantage is their complexity, data-intensity nature and lack of interpretability (Zhang et al., 2018). Generally, when applied to critical components, AI provides a risk mitigation layer for mission and safety critical systems; where critical components are determined using fault tree analysis (FTA) and/or failure mode effect and criticality analysis (FMECA) (Souza et al., 2014).

Metrics can track the benefits of the strategies on reliability, but are mostly asset-specific and range from top-tier strategic to low-tier operational, and depend on targeted industries which makes standardisation and generalisation difficult (Mitchell, 2006; Mkandawire et al., 2011a, p.267). The difficulty in standardisation makes benchmarking implausible (Jagers and Tenbohlen, 2009). Despite the diversities in industries, there is one salient feature of metrics in that most of them are applied within the hierarchical level 3 of the AM process (see, e.g., Figure 2). For instance, the impact of the risk of failure of power Dx assets on the system and customers can be assessed using reliability indices (e.g., SAIDI, SAIFI, CAIDI, SAIDI) (Endrenyi et al., 1998). These indices are flawed as they can only give a short-term outlook of risk, usually a one-year time-horizon. Data mining techniques, needed for machine learning in AI, have inherent risks that relate to misidentification of the data when the classification model used gets confused, thereby degrading the performance of the model; and the Confusion Matrix is the method most commonly used to overcome that problem by deriving classification performance metrics (point metrics). These metrics are accuracy, i.e., comparing the actual with predicted class; precision, i.e., how well the model does when a positive prediction is made; and recall or sensitivity, i.e., how good the model performs in identifying positive and negative labels (Luque et al., 2019; Ting, 2011). Uncertainty in the estimation of unobserved values, such as the remaining life of physical assets, is another inherent risk; and model evaluation metrics such as the Mean Squared Error (MSE) can reduce that risk (Sammut and Webb, 2017).

Risk matrix methods such as the robot type, the distance-d-technique and the loss distribution approach (LDA) are among the conventional risk assessment techniques. The robot types are usually in simple tri-coloured (yellow, green, red) matrix form as in Table 1 (Gjerde and Nordgard, 2009) or in a more detailed tri-coloured matrix form with narrations of various risk scales as in Table 2 (Mkandawire, 2010).

The advantage of the robot type (Table 1) is that it is easy to use, but it fails to show the effects of low- probability-high-impact risks as it assumes that the improbable risks do not have any severe impact, which may not always be true; hence, physical asset managers tend to use the type presented in Table 2 to offset some of the shortfalls. The other shortfall is that they are generally unable to portray the whole-life (long-term) outlook of risk. In addition, the determination of the risk level and impact depends on subjective judgement of the risk analysts, which may vary from one analyst to the other (Gjerde and Nordgard, 2009; Suwnansri, 2014; Nordgård et al., 2007). The matrix methods express the risk level as the product of probability and consequence factors (IEEE, 2006; Mkandawire et al., 2011a, p.273).

The loss distribution approach (LDA) is a variant of the risk-matrix method that uses a metric called value at risk (VAR) according to the IEC60300-3-9 standard to identify, analyse, evaluate and control risk (Nordgård et al., 2007), but the approach fails to give a long term outlook of risk (Mkandawire, 2015). The distance-d-technique (Figure 5), used to select maintenance strategies, expresses the risk by equal weighting between condition and significance criteria in terms of distances d_1, d_2, and d_3 relative to a 45° reference line; where the distances are proportional to the risk level (Suwnansri, 2014), but it fails to determine whether the asset condition is age related or otherwise.

The net present value (NPV) analysis can present a firm's business case by selecting re-investment strategies. In a study on air blast circuit breakers, Anders et al. (2001), used an optimised NPV decision criterion to convert engineering analysis into economic impacts associated with various management decisions, to generate equipment life cycle curves (deterioration states); and to employ probabilistic modelling with Markov-process' first-passage-times (FPT). However, the NPV analysis fails to correlate the impact of strategies to technologies applied (Davidson, 2005; Mkandawire et al., 2011b).

Table 1 A risk matrix of the robot type (see online version for colours)

		Impact				
		High level		*Medium level*		*Low level*
		Immaterial	*Minor*	*Moderate*	*Major*	*Catastrophic*
Probability	Frequent					
	Probable					
	Occasional					
	Remote					
	Improbable					

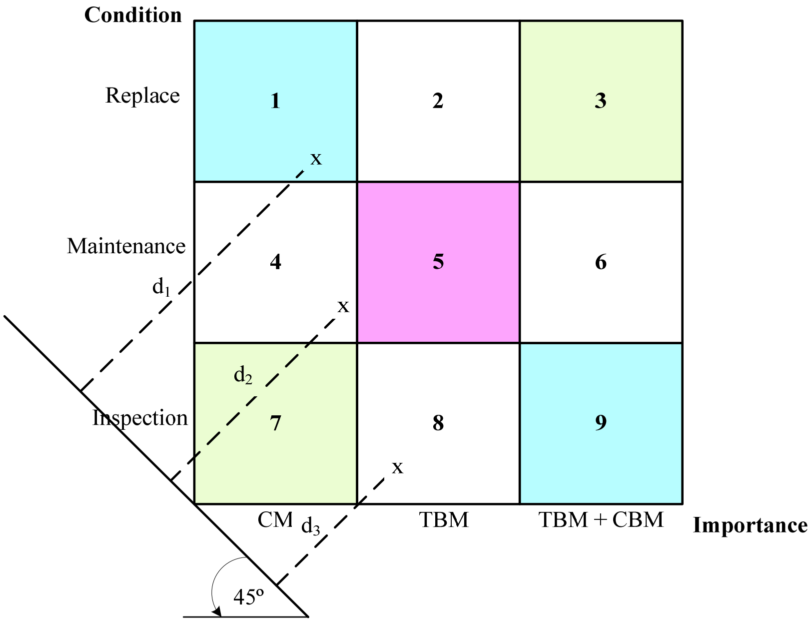
Source: Adapted from Suwnansri (2014)

Table 2 Robot type of risk matrix with probability and impact scales (see online version for colours)

Level of risk								Economic ($ million)	OSH	Public	Enviro sustainability	Co-existence with the government
3	3	3	1	1	1	1	7	>50	> 10 fatalities	>1 fatality	`	Damaged relations with Central Govt.
3	3	3	2	2	2	1	6	10–50	>1 fatalities	1 fatality	Serious national impact	Breakdown in relations provincial Govt.
4	4	4	3	2	2	2	5	1–10	1 fatality	Hospitalisation or great public concerns	Very serious long-term environmental impact regional	Damaged relations with people in Govt. dept.
5	5	5	3	3	3	3	4	0.1-1	Hospitalisation	Complaint leads to press paper	Serious regional long term impact	Damaged relations at local Govt. level
6	6	6	5	5	5	4	3	0.01-0.1	LWDC	Protest against odour	Serious regional reversible impact	None
6	6	6	6	6	6	5	2	0.001–0.01	Light medical treatment	None	Moderate local reversible impact	None
6	6	6	6	6	6	6	1	0.0001–0.001	Light treatment	None	Moderate local reversible impact	None
1	2	3	4	5	6	7		< 0.0001	First aid/ no injury	None	Limited effect within asset boundaries	None
Remote	Highly unlikely	Never in lifetime	Once in lifetime	Once in 10 years	Once per Year	> once per year						
0.0005%	0.005%	0.05%	.05–10%	10–68%	69–90%	91–100%		Key: LWDC = Lost Work Day Cases				
Probability								Impact scales				

Source: Adapted from Mkandawire (2010)

Figure 5 Distance-d-technique (see online version for colours)



Key:
CM: Corrective maintenance; TBM: Time based maintenance; CBM: Condition Based Maintenance

Source: Adapted from Suwnansri (2014)

Most risk trending or assessment models aim at monitoring and controlling the risk rather than optimising strategies involved in the risk mitigation process (Suwnansri, 2014; Nordgård et al., 2007; IEEE, 2006; Mkandawire et al., 2011b). The ultimate goal of these models is to determine the best combination of tools, strategies and techniques that can be applied in the process (British Standard, 2008; Woodhouse, 2001). Models for optimisation of strategies also exist, e.g., where maintenance is assumed to be a Poisson Process, hence stockholding levels are established (Chen and Trivedi, 2005; Chowdhury and Koval, 2005); and where the maintenance is assumed to be a Markov Decision Process (MDP) and by applying it in RCM, an inverse proportionality of maintenance costs and the mean-time-to-first-failure (MTTF) is established (Mkandawire et al., 2015a, p.475); or where it is assumed to be a semi-Markov decision process (SMDP) and is used to optimise maintenance policies and inspection rates (Chan and Asgarpoor, 2006; Rigdon and Basu, 2000). Their major strength is in the ability to simulate the uptime and failure states for repairable machines (Mkandawire et al., 2015a; Billinton and Allan, 1992). However these are not suitable for plant-wide risk profiling; and due to their high level of computational complexity, practitioners tend to relegate them to mere theoretical tools, contrary to best practice that advocates for reduction in complexity (Velten, 2009). It is advanced that probabilistic characterisation of system behaviours by monitoring hazard rates as well as failure and survival functions (see also Sections 3.2 and 4.2) is the best conservative risk rating approach and is pivotal to end of life-time reliability evaluations (Rigdon and Basu, 2000; Jardine and Tsang, 2013, pp.225–230).

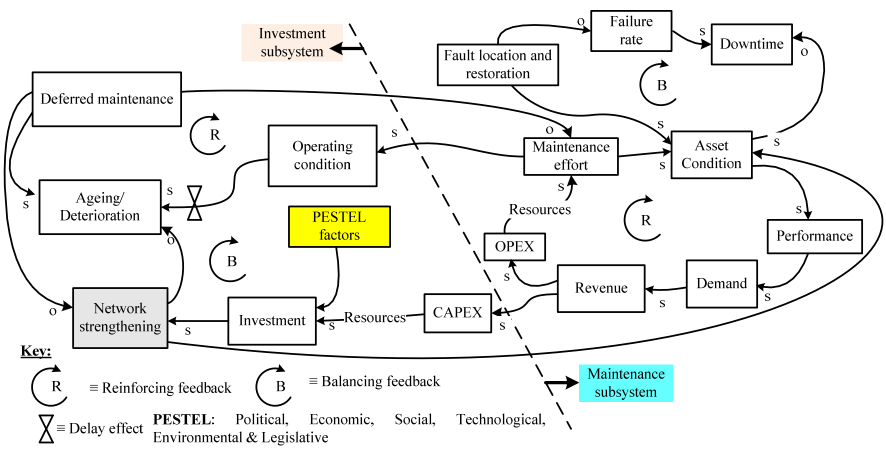
Emergence of the systems theory or systems-thinking has marked a distinct shift into the fourth paradigm (see, e.g., Figures 3–4). In the past few decades, the theory was traditionally applied for the management of risk in insurance firms, but most recently it has been adopted in engineering as a means of integrating several techniques and to reveal cause and effect relationships (Schneider et al., 2006; Mkandawire, 2015, pp.14–21; Mkandawire et al., 2015b, pp.1185–1186); and as a means of dealing with ill-structured messes, and complex socio-technical systems (White, 1995). Systems-thinking was for a long time criticised as being too theoretical, abstract and without merit (Mkandawire et al., 2011b, p.321, 2015b, p.1185) until, in a recent study, Mkandawire (2015) introduced quantitative capabilities into it using parametric probability distribution models for physical asset risk-trending. The sections that follow expound the application of systems-thinking for risk trending and the associated cost benefits.

3 Exposition of leverages of the systems-thinking paradigm

3.1 Overview of the systems approach

Mkandawire et al. (2015b) postulated that, from a system-thinking perspective, the asset management is an aggregate of interacting sub-systems, as shown in Figure 6.

Figure 6 Asset management as a cluster of interacting systems (see online version for colours)

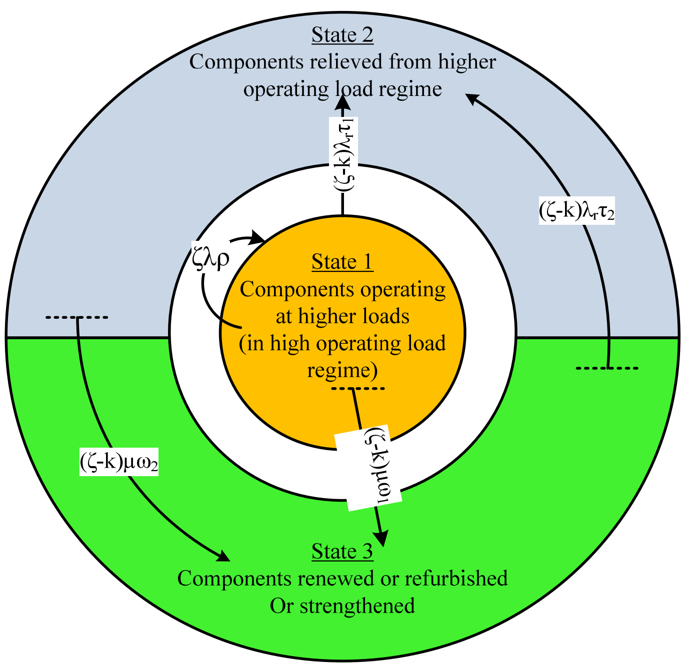


The maintenance subsystem (supported by OPEX) is on the right of the dotted line and the investment subsystem (supported by CAPEX) is on the left hand side. In the figure, 's' means the variable produces an amplification effect; while 'o' means it produces a decreasing effect in the direction of the arrow. Using Markov inference models, these systems can be considered as consisting of various state-transitions as different lifecycle management strategies are carried out and they make the whole system oscillate before reaching an equilibrium (Figure 7). The empirical systems-thinking model as presented by Mkandawire et al. (2015b) is as shown in equation (1).

$$RF = \frac{\varphi}{\gamma} + \frac{F(\zeta)}{\varphi}\{\sigma + [\zeta\lambda\rho] - [(\zeta-1)\lambda_r\tau] - [(\zeta-1)\mu\omega]\}\,|1<\zeta<t/_n, \varphi>0 \tag{1}$$

where φ, γ, σ, ρ, τ, and ω are component quantities as follows: critical, total, overloaded, normally loaded, relieved from the overloaded regime, and refurbished, respectively. Zeta, ζ, represents lifecycle phases as in the bath-tub curve; λ, λ_r and μ are, respectively, transitional probabilities of being overloaded, relieved from the overload regime, and refurbished; t and n are, respectively, the technical life and the age bracket that determines ζ. The term $F(\zeta)$ is the cumulative density function (CDF), obtained by integrating the probability density function (PDF). It is assumed that $\tau = \tau_1 + \tau_2$, and $\omega = \omega_1 + \omega_2$ (see Figure 7). The expressions $\zeta \lambda \rho$, $(\zeta - k)\lambda_r \tau$ and $(\zeta - k)\mu \omega$ represent amplification and attenuation effects of interacting elements in the engineering system. The failure risk and service level vary as the maintenance and renewal or refurbishment strategies are applied on assets during the lifespan, which can be trended by superimposing some empirical models into equation (1). Mkandawire et al. (2015b) showed that the model (equation (1)) is an improvement over the traditional physical asset risk assessment approaches, because it can trend the asset risk throughout the expected technical life; because $F(\zeta)$ is a function of the operating time.

Figure 7 A typical system dynamics' state-space model (Arrows show the transitions) (see online version for colours)



However, the equation (model) does not express the risk level in terms of costs or monetary value, which could be more useful to physical asset managers, as best practice demands (British Standard, 2008). In the sections that follow, operations and maintenance (O & M) costs are incorporated into the model to demonstrate the cost benefits of risk mitigation measures.

3.2 Overview of lifecycle-modelling distributions

Various lifetime distributions exist for application to repairable and non-repairable asset-systems modelling. The most common distribution functions for electro-mechanical equipment life data fitting are the Normal, Lognormal, Extreme Value, Weibull, Exponential and the Poisson (Nelson, 2009). The Normal distribution is suitable for wear-out types of failure (Mkandawire, 2015; Nelson, 2009), and it belongs to a group of distributions called the parametric family of distributions (Rinnie, 2009). The others in this family comprise the Gamma distribution, the Change-Point Model, the Mixed Exponential distribution and the Erlang distribution (Gupta et al., 2010). The Weibull parameters can be computed, using methods outlined in Section 3.3, and then they can be applied to model component reliability and the hazard rate. The hazard rate can in turn be used to evaluate maintenance strategies, based on the relative risk of failure. This is demonstrated in Section 3.4. The hazard rate *h* (*t*) is the survival probability up to time t, given as (Mkandawire et al., 2014):

$$h(t) = \frac{\beta}{\eta}\left(\frac{t}{\eta}\right)^{\beta-1} \tag{2}$$

where β is the shape parameter and η is the scale parameter of the Weibull distribution.

The Weibull distribution is preferred to other types of distributions as it can be used to model a variety of distributions based on the variation of the shape parameter (β), using a set of failure data from similar types of assets (O'Connor and Kleyner, 2012). The lognormal distribution empirically fits many types of data adequately, especially suitable for metal fatigue and electrical insulation data (Nelson, 2009). The major concern is that the focus of these has been more on non-repairable items than on repairable systems (Rigdon and Basu, 2000). The Poisson distribution is probably the most versatile for minimal-repair and renewal modelling of both non-repairable and repairable items (Rigdon and Basu, 2000), and it was shown that it can be used to model optimum spare parts holding levels for power transformers (Chowdhury and Koval, 2005).

3.3 Parameter inputs for the risk-trend modelling

The failure function *F*(*t*) in equation (1), is expressed as a two-parameter Weibull distribution instead of a three-parameter model; because it is simpler yet it sufficiently models failure data as follows (Mkandawire et al., 2014):

$$F(t) = \int_0^t f(t)\,\mathrm{d}t = 1 - R(t) \tag{3}$$

where

$$R(t) = \exp\left[-\left(\frac{t}{\eta}\right)^{\beta}\right] \tag{4}$$

where *f*(*t*) is the PDF, *t* is the expected lifespan and *R*(*t*) is the survival likelihood. The β and η are derived by applying the maximum likelihood estimation (MLE) and the method of moments (MOM) to failure statistics. Through iterative numerical methods, the MLE can be applied to equation (5) and (6) to estimate *β* and *η* for a random variable x_i (Chan, 2004):

$$\eta = \left[\frac{1}{n} \sum_{i=1}^{n} x_i^{\beta} \right] \tag{5}$$

$$\beta = \left[\frac{\sum_{i=1}^{n} (x_i)^{\beta} \ln x_i}{\sum_{i=1}^{n} (x_i)^{\beta}} - \frac{1}{n} \sum_{i=1}^{n} \ln x_i \right]^{-1} \tag{6}$$

The MOM applies the mathematical expectation theory to a moment generating function for a given random variable to estimate the parameters as follows (Walpole et al., 2002):

$$M_X(t) = E\left(e^{tX}\right) \begin{cases} \sum e^{tx} f(x), & \text{if } x \text{ discrete} \\ \infty \\ \int_{-\infty}^{\infty} e^{tx} f(x)\, dx, & \text{if } x \text{ continuous} \end{cases} \tag{7}$$

If $h(X) = X_r$ for $r = 1, 2, \ldots$ n, is the expected value, the inner summation and integral in equation (7) can be differentiated to give the *r*th moment, μ_r', about the origin of the random variable *X*, for the real variable *t* expressed as follows (Walpole et al., 2002):

$$\therefore \left. \frac{d^r M_X}{dt^r} \right|_{t=0} = E(X^r) = \mu_r' \tag{8}$$

For the Weibull PDF,

$$f(x;\theta) = f(x;\beta,\eta) = \left(\frac{\beta}{\eta}\right)\left(\frac{x}{\eta}\right)^{\beta-1} e^{-\left(\frac{x}{\eta}\right)\beta}, \quad x > 0 \tag{9}$$

where $\theta = \beta, \eta$

From equation (9), it can be shown that:

$$E\left(X^r\right) = \int_0^{\infty} x^r \beta \left(\frac{1}{\eta}\right)^{\beta} x^{\beta-1}\, e^{-\left(\frac{x}{\eta}\right)^{\beta}} \mathrm{d}x \tag{10}$$

Further manipulation of equation (10) results in the following (Li, 2004; Al-Fawzan, 2020; Gove, 2003; Lei, 2008; Gupta et al., 2010):

$$CV = \sqrt{\left(\mu_2'\right) \Big/ \left(\mu_1'\right)^2} = \left[\Gamma\left(1 + \frac{2}{\beta}\right) - \Gamma^2\left(1 + \frac{1}{\beta}\right) \right]^{1/2} \Bigg/ \Gamma^2\left(1 + \frac{1}{\beta}\right) \tag{11}$$

$$\hat{\eta} = \left[\frac{\bar{x}}{\Gamma(1/\hat{\beta} + 1)} \right]^{\hat{\beta}} \tag{12}$$

where, CV, $\hat{\eta}$, $\hat{\beta}$, and $\bar{x}$ are, respectively, the coefficient of variation, the estimate of *η*, the estimate of *β*, and the mean of the data. Statistical software like R-Statistics and

MATLAB, or tabulation methods may be applied to equations (11) and (12) in order to compute $\hat{\beta}$, and $\hat{\eta}$.

3.4 Integrating strategies and systems-thinking with parametric-probability inferences

Since the case study data applied in this study is from transformers which are normally subjected to electrical, thermal and mechanical stresses, the Weibull distribution can be used to generate parameters for the model (Zhang and Gockenbach, 2007), and it can easily be used to model survival and failure probabilities (O'Connor and Kleyner, 2012; Smith, 2011). It is worth noting that it is imperative to carry out a test to determine whether the hypothesised distribution fits the dataset (Jardine and Tsang, 2013, p.248) (see, e.g., Section 4.1). Models that utilise both surviving and failing components also exist as in Li (2004); however, they are data intensive as they require large sample sizes (Schneider et al., 2006; Mkandawire et al., 2015b). The Weibull-based modelling of costs can be pitched according to the renewal theory as per (Zhang and Gockenbach, 2011) or according to planned maintenance as a function of the survival and failure likelihoods (O'Connor, 1991); where the maintenance cost rate $C(\tau)$ incorporating imperfect (c_r), corrective (c_c), and preventive (c_p) maintenance strategies carried out at time interval (τ) is given according to Zhang and Gockenbach (2011) as:

$$C(\tau) = c_r N_r(\tau) + c_c N_c(\tau) + c_p \tag{13}$$

where Nr and Nc are, respectively, number of components under repair and corrective maintenance. Equation (13) takes electrical, thermal and mechanical stresses of components into consideration, and is elaborated in Zhang and Gockenbach (2007). Furthermore, the total cost per year found in O'Connor and Kleyner (2012) is modified to express corrective and preventive maintenance costs given as:

$$C_T = \frac{Y_{ac}.\$_{pm}}{m} + \frac{Y_{ac}.\$_{cm}}{m}\left\{1 - \exp\left[-\left(\frac{t}{\eta}\right)^{\beta}\right]\right\} \tag{14}$$

where Y_{ac} = annualised maintenance hours; m = preventive maintenance interval;

$\$_{pm}$ and $\$_{cm}$ are, respectively, preventive and corrective maintenance cost rates, whereby maintenance is conducted at 'm' intervals; t is the operating time; η and β are as stated earlier on (see, e.g., equation (4)). The model assumes a constant maintenance rate and that failures are rectified only during the time of execution of planned preventive maintenance, which may not always be the case as the repairs may be triggered by catastrophic and/or breakdown failures. According to Smith (2011), the unit cost $£_{cm}$ and £pm for corrective and preventive maintenance, respectively, is given as:

$$C_T = £_{cm}.\left(1 - \exp^{-\frac{t}{\eta}}\right) + £_{pm}.R(t) \Big/ \int_0^T R(t)\mathrm{d}t \tag{15}$$

where, $R(t)$ is defined as in equation (3).

Although equation (13) models cost rates well, it is not used in this work because it requires a lot of data which may not be readily available to a practitioner in the field (Schneider et al., 2006; Zhang and Gockenbach, 2007); whereas equation (14) assumes the maintenance tasks are restricted to a year, hence it is not chosen. Instead, equation (15) is adopted with modifications, because it is flexible to apply to the systems-thinking risk model (equation (1)), as follows:

$$C_T = £_{cm} . \int_0^t f(t)\,\mathrm{d}t + £_{pm} . \exp\left(-\frac{t}{\eta}\right)^{\beta} \tag{16}$$

where $£_{cm} . \int_0^t f(t)\,\mathrm{d}t$ is a failure cost model and $£_{pm} . \exp\left(-\frac{t}{\eta}\right)^{\beta}$ is a planned preventive maintenance cost model.

3.5 *Application of the systems-thinking model with parametric-Probability inferences*

Planned and unplanned maintenance costs and time-to-failure data for transmission (*Tx*) and distribution (*Dx*) transformers (TSRF), respectively, are presented in Tables 3 and 4 (Mkandawire, 2015). These are used to demonstrate the risk trending methodology.

Table 3 Average maintenance costs for transformers

	Maintenance costs	
Transformer size	*Preventive maintenance costs* *($£_{pm}$)* [\$]	*Corrective maintenance costs* *($£_{cm}$)* [\$]
12 MVA Tx TSRF	17,467	30,000
0.2 MVA Dx TSRF	748	1300

MVA = Mega-volt-ampere; Tx = Transmission; Dx = Distribution; TSRF = Transformer.

Table 4 Transformer failure statistics

Life span (Operating hours before decommissioning)	
12 MVA Tx TSRF [10^5 h]	*0.2 MVA Dx TSRF [10^3 h]*
1.892	0.07488
4.188	0.07488
3.925	0.01123
1.971	0.03182
2.182	0.06739
1.971	0.07301
4.366	0.0805
2.365	0.8237
2.418	0.09173
4.03	1.554
2.31	2.771
3.715	4.512

MVA = Mega-volt-ampere; Tx = Transmission; Dx = Distribution; TSRF = Transformer.

4 Analysis and discussion of study results

The data in Tables 3 and 4 were used to derive the parameter estimates using equations (5) and (6) for the MLE, and equations (11) and (12) for the MOM as presented in Section 3.

4.1 Analysis of computed statistical parameter estimates

Table 5 outlines parameter estimates that were computed and compares the results from the MLE and MOM techniques (see, e.g., Section 3.2) for both the transmission and distribution transformers that were operated under the planned maintenance and reactive maintenance regimes, respectively. The distribution transformers were being subjected to the run-to-failure maintenance strategy (Mkandawire, 2015), an approach in the first paradigm (see also Figure 3). The Kolmogorov-Smirnov (K-S) goodness-of-fit test was applied to determine whether the hypothesised distribution (the Weibull) fits the dataset (Jardine and Tsang, 2013, p.248). The acceptance of the K-S test for the hypothesis was based on $p > 0.05$, and the p-value was 0.2185; thus supporting that the results of the β and η indeed came from the Weibull distribution. Table 5 shows that the MLE is the most suitable for short hours-to-failure; but when hours-to-failure increase the MLE and MOM produce results that are equally accurate, hence the two methods can be applied interchangeably.

Table 5 Computed parameter estimates by the MLE and MOM (see online version for colours)

Transformer rating	*Weibull parameters*	*MLE*	*MOM*
12 MVA Transmission transformers	β	3.43	3.50
	95% ci [LL, UL]	[2.19, 5.39]	[2.91, 4.51]
	η [10^5 hrs.]	3.29	3.28
	95% ci [LL, UL]	[2.76, 3.92]	[2.70, 3.83]
200 kVA Distribution transformers	β	1.17	1.45
	95% ci [LL, UL]	[0.77, 1.76]	[0.70, 2.99]
	η [$\times 10^3$ hrs.]	0.13	0.08
	95% ci [LL, UL]	[0.08, 0.22]	[0.04, 0.20]

ci = confidence interval; LL = Lower limit; UL = Upper Limit.

4.2 Analysis of reliability, maintenance and risk

Now, equations (2)–(4) are applied, using values from Table 5, to plot the cumulative density function (CDF) and the hazard rate, $h(t)$ as portrayed in Figure 8.

The figure shows an increasing hazard rate, $h(x)$, which means the TBM alone would not suffice in preventing failure unless it is augmented by predictive maintenance or CBM; thereby justifying a shift from the second to the third paradigm (see, e.g., Figures 3 and 4).

Figure 8 CDF and hazard rate for the 12 MVA transformers (see online version for colours)

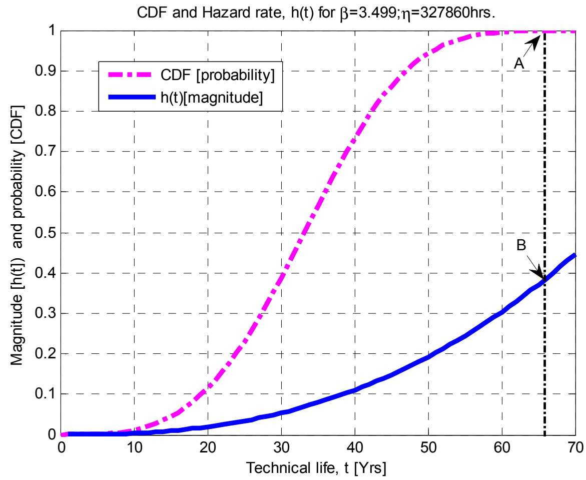


Figure 9 compares cost patterns for the 200 kVA (0.2 MVA) distribution and 12 MVA transmission transformers (see, e.g., Tables 3 and 4), operated within the first and second paradigms (see Figure 3(a) and (b), respectively; by applying equation (16) (Mkandawire et al., 2015b). The reactive strategy applied in the first paradigm (Figure 3(a)) fails to optimise the capacity utilisation of assets as the annualised corrective maintenance costs pick up so quickly that they exceed costs of assets managed under the second paradigm over a ten year period. This is particularly so because there are numerous distribution transformers in the electric grid. This is against the perception that some utility companies have, in subjecting the less capital intensive assets to reactive strategies, and the more capital intensive ones to preventive and proactive strategies. This, however, results in increased O&M costs as this study has shown; which collaborates the findings of Otal and Bakulev (2014) and Mitchell (2006). The points marked I and II are critical decision thresholds when corrective maintenance costs tend to exceed preventive costs; the point the asset manager should watch for and take appropriate interventions.

4.3 Application of the systems-thinking model with parametric-Probability inferences to trend risks

Next, equation (1) is applied in the trending of risks and costs, by superimposing equation (16) on the cumulative density function (CDF) or failure function (F) using parameters (β, η) in Table 5 for the 12 MVA transformers for the following three scenarios: risk with business as usual, with refurbishment carried out in the middle of the life span, and refurbishment carried out towards the end of the life span; and for $\varphi = 3$, $\gamma = 20$, $\sigma = 6$, $\lambda = \lambda_r = 0.02$, and $\mu = 0.03$. The PDF is obtained using equation (9).

Figure 9 Comparison of (a) 200 kVA and (b) 12 MVA transformer cost patterns (see online version for colours)

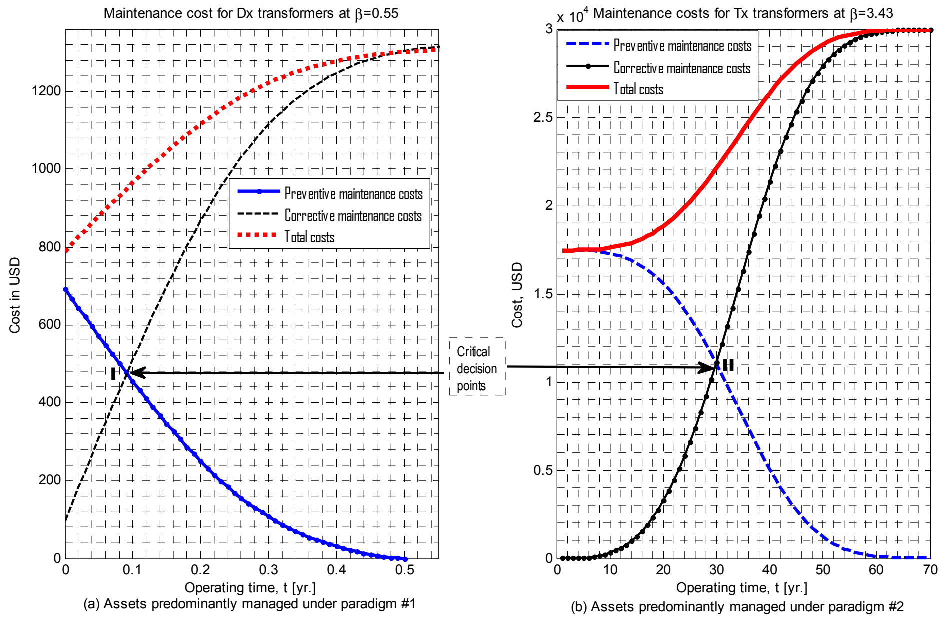
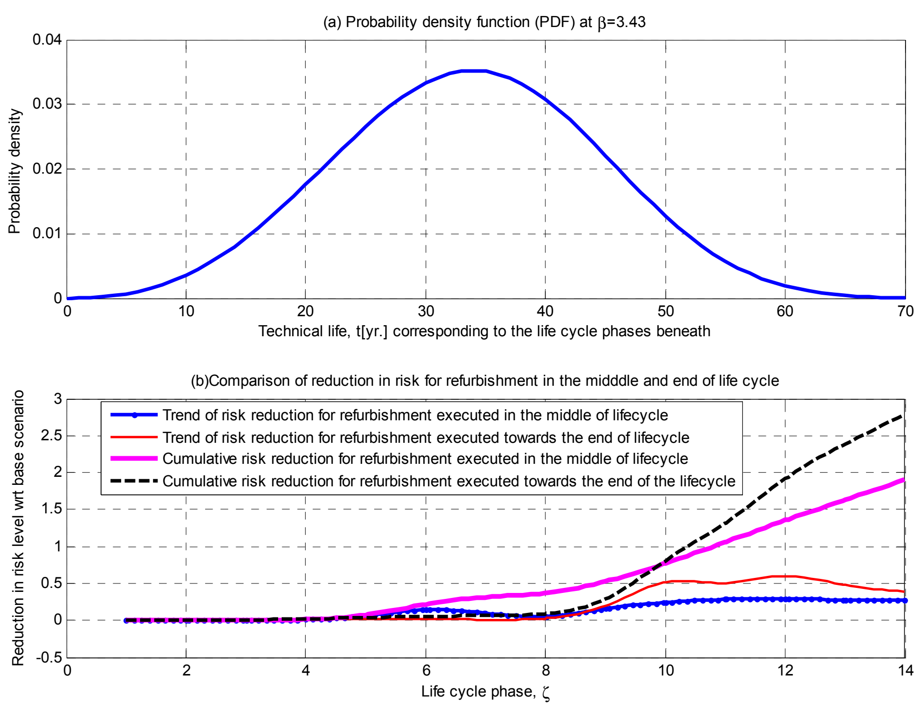


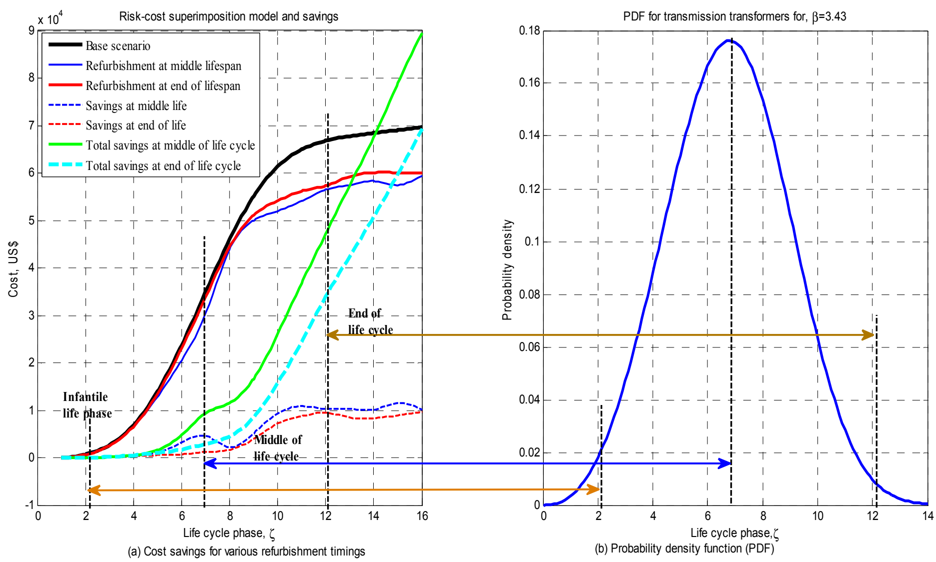
Figure 10 Comparison of reduction of risk level: refurbishment at middle and end of life cycle (see online version for colours)



Then, the variation of the risk factor to changes in ρ, τ and ω are plotted as shown in Figures 10 and 11, representing risk reductions due to the application of refurbishment strategies during the middle of the life cycle ($\xi = 5$–10) and during the end of the life cycle ($\xi = 10$–11) of the assets relative to the business as usual scenario. It is shown that the greater the reduction in the risk factor, the more effective are the strategies in reducing the risk of failure.

Thus, the Systems-thinking Model with parametric-probability inferences is able to trend physical asset risks. Furthermore, Figure 11 outlines trends of risk for the three scenarios that are used in Figure 10 as well as the PDF (ref. equation (9)) of these transformers; whereby, the risks are expressed in terms of benefits of reduction in O & M costs. It is shown that business as usual scenario presents the highest risk, followed by the end-life renewal and the mid-life renewal with the least risk level. The mid-life renewal strategies yield cost benefits early enough to be re-invested in the business, hence, that is the best option from an asset management point of view. Since the economic benefits of refurbishment are mostly difficult to validate and convince shareholders to invest in the undertaking, the results derived from this model could be of help in seeking approvals from the top management for refurbishment budget plans, for their buy-in.

Figure 11 Risk-cost trending derived from systems-thinking model with parametric-probability inferences (see online version for colours)

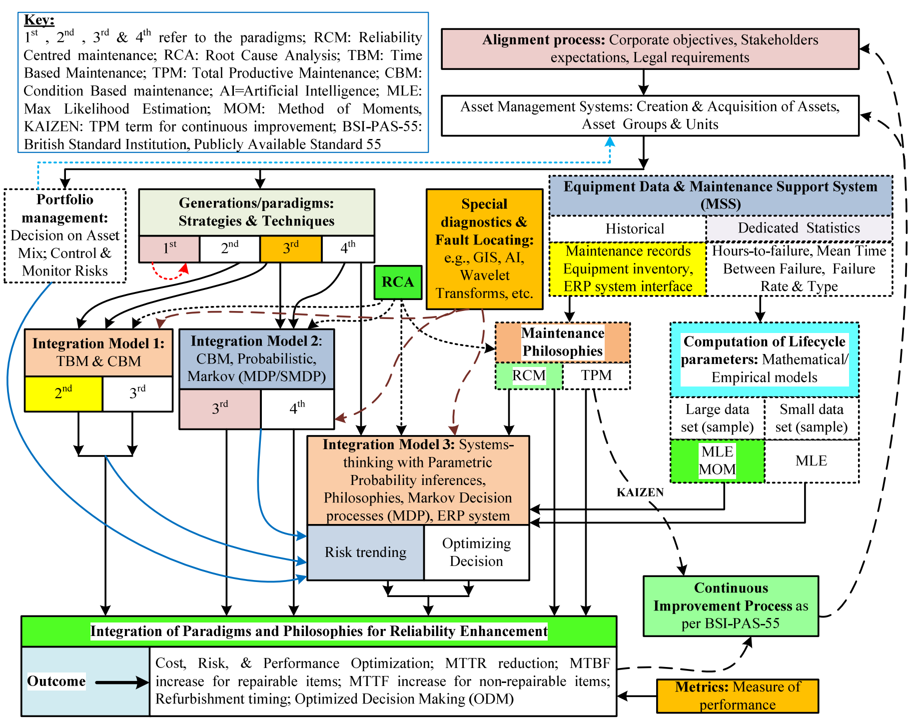


5 Synthesis of approaches and paradigms for reliability enhancement

Figure 12 is a model-based approach summarising synergies of various AM paradigms that have been reviewed and advanced in this study, including clusters of tools, techniques, strategies and methodologies that are aimed at enhancing reliability. In the figure, the first paradigm is not interconnected with any other because it is not a best practice; it may be used as a default strategy when no appropriate preventive measure is available as in the RCM (Moubray, 1997). Corporate objectives and stakeholder requirements are at the top, because they determine the type of asset portfolio for an organisation (British Standard, 2008). No single cluster of techniques or methodology suffices in reducing the risk of failure, hence asset managers should apply the best assortment of strategies, techniques and philosophies contained in an appropriate model in order to optimise returns on their assets. The optimum point is where the cost, risk and performance trade-off is of minimal impact on the whole life cycle of the asset (Woodhouse, 2004). The parametric modelling applied in the study generated parameters that are unique and customised to the type of equipment. In general, the main merit of parametric modelling is the customisation of deliverables (Thajudeen et al., 2020, pp.571–572).

Three models of integration are presented in Figure 12. Model 1: TBM with CBM; Model 2: CBM with Probabilistic and Markov techniques; Model 3: systems-thinking with probability inference models, philosophies, Markov decision processes and AI. Just like in other complex systems like manufacturing where product service system (PSS) is advocated (Mo, 2012), there must be a maintenance support system (MSS) in physical asset management, which for Figure 12 consists of enablers (enclosed in dotted boxes), namely: equipment data which provides information for life cycle modelling, ERP, philosophies like RCM and TPM, and BSI-PAS-55 (see definition on the top left box in Figure 12) which help to instill the KAIZEN or continuous improvement process and to select the right maintenance strategy; and portfolio management, consisting of decisions on asset mix as well as the risk profiling which assesses, monitors and controls corporate risks and service level as shown by (Mo and Richardson, 2017).

Figure 12 A model-based multi-method, multi-criteria risk and physical asset management approach (see online version for colours)



The motivation and argumentation for the modelling choices initially rest on the precept that assets must be aligned with strategic objectives, stakeholder expectations and legal requirements as seen on the top-right box (see also PAS-55 (British Standard, 2008; Schneider et al., 2006)). Then, the decision on the asset mix that best lowers the risk, and on strategies and techniques applicable to the assets follows (see box 2nd from top-right). Thereafter, based on asset management maturity level, a firm should decide on the most appropriate integration model which when augmented with relevant data can ably inform decision making.

To contextualise the validity of the added value of the asset management approach proposed (Figure 12), we consider the application of the 4th paradigm where CBM and probabilistic techniques are applied (Integration Model 2). The CBM will help in the prediction of physical asset condition for failure prevention, however, it may not deal with some occasional catastrophic failures; hence the value addition of probabilistic approaches such as the Poisson process comes handy in estimating optimal quantities of spares needed to reduce the MTTR, among other things, as supported by Rigdon and Basu (2000), and Chowdhury and Koval (2005). The value addition can be quantified by metrics such as avoided costs (due to reduced safety violations) and savings from the CBM as well as from reduced forced outages as the stock (spares) holding will speed-up parts replacement during maintenance; thereby extending the MTBF. Cross-cutting concepts, e.g., RCM and TPM are useful for continuous improvement.

The model developed has been piloted at a large plant containing electromechanical machines in Southern Africa for five years and has shown that the Level 1 model reduces maintenance costs by almost 15%, Level 2 by 25%, Level 3 (where systems-thinking approach is predominant) reduces maintenance costs by up to 40% and savings in avoided costs of up to 15%. In addition, it was revealed that the annualised average cost of condition monitoring (CM) technology within the Level 1 mode of integration was less than the additional annualised cost of replacement of one damaged hydraulic pump bearing assembly (due to unplanned failure) by 19.6%; and less than the additional annualised cost of replacement of all bearing assemblies by almost 90%. This finding provided the motivation for advocating that more investment should be put into CM technologies and it got the much needed support from the executive management.

6 Conclusions

This paper has demonstrated that for an asset management system to effectively manage failure risks and optimise returns on the physical assets, a systems-approach should be applied to determine all the underlying and potential causes of failure. There has been distinct evolutions of asset management paradigms since World War II to 2021: from reactive through preventive, condition based with advanced diagnostic techniques and artificial intelligence, proactive with probabilistic and stochastic approaches, to proactive with systems-thinking and parametric-probability inference models. The asset management paradigm chosen for a given asset portfolio must integrate several strategies, including the RCA – where the systems-thinking approach can be leveraged upon; because even the most advanced modern proactive strategies that employ artificial intelligence, probabilistic and Markovian inferences, and those with predictive capability like the CBM do falter if not supported by lower ranking enabling techniques and strategies. The multi-method, multi-criteria risk and asset management approach has been proposed. Its merits are in its ability to apply asset management techniques, diagnostic tools and risk management tools in not only the short time horizon but also over the entire lifespan so that whole-life impacts of risks on the business are evaluated and mitigation measures are taken. The study has demonstrated that the Systems-thinking approach is a vital tool for collating data for integration of the various strategies, and when combined with parametric probability inferences it can help to reveal patterns that are not possible to depict with analysis only; and to trend the risk levels of physical assets. These parameters are component-specific, based on failure data from these components or similar families of items, and when applied to appropriate empirical models they can generate equally unique metrics for reliability enhancement in the industry; and can assist in the evaluation of the effectiveness and timing of renewal strategies. The study findings can help asset managers in deciding which equipment management paradigms and set of strategies, tools, and methodologies best fits their asset portfolio in industry. Pilot studies over the past five years have shown that using the model developed can bring about savings in maintenance costs of 15-40% and in avoided costs of up to 15%. Future research should explore characteristics that will mark the evolution of the next physical asset management generation, that is, the fifth paradigm.

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