

ADDING VALUE BY ENABLING KNOWLEDGE BASED MAINTENANCE (KBM) STRATEGIES

A discussion of practical maintenance solutions -
and proposed empirical investigation of a system
dependent on a fatiguing spring element.

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Abstract

The categories of KBM and alternative maintenance strategies are examined in the light of past and current literature. The cost benefits and inherent complexities are discussed for each main categories and a recommendation is concluded for a particular product under development. An experimental design is proposed to evaluate the minimal instrumentation needed to satisfy the input requirements of the preferred strategy.

Introduction

As technology has evolved, the Internet of Things (IoT), artificial intelligence (AI) and availability of cloud computing have disrupted the fundamentals underpinning the deployment of Internet enabled and mass-produced new products, services and assets deployed within a wide range of industry sectors. Within the context of the smart factory. Cyber Physical systems and the Internet of Services along with IoT and big data collectively enable industry 4.0 to exploit latent potential in respect of performance and quality of both services and products (Mabkhot et al., 2018).

Manufacturers have realised the value of the individuality of data generated by devices operated remotely by their clients. Big Data insights offer insights to potentially increase operational efficiency and improve new product development in a highly collaborative dynamic manner (Tao et al., 2017).

Digital technologies can be utilised for fault monitoring and continual assessment of operational efficacy. To succeed manufacturers must carefully consider the nature of the required communication componentry and added measurement instrumentation, its complexity and added cost, and strategies to take advantage of the IoT leverage the acquisition of real-time data as an opportunity in the continually changing business environment.

The digital twin (DT) has recently become increasingly important within the field of asset maintenance. The concept of the digital twin was first described by Grieves in 2012. Grieves described physical asset and the virtual asset bound together by the showing of communication of data and information. However, though the implementation of the digital twin the volume data generated can lead to too much exact data which on analysis has negligible effect on meaningful improvements under strategic approach need be adopted to maximise the benefit of such abundant intelligence (Liu et al., 2020).

The Healthcare sector occupies a position in one of the fast-changing landscapes. real time intelligence on the operational efficiency of their devices and services is becoming a critical requirement for manufacturers striving to achieve market position and to meet the evolving demands of their customers.

A start-up based in North Wales is engaged in the development of one such product. The new product incorporates an electro-mechanical structure purposed to the reconstitution of lyophilised pharmaceutical actives (LPA). A key component in the assembly is a spring element which experiences multi axis dynamic stresses and strains as energy is input at one spring end, the other end is subject to a secondary varying load. As a result, the spring element will fatigue and eventually fail normally where stresses are maximally concentrated.

During the element's service life, the changing flexural characteristics of the element will cause the attached load to move in a progressively differing repeating trajectory. Whilst the load's movement path is largely acceptable as early fatigue progresses and the desired process outcome is achieved, better intelligence on fatigue/load behaviour over the anticipated service life would be valuable.

Depending on the instrumentation incorporated into the product, many layers of useful data can be harvested through the IoT. Pseudo real time analysis provides manufacturers or service providers with pertinent data from which to make actionable decisions and to gain insight into client usage. The data not only supports strong service provision but also directs next generation product design focused on meeting previously unknown customer demands.

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The value in respect of the proposed study would aid the development of strategies for:

- Preventative Maintenance
 - The new product design file would potentially benefit from a study examining the changes in operational characteristics due to repeating flexing of a spring structure in service lifetime, in other words the effects of fatigue across the anticipated operational life of the device.
- Predictive Maintenance
 - Intelligence on the frequency and rate of consumption of the spring's flexural efficacy helps consideration of specific devices from a service point of view, within a site fleet, is one device consumed more rapidly than others, is there a case for 'load balancing'.
- Estimation of Remaining Useful Life
 - Scheduling service personnel as a finite resource demands intelligence not only on individual devices, but also on a health of a fleet of devices found within one site. Initiative-taking service scheduling would not only support the site fleet in satisfactory operation, but also in cooperation with predictive maintenance analysis and to satisfy customer expectations fleet operational efficacy.

(Rotter, 2016)

From casual observation of the device in operation, it is predicted flexural resilience will gradually decay until catastrophic failure occurs, starting from the area of maximum stress concentrations.

This experimental quantitative study will generate datasets from instrumentation observing the multi axis motion of one or more passive visual targets temporarily applied to the spring element, designed to indicate the movement profile of one or more features of a spring element and further appropriate sensors to measure the energy input profile, in both current /voltage time domains applied to the actuator (a small form brushed DC motor) to bring about the desired load movement trajectories.

The outcome of the study aims to Inform the development of strategies directed at service management of fleets of deployed devices installed at numerous sites, by supplying Predictive maintenance data and enabling estimation of remaining useful life of a key component, namely the fatiguing spring element.

Literature review

Maintenance strategies and their consequences

Reactive maintenance

This approach is only suitable for non-critical assets or emergency responses (Swanson, 2001), if adopted as a badly thought-out strategy, reactive maintenance can lead to significant costs in both repair or replacement of the asset compounded by the additional losses associated with interruption of the related service or output.

Preventive maintenance

A schedule a pre-planned maintenance aimed at reducing the incidence of reactive maintenance actions may be adopted by the asset manager (Shafiee, 2015). Whilst preferable to purely reactive maintenance, over-maintenance associated with preventive maintenance can result in unnecessarily high economic costs to the asset owner (Maktoubian and Ansari, 2019).

Condition based maintenance

The application of IoT and cloud-based computing facilitates condition-based maintenance (CBM). This approach is based on the trending migration of the assets operational behaviour from that determined to be normal (Belov et al.2020), also referred to as diagnosis-based maintenance. The behavioural outliers can be identified with the aid of IoT data acquisition and later AI based algorithms.

Predictive maintenance

Predictive maintenance utilises much of the information measurable within and about the asset surroundings. the interaction between multiple interacting assets can result in complex architectures complicating analysis and decision making.

Within predictive maintenance a data driven approach can be adopted. Data driven and model driven strategies may be adopted:

- Large volumes of data are acquired and treated using AI algorithms based on proper models, potential operational failure trends can be generated in advance of the actual behaviour of the asset. Further the dynamic implementation of such AI algorithms allows for the in-service compensation of the operational parameters of the asset to support or optimise its execution (Liu et al., 2018).
- A mathematical model may describe the asset in functional, numerical, or physical terms. Models can be capable of describing the degradation timeline of the asset accurately, renewable energy generation wind turbine have benefited from such extensive modelling in both maintenance and future design (Moghadam, Geraldo and Nejad, 2021). The availability of almost unlimited affordable cloud-based computing resources has enabled significant recent improvements in the efficacy of such modelling strategies.

A hybrid approach (Liao and Köttig, 2016) advocates an interesting application of Predictive Maintenance. In the first instance a data driven model is developed using data from the current and historical operation of the asset, to 'infer' a functional description of the asset, the measurement model. This often requires observations of the life cycle of the asset to fault detection and can be costly.

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An alternative system model can also be costly, potentially involving numerous complex Finite Element Analysis (FEA) computations. The differing asset conditions such as variability in inputs and environmental fluctuations can also result in significantly increased FEA input sets and later analysis and presents a significant effort to achieve situational completeness.

In combination, a data driven model and a model-based method can potentially average their results (e.g., Goebel et al, 2006) to achieve a more exact prediction of asset functional behaviour.

Prescriptive maintenance

The final approach for consideration is prescriptive or knowledge-based maintenance which relies on predictions. Planned maintenance tasks are created based on the analysis of both past and current data sets.

Some systems integrate prescriptive maintenance within a cyber physical ecosystem, incorporating multidimensional data acquisition, AI based data analysis, a data driven and knowledge-based action recommendation engine, a cloud-based dashboard and integration with physical controllers such as solution.

Over and above the benefits of Predictive Maintenance, prescriptive maintenance leverages custom built prescriptive algorithms to extrapolate several possible outcomes and rank those outcomes in an order defined at the time of development of the custom algorithms. This rank may be of cost to various value areas. It may be production volume, cost to operate or human injury or satisfaction. Knowledge based maintenance considers long-term effects of such policies and decisions on economic terms, as an integrated component of the production system, which effects value creations of the high-level commercial entity (Matyas et al., 2017).

(Ansari et al, 2019) summarise the four preferred flavours of Knowledge Based Maintenance in eloquent and succinct paragraphs.

“Descriptive maintenance (Type I, Low Complexity, Low Maturity) answers the question ‘What happened?’ by providing information about previous maintenance operations. Thus, it supports information collection and analysis and increases the level of information visibility.

Diagnostic maintenance (Type II, Medium Complexity, Low Maturity) answers the question ‘Why did it happen?’ by analysing cause-effect relations, reasoning, and providing further technical details about former maintenance operations. Therefore, it supports knowledge generation and increases the level of knowledge transparency.

Predictive maintenance (Type III, High Complexity, Medium Maturity) answers the question ‘What will happen when?’ by learning from historical maintenance data, possibly in real-time, and predicting future events. Thus, it supports knowledge discovery and enhances the level of (semi-)supervised or unsupervised prognostic capabilities. Notably, this is often referred to as ‘Smart Maintenance’, ‘Data-Driven Maintenance’ and ‘Maintenance 4.0’, not only in scientific but also in commercial contexts.

Prescriptive maintenance (Type IV, High Complexity, High Maturity) answers the question ‘How can we control the occurrence of a specific event?’ (How should it happen?) by providing actionable recommendations for decision-making and improving and/or optimising forthcoming maintenance processes. It also refers to the recent advances in enhancing self-organisation and self-direction capabilities of CPPS, which ideally aim at machine self-diagnosis and self-scheduled maintenance. Hence, prescriptive maintenance may reach the highest degree of maturity which involves complex methods to produce and reinforce adaptation and optimisation capability”.

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Why consider a maintenance strategy and what are the determinants?

Consider a preference between the four main maintenance strategies in context of the service provider (manufacturer) of the new product incorporating the fatiguing element, and the end user, both referring to the questions asked in the descriptive paragraphs cited (Ansari et al, 2019) and referring Fig 1 of (Errandonea et al, 2020b).

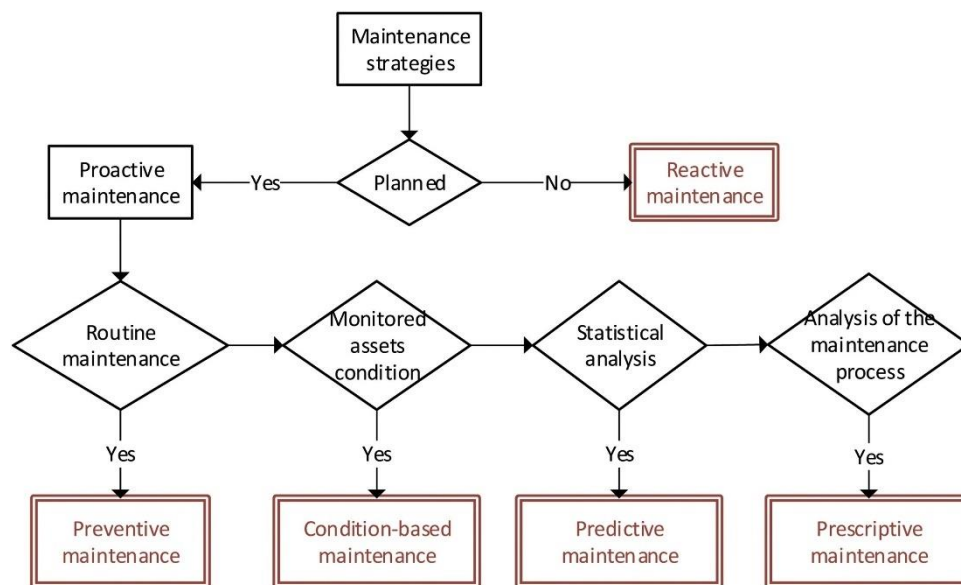


Fig. 1 Maintenance strategies diagram (Errandonea et al, 2020b)

Reactive Maintenance in an Industry 4.0 age would offer few advantages unless there was an exceedingly high degree of confidence in the operational resilience of a product over its complete service life, in such a case the service cost saving could be maximised in a 'deploy and forget' strategy. The "spring" is inherently subject to variable fatiguing stresses and arguably unsuitable for reactive service provision.

Preventative Maintenance would entail a fixed cost however each service event may not be necessary and therefore would be expected to be wasteful, however the user may benefit from a tangible peace of mind in their optimally maintained asset.

Condition based maintenance does require a means of asset monitoring, extra cost will be incurred in applying appropriate instrumentation to the product to enable the harvesting of relevant parameters and further technologies to communicate that data to a local or remote service for further analysis and decision making. The new product in development "the spring" does lend itself to the required metrological instrumentation.

Predictive Maintenance prerequisites a model of behaviour of the "spring" over its operational service life, i.e., historical data and a mathematical model to statistically predict what is about to happen and its likely severity. By incorporating real-time acquisition of operational metrological data

with the proper facility to automatically enhance existing models, a highly effective approach could be adopted for the “spring” without adding additional product measurement and communication provision over that required by a condition-based maintenance approach.

The maximum perceived benefits come from the Prescriptive Maintenance strategy. The cost of embedding sensors, related conditioning circuitry and communication capability remain similar to that of the previous two approaches (condition based and predictive) but the capability to modify the operation of the device (spring) to achieve an operational mode which promotes a desired function, despite the fatigue induced operational characteristics of the main spring element, would serve to firstly keep the device operating in a customer acceptable mode. Further, potentially predicting a catastrophic failure point in the future, would allow a service event (spring replacement) to be autonomously scheduled in advance.

Fig 2 illustrates the closed loop nature of Prescriptive Maintenance, showing the instrumentation for data acquisition, analytics and simulation opportunities, and prescriptive decision intervention according to Matyas et al., 2017, however the inclusion of reaction maintenance for the instance of the spring product would be only valid in the case of temporally proximal or near proximal spring element failure. Reactive model infers, in the ‘spring’ case, an unanticipated failure of the ‘spring element. An effective model would have forecast the ‘spring’s’ failure in advance, pre-empting a reactive response.

It is not expected that the non-moving electronic control or communication sub-systems would be either prone to failure or would indicate an advance failure which was predictable through system monitoring, otherwise necessitating a reactive response.

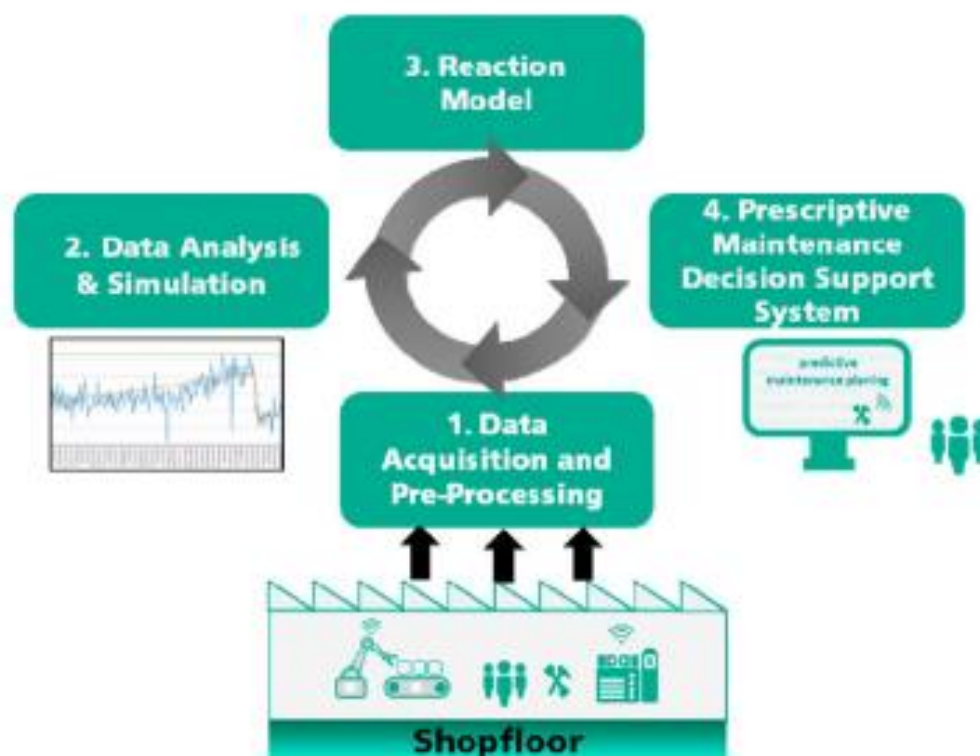


Fig 2, Procedural approach for prescriptive maintenance planning. (Matyas et al., 2017)

The device user expects the product and service to be operationally available when needed, if this were not the case, patient outcomes could be compromised (the product mixes medicines). Referring Fig 3., a decision on the balance between cost of maintenance (cost to improve reliability) and the commercial value of customer confidence (cost to improve reliability) must be evaluated. Should customer confidence in operational outcome rate highly as a key aim, a move away from the inflection point of the “optimal time for maintenance” is justified.

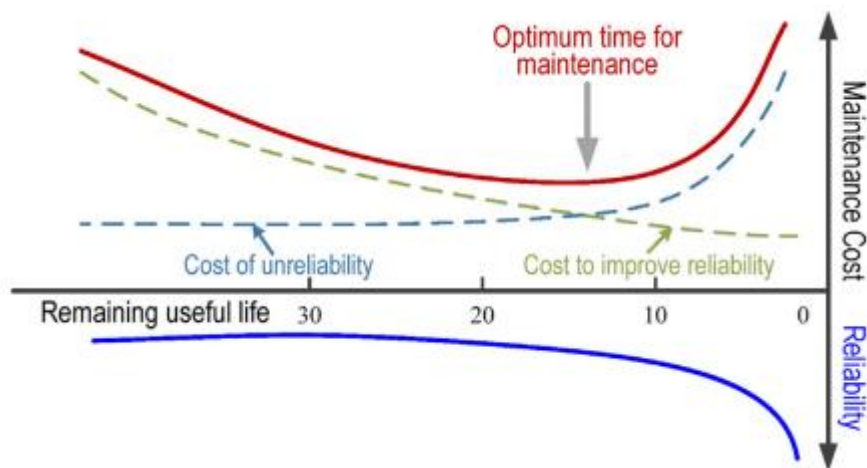


Fig 3. Relationship between RUL, reliability, and maintenance cost, (adapted from Peng et al, 2010)

In contrast to the again to the illustration of Fig 3, this may not always be achieved by replacing the device well in advance of significant reduction in its remaining useful life but could also be achieved by intervention in the operation of the device based on its current condition, what the predictive models anticipate and what the prescriptive models direct the device to change, to achieve the desired, optimally achievable, operation of the device.

The role of the Digital Twin

Briefly, we can consider how the different strategies applied in the twinning of virtual and physical cyber systems,

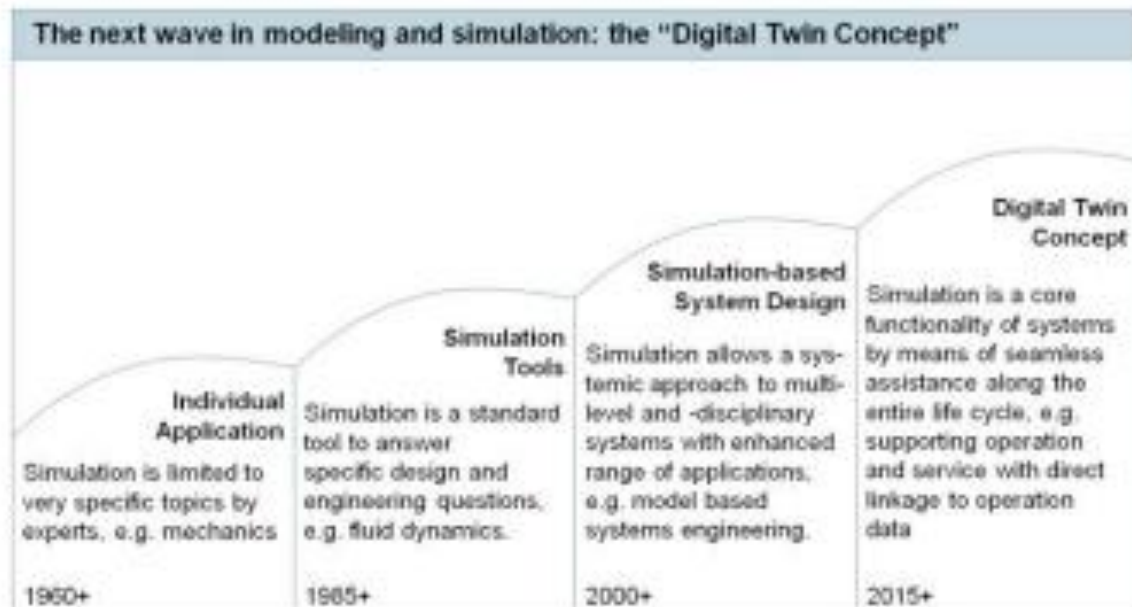


Figure 4: The Digital Twin - the next wave in Simulation Technology (from Rosen et al., 2015)

Fig 4 illustrates the evolution of the digital Twin and sets the backdrop for its currency in the context of 'seamless assistance along the entire life cycle' where maintenance strategies are being considered. As the extant use case appears to point to the preferred adoption of a prescriptive maintenance strategy, with the aid of Fig 5, a necessity for fully autonomous bidirectional data or control pipelines can be established as a determinant for this strategy to be effective (Kritzinger et al., 2018). Therefore sensors, communication and support circuitry are mandated.

Alternative maintenance strategies do not always require the full Digital Twin of Fig 5., for example Reactive maintenance can be 'twin less', condition-based and predictive strategies necessitate at least a digital model or a digital shadow. (Kritzinger et al., 2018).

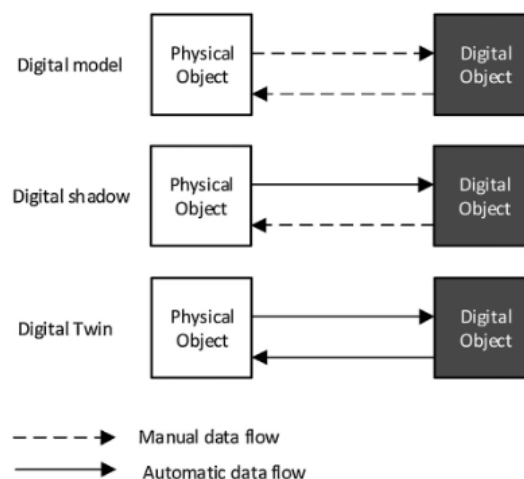


Fig. 5. Flow on different integration modes (Kritzinger et al., 2018)

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Case studies

Case study 1

(Hadi et al., 2020)

The prediction of fatigue life in respect of engineering plastics or metals including alloys are a key factor and considered by Hadi et al., 2020, The rudimentary investigation was conducted on Nylon6.6 and cast-iron specimens drive rods. Centrally driven in rotation while the distal and proximal ends are supported, the central portion of the driveshaft is progressively loaded until failure, while the shaft is in rotation.

Very simply the results were analysed by plotting the centrally applied stresses against the number of successful rotations before failure occurred.

The study was relatively straightforward, and the results were of potential use in selecting optimal material and diameters for limited to a centrally loaded driveshaft, manufactured from one of the test materials, under known stress loading conditions. The results can be used to develop a potential model for several the knowledge-based maintenance strategies where the load, material type and number of drive shaft cycles can be monitored.

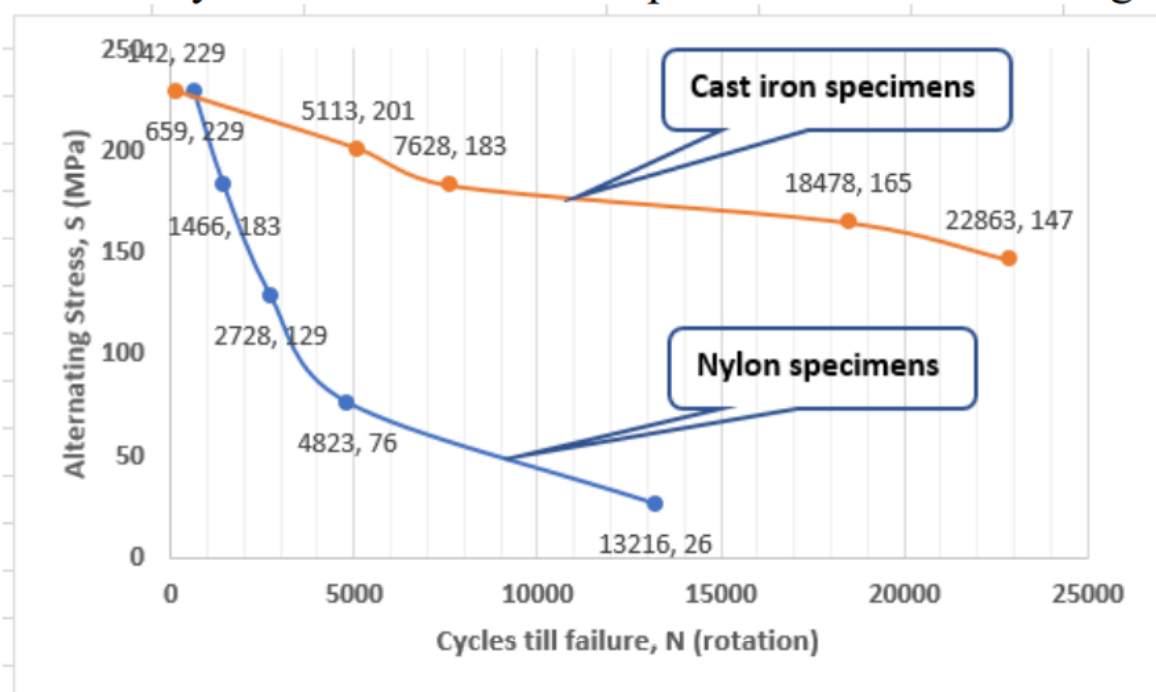


Figure 7. The fatigue test result for Nylon 6.6 and Cast-Iron specimens (from Hadi et al., 2020)

Case study 2

A study of the application of IIoT, condition monitoring systems (CMS) and machine learning (ML) driven processing is applied to fault modelling of ubiquitous electrical induction motors, potentially informing maintenance strategy adoption and actions.

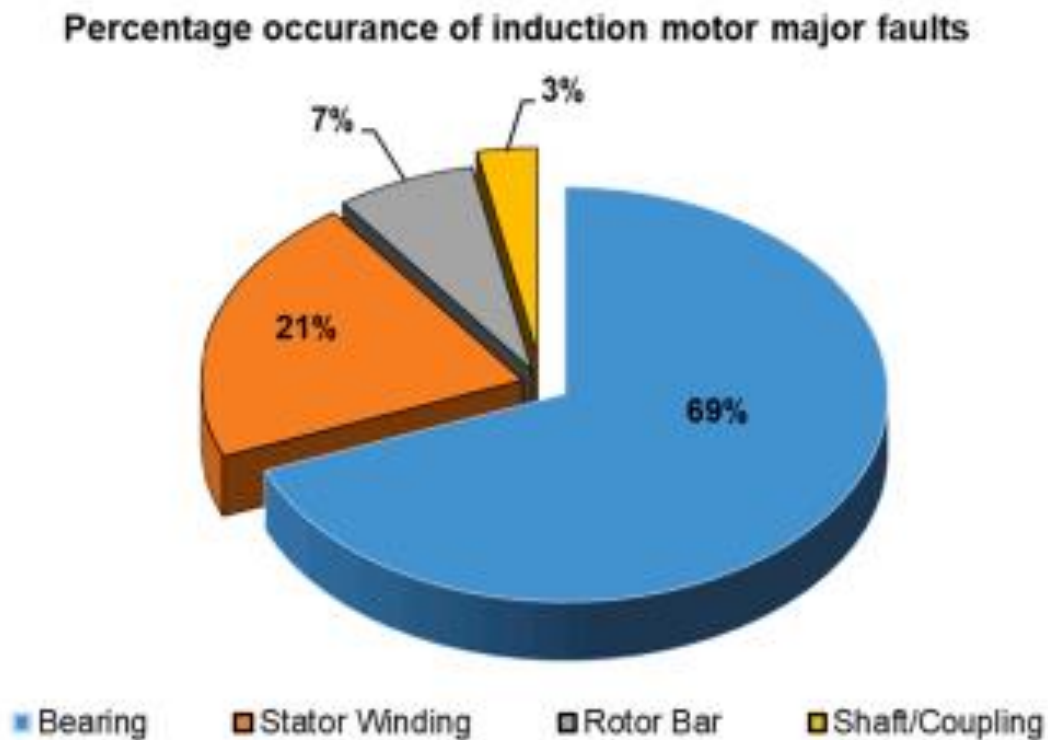


Fig. 8. Induction motor major faults occurrence rate (Jose & Jose, 2013).

Fig 8 illustrates the relative size of known failure inducing source by motor component. Knowing the areas for investigation eased the choice of measurement and monitoring instrumentation. The acquired data was communicated via an IIoT notification system of the investigators' design.

One feature of this study was the generation of copious amounts of data and ML strategies for the processing of the data to models further generating actionable events or control modifications. ML driven approaches for handling the big datasets have been previously discussed (Liao and Köttig, 2016).

While the study paper broadly discusses Knowledge based maintenance strategies and provides an excellent overview of ML as a subfield of Artificial Intelligence, of particular interest is the accessibility of the CMS systems based on available data acquisitions and processing technologies, open-source libraries, and sensors.

The maintenance aspect of the study was enabled by 'out of range' notifications for any of the parameters under continual monitoring.

In parallel the data was continually captured and feed an ML based processing model, developed though a data flow as illustrated in Fig 9 where the model was manually trained on 70% of a typical data set and tested on the remaining 30% of the dataset. Training and test data are normally randomly selected.

The Decision Tree (DT) algorithm was considered the preferred choice for CMS In respect of not only its convenience in determining threshold values but also in computing rapid and acceptable classification rates (Cakir et al, 2020).

Analysis of vibration data is most used in the classification of bearing deterioration (Wang et al, 2016). Temperature, sound, rotational speed, and temperature can all potentially be additionally acquired and integrate it in the data set to increase classification success (Sun et al, 2011).

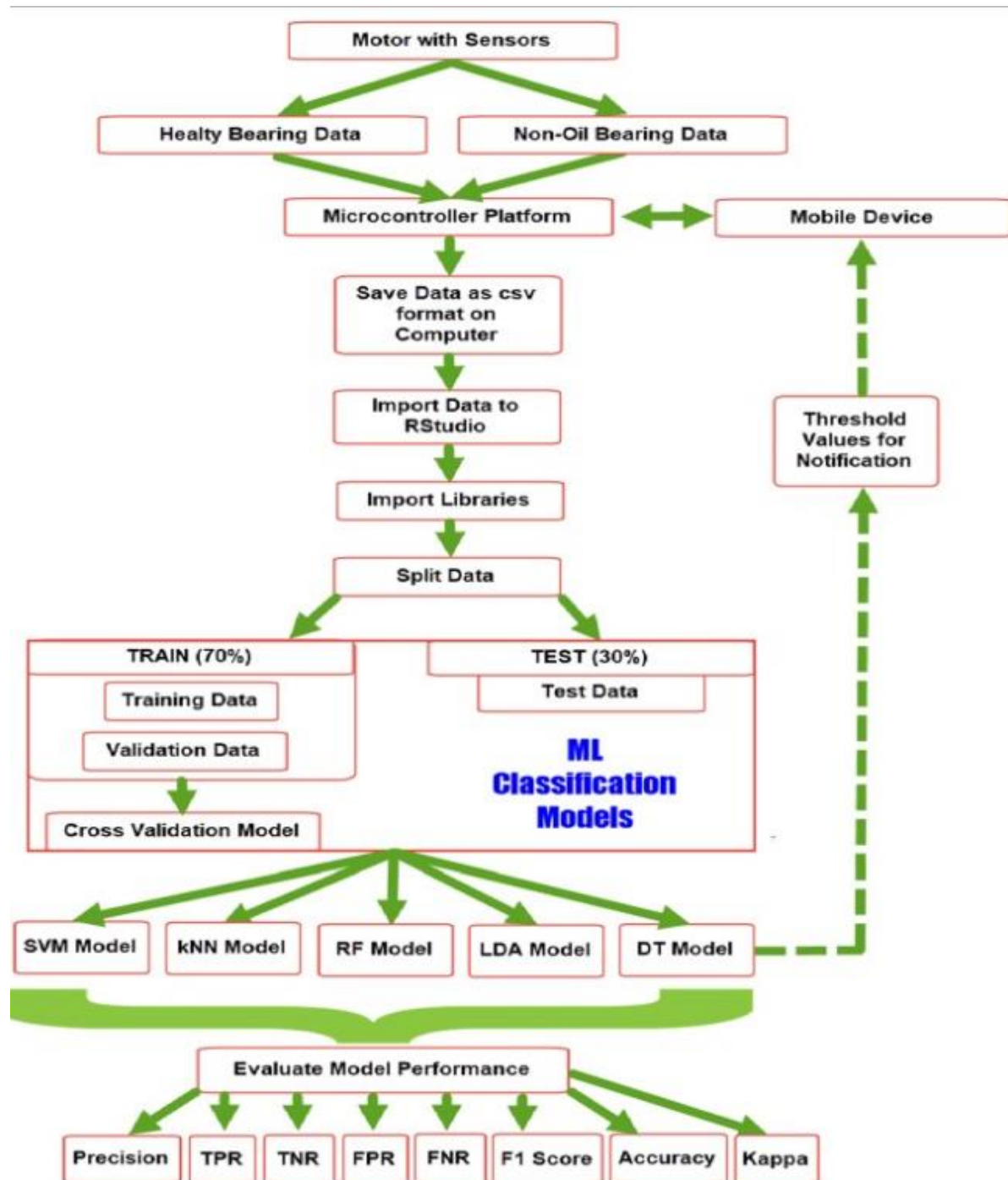


Fig. 9. Flowchart of data analysis with ML algorithms and evaluation process (from Cakir et al, 2020).

The approach of Cakir et al, appears to provide a suitable general template to adopt in respect of the proposed methodology, particularly as the author's proposed study also to monitor, analyse, and through machine learning develop a model which would prove an asset in future decision-making processes in respect of knowledge-based maintenance policy adoption.

Case study 3

Of interest to the current proposed study is the consideration of the design of a 3D printed vehicle leaf spring. the carbon PEEK (poly ether ether ketone) polymer composite element was manufactured for test with multiple design variations. (Kessentini, et al, 2019). Fibre lengths, fibre diameter, percentage volume of fibres and orientation angle of fibres were modified to produce several test samples of the leaf spring.

Under different loading conditions deflection, spring rate, stiffness, bending stress and Von Mises stresses were examined to assist in the optimization of the design parameters. The effect varying the design parameters were considered using Finite Element Analysis.

Artificial neural networks were further employed to determine the optimal stresses under the influence of span and camber of the leaf spring. the results enabled the designers to potentially reduce weight and increase load carrying capability.

Aspects of this case study may be advantageously incorporated into future revisions of the current study proposal. Preliminary FEA has previously been conducted to gain intelligence on potential stress induced failure risk and displacement interactions whilst under dynamic loads. An example is illustrated in Fig 10.

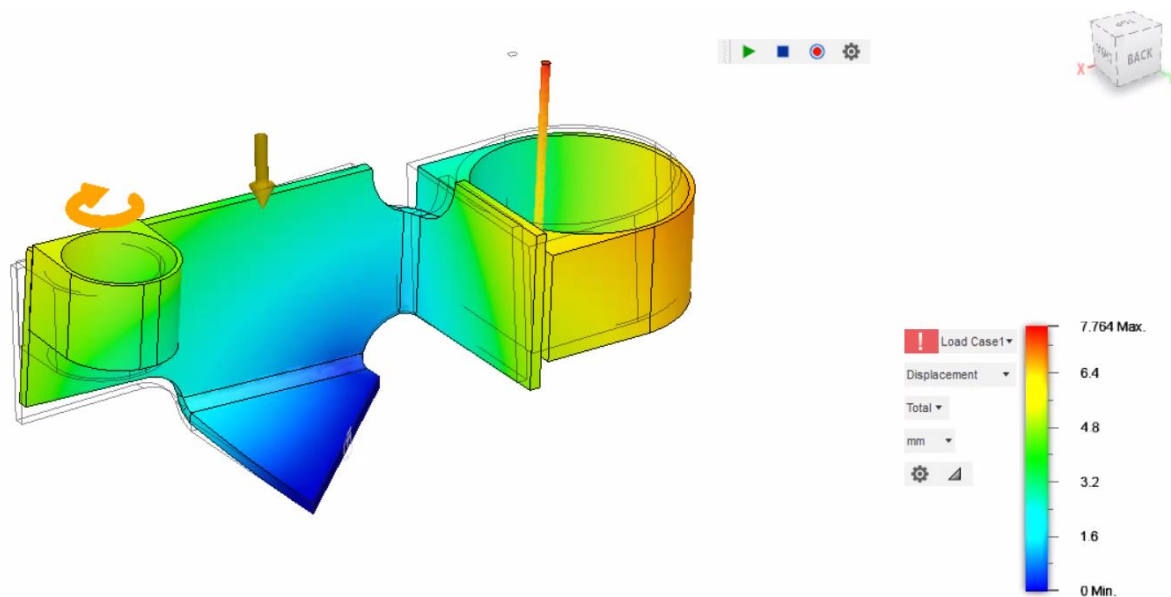


Fig 10 Spring element displacement FEA.

The Research Question:

Can minimal added sensors generate data enabling a sufficiently exact Machine Learning driven model, allowing for the adoption of a Knowledge Based Maintenance strategy?

(The host system is a healthcare product which includes a critical electromechanical actuator)

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Methodology

The experimental setup is a quantitative study of a Device Under Test (DUT) which comprises a spring element, an eccentric mass revolved by DC brushed motor, a distal load in the form of an enclosed glass vial containing a prescribed volume of liquid.

The motor (1&6,) and vial (2) assemblies are fixed to the distal and proximal ends of a flexible beam of the spring element. The spring element assembly is sparsely illustrated in Fig. 11.

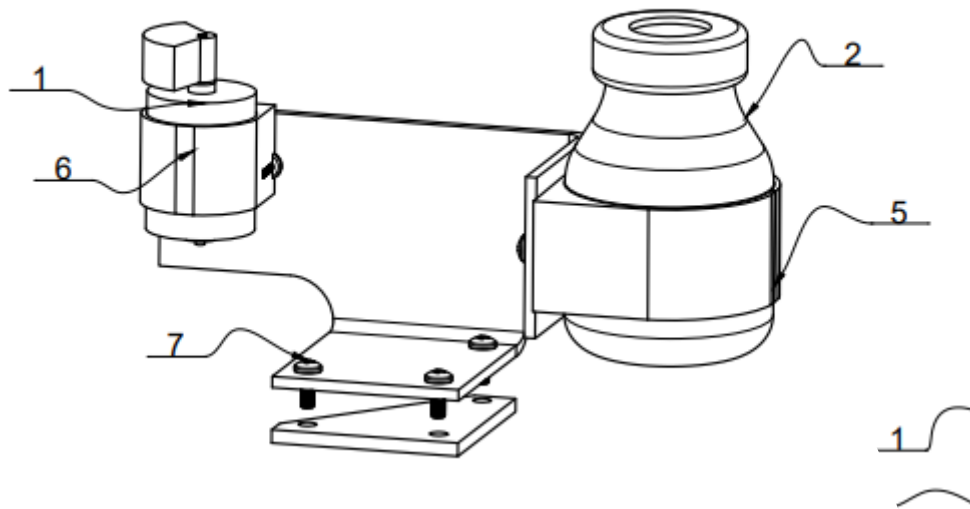


Fig 11 The spring element and related loads

Experimental design overview (See flow diagram Fig. 11)

We propose to observe the DUT from a plan view, with several small reflective discs or spheres attached at multiple points of interest, employing a broad-spectrum LED source (constant illumination). A high speed (approx. 500fps) monochrome digital camera enabled with a global shutter capable of low integration periods ($> 0.6\text{ms}$) will capture the relative trajectory of each of the points of interest.

The DUT will be energised by a pulse width modulated voltage, the applied PWM additionally frequency modulated, under programmable circuitry.

As the motor is energised and the rotor turns, the relative positions of the key features will be visually tracked by the imaging system and recorded in synchrony with Pulse Width Modulation (PWM) and the frequency applied by the motor controller. Voltage and current sensor values will also be acquired at capture rates which meet the Nyquist criteria.

Computer vision-based particle tracking algorithms will be applied to the timestamped frame sequence of each episode and a trajectory calculated for each of the reflective spheres, indicating the planar displacement of each feature in relation to a static reference.

A multi-channel data set comprising current, voltage, and trajectory as two-dimensional_ x, y positions or vectors, representing each of the visual targets will be collated for input to the ML classification and test model. The system performance as computed from the DT model will be evaluated for efficacy.

It is expected that should the ED study prove acceptable system performance can be inferred from a current sensor alone, a low-cost sensor could enable monitoring of a system's inferred efficacy rather than its absolute measured efficacy employing multiple sensor subsystems. The inference of a systems acceptable performance may satisfy the input requirements of Knowledge-based maintenance strategy, as analysed by a Decision Tree ML algorithm.

Some considerable further work may be needed to close the loop and generate optimising actions by a Prescriptive Maintenance approach i.e., a custom model, but early uncertainties can be resolved in respect of the mandatory minimal instrumentation.

(Current flowing in the system is not only based on Ohm's law, but also dependent on the back EMF generated by the rotor in motion because of external loads and the rate of change of the magnetic flux in the motor due to speed fluctuations).

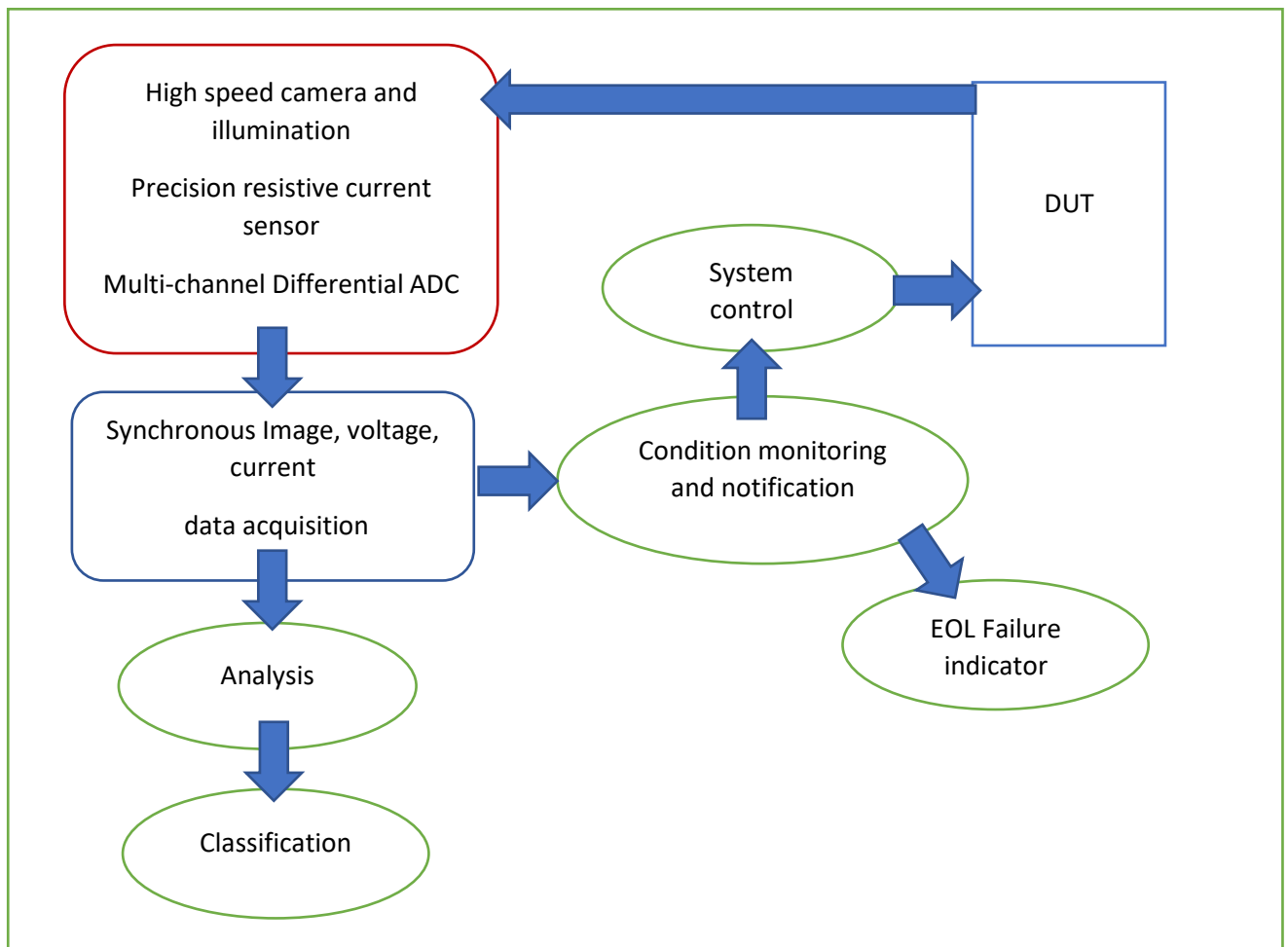


Fig 11 DUT control and data flow diagram

Conclusion

A literature review of KBM strategies has been considered, Predictive and Prescriptive Maintenance approaches are considered to provide the optimal benefits for value-based service provision in respect of a new healthcare product employing a novel spring element.

An experimental design is proposed where data is acquired from a number of variables during the operation of the novel spring element. Motion trajectory of a number of features of the spring are to be recorded, along with the current and voltage profiles as supplied to the DC motor of the novel spring actuator.

ML algorithms will classify the data sets for further analysis by a Decision Tree (DT) algorithm. The accuracy of the DT outputs of the current only dataset will be compared to that of the datasets combining trajectories, voltage and current.

The results will inform the decision regarding the level of instrumentation required to enable adoption of a KBM strategy, answering the question, is a current only sensor approach sufficiently accurate to enable a preferred Prescriptive Maintenance solution as a service strategy?

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