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Optimising Asset Management within Complex Service Networks: The Role of Data

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This is a working paper

Why this paper might be of interest to Alliance Partners:

This paper reports a study which provides a series of implications that may be particularly helpful to companies considering 'big data' for their businesses. Considerable research effort has been expended on understanding how firms create and capture value from analytics in single organisations, focusing only on technical issues. Therefore, this paper proposes a diagnostic framework for optimising and improving complex services in organisations. The framework addresses key factors such as enablers, contextual barriers beyond the technical issues, value and benefits, and key dimensions of data necessary to optimise the delivery of their complex services. More specifically, the study focuses on understanding how asset heavy firms can make better use of data to optimise repair service delivery by using proactive condition monitoring services.

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Optimising Asset Management within Complex Service Networks: The Role of Data

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This paper proposes a diagnostic framework for optimising and improving complex services in asset-heavy firms. The purpose of the proposed framework is to help asset-heavy organisations understand the key factors, enablers, barriers, value and benefits, and the key dimensions of data necessary to optimise the delivery of their complex services. The initial framework was evaluated and refined through two sets of matched-pair case studies in condition-monitoring services. The research contributes to understanding how asset-heavy firms can make better use of data to optimise repair service delivery by using proactive condition-monitoring services.

Purpose

The aim of this paper is to propose a diagnostic framework for optimising and improving complex services in asset-heavy firms. In recent years there have been tremendous advances in hardware technology, such as the development of sensors, GPS enabled devices and telemetry systems, all of which can be used to collect different types of data (Aggarwal 2013). This has resulted in an exponential growth of sensor and machine-to-machine (M2M) data, which generates many challenges and opportunities for asset-heavy organisations. The scale of the growth in data is illustrated by an IDC forecast that suggests M2M generated data will increase to 42 per cent of all data by 2020, up from 11 per cent in 2005 (TSB 2013).

'Big data' is one of the most hyped technology terms of the moment. The investment numbers across industries between 2012 and 2013 continue to rise, with 64 per cent of organisations investing or planning to invest in big data technology, compared to 58 per cent in 2012 (Kart et al. 2013). However, a recent study by Gartner (2013) stated that adopting 'big data' is a challenge for companies as they are struggling to obtain value from 'big data'. It is not about technology, but rather (most probably) about 'where' and 'how' big data is creating value. Although several industrial papers and White Papers address these questions (e.g. Hagen et al. 2013; Manyika et al. 2011; Schroeck et al. 2012), and also vendors (CEBR 2012; Petter & Peppard 2012), it is still lacking within the academic literature. Synthesising the main ideas of those papers, two areas have been identified: 1) (big) data is used for the incremental improvement and optimisation of existing services; and 2) new products and business models can be innovated based on the use of data (Hartmann et al. 2014).

This paper will focus on the second area and demonstrate the role of data in optimising asset management within complex service networks. By a complex service we mean the provision of a set of technical capabilities based on a complex system to a customer at a contractually defined performance level (Neely et al. 2011). The fundamental nature of the firm's connection to the customer changes; it becomes better, a more personalised service can be offered and, consequently, more profitable customers grow the influence of service within the product sector and generally expand the service sector in the economy (Rust & Huang 2014). Data and feedback enables organisations to communicate better with customers, and service relationships are deepened.

A servitized asset-heavy organisation designs, builds and delivers an integrated product and service offering that delivers value in use level (Neely et al. 2011). In particular, they produce, sell and lease assets integrated with maintenance and repair services. In modern, asset-heavy manufacturing environments, vast amounts of data are collected from the asset sensors. Therefore, data has emerged as an important tool for monitoring the asset health and fault diagnostics, also known as condition-based monitoring service. A condition-based monitoring solution applies existing operational data, real-time sensor data, advanced engineering analytics and forward-looking business intelligence to produce recommendation analyses in order to identify potential equipment faults (Qiu et al. 2013).

A condition-based monitoring service is not a new field, as many existing studies have demonstrated the applicability of using different data analytic techniques to predict asset failures. For example, Sylvain et al. (1999) demonstrated the design of preventive maintenance policies to predict the asset failure based on the data collected from aircraft sensors. Many data analytics techniques have been employed, such as decision trees, rough sets, regression and neural networks. Yam et al. (2001) presented another example of an intelligent predictive decision support system (IPDSS) for condition-based maintenance. IPDSS used the recurrent neural network technique to predict equipment fault at a power plant. The value of such a system is to provide early alerts of failure to provide enough time for maintenance planning and scheduling. Lin and Tseng (2005) introduced a cerebellar model articulation controller (CMAC) neural-network-based machine performance estimation model. The CMAC-PEM was used to fuse sensory data to predict machine reliabilities, and for condition-based predictive maintenance. Similarly, Zhou et al. (2005) presented an agent-based framework using data mining for monitoring and predicting equipment failure and thereby supporting equipment prognostics and diagnostics. Kusiak and Shah (2006) proposed data-mining-based robust alarm system architecture for predicting incoming faults of water chemistry. Tsai et al. (2006) used a knowledge elicitation technique (developing rules based on human expertise) in a case-based reasoning (CBR) system for PCB defect prediction. Widodo and Yang (2007) presented a survey of machine condition monitoring and fault diagnosis using a support vector machine (SVM). The findings of the paper showed that numerous data analytics techniques have been developed. However, SVM has excellent performance in generalisation and can produce high accuracy in classification for machine condition monitoring and diagnosis. Qiu et al. (2013) demonstrated the AEP asset health systems that use operational data, real-time smart sensor data, reports, advanced engineering analytics, and business intelligence to manage the condition of its transmission equipment. Palem (2013) presents the approach of condition-based maintenance using real-time sensor monitoring, telematics and predictive data analytics to prioritise and optimise maintenance resources.

The aforementioned literature focused only on technical issues and showing the applicability of employing different data analytics techniques in condition-monitoring solutions. There is a general gap concerning understanding of the contextual barriers beyond the technical issues that could hinder organisations from employing data analytics to improve their services. Building on the motivation and literature overview outlined above, this paper aims to propose a data diagnostic framework that contributes to answering the overarching research question***: 'How can data be used to optimise service delivery in an asset-heavy organisation?***' More specifically, the purpose of the proposed framework is to help asset-heavy organisations understand the key factors, enablers, barriers, competencies, value and benefits, and key dimensions of data necessary to optimise the delivery of their complex services.

Design/methodology/approach

The research evolved in several phases: data collection and description to coding, analysis and validation. The systematic literature review has documented key findings from practice and research to date. It helped to establish reference points and an outline framework for use in the case study phase of this work. The outline framework covered key themes such as data dimensions (data availability and capture, data governance, data ownership, security and privacy), enablers, competencies and barriers (people and culture, service operation, technology, and strategy), and value and benefits (providers and clients). The initial framework was evaluated and refined through two sets of matched-pair case studies in asset-heavy industries. By asset-heavy industry we mean organisations that produce earthmoving equipment for construction and mining operations, marine and diesel engines, and power generators.

Matched pairs of case study firms were selected to include those with high and those with low levels of experience in using sensor/M2M data to optimise asset-management services. Data was collected in all case studies through a combination of workshop, interviews and supplementary document reviews. The method has several advantages, such as in high-experienced cases when memory is important and a structured workshop enables participants to produce a fuller and richer record of past events, especially when individuals have had and share different perspectives on particular events. Furthermore, although low-experienced cases have a shorter lifespan, the discussions will have raised many of the barriers, enablers and competencies needed to make the service a success. Members of the workshop validated one another's contributions. It was required to get agreement on the validity of the events.

Post data-collection phase, templates and thematic analysis were used for data analysis. The essence of template analysis is that the researchers produced a list of codes ('template') representing themes identified in the data (Cassell & Symon 2006). Some of these were defined a priori in the outline framework, but they were modified and new themes have been added as the researcher reads and interprets the data. The themes were organised in a way that represents the relationships between themes, most commonly involving a hierarchical structure. To validate findings the results were presented to case study representatives, so that they had the opportunity to correct and provide feedback on some of the specifics that had possibly been misunderstood. The proposed data diagnostic framework is the output of the thematic analysis. The framework addresses the most significant barriers to using data within CSNs and how these barriers could be overcome.

Findings

Value and Benefits

The research has many findings that contribute to our understanding of how asset-heavy firms can make better use of data. Currently, many vehicles are factory-fitted with sensors to monitor a range of parameters, such as engine speed, operating temperature and GPS position. Smart use of these sensors, for example, measuring and monitoring the status of the engines, includes cooling water, lubricating oil and fuel systems, power (supplied) and temperatures per cylinder. This allows problems to be detected even when parameters lie within the normal range. Therefore, asset-heavy organisations use various sources of data collected from equipment and engine telemetry data, fluid analysis, inspections, repair history and site conditions to monitor the health and usage of assets. As a result, a proactive condition-monitoring service has many advantages for many players in the asset-heavy service networks, as shown in Table 1.

Providers	Internal	OEM/Dealers	Growing spare parts and repairs business
			Customer recruitment and retention
			Understanding equipment behaviour
			Improving product quality
			Reducing overhaul repair routine services
			Revenue outcome
			Optimising use of network resources
	External	Legislative Bodies (Health and Safety regulator) such as LOLER or PUWER regulatory inspection Independent third-party assessor	Equipment health and safety report
			Demonstrating 'fit for work'
		Collaborative Bodies	Proof of model concept
			Sharing best practices
		Technological Bodies and Service Providers	The value of the contract
			Prediction of value for new clients
Customer			Maximising machine productivity
			Reduction in maintenance operation and cost (cost savings)
			Elimination of breakdowns
			Minimising equipment or process downtime
			Improving customer support services
			Enhancing equipment safety
			Extending the life of components
			Sharing risk

Table 1 Condition-Monitoring Service Value and Benefits

For OEM and dealers, a condition-monitoring service has been identified as a way to grow its parts and repairs business and to increase the sales of spare parts, which reflects on OEM's and dealer's sales. There are real benefits to using data to monitor fleet/engines, which strengthens OEM/dealer relationships with its customers and could enable a long-term relationship. It also attracts new customers who don't have a service maintenance contract. Overall, the service improves the customer support service (especially in asset maintenance and repair services), generates more revenue and increases customer loyalty and retention.

For customers, condition-monitoring solutions are valuable because the solution produces recommendation analyses in order to identify potential mechanical faults, to avoid, eliminate, or minimise equipment failure or to help prevent faults reoccurring. The elimination of unexpected downtime, reduction of repair costs and increased service intervals all lead to reduced product costs. Furthermore, predictive analytics highlight areas where operator performance and equipment utilisation can be improved. Forecasting analysis gives an overall future performance matrix of the asset, advising how the assets behave, using the engine parts, the fuel part labs, and the oil samples to advise the customer. Comparison analysis compares service reports and past maintenance records to provide the current status of assets and fluid analysis results. Alerts represent the fleets' health and performance and illustrate them via a dashboard. The solution generates quarterly health and performance reports about fleets. The offered analytics could minimise costs for customers by calculating the cost impact of poorly trained maintenance staff and practices, or of low-quality spare parts, used by customers without service contracts. The data analytics help decrease the total cost of ownership and minimise the cost of maintenance for customers. Furthermore, the proactive solution extends the life of components. A well-maintained machine lasts longer than a poorly maintained one. As a result, dealers share the risk with their customers by introducing outcome-based contracts to reduce the impact of faults such as refurbishing an engine.

For external providers, including legislative bodies represented by health and safety regulators such as LOLER or PUWER, regulatory inspections use data to guarantee and enhance equipment safety. Due to a lack of data analytics capability within asset-heavy organisations, the technology provided could be considered to develop the solution. Asset-heavy firms share their best experience and domain expertise to provide the right configuration and exchange it with technology providers to develop the right solution. The benefit of the technology provider is the value of the contract and prediction of value for new clients.

Contextual Barriers

The proposed framework suggests that asset-heavy organisations face contextual barriers to using data, as shown in Figure 1. The internal context includes soft issues and hard issues. Soft issues include *data culture*, cultivating new practices around the use of data and how to establish a strong culture of data use to ensure that data-based decisions are made frequently and consistently. Furthermore, players quite ften mistrust institutional data, measurement, analysis and reporting due to data quality issues. In some cases, there is customer resistance to monitoring, collecting and analysing data from assets. Asset-heavy firms are struggling to hire *data scientists* and lacking the experience to identify the criteria to recruit the right team at all levels of analytics who understand what data to collect, prepare and process, and which questions to analyse. The hiring and training of data analysts who have experience both in the domain and analytics are challenging. Sometimes, an organisation underestimates the time and expertise required to run the analytic program.

Collaboration issues on occasion lead to adversarial relationships with customers and increase the risks and obligations in contracts, possibly resulting in contract failure.

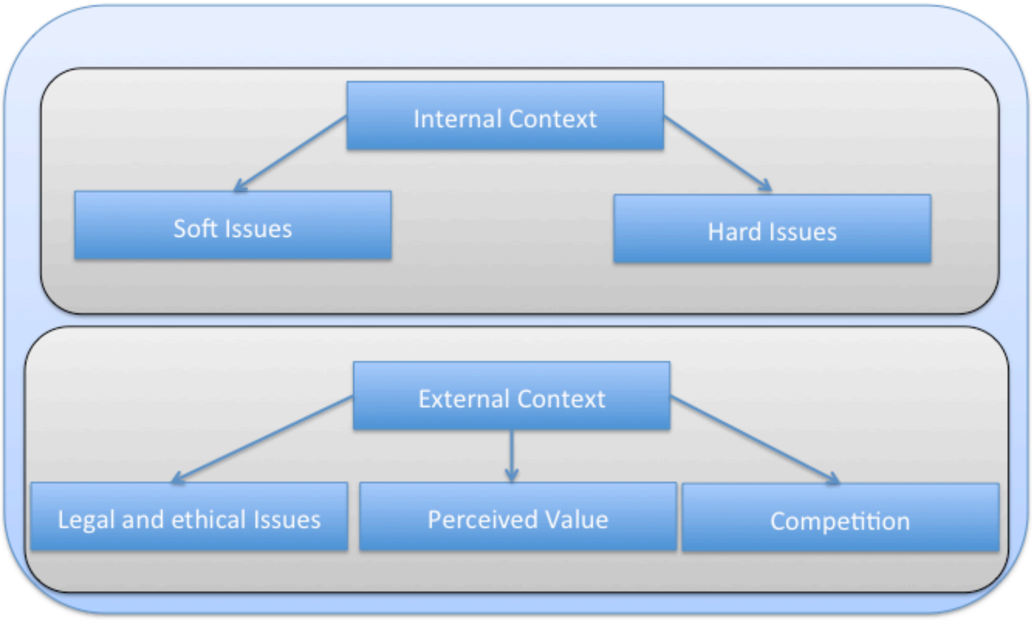

Figure 1 Contextual Barriers to using data with CSNs

Hard issues involve lack of data interoperability*:*

1. *Data availability and capture:* This includes issues related to data transmission accessibility, as telematics rely on satellite systems that are sometimes out of coverage. Alternatively, telematics could use digital telephone systems; however, they don't work everywhere. Data volume is massive in this domain, and growing, covering fuel usage, oil pressures, temperatures, running hours, incidents and events; it is collected in excel format, which is not sustainable for such volume. Often the collected data is not compatible because it comes from different engines and machines. It is sometimes challenging for territorial moving assets to send telemetry data, which could lead to time gaps, maybe reaching hours.
2. *Data governance, quality and integrity:* Data is collected from different systems and it is challenging to integrate it from different data sources. In particular, automatic data collection from many sources such as equipment telemetry, equipment history (retrieved from the ERP system), CRM, service tech and fluid analysis. However, manual data collection is from two sources: inspection data and site condition data. Data is not used effectively and there was no consistent approach to making use of this data before starting the condition-monitoring service.
3. *Data ownership and sharing:* The absence of data ownership and sharing could be taken as a traditional, cultural, privacy matter between networks. Data is not shared with any service provider outside the OEM group, unless under strict agreement. There are different claims from OEM/dealers/customers about who owns the data. For example, OEM/dealers could claim data

ownership because it is processed by their system. However, customers could claim ownership of the asset and still own any generated data.

4. *Performance measurement of data analytics:* Most asset-heavy organisations are using condition-monitoring services for business intelligence reports and alerts. In particular, event-based monitoring reports rely on 2,000 events from engines and the support team monitors these parameters around heat exchangers, water pumps and others to check engine status and inform customers. Alerts are used to identify potential mechanical faults and highlight areas where operator performance and equipment utilisation can be improved. These alerts represent the fleets' health and performance and illustrate them via a dashboard. There is a quick response from the support team to any warning indicators. However, many analytics are in silos and they have been implemented at individual machine level (fleet/engine) rather than across different assets to design better products/services (feedback to OEM) or to open new business opportunities. This is the result of a lack of employing data and text-mining models, which include statistical modelling, forecasting, predictive modelling and agent-based models (optimisation simulations).

Other hard issues, such as technical issues, include legacy and integration issues and practical issues, for example, each territory needing a licence to transmit and receive data, and in certain territories of the world satellite communication being limited for security reasons. External context has legal and ethical issues, including *intellectual property*. Sometimes, the technology providers/developers, who developed the software, claim software ownership. However, it is based on the OEM/dealer intellectual and experience specs. *Cost of ownership* and viewing analytics as a cost rather than investments are other key challenges in this sector. *Demonstrating the real value* of the offered analyses and convincing customers to pay for the service after expiration of the customer service support agreement are particularly challenging. Sometimes, the condition-monitoring service is not fully integrated with support service contracts. Some customers, especially in the marine services, are not yet ready to allow dealers to apply a data-driven approach to monitoring and controlling the vessel.

Best Practices to Overcome Contextual Barriers

To enable data to be used to optimise the performance of complex service networks, the research suggests that a path dependency model is important. Where an organisation starts is critical, especially in terms of developing better customer service, increasing customer satisfaction and ensuring maturity of technology to enable this. In an asset-heavy world, cases show that it starts when customers have shown little interest in renewing this monitoring, suggesting it has provided little value in use. Furthermore, identifying potential business opportunities to grow the spare parts and repairs business to generate revenue is important. The data also suggests that having an aligned strategy and deep collaboration with the *right stakeholders* is important; otherwise, alternative providers will enter the market, resulting in a lost opportunity for the original equipment manufacturer.

In terms of cultural issues, *top management support* with clear vision and strategy is essential to designing and deploying the service. This includes the difference between ambitious strategy, which involves leadership role, and developing an innovative approach in the market or 'me too'/defensive strategy, which includes the organisation not wanting to be left behind in condition-monitoring services. *Creating awareness* is important, which includes a significant effort to communicate with different departments to resolve any internal conflicts and to create awareness around this service and ability to deliver and improve services.

Careful piloting and involving innovative supporters is another key enabler. This includes technology providers and innovative customers. The cases suggest that some innovative customers (10 per cent) worked together with dealers to build the monitoring system (joint experiment). These customers are normally interested in such innovation to decrease the total cost of ownership, to use the data to minimise the cost of maintenance, and to make this equipment more efficient and increase up-time, because in the event of engines blowing up, they are very expensive to replace.

Data ownership is crucial, as is the pace of movement on analytics. The absence of data sharing is a common barrier, as are issues of tradition, culture and privacy. Thus, there is a need to have a clear focus on the process of data handling and analysis, with explicit guidance on the roles of each stakeholder and their access/ownership of data. Furthermore, a collaboratively shared data platform facilitates data access and data sharing, and analytics across partners will be innovative to create better analyses.

Organisations have to recognise that analytics is about people. Investment is required at the level of hiring and/or training analysts to begin addressing strategic questions. These strategic questions have to cover different assets to design better services and not focus only on the individual level of analysis. It is difficult to hire data scientists; therefore, an organisation has to build a cross-functional team covering the following skills to support the service: *IT skills* – database and warehousing skills, data modelling, information management, programming skills (e.g. python, java); *Analytical and problem-solving skills* – maths/statistical modelling, structured data analytics supervised/unsupervised, text and visual analytics; *Soft skills* – professional skills, public speaking and great political understanding and communication; and, finally, *Business domain skills* – specialised in the domain to facilitate valuable data analyses and ask the right questions. Organisations have to have many mock-up sessions with this cross-functional team in order to make it configurable.

For data practices, organisations have to transcend data silos and *create data master (MDM)* repository with a single data of truth by having multilayer database stores with different data sources from multiple systems (internal and external). Sophisticated data strategies (operations such as filtering, transforming and sorting) are required to collect reliable and up-to-date data from trusted resources automatically. The MDM repository will be used to remove duplicates, standardising data (mass maintaining) and incorporating rules to eliminate incorrect data from entering the system in order to create an authoritative source of master data. Collecting sufficient and comprehensive data to support insightful analyses (internal and external) is important, as is using the right technology to allow data compatibility of different formats (structured, semi-structured, unstructured). However, the ability to combine data from different sources or systems is challenging. Therefore, an organisation needs to employ the following mature models. *Business process integration,* which refers to the ability to define a commonly acceptable business process model that specifies the sequence, hierarchy, events, execution logic and information movement between systems residing in the same enterprise. *Master data integration,* which comprises the processes, governance, policies, standards and tools that consistently define and manage the critical data of an organisation to provide a single point of reference. *Data life cycle management* is a policy-based approach to managing the flow of an information system's data throughout its life cycle: from creation and initial storage to the time when it becomes obsolete and is deleted. DLM tools automate the processes involved, typically organising data into separate tiers according to specified policies, and automating data migration from one tier to another, based on those criteria.

Relevance/contribution

Considerable research effort has been expended on understanding how firms create and capture value from analytics in single organisations, focusing only on technical issues. However, this paper contributes to our understanding of the contextual barriers beyond the technical issues that could hinder organisations from employing data analytics to improve their services. This paper proposed a data diagnostic framework that contributes to understanding how asset-heavy firms can make better use of data to optimise and improve complex services. In particular, it is crucial to understand the key factors, enablers, barriers, competencies, value and benefits, and the key dimensions of data necessary to optimise the delivery of their complex services.

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