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Achieving Data Quality in Engineering Asset Management

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ABSTRACT

Data Quality (DQ) is a critical issue for effective asset management (AM). DQ problems can result in severe negative consequences for an organisation. Several research studies have indicated that most organizations have DQ problems. This paper aims to explore DQ issues associated with engineering asset management (EAM). The study applies an AM DQ research framework in a preliminary case study of two large Australian utility organisations. The findings of the study suggest that the importance of DQ issues for engineering asset management is often overlooked; thus, there is a need for more scrutinised studies in order to raise general awareness.

1. INTRODUCTION

Industry has recently put a strong emphasis on to the area of asset management (AM). In order for organizations to generate revenue they need to utilize assets in an effective and efficient way. Nevertheless, there is strong evidence that most organisations have far more data than they possibly use; yet, at the same time, they do not have the data they really need (Levitan and Redman, 1998). According to Gartner Research (2005), modern organizations are continually generating incredibly large volume of data, including structured and unstructured, enduring and temporal, content data, and an increasing amount of structural and discovery metadata. Outside the business environment, there is an increasing number of embedded systems such as condition monitoring systems in ships, aircraft, process plants and other engineering assets, all producing gargantuan amounts of data. Despite this apparent explosion in the generation of data it appears that, at the management level, executives are not confident that they have enough correct, reliable, consistent and timely data upon which to make decisions. Many say "we are drowning in data and are starved of information".

This lack of quality data often leads to decisions being made more on the basis of judgment rather than being data driven. This can lead to less effective strategic business decisions, an inability to reengineer, mistrust between internal organizational units, increased costs, customer dissatisfaction, and loss of revenue. In some cases, it could also lead to catastrophic consequences such massive power failures, industrial or aviation disasters. Data and information are often used synonymously. In practice, managers differentiate information from data intuitively, and describe information as data that has been processed. Unless specified otherwise, this paper will use data interchangeably with information.

2. DATA QUALITY

Numerous researchers have attempted to define data quality and to identify its dimensions (Fox, Levitin & Redman, 1994; Wand & Wang, 1996; Wang & Strong, 1996; Shanks & Darke, 1998; Kahn, Strong & Wang, 2002). Traditionally, data quality has been described from the perspective of accuracy. However, this description has been challenged by a number of researchers (Strong, 1997; English, 1999; Salaun & Flores, 2001; Ballou, Wang, Pazer & Tayi, 1998; Orr, 1998), from the point of view that data quality should be defined beyond the accuracy dimension. Although there is no universal agreement on the meaning of "quality data", a common understanding found in the literature is that: "*quality data are data that are fit for use by the data consumer"* - Wang and Strong (1996). Orr (1998) also suggests that the issue of data quality is intertwined with how users actually use the data in the system, since the users are the ultimate judges of the quality of the data produced for them. With the aim of improving data quality, Wang (1998) suggests a Total Data Quality Management (TDQM) framework for continuously managing data quality problems.

Dimensions of data quality typically include accuracy, reliability, consistency, completeness, timeliness, fineness, understandability, conciseness, and usefulness. Wand and Wang (1996) use ontological concepts to define data quality dimensions: completeness, unambiguousness, meaningfulness, and correctness. Wang and Strong (1996) categorize data quality into four dimensions: intrinsic, contextual, representational, and through accessibility. Shanks and Darke (1998) use semiotic theory to divide data quality into four levels: syntactic, semantic, pragmatic, and social. Recently, Kahn et al. (2002) have used product and service quality theory to categorize information quality into four categories: sound, useful, dependable, and usable.

Maintaining the quality of data is often acknowledged as problematic, but is also seen as critical to effective decision-making. Examples of the many factors that can impede DQ are identified within various elements of the DQ literature. These include: inadequate management structures for ensuring complete, timely and accurate reporting of data; inadequate rules, training, and procedural guidelines for those involved in data collection; fragmentation and inconsistencies among the services associated with data collection; and the requirement for new management methods which utilize accurate and relevant data to support the dynamic management environment.

Clearly, personnel management and organizational factors, as well as effective technological mechanisms, affect the ability to maintain data quality. Wang (1998) clarifies this relationship by drawing an analogy between manufacturing and the production of data. In this way they derive a hierarchy of responsibilities for data quality, ranging from management processes down to individual procedures and mechanisms. Their framework specifies a top management role for DQ policy, and a DQ management function to determine how that policy is to be implemented. This, in turn, should result in a DQ system for implementing DQ management, within which DQ control is enforced through operational techniques and activities. DQ assurance then comprises all of the planned and systematic actions required to provide confidence that data meet the quality requirements.

The following DQ factors table (Figure 1) summarizes findings from the available literature, in order to understand the emerging DQ issues.

3. ENGINEERING ASSET MANAGEMENT

Manufacturing assets are complex and expensive with multi-stage lifecycles. They begin as simple concepts to address an organization's needs and rapidly become physical entities that must be acquired, installed and handed-over to operating departments for use in generating

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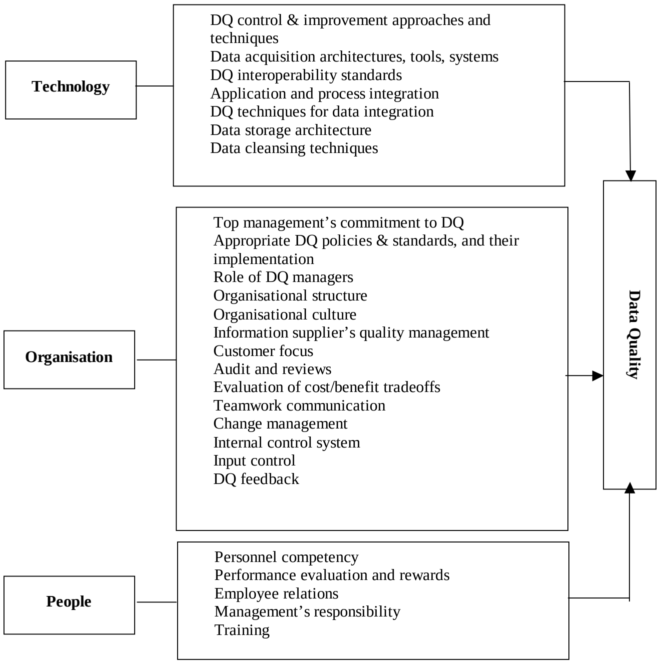
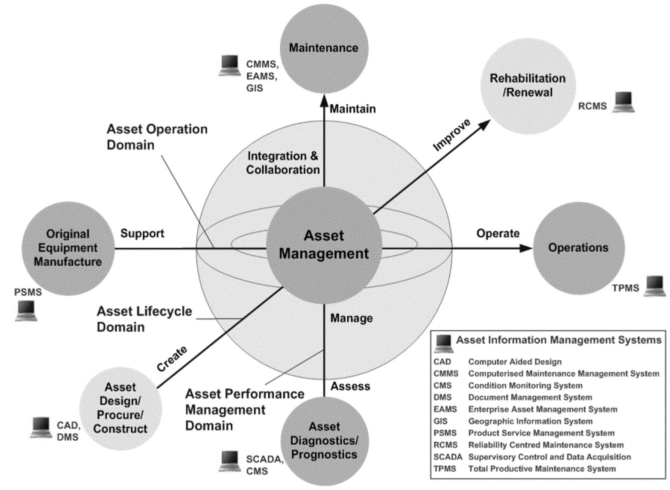
Figure 1. Summary of factors influencing DQ



(Source: English, 1999; Wang, 1998; Segev, 1996; Firth, 1996; Saraph, 1989)

Figure 2. Collaborative asset lifecycle management and asset information management



(Source: Adopted from ARC Advisory Group, 2004)

revenues. During operation they must be carefully maintained to get maximum performance and longevity. Eventually they become obsolete and must be retired. Achieving maximum return-on-assets requires use of asset information and best practices for every activity, across all of these stages. In order to provide an in-depth understanding of the complex lifecycle asset management processes, the collaborative asset lifecycle management model (ARC Advisory Group, 2004) is illustrated in the following diagram (Figure 2).

4. AM DQ FRAMEWORK

Mitroff and Linstone (1993) argue that any phenomenon or system needs to be analyzed from what they call a Multiple Perspective method – employing different ways of seeing, to seek perspectives on the problem. These different ways of seeing are demonstrated in the TOP model of Linstone (1999) and Mitroff and Linstone (1993). The TOP model allows analysts to look at the problem context from either Technical or Organizational or Personal points of view:

- The technical perspective (T) sees organizations as hierarchical structures or networks of interrelationships between individuals, groups, organizations and systems
- The organisational perspective (O) considers an organization's performance in terms of effectiveness and efficiencies. For example, leadership is one of the concerns.
- The personal perspective (P) focuses on the individual's concerns. For example, the issues of job description and job security are main concerns in this perspective.

Mitroff and Linstone (1993) suggest that these three perspectives can be applied as "three ways of seeing" any problems arising for or within a given phenomenon or system. Werhane (2002) further notes that the dynamic exchanges of ideas which emerge from using the TOP perspectives are essential, because they take into account "the fact that each of us individually, or as groups, organizations, or systems, creates and frames the world through a series of mental models, each of which, by itself, is incomplete". In other words, a single perspective on the problem context is not sufficient to elicit an insightful appreciation of it. *Based on the discussions on various DQ issues (*Wang, Storey & Firth, 1995; Gelle, & Karhu, 2003; Xu et al., 2002; Xu et al., 2003; GAO, 2004) *and the unique characteristics of asset management, i*t is found that the DQ requirements can be best described by using the TOP multiple-perspectives approach. T*he* AM specific DQ framework was developed as shown in Figure 3. This model is useful to guide the research into AM DQ issues, because it highlights the three root perspectives on DQ problems, illustrates how they emerge during the AM process; and outlines the basic DQ management criteria.

The process of AM is complicated. Asset information is a key enabler in gaining control of assets. Asset information is created, stored, processed, analyzed, and used throughout an asset's lifecycle by a variety of stakeholders together with an assortment of technical and business systems during the whole AM process. Asset information management (AIM) underlies all the AM processes, and the ensured DQ in AIM assists AM decision making optimization. The intent of the asset structure/organisation is to provide the business with the framework in which data are collected, information is reported, and decisions are made. In most cases, organizations work with an informal asset hierarchy. This often leads to data being collected to inappropriate levels, either creating situations where costs escalate with minimal increases in benefits, or insufficient information is available to make informed decisions (IPWEA, 2002). The information needs of the organization vary throughout the management structure. At the workface the key elements are operations, maintenance, and resource management, at a component level. At higher management levels this information needs to be aggregated to provide details on assets, facilities and systems as a whole in terms of finance, strategic and policy.

The AM process is an engineering and planning process that can span a long period of time. The process is associated with capital planning, asset acquisition, condition & performance assessment, and asset-related data strategy & guideline. A variety of specialized technical and business systems exist in asset management including Supervisory Control and Data Acquisition (SCADA), CMMS, EAM, GIS, ERP etc, which not only manage the operation of asset equipment but also provide maintenance support throughout the entire asset lifecycle (Koronios et al, 2003). In addition to the requirements for specialized IS/IT supporting systems, the AM process also require the participation of assorted engineering and business stakeholders, internally and externally. Because of the diversity and high turnover of AM stakeholders, AM

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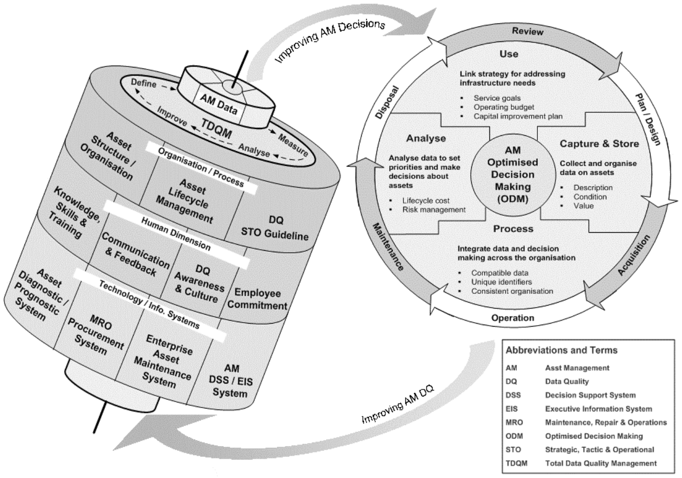
Figure 3. AM DQ Framework (Source: Developed by the authors)



outcome is greatly associated with organizational culture, management commitment, staff competency, communication & feedback, and training.

5. RESEARCH DESIGN

Based on the previous discussion about the EAM problems, an interview-based case study was designed to explore the DQ issues emerging within the chosen organizations. The organizations included two large Australian water utilities, as well as several of their subcontractors. A number of stakeholders at all levels of the organizations were interviewed, chosen on the basis of their experience in the use and management of engineering assets. The target organisations used a variety of information systems for EAM (e.g. GIS for asset location, Maximo for asset maintenance). Thirty interviews were conducted involving senior executives, asset managers, maintenance engineers, technicians, and data operators. In functional these stakeholders came from different position levels with different data roles at various office locations, including data provider, data custodian, data user, and data manager. In cases of conflicting issues, crosschecking for interviews was also conducted to validate the results.

Responses to our research questions were collated, stored, and analysed using qualitative data analysis software. This analysis allowed us to explore the raw data, identify and code the common themes, and identify relationships between themes in a rigorous manner. In analyzing the collected data, an extensive examination of the viewpoints of various stakeholders was conducted. The views and actions of various interviewees in terms of their organizational interests were also examined. A very preliminary validation of the DQ for asset management model was achieved. While there may be some limitations in the approach used, we feel that the richness of the data collected far outweighed the methodological shortcomings of such an approach.

6. RESEARCH FINDINGS

The followings represent some of the preliminary findings based on using the TOP model. The integration of AM-related technical systems, as well as the integration between business systems and technical systems, is particularly important.

Integration of Technical Systems in Asset Management

A variety of specialized AM technical systems exist including reliability assessment systems, asset condition monitoring systems, asset maintenance systems. Such specialized systems are quite disparate, and acquired from multiple vendors, they often lead significant integration problems. There appears to be little cognizance when adopting business systems such as financial, human resource information systems of the need to ensure compatibility with technical systems such as asset register systems, condition monitoring systems. Most users are unable to translate the vast amounts of available asset data into meaningful management information to optimize their operation and control the total asset base. This has led to the notion of 'islands of information'.

There are disconnects between the transaction-driven, product-centric business data environment and the continuous data, process-centric open control system and manufacturing data environments. Such disconnects make it extremely difficult to bring real-time information from the plant into business systems. The lack of process-to-product data transformation capabilities in linking business systems and plant floor EAM applications have significant DQ consequences and thus negatively affect data-driven decision-making.

Sensor Calibration and Integrity Check for Condition Monitoring

Interviews with asset maintenance field workers indicate that data captured by intelligent sensors may not always be accurate. Data capturing devices typically used in condition monitoring are electronic sensors or transducers, which convert numerous types of mechanical behavior into proportional electronic signals, usually voltage-sensitive signals, producing analog signals which in turn are processed in a number of ways using various electronic instruments. As signals are generally very weak, a charge amplifier is connected to the sensor or transducer to minimize noise interference and prevent signal loss. The amplified analogue signal can then be sent to filtering devices to remove or reduce noise, before being routed to a signal conditioner and/or analogue-to-digital converters for digital storage and analysis. To ensure the data received by the SCADA system conforms to the original signal data captured by sensors, integrity checks for signal transmission process and sensor calibration need to be performed and maintained. However, as the sensor calibration and integrity checks are often neglected in asset maintenance, the extent to which acquired data is correct and reliable was shown to be of concern with respondents.

Data Standard for Condition Monitoring Systems

Although it appears that condition monitoring equipment and systems are proliferating, an apparent lack of dialogue among vendors has led to incompatibilities among hardware, software and instrumentation. Data collected by current outdated equipment could become obsolete and inaccessible to new upgraded systems. To fully realize the integration of systems over the various levels of asset maintenance and management, new standards and protocols are needed. A focus on standardization of condition monitoring data modeling and exchange tools and methodologies, such as Standard for the Exchange of Product model data (STEP) is critical.

Database Synchronization

The capability of EAM systems can be enhanced through a link with GIS to provide the ability to access, use, display, and manage spatial data. The ability to effectively use spatial asset data is important for utilities with geographically dispersed utility networks. However, it was found that one of the most critical activities is to establish synchronization between the two database environments. One asset manager indicated that there has been an issue existed for overcoming the synchronization of asset register in a very common work management system with GIS in the company. Both automated and manual processes needed to be defined and implemented to maintain synchronization between the GIS and EAM databases. Data-base triggers and stored procedures need to be defined to automate the attribute update process maintaining synchronization between the GIS and EAM databases. Workflows and business rules must be developed for GIS and EAM data editing, to ensure synchronization from both applications.

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Business Process Reengineering

Organisational fit and adaptation are important to implementation of modern large-scale enterprise systems. Like enterprise resource planning systems, EAM systems are also built with a pre-determined business process methodology that requires a fairly rigid business structure in order for it to work successfully. They are only as effective as the processes in which they operate. Companies that place faith in EAM systems often do so without reengineering their processes to fit the system requirements. Consequently, this often results in negative impacts on the effectiveness of both the EAM system and the AM practices. It was found that a mismatch existed between the business processes requirements of the EAM and actual practice in the organisation.

Data Recording

Research in data collection has found that DQ and validation effectiveness improve, the sooner the collected data is entered and the nearer the data entry is to the asset and its work. If a data entry point is remote from the asset, then the capability for accurately confirming the data is considerably reduced and the temptation to enter something - anything that the system will accept - is great. One manager said in the interview that "I feel that most of the (data) errors over time have been because of the lag between the field data and being continued in the computer somewhere….they (field staff) might wait a week before they complete their work order (entry)". It was found that the longer the time lag between using the entered data and the time it was initially created, the less chance of cleaning up the data to make it useful.

Training

AM requires all aspects of training as well as appropriate documentation of the system. It was found that organisations tended to focus more on the "hardware" part of the systems development process, putting less effort on the "soft" part, that is, the training of how to operate and manage the system. Several respondents indicated that the training was tailored for the specific areas but the same for everyone and thus of limited use to some. Many respondents contended that what they knew about the system was in fact 'self taught'. Awareness of issues such as how the data being collected was going to be used was not existent; yet they agreed that such knowledge would increase motivation and performance by the asset operators/technicians. Lack of training can have an adverse impact on information quality. It is easy for organisations to find reasons/excuses for avoiding adequate training for the staff and management.

Communication & Management Feedback

Competitive asset-intensive companies have reported that most of their asset improvements come from their workforce. Despite the fact that "people are our greatest asset", evidence of the opposite is often found. People's problems, relationships, aspirations and their personal agendas are seldom given any consideration. In the implementation and management of EAM systems it appears that this is not different and was quite evident in the responses. Respondents were quite convinced that the system implementation neglected the human dimensions and thus contributed to the partial failure of these systems.

"year after year they (field workers) filled out field data without feedback……if we did nothing, nothing happens so why bother?"

7. IMPLICATIONS & CONCLUSION

DQ issues are critical to the AM success, and need to be widely understood and managed in order to ensure effective EAM. The framework proposed in this paper provides a useful tool for planning the establishment of an awareness of AM DQ issues. The discussion in this paper has highlighted some DQ problems, which existed in the current condition monitoring systems and EAM systems, and the key factors that impact on AM DQ. This research provides a better understanding of AM DQ issues and assists in identifying elements which will contribute towards the development of an AM DQ model. This in turn will assist in providing useful advice for improving DQ in AM. Key DQ issues discussed and the use of the identified framework should help organisations obtain a better understanding of DQ issues throughout the process, leading to activities which will help ensure DQ. The identification of AM DQ issues will serve to provide additional research opportunities for the development of tangible solutions to AM DQ problems.

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