Ensuring Data Quality for Asset Management in Engineering Organisations*

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ABSTRACT
Data Quality (DQ) has been an acknowledged issue for a long time. Researches have indicated that maintaining the quality of data is often acknowledged as problematic, but is also seen as critical to effective decision-making. This paper investigates the issues emerging from unique nature of engineering asset data. It discusses the various asset management (AM) DQ issues and presents exploratory research on how engineering asset organizations in Australia are addressing DQ issues based on a large scale national-wide DQ survey that was conducted. It provides a better understanding of AM DQ issues and assists in identifying elements which will contribute towards the development of an AM specific DQ framework. The research findings suggest that while the organizations are concerning the quality of data, there is a disconnection between data custodians and data producers and high level data owners. The majority of AM organizations still adopt a reactive approach on DQ management.

1. INTRODUCTION
Almost every process and activity in the organisations involves data. Levitan and Redman (1998) suggest that data provides the foundation for operational, tactical, and strategic decisions. As data becomes increasingly important in supporting organizational decisions, modern organizations, both public and private, are now continually generating more data than at any other time before. More data, however, does not necessarily mean better information, or more informed business decisions. In fact, many are finding it difficult to use the data. It is estimated that more than 70% of generated data is never used (Koronios, 2006). Gartner Research (Desisto, 2004) found that bad data is worse than no data at all. 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). 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 they are drowning in data and are starved of information.

Consequently, the quality of the data that managers use becomes critical. Poor-quality data, if not identified and corrected, often leads to decisions being made more on the basis of judgment rather than being data driven (Koronios et al., 2005). Without quality data, organisations are running blind and make any decision a gamble (ARC, 2004). This can lead to disastrous economic impacts on the health of the company. In some cases, it could also lead to catastrophic social consequences such massive power failures, industrial or aviation disasters.

Industry has recently put a strong emphasis on to the area of asset management (AM). In order for engineering organizations to generate revenue they need to utilize assets in an effective and efficient way. Often the success of an enterprise depends largely on its ability to utilize assets efficiently. In other words, asset management has been regarded as an essential business process in many organizations, and is moving to the forefront of contributing to an organization's financial objectives.

Previous studies in asset management suggest that a common, critical concern with engineering asset management is the lack of quality data (Eerens, 2003; IPWEA, 2002). Recent researches by U.S. GAO (2004) clearly demonstrates that achieving data quality is the key challenge engineering organisations face today in successfully implementing effective engineering asset management. Saunders (2004) indicated that although very large amounts of data is being generated from asset condition monitoring systems, little thought has been given to the quality of such generated data. Thus the quality of data from such systems may suffer from severe quality limitations.

As an important initiative proposed by the Australian federal government and the industry sector, studies were commenced in 2003 into the impact of the quality of data on AM organisations including the Royal Australian Navy, utilities, transportation and mining companies, and local governments. In 2006, a large scale national-wide survey was conducted into data quality issues in engineering asset management, with a sample size of 2000 and a response rate of over 23.9%. This is one of the largest nation-wide surveys of its kind, aimed as directly addressing data quality issues in engineering asset management organisations in Australia. This paper discusses the development of the data quality framework through this survey and presents some of its findings. 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 (DQ) and to identify its dimensions (Wang et al., 1993; Fox et al., 1994; Wand et al., 1996; Wang et al., 1996; Shanks et al., 1998; Kahn et al., 2002). Traditionally, data quality has been described from the perspective of accuracy. However, many researches have indicated that DQ should be defined as beyond accuracy and is identified as encompassing multiple dimensions. Through literature, many authors have tried to explain the meaning of all relevant dimensions from several points of view (Strong, 1997; English, 1999; Ballou et al., 1998; Orr, 1998). Even, any of them have tried to identify a standard set of DQ dimensions valid for any data product; but as Huang et al. (1999) state, it is nearly impossible due to different nature of different data environment.

Four most frequently mentioned data quality dimensions in the literature are accuracy, completeness, timeliness and consistency (Liu, 2002; Naumann, 2002; Bouzeghoub et al., 2004; Batini et al., 2004; Strong, 1997). Unfortunately, a set of data may be completely satisfactory on most dimensions but inadequate on a critical few. Furthermore, improving on one DQ dimension can impair another dimension. For example, it may be possible to improve the timeliness of data at the expense of accuracy (Ballou et al., 1995). It may be complete at the cost of concise representation (Neely 2002). Moreover, different stakeholders in an organisation may have different DQ requirements and concerns (Giannoccaro et al., 1999). Data whose quality is appropriate for one may not be sufficient for another (Neely, 2002). The DQ dimensions considered appropriate for one decision may not be sufficient for other types of decisions. As a result, Wang and Strong (1996)'s widely-accepted definition of data quality "*quality data are data that are fit for use by the data consumer*" is adopted in this research.

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 data quality are identified within various elements of the data quality 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 DQ responsibilities, ranging from management processes down to individual procedures and mechanisms (Wang et al., 1995). Their framework specifies a top management role for DQ policy, i.e. overall intention and direction related to DQ, 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. With the aim of improving DQ, Wang (1998) also suggests a Total Data Quality Management (TDQM) framework (define, measure, analyze and improve) for continuously managing data quality problems.

3. ENGINEERING ASSET MANAGEMENT

According to British Standards Institute (2004), asset management encompasses activities that are aimed at establishing the optimum way of managing assets to achieve a desired and sustained outcome. The objective of asset management is to optimize the lifecycle value of the physical assets by minimizing the long term cost of owning, operating, maintaining, and replacing the asset, while ensuring the required level of reliable and uninterrupted delivery of quality service (Eerens, 2003; Spires, 1996; IPWEA, 2002). At its core, asset management seeks to manage the facility's asset from before it is operationally activated until long after it has been deactivated. This is because, in addition to managing the present and active asset, asset management also addresses planning and historical requirements.

Asset management is process-oriented. The AM process itself is quite sophisticated and involves the whole asset lifecycle that can span a long period of time (Steed, 1988). The lifecycle for a typical asset involves several interdependent stages including design, plan, acquisition, installation, operation, maintenance, rehabilitation and disposal. At every stage of the process, AM also needs to collaborate and synchronize with other business processes, which is vital to the effective management of engineering assets. The cost and complexity of engineering assets demands considerable planning to identify appropriate solutions and evaluate investment opportunities. These same characteristics are reflected in the need for an extended acquisition process, a comprehensive request for proposal, and an equally comprehensive purchase agreement that addresses guarantees and warranties. Installation and placing in service of engineering assets is also complex and requires a proper set of processes to manage contractors. Once the asset is acquired, it must be tracked throughout its useful life. Finally, records must be made of its eventual disposition.

The sophistication of the engineering asset management process requires substantial information to be collected throughout all stages of a typical asset's lifecycle. This information needs to be maintained for a very long time, often dozens of years in order to identify long-term trends. This kind of process also uses this information to plan and schedule asset maintenance, rehabilitation, and replacement activities. In order to manage and support the complicated AM process and its data requirements, a variety of specialized technical, operational and administrative systems exist in asset management. These not only manage, control and track the asset through its entire lifecycle, but also provide maintenance support throughout the lifecycle of the asset. Considering the complexity and importance of asset management, these systems are normally bought from multiple vendors and each is specialized to accomplish its task. Unfortunately, this leads to an extremely difficult integration job for the end-user.

Engineering processes rely heavily on input of data and also produce a large amount data. Engineering data itself is quite different to typical business-oriented data as illustrated in Table 1. It has unique data characteristics and complex data capture processes from a large variety of data sources. This large amount of data therefore can suffer from data quality problems. The nature of such data quality problems has not previously been investigated in Australian engineering-oriented organizations.

4. RESEARCH DESIGN

In DQ studies, four types of stakeholders have been identified: data collector, data custodian, data consumer, and data owner (Strong, 1997; Wang, 1998). In this study, DQ stakeholders in asset management are defined as follow:

- Data collectors are those who create or collect asset data e.g. technician, data entry staff;
- Data custodians are those who design, develop, manage, and operate the asset management information systems e.g. IT manager, data manager;
- Data consumers are those who use the asset information in their work activities e.g. maintenance engineer, senior manager;
- Data owners are those who own and responsible for managing the entire data in asset management systems e.g. asset manager.

The DQ survey was designed to address the questions developed in the literature review, in order to understand the general perceptions towards data management issues and further establish the extent of data quality maturity. A multi-section questionnaire were mailed to a 2000 large random sample of asset manager, data collector, data custodian and data consumer, in 1100 geographically dispersed engineering asset management organizations in Australia (including 572 organizations in the public sector). The questionnaire provided a guideline in the beginning to ensure that respondents had a common understanding of the various sections and definitions. The questionnaire was pre-tested by initially mailing it to 15 companies. Changes were incorporated and the questionnaires were then mailed to the remaining companies. The survey population for the questionnaire was chosen from engineering asset management organizations based in Australia. These organizations represent a variety of industries:

- utility (water, electricity, gas, oil);
- mining & resources;
- transport (rail, airline, ship, automobile);
- defence; and
- local government.

This list was matched with databases like the Business Who's Who of Australia and the specific industry-related associations to develop a list of Australian AM organizations. We believed that being the key participants or leaders in the major areas of engineering asset management, these organizations would be potential candidates for having AM information systems. Once the data was collected, statistical tools & methods were used to analyze the data and report the results. The results of this survey study were used to develop an AM DQ framework. The AM DQ framework will form the foundation for further research in order to perform data audit to identify nature and volume of DQ problems, and to develop a specification of the functional requirements for asset management data cleansing & enrichment software packages

5. THE AM DQ FRAMEWORK

Based on the analysis of DQ and AM literature together with the empirical findings from the DQ survey, *an* AM specific DQ framework was developed as shown in Figure 1. This framework is useful to guide the research into AM DQ issues, because it highlights the root perspectives on DQ problems, illustrates how they emerge during the process of AM; and outlines the basic DQ management criteria.

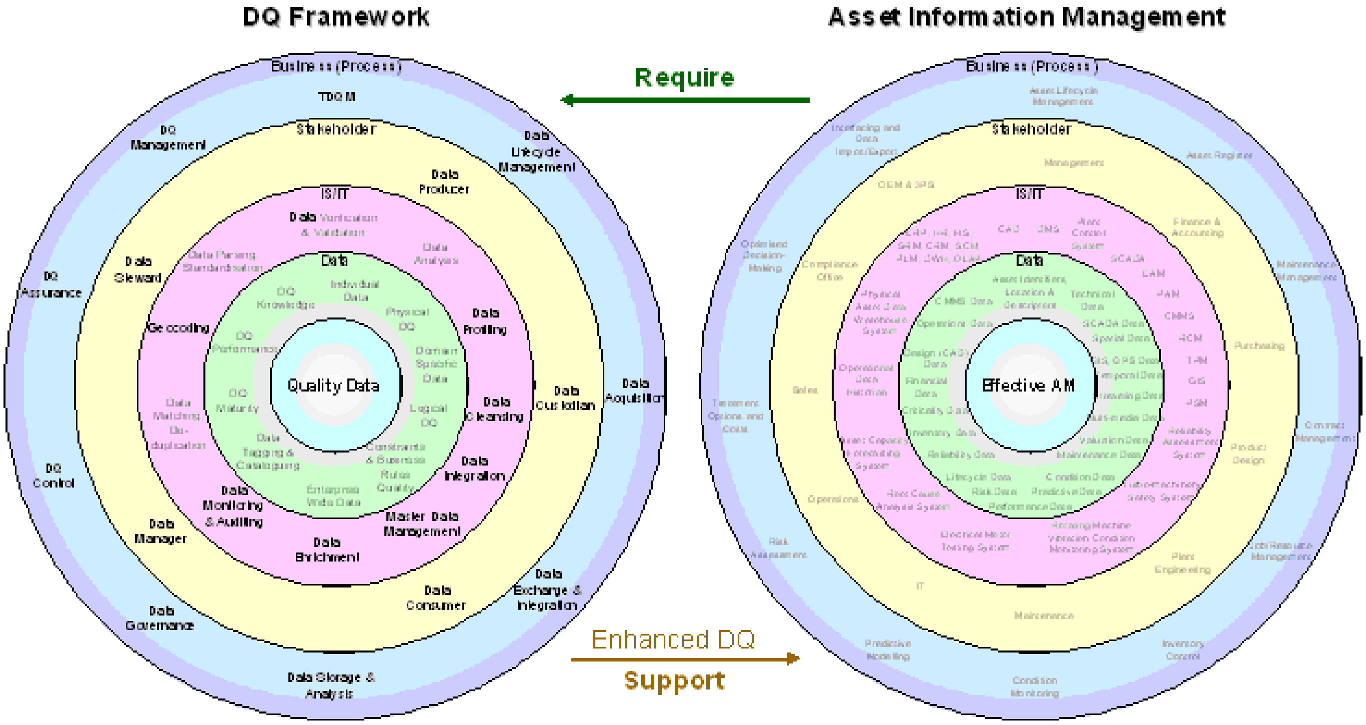
Asset data is the key enabler in gaining control of assets. These asset data is created, processed, stored, and used throughout an asset's lifecycle by a variety of stakeholders together with an assortment of technical and business systems during the whole AM process. The quality asset data in turn provides foundation for effective asset management. As asset information management underlies all the asset-based management processes, the ensured DQ for asset information management assists the optimization of AM decision-making.

Because these asset data are quite different to typical business data, in order to ensure the quality of these asset data, AM DQ also has its own process, which also involve multiple DQ stakeholders such as data collector, data custodian, and

Table 1. Differences between engineering asset data and typical business data (Source: Developed by the authors)

Element	Typical Business Environment	Engineering Asset Management
Data Environment	Transaction-driven, product-centric business data environments	Continuous data, process-centric open control system and manufacturing data environments
Data Characteristics	• Self-descriptive • Static • Intrinsic quality • Discrete value with fewer or no constraints • Current • Transactional data • Often structured • Easy to audit • Can be cleansed using existing tools • Similar data types	• Non self-descriptive • Dynamic • Intrinsic / extrinsic quality • Continuous value with constraints (e.g. within a range), precision value • Temporal • Time-series streaming data • Often unstructured • Difficult to be audited • Difficult to be cleansed using existing tools • Diversity of data types
Data Category	Inventory data, customer data, financial data, supplier data, transaction data etc	Inventory data, condition data, performance data, criticality data, lifecycle data, valuation data, financial data, risk data, reliability data, technical data, physical data, GPS data etc
Data Sources	Mainly transaction-based textual records from business activities	Disparate data sources • Spatial data – plans/maps, drawings, photo • Textual records – inspection sheets, payment schedules • Attribute records – separate databases, maintenance/renewal records, fault/failure records, field books • Real-time CMS/SCADA • Other sources – existing/previous staff and contractors, photos
Data Capture	• Often manually by data providers in fixed format • Data often entered by reasonably trained, dedicated personnel with proper relevant knowledge • Data collection environment is stable, well pre-organized • Data entry point is within the business	• Electronically, involving sensors, technical systems such as SCADA systems, condition monitoring systems • Manually, involving field devices, field force, contractors, business rules • Data collected in a variety of formats • Requires to collect substantial data from many different parts of the organization • Data often entered by less/un trained, less dedicated personnel without proper relevant knowledge • Data entry environment can be unstable, harsh, less pre-organized • Data entry point can be far from the organization site
Data Storage	• Data to be kept in accordance with appropriate compliance requirements • Data stored on functional information systems	• Very large amount of data to be maintained for extended time for AM engineering and planning process • Data stored on various operational and administrative systems
Data Processing	• Comprehensive • Process independent • Easy for data integration	• Not comprehensive • Process dependent • Complex to integrate data, need both vertical and horizontal data integration
Data Usage & Analysis	o Data to be shared only among relevant business systems o Data to be communicated to internal stakeholders o Use general, common knowledge to interpret data o Easy for management use	o Data to be shared among various technical (e.g. design, operations, maintenance) and business systems o Data to be communicated to an array of stakeholders, business partners and contractors, subcontractors o Need experts with professional knowledge to interpret data o Difficult to translate asset data into meaningful management information

Figure 1. The AM DQ framework (Source: Developed by the authors)



require specialised supports of DQ technology and systems. The AM data will need to go through the DQ process, by a variety of DQ stakeholders and various DQ technology & systems, in order to ensure its quality. The asset data of enhanced DQ can then provide the foundation for effective asset management.

6. RESEARCH FINDINGS

This survey is the first national data quality survey performed in Australia, focusing specifically on the data quality issues of engineering asset management organisations. The following findings show the different attitudes and perceptions towards data quality. More importantly, it shows that the current strategy, policy and tools that the organisations employ for their data management solution.

6.1 Current Attitude & Awareness Towards Data Quality

The above result shows that the majority of survey participants recognise the important role that data quality is playing in achieving the success of an asset-intensive organisation.

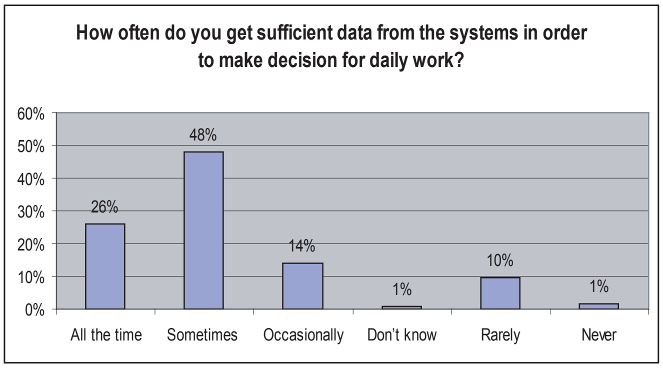
TOP Approach	Element	Chi-square Test	Kruskal-Wallis Test
Organisation	Industry	0.012	0.000
	Organisation size	0.772	0.459
	Organisation site(s)	0.215	0.007
People	Job position level	0.037	0.020
	Job function	0.704	0.138
	Data role	0.164	0.016

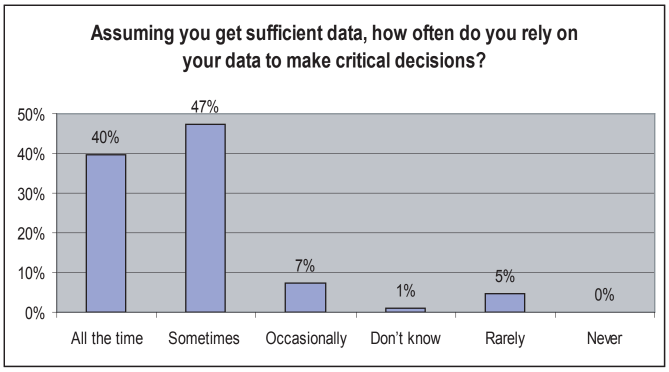
However, there is a statistically significant difference in the levels of DQ awareness across the different industry groups, and various job position levels as shown in Chi-square test and Kruskal-Wallist test. An inspection on the mean rank for the industry groups suggests that defence had the highest awareness scores, with local government reporting the lowest. In terms of job position levels, senior manager in strategic level had the highest awareness of DQ importance, with operational staff in lower level being the lowest. There is no significant relationship found between DQ awareness level and organisation size or job function.

6.2 Current Perception of DQ Confidence

Despite the overwhelming DQ awareness, a DQ confidence gap exists among the different data roles.

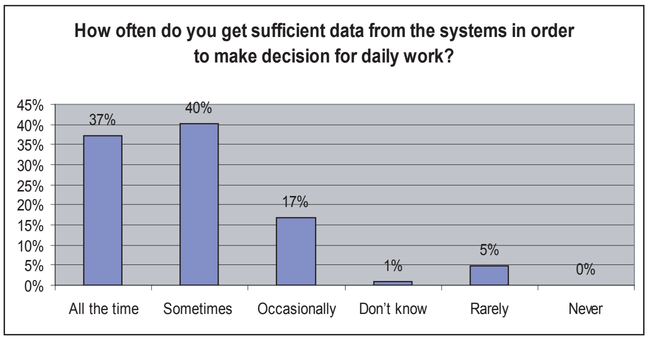
6.2.1 From Data Owners' Point of View

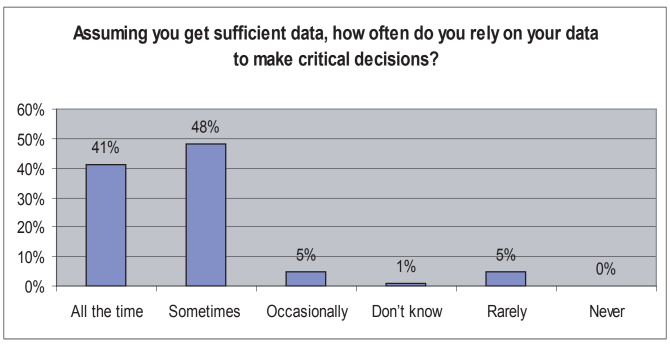




The above left figure shows that the majority of data owners (Asset managers) are happy with the amount of the data that they can access. However, there is a relatively small group (about 7%), who is not satisfied with the quality of data for decision making as shown in the figure on the right.

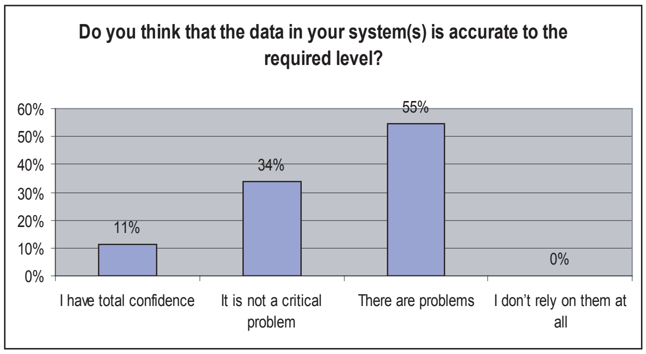
6.2.2 From Data Consumers' Point of View

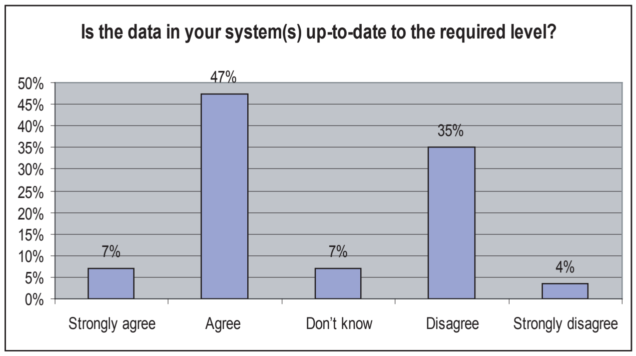




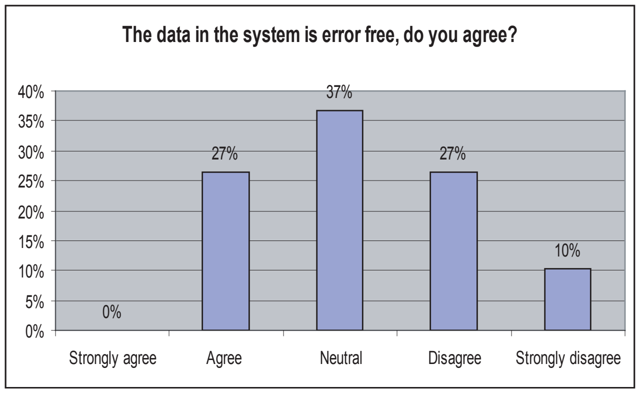
A consistent opinion is suggested by the data consumers' group. However, it does necessarily show that the data quality problem is not a major concern within the participating organisations.

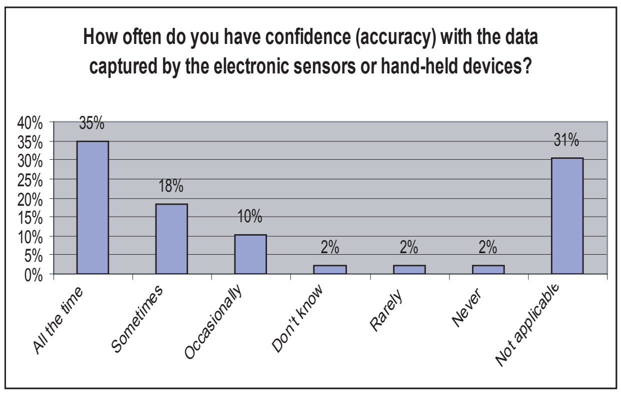
6.2.3 From Data Custodians' Point of View





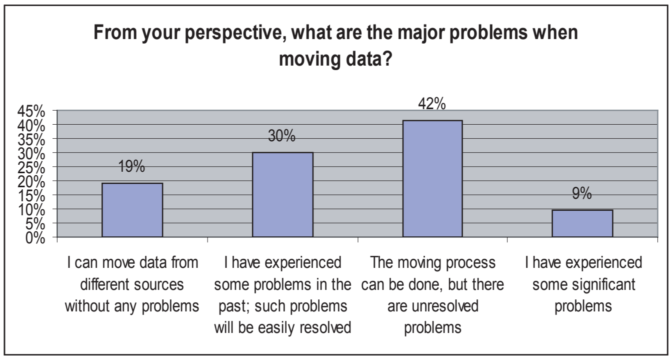
6.2.4 From Data Producers' Point of View





The above figures shows that the data producers and data custodians acknowledged that there were data quality problems. Especially, data producers do not have much confidence on their data quality. Perhaps, the data owners and data consumers may have higher levels tolerance of poor quality data. Nevertheless data quality problem is still facing critical challenges in most organisations. Also, the different attitudes found between groups may ring the alert bell that there may be a disconnection between the operational level personnel and the strategic level managers.

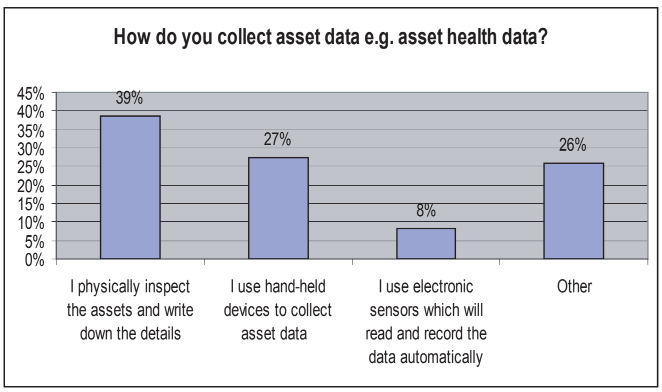
Some problems are suggested by the data custodians. For example, it suggests that moving/migrating data may generate many quality related problems, as shown below.

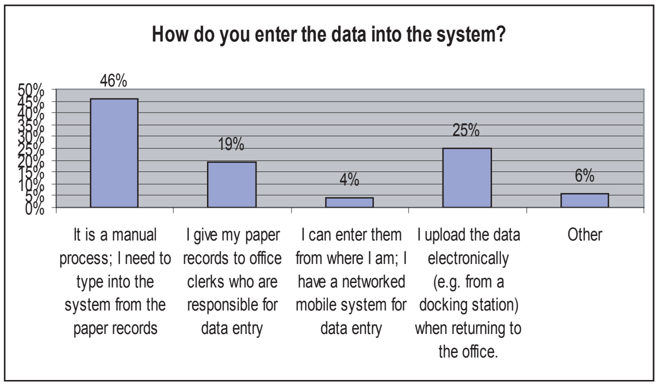


6.3 Current Strategies, Policies & Tools Employed for Achieving High Quality of Data

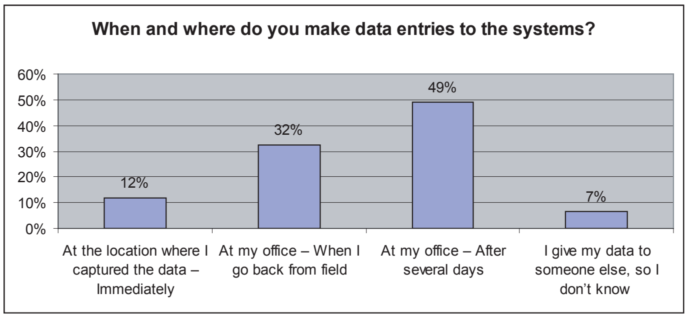
According to the 60% of data owners, there is data management strategy for data quality in place in their organisations, as shown in below.

Down to the data capture level, data producers listed different ways of data collection and entry.



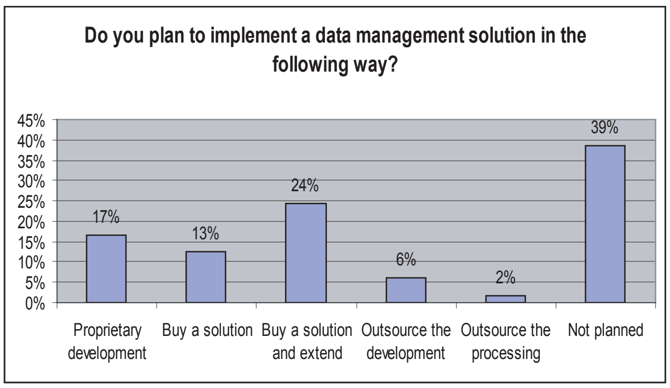


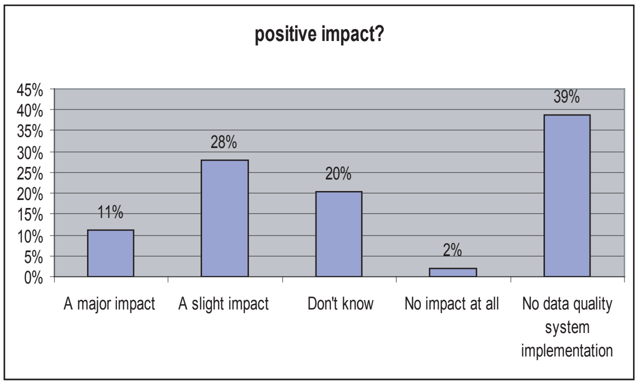
The majority of data producers still adopt a manual data entry process, which primarily rely on paper records. Especially, the figure below suggests that these data may not be entered immediately on site. Approximately 49% of these data were entered at the office after several days. Thus, the accuracy and completeness of these data may not be satisfactorily achieved.



6.4 Towards Future

It is "interesting" to find that 39% of asset owners have no plans to implement any data management solutions in near future. While the answer from Data custodians to the question *"Has implementing a data quality system had a positive impact on the success of any major IT implementations which your organization has put in place (e.g. Enterprise Resource Planning)?"* shows that no data quality systems (e.g. data profiling and cleansing systems) were implemented or planned to be implemented.





7. CONCLUSION

This paper included a proportion of survey findings. Nevertheless, these results suggest that while the organizations are concerned about the quality of data, there is lack of scrutinized discussion on the various issues associated with data quality problems. More importantly, there is a disconnection between data custodians and data producers and high level data owners. The majority of engineering asset organisations in Australia has no plans to neither implement any data quality management solutions nor develop any strategic plans. This finding is very different from AIM and PricewaterhouseCoopers findings. Perhaps, the engineering asset management organisations in Australia still adopt a reactive approach and only focus on the daily operations. A more comprehensive analysis will show the different attitudes and management strategies in relation to sizes of the organisations and the industries that they operate within. Further, these findings will be compared with the general data quality surveys.

This paper provided a better understanding of data quality issues for asset management and is assisting in identifying elements which will contribute towards the development of a data quality framework specific to engineering asset management. This in turn will assist in providing useful advice for improving data quality in this area. As an increasing number of organisations are putting in resources in data management solutions, there is growing need for suitable guidelines to help them develop appropriate strategies and employ right tools. Perhaps this is why data quality research becomes more critical.

8. ACKNOWLEDGMENTS

This research is conducted through the Centre for Integrated Engineering Assets Management (CIEAM). The support of CIEAM partners is gratefully acknowledged.

ENDNOTE

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