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**ABSTRACT**

Data and information quality is a well-established research topic and gradually appears on the decision-makers' top concern lists. Many studies have been conducted on how to investigate the generic data/information quality issues and factors by providing a high-level abstract framework or model. Based on these previous studies, the researchers of this paper tried to discuss the actual data quality problems with the operation-level and middle-level managers in engineering asset management organizations. By identifying the unique data quality problems (fitness for use) in asset management and reviewing the existing data cleansing software tools against real engineering asset databases, the deficiencies of the existing data cleansing approach are highlighted.

**Keywords**

Data Quality, Data Cleansing, Engineering Asset Management, Software Tools

## INTRODUCTION

### Engineering Asset and Engineering Asset Data

Assets are the lifeblood of most organizations. They may include digital assets, human assets, and financial assets. Most companies also have physical assets. These physical engineering assets (e.g. machinery, plant and equipment, etc) can be used to turn raw material into finished goods, supply electricity and energy, provide transportation services, or control huge utility operations. Many organizations rely heavily on these engineering assets to maintain and monitor daily operations. During the lifecycle of these engineering assets, an enormous amount of data is produced. The data is captured, processed and used in many computer information systems such as Supervisory Control and Data Acquisition (SCADA) systems, Facility Maintenance and Management Systems (FMMS), and Geographic Information Systems (GIS), to name a few. It is therefore acknowledged by many researchers (e.g. Steed 1988; IPWEA 2002; Sokianos, Druke & Toutatoui 1998; Woodhouse 2001 & 2003) that the study into asset management is worthy of investigation.

In general, there are two major types of engineering asset data (configuration data and transaction data). The first type of data (configuration data) is that associated with the physical asset attributes. Included in this data would be data such as acquisition date, acquisition cost, and physical location of the asset. The second type of data (transaction data) is data generated as a result of operation (or use) of the assets. This data can be self-generated (i.e. the asset has embedded sensors that can track when maintenance is necessary and has been completed) or manually generated (i.e. a service technician may perform routine maintenance checks, complete required activities, and record this data in a system separate from the asset itself).

In practice, both the configuration and transaction data can be captured automatically and manually and may involve sensors, field devices, human operators, field technicians and contractors, in a variety of formats, processed in isolation and stored in an array of legacy systems. Data captured and processed by these systems is generally not comprehensive; it is usually process dependent, making it difficult to be reused for other processes or process innovation. For example, the data captured by the sensor may only be readable in the specially designed monitoring systems, and cannot be exported and used for any other purposes.

In addition, many assets can also generate data that is not directly related to the management of the asset. For example, a water station pump will produce data of the current water pressure. Since this paper is concerned with the specific domain of asset management, this kind of data is not the focus of this paper.

This paper will focus on the first phase of a multi-phase research project. We will show that the data quality issues associated with engineering asset management systems (EAMs) are significantly different from the issues that we see with traditional transaction processing and/or business information systems. In addition, we will evaluate several data quality tools within the context of EAMs. From this evaluation we have determined that there are several data quality issues associated with EAMs that cannot be addressed with the current set of tools. This research contributes to the current literature by identifying unique issues with EAMs, and adapting the fitness for use concepts within the realm of EAMs.

The rest of the paper is outlined as follows. We first describe the engineering asset environment, followed by a brief discussion of data quality. We then describe how current data quality tools work. The next section highlights the differences between EAMs and traditional information systems, a key contribution of our research. Next we discuss the overall research that we are undertaking, emphasizing the portion of the research that is being reported in this paper. We then provide an analysis of the data quality tools that we evaluated, again within the context of EAMS. Finally we report the conclusions and limitations of this phase of the research.

## Engineering Asset Management

According to Eerens (2003), Spires (1996) and IPWEA (2002), 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. 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. The process of asset management is thus 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. Coordinating and collaborating these processes is vital to effective engineering asset management. 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 (RFP), 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, record must be made of its eventual disposition. A variety of specialized technical, operational and administrative systems exist in asset management, which not only manage and track the asset through its entire lifecycle, but also provide maintenance support throughout the lifecycle of the asset. See Figure 1 for a visual representation.

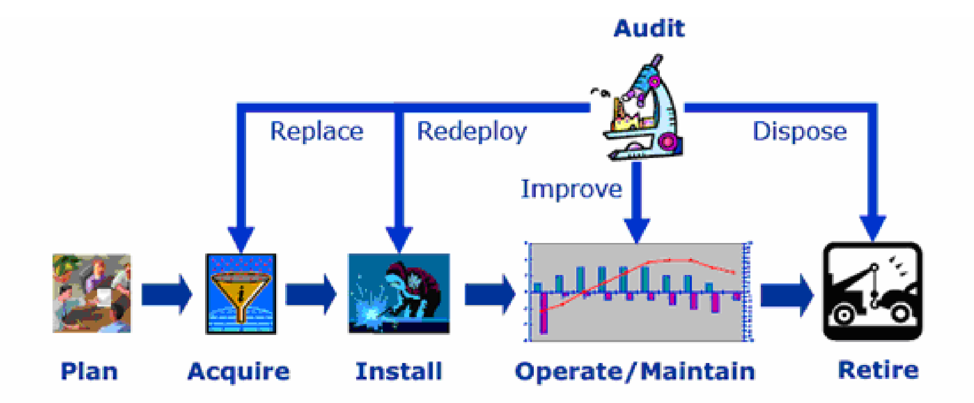


**Figure 1- Asset Lifecycle Stages (Source: Snitkin 2003)**

The process of engineering asset management is sophisticated. The process itself is data centric – relying heavily on input data and simultaneously producing data. Following the principle of cause and effect (“garbage in, garbage out”) and considering the large amount of data produced during the process, the quality of the data eventually becomes an issue. Figure 2 shows this.

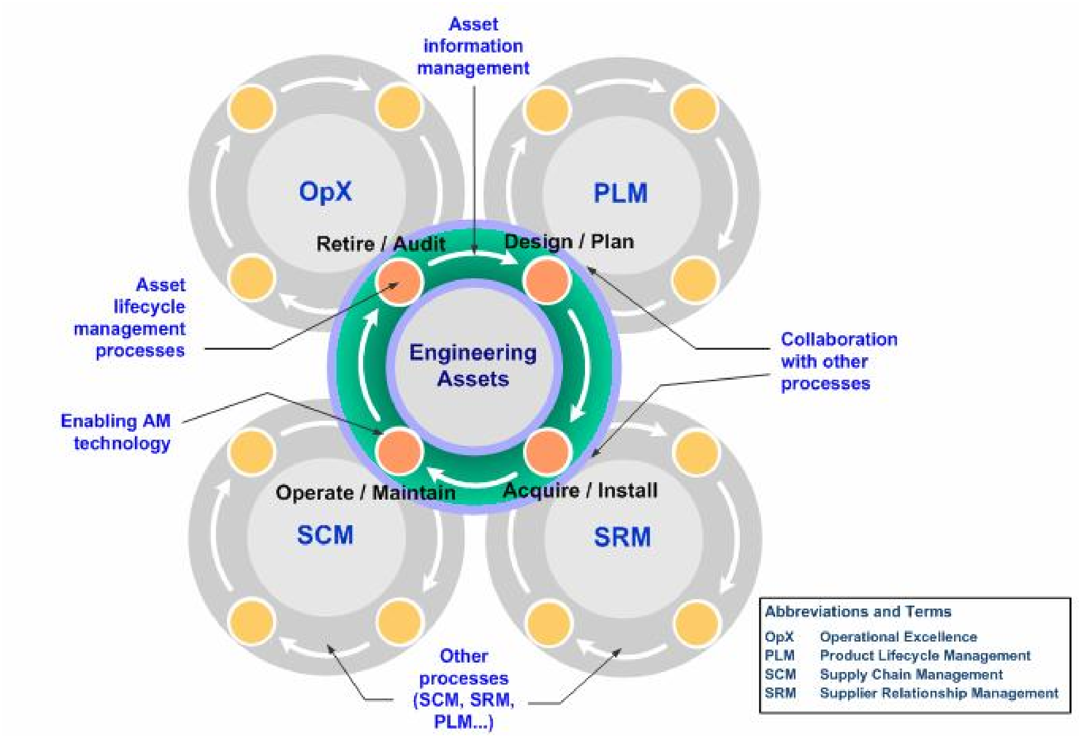


**Figure 2- Collaborative Asset Lifecycle Management**

**(Source: Adopted and modified from Snitkin ARC CALM Model 2003)**

## DATA QUALITY

Data and information are often used synonymously particularly when addressing quality issues. 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, as well as use data quality (DQ) interchangeably with information quality (IQ).

The quality of data is multi-dimensional (Wang & Strong 1998) including accuracy, reliability, importance, consistency, precision, timeliness, fineness, understandability, conciseness, and usefulness (Ballou & Pazer 1995; Wand & Wang 1996). It is also suggested that the quality of data is dependent on how the data will be used (Ballou & Pazer 1995; Neely 2001; Strong 1997; English 1999; Salaun and Flores 2001; Orr 1998). This fitness for use can be defined as the intersection of the quality dimension being considered, the use of data (purpose) and which data fields are used in order to fulfill the purpose (Neely 2002).

A number of information quality frameworks (e.g., Wand and Wang 1996; Wang and Strong 1996; Wang 1998; Shanks & Darke 1998; Price & Shanks 2004; Kahn, Strong & Wang 2002; Giannoccaro, Shanks & Darke 1999; Caballero & Piattini 2003; Eppler 2001; Nauman & Roth 2004; Jarke, Jeusfeld, Quix & Vassiliadis 1998; Firth 1996) have been proposed to organize and structure important issues in information quality from different points of views. Some of these research ideas are guiding the development of the data quality software tools in the commercial market. The next section discusses some of these tools.

## DATA QUALITY TOOLS

Data quality tools can be categorized as auditing tools, cleansing tools, and migration tools (Neely 1998). Auditing tools are designed to work at the data source. The auditing tools can either be programmed with existing business rules, or a subset of the data can be mined to extract the business rules. The end result of either approach is the development of a set of rules against which the entire dataset can be compared. The goal of the auditing tool is to create a variance report where data that does not conform to the business rules can be manually examined.

Cleansing tools, which initially started as name and address tools, also use comparison techniques. The cleansing tools parse the data into atomic units, standardize it to a required format, correct and verify it against known records such as postal code listings, physically transform the data, and match data records to check for duplicates. The goal of the cleansing tools is the automatic verification and correction of data.

Migration tools are designed to physically move the data from one location to another. They are responsible for converting the data from one platform to another, and are not concerned with the actual data values. However, ensuring the value of data is constant and the data format, range and field constraints are consistent during and after the migration process becomes an important quality aspect of the tool.

Data quality tools were evaluated in 1998 (Neely), with the conclusion that the tools are primarily directed at the quality dimension of accuracy and are only effective if the “correct answer” is known. For example, names and addresses must be compared to accurate postal code listings. Or business rules, such as “if a person receives food stamps, then they will also receive a housing allowance”, must be constructed. As will be seen later, this is not sufficient for the data quality issues associated with asset management systems.

Although the tools that were evaluated in 1998 were separate and distinct, with most of the tools performing one of the three tasks, we find that the tools have become more comprehensive over time. Many of the tools that were evaluated had a core focus of auditing or cleansing capabilities, but also had additional capabilities which blur the lines described above. Thus, it would appear that that we have evaluated predominantly cleansing tools, when in fact many of the tools have auditing capabilities as well.

## DATA QUALITY AND ASSET MANAGEMENT

Much of the literature regarding data quality is concerned with transaction processing data in databases where the data can be controlled. However, much like the data issues associated with a data warehouse (Wixom and Watson 2001), the data associated with asset management must be integrated with data from other systems. 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. As can be seen in table 2, there are significant differences in the data to be found in engineering asset management systems and traditional business systems.

## RESEARCH METHOD

A comprehensive analysis of the major vendors and their data quality related products attests that the issues posed to data quality for asset management are quite unique in nature and cannot be resolved through the existing commercial off the shelf products. From the differences shown above, as well as the issues delineated in the previous section, we posit several research questions.

Research question 1: Why is the existing data cleansing software unable to address the quality problems in engineering asset data?

Research question 2: Given that the quality of data is dependent on how the data will be used (fitness for use), are there features of the data quality tools that will support the identification of the quality under these conditions?

Research question 3: What are other desired features of engineering asset specific data cleansing software tools?

The research presented in this paper has been completed. There are additional steps that we plan to do as a future research project. Below we describe the entire research project. The completed portion fits into the “Review” portion of the research method.

We have completed the literature review and compiled a table relating the uniqueness of asset management (AM) data when compared to general business data. Additionally, we have completed the initial software review process. We have identified a brief list of functions and features relevant to AM data. We have also begun examining the primary domains that the various current tools are designed to support.

| | Typical Business Environment | Engineering Asset Management |
|---|---|---|
| Data Characteristics | Transaction-driven, product-centric business data environment<br>• Self-descriptive<br>• Static<br>• Fewer or no constraints<br>• Discrete value<br>• Not difficult to be audited | Continuous data, process-centric open control system and manufacturing data environments<br>• Non self-descriptive<br>• Dynamic<br>• Need professional knowledge to interpret data<br>• Continuous value with constraints (e.g. within a range)<br>• Time-series streaming data<br>• Precision value<br>• Difficult to be audited |
| Data sources | mainly transaction-based textual records | Disparate data sources<br>o Spatial data – plans/maps, drawings, photo<br>o Textual records – inspection sheets, payment schedules<br>o Attribute records – separate databases, maintenance/renewal records, fault/failure records, field books<br>o Other sources – existing/previous staff and contractors, photos |
| 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 capture | o Often manually by data providers in fixed format<br>o Data often entered by reasonably trained, dedicated personnel with proper relevant knowledge<br>o Data entry environment is stable, well pre-organized<br>o Data entry point is within the business | o Electronically, involving sensors, technical systems such as SCADA systems, condition monitoring systems<br>o Manually, involving field devices, field people, contractors, business rules<br>o Data collected in a variety of formats<br>o Requires to collect substantial data from many different parts of the organization<br>o Data often entered by less trained, less dedicated personnel without proper relevant knowledge<br>o Data entry environment can be unstable, harsh, less pre-organized<br>o Data entry point can be far from the organization site |
| Data storage | o Data to be kept in accordance with appropriate compliance requirements<br>o Data stored on functional information systems | o Very large amount of data to be maintained for extended time for AM engineering and planning process<br>o Data stored on various operational and administrative systems |
| Data process | o Comprehensive<br>o Process independent | o Not comprehensive<br>o Process dependent |
| Data usage/analysis | o Data to be shared only among relevant business systems<br>o Data to be communicated to internal stakeholders | o Data to be shared among various technical and business systems<br>o Data to be communicated to an array of stakeholders, business partners and contractors, subcontractors |

**Table 1: Difference between Engineering Asset Data and Typical Business Data (Source: Koronios, et al 2005)**

In future phases of this work, we will continue this process of software review by contacting company representatives as well as an independent review of web resources.

Subsequent phases of this work will entail the identification of the problems common to AM systems using two real engineering asset databases. Each database will serve a different purpose. The SCADA system, which contains streaming sensor data, is an example of AM transaction data. It is about 360MB in size. The Asset Maintenance system, about 70MB in size, is an example of data that is both configuration and transaction. Thus, we have databases of differing types as well as differing sizes.

In order to answer research question 2, we will need to determine how the relevant software tools account for the use of the data. In order to do this, we must define multiple uses for the data that we are testing. The primary uses of data will be discussed with the operational level employees and the middle level managers from the companies who supplied the database. Since the middle-level managers are responsible for using the data to supervise and control operations as well as transforming the data to a more abstract form to support high-level strategic decision making, the discussion with these people is likely to generate useful and precise information on the fitness of data use and various issues associated with data quality management.

After identifying the data quality problems in the tested databases in relation to the fitness of use, direct contact with data cleansing software vendors will be made to explore the software approach for the identified problems. More importantly, several software suites will be used to simulate the actual data cleansing tasks on the two selected databases.

The following diagram shows the overall research approach. Conclusions will be drawn from the research findings.

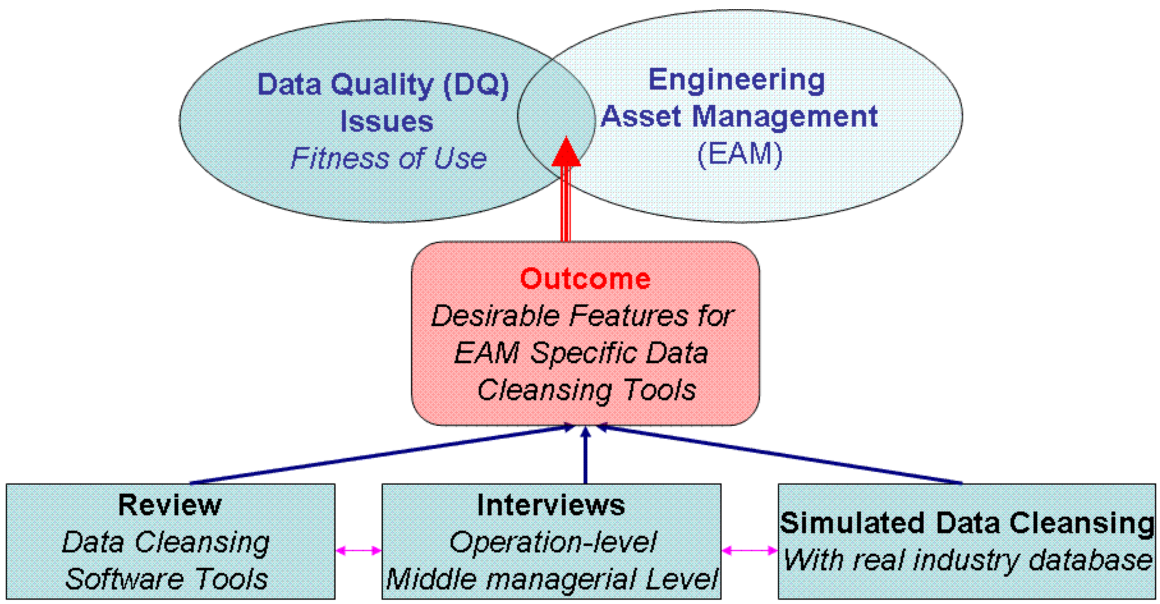


**Figure 3- Research Method**

This research starts from the review of various data cleansing software tools and tries to identify and compare & contrast the common and unique features. With the feature lists obtained from the review, we conduct interviews with the client / user groups to determine whether the proposed features can match the industry requirement (especially, whether these features can deal with the uniqueness of the asset management data). In addition, a simulation will be conducted to evaluate the actual performance of the software tools when performing data cleansing on real asset management databases. After all, recommendations to the improvement of data cleansing tools will be suggested.

## FINDINGS

A review of the current data quality tools indicates that the tools have not changed significantly since the Neely study (1998). The functionality of the tools follows:

- Data Parsing/Profiling Function- the action of breaking data files into atomic units; includes the analysis of data values to find areas that are incomplete or inaccurate, and verification of relationships across columns and tables
- Data Cleansing & Verification/Matching Function- field contents are checked and standardized to present a consistent format; verified against known lists; matching of records to eliminate redundancy
- Data Enrichment/Enhancement Function- generate and append additional bits of information from other internal or external data sources to information already in use
- Data Monitoring Function- examining data continuously to detect new inconsistencies and to indicate where changes in data sources and business rules may necessitate further; intended to identify trends in data quality, providing alerts of violations in established business rules, understanding the costs associated with business rule violations and detecting variances from cyclical runs; this functionality was not evident in the 1998 study

In addition to the basic functionality of the data quality tools reviewed, several features enhance the usefulness of the tools:

- Multiple Data Source Support
- Data analysis**-** the tools generate their own set of data regarding the conformity of the data values to the target values; analysis of this data can be a part of the tool features
- Visualization**-** the ability to view the results of the data quality process in a visual manner; graphically, as plots, etc.
- Question and Answers **-** QA support **-** how well does the company respond to questions regarding their product?
- Integration**-** does the data quality tool integrate with other tools, such as ETL tools
- Consolidation and Linking**-** merging data records from different tables using relationships
- Metadata**-** the recognition that metadata quality is critical to data quality (Iverson, 2001) means that tools now have the ability to capture and document the metadata associated with the quality process
- Quality Assurance (QA) **-** The ability to conclude the confidence of the data being examined (e.g. generating an audit report)

| | Ascential Enterprise Integration Suite | Avellino Discovery 3.2 | Datanomic | Evoke Axio | Firstlogic Information Quality Suite | Informica PowerCenter 7 | Innovative Systems i/Lytics | KDI Data Investigator | SAS ETLQ | Similarity Systems ATHANOR Suite | The Trillium Software System |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Matching / De-duplication | Good | None | Good | None | Very Good | None | Good | None | Good | Good | Good |
| Verification / Validation | Good | None | Good | None | Good | None | Very Good | Poor | Good | Good | Good |
| Geocoding | None | None | None | None | None | None | None | None | None | None | None |
| Source Support | good | very good | good | good | good | good | poor | good | good | good | poor |
| Data Profiling | good | very good | good | very good | good | good | poor | poor | good | poor | poor |
| Data Analysis | good | very good | good | very good | good | good | poor | good | good | very good | poor |
| Visualisation | good | good | good | good | good | very good | poor | poor | very good | good | poor |
| QA Support | very good | good | good | good | good | good | poor | poor | good | good | poor |
| Integration | very good | good | very good | good | good | good | poor | good | good | good | poor |
| Consolidation & Linking | Available | Not Available | Partial availability | Not Available | Available | Not Available | Available | Not Available. | Available | Available | Available |
| Metadata | "MetaStage" integrates metadata from entire suite. web service metadata importer. | Can infer metadata rules based on discovery | Not mentioned | Graphical Inspection of Metadata Can infer metadata rules based on discovery | Metadata Repository can be single, or distributed | Provides the ability to assemble, relate and visualise metadata | Not mentioned | Not Mentioned | Uses shared metadata repository | Not mentioned | Relies heavily on user-defined rules. |
| QA | "AuditStage" can be used to both identify and track error correction. | Not mentioned | Supported with Datanomic Audit to monitor progress of DQ programs | Not mentioned | IQ Insight provides trend analysis to support QA programs. | SuperGlue monitors and assesses DQ. Can be used for QA purposes. | Not mentioned | Not supported - data validation tool only. | Not mentione d | Supports quality assurance programs. | Data quality score for QA programs. |

**Table 2- Small Sample of Current Data Quality Tools Comparison (Source: CIEAM 2005)**

As can be seen in Table 2, we have reviewed several products and evaluated them in terms of functionality and features. This work was done by the authors as part of a government funded project for the Center for Integrated Engineering Asset Management (CIEAM). By following the data quality improvement cycle from data parsing to data monitoring, a comprehensive analysis of the major vendors and their data quality related products has been undertaken. Comparative analysis of the product data quality features is also given. Ultimately, the existing data quality tools are not effective for assessing the quality of the data in an asset management system. Unlike financial transaction processing systems, much of the data in asset management systems is textual and unverifiable by the current automated processes. For example, asset location data is usually started with a short-form of asset location name, followed by an asset id. It could be perfectly valid according to the existing data cleansing tools (e.g. correct length), but is meaningless because the short-form of asset location is wrong.

In addition, no data quality tools were found to be able to verify if the acquisition date is correct in an asset management system. Nor can it verify that the service technician entered the correct maintenance records when he or she finally sat down at the desk on Friday to catch up on paperwork. Further findings will be presented when the research is completed.

## RESEARCH LIMITATIONS AND CONCLUSION

This paper looked at the dominating commercial data quality and cleansing applications available today and does not cover all available solutions. It is also acknowledged that there is a time lag between the availability of the paper about these applications and the latest set of features released with these products. It is possible that new or improved features may have been included in the products compared during the time that this paper was compiled. Results are thus indicative of the more important data quality issues and data cleansing approaches to consider and do not represent conclusive answers.

Database management software systems have improved built-in capabilities to provide system support for imposing constraints, data relations and metadata structure to data. These functions have reduced the need for data cleansing. Even though these functions were considered in preparation of this paper; the primary focus remained on an understanding of how organizations could manage the quality of the existing data in their engineering asset life-cycle management.

This research has highlighted issues of data quality in asset management organisations. From the initial stage of this research, it is found that all data quality solutions examined during the exhaustive literature review are focused very much on customer databases and CRM systems. In fact, as asset management data and informational needs are very different to a typical business environment a gap exists in the availability of data quality solutions for engineering asset management. There is thus a need for the development of data quality solutions for engineering asset management.

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