Summary:
This paper demonstrates a Rapid Development Availability Model (RDAM) process using production time-delay accounting data. The approach reduces the time required for model construction by approximately half in comparison to traditional methods where failure distribution parameters are derived from work-order statistics. Historical maintenance work-order data is often not fit-for-purpose resulting in time-consuming work to attain a sufficient standard for model construction. Time-delay accounting, which records unscheduled losses against failure event codes, requires significantly less manipulation to develop a usable data set.

The RDAM framework development is discussed in this paper and supported by a case study based on data from a mining operation. The case study uses modelling to identify where availability can be increased in order to enhance production throughput. Data quality issues are investigated as well as the effect model assumptions have on simulation results. The paper also compares differences and similarities between work-order statistics and production time-delay accounting data.

Keywords: Availability, Reliability, Simulation, Delay Accounting, Data Quality.

1 INTRODUCTION
Asset management is a planning framework that enables decision making for the effective management of plant and machinery to deliver business outcomes. One asset management tool traditionally used in the design stage of the asset life cycle is availability modelling. Availability modelling uses actual or estimated failure data and a graphical reliability block model representative of the system to predict a set of outcomes with the use of Monte Carlo simulation. As plant reliability becomes more of an issue for industry, a desire to find effective tools to aid in the day-to-day maintenance decision making has increased, with availability modelling specifically identified as an option. Of particular interest are tools that help to direct and prioritise limited resources to have maximum effect on improving availability.

Simulation modelling can assist to identify focus areas, justify recommendations and as input to business case development by providing estimates concerning system availability. These models also explore the effect on system availability from hypothetical component modifications and what-if scenario analysis. Examples of simulation models include the work of Marseguerra & Zio (2000), Borgonova et al (2000), Duffuaa et al (2001), Marquez et al (2005) and Visser (2004). Despite benefits, the use of models is often unpopular among on-site reliability personnel as a day-to-day decision tool because they are generally time consuming to build and maintain (Gouws & Trevelyan 2006). The aim of our research program is the development and documentation of a framework for model development that reduces the resources required for availability modelling for in-service asset decisions. The objective of this paper is to test the hypothesis that use of production time-delay accounting data is appropriate for availability model development for in-service assets.
2 LITERATURE REVIEW

Availability modelling is a tool to answer design and maintenance questions through the use of failure and repair data, an understanding of system configuration, a mathematical model and Monte Carlo simulation. A model consisting of reliability blocks called a Reliability Block Diagram (RBD) aids in the graphical representation of the problem. RBDs are a logical representation of a system represented with combinations of series (“and” logic) and parallel (“or” logic) connections. A failure of the system occurs when no complete path remains between the nodes, with individual component and sub-component failures represented by a break in the link across a block (Guo & Yang 2007).

The use of availability models is common in project design stages. With the competitive resource industry demanding more out of its existing assets, a desire to use availability and asset management tools to help justify day-to-day maintenance decision making for in-service assets is becoming prevalent. However, the time to develop these models is highly correlated with the quality and availability of failure and repair data.

Research concludes time and resource consuming models are often a result of poor quality work-order data requiring significant investigation and statistical manipulation in order to achieve a sufficient standard (Redman 2005; Thorn 2005). Figure 1 displays resource examples that can be used to achieve this benchmark and the role these sources have in the modelling process (Hodkiewicz 2008; Thorn 2005). The use of Computerised Maintenance Management Systems (CMMS) aids in the storage of data including historical costs, breakdown repairs and preventative maintenance. However, in order to produce an effective analysis a sufficient standard in the data is required. No current technique is available to produce a robust model otherwise (Narayan 2004). The quality of data is a major challenge existing in many knowledge management and maintenance databases (Hodkiewicz et al. 2006; Gouws & Trevelyan 2006; Levitt 2002).

The current state of the art for availability modelling as a design tool is well established. The greatest obstacle to the method becoming a day-to-day asset decision-making tool is the time and resource-consuming element of the data preparation. There appears two realistic alternatives to the problem; identification of a substitute data source which can be used to form a solid set of failure modes, distributions and parameters; and, the creation of a culture where an understanding of the requirement for integrity in work-order data results in a substantial and sustained increase in the quality of records. The first option appears to be more realistically achievable; however, this paper aims to discuss both alternatives.

3 MODEL FORMULATION

A number of frameworks (Barabady & Kumar 2008; Banks 1998; Banks et al. 2005; Law & Kelton 2000) are used in development of the Rapid Development Availability Model (RDAM) methodology. Figure 2 displays the basic RDAM process framework.

Step One: Problem Formulation – Availability models are tools allowing the user to answer design and maintenance questions, hence, the first step of the RDAM process is to state the problem the model aims to aid in solving (displayed in Figure 2). The problem guides the model direction and emphasises the priority of model components, subcomponents and failure modes. The problem formulation also depicts the model boundaries which in turn determine what quantity and level of data is required as input. The collection of robust data and its combination with the problem enables the user to build a model with outputs designed to find a solution as well as backing up the design and maintenance decision-making process (Banks 1998).

Step Two: Model Conceptualisation – The generation of an accurate model that diagrammatically and mathematically represents a real system requires a RBD as a base to the model. The RDAM process conceptualisation step requires the generation of an initial high-level RBD while ensuring the user gains an understanding of the system. The step also defines the system boundary and in combination with the problem determines the consideration of components included in the model. Consequently, RBD construction requires consultation with engineering, operations and maintenance staff and not merely examination of the data.
The data collection and processing step commences with an export of the raw data (exported directly from the database without investigation and manipulation) into a spreadsheet. The classification of data into various categories depending on the specifics of the delay event can then occur with all classifications required to enable validation of the model at a later stage. It is important to note that the failure modes represented in this paper comply with the Analysis techniques for system reliability – Procedures for failure mode and effects analysis (FMEA) Australian Standard (Standards Australia 2008). It defines failures as “the termination of the ability of an item to perform a required function” and a failure mode as the “manner in which an item fails”. Figure B.4 of the Standard demonstrates that failure modes can include faults; a direct result of another failure. The RDAM focus is to shorten the time and reduce the resources required to assemble an availability model in comparison to traditional methods. The data collection and processing step includes an opportunity to create a high-level model by prioritising the subcomponents that exhibit the highest breakdown losses resulting in system unavailability. By choosing the critical subcomponents for the analysis, the user avoids the requirement for a model that accurately represents every detail of the whole system and instead focuses on the major unscheduled loss failure modes. We acknowledge that the user risks overlooking failure modes on the less critical subcomponent totals, however the high-level model enables quick analysis on some major breakdown causes to target resources for some ‘quick wins’ to improve system availability. Downtime duration trend analysis is another tool for selecting the subcomponents to be analysed in the case of a brief model.

Before performing a distribution analysis, data cleansing and finalisation of failure modes needs to occur for all relevant subcomponents. Most significantly, the occurrence of repeat events must be investigated. Our definition of a repeat event is an unscheduled loss incident that would ordinarily be recorded as one breakdown under a work-order regime but is recorded as multiple events in production time-delay accounting databases. Repeat events occur when the identification of the failure root cause and resultant component repair does not take place within the first incidence. For example, a failure occurs on an electrical component and the maintenance team inspect the system. The team identifies a blown fuse and replaces the component, and resultant component repair does not take place within the first incidence. For example, an event is recorded when a component causes complete or partial shutdown of the system for greater than two minutes and the code is then entered by operations personnel. The analysis of time delay accounting data to identify all losses from ideal and manage them is fundamental to the Total Productive Maintenance approach used in manufacturing plants (Nakajima 1993). As the data contains unscheduled loss events the information can be used to compliment or in lieu of the work-order statistics requiring only minor manipulation to enable data analysis and distribution generation. Delay accounting data is often used to calculate metrics that are used to compare performance across sites. As a result, this data set is audited on a more regular basis in comparison to work-order statistics. The management interest in these metrics and the data they come from results in a more reliable data set.

Prior to model simulation, a distribution is allocated to each failure mode, with parameters from the cleansed data. This enables the user through Monte Carlo simulation (usually deploying a computer software package) to sample the complete model and ultimately conclude the system availability. Each failure mode requires a distribution to represent the Time to Repair (TTR) and Time Between Failure (TBF) data and can be represented by standard statistical distribution in conjunction with a statistically sufficient data set. Exponential (random failure) and normal (failure of a standard deviation around a mean) distributions can be represented by the versatile Weibull function with β equal 1.0 and 3.4 respectively. Accordingly, the two or three-parameter Weibull function is favoured for the RDAM due to the versatility in representing TTR and TBF distribution.
data. The use of a software tool enables the best fitting distributions to be determined for TTR and TBF data sets. If a
goodness-of-fit test rejects the distribution then assumptions are required to enable the definition of an appropriate distribution.
A Weibull function with $\beta = 1$ and $\eta = 1/\text{MTBF}$ (Mean Time Between Failure), or Mean Time To Repair (MTTR), may be
appropriate. By assessing the plots, the goodness-of-fit distribution recommendations and the correlation coefficient a
distribution and appropriate variables can be estimated for each subcomponent failure mode.

Step Four: Model Simulation, Validation and Verification – The model requires a completed RBD of components, subcomponents and failures modes accompanied by appropriate distributions and parameters before simulation can occur. The
data collection and processing stage of the model produces a cleansed data set incorporating all relevant information for the
model. The use of this data set enables RBDM finalisation. A lower level RBDM for each subcomponent is constructed before the
master RBDM is assembled, audited, amended (if necessary) and completed. The construction of the RBM is now possible with
a master RBDM and a complete set of subcomponent failure modes, distributions and parameters.

The RDAM requires the use of, and relevant training in, a simulation software package such as AvSim+, BlockSim or similar
to perform the Monte Carlo analysis on the RBM. The process requires many simulations to confirm results and minimise
simulation error, impossible to complete rapidly without a software package. An alternative is to create a program enabling the
simulations in a mathematical computing language, however, this requires specialist skills and significant resources (including
time), characteristics that the RDAM aims to avoid. With software available, the RBD can be drawn into the tool with the
accompaniment of TTR and TBF distributions and parameters.

Having assembled and written the RBM into software, model verification proceeds. Commercial availability modelling
packages reduce the work involved for the model verification step. Simulation and validation proceeds when the RBM has
been debugged and verified. The simulation lifetime should have units that reflect the other time parameters prescribed in the
distribution analysis and the number of simulations should be large enough that the total downtime (TDT) error plateaus with
an increasing number of simulations.

Validation is the process of trial and error until the objective of producing a model that reflects the real system is achieved.
Various RBM characteristics such as swapping delays, k-of-n nodal definitions, as-good-as-new assumptions, Weibull
distributions and parameters are examples of manipulation that examine the effects on model results. Engineering and
maintenance staff must be consulted when deciding on which model best reflects the characteristics and behaviour of the real
system.

Step Five: Model Analysis and Problem Solving – The final step, model analysis and problem solution, concludes the
modelling process and answers the initial problem. Completed model analysis can take two forms: 1) Examination of the
current situation including the subcomponents and failure modes that contribute most to system unavailability, and 2)
Investigation of overall system availability given a change in the system.

By manipulating various system characteristics (discussed later), the user is able to analyse hypothetic changes in system
performance. However, it is important to note that results are estimates given that model data is based on the current situation
and not considering external factors affected by system alterations. If such analysis is required, it may be necessary to complete
additional model simulations to achieve a robust solution.

The completed model and analysis is a tool to answer a specific question and the results can be used as part of a business case
justification by providing tangible data and results concerning system availability. Completed work should be documented and
reported before storing the analysis in an appropriate knowledge database for access at a later date. This allows others to
observe the availability modelling process as well as results to the problem addressed by the model. The model application or
results may be of use to other sites or of interest to management.

4 CASE STUDY

Case studies practically display theoretical concepts discussed. The RDAM was developed and tested in conjunction with a
case study. It tested the model methodology, analysis and solutions while enabling system alteration recommendations. The
details follow.

Step 1: Problem Formulation – The case study involved a train unloading and conveyor system. The model objective is to
ascertain which system components and failure modes are attributable to significant levels of system unavailability. The
problem formulation step justifies the system boundaries by establishing which components directly affect system availability
and which do not. The boundaries of the model include all system components from the train unloaders through the field
conveyors to the stockpile stackers.

Step 2: Model conceptualisation – This involved (1) The generation of a high-level RBD, and (2) The appreciation of the
system characteristics, assumptions and various inputs. The high-level RBDM was finalised after consultation with the
engineering technical support staff and a site inspection involved walking over the equipment, viewing relevant drawings and
training packages and discussions with staff involving the system, its operation and the RBDM.

Step 3: Data collection and processing – Raw data was downloaded from the loss accounting system for a 12-month period to
March 2008. From this the overall circuit unavailability, MTBF and MTTR are calculated. Several Pareto charts are completed
to gain an understanding of the major contributors to system failure. One such Pareto chart, attached as Figure 3, shows the

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subcomponents with the highest unscheduled losses over a certain time period and is an example of a failure prioritisation analysis. Please note that all numbers have been removed and names modified to protect commercial information. If a brief model is acceptable, the Pareto and trend analyses are used as a guide to the number of subcomponents to be investigated.

With the subcomponents established, the next step is to finalise the failure modes. The Repeat Event Assumption is defined for the purpose of this study as an event occurring 10 minutes or less after the previous failure system restart and the Data Decision Criterion is also used. The application of this ‘Data Decision Criterion’ groups the failure modes ensuring they are significant enough to enable distribution analysis. This is done by (1) rejecting insignificant data sets, (2) incorporating similar failure modes into one more broad or (3) accepting the data as is. In this case, the Failure Mode Analysis produces a set of 100 failure modes for the system that pass the Data Decision Criterion. Unscheduled loss failures (a small percentage) are ignored as they are considered isolated events (occur less than three times per year), insignificant events (less than 100mins per year) or events not affecting system reliability (i.e. emergency stops). The remaining failures are allocated to specific failure modes.

Weibull analysis is conducted on the subcomponent failure mode set with distributions and parameters used in the model. The data is prepared for distribution analysis by first applying the Repeat Event Assumption, finding the TTR and TBF for each failure event and organising them in appreciating order. Initially, the data was fit using two-parameter Weibull distributions and examining the goodness-of-fit. The Weibull++ software used determines the parameters, in our case β and η, a Weibull plot and the correlation coefficient. As part of the analysis, alternative distributions were found in case the two-parameter Weibull distribution had a poor goodness-of-fit.

Figure 4 shows an example of results from the Monte Carlo Simulation. Please note that the sub-component details were modified to protect commercial information. The model predicts what percentage of the year is attributable to unscheduled failures, the TDT and TTR. The difference between the predicted number failure events per year and the actual number of failure events was less than 3%. The model predicts a TTR which is 25% lower than the TTR from the alternative estimates. This difference in TTR has a flow on effect to the modelled system TDT and mean unavailability values.
The model allows the identification of components that contribute the most to system unavailability. In this model, the top two failure modes contribute the greatest to system unavailability at over 20% of the total unscheduled losses predicted. The availability analysis on a system identified approximately 10 significant enhancement opportunities which if rectified can increase total system availability by approximately 1000 hours per year. This confirmed analysis already undertaken by the company and the evaluation of failure modes resulted in funds being invested with the intention of achieving increased availability.

5 DISCUSSION

The case study was developed to test the hypothesis that production time-delay accounting data is appropriate for availability model development. The desired business outcome was to identify and help manage bottleneck components causing system unscheduled losses constraining product supply through existing assets. The collection of production time-delay accounting data instead of work-order data is tested as a method to reduce the time required to undertake the traditionally lengthy model data preparation stage. The process set out to find the components that contributed greatest to unscheduled losses and to test the new framework. The following discusses the problem solution as well as the model analysis, findings and limitations.

Analysis of the model results identifies the top two failure modes causing system unavailability. 20.1% of all unscheduled losses are attributable to two single failure modes. Using the results, consultation with engineering staff enabled identification of the primary reason behind these faults. The analysis provides an estimate of the improvement in availability that could be realised through elimination of these faults. The analysis results enable engineers to develop business cases justifying resource allocation intended on removing faults and increasing availability.

Previous research concludes that the total time to create a model is heavily reliant on the data collection and data processing steps required to determine failure modes and TBF/TTR distributions. Specifically, the single most resource consuming aspect of modelling is the investigation and manipulation of work-order data to ensure the quality is robust. The case study identified that the integrity of work-order databases had become a focus of the owner and several improvement projects had been implemented. These projects ensure that work-order statistics data will be more accurate in future, creating value in the database and enabling analysis. However, this case study uses historical data collected prior to these improvement projects and understandably it contains inconsistencies. The RDAM uses production time-delay accounting in lieu of work-order statistics resulting in an estimated reduction of 50% to the total modelling time. This 50% is an estimate based on the author’s experience with creating similar models (Redman 2005; Thorn 2005). In most cases the data manipulation and investigation is significantly reduced by the RDAM, which in conjunction with the failure mode prioritisation option, has the potential to reduce the modelling time considerably.

The distribution analysis results (conducted in the data collection and processing step) for this case found that the many of failure modes are represented by Weibull distributions with a beta value of less than one. This implies that the subcomponent failures exhibit wear-in characteristics, with beta values approximately equal to one considered to be random and beta values greater than one are wear-out. Wear-in failures are typically observed in electrical components and components incorrectly installed. Lower than expected beta values are also obtained when suspensions are not properly included in the data set. Wear-out failures are commonly observed in mechanical components more likely to fail as use increases. Trips causing system stoppages may also reduce distribution beta values. For example, random spikes in motor speeds, currents or external factors may result in precautionary system stoppages reducing the chance of asset damage. These events are captured in the delay-accounting data.

One explanation for these lower than expected beta values is the incidence of repeat failures separated by more than 10 minutes. These events are excluded from the Repeat Event Assumption and instead form failures with very short TBF characteristics; events representing breakdowns which exhibit early life failure characteristics. However, complete elimination of repeat events would require extensive investigation and manipulation of the data. The use of Weibull plots produced in the distribution analysis helps identify and, if deemed appropriate, remove outliers with the aim of achieving a better goodness-of-fit while removing repeat events.

The decision was made to explore using only two-parameter Weibull distributions for the case study. The intent was to simplify the process step and enable rapidity. In most cases this worked well, with the best alternative distribution assessed as
The system using a repeatable and efficient method.

An investigation was conducted into what was and what was not captured by the two systems; work-order and production time-delay accounting data. The delay data does not capture in-service repair records: repairs where maintainers are able to safely replace standby equipment while the circuit still operational. In this case a work-order is completed for the repairs, however, as the system is operational, the delay data does not record an event. Failures scheduled for planned shutdowns are also commonly excluded from delay accounting data. These are standby equipment failures where repairs may or may not be able to be safely completed while the system is operational but are also not critical to the operation of the system. With respect to the initial problem, these two failure types are not crucial to the finding of components significantly affecting system availability as the system can be operated even though these failures occur.

The investigation also found that the delay data captures small failures that are not always recorded in work-orders. As an example, occasionally there are failure events that can be repaired with limited resources and requiring little time. It may not be feasible in this case to carry out the exhaustive work-order recording process when conducting such simple maintenance. Accordingly, these events are not recorded in the CMMS. However, the semi-automatic recording of events in the production time-delay accounting systems mean that even small failures are captured in the data. Another example is the occurrence of capacity reducing events that do not always result in a recorded breakdown work-order. There are events contained in the delay data where a failure may not be evident, however, a constraint is placed on the circuit resulting in a reduction in the system capacity. It can be argued that these events are irrelevant as they are not always considered to be failures, however, in respect to the initial problem, the occurrence of these events does restrict supply through the circuit and in a sense is an unscheduled loss. These two failure type examples should therefore be considered (and have been considered) under the initial problem.

This project ran concurrently with a number of continuous improvement projects. These projects invested resources with the aim of eliminating several defects constraining supply and reducing asset availability. As the data was extracted over a 12-month period some previously identified and eliminated defects were still evident in the statistics. Trend analysis on a month-by-month basis was able to identify eliminated failure defects, allowing the model to focus on current issues and not historical events.

One of the main limitations on model accuracy is the quality of the data used to identify the failure modes and construct the failure and repair distributions used in the model. Production time-delay accounting utilises a coding system where technicians record an event and various other details against a cause location code. Some the issues observed include:

- The grouping of multiple failure modes – The delay accounting data can sometimes contain failures that are combined under a higher-level failure mode. For example, a sensor failure, a harness failure or a gauge failure can all be classed as instrument faults but are sometimes found combined into one failure mode. Once grouped, it is hard to expand the data for the purposes of analysis.

- Incorrect code, failure or information entry – In some cases the event code is recorded against the wrong equipment. This may be a result of incorrect failure diagnosis or human error in communication and data entry. This is hard to identify and manage and frequently occurs in manual data entry systems.

- Issues in technical translation between maintainers and technicians – Maintainers enter description of the work done to repair the equipment and an assessment of why the unit failed into the work-order system, this occurs after their investigation and work is complete. Production technicians and operators enter why the think the unit failed at the time of failure into the time-delay accounting often before opportunity for a detailed investigation is complete. The variation in timing of the data entry to the two different systems, the different perspectives and expertise of the two groups and the difference in motivation for the data collection all contribute to challenges in aligning information from the two systems.

- Failure to enter information altogether – The delay accounting system captures events and event details, entered by technicians. Sometimes this data is not recorded or the information not saved or finalised. This occurrence results in events being ignored in the RDAM as there are no way of knowing which classification they operate under without extensive investigation. In this case study only 0.3% of data entries that have no information recorded against them.

The effect of excluding scheduled maintenance from the model was considered relatively early in the RDAM development. In order to create a rapid model and in solving of the initial problem, we assumed that planned maintenance only indirectly affects system availability due to unscheduled losses. As a result, the effect on the model outcomes is negligible as we are primarily concerned with identifying critical items whose failure impacts system availability. The system itself has parallel circuits and in practice, scheduled preventative maintenance activities do not contribute to loss of system. Nevertheless, the scheduled maintenance data can easily be included into the model if required.

This research has shown how the use of a validated RDAM is valuable in aiding solutions to maintenance problems and aid in day-to-day decision-making. Based on using time-delay accounting data we observe that the RDAM process is appropriate for use in availability modelling to support maintenance actions. It allows for identification of the failures which most impact on the system using a repeatable and efficient method.
6 RECOMMENDATIONS

In order for the RDAM to be successful, the process includes two main assumptions; specifically the Repeat Event Assumption and the Data Decision Criterion. These assumptions are necessary to create a model representing the actual flow of product through the circuit and reflect a more realistic number of system failures. These assumptions have implications on model accuracy by:

- Increasing the TDT associated with each failure mode.
- Decreasing the total recorded number of failure events.
- Excluding approximately 10% of unscheduled loss records.

With the aim of reducing the required model resources, the Data Decision Criterion also results in the disregard of 175 failure modes. These events are not significant (approximately 10% of total unscheduled loss duration) in the context of the initial problem and therefore not required for the solution formulation. The following categories exhibit the three types of failure modes ignored in the modelling process:

- Events considered insignificant in TDT.
- One-off failures events.
- Events not affecting system reliability (i.e. emergency safety stops).

One of the most significant issues established in process development stages was the combination of multiple failure modes into one event code description. This increases the difficulty in expanding the data to its component failure modes for use in the simulation. A review of event codes can potentially reduced the time and resource requirements for future models.

The timely development and standardisation of the RDAM method means that accuracy is sacrificed for rapidity and repeatability. Future work should focus on the trade-offs between the process standardisation, timely development and model accuracy and to what level accuracy, in particular, affects the RDAM process, its assumptions and the removal of scheduled maintenance from the model.

7 CONCLUSIONS

Availability models are widely used in the design stage of the asset/system life cycle to improve asset reliability. This paper demonstrates that availability models can also be used (1) with existing asset system to prioritise resources for asset improvement programs, and (2) as an aid in business case development by providing tangible data and results concerning system availability and exploring what-if scenarios.

However, the use of availability models is often unpopular among on-site reliability personnel as a day-to-day maintenance decision tool as they are time and resource demanding to develop and maintain. An alternative to the traditionally time consuming process is desired of model development. Previous research concludes that the resource-demanding component of traditional availability models evolves from the use of work-order data. In general the work order data in CMMS systems is not fit for purpose for efficient construction and validation of availability models due to data quality issues two alternatives are suggested to promote more rapid model development:

- Culture and process changes to improve work-order data quality.
- Identification and use of an alternative set of data that is more reliable and of higher quality.

Option two is explored here and results in the development of the RDAM.

The use of production time-delay accounting data is becoming more common particularly in the mining industry. Its use in combination with, but predominantly in lieu of, work-order statistics provides an alternative data source for use in availability models. The use of work order data in traditional methods is time consuming due to data quality issues; time-delay accounting data is more efficient due to the reduction in cleansing required. The delay data is typically of comparatively higher quality than work-order data as it is frequently used as a base for site-to-site metrics and comparisons. This means that it is audited (by management) on a regular basis.

The RDAM framework demonstrates a process for the rapid development of availability models using production time-delay accounting data. The resulting model is valuable in identifying priority areas for improvement projects for the asset management team. Traditionally, availability models are used in the design and development stages, however, this process demonstrates how availability models can be built to support in-service maintenance decisions.

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