USING THE DECISION MODEL DEVELOPMENT PROCESS TO ASSIST IN KNOWLEDGE MANAGEMENT

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Summary:
The process of developing, constructing and validating decision support models to assist in maintenance-related decisions for industry partners is examined from a knowledge management perspective. This paper will illustrate, using cases studies, how selected elements of the knowledge management process are involved in the construction and validating of maintenance decision-support models. The case studies include models based on (1) Monte Carlo simulation and (2) Bayesian Belief Network. The potential benefits in ensuring a common understanding of the value of the modeling process are described.

Keywords: Asset Management, Knowledge, Maintenance, Reliability, Model development

1 INTRODUCTION

Developing effective Knowledge Management systems is emerging as a vital component in Engineering Asset Management. As organisations move towards making asset-oriented decisions that are holistic, systematic, systemic, risk-based, optimal and sustainable [1], the importance of having the right information is paramount. Establishing KM systems for asset operational and maintenance is challenging due to the tacit nature of this knowledge, social and cognitive constraints to its capture, and challenges in representing the knowledge in an effective and practical manner to facilitate knowledge use and transfer.

The case studies presented in this paper represent examples from a number of reliability modelling projects supported by Western Australian organisations in the last five years. These models have primarily, though not exclusively, been developed as part of final year honours projects in the School of Mechanical Engineering at the University of Western Australia. During the honours year the student works with a client company to develop a model to address a particular asset management problem or question. In reflecting on the progress of the project with this student body, some core themes have emerged around the subjects of knowledge management and data quality. This paper explores these themes in the context of current issues and challenges in both the knowledge and engineering asset management fields. It also seeks to promote recognition of the dual values of model construction. The primary value driver is the value derived from the use of the model for its intended purpose. The second value driver is the role of the model development process as a knowledge enabler for the organisation. This role has not been explicitly defined or explored in the literature and is, the author observes, largely unrecognised by management professionals.

2 LITERATURE REVIEW

What is knowledge management?

Providing a definition for Knowledge Management (KM) is a challenge because there are almost as many definitions as books on the subject. "*Knowledge is neither data nor information, though it is related to both, and the differences between these terms are often a matter of degree*" [2]. Data are discrete, objective facts about events, which by themselves have little relevance or purpose. Information is data endowed with relevance and purpose , and knowledge is the assimilation of information and an understanding of how to use it. Organisational success and failure can often depend on knowing which of them you need, which you have, and what you can and can't do with each [2]. For the purposes of this paper, definitions from the recent Australian Standard AS 5037 – 2005 are used. This defines KM as "*a trans-disciplinary approach to improving organisational outcomes through maximising the use of knowledge*" [3]. In everyday language we can interpret this to mean knowing the who, what, why, when, where and how, and harnessing these for competitive advantage.

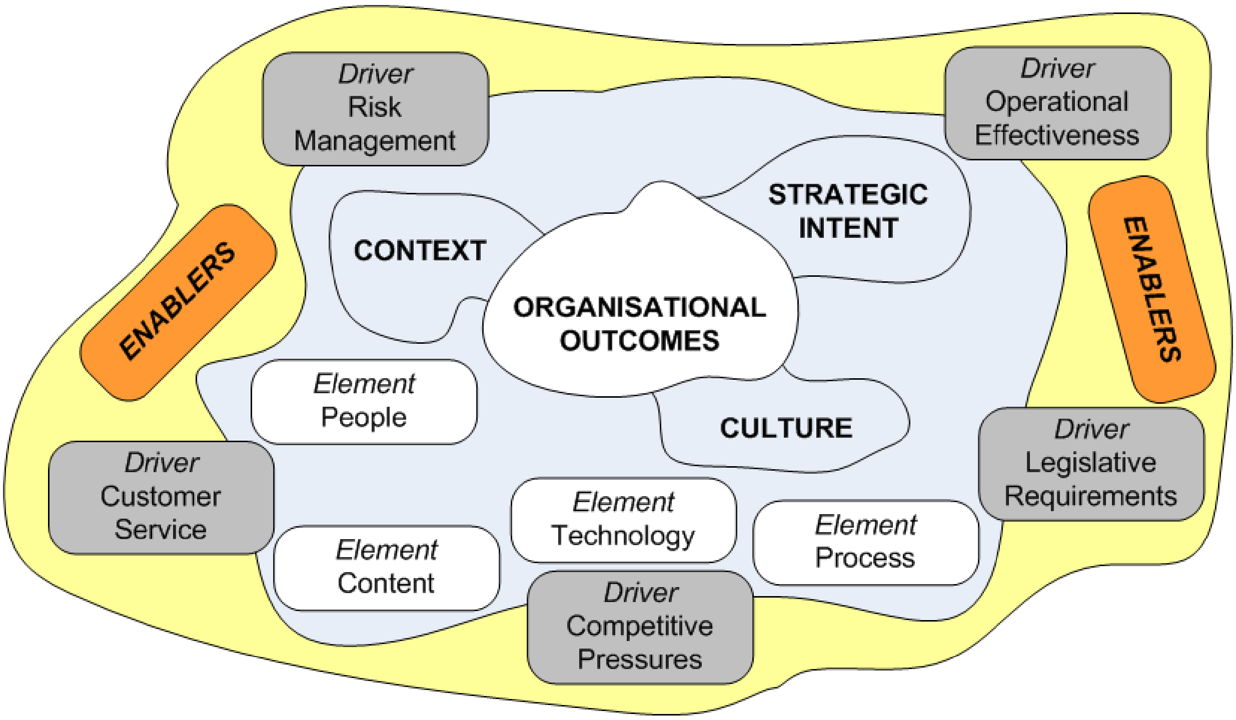

Figure 1: The Knowledge Ecosystem (AS 5037 2005)

Two core features in AS 5037 – 2005 Standard are the concept of a 'Knowledge Ecosystem' and the use of 'Knowledge Enablers' to facilitate a Map-Build-Operationalise cycle for knowledge interventions. The Knowledge Ecosystem is shown in Figure 1. The figure has organisational outcomes at its core, which are influenced by strategic the intent, culture and context of the organisation in which it operates. Around this, the Standard identifies a number of Knowledge Enablers. These are defined as "specific tools, techniques and activities through which knowledge management is implemented in an operational environment" [3].

The Standard identifies a wide range of knowledge enablers including After-action reviews and Critical Incident techniques, Business Process mapping, Content and Document Management systems, Communities of Practice, Auditing, Mentoring and Coaching. Table 1 shows a complete list. Of specific interest to this paper is the absence of any mention in AS 5037-2005 of the Model Development process as a Knowledge Enabler.

Table 1: Enablers - tools, techniques and activities used to implement KM (AS 5037, 2005)

After action reviews	Knowledge auditing	Play theory
Business process mapping	Knowledge literacy	Reflection and recognition
Champions and advocates	Knowledge mapping	Social network analysis
Change management	Leadership	Storytelling
Content management	Learning and development	Strategic conversations
Communities of interest	Leveraging information repositories	Taxonomies and thesauri
Communities of practice	Meetings and 'share fairs'	Technological integration
Critical incident technique	Mentoring and coaching	Technologies for communisation and knowledge sharing
Document management	Narrative management	Technologies for discovery and creation
Environmental scanning	Networks and communities	Technologies for managing repositories
Information auditing	Physical environment (work space)	

Although Knowledge Management is sometimes equated with Information Management and the IT function, a quick look at the Table 1 shows that only a small sub-set of enablers are concerned with documentation and information management. McDermott observed that "*information technology cannot deliver knowledge management because human relationships are needed to share knowledge that is neither obvious nor easy to document*" [4]. This statement is supported by the number of socially oriented processes such as networks and communities of practice identified in Table 1. This factor is particularly prevalent amongst those involved in the operation and maintenance of assets. The author observes that despite the prevalence of computerised maintenance management systems, there is still a prevailing sense amongst practitioners that timely, accurate and relevant information is more likely to come from members of the practitioner community rather than from an IT system.

Does previous work in the literature explicitly identify the model building process as a knowledge enabler? Agosta observes that the process of building a diagnostic model based on a Bayesian Belief network, involving capture of expert knowledge and then the coding of the knowledge to support diagnostic inference, was the basis of a "knowledge engineering tool" [5]. Davenport [2] acknowledges that modelling can help managers understand and improve specific operations when rules, entitites and routines are stable. However he notes that "*there is still much to discover about the value of its application to knowledge centred operations*".

In reviewing the literature on KM the following themes appear across publications. These are listed below and examined in the context of the case studies later in the paper.

- Organisations are well equipped to access data but "*all too rarely is that data sifted into the sort of knowledge that can inform business decisions and create positive results*" [2]
- Informal channels become the defacto KM system when formal systems have proved inadequate. The inefficiency of the formal database system results in adoption of a "hunting and gathering" approach to information and knowledge sourcing, relying on personal networks developed through previous projects or social interaction [6]
- Managers face difficulties not in accessing knowledge, but in utilising knowledge in decision making [7].
- The use of knowledge and information generates a more thorough analysis of the options, creates consensus, creates new ideas and insights to the problem [6]
- KM systems that facilitate the actions of development, sharing and utilisation in combination, contribute to greater innovative output, either in terms of new products or services or operational performance [6]
- "Know-what" (where to find the information) and "know-how" (how to run operations smoothly) are considered key components of organisational knowledge in the process of manufacturing (and asset management) strategy formulation [8].
- Organisational knowledge is created or improved through cross functional interaction [8]

Why is Knowledge Management important?

The effective management of knowledge contributes to organisational performance through a reduction in risk and uncertainties [9], and use of the knowledge for competitive advantage [8]. The open sharing of information and knowledge with colleagues both inside and across departmental boundaries is a distinguishing factor in High Reliability Organisations [10]. The trend towards leaner organisations has also contributed to heightened interest in knowledge, on the principle that you only understand the value of something when it is gone [2].

Discussions with asset managers about Knowledge Management often lead directly to a conversation related to the training, retention and retirement of experienced maintenance practitioners and engineers. Often it is only through the absence of the supervisor, engineer or maintenance planner that we realise the knowledge coordination and synthesising role that they played went well beyond what their official job descriptions suggest [2]. This is particularly acute in Western Australia, which has been in the grip of a resource-driven boom since the early 2000s resulting in a scarcity of qualified and experienced technical people. We also face a looming knowledge crunch as many experienced personnel in our workforce approach retirement.

Focussing question

In an effort to assist with the process of knowledge management in engineering asset management, this work examines the potential of the decision support modelling process to assist in capturing, storing and using asset and maintenance related knowledge. The focussing question for this paper is "*can we demonstrate through the use of case studies that building models to address maintenance decisions is a knowledge enabling process?*"

3 CASE STUDIES

The case studies described in this section involve the development of models to support decision making for engineering asset systems. Case A describes an Availability model for a Waste Water treatment Plant, and Case B a Baysian Belief Model for a Cooling Tower. In both cases the aim of building the model is to address a specific set of questions relating to the identification of improvement opportunities (Case A) and risk management (Case B).

Both models involve three inputs, (1) Problem Statement, (2) Modeller's expertise and (3) System data [11]. The outputs of the modelling process are inputs for decisions and policies. This is shown schematically in Figure 2.

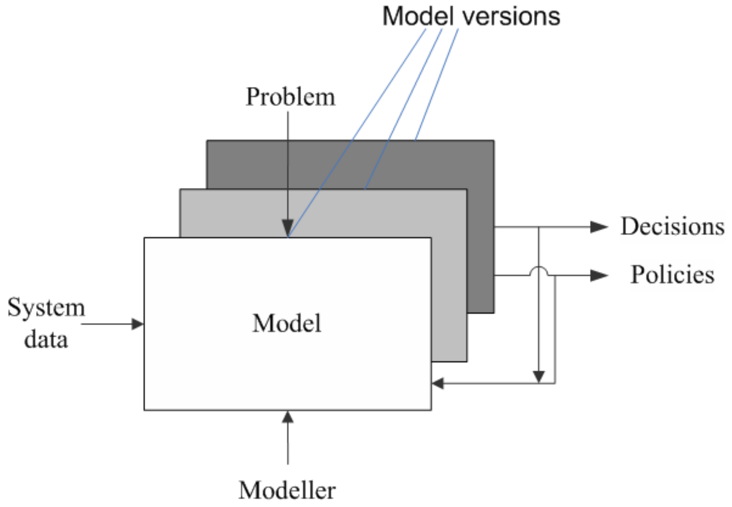

Figure 2: Conceptual modelling process (from Pritsker, 1998)

The three main steps in the Knowledge Management process identified in AS 5037 [3] are:.

- Map
- Build (Store and Share knowledge)
- Operationalise

In the case studies, we will explore how the activities involved in the model construction process fit into these Knowledge Management steps.

Case Study 1: Availability Model

The availability model was constructed to assist in identifying bottlenecks and assess risks to system failure for a waste water treatment plant. The plant is a complex configuration of mechanical, electrical and civil structures. A simulation modelling approach was selected as it is an appropriate tool to study the behaviour of complex, stochastic systems that cannot be described by mathematical models that allow for analytical solutions [12]. This modelling process involves the development of reliability block diagrams and use of Monte Carlo simulation tools.

The main steps in the modelling process are described by the Map-Build-Operationalise Blocks in Figure 3. The diagram was created by combining the actual steps taken in the model development process as recorded by the modeller with the steps identified in the interim and current Knowledge Management Standards [3, 13]

This was a large modelling project consisting initially of 186 essential components and 17 buffer blocks. These were arranged in a variety of series and parallel arrangements assisted by the commercial software program Avsim©. Information for layout and configuration part of the model was drawn from interviews with Plant Operations personnel and access to drawings and documentation in the organisation's technical library [14].

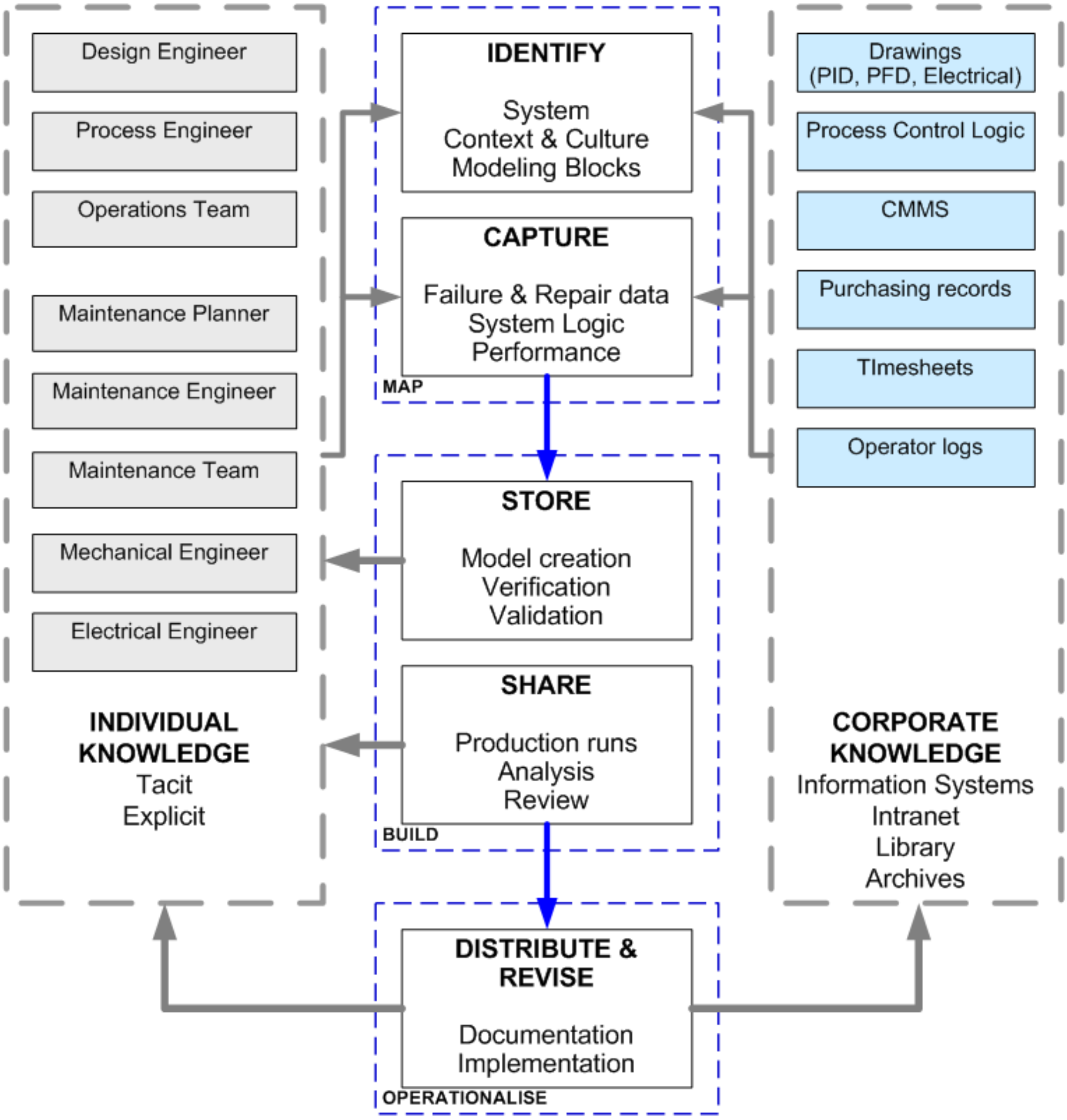

Figure 3 Knowledge management view of the availability model construction process

In order to populate the reliability blocks with information relating to the failure and repair intervals for 186 components in the model and 5 years of operation, thousands of work orders were reviewed. Failure data was collected primarily from work orders in the Computerised Maintenance Management System (CMMS). Work orders are recorded in the system when any work is completed on a component. This information is used to determine the time between each failure and the cause of failure. Cleansing and filtering of the work order data took significant time. Each work order has the potential to record the failure item, failure type and cause of failure. However, it is our experience that these parameters are rarely recorded in full, using a fit-for-purpose coding system [15]. Often equipment failures have to be inferred from the job description and comments recorded by the maintenance personnel in a text field. It is also necessary to validate the final data set with someone familiar with the equipment performance, usually the maintenance engineer or planner to check that the metrics calculated from the data set are realistic.

Ideally repair data can be acquired from labour records and time sheets. However, due to inconsistencies in time sheets, data were obtained through interviews with the Planner who was able to provide estimates for the mean time to repair (MTTR). These times assumed there is no logistics downtime, due to tools and spare parts not being available. Other information obtained from the Planner, Technicians and CMMS included (1) preventative maintenance tasks and schedule, (2) mean inspection task time and interval.

The knowledge management aspects of this work extended beyond just collecting information from the individual and organisational sources but also, communication with the individuals after the model was constructed and run. This is vital to ensure that the output of the model, when tested for specific well-understood events, conforms to the actual experience of the plant personnel. In the case of this model, the predicted system availability was lower than the expected values. This result prompted a review of the model inputs and design. Two main contributors were identified. The first relates to the “culture” of the organisation, where culture can be broadly described as “the way we do things around here”. In practice there are a large number of possible bypasses and storage combinations that are used to avoid system downtime. It is not practical or useful to model all these permutations. From a practical point of view, the model was able to identify the bottlenecks and relative contributions of the critical units to the system availability.

The second issue influencing the calculated availability was that many of the MTTF values for the equipment were lower than the values expected. There were no existing values for comparison as this was the first time that MTTF values had been calculated. A number of possible reasons for these low MTTF values include the absence of suspension in the equipment. Suspensions occur when equipment is removed from operation prior to failure and accounting for suspensions generally increases the MTTF. There was no documentation to generate suspension data; so failure data sets were based on recorded failures only. The modelling process identified that this “gap” in data collection existed and also provides an example of how the absence of this data contributed to uncertainty in the model. A number of actions were initiated by the model owner to rectify this and other data collection issues identified in the model selection process.

Case Study 2: Risk assessment and Bayesian Belief Network Model

The case involved the development of a Bayesian Belief Network (BBN) model to assess the impact of changes in maintenance tactics on risks and associated costs for managing a cooling water system. One of the rationales for this project is the recognition that judgement and experience play a significant part in decisions made by maintenance managers. If the research community is going to make effective and useful decision support tools for maintenance then it is going to have to recognise and deal with quantitative and qualitative factors and uncertainty and used intuitively by experienced personnel. The BBN approach is particularly relevant to models relying on maintenance input because the information often exists in an unstructured and informal way in equipment and other logs and systems. Typically, it is difficult to relate the information available for the equipment to subsequent events. Examples of BBN models in the maintenance area include diagnostics [5], predicting parts demand [16], failure detection systems [17] and root cause analysis [18] [19]. They are also of growing interest to the reliability community [20].

BBNs consist of nodes representing random variables connected by arcs that quantify a causal (cause-effect) relationship between the nodes. A simple example is given in Figure 4. Causal relationships are represented by conditional probabilities, encoded in the distributions associate with each node, to capture the strength of the relationship [5].

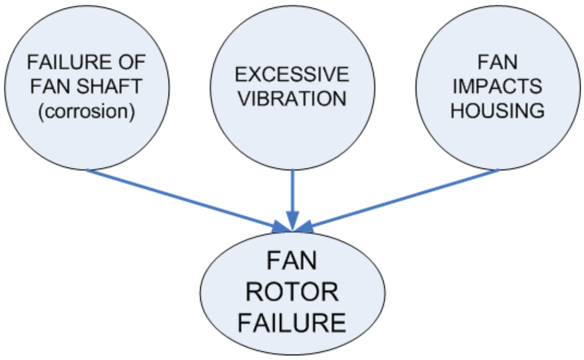

Figure 4: Simple Bayesian Belief Network (from Holborn 2007)

The Bayesian approach offers an intuitive way to develop models based on the combination of statistical data and domain experts [20]. In the Cooling tower BBN model, the model development process described by Langseth [20] was followed consisting of five basic steps,

- Decide what to model and define the variables,
- Define the graphical structure for the network with associated dependencies (qualitative part),
- Select distribution families for each variable (node) and fix parameters to specify the distributions (quantitative part),
- Verify through observation of model behaviour for known scenarios and sensitivity analysis, and
- Refine model and create documentation.

The actual process of completing these steps was far more involved as it required input from a number of people in the facilities management team, contractors, and access to log books, paper based records and the computerised maintenance management system [21]. The model was built using the AgenaRisk© Bayesian network software.

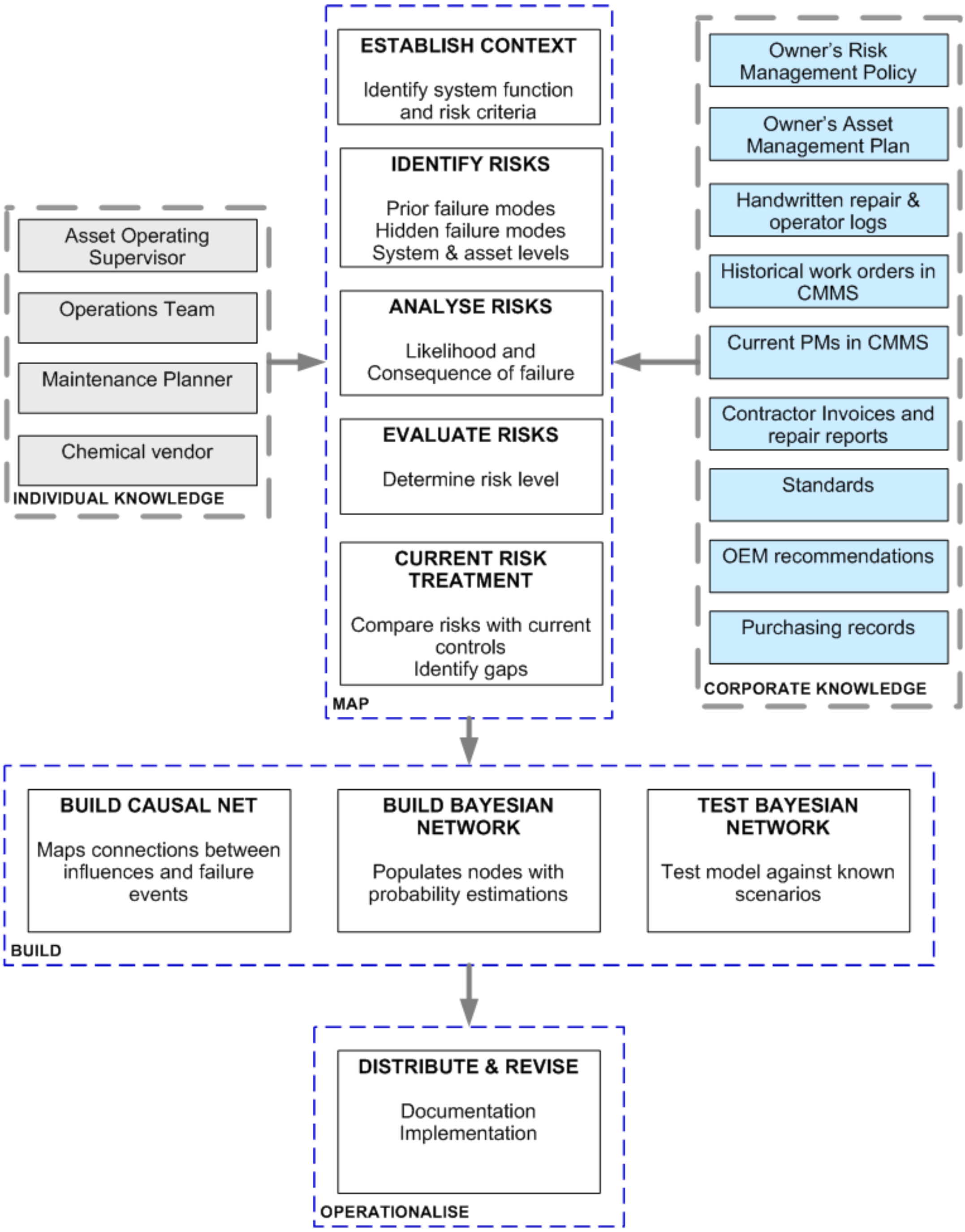

Figure 5 Knowledge management view of the Bayesian Belief Network construction process

There were three phases in this project,

(1) Risk assessment, this can be considered the Knowledge Mapping phase,

(2) Bayesian Belief Network model construction and validation, regarded here as the Knowledge Building phase, and

(3) Documentation and distribution to stakeholders, or Operationalise phase.

These phases are shown in the Map, Build, and Operationalise Blocks in Figure 5.

The first step in the Risk Assessment process illustrates the knowledge acquisition process. Initially, the project had to establish criteria to evaluate the risks following Australian Standard AS 4360 [22]. These criteria should reflect the organisation's internal policies, goals and objectives and the interests of its stakeholders. In this model the criteria are financial, health and safety and downtime (or loss of system availability) [21]. One of the primary aims of the University's Risk Management Policy [23] is to protect the health of all staff, students and visitors. Health and Safety is therefore an important criterion against which to assess cooling tower risks. A major issue for the operation of cooling towers is the risk of Legionella infection. The financial cost of the Facility is relevant to the Plant Management because the minimisation of repair and replacement costs is a key value driver. The primary goal of the Owner's Capital Asset Management Plan [24] is to 'optimise the efficient and effective use of the funds'. Asset downtime is also an important criterion as it affects plant availability to supply cooling water for a number of critical applications, including the Campus Data Centre, which houses the main university computer servers.

The initial part of the Knowledge Mapping phase is the construction of a Causal Net (CN). The modeller observed that the CN has inherent Knowledge Share value because end users can quickly understand the system's process, the interrelationships between failure modes and the factors affecting its operation. The process of building the CN, and the CN itself, improves knowledge about the system in two ways:

(1)The CN shows that some risk events can cause, or increase the probability of other risk events. For example: motor failure, fan failure, drive system failure and insufficient cooling were initially considered mutually exclusive events. The CN reveals that drive system failure, motor failure and fan failure all result in 'insufficient induced air flow'. The 'insufficient induced air flow' node was subsequently added as a cause of the insufficient cooling event. These events are recorded separately on the risk matrix as they have different failure modes associated with them. However, the CN demonstrates the interrelationships between failure modes and risk events.

(2)The CN identified that some failure modes result in multiple risk events. For example, accumulation of debris in the strainer can result in a low flow trip and/or splash-out/overflow. While we can duplicate the failure mode in the risk matrix, the CN graphical display explicitly demonstrates this relationship.

Further details of the BBN model construction process are available in [21]. Through this modelling process the stakeholders gain knowledge about the Cooling water system (1) in the form of documentation on the risks and current controls, and (2) through the BBN model. The model expresses the complex web of relationships between cause and effect and is used to evaluate changes in maintenance tactics on the cost, safety, and availability risks to the system.

The value of the BBN technique in this example is its ability to organise and allow manipulation of an expert's knowledge. Capturing the expert's knowledge in this form, quantitatively (BNN) and qualitatively (CN), has value for other stakeholders and new personnel who do not have equivalent expertise.

4 DISCUSSION

The previous section described two case studies on the construction of models to assist in asset management decision making. The model construction process is described through a Knowledge Management lens, mapping each development stage into the Map-Build-Operationalise phases described in AS 5037 [3].

Inputs to the modelling process are shown inside the boxes on the left and right sides of the process maps in Figures 3 and 5. The boxes identify the sources of knowledge and can be described as a 'Knowledge Map'. Developing a Knowledge Map involves locating knowledge in the organisation and showing where to find it [2]. The content of the maps in these figures demonstrate that in seeking information for the model, the modeller had to cross departmental boundaries and reporting structures to get what was needed. We found that expertise is not reflected in titles and job descriptions. The sources of knowledge identified in these boxes are further classified as either coming from 'Individual Knowledge' or 'Corporate Knowledge' according to the description provided by Debowski [25]. As can be seen from Figure 6, both individual and corporate inputs contribute to Organisational Knowledge.

This paper has demonstrated, through the use of case studies, that the collection and collation of knowledge through the modelling process can be considered a knowledge enabling process. The model also provides a mechanism to store and distribute the assembled knowledge for the benefit of improved decision making.

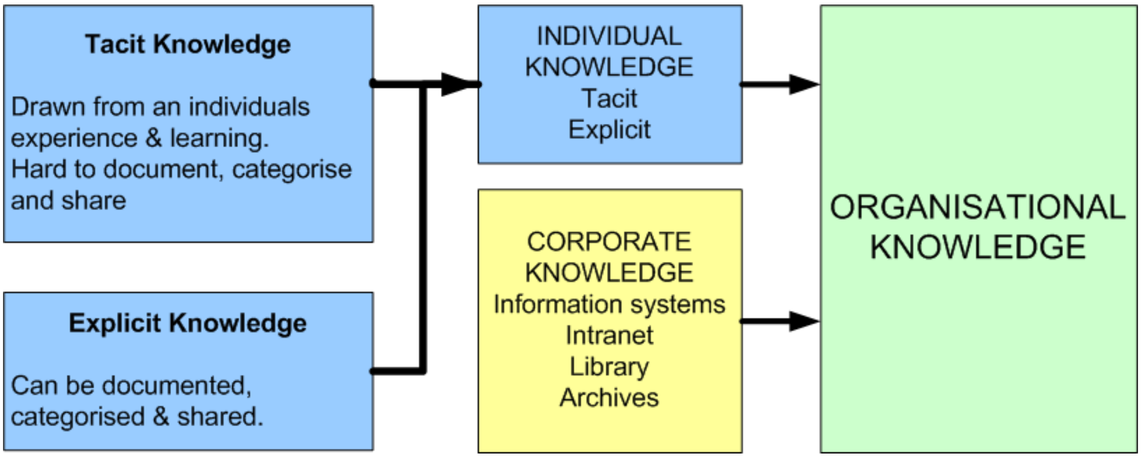

Figure 6 Sources of organisational learning (from Debowski, 2006)

In the course of these Case Studies the outcomes listed below contribute to improving evidence-based decision-making.

- Identify a set of failure modes for selected assets
- Develop a baseline set of failure and repair metrics (Case 1) and likelihood and consequence values (Case 2)
- Identify opportunities to improve codification of data
- Create impetus to improve collection of failure and repair data and direction as to what needs collect and why.
- Capture knowledge and experience of operational and maintenance personnel
- Identify constraints and failure event or situational combinations that can result in enhanced risk exposure
- Establish a Common view for storing future event data
- Create communication links between different groups involved in management of the asset
- Create a common view of the plant's operation and risks
- Improve communication with senior management, particularly with the Causal Net in Case 2.

These benefits also enhance the Knowledge Management process, through the creation, capture, codification, storage and distribution of knowledge about the assets to stakeholders involved in decision-making.

The issue of knowledge capture is particularly important in both of these Cases as many of the 'expert' personnel involved in the projects are in their late 50s. When they eventually retire, their experience and knowledge also leaves, leaving new personnel with no understanding or reasoning behind decisions made on the plant. These types of models assist in training new personnel and in allowing less experienced personnel to gain a view of the complexity of the system and the decision process.

Making decisions regarding assets is a multi-faceted and complex process. Senior managers who do not have direct asset maintenance or operational experience do not always appreciate this. It is not uncommon to observe that simple answers are sought to complex problems and uncertainties are dealt with by pretending they don't exist [2]. The managers that supported the construction of these models understood that the process would lead to a "knowing more" situation but was also likely to dispel some of the clarity and certainty of the simplified views held about the process.

What are some of the drawbacks or challenges with the project? The first is the time and personnel costs to develop the model and second the challenges of keeping the model updated so that it can continue to support decisions as circumstances change. Depending on the degree of asset management maturity in the organisation, the costs of building these models can be high in terms of manhours and capability to collect and process the data required for model construction and validation. We estimate that over 80% of the time spent on both models was taken up with collection and cleansing of failure and repair data. However, the process of doing this for the first time has identified gaps in data systems and created some impetus for change, through an appreciation of the value of improved decisions and a desire to have greater confidence in the outputs. The data challenges also affect the issue of keeping the models up to date. We suspect that this will be dependent on the perceived value of the model to both the users and their managers. The processes to collect, cleanse and update data take time to establish. Until the burden of acquiring relevant cleansed data is reduced, we see limited life for these types of models for routine decision support. Fortunately, we observe that moves are underway in a number of organisations to improve the quality of the data necessary to construct and validate these models.

How do we determine the value of the knowledge captured and stored in the cases described above? Perhaps we can do as the Quality Movement does and focus on calculating the costs when it is absent. What makes knowledge valuable to organisations is ultimately the ability to make better decisions. The value of the Knowledge Management process is the cost of sub-optimal decisions. The barriers to trying to quantify this are significant. Very few organisations have the processes and culture to support post-decision reviews. However, there are encouraging signs that this is beginning to change [26] [27].

There is much more to be done to encourage a comfort level amongst asset management personnel regarding the use of these types of practical decision support models. For those who wish to pursue the development of models to assist with maintenance decision making, a number of examples of maintenance models are described by [28]. We hope that the cases presented here encourage people with maintenance modelling skills and interests to work with maintenance engineers and managers on real problems. Such collaboration is essential if maintenance modelling is to be accepted within the engineering community [28].

5 CONCLUSIONS

The focussing question for this work is "*can we demonstrate through the use of case studies that building models to address maintenance decisions is a knowledge enabling process?*" The Map-Build-Operationalise steps from the Knowledge management Standard AS 5037 are mapped onto the maintenance model development process. The case studies presented in this paper demonstrate that the development of specific models to support decision making in maintenance is a Knowledge Enabling process.

Paul Romer described knowledge as "*the only unlimited resource, the one asset that grows with use*"[29]. We hope that a greater appreciation of the dual benefits of the model building process results in increased impetus to build models. These benefits are the value from improved decisions and the value in the model building process as a knowledge enabler.

6 ACKNOWLEDGEMENTS

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