GMU-AM-18-224

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Developing an Analytic Model of Success for Acquisition Decision Making

14 August 2018

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The research presented in this report was supported by the Acquisition Research Program of the Graduate School of Business & Public Policy at the Naval Postgraduate School.

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Abstract

Developing an Information Technology (IT) system to meet organizational needs is becoming more complicated. It is often very extensive, taking a long time to realize, and is almost always more costly and more difficult than originally planned. This is especially true for large IT projects. A significant amount of data and large numbers of artifacts these large IT programs produce make it extremely challenging to digest in order to support their decision making. The most challenging issue is that there is often an abundance of data, but limited analytical tools to properly combine the evidence to support the business decisions. To help with this complexity, many businesses use the Information Technology Infrastructure Library (ITIL) to guide the design, procurement, and operation of their IT systems. The ITIL is intended to optimally synchronize IT departments to function in accordance with the needs of business. However, even though the ITIL process helps standardize the IT service management, it is itself a complicated and involved system that may seem confusing and difficult to navigate.

To address these challenging issues, this research aims to provide IT program managers a decision support tool in order to help them make better business management decisions. The technical approach of the research began with literature review and gathering results from past research, including the Defense Business Systems Acquisition Probability of Success (DAPS) Model, a technical framework developed at GMU. DAPS was employed and enhanced into the Information Technology Decision Management System (ITDMS), an analytic decision support system with an automatic quantitative reasoning engine. The key difference between DAPS and ITDMS is the explicit incorporation of the utility and decision factors in the Bayesian influence diagram model as well as the incorporation of the ITIL process. The goal is to help systems engineers and program managers holistically process the available data/evidence in order to make better management decisions in a dynamic and complex environment. The ITDMS models the complex interrelationships as well as dynamic/temporal relationships in the ITIL process. It allows a decision maker to assess program performance in specific subject matter knowledge areas and the overall likelihood of program success by taking into account both data and temporal uncertainty.

This research aims to develop a useful decision support tool to help the IT professional, specifically in a data-rich dynamic environment. The contributions of this research effort include developing a quantitative reasoning system to aid IT professionals holistically process the available evidence to make optimal business decision as well as an analytical tool to compute the resulting predicted future project probability of success with a Bayesian dynamic model.

Key Words: Dynamic Bayesian networks, influence diagram, Information Technology Infrastructure Library, Analytic decision support system, Program performance assessment.

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Introduction

Information Technology System development and management came to the forefront of U.S. federal government in 1996 when the Clinger-Cohen Act was signed into federal law, mandating oversight and management of Information Technology. The issues were that many of the Enterprise Resource Planning (ERP) Defense Business System (DBS) acquisition programs were too big, too complex, and took too long to complete [1]. It's clear that developing an Information Technology (IT) system to meet organizational needs is not a simple task. It is often very extensive, taking a long time to realize, and is almost always more costly and more difficult than originally imagined. This is especially true for large IT projects. It was reported that on average (based on 5400 IT projects), large IT projects run 45 percent over budget, 7 percent over time, and delivered with 56 percent less value [2]. A Government Accountability Office (GAO) report also indicates that of 10 Enterprise Resource Planning (ERP) programs Department of Defense (DoD) identified as critical to business operations transformation, 9 program are experiencing schedule delays up to six years, and 7 programs are facing estimated cost increases up to over $2 billion dollars [1]. This is occurring even though there are strict acquisition laws, regulations, policies, guidance, independent assessments, as well as technical reviews and milestone reviews to guide DBS acquisitions.

A significant amount of data and large numbers of artifacts such as Program Schedule, Earned Value Management System (EVMS) Metrics, Business Case, and Systems Engineering Plan are generated during execution of DBS programs. These data/artifacts are commonly used by decision makers at technical reviews and milestone reviews as evidence of program progress to support their acquisition decisions. However, the evidence by itself is by nature incomplete, ambiguous, unreliable, and often conflicting [3-4], making integration of the evidence to finalize decisions a challenging endeavor. Procurement and acquisition professionals including systems engineers and program managers constantly have to deal with the stress of managing the budget, deliverables, and system quality while trying to meet internal or external regulatory requirements.

The most challenging issue is that there is often an abundance of data/evidence, but limited analytical tools to figure out what all the evidence means collectively, and how they support the hypothesis being sought. Good decision-making requires not only information and evidence, but also the inference and representation of the evidence to support decision making. There are currently limited means to aid DBS acquisition decision makers holistically and logically process all the available evidence efficiently and limited means to assimilate all evidence to identify program critical areas and the likelihood of achieving program success. This problem is not different from what other disciplines have been experiencing in wide range of enterprises and private sectors such as social services, transportation, and health care systems.

To overcome this problem, a Probability of Program Success (PoPS) model was first developed in 2005 with a goal of identifying a program's health assessment using a scoring system [5]. While the PoPS model provides a logical framework to assess an acquisition program, the system aggregates the scores in a hierarchical manner and does not have a mechanism to model uncertainty or the complex interrelationships between key driving factors. In addition, PoPS is designed to represent a snapshot of the current status of the program; it does not factor in the past scores or how the current scores might affect the future scores. In other words, there is no built-in dynamic model in PoPS to predict the probability of failure at a later stage of the program.

To address these critical issues, a Defense Business System Acquisition Probability of Success (DAPS) was developed [6-7] to enhance the qualitative framework of PoPS with a sophisticated quantitative reasoning approach. DAPS is an expert-based model developed using probabilistic graphical models (i.e., Bayesian Networks) [8-9] to help decision makers collectively process the available evidence produced during the course of DBS acquisition. Based on observations and inferences of evidence, the DAPS model is able to assess project performance in specific subject matter knowledge areas (KAs) and assess the overall likelihood for program success.

The DAPS model framework is based on the concept of knowledge-based acquisition described by the Government Accountability Office (GAO) [10-12]. It was found that the transition to knowledge-based acquisition framework could significantly improve acquisition program performance. By using a Dynamic Bayesian network (DBN) model [13-15], DAPS constructs a complex inference network to model each subject matter knowledge area in order to assess the level of success at various knowledge checkpoints (KCs). The measurable knowledge areas include scope, cost, time, and quality, which all directly affect measures of program success. The DAPS Bayesian Network model contains a three-level structure. The topology of the top two levels – knowledge checkpoints and knowledge areas – is repeated for each of the different knowledge checkpoints, while the bottom level – the observed evidence in the DAPS model – varies at each knowledge checkpoint, depending on the evidence requirements and availability. In addition, the DAPS model contains “dynamic arc” representing the temporal relationships between nodes that allows a decision maker to assess the probability of success at future knowledge checkpoints. The predicted probability of success may provide a prognosis and potential insight to the program health in a future checkpoint.

However, DAPS was specifically designed for Defense Business System (DBS) acquisition applications to assess program success with no explicit linkage to decision maker’s subjective utility or recommended actions/decisions. This research aims to provide IT business managers a decision support tool by adopting and enhancing the DAPS integrated with the popular Information Technology Infrastructure Library (ITIL) model. The key difference between the resulting Information Technology Decision Management System (ITDMS) and DAPS is the explicit incorporation of the utility and decision factors in the Bayesian influence diagram model as well as the incorporation of the ITIL process.

The technical approach of the research began with literature review and gathering results from past research, including the DAPS Model developed at GMU. DAPS was employed and enhanced into the ITDMS with an automatic quantitative reasoning engine. The ITDMS models the complex interrelationships as well as dynamic/temporal relationships in the ITIL process. It allows a decision maker to assess program performance in each knowledge checkpoint with recommended actions and the resulting likelihood of program success by considering both evidence and temporal uncertainty.

To support good decision-making, it requires not only reliable information and evidence, but also logical representation and inference of the evidence. This research takes a program manager's perspective to build an evidential reasoning model oriented around the hypothesis of program success. The research aims to contribute a useful tool/model to help improve the decision quality of the systems engineering and IT acquisition professional, specifically in a data-rich dynamic environment. The contributions of this research effort include: 1) Development of a quantitative system to aid decision makers holistically process the available IT acquisition program data and evidence; 2) Provide recommended actions based on decision maker's perceived utility and the resulting key project success measurement in each of the management areas at a review milestone (the knowledge checkpoint); and 3) Prediction of future project success through a dynamic Bayesian model.

Background Research

Motivations and Background

Large business acquisition programs experience a great deal of complexities, difficulties, and inefficiencies. Acquisition professionals including systems engineers and project/program managers constantly try to manage the scope, cost, schedule, and system quality of a project while trying to meet statutory and regulatory acquisition requirements. However, many of the system's life cycle risks are currently assessed subjectively by imprecise qualitative methodologies and subsequently suffer from unforeseen failures as well as cost and schedule overruns. This is particular the case for Defense Business Systems (DBS) and large IT systems where many programs critical to business operation transformation are experiencing major schedule delays and/or significant cost increases [16].

To improve acquisition program performance, a knowledge-based (KB) acquisition framework has been recommended for DBS [10]. According to the GAO report [10], the KB acquisition is defined as "A knowledge-based approach to product development efforts enables developers to be reasonably certain, at critical junctures or "knowledge points" in the acquisition life cycle, that their products are more likely to meet established cost, schedule, and performance baselines and, therefore provides them with information needed to make sound investment decisions" [10]. Sufficient *knowledge* reduces the risk associated with the acquisition program and provides decision makers and program manager higher degrees of certainty to make better decisions.

The concept of the Knowledge-based acquisition is fully adapted in this research and built into the ITDMS model. With the perspective of a program manager, the goal of the research is to develop a probabilistic reasoning quantitative system using a graphical model (Bayesian Networks) to facilitate evidence-based decision making for an IT acquisition process [8-9]. The previously developed DAPS model is extended by expanding the body of domain knowledge and adapted to IT and engineered system programs in general. In particular, to align information technology services with the needs of business, the ITIL model is incorporated into the overall system.

The resulting ITDMS model could model processes, procedures, knowledge areas, and performance checklists as described by ITIL process that are not organization-specific, but can be applied by any organization to ensure delivering value and maintaining competency. It could help systems engineers, program managers, and decision makers better analyzing the available data/evidence in relation to project success, and make better decisions toward success. ITDMS can be applied to support the difficult acquisition decisions to continue projects that will be successful and discontinue projects which will not, subsequently maximize return on investment in large scale IT acquisition process.

Defining Project Success

It is generally understood that project success and project management success are related but not the same [17-19]. Defense Acquisition University (DAU) first developed Probability of Success (PS) to identify a program's health assessment with a numerical indicator [20]. The DAU Probability of Success framework is shown in Figure 1 below. This framework consisted of three levels. The top level is the Program Success indicator, the second level contains five factors include internal program factors: 1) Requirements 2) Resources, and 3) Execution, and external factors, defined as 4) Fit in Vision, and 5) Advocacy. The third level contains the metrics under each of the internal and external factors.

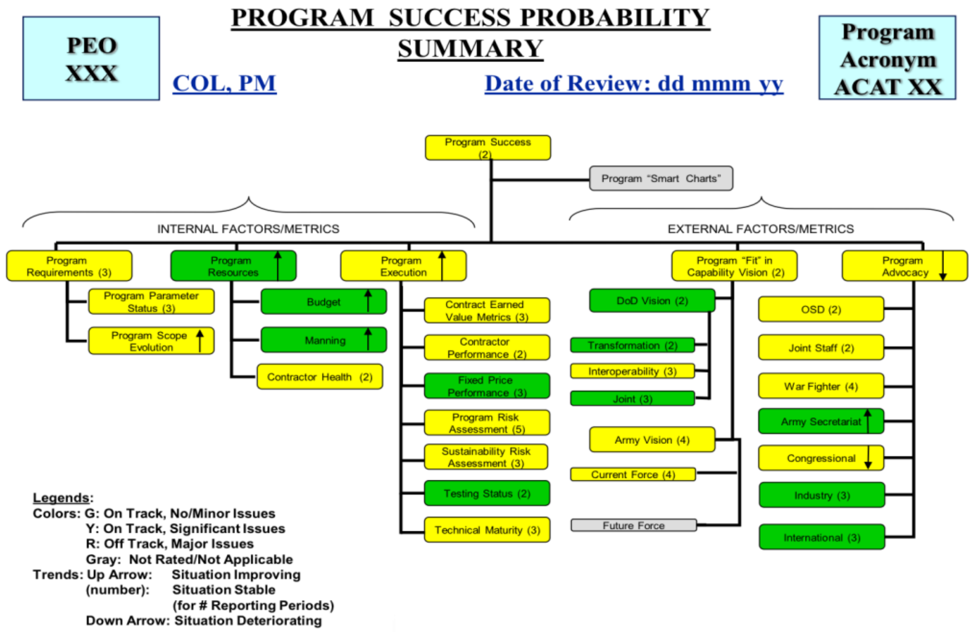

Figure 1. Probability of Success Summary [20]

DAU's PS has since been adapted by each military branch to assess the health of defense acquisition programs. A latest version of Probability of Program Success (PoPS) is the Naval Probability of Program Success Version 2.2 [5]. Figure 2 shows the Naval PoPS structure contains four levels. The top level is the Program Health indicator. The second level contains four factors: 1) Program Requirements, 2) Program Resources, 3) Program Planning/Execution, and 4) External Influencers. The third level includes the metrics under each of the four factors. The fourth and bottom level consists of the criteria assessments under each of the metrics.

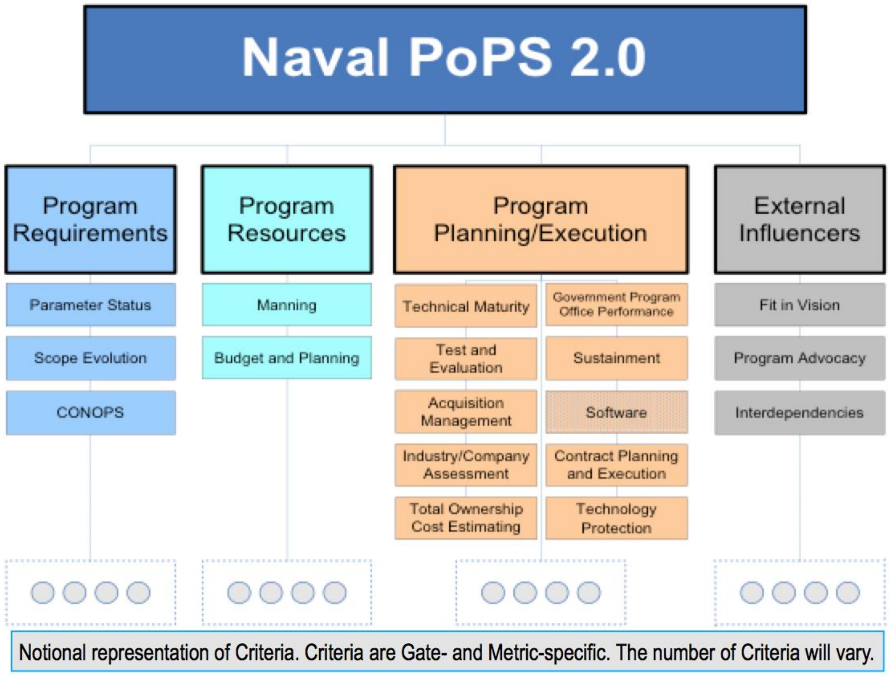

Figure 2. Naval PoPS Structure [5]

The scoring weight distribution for each factor and metric for Naval PoPS v2 are provided below in Figure 3. Scoring weights for Naval PoPS v2 evolve throughout the acquisition lifecycle.

While naval PoPS provides a sound framework to assess an acquisition program, the scoring system does not have the mechanics to model the intricate complex interrelationships between multiple metrics, neither can it factor in the temporal influence of the past scores to the future scores. In other words, there was no explicit causal model or dynamic model incorporated in the scoring system. To this end, Bayesian network provide an ideal framework to enhance the PoPS system [21-22].

FACTOR Maximum Scores	GATE 1 ICD	GATE 2 AoA	GATE 3 CDD/ CONOPS	GATE 4 SDS	GATE 5 RFP	GATE 6				
						Post IBR	Post CDR	CPD	Pre FRP DR	Sustainment
Program Requirements	31	35	36	22	14	13	13	12	12	8
Program Resources	17	17	17	20	20	16	15	14	14	25
Program Planning/Execution	25	36	43	55	62	66	67	68	68	59
External Influencers	27	12	4	3	4	5	5	6	6	8
Total Points Maximum	100	100	100	100	100	100	100	100	100	100

METRIC Maximum Scores	GATE 1 ICD	GATE 2 AoA	GATE 3 CDD/ CONOPS	GATE 4 SDS	GATE 5 RFP	GATE 6				
						Post IBR	Post CDR	CPD	Pre FRP DR	Sustainment
Parameter Status	24	19	17	14	9	9	9	9	9	8
Scope Evolution	N/A	5	8	6	4	3	3	2	2	N/A
CONOPS	7	11	11	2	1	1	1	1	1	N/A
Budget and Planning	13	13	13	14	14	10	9	9	9	13
Manning	4	4	4	6	6	6	6	5	5	12
Acquisition Management	N/A	3	6	9	9	7	6	6	6	N/A
Industry/Company Assessment	N/A	4	3	3	3	3	2	2	2	N/A
Total Ownership Cost Estimating	10	10	10	14	14	10	9	8	8	10
Test and Evaluation	2	2	3	4	6	9	9	9	9	2
Technical Maturity	6	8	8	9	9	9	9	8	8	2
Sustainment	6	5	5	5	5	5	6	7	7	16
Software	N/A	N/A	N/A	3	3	5	7	7	7	5
Contract Planning/Execution	N/A	2	4	4	9	10	10	10	10	9
Government Program Office Performance	N/A	1	3	3	3	6	6	8	8	9
Technology Protection	1	1	1	1	1	2	3	3	3	6
Fit in Vision	8	5	1	1	1	1	1	1	1	N/A
Program Advocacy	13	6	2	1	1	1	1	1	1	N/A
Interdependencies	6	1	1	1	2	3	3	4	4	8
Total Points Maximum	100	100	100	100	100	100	100	100	100	100

Figure 3. Naval PoPS v2 Factor Scores [5]

Bayesian Network and Knowledge Representation

Bayesian Network (BN) is a formal language for representing knowledge about uncertain quantities. It is based on the Bayesian approach of probability and statistics, which takes into account prior belief and uses probability inference to update belief based on observed evidence. Bayesian Networks are direct acyclic graphs that contain nodes representing hypotheses, arcs representing direct dependency relationships among hypotheses, and conditional probabilities that encode the inferential force of the dependency relationship [23].

BN is a natural representation of Causal-Influence Relationships (CIRs), the type of direct dependency relationships built in the DBS DAPS model where CIRs are relationships between an event (the cause) and a second event (the effect). BN was used to construct the DAPS Model, assessing the observable evidence and make inference on the probability to meet the cost, schedule, performance quality, and scope goals. The evidence within the framework of an acquisition program includes the artifacts, technical plans, facts, data, and expert assessments that will tend to support or refute the hypothesis of program success. Evidential Reasoning utilizes inference networks to build an argument of the observable evidence items to the hypothesis being sought [24]. For the case of DBS acquisition, the DAPS model argues for the hypothesis of program success or the alternative hypothesis of program failure based on the observations of evidence.

For example, to demonstrate the BN's ability to model complex relationships, a prototype BN structure was constructed based on the hierarchical relationship of the Naval PoPS framework as shown in Figure 2 with added logical CIRs [6] to demonstrate the Bayesian Network's ability to model complex relationships. The PoPS prototype network shown in Figure 4 represents a snapshot of the current status of the program; however, it does not include the temporal relationship for assessing the probability of risk/failure at a future time, nor does it include the decision and value nodes for recommending responding actions, such as continuing the program or acquiring more information.

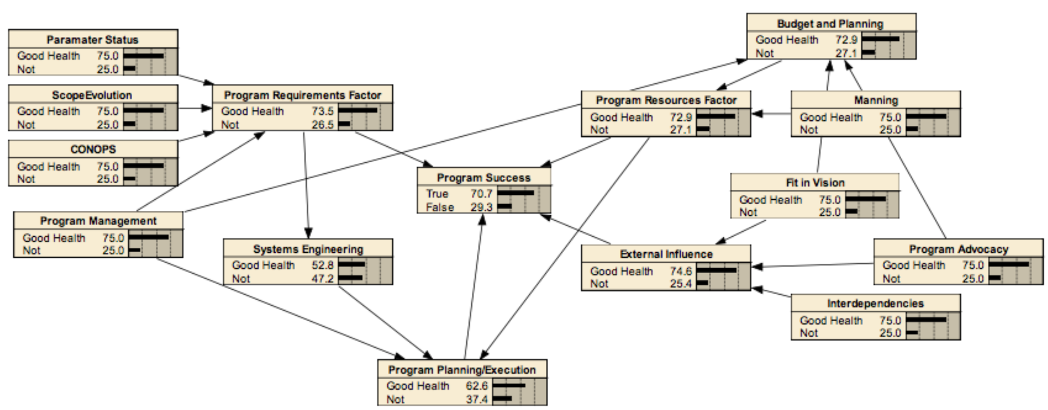

Figure 4. A Bayesian Network Prototype for Navy PoPS [6]

Methodologies

DAPS Bayesian Network Model

DAPS was developed with a Bayesian Network model using the Netica software tool [25]. By using Bayesian Network, DAPS was able to construct a complex inference network to measure the uncertainties in subject matter Knowledge Areas, assess the level of success achieved at Knowledge Checkpoints, and predict the likelihood for future program success or failure.

The DAPS Bayesian network model contains a three level structure, representing the three types of nodes/variables in the model. There are also three types of static arcs representing the interrelationships among the variables at a point in time, and one type of dynamic arc representing the temporal relationships from one point in time to another. For example, Figure 5 shows the DAPS model at the first Knowledge Checkpoint, Material Development Decision (MDD).

The topology of the top two levels, Knowledge Checkpoint and Knowledge Areas, are repeated at each of the Knowledge Checkpoint. The bottom level containing the evidence nodes, the observation points of the DAPS model at each Knowledge Checkpoint. The complete DAPS model contains 15 Knowledge Checkpoints. These DAPS model elements are outlined below,

1. Nodes:
    - Knowledge Checkpoints Nodes (KC)
    - Knowledge Area Nodes (KA)
    - Evidence Nodes (E)
2. Static Arcs
    - Knowledge Area Node to Knowledge Checkpoint Node Arcs
    - Knowledge Area Node to Knowledge Area Node Static Arcs
    - Knowledge Area Node to Evidence Node Arcs

3. Dynamic Arc

- Prior Knowledge Area Node at the previous Knowledge Checkpoint to the same Knowledge Area Node at the next Knowledge Checkpoint Dynamic Arcs

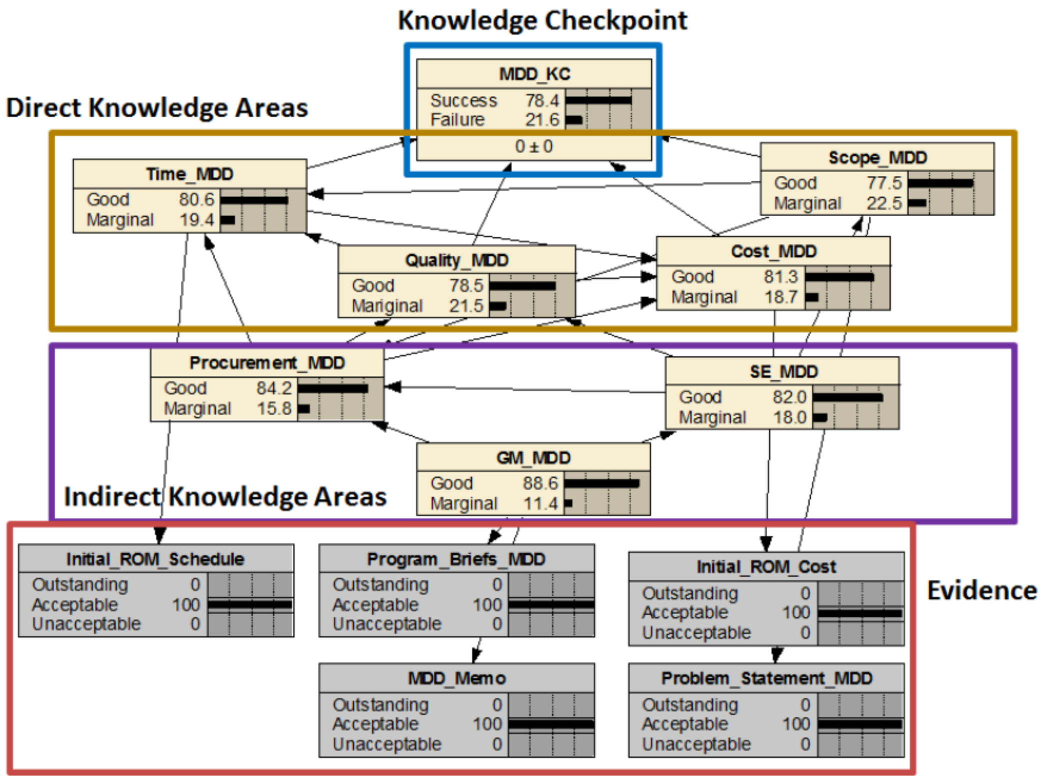

Figure 5. DAPS Knowledge Inference Structure [7]

DAPS Model Specifications

The Knowledge Checkpoint is the top level node which cumulates all information about the DBS acquisition program at that decision point, assessing the likelihood of program success. It provides a cumulative measurement of success achieved by the program up to the current Knowledge Checkpoint, and is the metric that can be used to help decision makers decide whether the program has demonstrated enough certainty and maturity to move on to the next phase of the acquisition program. Knowledge Checkpoints contain four Knowledge Area nodes as parent nodes, Time, Quality, Cost, and Scope Knowledge Areas. They represent the four direct measures of success which is defined in DAPS as meeting Program Time, Cost, and Quality goals within the

Program Scope. The fifteen Technical Reviews and Milestone Reviews modeled in DAPS as Knowledge Checkpoints are shown in Figure 6 [26-27]. Knowledge Checkpoint nodes contain two states describing the state of the program, “Success” and “Failure.” The probability of these states reflects the assessment of the program performance at the Knowledge Checkpoint.

Knowledge Areas are the second level node that measures the certainty and maturity attained for that particular subject matter area of DBS acquisition at the Knowledge Checkpoint. Knowledge Areas in DAPS are derived from the nine Project Management Body of Knowledge (PMBOK) Knowledge Areas [28-29], integrated with the systems engineering elements of defense acquisition. It is further divided into the Measurable (Direct) and Enabling (Indirect) Knowledge Areas. Measurable Knowledge Areas include Scope, Cost, Time, and Quality subject matter areas which directly affect the measures of program success in DAPS. Enabling Knowledge Areas include General Management, Systems Engineering, and Procurement subject areas that do not directly affect the measure of program success, but however are important enabling factors that drive success.

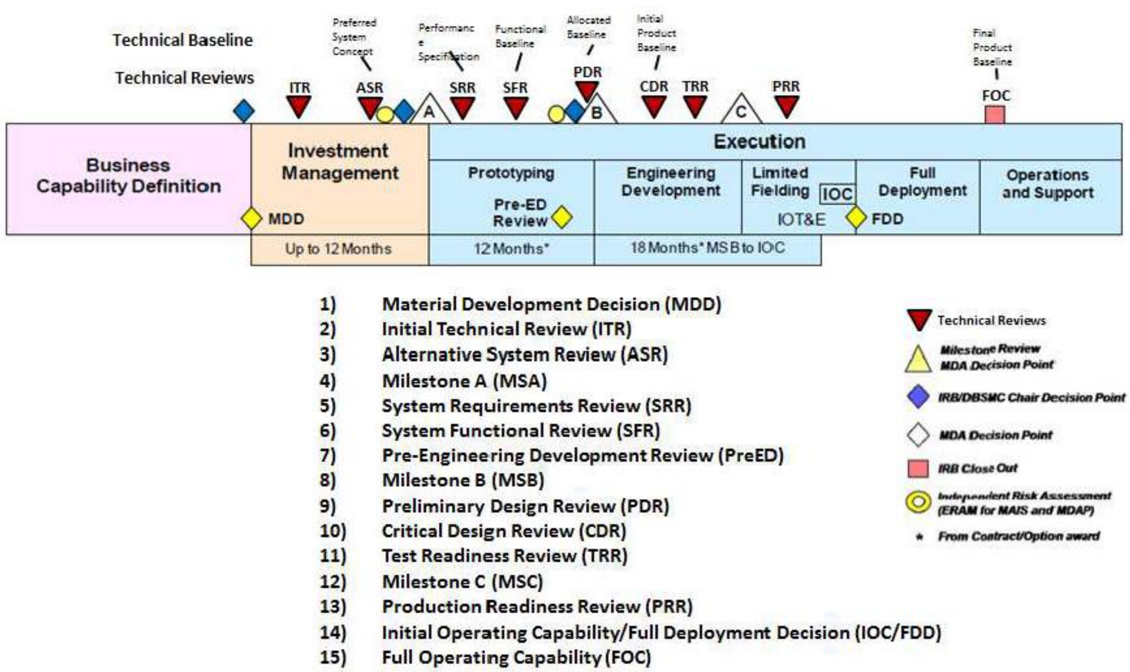

Figure 6. Business Capability Lifecycle Model [26]

The dynamic arcs, starting from Knowledge Area Node at the prior Knowledge Checkpoint to the same Knowledge Area Node at the posterior Knowledge Checkpoint, model the relationships of DBS acquisition through time. It represents the knowledge in a Knowledge Area at prior Checkpoint influencing the knowledge of the same Knowledge Area at the next Checkpoint. DAPS uses Knowledge Area nodes to model the dynamic effects in the progression of knowledge during an acquisition project. Thus, each Knowledge Area node gains information from the observations at the current Knowledge Checkpoint, as well as the information cumulated from prior Knowledge Checkpoints. Figure 7 provides an example graph of the dynamic arcs in green arrows from the Material Development Decision Knowledge Checkpoint to the next Initial Technical Review Knowledge Checkpoint.

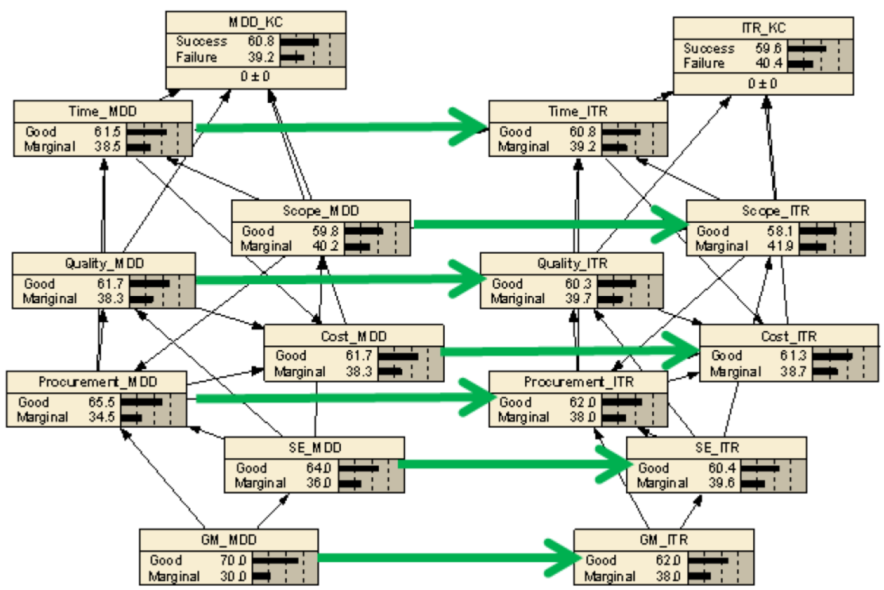

Figure 7. Knowledge Area to Knowledge Area Dynamic Arcs Example [7]

The third and bottom level nodes are the evidence nodes in the DAPS model. Observations of evidence are entered here at this level to drive inference for assessing a program's probability of success. The only CIRs for this level are the arcs from Knowledge Area nodes to Evidence nodes. Evidence nodes contain three states describing the state of the evidence, "Outstanding," “Acceptable,” or “Unacceptable.” These states reflect the risk assessment of the program in the specific Knowledge Area. Since these are the observation nodes, one of the states is chosen to describe the real world observation of the evidence. This provides information to update the belief in the parent Knowledge Area.

To summarize the model, Figure 8 shows an example inference network at the Critical Design Review (CDR) knowledge checkpoint. At this point, Evidence nodes are observed in accordance with the three node states [Outstanding, Acceptable, Unacceptable] to provide information on the assessment of the certainty/maturity in the seven Knowledge Area nodes. The assessments are evaluated according to the two Knowledge Area node states: [Good, Marginal]. The Knowledge Area nodes then propagate the information to combine the belief based on the evidence observed under the Knowledge Area, as well as the belief in other KAs where there is a CIR relationship. Finally, the Direct Knowledge Areas provide information to the Knowledge Checkpoint Node to assess the belief in the KC node states: [Success, Failure], which completed the information flow within a static Knowledge Checkpoint. The information at the Knowledge Checkpoint is then passed on to the next Knowledge Checkpoint utilizing the seven Knowledge Area Nodes through the dynamic arcs, where Evidence Node assessment observations will again be made. The information flow process is then repeated multiple times until the last Knowledge Checkpoint, the Full Operating Capability (FOC) Knowledge Checkpoint is reached.

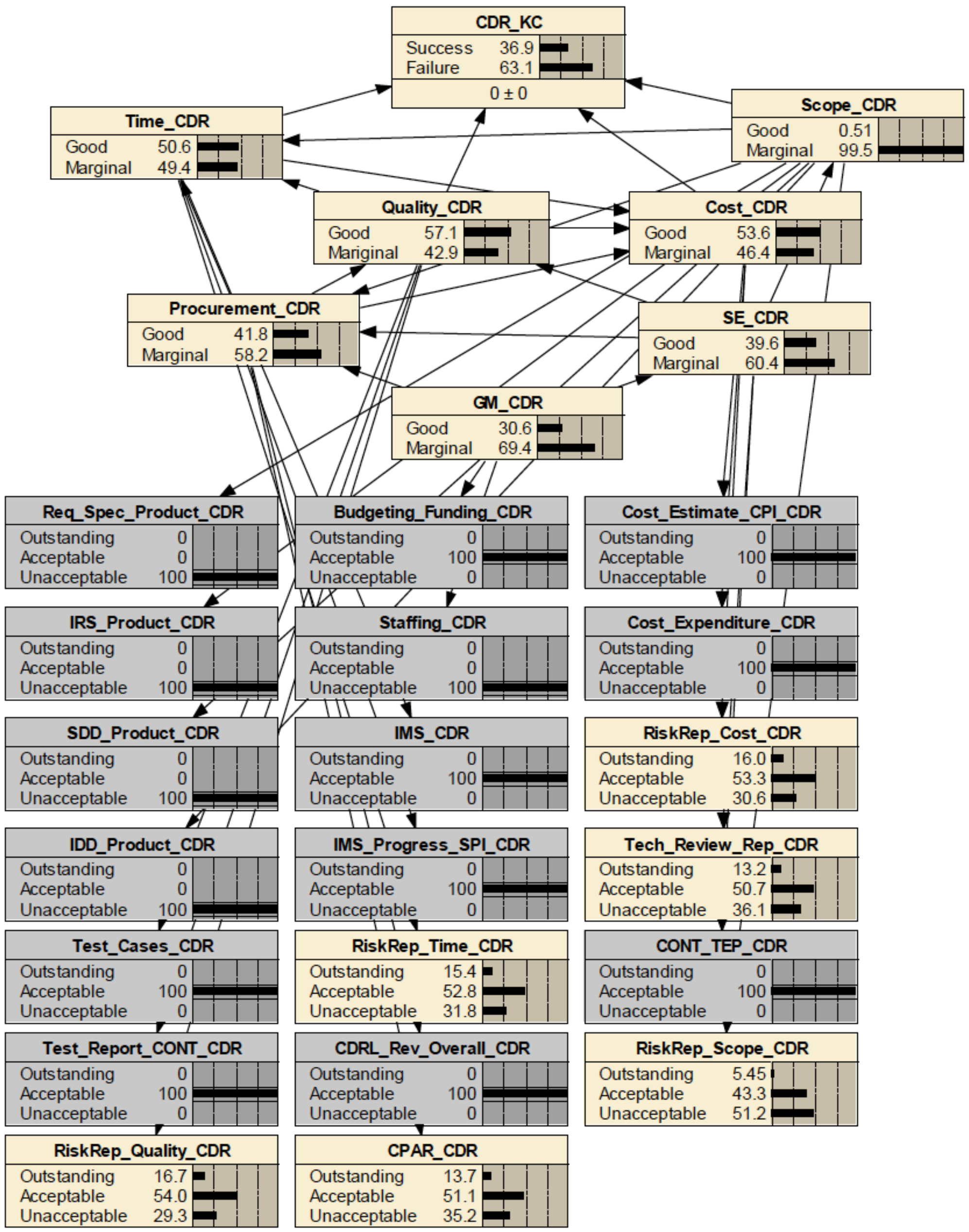

Figure 8. Inference Example at CDR Check Point

Decision Theoretic Approach with Bayesian Decision Networks

To incorporate utility and decision factors into the DAPS model, we adopt Influence Diagram (ID) (also called Bayesian Decision Network (BDN)) to enhance the DAPS model [30-31]. A BDN is a directed acyclic graph consisting of three types of nodes: decision, state, and value nodes. Decision nodes represent the decisions to be made and their set of possible alternatives. State nodes represent uncertain variables or hypotheses relevant to the decision problem. Value nodes are associated with decision and state nodes to characterize their benefits and costs. Arcs between two nodes represent their probabilistic causal influence or deterministic relationship. Figure 9 shows a simple BDN to represent various components related to R&D investment decision-making where the utility/value node representing benefits (market value) of the actions.

Within BDN, the uncertainties and dependences among the state and decision variables are systematically captured by its explicit graphical representation, making it ideal for modeling decision problems such as the one in ITDMS. A BDN is able to update (assess or predict) the probabilities of the states of a variable given observation (evidence) from other related nodes. To facilitate efficient probabilistic inference for optimal decision, a decision-theoretic framework is adopted to evaluate and compare the expected utility of each decision [31-32]. The framework provides solid theoretical foundations and has the capabilities of integrating evidence and knowledge in a principled manner. In the framework, an optimal decision is the one that *maximizes the overall expected utility*.

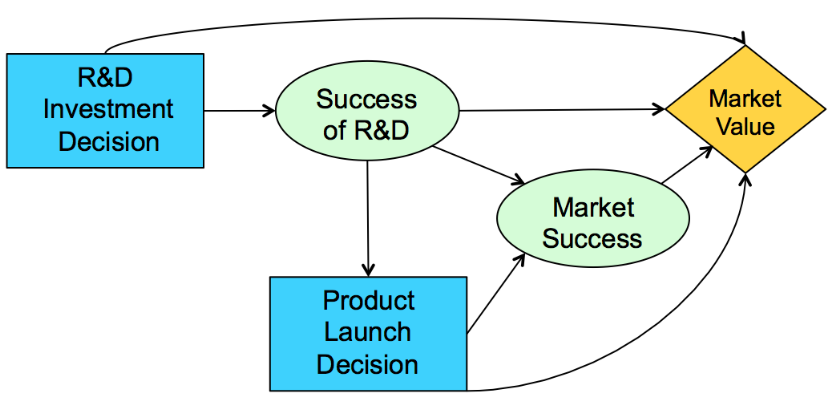

Figure 9. A BDN for Modeling Product Investment Decision Making under Uncertainty

ITIL Model Description

The Information Technology Infrastructure Library (ITIL) is a well-known industry-standard for IT and cloud services [33]. The ITIL functions as a guide to system lifecycle management of IT systems, including acquisition and operations. ITIL helps organizations across industries offer their services in a quality-driven and economical way. The ITIL standard is a set of five volumes of guidelines that largely leave the implementation of the process up to the organization [34-35]. As shown in Figure 10, the five main components of the ITIL Service Lifecycle cover various other sub-categories, including Demand Management, Capacity Management, Release Management, Incident Management, Event Management, etc. They are meant to cover all areas of IT Service Management.

A core component of the ITIL model is the service strategy design, transition, and operation (see Figure 11) [36]. The goal is to provide a strategy for the service lifecycle in sync with the customer's business objectives as well as to manage services within its scope. The strategies are designed to ensure that the service is fit for purpose and fit for use in order to add value to the customers. There are many benefits of using ITIL, such as lower operating costs, increased awareness of IT infrastructure status, higher customer satisfaction, and better help/service desk response. Furthermore, the non-proprietary and heterogeneous nature of ITIL enables it to be applied in almost any organization [33]. Because of these benefits, ITIL has become a standard in IT Service Management and is experiencing significant growth and awareness worldwide.

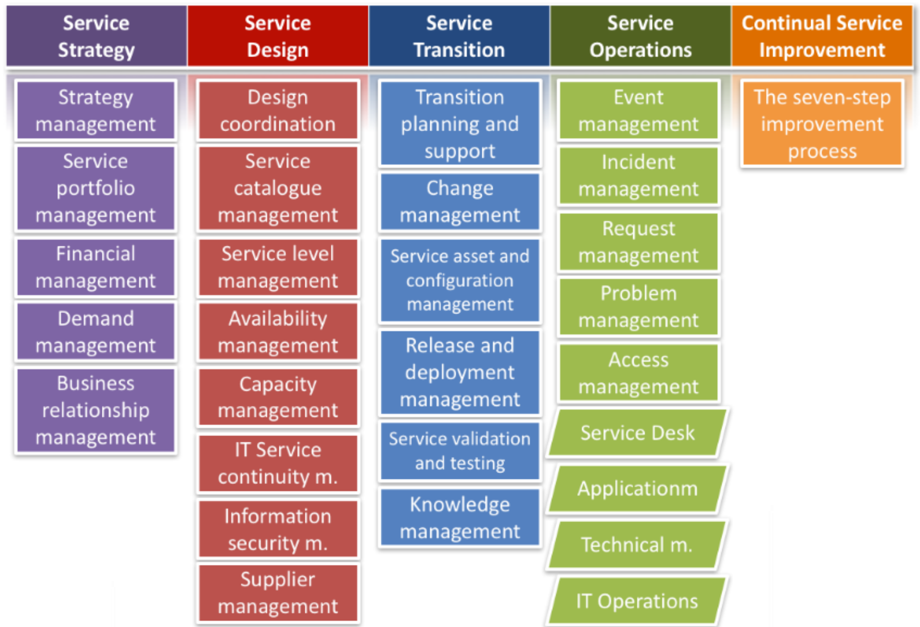

Figure 10. ITIL Components for Service Management [34]

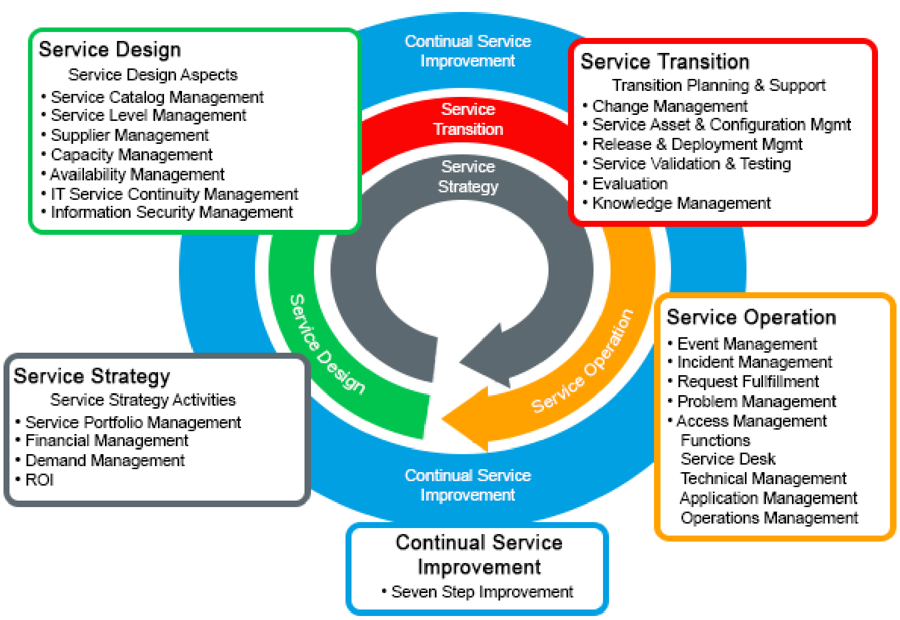

Figure 11. ITIL Service Strategy for Service Lifecycle [36]

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Modeling and Analysis

ITDMS Model Specifications

The ITIL library [34-36] provides a set of detailed practices for IT service management. In the ITIL system, the broad lifecycle phases serve a similar function as the review phases in the defense acquisition process [26-27]. It was pointed out specifically that success or failure of ITIL implementations is hard to define and that strong project management is a key to implementation [33]. Lengthy implementation, high risk, and the need for senior leader involvement can be surmounted through a formal approach to tracking and evaluation of progress. This problem directly involves the Systems Engineering disciplines of Project Assessment and Control, Decision Management and Risk Management. To help overcome these difficulties, we integrate the ITIL library with the DAPS model to develop ITDMS.

As in DAPS, in ITDMS the knowledge checkpoints are the project success indicators at certain stages of the acquisition process. However, unlike the 15 stages used in DAPS, in ITDMS, four of the five ITIL processes make up the knowledge checkpoints (KC's) from the DAPS Model. Specifically, the four checkpoints are:

- Service Strategy (SVC_STRAT_KC)
- Service Design (SVC_DSGN_KC)
- Service Transition (SVC_XSN_KC)
- Service Operation (SVC_OPS_KC)

These four ITIL lifecycle phases roughly correlate to the Initial Technical Review (ITR), Preliminary Design Review (PDR), Initial Operational Capability (IOC), and System Final Review (SFR) of the defense acquisition process in DAPS. The fifth process, Continual Service Improvement, does not fit into the construct of a checkpoint in that the process is ongoing and cyclical, representing an already fielded system and not a new development/deployment. This process might be addressed through a series of ongoing cyclical knowledge checkpoints, however, that option is not addressed herein, but could form an area of future work. As an aside, one might notice how the above processes closely align with the Systems Engineering phases of Concept Development, Production, and Utilization and Support.

Although the ITIL processes are meant to cover a particular phase of IT service management, and the reviews mentioned above are approval points, the activities and measurements conducted during each of the individual ITIL processes correlate with the activities one would perform prior to the decision to move to the next phase of an acquisition cycle. As shown in Figure 10, each of the ITIL phases have a number of formal processes, sub-processes, procedures, tasks, and checklists that are applied by an organization to successfully integrate new or updated IT functions [33-36].

In the design, we use these process outputs as evidence supporting the knowledge areas that inform the knowledge checkpoint. As with the DAPS model, the knowledge areas in ITDMS represent the complex interrelationships of a successful program and organize the evidence of sub-processes, as well as provide input to the knowledge checkpoint (KC). The seven Knowledge Areas are further defined into Measurable (Direct) Knowledge Areas, which can be considered direct and qualitative measures of success, and Enabling (Indirect) Knowledge Areas, which although qualitatively measureable, are considered as an enabling factor to success [6]. Seventeen procurement subject matter experts were interviewed to collect the necessary data for network structure and probability specification for the model [7]. The subject matter experts (SME) opinions were converted into the conditional probability tables associated with the knowledge areas.

The Measurable (Direct) Knowledge Areas to Knowledge Checkpoint are:

- Time Management – Schedule Plan, Schedule Progress, Schedule Performance, Earned Value Schedule Metrics
- Cost Management – Cost Estimate, Cost Expenditure, Cost Performance, Earned Value Cost Metrics
- Scope Management– Scope of project - Objectives, Goals, Requirements

and Specifications, Work Performance Requirements

- Quality Management – Product performance, Defects, Product Verification, Validation, Acceptance, Product Supportability, Data Deliverable

Direct Knowledge Areas are considered directly measurable, where the effects of the Knowledge Area can be directly quantified and are considered an indicative measure of final project success outcome. Indirect Knowledge Areas are not considered directly measurable to project success, where the effects of the knowledge area are not easily quantifiable and are not commonly used as a measure of final project success outcome.

The Enabling (Indirect) Knowledge Areas to Knowledge Checkpoints are:

- Procurement Management – Planning and Execution, Contract Solicitation, Contract Terms, Software Licensing Agreements
- Systems Engineering Management – Project Integration and Project Risk
- General Management – Staffing and Human Resources management, Communication, Environmental Management, Budgeting, and Funding, Project Management Plan, Program Charter

ITDMS Model Development

In ITDMS the evidence nodes of the DAPS model are replaced by the process and sub-processes associated with each of the ITIL services. The linkages to the KA's were determined by a review of the sub-processes and metrics associate with the respective ITIL process. For instance, the financial planning sub-process for service strategy knowledge checkpoint provides evidence of the cost knowledge area.

The ITDMS is enhanced by adding two decision nodes and associated value/utility nodes to each knowledge checkpoint. The first decision is whether to conduct a separate review of the program in addition to the evidence used to determine the probability of a success or failure of the program. If it looks like the program is going to be successful from the evidence, the model does not recommended a review. However, if the program evidence indicates that there is a possibility of failure, the program manager may decide to conduct an independent review. There are three types of reports that may come out of the review; a positive report, a negative report, or no report. The no report is for completeness in case the program manager decides not to conduct a review. The cost and time knowledge areas provide the evidence of the type of report given. Since a review costs money and time, there is a value associated with the review and the value node “Conduct_Review_Value” accounts for this value in the model.

The next decision required of the program manager, based on the knowledge checkpoint success/failure rating and the review recommendation, is whether to continue with the project. In this case, there are three choices; continue the project as is, continue the project with modifications to the schedule or budget, or do not continue the project. The decision to continue the project also has a value and the “Continue_Project_Value” node of the mode accounts for this value. The project probability of success, the review recommendation, and a decision to continue the project determine the value of the recommendation. For example, the value table reflects this with a high value given for a project that has a high success rate, receives a positive review report, and is chosen to continue. Figure 12 shows the ITDMS at the Service Strategy knowledge check point with the conduct review and continue project decision nodes. The complete BDN model is shown in Figure 13 where the interconnections between the phases can be seen explicitly.

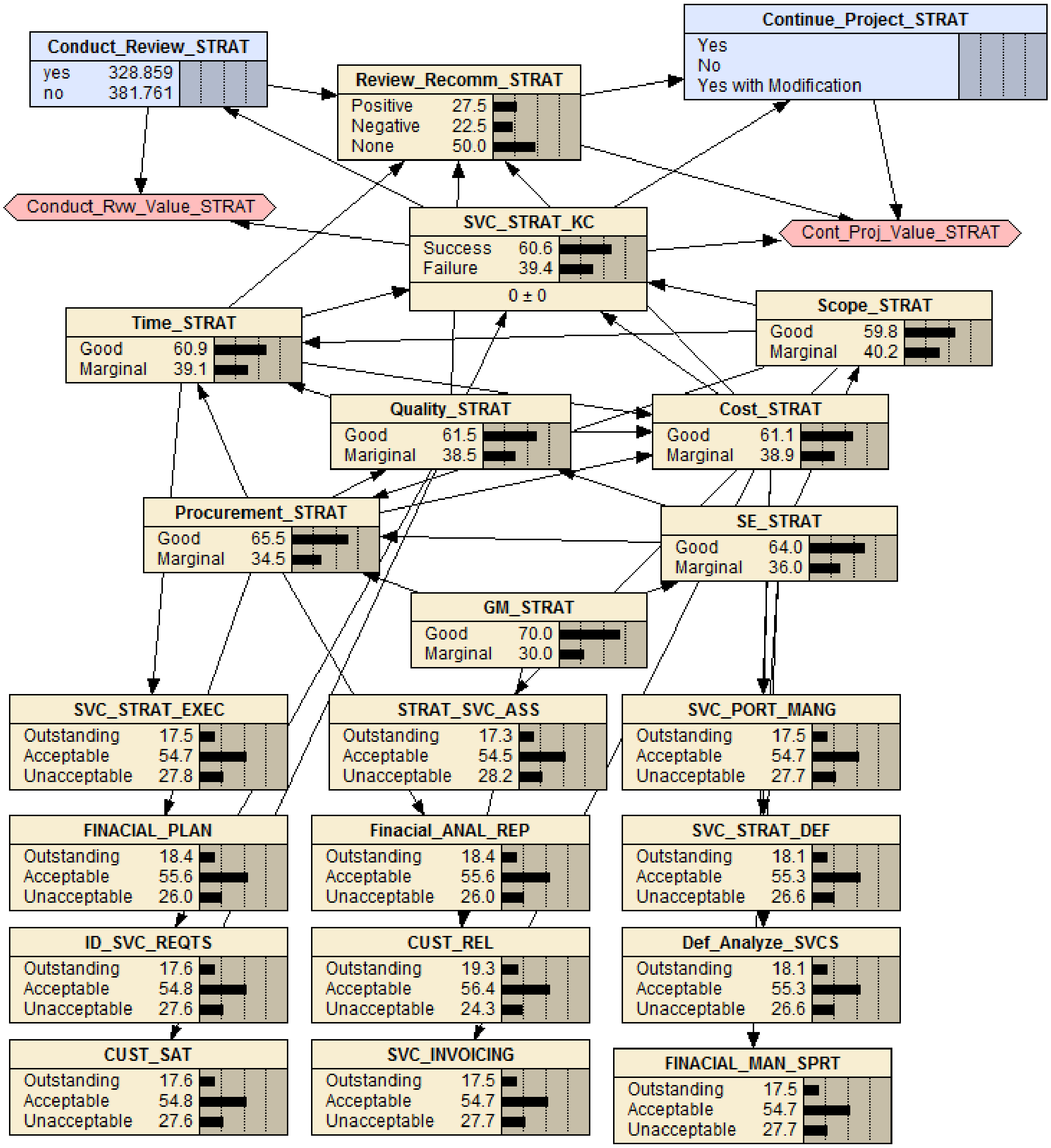


Figure 12. ITDMS Model at the Service Strategy Knowledge Checkpoint

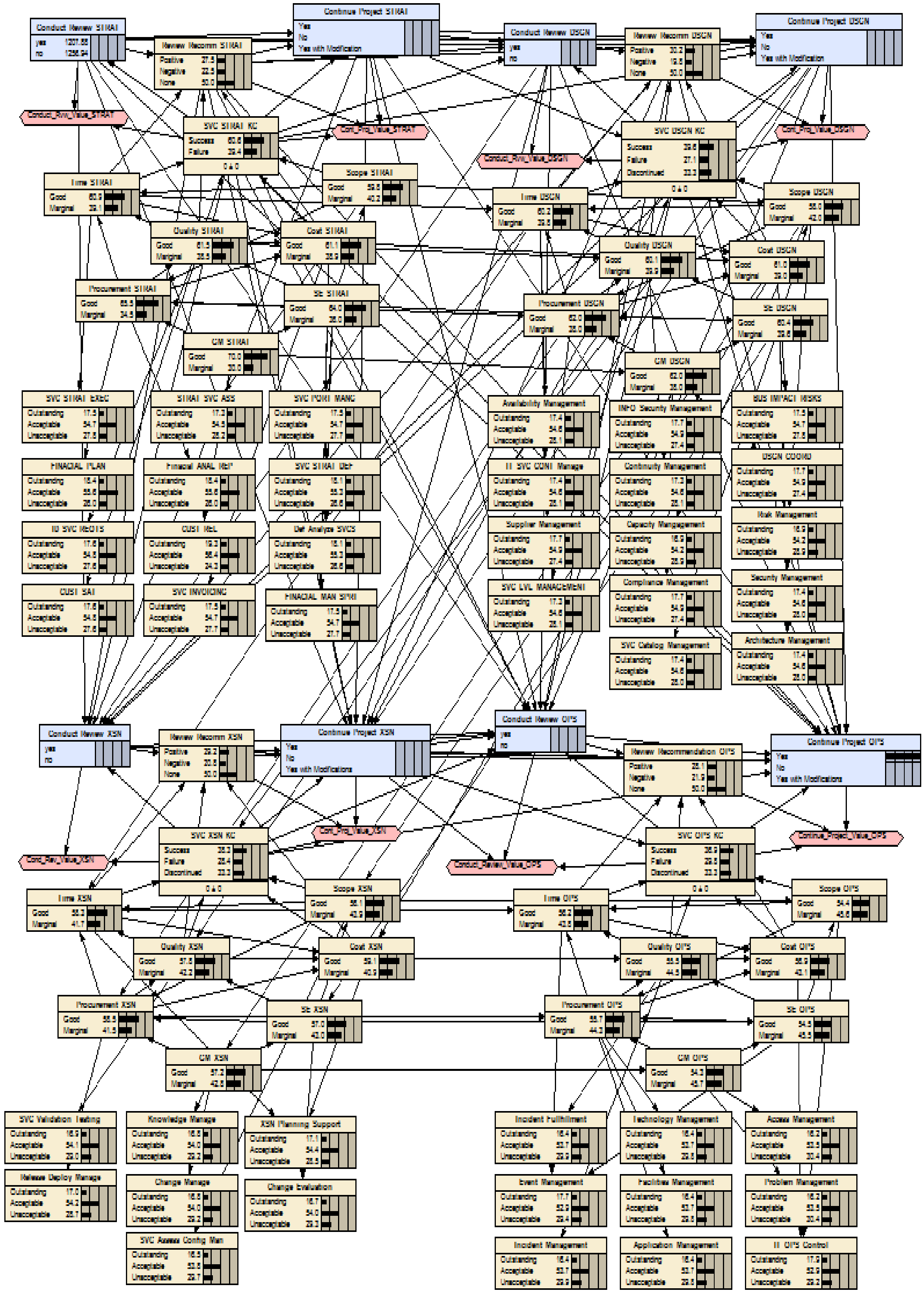


Figure 13. The Complete ITDMS Model

Scenarios and Case Study

We developed several scenarios to demonstrate the functionality of the ITDMS model. For example, in a scenario where a company has chosen to significantly upgrade their existing IT systems and will use ITIL as a guiding principle. Although the company can choose which sup-processes they want to use, for completeness in demonstration we will assume that the company will use all sub-processes associated with each ITIL phase. In setting up the BN for their acquisition project, the leadership of the company has assigned subjective utility values for their decision nodes. For example, Figure 14 shows the values assigned for the decision of whether or not to conduct an additional review of the program in the Service Strategy Phase. Due to the time and cost associated with a review, there is a positive value assigned to a successful program not requiring a review. Likewise, a review is most important when a program that is in threat of failure so the managers also assigned a high value for a conducting a review of a failing program. Conversely, a negative value is assigned to the case where a review would not be conducted for a failing program. Finally, conducting a review of a successful program will not necessarily be good or bad, so a neutral value (0) is assigned to that choice.

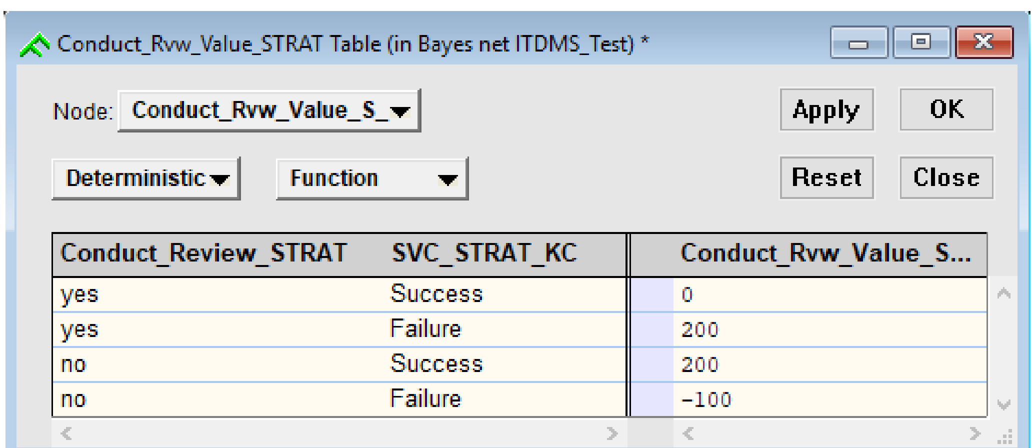
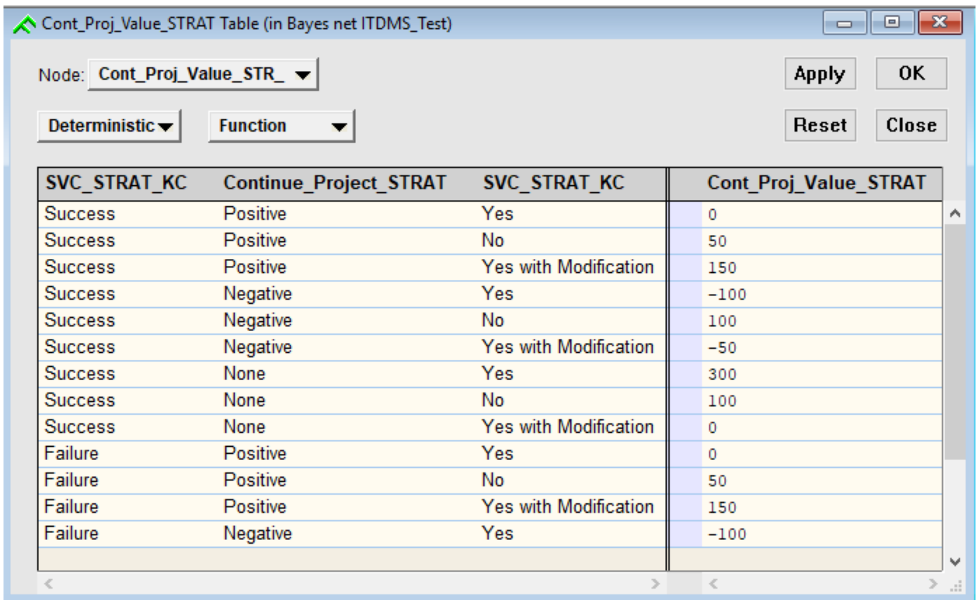


Figure 14. Values Assigned to Decision Value Node for Program Review

Similar reasoning is followed for the decision whether or not to continue with the program given the probability of program success and the results of a review if one were conducted. Because there are two inputs to this decision (Knowledge Checkpoint and Review results) the set of values is much more complex. In summary, most value is associated with continuing a successful project and terminating a program in trouble. Relatively high value is assigned to continuing a program with some modifications, such as extra resources or timeline changes if a positive review is received on a failing program. An example of the assigned values are shown in Figure 15.



SVC_STRAT_KC	Continue_Project_STRAT	SVC_STRAT_KC	Cont_Proj_Value_STRAT
Success	Positive	Yes	0
Success	Positive	No	50
Success	Positive	Yes with Modification	150
Success	Negative	Yes	-100
Success	Negative	No	100
Success	Negative	Yes with Modification	-50
Success	None	Yes	300
Success	None	No	100
Success	None	Yes with Modification	0
Failure	Positive	Yes	0
Failure	Positive	No	50
Failure	Positive	Yes with Modification	150
Failure	Negative	Yes	-100

Figure 15. Values Assigned to Continuing Project Value Node

Let's suppose that after completing some initial work developing their Service Strategy, the program manager (PM) conducts a review of progress to date. In our scenario the program has a mixture of two outstanding, seven acceptable, and three unacceptable sub-processes. Since a majority of the sub-processes are satisfactory or better, all the Knowledge Areas show a high probability of "Good" progress and the model predicts the program has a 70 percent probability of success (see Figure 16). Due to this high chance of a successful program, the model places a higher value (1351 to 1221) on not conducting a program review. Let's say that the decision maker follows the model's advice and decides not to conduct a further review and that option is chosen in the model. The result is that the model then places a higher value on continuing the project (Yes: ~1200; No: ~900; Yes, with modification: ~1000) (see Figure 17). It should be noted that there is no reason that the program status be assessed only once during the phase. The program manager can use this assessment periodically or as situations warrant throughout the program.

With the assumption that the decision maker has chosen to continue the project we've proceeded to the Service Design Phase. A few months into this phase the PM again calls for another program assessment. However, here we find that things in our scenario are not going as well. Let's say here that the program has taken a turn for the worse and now a number of sub-processes in the Service Design Phase have unacceptable ratings (2 outstanding, 8 acceptable, 4 unacceptable) as shown in Figure 18. Many of the Knowledge Areas are now "Marginal" and this has pushed the probability of program success down to 43 percent. The model now places more value in conducting an in-depth review (~750 vs. ~650 in favor of review). If the program manager follows this recommendation and chooses to conduct the review, we find that there is a 66 percent probability the review will be negative.

Let's assume the review is conducted, but shows that, with some changes to the program funding, it will be successful. We'll consider this a positive review recommendation and the model recommends continuing the project with modifications. The decision maker chooses to provide additional funding to the project and thus continue the project with modifications (see Figure 19). These modifications could include schedule changes, budget adjustments or personnel changes as the program manager and decision makers see fit. On the contrary, if the review did come back negative, the Continue Project decision node would reflect more value to ending the program. Again, the program manager can opt to proceed to the next phase, Program Transition, or remain in the Design Phase and conduct another program assessment after changes are made.

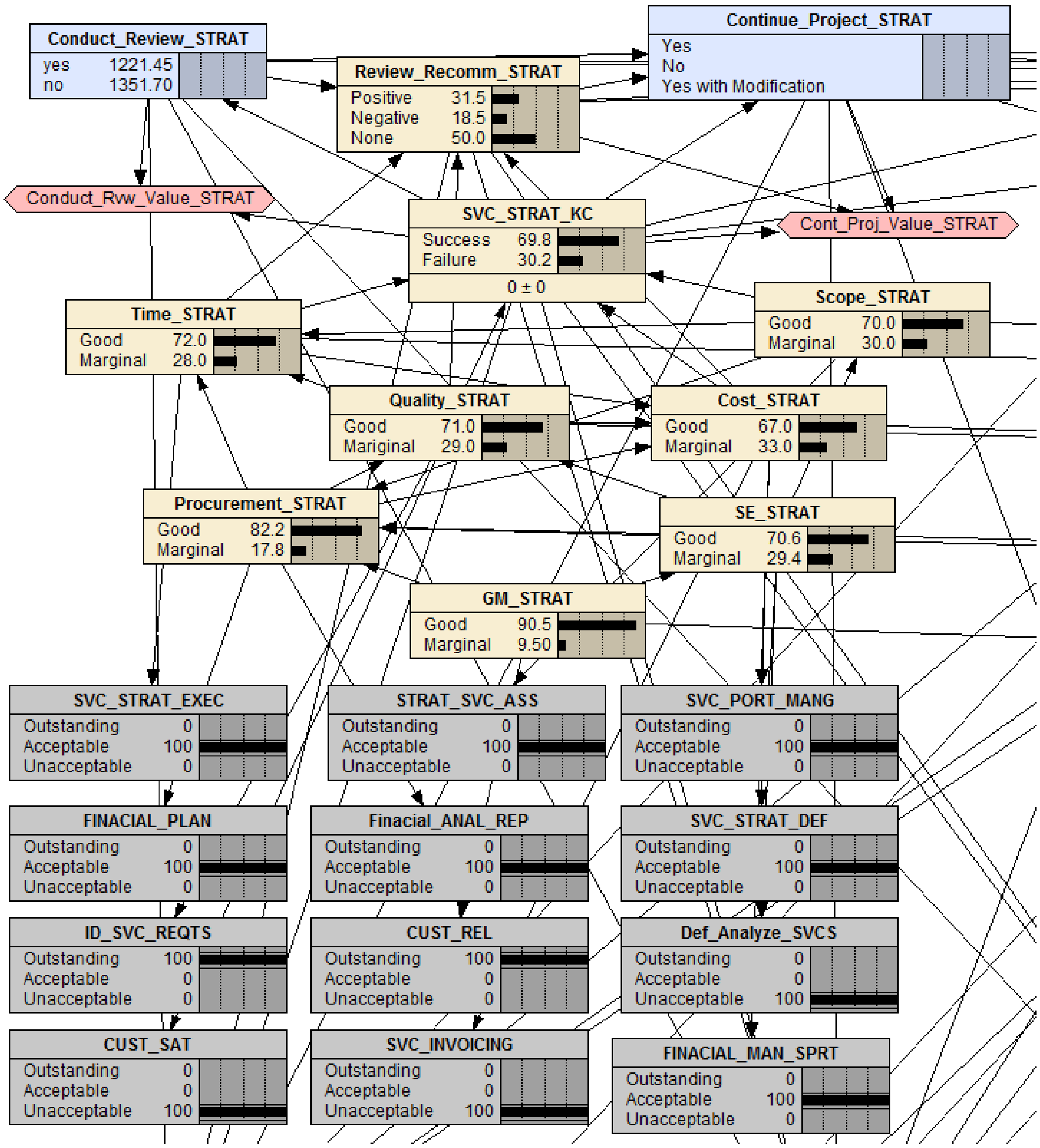


Figure 16. Service Strategy Scenario

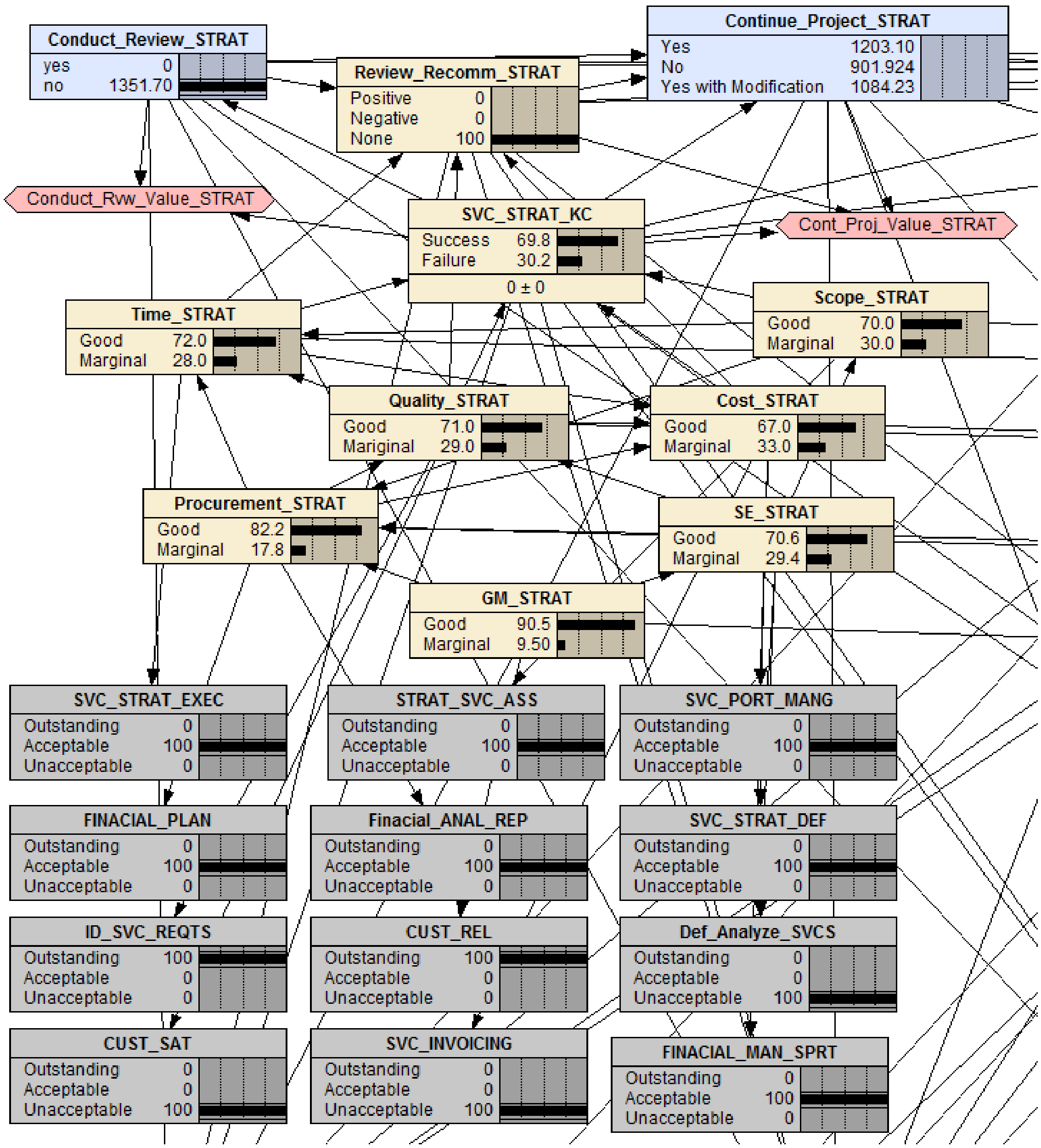


Figure 17. Service Strategy Scenario w/o Program Review

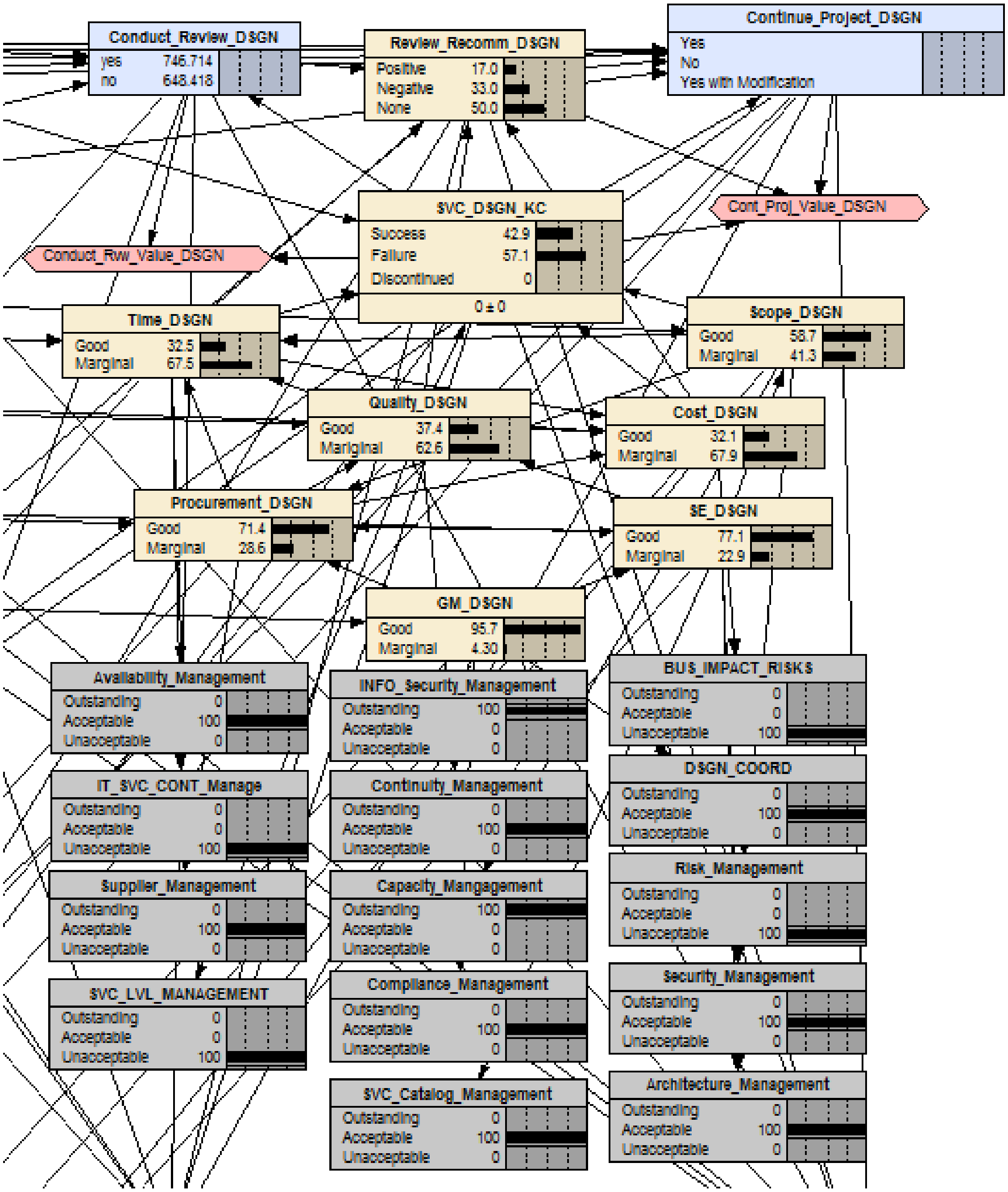


Figure 18. ITDMS Service Design Phase with a Failing Program

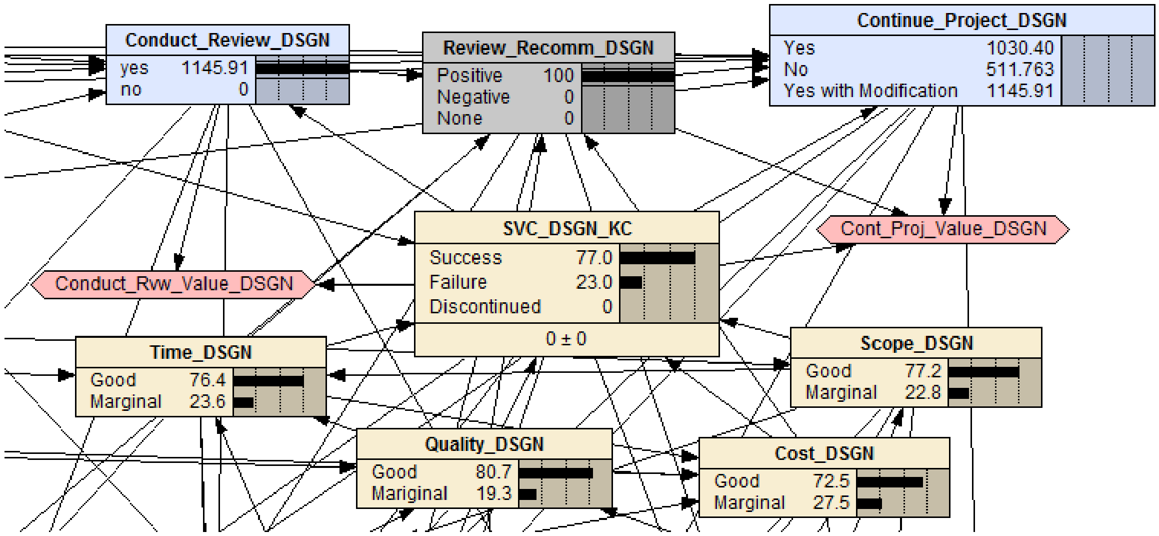


Figure 19. Service Design Phase Recommendation given a Satisfactory Review of a Failing Project

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Conclusion and Recommendations

This research developed a potentially useful model/tool to help the systems engineering and IT acquisition professional. Specifically, a quantitative probabilistic reasoning system using BDN to model nonlinear and dynamic relationship within IT acquisition process was developed to gauge program performance and suggest necessary actions. The resulting ITDMS model demonstrates the ability to provide IT managers and decision makers an analytical tool to assess the probability of success with the recommended actions at various points of the project.

The contributions of this research effort include: 1) Development of a quantitative system to aid decision makers holistically process the available IT acquisition program data and evidence, providing key project success measurement in each of the management areas, and a measurement of success at a review milestone (the knowledge checkpoint); 2) Prediction of future project success with recommended actions through a dynamic Bayesian decision network. The advantage of this approach is its attempt to put the complexity of the ITIL process into a simple model. It is well known, however, that when one is trying to encode a complex problem like the large and highly interconnected one in this study with a simplified model such as a dynamic Bayesian network, one encounters the trade-off between computational complexity and accuracy.

The research finding has been documented in a technical paper published in the *15th Annual Acquisition Research Symposium* [37] as well as a paper in the 28th annual *INCOSE* international symposium, a premium international forum for Systems Engineering [38]. Future work on the model would be to measure the model with a real world example of a company or organization using ITIL in their IT service acquisition to determine if it provided correct recommendations. Additionally, a user-friendly interface could be added to the model to enable personnel who are unfamiliar with the Bayesian network model to input data and receive easily interpreted outputs. Finally, the model is organized for managing an IT system using the ITIL structure from ground-zero to full service implementation. Not all IT acquisitions require the complete ITIL structure and a decision maker may only need to use a few phases of the structure. Therefore, it would be useful to provide a model that is adaptable to the user needs.

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