Chapter

The Application of Simple Additive Bayesian Allocation Network Process in System Obsolescence

Oluwatomi Adetunji

Abstract

In designing a system, multi-dimensional obsolescence design criteria such as Scheduling; Reliability, Availability, Maintainability; Performance and Functionality; and Costs affect its overall lifespan. This work examines the impacts of these factors on systems during the design phase using a new application called the Simple Additive Bayesian Allocation Network Process (SABANP). The application uses a combination of Multi-Criteria Decision Making (MCDM) methodology and a Bayesian Belief Network to address the impact of obsolescence on a system. Unlike the requirement of weights that are prevalent in the analysis of MCDM, this application does not require weights. Moreover, this application accounts for functional dependencies of criteria, which is not possible with the MCDM methodologies. A case study was conducted using military and civilian experts. Data were collected on systems' obsolescence criteria and analyzed using the application to make trade-off decisions. The results show that the application can address complex obsolescence decisions that are both quantitative and qualitative. Expert validation showed that SABANP successfully identified the best system for mitigating obsolescence.

Keywords: Obsolescence, Multi-Criteria Decision Making, Bayesian Belief Network, Simple Additive Bayesian Allocation Network Process, Diminishing Manufacturing Sources and Material Shortages (DMSMS)

1. Introduction

Obsolescence is an event bound to happen. It occurs when a component or system (hardware and software) cannot carry out required functions or continue to be useful. Reasons include the component not being available for purchase in its original form from the original manufacturer or producer; not being maintainable, affordable to repair, or reliable; technology evolution; and anything else that causes a component or system to no longer be viable [1–3]. Obsolescence also encompasses discontinuance. However, Pecht and Das [4] made a distinction between the "obsolescence" and "discontinuance" concepts. Discontinuance takes place when the manufacturer stops the production of a component, which occurs at a part-number or manufacturer-specific level, while obsolescence occurs at a technology level [4, 5]. Obsolescence can happen to products, systems, processes, software, policy, standards and organizations.

Many solutions have been proposed for managing obsolescence. However, over the past decade, it is estimated that over $9 billion has been wasted on this problem [6]. The problem is often a result of the rate of technological advancement in systems rendering them obsolete. Managing obsolescence has traditionally been done with a reactive approach. This means that the action taken to resolve the issue occurs after the obsolescence is found. Today, with the rapid growth of digital technology, digital systems and software are reaching their end-of-life sooner rather than later.

Moreover, the contractual agreement between Original Equipment Manufacturer (OEM) and the government is often limited in scope and reactive in nature. This chapter proposes a new application model — a proactive approach that takes into account obsolescence factors that affect systems during the design phase.

The proposed model uses a combination of a Bayesian Belief Network and an MCDM for identifying systems that are more susceptible to obsolescence, which can provide an alert to the system owners to take action before the obsolescence occurs. The combined application of Bayesian Belief Network and MCDM to manage obsolescence in this work serves as the addition to the body of knowledge. This chapter refers to the extension of this methodology as the Simple Additive Bayesian Allocation Network Process (SABANP). The SABANP enables the analyst to define the complex model by connecting a particular Bayesian Believe Network process to the system components (i.e., the leaf nodes), whereby obsolescence characteristics are modeled as an event. When modeling the dynamic characteristics as events, the following set of processes is developed to model the variety of obsolescence criteria:

1. The time when the event occurs or the time to obsolescence,

2. The order by which the events will likely occur, and

3. The event occurrence dependence on time and costs.

The costs that include procurement are required because of their ramifications on the obsolescence problem. The end result of obsolescence in a system is the significant costs it incurs for the organization. The DoD estimated costs upward of $750 M annually for managing obsolescence [7]. Obsolescence is time-dependent; therefore, the model assumed a 95% confidence that systems would be obsolete within two years.

2. Background

In managing system obsolescence, three approaches are used: reactive, proactive and strategic. The reactive approach addresses the obsolescence after the component or part is obsolete, while the proactive one addresses the obsolescence before it occurs [8]. The strategic approach often uses a combination of reactive and proactive approaches to manage the risk of obsolescence; however, the decision models that address obsolescence are underdeveloped [6]. The most agreed upon approach to managing obsolescence is the proactive strategy since it ensures that systems with long life spans are continuously and effectively maintained [9, 10].

Originally, the work began from the need to find better and more effective ways to deal with obsolescence in a proactive manner. To do so, the following obsolescence criteria were chosen from the literature [2, 11, 12]:

(1) Performance and Functionality (P&F); (2) Cost, which includes Acquisition, Licensing and Support; (3) Personnel Training (PT); (4) Reliability, Availability, and Maintainability (RAM); (5) Procurement (PR), which includes Vendor Assembly and Installation Support; (6) Configuration Management (CM); (7) Data Rights and Technical Documentation (DR&TD); and (8) Open Architecture and Standards (OA&S). We also added (9) Technology Readiness Level (TRL), which was adapted from the DoD Technology Readiness Assessment Guidance [13], and (10) Obsolescence Schedule Risk (O&SR).

Each criterion was assessed as either "higher is better" (HG) in the case of a criterion that has a benefit to the stakeholder, or "lower is better" (LW) in the case of non-benefit to the stakeholder to determine the criterion's weight factor. For example, Cost is defined as LW because high ownership and acquisition costs are a non-benefit to the stakeholder. The same can be said of O&SR. This convention is accounted for within the model construct as shown in **Table 1**.

Experts were asked to assess each system's P&F; Costs; required level of PT; RAM; whether they are easily Procurable (PR); installation support and vendor assembly in the design phase. These systems run on software programs, and experts were also asked via a survey to assess each system's CM, the availability of DR&TD, the OA&S, and the TRL by assigning grades on a scale ranging from 0 to 9. These criteria were agreed upon by the experts and are based on the literature review.

Experts rated the O&SR on a scale of 1–5, where 5 represents the highest score and 1 the lowest score. While the rest of the criteria scales are from 0–9, a scale of 1–5 was used for the O&SR because a risk matrix that goes from 1–5 is easily conceptualized by expert practitioners.

2.1 Criteria weights

Weights (w_j) were required to sum to one, and all criteria weights met this requirement. The ratings represent the weights of the ten criteria as provided by the decision maker based on experience and expertise. The weight data served as the inputs to the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) model. This decision making method, that is, TOPSIS was used to validate the Simple Additive Bayesian Allocation Network Process. **Table 2** shows the decision maker-weighted values for each criterion, which total to 1 or 100%.

Criteria (x_j)	**(1) P&F**	**(2) Cost**	**(3) PT**	**(4) RAM**	**(5) PR**	**(6) CM**	**(7) DR&TD**	**(8) OA&S**	**(9) TRL**	**(10) O&SR**
Weight Factors	HG	LW	HG	HG	HG	HG	HG	HG	HG	LW

Table 1.
Criteria benefit and non-benefit weight factors.

Criteria (x_j)	**(1) P&F**	**(2) Cost**	**(3) PT**	**(4) RAM**	**(5) PR**	**(6) CM**	**(7) DR&TD**	**(8) OA&S**	**(9) TRL**	**(10) O&SR**
Weights (w_j)	0.19	0.12	0.06	0.15	0.11	0.07	0.09	0.07	0.06	0.08

Table 2.
Decision maker-assigned weight values.

2.2 The time-discrete Bayesian belief network modeling

The Bayesian Networks are composed of nodes and arcs [14, 15]. Bayesian Networks have the capability to perform diagnostic analysis because of its rich graphical and embedded mathematical capability of modeling and analyzing dynamic behavior of systems [16]. Nodes, in this case, represent Random Variables and arcs between nodes represent the dependencies between the random variables [14]. It uniquely defines joint probability distribution of the random variables. Once the joint probability distribution is known, any random variable query can be solved. Furthermore, random variables can be either infinite (continuous random variable) or finite (discrete random variable) [14]. This chapter only considers discrete random variable since the data that are gathered are from experts and the distribution is discrete. There are three types of nodes: root nodes, sequential root nodes, and leaf nodes. Root nodes are nodes without incoming arcs or without parents, and sequential root nodes are nodes that have incoming arcs and outgoing arcs or are both parents and children. Leaf nodes are nodes without outgoing arcs or without children. Root nodes will have marginal prior probability tables that are associated with them, and sequential root nodes and leaf nodes have conditional probability tables that are associated with them [14]. A conditional probability table provides the probability of each random variable state conditional on the values of its parent nodes. To determine the joint probability distribution, the Chain Rule is used and assumes that the conditional independence is encoded in the designed Bayesian Believe Network structure between the variables.

The joint probability distribution of the variables set $X_1, X_2, \dots, X_M$ is given as follows [4]:

$$P(X_1, X_2, \dots, X_m) = \prod_{i=1}^{n} P(X_i \mid parents(X_i)), i = 1, 2, 3 \dots, m \tag{1}$$

Recent research works have resulted in better and more efficient algorithms for computing and inferring probabilities in Bayesian Networks. The inference has become easier to the point that algorithms can utilize the independence assumptions between variables and its powerful computations make the command execution quicker for the user. Bayesian Networks have been used extensively in areas such as medical diagnosis, troubleshooting systems, manufacturing control, etc. Nevertheless, it has not been used to mitigate or predict obsolescence in systems with Subject Matter Experts' (SMEs) input or qualitative analysis.

To develop the model, a discrete-time Bayesian Believe Network is formulated to model the system obsolescence. The leaf node or random variable represents the system component. The system component herein is categorized as a component, sub-system or system that interacts between collections of components. These leaf nodes that are used in the experiment are the Integrated Bridge System that are found on Naval Vessels, as described in Section 2.4.

By using this model, one can analyze the interactions among the criteria and find the critical criteria that could have the most adverse effects on a system's operations. This model is used to develop simulation test scenarios, such as what if the costs were not a significant factor in the tradeoff analysis or what if the configuration management does not have any effect on the system's lifecycle. This analysis can also gather information on which obsolescence-related attributes should be prioritized with respect to the design, development, testing, and maintenance.

2.3 Expert judgment

The expert judgments were used to gather the required input data for this experiment. The expert-assigned scores were documented and aggregated for each leaf node based on the agreed upon obsolescence criteria, after normalization of the scores. Though the systems that were employed for the experiment were fielded on Navy ships, the experts were asked to initiate a scenario in which system development was being planned on a new ship class in order to determine the best system against obsolescence through which it can be mitigated.

The system of reference Integrated Bridge System was established after iterative discussions with experts. The research participants were recruited by e-mail with nineteen obsolescence experts completing and returning responses. The minimum requirement for expert judgment participation was set at fifteen returned surveys. Therefore, this number of responses is acceptable for expert judgment. The demographic data also reflected the experts' diverse experiences. All participants had at least four years of experience in managing obsolescence and DMSMSs with some exceeding 35 years of experience. Approximately 10% had a Ph.D., 58% had a master's degree, and 32% had a bachelor's degree. The analysis also revealed that 70% were employed by organizations with 500 or more employees, and these organization sizes ranged from 500 to 100,000 employees.

Participants were asked to complete the study that consisted of approximately 90 data fields. The survey data responses were documented, and the ranking of each alternative on each criterion across the experts was aggregated, normalized and transposed into the model. Exceptions were made for the Cost criterion data scale where the actual cost range data were used. The criteria agreed upon by the experts were used to formulate the survey questions.

2.4 An integrated bridge system (IBS)

An IBS serves as the context of the survey instrument. The IBS on the Naval vessels of the USS Arleigh (DDG-51), the USS Ticonderoga (CG-47) and the USS Nimitz (CVN-68) were examined in this work. The IBS serves as the system-under-test. An IBS is designed to assist the vessel navigator in selecting information that is relevant to the operational context by collecting, processing, and presenting relevant data without cluttering displays with other information that may not be needed at that point. It takes a systems approach to the automated collection, processing, control, and display of ship-control and vital navigational sensor data to maximize the bridge watch efficiency and safety. An IBS is based on human-machine interaction, which integrates all navigational functions and provides accurate navigational information to operators or users with no human error. Its capabilities include multifunction workstations, multiple layers of redundancy, Commercial Off-the-Shelf (COTS) hardware, ease of maintenance, and open system design (i.e., intersystem links to other systems). These systems fall under the purview of being mission essential. Mission essential systems are systems that can have an adverse impact on the mission if they are not operational due to obsolescence.

2.5 Research process

The following steps were used in the research process. One must first determine the current deterministic MCDM methods that are applicable for use in nonlinear (multidimensional) decision analysis. Then, currently available mission-ready systems that serve as points of reference for the study was identified. Finally, an analysis was conducted using the Simple Additive Bayesian Allocation Network Process model with expert judgments in the analysis of alternatives in order to select the best system against obsolescence.

3. Methodology

Simple Additive Bayesian Allocation Network Process (SABANP) utilized the components of the Simple Additive Weighing (SAW) method as the input variables to the Bayesian Belief Network. SAW is an MCDM. To better understand SABANP, it is necessary to provide details of what SAW is and how it is used in the model. The SAW model, which is also known as the WSM or the "weighted average," is a common approach used for multicriteria analysis [17].

One must first calculate the normalized decision matrix for the benefit criteria (higher is better), where n_{ij} is the normalized score of the i^{th} alternative with respect to j^{th} criterion, and r_{ij} are the values in the decision matrix provided by the experts [17, 18]:

$$n_{ij} = \frac{r_{ij}}{r_{ij}^{max}}, i = 1, 2, 3, \ldots m, j = 1, 2, 3 \ldots, n \tag{2}$$

r_{ij}^{max} is the maximum value of the i^{th} alternative with respect to each j^{th} criterion in the decision matrix.

For the non-benefit criteria (lower is better), r_{ij}^{min} is the minimum value of the i^{th} alternative with respect to each j^{th} criterion in the decision matrix [6]:

$$n_{ij} = \frac{r_{ij}^{min}}{r_{ij}}, i = 1, 2, 3, \ldots m, j = 1, 2, 3 \ldots, n \tag{3}$$

The normalized Matrix for IBS is found in **Table 3**.

The best alternative is the one that maximizes A_i in Eq. (4) below. The weights (w_j) are the weighted criteria values, and they sum to 1 as shown in **Table 2**.

Criteria	IBS DDG-51 Class	IBS CG-47 Class	IBS CVN-68 Class
(1) P&F	1	0.920	1
(2) Cost	0.984	1	0.815
(3) PT	0.9717	0.937	1
(4) RAM	1	0.889	0.959
(5) PR	1	0.896	0.976
(6) CM	1	0.896	0.976
(7) DR&TD	0.947	0.895	1
(8) OA&S	0.987	1	0.939
(9) TRL	1	1	0.979
(10) O&SR	1	0.938	0.978

The time for the system to reach obsolescence was modeled with a 95% confidence interval, i.e., the software and hardware would be obsolete within two years.

Table 3.
SAW normalized matrix.