Using Multi Criteria Decision Making in Analysis of Alternatives for Selection of Enabling Technology

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Received 1 February 2012; Revised 19 June 2012; Accepted 19 June 2012, after one or more revisions
Published online in Wiley Online Library (wileyonlinelibrary.com).
DOI 10.1002/sys.21233

ABSTRACT

In September 2009 the U.S. Government Accountability Office (GAO) reported, “Defense Acquisitions: Many Analyses of Alternatives Have Not Provided a Robust Assessment of Weapon System Options” [U.S. Government Accountability Office, Pub. No. GAO-09-665, 2009, p. 1]. In their focused review of 32 Acquisition Category I programs, it was found that 10 did not conduct an Analysis of Alternatives (AoA), but rather focused on an already selected weapon system solution. Prior to Milestone A, the Department of Defense (DoD) requires that service sponsors conduct an Analysis of Alternatives (AoA). The AoA is an analytical comparison of multiple alternatives to be completed prior to committing and investing costly resources to one project or decision. Typically, however, sponsors will circumvent the process in an effort to save money or schedule, and capability requirements are proposed that are so specific that they effectively eliminate all but the preferred concepts, practically ignoring other alternatives. Decision making is one of the most challenging parts of Systems Engineering. How one feeds the decision making process is key to eliminating long term waste. “About three-quarters of a program's total life cycle cost is influenced by decisions made before it is approved to start development” [U.S. Government Accountability Office, Pub. No. GAO-09-665, 2009, pp. 1–2]. This study evaluates the positive benefits of defining the problem domain prior to expeditiously turning to the solution domain. The goal in any decision making process is to provide the decision maker with the ability to look into the future, and to make the best possible decision based on past and present information and future predictions. There is a need for approaches that combine available quantitative data with the more subjective knowledge of experts. Decision theory techniques have been successfully used for contrasting expert judgments and making educated choices for many years. For a successful analysis, one must focus on selection of specific criteria that are key performance drivers that can lead to an informed selection of the enabling technology. Understanding the requirements of the end state goal is key to a successful analysis and should also assist in the selection of key performance parameters. A case study example is presented to demonstrate a third tier AoA identifying an enabling technology using the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) while successfully accounting for tacit knowledge of expert practitioners. © 2012 Wiley Periodicals, Inc. Syst Eng 16

Key words: multi criteria decision making; TOPSIS; analysis of alternatives; AoA; enabling technology

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1. INTRODUCTION

Conducting an Analysis of Alternatives (AoA) is a statutory requirement for military programs mandated by U.S. Law under Title 10, U.S. Code, which outlines the role of the Armed Forces. The Department of Defense (DoD) Instruction 5000.02 [DoD, 2008] documents the requirement that an AoA be conducted early in the program planning to determine and compare effective materiel solutions. The AoA is one of several inputs required for a program’s initiation, and it is a key element in planning and establishing a sound business case for a weapon system program.

The AoA is an analytical comparison of multiple alternatives to be completed prior to committing and investing costly resources to one project or decision. The AoA is intended to compare the operational effectiveness, cost, and risk of a number of alternatives to address valid needs and shortfalls in current operational capability. “The AoA shall focus on identification and analysis of alternatives, measures of effectiveness, cost, schedule, concepts of operations, and overall risk. The AoA shall assess the critical technology elements (CTEs) associated with each proposed materiel solution, including technology maturity, integration risk, manufacturing feasibility, and, where necessary, technology maturation and demonstration needs” [DoD, 2008, p. 15]. Figure 1 illustrates the preferred DoD strategy, evolutionary acquisition, for rapid acquisition of mature technology. The AoA is conducted during the Material Solution Analysis phase prior to milestone A and is circled in red.

Despite this mandatory requirement, in September 2009, the U.S. Government Accountability Office (GAO), in “Many Analyses of Alternatives Have Not Provided a Robust Assessment of Weapon System Options,” found that, in many cases, “DoD allows programs to begin without a sound match between requirements and the resources needed to achieve them. That is, programs enter the acquisition process with requirements that are not fully understood, cost and schedule estimates that are based on optimistic assumptions, and a lack of sufficient knowledge about technology, design, and manufacturing” [U.S. Government Accountability Office, 2009, p. 1].

Programs within the GAO study that had limited assessment of alternatives tended to have poorer outcomes than those that had more robust AoAs. They found a lack of guidance across the DoD for conducting AoAs and that service sponsors sometimes identify a preferred solution or a narrow range of solutions early on, before an AoA is conducted. “According to several DoD and program officials, AoAs have often simply validated a concept selected by the sponsor and are not used as intended to make trade offs among performance, cost, and risks to achieve an optimal weapon system concept that satisfies the warfighter’s needs within available resource constraints” [U.S. Government Accountability Office, 2009, p. 6].

Figure 2 illustrates notional life cycle efforts that drive systems engineering decision making. According to the authors’ estimates, the requirements determination and AoA period is roughly 2% of the total life cycle efforts. The effect of this initial 2% effort should never be underestimated as it greatly affects what happens during the rest of the 98% of the life cycle efforts [Georgiadis, Mazuchi, and Sarkani, 2011].

Decision making within the context of conducting AoAs is rarely as simple as picking the cheapest, quickest to deliver, or the best performing system. Multi Criteria Decision Making (MCDM) methods offer a way of merging qualitative subject matter expert opinion with quantitative performance data of various alternatives. When nonlinear metrics are presented within an AoA, MCDM techniques become very useful for discriminating among alternatives. “It is this nature of having to consider different units which makes MCDM to be intrinsically hard to solve” [Triantaphyllou et al., 1998, p. 2]. MCDM does have limitations. It remains very difficult to model inputs such as political influence or public opinion using MCDM. Despite these limitations, MCDM models provide a very powerful decision support role.

![Figure 1. Requirements and acquisition process flow [DoD, 2008].](Color figure can be viewed in the online issue, which is available at wileyonlinelibrary.com)
According to Hanks, Axelband, and Linsay [2005] 63 acquisition reform initiatives took place within the DoD between 1989 and 2002. In their book, *Reexamining Acquisition Reform: Are We There Yet?*, a comprehensive research effort was conducted to evaluate these 63 reform initiatives, categorize them, and draw some fundamental conclusions on how these initiatives have altered the way DoD does business. Interestingly, 44% of these reform initiatives were centered on requirements determination which demonstrates this is a challenging part of the acquisition process. It remains clear that many continue to circumvent the process of conducting an AoA despite multiple reform initiatives.

The GAO report [U.S. Government Accountability Office, 2009], the authors’ interest in nonlinear decision making, Hanks et al.’s book on acquisition reform [Hanks, Axelband, and Linsay, 2005], and the study of MCDM methods for selection of enabling technologies provided motivation for this research. This paper presents the results of research on MCDM methods, defines a case study reference mission and criteria hierarchy, discusses the data collection survey, provides an overview of the analysis including the model construct and implementation, and finally provides discussion which includes recommended future research. The contribution of this paper includes the research of methods to perform robust AoAs that successfully limit bias and account for independent expert judgments and should be useful to the DoD in the selection of enabling technologies. The Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) is used as an example of successfully accounting for tacit knowledge of expert practitioners in decision making.

2. RESEARCH

The goal of this research effort was to consider a MCDM model to use when conducting AoAs in the selection of enabling technology. The solution model chosen should have simple computation and participation of human judgment in the outcome. The model should allow decision makers to make informed decisions when choosing specific alternatives and down selecting the enabling technology that best suits the system design requirements.

The objectives of the research were three fold: identify current applicable MCDM models and methods to use in nonlinear decision analysis; identify a current technology as a reference mission and hierarchy for the decision making case study; conduct a case study using a MCDM model in an AoA to down-select an enabling technology while accounting for subjective inputs. This research and proposed model is not intended to be an authoritative decision mechanism, but a tool to provide decision guidance.

2.1. Multi Criteria Decision Making Methodologies

Decision theory techniques were first formally documented during the 1960s. The ability to synthesize quantitative and qualitative factors in a decision is extremely important [Forman and Selly, 2001]. A literature review has revealed that there is no shortage of models for conducting MCDM. Table I provides an incomplete list of models researched while fuzzy models and their variants are omitted.

According to Triantaphyllou et al. [1998], there are three common steps in utilizing any decision-making technique involving numerical analysis of alternatives. A fourth step was added by the authors to clarify the importance of assess-
<table>
<thead>
<tr>
<th>Table I. Multi Criteria Decision Making Models</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>MCDM Models</strong></td>
</tr>
<tr>
<td>Simple Additive Weighting (SAW) or Weighted Sum Method (WSM)</td>
</tr>
<tr>
<td>Weighted product model (WPM)</td>
</tr>
<tr>
<td>Revised Analytic Hierarchy Process (AHP)</td>
</tr>
<tr>
<td>Multi-attribute utility theory (MAUT)</td>
</tr>
<tr>
<td>Multiple Attribute Group Decision Making (MAGDM)</td>
</tr>
<tr>
<td>Geometrical Analysis for Interactive Aid (GAIA)</td>
</tr>
<tr>
<td>Superiority and inferiority ranking method (SIR method)</td>
</tr>
<tr>
<td>Potentially All Pairwise Rankings of all possible Alternatives (PAPRIKA)</td>
</tr>
<tr>
<td>Aggregated Indices Randomization Method (AIRM)</td>
</tr>
<tr>
<td>Decision Making Trial and Evaluation Laboratory (DEMATEL)</td>
</tr>
<tr>
<td>Data Envelopment Analysis (DEA)</td>
</tr>
<tr>
<td>Complex Proportional Assessment of Alternatives (COPRAS)</td>
</tr>
<tr>
<td>Multi-Objective Optimization on the Basis of Ratio Analysis (MOORA)</td>
</tr>
<tr>
<td>Dominance Based Rough Set Approach (DRSA)</td>
</tr>
<tr>
<td>The Evidential Reasoning Approach (ER)</td>
</tr>
<tr>
<td>Measuring Attractiveness by a Categorical Based Evaluation Technique (MACBETH)</td>
</tr>
<tr>
<td>Goal programming</td>
</tr>
<tr>
<td>Grey Relational Analysis (GRA)</td>
</tr>
<tr>
<td>Step Method (STEM)</td>
</tr>
<tr>
<td>CODASID</td>
</tr>
<tr>
<td>New Approach to Appraisal (NATA)</td>
</tr>
<tr>
<td>Value Analysis (VA), Value engineering (VE)</td>
</tr>
<tr>
<td>The VIKOR method</td>
</tr>
<tr>
<td>Group Decision Support System (GDSS)</td>
</tr>
<tr>
<td>Interpretive Structural Modeling (ISM)</td>
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<tr>
<td>Games Theory Methods</td>
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<tr>
<td>Policy Goal Percentaging Analysis</td>
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<td>UTA (UTiités Additives) method</td>
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ing the nonlinearity associated with system considerations when selecting the MCDM methodology. This additional step is listed as number 3 in the following list:

1. Determining the relevant criteria and alternatives
2. Attaching numerical measures to the relative importance (weights) of the criteria and to the impacts of the alternatives on these criteria
3. Assessing nonlinearity associated with system considerations when selecting MCDM methodology
4. Processing the numerical values to determine a ranking of each alternative.

Determining criteria and alternatives is usually done by expert judgment and a scan of current technologies and their performance. Assigning weights of importance obviously adds subjectivity to the methodology, and it is often quite difficult for the decision maker to quantify his/her preferences on performance attributes. Models that do not require subjective weight inputs are outside the scope of this paper and were not considered.

There are various methods published in literature for determining criteria weights. There are also weight assessment models published that can be used [Heerkens, 2006]. Some claim that there are no criteria for determining which method is the true weight since it is not clear which elicitation procedure is the least biased [Borcherding and Weber, 1993]. These methods can be classified by whether the weighting procedure is statistical or algebraic, holistic or decomposed, or whether it is direct or indirect. Others categorize methods by either being objective or subjective [Ustinovichius, Zavadskas, and Podvezko, 2007].

“Algebraic procedures calculate the n weights from a set of n – 1 judgments often using a system of equations; statistical procedures are based on a redundant set of judgments, and the weights are derived with some statistical procedure such as multiple regression analysis or maximum likelihood estimation. Holistic procedures require the decision maker to evaluate (holistic) alternatives, i.e., rate or rank alternatives; decomposed methods look at one attribute or attribute pair at a time. Direct procedures ask the decision maker to compare the ranges of two attributes in terms of ratio judgments whereas indirect procedures infer weights from preference judgments” [Borcherding and Weber, 1993, p. 2]. Many researchers use pairwise comparison matrices to compute the relative importance of criteria (weights) [Afshari, Mojahed, and Yusuff, 2010; Nydick and Hill, 1992]. Literature reveals many variations of weighting methodologies [Olson, 2004].

Additionally, there are many ways one can classify MCDM methods. One way is to classify them according to the type of data they use. That is, MCDM methods can be deterministic, stochastic, or fuzzy [Triantaphyllou et al., 1998]. This research considered only deterministic methods for the case study. The choice of which model to use is left up to the decision maker, and many times the process of selecting a model can lead to a decision making challenge itself [Triantaphyllou and Mann, 1989]. All MCDM models must start with a data set. Equation (1) is a decision matrix (D) and is generally created to arrange the data for any MCDM model which has m alternatives (Ai), n criteria (xi), and n weights (wi) assigned to all criteria to indicate importance or preference via judgments. The weights are expected to sum to 1. The criteria are assessed within the matrix as rij for each alternative.

\[
x_1 \ x_2 \ x_3 \ \cdots \ x_n
\]
\[
A_i \left[ \begin{array}{cccc} r_{11} & r_{12} & r_{13} & \cdots & r_{1n} \\ r_{21} & r_{22} & r_{23} & \cdots & r_{2n} \\ r_{31} & r_{32} & r_{33} & \cdots & r_{3n} \\ \cdots & \cdots & \cdots & \cdots & \cdots \\ A_m & r_{m1} & r_{m2} & \cdots & r_{mn} \end{array} \right] = D
\]
\[
w_1 \ w_2 \ w_3 \ \cdots \ w_n
\]

Three very simple and well documented deterministic MCDM methods include the Simple Additive Weighting (SAW) model, the Weighted Product Model (WPM), and the Analytic Hierarchy Process (AHP). It is useful to provide a brief introduction of these common MCDM models for context.

The SAW model, also commonly known as the weighted sum model (or WSM) is probably the most commonly used approach, especially in single dimensional problems. First one must calculate the normalized decision matrix for benefit criteria (higher is better) where nij replaces rij values within Eq. (1):

\[
n_{ij} = \frac{r_{ij}}{r_{ij}^{	ext{max}}}, \quad i = 1, 2, \ldots, m, \quad j = 1, 2, \ldots, n.
\]

And for “cost” or loss criteria (lower is better), where nij replaces rij values within Eq. (1):

\[
n_{ij} = \frac{r_{ij}^{	ext{min}}}{r_{ij}}, \quad i = 1, 2, \ldots, m, \quad j = 1, 2, \ldots, n.
\]

The best alternative using SAW is the one that maximizes Ai in Eq. (4). The weights (wj) are expected to sum to 1.

\[
A_i = \sum_{j=1}^{n} w_j n_{ij}, \quad i = 1, 2, \ldots, m.
\]

The assumption that governs this model is the additive utility assumption [Fishburn, 1965, 1966, 1967, 1968]. That is, the total value of each alternative is equal to the sum of products given as in Eq. (4). “In single dimensional cases, in which all the units are the same (e.g., dollars, feet, or seconds), the WSM method can be used without difficulty. Difficulty with this method emerges when it is applied to multidimensional decision-making problems” [Triantaphyllou et al., 1998, p. 4].

The WPM is very similar to the SAW model. The main difference is that multiplication is used instead of addition. Each alternative (Ai) is compared with the others by multiplying a number of ratios (Rij), one for each criterion (xi). Each ratio is raised to the power equivalent to the relative weight (wi) of the corresponding criterion. WPM is sometimes re-
ferred to as “dimensionless analysis because its structure eliminates any units of measure” [Triantaphyllou et al., 1998, p. 5]. Transformation is not necessary when one uses multiplication among criterion values. The weights become exponents associated with each criterion value, and a positive power is used for benefit criterion and a negative power for cost criterion ($x^i_j$). Equation (5) represents the WPM method:

$$R_i = \left( \frac{V(A_i)}{V(A^*)} \right)^{w_j} = \frac{\prod_{j=1}^{n} x_{ij}^{w_j}}{\prod_{j=1}^{n} (x^*)^{w_j}}, \quad i = 1, 2, ..., m$$  \hspace{1cm} (5)

The analytic hierarchy process (or AHP) developed by Saaty [1980] uses subjective judgments expressed in terms of pairwise comparisons of items on a given level of the hierarchy with respect to their impact on the next higher level. The comparisons represent an estimate of the ratio of the weights of the two criteria being compared. This ratio scale for processing human judgments has been applied to a variety of decision-making problems. Because AHP utilizes a ratio scale for human judgments, the alternative weights ($w_j$) reflect the relative importance of the criteria ($x_{ij}$) in achieving the goal of the hierarchy. Equation (6) demonstrates how to calculate the best alternative ($A^*_{AHP}$) using AHP:

$$A^*_{AHP} = \max_i \sum_{j=1}^{n} w_j x_{ij}, \quad i = 1, 2, ..., m. \hspace{1cm} (6)$$

The similarity between the SAW and the AHP is evident in Eq. (6); however, “the AHP uses relative values instead of actual ones. Thus, it can be used in single or multidimensional decision-making problems” [Triantaphyllou et al., 1998, p. 6]. Other commonly used models give a standard utility interpretation to the quantities in these additive methods by using utility functions [Keeney and Raiffa, 1993; Raiffa, 2006].

For the purpose of this research case study, the authors have selected to use the TOPSIS method. TOPSIS was chosen for its geometric properties, deterministic data approach, account for the multidimensional criteria space, successful historical use, simple representation and explanation, strong literature base, and clear participation of expert judgment in the solution model.

The TOPSIS method is a popular approach to MCDM and has been widely used in the literature. TOPSIS was first developed by Yoon [1980] for solving a MCDM problem. Hwang and Yoon [1981] expound further on the use of TOPSIS when assessing applications of MCDM. TOPSIS assumes that each attribute has a tendency of monotonically increasing or decreasing utility [Triantaphyllou et al., 1998]. Therefore, it is easy to locate the ideal and negative-ideal solutions. “A relative advantage of TOPSIS is the ability to identify the best alternative quickly” [Lofti, Fallahnejad, and Navidi, 2011, p. 807]. TOPSIS is also attractive because limited subjective input is needed from decision makers. The only subjective input needed is weights [Olson, 2004]. This study proposes a new method by adding subjective criteria, such as risk, into TOPSIS requiring expert judgment and demonstrating that such a method is effective and efficient.

The basic premise of TOPSIS is that the chosen alternative should be as close to the positive ideal solution ($A^*$) as possible and as far from the negative ideal solution ($A^-$) as possible. The positive ideal solution is a composite of the best performance values of all alternatives ($A_i$). The negative ideal solution is a composite of the worst performance values of all alternatives.

Figure 3 illustrates a general graphical representation of TOPSIS [Georgiadis, Mazzuchi, and Sarkani, 2011]. For example, it is very difficult to justify choosing $A_1$ in this visual example, so proximity to each of these performance poles is measured in the Euclidean sense (e.g., square root of the sum of the squared distances along each axis in the criteria space). The mathematical process of conducting this model using vector normalization is listed within the model construct Section 4.3 of this paper.

TOPSIS is not nearly as widely applied or advertised as other MCDM methods. Its lack of popularity could be attributed to it being introduced 20 years after earlier methods and possibly less commercialization. Despite these considerations, there have been many successful uses of TOPSIS documented within literature. In the 1990s the U.S. Army successfully used TOPSIS to support the development of their Program Objective Memorandum or POM budget plan (CAA-SR-91-9) [Buede and Maxwell, 1995]. TOPSIS has been used for various applications in the selection of robots and robotic technology [Agrawal, Kohli, and Gupta, 1991; Bhangale, Agrawal, and Saha, 2004]. It has been used in selecting manufacturing methods of semiconductors and for financial investments [Chau and Parkan, 1995]. TOPSIS has also been used to compare company performances [Deng, Yeh, and Willis, 2000] and financial ratio performance within the highway bus industry [Feng and Wang, 2001]. A systematic methodology for classification and evaluation of the different available offshore wind turbine support structure options was developed using TOPSIS [Kolios et al., 2010]. TOPSIS was also successfully used to rank operating systems [Balli and Korokulu, 2009].

**2.2. Research Methodology**

Current applicable MCDM methods were researched for use in nonlinear decision analysis, and TOPSIS was chosen to be used within a case study example of a multtiered AoA to
down select an enabling technology. The case study includes defining the reference mission and the subsystem enabling technology. The reference hierarchy was then established after iterative discussions with experts. A survey was used to elicit expert judgments to assess six unique technology alternatives using eight specific criteria questions. TOPSIS was then used to rank the alternatives. Finally, multiple sensitivity analyses were conducted to demonstrate the stability of the model’s ranking results.

2.2.1. Reference Mission
A relatively new technology, Light Detection and Ranging (LIDAR), is considered an excellent candidate for examining the use of MCDM. The reference mission, an airborne LIDAR mine detection system, is considered state of the art, current, and suitable for a case study using TOPSIS in the selection of its enabling technology. After iterative discussions with experts in the field of LIDAR, it was agreed that the optical receiver is the key enabling technology within a LIDAR system. The reference mission to which the receiver types were evaluated is a dual medium (air and water) airborne LIDAR system. Figure 4 illustrates the reference mission taxonomy setting the context of the survey instrument.

2.2.2. Reference Hierarchy
The second step after the reference mission was defined was to establish the hierarchy of the decision that is being evaluated. Figure 5 displays a multitiered hierarchy of selecting the mission platform, mission capability, and the enabling technology. Creating this multitiered hierarchy (multitiered AoA) can assist in understanding the relationships between the enabling technology and the specific criteria that are selected to evaluate the alternatives.

It is clear that multitiered AoAs begin to add complexity to a decision when more than a single tier is considered in the hierarchy. The third tier, selection of the enabling technology, exemplifies the nonlinear research question being addressed within this paper. A complete AoA should consider all the enabling technologies at the same time, thus capturing the interrelationships and system parameters that are critical to assess together. For the purpose of brevity, however, this paper is limited to an AoA to select only the optical receiver.

Most AoAs are conducted to the first-tier level proposing or justifying a specific mission platform or mission capability but fail to go further in analyzing which enabling technology is most appropriate for the system design. It is clear that the DoD realizes this problem in that they now require that critical technology elements be evaluated within the AoA [DoD, 2008]. The authors allege that the enabling technology is where most of the system design risk exists in the early stages of the program development. This research recognizes the need for multitiered AoAs to be conducted, but specifically down to the level of the enabling technology.

3. SURVEY
A survey was used to collect data from subject matter experts in the field of electrooptics as inputs to TOPSIS. The survey consisted of a minimum of 56 data fields the participants were required to fill in. This included a total of eight rankings of six different alternatives requiring 48 fields, and a total of eight weights had to be assessed for each criterion. Eight optional fields were provided for the participants to list their rationale for each assessment. In addition, six optional demographic questions and an open-ended comment section were also included in the survey. All of the survey responses were recorded and the means transposed into the TOPSIS model for conducting the third tier AoA.

3.1. Participants
A total of 34 optical engineering experts were selected as participants. Each participant was selected from an organization that is involved in electrooptics development and acquisition. The minimum requirement to be selected as a survey participant required at least 3 years of experience in electrooptics.

3.2. Criteria Matrix
During preliminary investigative research, several well-respected electrooptics experts were queried about which criteria and alternatives would be most important to discern when making a selection of an optical receiver. Each question to assess the criteria within the matrix must be understood as benefit criteria (higher is better) or as cost criteria (lower is better) because the convention of each must be accounted for within the model construct.

The criteria within the decision matrix selected for this research include [labeled either as a cost (c) or a benefit (b) criteria]: Operational schedule risk (c), Receiver cost (c), Limiting range resolution (c), Signal to noise ratio (b), Technology readiness level using Table II (b), Dynamic range or scene luminance (b), Quantum efficiency—electrical sensitivity to blue green wavelengths (b), and Operational availability (b). These criteria include both subjective expert judgment and quantitative performance inputs. The participants were then required to assess the weighted importance of the eight criteria (summing to 1.0) in the context of the reference mission.

Figure 4. Reference mission—detect underwater mines from air.
The alternative receiver types selected for this research include photo multiplier tube (PMT), streak tube, Geiger mode avalanche photo diode (APD), gated LIDAR, 3D camera, and multispectral imager.

3.3. Delivery Mechanism
Participants were solicited by electronic mail to participate in the survey. A Microsoft Excel spreadsheet was used for the survey instrument. Each participant was provided an information/consent form, an example survey filled in, and the survey file. Once received, the survey files were saved and password protected. The participation in this survey will remain anonymous.

4. ANALYSIS
The analysis of survey data was conducted in six primary areas: participant demographic analysis, survey criteria weighting, model construct, model implementation and com-
comparison to other MCDM rankings, model output interpretation, and model sensitivity analyses.

4.1. Participant Demographic Analysis

Of the 34 invitations distributed, 20 were completed and returned, which exceeded the minimum requirement of expert judgments for this research, which was set at 15 returned surveys. All participants that submitted surveys had at least 3 years experience in electrooptics while some exceeded 30 years of experience. Participant demographic analysis shows that of those who completed the survey, 30% held a PhD, 45% held an MS, and 25% held a BS. Approximately 45% of the participants worked for organizations with 500 or less employees. Organization sizes ranged from 10 to 120,000 employees. The demographic data demonstrates a diverse level of participation. A check for data inconsistencies was performed by analyzing all data together within a spreadsheet and plotting individual responses to criteria weights and receiver rankings. As a result, there were no outliers identified, and this is attributed to a well educated and credible sample of expert practitioners.

4.2. Survey Criteria Weighting

The questionnaire used within the survey of electrooptics experts rated six different optical receivers and captured the relative importance (or weight) of eight different criteria. The weights \( w_j \) must sum to one as required:

\[
\sum_{j=1}^{n} w_j = 1. \quad (7)
\]

Because there is no decision maker for this case study, the indirect method of inferring subjective weights from combining expert judgments and solving for the means was used as an input to the TOPSIS model.

4.3. Model Construct

The procedure of TOPSIS is summarized as follows:

1. Populate the decision matrix with raw data found from surveys; where \( X_{ij} \) is the rating of alternative \( i \) with respect to criterion \( j \) and \( W_j \) is the weight of criterion \( j \) (see Table III).

2. Calculation of the normalized decision matrix: The normalized value \( r_{ij} \) is calculated to transform the various attribute dimensions \( X_{ij} \) into nondimensional attributes, which allows comparison across the attributes [Wang, 2011]:

\[
r_{ij} = \frac{X_{ij}}{\sqrt{\sum_{j=1}^{n} X_{ij}^2}}, \quad j = 1, \ldots, n, i = 1, \ldots, m. \quad (8)
\]

3. Calculation of the weighted normalized values \( v_{ij} \) by multiplying the normalized values \( r_{ij} \) by the criterion weights \( W_j \); calculation of the weighted normalized matrix \( V \) [see Table IV and Eqs. (9) and (10)]:

\[
v_{ij} = W_j r_{ij}, \quad j = 1, \ldots, n, i = 1, \ldots, m.
\]

\[
V = \begin{bmatrix}
V_{11} & V_{12} & \cdots & V_{1j} & \cdots & V_{1m} \\
\vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\
\vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\
V_{n1} & V_{n2} & \cdots & V_{nj} & \cdots & V_{nm}
\end{bmatrix}
\]

\[
W_1 R_{11} & W_1 R_{12} & \cdots & W_1 R_{1j} & \cdots & W_1 R_{1m} \\
\vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\
\vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\
W_n R_{n1} & W_n R_{n2} & \cdots & W_n R_{nj} & \cdots & W_n R_{nm}
\]

\[
(10)
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<tr>
<th>Table III. Decision Matrix</th>
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<tr>
<td>( \vdots )</td>
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<tr>
<td>( X_{m1} )</td>
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\[
W_1 & W_2 & \cdots & W_n
\]
4. Determination of the positive ideal ($A^+$) and negative ideal solution ($A^-$):

\[ A^+ = \{(\max_{j \in J} v_{ij}^+), (\min_{j \in J} v_{ij}^-) | j = 1, 2, ..., m\} \]
\[ A^- = \{(\min_{j \in J} v_{ij}^+), (\max_{j \in J} v_{ij}^-) | j = 1, 2, ..., m\} \]

where \( J = \{j = 1, 2, ..., n| j \text{ associated with benefit criteria}\} \)
\( \tilde{J} = \{j = 1, 2, ..., n| j \text{ associated with loss criteria}\} \).

5. Calculation of the separation of each alternative from the positive ideal ($s_i^+$) and negative ideal ($s_i^-$) solution measures, using the \( n \)-dimensional Euclidean distance:

\[ S_i^+ = \sqrt{\sum_{j=1}^{n} (v_{ij}^+ - V_{ij}^+)^2} \quad i = 1, 2, ..., m, \]
\[ S_i^- = \sqrt{\sum_{j=1}^{n} (v_{ij}^- - V_{ij}^-)^2} \quad i = 1, 2, ..., m. \]  

6. Calculation of the relative closeness to the ideal solution ($c_i^+$):

\[ c_i^+ = \frac{s_i^-}{s_i^+ + s_i^-} \quad 0 < c_i^+ < 1 \quad i = 1, 2, ..., m, \]
\[ c_i^- = \frac{s_i^-}{s_i^+ + s_i^-} = \frac{\sqrt{\sum_{j=1}^{n} (v_{ij}^- - V_{ij}^-)^2}}{\sqrt{\sum_{j=1}^{n} (v_{ij}^- - V_{ij}^-)^2} + \sqrt{\sum_{j=1}^{n} (v_{ij}^- - V_{ij}^-)^2}} \quad i = 1, 2, ..., m. \]  

7. Ranking the preference order: The closer the $c_i^+$ is to 1 implies the higher priority of the \( j \)th alternative. The set of alternatives can now be preference-ranked according to the descending order of $c_i^+$.

### 4.4. Model Implementation

The raw data, that is, the arithmetic sample means from the survey ratings and weights, were first input to the decision matrix for TOPSIS as shown in Table V. Using Eq. (8), the decision matrix was then normalized as shown in Table VI. Using Eqs. (9) and (10), the weighted normalized decision matrix is then calculated as shown in Table VII. Using Eq. (11), the positive ideal ($A^+$) and negative ideal ($A^-$) solutions are calculated as shown in Table VIII. Using Eq. (12), the separation measure to the positive ideal solution ($S^+$) and separation to the negative ideal solution ($S^-$) are calculated as shown in Table IX. Finally, the relative closeness to the positive ideal solution was measured for each alternative using Eq. (13), and the resultant ranking is shown in Table X. The model indicates that the streak tube receiver alternative should be considered the most preferred for the enabling technology of the reference mission. A check for consistency was conducted using two additional MCDM methods introduced within this paper (SAW and WPM) to compare ranking results.

The results are consistent between TOPSIS and WPM; however, ranking swapped between two alternatives when comparing TOPSIS and SAW. It is observed that SAW has very little discrimination between the 3rd- and 4th-ranked results, so this difference is not significant.

### 4.5. Model Output Interpretation

Among eight evaluation criteria, the technology readiness level is shown to be the most important criterion affecting selection of the optical receiver, followed by dynamic range, signal to noise ratio, reliability, limiting resolution, risk, quantum efficiency, and cost being the least important. This study has shown a new method using subjective inputs into the TOPSIS criteria set, demonstrating that such a method can effectively use expert judgment. Subjectively measuring risk, for example, was successfully incorporated into the TOPSIS model. The model output clearly identifies the ranking order of alternatives with the streak tube receiver being ranked first and the 3D camera ranked last for the reference mission. TOPSIS is shown to be a method that successfully takes performance data and subjective expert judgment into account when ranking the order of preference for each alternative.

### Table IV. Weighted Normalized Decision Matrix (V)

<table>
<thead>
<tr>
<th>Alternative 1</th>
<th>v_{11}</th>
<th>v_{12}</th>
<th>...</th>
<th>v_{1m}</th>
</tr>
</thead>
<tbody>
<tr>
<td>Alternative 2</td>
<td>v_{12}</td>
<td>v_{22}</td>
<td>...</td>
<td>v_{2m}</td>
</tr>
<tr>
<td>...</td>
<td>...</td>
<td>...</td>
<td></td>
<td>...</td>
</tr>
<tr>
<td>Alternative m</td>
<td>v_{ml}</td>
<td>v_{ml}</td>
<td>...</td>
<td>v_{mn}</td>
</tr>
</tbody>
</table>

### Table V. Raw Data Decision Matrix

<table>
<thead>
<tr>
<th>Criterion (Xj)</th>
<th>Risk Index</th>
<th>Cost (K)</th>
<th>Limiting Resolution (in inch)</th>
<th>SNR (dB) /Sensitivity</th>
<th>Technology Readiness Level</th>
<th>Dynamic Range (bit)</th>
<th>Quantum Efficiency</th>
<th>Reliability</th>
</tr>
</thead>
<tbody>
<tr>
<td>PMT</td>
<td>2</td>
<td>252.75</td>
<td>11</td>
<td>39</td>
<td>8</td>
<td>11</td>
<td>4</td>
<td>0.70</td>
</tr>
<tr>
<td>Streak Tube</td>
<td>1</td>
<td>343.75</td>
<td>6</td>
<td>37</td>
<td>8</td>
<td>13</td>
<td>4</td>
<td>0.54</td>
</tr>
<tr>
<td>Geiger Mode APD</td>
<td>4</td>
<td>705.00</td>
<td>8</td>
<td>53</td>
<td>5</td>
<td>12</td>
<td>6</td>
<td>0.65</td>
</tr>
<tr>
<td>Gated LIDAR</td>
<td>3</td>
<td>465.00</td>
<td>10</td>
<td>44</td>
<td>7</td>
<td>12</td>
<td>4</td>
<td>0.64</td>
</tr>
<tr>
<td>3D Camera</td>
<td>4</td>
<td>717.50</td>
<td>11</td>
<td>44</td>
<td>5</td>
<td>13</td>
<td>5</td>
<td>0.62</td>
</tr>
<tr>
<td>Multi Spec</td>
<td>2</td>
<td>523.75</td>
<td>13</td>
<td>24</td>
<td>7</td>
<td>14</td>
<td>4</td>
<td>0.73</td>
</tr>
<tr>
<td>Weight (Wj)</td>
<td>0.100</td>
<td>0.074</td>
<td>0.117</td>
<td>0.158</td>
<td>0.170</td>
<td>0.167</td>
<td>0.090</td>
<td>0.127</td>
</tr>
</tbody>
</table>

Systems Engineering DOI 10.1002/sys
4.6. Model Sensitivity Analysis

Often data in MCDM problems are imprecise and changeable. Therefore, an important step in applications of MCDM is to perform a Sensitivity Analysis (SA) [Simanaviciene and Ustiniovichius, 2010]. Broadly defined, SA is the investigation of potential changes and errors within the model input parameters and their impacts on conclusions to be drawn from the model. When parameters are uncertain, Pannell [1997] has suggested that SA can give information such as:

Table VI. Normalized Decision Matrix

<table>
<thead>
<tr>
<th></th>
<th>X_1</th>
<th>X_2</th>
<th>X_3</th>
<th>X_4</th>
<th>X_5</th>
<th>X_6</th>
<th>X_7</th>
<th>X_8</th>
</tr>
</thead>
<tbody>
<tr>
<td>A_1</td>
<td>0.239</td>
<td>0.195</td>
<td>0.446</td>
<td>0.388</td>
<td>0.475</td>
<td>0.371</td>
<td>0.339</td>
<td>0.437</td>
</tr>
<tr>
<td>A_2</td>
<td>0.202</td>
<td>0.265</td>
<td>0.241</td>
<td>0.371</td>
<td>0.497</td>
<td>0.426</td>
<td>0.350</td>
<td>0.341</td>
</tr>
<tr>
<td>A_3</td>
<td>0.575</td>
<td>0.543</td>
<td>0.319</td>
<td>0.525</td>
<td>0.298</td>
<td>0.387</td>
<td>0.552</td>
<td>0.409</td>
</tr>
<tr>
<td>A_4</td>
<td>0.373</td>
<td>0.358</td>
<td>0.420</td>
<td>0.435</td>
<td>0.414</td>
<td>0.387</td>
<td>0.376</td>
<td>0.403</td>
</tr>
<tr>
<td>A_5</td>
<td>0.597</td>
<td>0.553</td>
<td>0.436</td>
<td>0.438</td>
<td>0.301</td>
<td>0.428</td>
<td>0.445</td>
<td>0.389</td>
</tr>
<tr>
<td>A_6</td>
<td>0.276</td>
<td>0.404</td>
<td>0.524</td>
<td>0.234</td>
<td>0.420</td>
<td>0.444</td>
<td>0.344</td>
<td>0.460</td>
</tr>
<tr>
<td>W_j</td>
<td>0.100</td>
<td>0.074</td>
<td>0.117</td>
<td>0.158</td>
<td>0.170</td>
<td>0.167</td>
<td>0.090</td>
<td>0.127</td>
</tr>
</tbody>
</table>

Table VII. Weighted Normalized Decision Matrix

<table>
<thead>
<tr>
<th></th>
<th>X_1</th>
<th>X_2</th>
<th>X_3</th>
<th>X_4</th>
<th>X_5</th>
<th>X_6</th>
<th>X_7</th>
<th>X_8</th>
</tr>
</thead>
<tbody>
<tr>
<td>A_1</td>
<td>0.024</td>
<td>0.014</td>
<td>0.052</td>
<td>0.061</td>
<td>0.081</td>
<td>0.062</td>
<td>0.030</td>
<td>0.055</td>
</tr>
<tr>
<td>A_2</td>
<td>0.020</td>
<td>0.019</td>
<td>0.028</td>
<td>0.058</td>
<td>0.084</td>
<td>0.071</td>
<td>0.031</td>
<td>0.043</td>
</tr>
<tr>
<td>A_3</td>
<td>0.057</td>
<td>0.040</td>
<td>0.037</td>
<td>0.083</td>
<td>0.051</td>
<td>0.065</td>
<td>0.049</td>
<td>0.052</td>
</tr>
<tr>
<td>A_4</td>
<td>0.037</td>
<td>0.026</td>
<td>0.049</td>
<td>0.069</td>
<td>0.070</td>
<td>0.065</td>
<td>0.034</td>
<td>0.051</td>
</tr>
<tr>
<td>A_5</td>
<td>0.060</td>
<td>0.041</td>
<td>0.051</td>
<td>0.069</td>
<td>0.051</td>
<td>0.071</td>
<td>0.040</td>
<td>0.049</td>
</tr>
<tr>
<td>A_6</td>
<td>0.028</td>
<td>0.030</td>
<td>0.061</td>
<td>0.037</td>
<td>0.071</td>
<td>0.074</td>
<td>0.031</td>
<td>0.058</td>
</tr>
<tr>
<td>W_j</td>
<td>0.100</td>
<td>0.074</td>
<td>0.117</td>
<td>0.158</td>
<td>0.170</td>
<td>0.167</td>
<td>0.090</td>
<td>0.127</td>
</tr>
</tbody>
</table>

Table VIII. Positive Ideal and Negative Ideal Solutions

<table>
<thead>
<tr>
<th></th>
<th>V_1^+</th>
<th>V_2^+</th>
<th>V_3^+</th>
<th>V_4^+</th>
<th>V_5^+</th>
<th>V_6^+</th>
<th>V_7^+</th>
<th>V_8^+</th>
</tr>
</thead>
<tbody>
<tr>
<td>A^+</td>
<td>0.020</td>
<td>0.014</td>
<td>0.028</td>
<td>0.083</td>
<td>0.084</td>
<td>0.074</td>
<td>0.049</td>
<td>0.058</td>
</tr>
<tr>
<td></td>
<td>V_1^-</td>
<td>V_2^-</td>
<td>V_3^-</td>
<td>V_4^-</td>
<td>V_5^-</td>
<td>V_6^-</td>
<td>V_7^-</td>
<td>V_8^-</td>
</tr>
<tr>
<td>A^-</td>
<td>0.060</td>
<td>0.041</td>
<td>0.061</td>
<td>0.037</td>
<td>0.051</td>
<td>0.062</td>
<td>0.030</td>
<td>0.043</td>
</tr>
</tbody>
</table>

Table IX. Separation Measures to the Positive and Negative Ideal Solutions

<table>
<thead>
<tr>
<th></th>
<th>S_1^+</th>
<th>S_2^+</th>
<th>S_3^+</th>
<th>S_4^+</th>
<th>S_5^+</th>
<th>S_6^+</th>
<th>S_7^+</th>
<th>S_8^+</th>
</tr>
</thead>
<tbody>
<tr>
<td>S_1^-</td>
<td>0.040</td>
<td>S_2^-</td>
<td>0.061</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>S_2^-</td>
<td>0.034</td>
<td>S_2^-</td>
<td>0.069</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>S_3^-</td>
<td>0.058</td>
<td>S_3^-</td>
<td>0.056</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>S_4^-</td>
<td>0.041</td>
<td>S_4^-</td>
<td>0.048</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>S_5^-</td>
<td>0.065</td>
<td>S_5^-</td>
<td>0.037</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>S_6^-</td>
<td>0.063</td>
<td>S_6^-</td>
<td>0.044</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

4.6. Model Sensitivity Analysis

Often data in MCDM problems are imprecise and changeable. Therefore, an important step in applications of MCDM is to perform a Sensitivity Analysis (SA) [Simanaviciene and Ustiniovichius, 2010]. Broadly defined, SA is the investigation of potential changes and errors within the model input parameters and their impacts on conclusions to be drawn from the model. When parameters are uncertain, Pannell [1997] has suggested that SA can give information such as:

Table X. Rankings of Alternatives (TOPSIS, SAW, WPM)

<table>
<thead>
<tr>
<th>Receiver Type</th>
<th>TOPSIS Relative Closeness</th>
<th>TOPSIS Ranking</th>
<th>SAW Scores</th>
<th>SAW Ranking</th>
<th>WPM Scores</th>
<th>WPM Ranking</th>
</tr>
</thead>
<tbody>
<tr>
<td>PMT</td>
<td>C_1</td>
<td>0.605</td>
<td>2</td>
<td>0.814</td>
<td>2</td>
<td>1.961</td>
</tr>
<tr>
<td>Streak Tube</td>
<td>C_2</td>
<td>0.668</td>
<td>1</td>
<td>0.862</td>
<td>1</td>
<td>2.084</td>
</tr>
<tr>
<td>Geiger Mode APD</td>
<td>C_3</td>
<td>0.489</td>
<td>4</td>
<td>0.756</td>
<td>3</td>
<td>1.750</td>
</tr>
<tr>
<td>Gated LIDAR</td>
<td>C_4</td>
<td>0.542</td>
<td>3</td>
<td>0.750</td>
<td>4</td>
<td>1.808</td>
</tr>
<tr>
<td>3D Camera</td>
<td>C_5</td>
<td>0.360</td>
<td>6</td>
<td>0.698</td>
<td>6</td>
<td>1.819</td>
</tr>
<tr>
<td>Multi Spec</td>
<td>C_6</td>
<td>0.412</td>
<td>5</td>
<td>0.725</td>
<td>5</td>
<td>1.889</td>
</tr>
</tbody>
</table>
1. How robust the optimal solution is in the face of different parameter values
2. Under what circumstances the optimal solution would change
3. How the optimal solution changes in different circumstances
4. How much worse off the decision makers would be if they ignored the changed circumstances and stayed with the original optimal strategy or some other strategy.

“This information is extremely valuable in making decisions or recommendation. If the optimal strategy is robust (insensitive to changes in parameters), this allows confidence in implementing or recommending it” [Pannell, 1997, p. 141].

Yoon [1989, p. 681] highlights that “measurements of (especially non-monetary) attribute ratings and assessments of attribute weights are often highly imprecise and subjective, yet most analytical methods lack provisions for handling imprecise data.” Although beyond the scope of this paper, Yoon presents an effective method using standard deviations to measure the propagation of errors in assessing the value of alternatives within a MCDM problem.

Three sensitivity analyses were conducted on the model within this paper. The first was conducted by iteratively and cumulatively calculating the arithmetic mean of survey inputs. Thus, the resultant iterative graph of rankings is expected to demonstrate the convergence of survey inputs. Rank results of the first SA can be seen in Figure 6. The results of this SA indicate stability in the result with the streak tube receiver alternative receiving the highest (first) rank and the 3D camera as the lowest (sixth) rank. The results of the first SA did not alter the preferred alternative.

The second SA was conducted by varying the weights while maintaining the criteria rating means. Each survey set of weights were iteratively introduced. Figure 7 displays the results of the second SA and indicates some stability in the result, while still maintaining (on average) the streak tube receiver alternative as the highest rank and the 3D camera as the lowest rank. Again, the results of the second SA did not alter the preferred alternative.

To further demonstrate the benefits of conducting a detailed sensitivity analysis, a third SA displays each survey ranked independently using TOPSIS in Figure 8. At first glance, this third SA appears very unstable; however, if the ranking histogram is plotted as in Figure 9, the streak tube and PMT receiver alternatives remain as the highest ranked alternatives.

Thus, this third SA further demonstrates that with very sensitive iterative runs of the model, the result indicates that the streak tube receiver alternative would still be among the top-ranked alternatives while the 3D camera remains among the consistently lowest-ranked alternatives.

It is clear that even experts will not agree on all ratings and weights; thus it is useful to maximize the number and averaging of expert judgments in the sample set.

It is observed that using subjective criteria within a MCDM model can lead to sensitive results if those inputs are run independently. This result also adds to the argument that criteria (subjective or objective) should be unambiguous and limit variation in interpretation. Additional study in conducting various sensitivity analyses on MCDM methods is recommended for future research as begun by Triantaphyllou and Sanchez [1997].
5. DISCUSSION

The goal of this research was to identify a method to conduct a more robust AoA down to the level of selecting the enabling technology for a system design. TOPSIS was chosen for its rational computation and its participation of human judgment in the solution model. This is not to say that TOPSIS is the only solution model that is useful for MCDM or for conducting AoAs. There are many useful models as listed in the MCDM models summary in Table I. This paper conducted a brief introduction of four of the deterministic models (SAW, WPM, AHP, and TOPSIS). Although three model ranking results (SAW, WPM, and TOPSIS) were briefly compared in this case study, comparisons of model performance was not a focus of this research.

Upon completion of conducting an AoA using MCDM, one could use the weighted criteria to then begin to select the key performance parameters of the system when writing requirements. Generating well-written requirements is another area in which the DoD could use improvement. According to Blanchard [2003, p. 2], “requirements in today’s dynamic worldwide conditions are constantly changing with mission thrusts, priorities, and introduction and evolution of new technologies.” MCDM can also be used to select the best requirements and ensure they meet some level of criteria when written. In his book on software requirements, Davis identifies 13 attributes of a well-written requirement. These are: “correct, unambiguous, complete, verifiable, consistent, understandable by customer, modifiable, traced, traceable, design independent, annotated, concise, organized” [Davis, 1993, p. 181]. Too many times, requirements are poorly written and misinterpreted. Poorly written requirements have multiple consequences in systems design including challenging test periods with various interpretations of test results.

Analyzing the use of MCDM to create well-written requirements is considered future research.

5.1. Survey Comments

A survey comment box was made available at the end of the survey for participants to provide feedback. In general, most of the comments received were recommendations to consider additional discriminating “system” criteria such as size and weight, scene discrimination, spatial resolution, vertical resolution, intrinsic availability, field-of-view, field-of-regard, acceptance angle with minimum distortion, illumination source (laser) and its cost, specific wavelength selection, aperture size, overall system design, time of day operations (day or night, or both), active or passive, scanner requirement and its reliability, tactics using the sensor, and area search rate. Additionally, one comment expressed that quantifying receiver suitability in the absence of an overall system design could invariably lead to the wrong conclusion and possibly present nonsensical results. Four alternative optical receivers were suggested for future consideration including: linear APD, active multi-spectral, solid state streak tube, and P-N diodes.

5.2. Boundaries of Study

The survey and analysis did not consider the first- and second-tier AoA to demonstrate selection of the platform or the mission capability. Concessions were made as to the number, complexity, and definition of the criteria and alternatives used within this research and therefore may not be completely comprehensive. Consequently, this model was limited to the six alternative receiver types and eight criteria presented in the survey. It is recommended to limit MCDM criteria to a reasonable set for comparison and trade off of technologies.
According to Thomas Saaty [2008], creator of AHP, too much information is as bad as little information when conducting MCDM.

Although TOPSIS has shown to be effective in providing the decision maker a recommended solution, the model does have criticism in literature. For example, Buede and Maxwell [1995] criticize TOPSIS for performing worse than other MCDM models when considering rank reversal. When new alternatives are added to a decision problem, the ranking of the old alternatives must not change, or “rank reversal” must not occur [Barzilai and Golany, 1994]. Rank reversal immunity is not a subject of this paper, and is considered future research. Some declare that using several MCDM methods simultaneously allows one to identify some stable alternatives rated similarly by various techniques [Ustinovichius, Zavadskas, and Podvezko, 2007]. This study was limited to exercise three methods simultaneously.

The authors recognize there are always intangibles that introduce error into decision making that are very difficult to model. As an example, the relationship between decision making, political influence, and public opinion are not considered within this research, but may offer interesting future research. Despite these criticisms, MCDM methods continue to be used by many decision makers because it is better to base one’s decisions on rational analysis than by ambiguity or intuition alone.

5.3. Summary

The Department of Defense clearly needs to apply greater attention in conducting thorough AoAs. Spending quality time evaluating alternatives up front during the first 2% of the systems engineering effort should reduce long-term waste and provide a means to document early decisions within a program. The authors recommend that MCDM be used in AoAs as demonstrated in this paper by ranking alternatives for the enabling technology within a system design. The enabling technology is where the performance and design risk exists in a system.

An airborne LIDAR was chosen as the reference mission for the case study of selecting an enabling technology. The optical receiver was selected as the enabling technology after concessions with subject matter experts. Utilizing expert inputs to a survey elicitation mechanism, TOPSIS was used for ranking six different optical receivers for the reference mission. SAW and WPM models were also exercised demonstrating similar results. The streak tube receiver alternative was the highest ranked optical receiver identified in this study. The results represent the tacit expert judgment of twenty participating electro optic experts. Previous studies using TOPSIS have limited subjective inputs to the weights; however, this study successfully introduces subjective criteria, such as risk, within the model construct.

Finally, sensitivity analysis should be conducted on the results by simulating changing priorities among the model inputs, thus providing the decision maker with confidence in the results. Three sensitivity analyses were conducted on the results within this paper indicating stability in the outcome. This paper successfully demonstrates that using MCDM in an AoA provides the decision maker with the ability to confidently select enabling technologies early within a system design.

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