Measuring Readiness and Sustainment within Analysis of Alternatives in Military Systems Acquisition

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Abstract

Analysis of Alternatives (AoA) is a crucial stage in the process of acquiring a new system for the DoD. AoA is essentially a multi-criteria decision process that involves several stakeholders. An AoA is an analytical comparison of the operational effectiveness, cost, and risks of proposed materiel solutions to gaps and shortfalls in operational capability. Two of the three criteria – effectiveness (what can the system do and how its capabilities fit the operational requirements) and comparative costs of potentially viable solutions draw the most attention in such studies. The third set, risks, which typically draws somewhat less attention in an AoA than the other two, is concerned with the technical, operational, and programmatic implications for each alternative. More precisely, we describe operational risks as the long-term readiness, sustainment, and logistics requirements for the specified alternative. In this paper we study in detail the content of this set of criteria, focusing on the factors that affect the long-term viability and usefulness of an alternative, and propose Data Envelopment Analysis (DEA) as the analytic framework for evaluating alternatives with respect to the criteria in this set.

1. Introduction

The Department of Defense (DoD) Acquisition System comprises three interconnected stages that start with specifying requirements – a procedure called Joint Capabilities Integration and Development System (JCIDS). The second stage, called Acquisition Process, determines appropriate materiel solutions for the requirements. The third stage is concerned with funding and financial-controlling activities contained in the Planning, Programming, and Budgeting Execution (PPBE) process. Most of the decisions that have long-term sustainment, readiness and logistics implications are taken at the second stage, where materiel choices are made. The overarching process dominating this stage is the Analysis of Alternatives (AoA) that, in general, trades off the effectiveness of a materiel solution with its risks and costs. DoD Instructions 5000.02, which provides policy guidelines and regulations for managing the acquisition system, states that "The AoA assesses potential materiel solutions that could satisfy validated capability requirement(s) documented in the Initial Capabilities Document, and supports a decision on the most cost effective solution to meeting the validated capability requirement(s). In developing feasible alternatives, the AoA will identify a wide range of solutions that have a reasonable likelihood of providing the needed capability" (DoD, 2020). In general, the instructions are pushing for the AoA to be conducted earlier in the acquisition process.

The AoA is essentially a large-scale multi-criteria decision analysis (MCDA) problem that involves multiple stakeholders and many uncertainties (Kress & Morgan, 2018). The set of criteria used in evaluating alternatives, and their weights or importance, depend, among others, on the technological maturity of the alternatives. For example, the risk associated with acquiring an off-the-shelf system may in some cases be considerably lower than the risk in developing a new system but in other cases using such components which were designed for other purposes may actually add risks to the new system. Thus, the "risk" criterion, with all its derivatives, is less prominent for the former than the latter. In this study we focus on systems that are still in various stages of development, which means that the AoA process is typically not a "one-shot" decision event but rather a sequence of decisions marked by achievements. In these settings, the AoA starts off with a set of potential alternatives being developed as prototypes. As time passes, more data is collected and this enables analysts to revisit earlier analysis outcomes with better insights. Prior to making decisions that commit the resources needed for development leading eventually to production and fielding, analysts solve additional MCDA problems to inform decision-makers on which specific product or design concepts will be pursued, and whether resources will be committed to mature technology and/or mitigate any risks in research and development. The process culminates in a preferred alternative.

Several MCDA methods have been proposed in the literature as the platform for AoA studies. Many of those methods belong to the "compensatory" family of parametric methods based on the ability of the analysts to determine values of alternatives and weights (importance) of criteria, leading to a weighted average score of each alternative. An interesting application of these classical methods in the context of realigning US Army bases is given in (Ewing, Tarantino, & Parnell, 2006). This family of parametric compensatory methods is very broad and includes models with a wide variety of features and properties. A notable example of this family of methods is the Analytic Hierarchy Process (AHP), where values and weights are determined via pairwise comparisons, see (Saaty, 2008). However, AHP, with its specific features associated with eigenvalues, was highly criticized as several of its basic concepts lie on shaky mathematical foundations, e.g., see (Barzilai & Golany, 1994).

Outranking is another family of MCDA methods. A representative method in this family is Elimination and Choice Expressing Reality (ELECTRE) where alternatives are gradually discarded on the basis of outranking rules (Roy, 1968). However, ELCTRE, and other similar methods, were criticized for their use of arbitrary rules and veto thresholds.

The main purpose of this paper is to develop a new paradigm, grounded on the well-established theory of Data Envelopment Analysis (Charnes, et al., 1978) for studying and promoting awareness to logistic considerations, readiness implications and total ownership cost during the acquisition process while applying suitable quantitative tools to handle uncertainties involved in some of the parameters. The unique feature of DEA, which stands out compared to other MCDA models, is that it is a non-parametric method. DEA avoids the pitfalls of previous methods mentioned above by letting the method choose an individual set of weights for each alternative through solving a series of linear programming problems, one for each alternative. DEA evaluates the "efficiency" of an alternative, compared to others, in the most equitable way and thus enables decision makers to focus on the most efficient alternatives for in-depth analysis.

2. Readiness, Sustainment, and Logistics

The DoD Dictionary (DoD, DOD Dictionary of Military and Associated Terms, 2019) defines *sustainment* as *the provision of logistics and personnel services required to maintain and prolong operations until successful mission accomplishment.* (JP 3-0). *Readiness* is defined as *the ability of military forces to fight and meet the demands of assigned missions.* (JP 1). *Logistics* is *planning and executing the movement and support of forces*. (JP 4-0). Notice that the term *logistics* is included in the definition of *sustainment.* Thus, henceforth we will focus on the two factors: readiness and sustainment.

Sustainment and readiness are terms that typically apply to the entire military force. They are considered two of the "four pillars" of military capability (Moore, Stockfisch, Goldberg, & Holroyd, 1991). Measures of sustainment and readiness describe features such as resources availability, level of training and percentage of platforms that are mission-ready at any time (Rich, Cohen, & Pyles, 1987).

In this study we consider these terms in a more restricted way; as they reflect the virtues and shortcomings of acquisition alternatives.

In the context of Analysis of Alternatives (AoA), see, e.g., (HAF, 2016), the relative value of a certain (new) acquisition alternative (compared to other alternatives) is based on three dimensions, each a combination of several criteria: (a) *effectiveness* during operations, (b) *cost*, and (c) *readiness & sustainment* (R&S) attributes. The *R&S* dimension accounts for all the factors not directly related to the first two, such as risks, dependencies on other systems and peripheral requirements. The three dimensions are not orthogonal. For example, sustainment involves (lifecycle) cost considerations, and effectiveness is affected by readiness.

Effectiveness of an alternative is measured through the gaps, if they exist, between the performances of each alternative and the operational requirements that were set during the JCIDS. Lifecycle *cost* (sometimes referred to as total ownership cost) is measured by accumulating the various expected costs directly associated with each alternative. Both dimensions have been studied in depth and there exist proven methodologies that address them in AoA studies (e.g., combat simulations and cost estimation methods). In this paper, we focus on the third dimension, *R&S,* which, we believe, demands as much attention as the other two dimensions. Failing to devote this attention, especially during the early stages of the AoA, may potentially lead to choosing an alternative that is most cost-effective from the point of view of the first two dimensions, but may become, economically burdensome and eventually even impossible to operate in the long run.

We next review some articles that highlight challenges in identifying the components of readiness and sustainability, and the complexities in analyzing them.

2.1 Challenges in evaluating readiness and sustainability

Several important issues related to the evaluation of readiness and sustainability in military context have been studied in recent years. (Canician & Daniels, 2018) emphasize the trade-offs in the "iron triangle" of readiness, modernization and force structure that military services must consider when making procurement decisions. They argue that equating readiness with "military capability" obscures the critical elements of training/maintenance/equipment and personnel fill in readiness. In our paper, we indeed adopt a holistic approach that includes all these elements in the procedures we suggest for measuring readiness. They further argue that the standard DoD measurement procedure of readiness, known as Defense Readiness Reporting System (DRRS), is inadequate as it focuses only on inputs and doesn't account for outputs. Again, our proposed model considers simultaneously inputs and outputs.

(Harrison, 2014) highlights the differences in the definition of readiness at the strategic, operational and tactical levels. He discusses the components that define readiness and emphasize, as we do, that understanding how best to resource readiness requires better metrics and a better understanding of the relationships between inputs (resources) and outputs (readiness).

The Defense Acquisition Guidebook (DAG, 2019) revision views sustainment as a distributed and long-term activity that requires the alignment of multiple and disparate stakeholders. It emphasizes the need to carry out sustainment planning from the earliest stages of the system's life cycle.

(Robbins, Broyles, Giradini, Abel, & Boren, 2019) describe the longstanding shortfall in the Weapon System Support Program (WSSP) performance. They state that a primary reason for the shortfall is the failure to use tools and methodologies for accurately determining true critical weapon system readiness drivers and differentiating these items from others. Our paper addresses exactly this issue by identifying and analyzing the readiness drivers.

(Doheney, Gray, McLemore, & Savage, 2019) argue that the U.S. military currently uses "readiness reports" to communicate the cumulative effects of details on its "big things". However, the word "readiness," like the word "risk," is inconsistently defined and discussions and planning around this topic are often ambiguous. They claim that standard representations of uncertainty now make it possible to roll up analytical models into larger models and call the services to embrace such representations and further develop them in the context of readiness accounting. These advancements could move military decision-makers from ambiguous estimates of "ready or not?" to unambiguously calculating, quantifying and communicating "how ready for what?". Our paper uses standard probability measures to assess risk and uncertainty and embed these estimates in a larger model that quantifies the degrees of readiness and sustainability.

Next, we describe the content of the R&S dimension and discuss its criticality.

2.2 Readiness

Readiness of an acquisition system has three different aspects: technological, technical and functional. While technological readiness describes the state of a system still being developed and the projected time of completing its production and testing, technical and functional readiness relate to the actual operation of the system when it is fully operational and already deployed.

2.2.1 Technological Readiness

The technological aspect of readiness describes the maturity of the technology, and the production and testing capabilities needed for the newly developed system. As mentioned above, this type of readiness only applies to the development phase of the system; it describes how close the system is to becoming fully operational. Analysts have used several scales to evaluate this aspect. Back in the 1980's the National Aeronautics and Space Administration (NASA) introduced the Technology Readiness Level (TRL) as a tool to assess the maturity of particular technologies which it planned to embed in new systems. The TRL is a nine-level scale that ranges from "Basic Principles Observed and Reported" (Level 1) to "Actual System Proven through Successful Mission Operations" (Level 9). According to the Department of Defense (DoD), a weapon system program cannot include a technology whose TRL is lower than level 7 (GAO, 1999). (Sauser, et al., 2008) combine the TRL, which is purely technology-oriented, with a system-integration measure – the Integration/Interface Readiness Level (IRL) – and produce the System Readiness Level (SRL), which is a more holistic engineering measure for the technological maturity of a system. (Atwater & Uzdzinski, 2014) generalized the SRL into a "wholistic" view of system maturity that includes also functionality (i.e. man-machine interface). Technological readiness is tied to the risk criteria in the AoA process. The risks associated with an alternative that is still in technological development stages reflect the uncertainties regarding the feasibility that the alternative will be mission-ready on time and within budget. Thus, during the AoA and the subsequent development and production phases, the technological readiness of a system can be defined by a value proportional to the assessed probability that the system will be completed on time and within budget.

As mentioned above, the technological readiness of a system has to do with projecting the completion time of the underlying research, development and production project, and the total cost of the system. The SRL, data from similar past projects, and most of all, inputs from subject matter experts are used to obtain the relative technological readiness values of the alternatives, using techniques similar to the one described in (Kress & Morgan, 2018).

Finally, note that technological readiness changes dynamically during the acquisition process. It is updated periodically as the project advances; the closer is the project to completion, the more accurate is the estimate of this type of readiness.

2.2.2 Technical Readiness

A system is technically ready if all its components are in a perfect working condition. Thus, technical readiness (TR) has to do with the reliability and maintainability of the system and its components. TR can be measured by the probability that the system is technically mission-ready at any point in time during its life cycle. TR is closely tied with *sustainment*, which is discussed later on. TR is also related to the nature of the missions planned for the system and particularly to the typical alert time the forces are expected to have before launching a mission. For example, missile interception systems are expected to become ready within seconds of an alert while submarine missions will typically have alert times of days or even weeks.

Three main factors determine the TR of a system: (a) reliability, which is measured by the mean time between failures (MTBF), (b) the effort needed to fix the system, which is measured by the average service time, and (c) the availability of spare-parts needed for its maintenance and repair. Note that factor (b) depends to large extent on factor (c); availability, or lack thereof, of repair-parts affect the total service time of a system.

In principle, factor (a) – MTBF – is measurable; the MTBF of each component in the system, along with the associated reliability-graph of the system, can project the system-wide MTBF. The problem is that the MTBF figures for the various components are only estimates, based on limited data and simulations. The actual MTBF of the system cannot be robustly estimated until the system is fully operational for some time and enough failure data is collected. Similarly, to factor (a), the impact of factor (b) – service time – is practically unknown until the system is operational for some time and enough service-time data are collected. The fact that data regarding the first two factors are unavailable at the time when the AoA is initiated does not mean that they should be ignored. Technical details, comparisons with similar systems, meticulously designed simulations, and early testing of critical components should be utilized for evaluating these two important factors of technical readiness. The third factor is the availability of repair parts, which is affected by the number, complexity, variability, and cost of the system's components, as well as by the robustness of the supply chain that provides the repair-parts. These characteristics could be evaluated well in advance and factored in quite smoothly into the evaluation of technical readiness. For example, the lead time for delivering a certain repair part, a parameter that could be estimated from the features of its supply chain, will be used to estimate total repair time. The impact of unavailable repair parts is determined by design factors such as redundancy of sub-systems and components. The modularity of subsystems affects the repair time (factor (b)). "Plug-and-Play"–type components obviously need less service time than components that require installing, reconfiguration and adjustments.

It is quite unlikely to have a reliable TR measure during the early phases of the AoA process. There will not be enough data to support it. However, as the system advances in its development process, more knowledge and experience are accumulated, and the TR measure – combining MTBF, service time and repair-parts lead time – gets updated accordingly. We discuss the specific features of a possible TR measures later on.

2.2.3 Functional Readiness

A system which is fully developed and technically ready for operations is not necessarily that fully operational. For a system to function effectively, one may need to ensure the functionality of other, supporting or peripheral, systems. Full functionality will also require that certain types of operators will be available to run it, and specific elements of infrastructure will be in place to support it. First, a system, as advanced and sophisticated as it may be, needs people to operate, control, maintain and utilize its outputs. These operators, controllers, support personnel and users need to be trained and available for their respective tasks. Shortage in any of the required manpower capabilities and expertise needed for the system may render the system nonoperational. Arguably, the impact of unavailable personnel varies among the tasks. A system that needs four operators during a shift may be operational, albeit less effectively, with just three operators. But, a repair technician who is not available when the system is down can be detrimental. A system may also need peripheral support such as protected environment, robust supply chain of resources, and access to communication networks. It may also depend on the operations of other systems, where failure in one or more of them may render our system nonoperational even if all other technical and functional factors are in perfect condition.

As mentioned above, we note the difference between the first type of *readiness* – technological readiness – and the other two. While the first type applies to the development/production stage of the alternative, the last two refer to the readiness of the system once it is deployable and ready for operation. In the following, when we refer to "*readiness*" as *operational readiness*, we restrict the definition to only the technical and functional aspects. The technological aspect does not apply to operational readiness and therefore should be treated separately.

Both technical and functional readiness can be further broken down into a vector of sub-factors that define it in greater granularity. Combining all these factors and sub-factors into a single operational readiness measure will require some weighting methods – a topic that will be discussed later.

2.3 Sustainment

In a nutshell, following acquisition, total ownership cost is the cost of sustainment – the cost of maintaining a system in an adequate operational condition. Technical and functional *readiness* are contingent on sustainment. *Sustainment* encompasses all the materiel and services needed for the effective and prolonged operation of a system so that it satisfies the missions for which it is designed. There are three facets to sustainment: supplies, facilities and personnel. Each facet requires efforts and resources in order to be an effective enabler of sustainment.

2.3.1 Supplies

Vehicles need fuel and repair parts, weapons need ammunition, source of energy, and repair parts, and operators of systems need food, water and other personal supplies. Systems with low TR score may require extra supplies for to handle more frequent repairs. The quantity and diversity of the supply items needed to operate the system affect the economic burden on sustaining the system, and the availability of these resources affects the operational readiness of the system. Other supply-related factors that affect the economic burden are transportation and storage costs of these supply items. The responsiveness and reliability of the supply chain affect availability of supplies and thus the operational readiness.

2.3.2 Facilities

Defense systems need storage, maintenance and support facilities. Advanced weapons and C2 systems may require also expensive training and simulation facilities. Systems with low TR score may require more extensive maintenance facilities as compared to systems with high TR scores. The size, quality and fitness of a facility will affect the readiness of the system that relies on them. For example, if a certain system requires certain environmental conditions, say, low temperature, for operating properly, then the quality and reliability of the air-condition capabilities in the facility are crucial for making the system mission ready.

2.3.3 Personnel

All systems, as advanced as they may be, need humans to operate, control and maintain them. Personnel with a variety of skills and trainings need to be available for those tasks. If, for example, a system requires a 24/7 human controller, then sustaining proper readiness will entail at least three qualified personnel, operating in 8 hours shifts, in order to keep the system mission ready.

3. R&S Factors

Based on the discussion in Section 2, we identify the following main factors that affect the R&S dimension:

- **Mean Time Between Failures (MTBF)**. This is one of the most significant factors affecting technical readiness. The complexity of the system, and the reliability of each of its components determine the failure rate of the system – the probability the system is technical fit at any given moment. Arguably, this parameter depends on the alternative's regular service and preventive maintenance schedule. This schedule, measured by the Mean Time Between Service (MTBS – see below), is inversely related to the MTBF; smaller MTBS will increase the MTBF of the system and thus enhance technical readiness, at an increased cost rate.
- **Mean Time Between Services (MTBS)**. Each alternative system comes with instructions concerning regular service schedule and preventive maintenance actions. MTBS is measured by the frequency of such actions, as specified by the manufacturer.
- **Repair Time & Service Time**. The system is *down* while it is in (scheduled) service or (unscheduled) repair following a failure. Obviously, during those down times the system is inoperable. The length of a down time depends on the complexity of the system and the availability of resources – personnel, facilities, tools and spare-parts. For example, a modular system that facilitates "plug & play"-type repair technique would require less repair effort and therefore experience less down time than a non-modular system. Note that *repair* and *service* are actions that only apply to *technical readiness*, as defined earlier.
- **Repair Cost & Service Cost**. These are the costs for maintaining the system technically ready. These costs include spare-parts, tools, infrastructure and personnel. These costs can be reasonably estimated from analyzing the components of the system and from the manufacturer's specifications regarding service and preventive maintenance. A possible service cost is derived from designated up-time. Certain systems require frequent uptime

to maintain their lifetime expectancy while others can stay dormant for longer times. The larger the uptime requirement is the more difficult it is to sustain the system.

- **Setup Time and Cost**. A system may be, by design, in a “cold” operational stand-by condition (e.g., a system that is only activated in an emergency). The setup time and cost that brings the system into a fully operational state is a crucial aspect in measuring readiness (time) and sustainment (cost).
- **Interdependency**. Dependency on other systems makes an alternative more vulnerable to failure and potentially more disruptive when failed than an alternative, which operates as stand-alone. Examples:
    - A vehicle that needs to be transported by other means of transportation to the area of deployment.
    - A moving platform (aerial, ground or sea) that depends on satellites availability for its navigation.
    - A system that requires extensive and expensive training facility to become operational.
    - A sensor, which is connected to an elaborate command and control system.
- **Personnel**. Any system requires operators, controllers and technicians. Finding qualified and skilled personnel, training them and then retaining them is always challenging. Ceteris paribus, a simpler alternative to operate and maintain, which requires a few, easily trained, operators and technicians is preferred to a more complex alternative, which requires highly skilled and trained personnel.
- **Supply Chain**. The availability of spare-parts that facilitate technical readiness depends on an efficient and robust supply chain. Supply chain is also one of the principal means for making a system *functionally ready.* A vehicle needs fuel, a sensor requires electrical power and a weapon will not operate without ammunition. The type of supplies (size, weight, scarcity, fragility, handling requirements), and the frequency at which they are needed, affect the cost of sustainment, and the length and robustness of the supply chain. Part of the supply chain is the logistic tail of the deployable system – certain systems require a large, expensive or difficult to maintain tail in order to ensure their functionality (e.g., a convoy of supply trucks) while others require little or even negligible tails (sometime referred to as "deploy & forget" systems). Obviously, larger logistic tail

requirements imply more difficulties in sustaining a system. An alternative that requires more frequent deliveries of expensive supplies by a more fragile supply chain is inferior to a more self-sustained alternative, which is supported by a simpler supply chain. There are several factors that determine the vulnerability of a supply chain – e.g., single source vs. multiple sources, geographical distances between the nodes in the chain, the required transportation means, their availability, and their robustness to environmental conditions such as weather and terrain.

We note that these factors are not necessarily independent. For example, the effect of the supply chain on the overall R&S rating of an alternative depends on the repair and service costs; lower demand for spare-parts makes a supply chain less crucial for the sustainment of the alternative. To avoid dealing with such dependencies, we will define measures for "meta-factors", which combine similar factors into (relative) measures.

4. Measuring the R&S Factors

Recall that this study is concerned with the R&S dimension in the context of AoA where *relative* evaluations – rather than *absolute ones* – are sufficient. This observation is important because many of the aforementioned factors, and the meta-factors defined below, are not easily measurable. This phenomenon is rather common in MCDA problems and analysts apply value or utility functions to combine such measures. For example, one may apply ordinal preferences, such as Likert scale (Allen & Seaman, 2007), and combine them, in some consistent way, with measurable factors to produce an overall ranking of the alternatives with respect to the R&S dimension.

Next, we describe measures for evaluating the various facets of the R&S dimension.

4.1 Mean Time Between Downs (MTBD)

The MTBD is a combination of the MTBF and the MTBS (see definitions above). The mean time between failure of a system can be statistically estimated only after it has been in operation for some time and enough failure data has been collected. This is obviously not the case in an AoA setting where the alternatives are still in a development stage. One possible way to assess the MTBF is by considering the way the components relate to each other in the system (i.e., in parallel or in series) and evaluating separately the reliability of each component, assuming such data is available. Integrating all this information, say, in a simulation, can produce a reasonable estimate for the MTBF. The MTBS is derived from the manufacturer recommended service and preventive maintenance schedule. This parameter should be given as part of the specification of the system. If T_S is the (deterministic) MTBS, and the failure process follows an exponential distribution with mean $\frac{1}{\lambda_F}$ (which may or may not be dependent on T_S) then, assuming a failure resets the service clock, the *MTBD* is given by $MTBD = T_S e^{-\lambda_F T_S} + \int_0^{T_S} t\lambda_F e^{-\lambda_F t} dt$.

4.2 Mean Down Time (MDT)

The system is down while in (unscheduled) repair or (scheduled) service. If the mean repair time and the mean service time are μ_F and μ_S, respectively, then, assuming exponential distribution, the *MDT* is given by $MDT = \mu_F(1-e^{-\lambda_F T_S}) + \mu_S e^{-\lambda_F T_S}$. Note that while μ_S can be directly estimated from the service and preventive maintenance specifications, μ_F is more elusive and may be estimated from simulation, similarly to the MTBF. Also note that the computation of both MTBD and MDT are easily generalized when the failure distribution is general, not necessarily exponential. Specifically, if the failure distribution has the CDF $F_F(t)$, and the down states generate a renewal process, then the MTBD and the MDT are $T_S(1-F_F(T_S)) + \int_0^{T_S} tdF_F(t)$ and $\mu_F F_F(T_S) + \mu_S(1-F_F(T_S))$, respectively.

4.3 Maintenance Cost (MC)

MC is truly a meta-factor encompassing all the resources needed to maintain the system in operational state. These expenditures include fix costs, denoted *FMC*, such as infrastructure (e.g., shops, storage facilities, labs, equipment, personnel) and variable cost covering replaceable parts, energy and other resources needed for a specific maintenance mission. Standard practices of cost estimation (Mislick & Nussbaum, 2015) may be used to obtain estimates for the two types of cost. If the average variable maintenance cost per maintenance incident is denoted by *VMC*, then the average variable maintenance cost *rate* is

$VMCR = \dfrac{VMC}{MTBD}$. Ignoring, for simplicity discount rates, and assuming a reference time horizon of length T time periods, the average maintenance cost per time period is

$$MC = \frac{FMC}{T} + VMCR.$$

4.4 Operational Cost (OC)

Operational cost is relatively simple to compute because it relates to a fixed set of actions that need to be executed by the system. Such a set is typically well defined as it establishes the foundation for functional readiness (see Section 2.1.3). The operational cost is the cost of daily, or recurrent, operations. It can be measured by the number of operators and controllers, broken down by required skills, cost of operating facility (when applicable) and the amount and type of energy needed for the operation. If the functional characteristics of the system to be selected is such that it is dormant most of the time and is activated only when needed, then the operational cost includes also the set-up cost and time required for activation. An alternative that can become active faster and at lower cost has lower operational cost than an alternative that takes time to set up. The parameter measuring OC is the average daily cost of operations.

4.5 Interdependency (INT)

The more a system depends on other systems and processes, the more it is vulnerable to possible breakdowns and failures of those peripheral systems and processes. Thus, such dependency leads to lower functional reliability. To capture this vulnerability, we first define, for each alternative, the set of peripheral systems and processes upon which it depends. We call it the *Systems' Dependency Set.* Arguably, ceteris paribus, the larger the dependency set the lower the functional reliability of the alternative because more things can go wrong. In particular, if an alternative is a fully stand-alone system, then interdependency has no effect.

We describe the state of the dependency set by a k-dimensional $\{0,1\}$ vector x, where k is the cardinality of that set. If a system in the dependency set is up and running its corresponding entry in the vector is 1, otherwise that entry is 0. For example, if $k = 3$, then the vector $x =$

(1,0,1) indicates that the first and third peripheral systems in the dependency set of the alternative are up and running while the second system is down.

The functional readiness of the alternative depends on the state vector of its associated dependency set. We denote that effect by the function $D(x)$. For example, if the number of peripheral systems of an alternative is $k = 3$, then $D(1,1,1) = 1$ (no effect) and $1 = D(1,1,1) > D(1,1,0) > D(1,0,0) > D(0,0,0) \geq 0$. In other words, fewer functioning peripheral systems imply lower functional reliability of the alternative. In general, $0 \leq D(x) \leq 1$.

Let p_i, $i = 1,...,k$ denote the probability that the *i*-th peripheral system in the dependency set of the alternative is operational and functioning. Assuming independence, which in many cases is a reasonable approximation, we have that

$$p(x) = \Pr[x = (x_1,...,x_k)] = \prod_{i=1}^{k} p_i^{x_i} (1 - p_i)^{1-x_i}$$

The power set 2^x is the set of all possible realizations of the *k*-dimensional vector describing the state of the dependency set. We define the *interdependency index* of an alternative by

$$INT = \sum_{x \in 2^x} p(x) D(x).$$

The higher the value of *INT* the more robust is the alternative with respect to its dependency on other systems.

4.6 Personnel (PER)

The cost of personnel is accounted for in the operational cost (OC) discussed above. There is another aspect of personnel that affects the functional and technical reliability of an alternative – the dependence on certain types of qualified personnel. The more a system relies on a large variety of skilled personnel the more it is vulnerable to their possible absence. Thus, like the interdependency factor *INT* described above, such dependency may lead to lower functional and technical reliability. To capture the personnel vulnerability, we propose the same approach used for interdependency.

We define for each alternative the *Personnel Dependency Set*, which comprises the skill set of persons needed for the operation of the system. We describe the state of the dependency set by a k-dimensional vector x of natural numbers, where k is the number of skill-types (e.g., technicians of certain types, operators of different training levels, etc.) needed for operating and maintaining the system, and $x_i, i = 1,...,k,$ is the number of people of type i available at any given time. Let $s_i, i = 1,...,k,$ denote the number of people of type i required by the system at any given time. As in the interdependency case, we define $R(x) = R(x_1,...,x_k),\ x_i \le s_i,$ as the effectiveness of the system when the available personnel team is x. We have that $R(s) = R(s_1,...,s_k) = 1$ and $R(x) \le 1$. Trivial calculation show that there are $S = \prod_{i=1}^{k}(s_i + 1)$ possible profiles of personnel availability.

The personnel-dependency measure is

$$PER = \frac{1}{S}\sum_{x_1=0}^{s_1}\cdots\sum_{x_k=0}^{s_k} R(x_1,...x_k)$$

An alternative that is reasonably functional with less personnel will have a higher *PER* score than an alternative that is sensitive to staffing.

For example suppose $k = 3$ (three different types of personnel) and $s_1 = 2, s_2 = 1, s_3 = 1$. In other words, the system requires a team of four, say, two operators ($i = 1$), one controller ($i = 2$) and one technician ($i = 3$). We have $1 = R(2,1,1) > R(1,1,1) > R(1,1,0)$, etc. The closer the PER of a system to 1 the smaller the effect of reduced staff.

4.7 Supply Chain

There are many factors that affect the robustness of a supply chain (SC) – e.g., single source vs. multiple sources of supply, geographical distances between the nodes in the chain, the type and availability of means of transportation, etc. The literature on SC has not reached a consensus on unified quantitative measures that can objectively assess the relative "value" of different SCs and hence we propose to use an ordinal scale where the alternatives in the AoA are simply ranked by subject matter experts in the AoA team. This is the only qualitative and subjective input into the R&S part of the AoA. We assume that subject matter experts can produce such a ranking that may have ties for alternatives that are evaluated as having equally effective and robust supply chain. Thus, the higher the rank SC of an alternative, the more robust and effective is its supply chain. Note that a higher rank implies a smaller (integer) value of SC.

5. Using DEA for Evaluating R&S

In this section we offer a methodology to assess the R&S value of an alternative. Recall that our goal is to evaluate the *relative* value of an alternative with respect to the R&S factors, not its *absolute* value.

Suppose, for simplicity, that the R&S dimension comprise only two factors: MTBD and MC. Obviously we wish to have a reliable alternative with high MTBD and low maintenance cost MC. A reasonable relative measure for the alternative would be the "reliability/cost" ratio MTBD/MC. The higher this ratio, the better the alternative with respect to the R&S dimension.

So, if the only R&S factors were MTBD and MC then we could easily rate the alternatives from best to worst. However, we have seven factors that affect this dimension. The challenge is how to extend the ratio idea described above with respect to MTBD and MC to all seven factors.

To meet this challenge, we propose to use the *Data Envelopment Analysis* (DEA) methodology. Since it was first proposed in the late 1970s by (Charnes, Cooper, & Rhodes, Measuring the Efficiency of Decision Making Units, 1978), DEA has been applied to hundreds of application areas including several DoD-related applications such as evaluating the efficiency of air-force maintenance units (Charnes, Clark, Cooper, & Golany, 1984). Other relevant applications include (Bowlin, 1996), which describes how DEA can be used to address various DoD evaluation procedures; (Brockett, Golany, Rousseau, Thomas, & Zhou, 1997) that evaluates the efficiency of US Army recruitment units; (Han & Sohn, 2011) which evaluates the performance of Korean Air-Force bases; (Falagario, Sciancalepore, Constantino, & Pietroforte, 2012) propose DEA as fair, equal and transparent decision making tool aimed at helping an awarding committee in in selecting tenders that will meet governmental procurement regulations and requirements in accordance with European Union directives; (Sutton & Dinitrov, 2013) who use DEA to assign sailors to tasks for the US Navy; (Yang, Wang, Wang, & Ma, 2016) present the way DEA was adopted by the Taiwanese government as a method-of-choice to evaluate procurement alternatives; (Lu, Kweh, Nourani, & Shih, 2019) propose DEA to evaluate alternatives in selecting major weapon in a cost-effective manner and demonstrate it with an example of procuring fighter jets for the Singaporean government and (Boehmke, et al., 2017) that measures installation support activities in the US Air Force.

Essentially, DEA is a non-parametric methodology for comparing multiple entities, all of which use the same set of inputs (albeit, in different quantities) to produce the set of outputs (again, with different quantities). If $O_1,...,O_m$ denote a vector of outputs and $I_1,...,I_n$ denotes a vector of inputs then the efficiency ratio is $\frac{x_1O_1+...+x_mO_m}{y_1I_1+...+y_nI_n}$. The question is what are the "right" weights $x_1,...,x_m$ and $y_1,...,y_n$.

DEA evaluates the relative efficiency (i.e., determines the values of $x_1,...,x_m$ and $y_1,...,y_n$) of each alternative by solving a corresponding linear programming model that determines for the alternative the values of the aforementioned weights. The idea is to present each alternative in the best possible way while meeting some logical constraints. Normalizing the value of the highest relative efficiency to 100%, a system that receives a score that is smaller than 100% (i.e., its associated model failed to find a set of weights that will present it as 100% efficient) is by definition inefficient and DEA can assess the gap between its current performance and the efficient frontier that the methodology construct on the basis of the entities that were found to be 100% efficient. DEA was specifically designed to handle situations such as the one we face here as it is capable of handling data that is not easily converted into universal quantitative measure such as dollar. In our case we have measures associated with time (MTBD, MDT), money (MC, OC) effectiveness (INT, PER), and an ordinal scale (SC).

In our context, we distinguish between factors for which more is better – MTBD, INT, PER – and factors for which less is better – MDT, MC, OC and SC. Accordingly, we will consider the "efficiency" ratio

$$ER = \frac{x_M MTBD + x_I INT + x_P PER}{y_D MDT + y_M MC + y_O OC + y_S SC}.$$

With the exception of the ordinal SC the standard DEA model will apply. The presence of the ordinal factor necessitates a modification of the standard DEA model, as described in (Cook, Kress, & Seiford, 1993).

Note that the selection of factors – the input and output variables in this DEA framework – is not rigid; it may vary according to the specific type of acquisition. For example, vehicles and weapons will have a common set of core variables but each may have additional factors, which are specific to the system.

6. The DEA Model

Let n denote the number of alternatives to be evaluated with respect to the R&S dimension. The index i, $i = 1,...,n$, indicates the identity of an alternative. We solve n linear programming problems – one for each alternative. The data for the optimization model are the quantitative parameters $MTBD_i, INT_i, PER_i, MDT_i, MC_i, OC_i$, and the qualitative ordinal parameter $SC_i(k),\ i = 1,...,n,\ k = 1,...,l$ where l is the number of rank positions, and

$$SC_i(k) = \begin{cases} 1 & \text{if alternative } i \text{ is ranked in the } k-th \text{ place} \\ 0 & \text{Otherwise} \end{cases}$$

The idea is as follows: each alternative, in its turn, is given the "opportunity" to select its coefficients such that it gets the highest possible efficiency ratio *ER*. It can do it as long as these "best" coefficients it selected, when applied to the efficiency ratio of any other alternative, does not exceed 1. Thus, the maximum possible efficiency ratio is *ER* = 1. Those alternatives, which reach 1, are considered R&S efficient. In addition to the normalization constraint that limits each efficiency ratio not to exceed 1, we require that all coefficients are non-negative and the weights of the ordinal parameter (*SC*) adhere to the rank positions, that is, a weight of rank 1 should be lower than the weight of rank 2, etc.

For each alternative, temporarily assigned the index 0, we solve the following linear optimization problem see (Cook, Kress, & Seiford, 1993) for details:

$$
\begin{aligned}
&Max\ x_M MTBD_0 + x_I INT_0 + x_P PER_0 \\
&st \\
&y_D MDT_0 + y_M MC_0 + y_O OC_0 + \sum_{k=1}^{l} w_k SC_0(k) = 1 \\
&x_M MTBD_i + x_I INT_i + x_P PER_i - (y_D MDT_i + y_M MC_i + y_O OC_i + \sum_{k=1}^{l} w_k SC_i(k)) \le 0,\ i = 1,\ldots,n \\
&w_{k+1} - w_k \ge \varepsilon \\
&\text{All decision variables } \ge \varepsilon
\end{aligned}
$$

where ε is an arbitrary separation parameter determined by the decision-maker. In the next section we illustrate this methodology on an example.

7. Example

At each milestone of the AoA more detailed and reliable information is gathered about the seven measures – MTBD, MDT, MC, OC, INT, PER and SC. The data is entered into the DEA model and the relative standings of the alternatives are obtained with respect to the R&S dimension. Suppose there are currently three alternatives under consideration, and the R&S measures are as shown in Table 1.

Alternatives (systems)	MTBD (days)	INT (Section 4.5)	PER (Section 4.6)	MDT (days)	MC (K$ per day)	OC (K$ per day)	SC (ranking)
Alt1	33	0.7	0.7	3	18	5	I
Alt2	30	0.6	0.7	3	16	2	II
Alt3	20	0.6	0.5	2	15	4	III

Table 1: R&S Data for Three Alternatives

We see from the data that no alternative dominates another with respect to all seven R&S measures. For example, Alt1 has the highest (best) MTBD, INT and PER scores (it is tied with Alt2 with respect to the latter). Alt 1 is also ranked highest for SC. Alt2 has the lowest operational cost (OC), and Alt 3 has the lowest down time (MDT) and lowest maintenance cost (MC). Thus, a simple inspection of the data will not reveal which alternative is more R&S efficient.

Running the DEA model presented in Section 5, where we select for each alternative its maximum feasible value of ε , we obtain that while the *ER* values for Alt1 and Alt2 are 1, that is, they are R&S efficient, for Alt 3 *ER* = 0.77, which means that the "best" coefficients it could find for its data still rate it 23% lower than Alt1 and Alt 2. Note that if ε is set at a value smaller than its maximum value, the differentiating power of the model decreases, that is, for a smaller ε all alternatives may be tied at the top. More on this differentiating effect in the next section.

8. Summary

This report bridges a gap in AoA, addressing the role of examining readiness and sustainment (R&S) in such analyses. In the first part of the report we define these characteristics and study their components. This study results in a set of MOEs that must be observed, and updated as new data becomes available, throughout the development process of a new system. In the second part of the report we propose an analytic procedure, grounded in the well-established methodology of DEA to continuously assess the R&S aspects of the AoA.

Like all other quantitative methodologies, DEA has certain weaknesses that users must be aware of and be ready to address when the need arises. We describe below two such weaknesses along with recommendations on ways to overcome them.

- Differentiation power

  DEA's differentiation power increases as the ratio between the number of alternatives and the number of MOEs increases. When this ratio is close to 1 (i.e., the number of alternatives is approximately the same as the number of MOEs), most alternatives are likely to be evaluated as fully efficient. In such scenarios, it is enough, for example, that the value of one of its numerator MOEs is larger than the corresponding values of all other alternatives to be evaluated as efficient. This phenomenon was discussed in Section 7. In the context of R&S evaluation, this scenario is quite likely as we have 7 MOEs and the typical number of alternatives in an AoA study is less than 12. To overcome this difficulty, we recommend two possible remedies that have been implemented in similar situations elsewhere:

- Weight restrictions. The objective function of the model we presented above seeks to maximize the efficiency score for the alternative it evaluates. Thus, adding constraints to this model will cause a decrease in the efficiency score. The constraints should reflect qualitative assessment by the decision makers involved in the process. For example, putting some priorities on the weights (Roll, Cook, & Golany, 1991).
- Adding alternatives. During the development of a certain alternative, there are several design and engineering options that could be explored – each generating another alternative. Also, one could add "utopian" alternatives, generated artificially based on past experience, and use them as benchmarks.

- Uniqueness

  Certain alternatives may be affiliated with some attribute that doesn't exist in other alternatives and hence it makes them unique. A unique alternative is, by definition, fully efficient as we can't compare it to any other alternative. For example, suppose we evaluate the procurement of platforms that would transfer combat personnel from sea to shore and backwards and that all but one of the alternatives are different kinds of vessels and only one alternative is airborne. The contractor of the airborne alternative may claim that his alternative is unique to ensure it is ranked as efficient, absent competitors. To avoid such claims, one should ensure that the MOEs are as general as possible but yet relevant and useful. The way we presented the MOEs in this report is indeed quite general and we believe that in most cases it can be used as is.

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