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The Impact of Reliability in Conceptual Design - An Integrated Trade-off Analysis

Tevari James Barker
University of Arkansas, Fayetteville

The Impact of Reliability in Conceptual Design - An Integrated Trade-off Analysis

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Tevari James Barker
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____
Gregory S. Parnell, Ph.D.
Thesis Director

____
Edward Pohl, Ph.D.
Committee Member

____
Eric Specking, Ph.D.
Committee Member

____
Simon Goerger, Ph.D.
Committee Member

Abstract

Research presented in this paper focuses on developing models to estimate the system reliability of Unmanned Ground Vehicles using knowledge and data from similar systems. Traditional reliability approaches often require detailed knowledge of a system and are used in later design stages as well as development, operational test and evaluation, and operations. The critical role of reliability and its impact on acquisition program performance, cost, and schedule motivate the need for improved system reliability models in the early design stages. Reliability is often a stand-alone requirement and not fully included in performance and life cycle cost models. This research seeks to integrate reliability, performance, and cost models in a trade-off analysis framework in the early acquisition stages. This research uses functional analysis methods to estimate reliability Pre-Milestone A and assess the impact of reliability on performance and cost models of early system concepts. This research uses technology readiness level (TRL), which is indexed, to select different levels of reliability for design. An integrated cost and performance model will inform decision-makers on the impact of reliability before choosing a system concept for further development.

Acknowledgments

This thesis could not have been completed without the input from my research advisors and the team at the U.S. Army Corps of Engineers – Engineer Research and Development Center (ERDC). Thank you to Dr. Parnell who served as my primary research advisor and was a principal investigator on this project. Thank you to Dr. Pohl who served as an advisor and principal investigator on this project as well. Finally, a thank you goes to the team at ERDC for providing this opportunity to work on a challenging project that later turned into my thesis work. All entities supported me at one point in time and I would not have completed this without them.

Dedication

I would like to dedicate this thesis to my parents, James and Rhadonna Barker, who sacrificed to provide me with an opportunity for a better education. Their strength and perseverance are an example I follow every day of my life.

I would be thoughtless if I did not dedicate this to my family and in remembrance of my ancestors who gave it all for their descendants to have a future. To the Barker and Mixon family, you are my heartbeat.

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1. Introduction

The United States Department of Defense (DoD) needs to incorporate reliability information before Milestone A because it significantly impacts program performance, cost, and schedule estimates [1]. This research investigates an approach that uses early life cycle reliability analysis to assess performance, cost, and schedule in an integrated framework of models for Pre-Milestone A. The intent is to illustrate the method by performing a trade-off analysis by identifying design decisions for Unmanned Ground Vehicles (UGVs). The research analyzes the impact of design decisions excluding reliability from the performance models. A UGV design tradespace is generated to assess the feasibility, performance, and cost of design concepts with the early system design's reliability model. The resultant tradespace will describe the value-added by early reliability assessment.

Our framework focused on the development of parametric models for system performance, reliability, and cost. Values models were constructed to assess the feasibility of design alternatives with system-level tradeoffs. We then visualized the impact of cost vs reliability, value vs cost, and value vs reliability. Given the nature of the research problem, our access to readily available data was limited. Therefore, we are using notional data to develop a case study based on how a system could perform in an operating environment. To do this, we researched relevant data and information from manned and unmanned vehicle characteristic reports as a proxy for real data.

Given there is limited design information in early system concept development. One of the challenges for an integrated UGV model is developing the appropriate parametric reliability and performance models in early concept design. Understanding the relationships between concept technology decisions and performance provides a path to the integrated models for trade-off analysis. Improvements in UGV technology for military applications are ongoing, and this research can provide insights for decision-makers on the impact of reliability on performance, cost, and schedule in early UGV design stages. Two hypotheses that are the foundation of our work are: 1) reliability has not been adequately modeled in conceptual design and 2) when we do model reliability in conceptual design, we get different value and life cycle cost estimates. Our work emphasizes the development of a conceptual design framework to model reliability and impact decision-making.

2. An Integrated Model

The integrated reliability model includes reliability in system design feasibility assessment, performance evaluation, and life cycle cost estimates of design concepts to support trade-off analysis. Reliability is included in performance measures using the mission chain and in the life cycle cost model using projected operational usage and the impact of reliability on life cycle cost elements [2].

2.1 Influence Diagram for Integrated Models

We developed an influence diagram (Figure 1) [3] to capture the relationships between stakeholder needs, requirements, system alternatives, technology/manufacturing, integration readiness, stakeholder objectives, models, and simulations used for reliability and system performance modeling the integrated trade-off analysis. The integrated models in the influence diagram use prescriptive (blue color), predictive models (green), and prescriptive models (in orange). The yellow indicates information that is not likely to change in the model. In the influence diagram, we also indicate if the information is a known constant, a decision, an uncertainty, a calculated uncertainty, or a value. The diamond shape represents known constants, the rectangle represents decisions, the single oval represents uncertainties, the double oval represents calculated uncertainties, and the hexagon shape represents the value for the measure of interest. We use direct acyclic graphs (arrows never form a loop in influence diagrams) to indicate the flow of information. It is essential to know that information becomes available in later stages indicated by the time scale at the bottom of Figure 1.

Figure 1 begins with stakeholder needs, under the assumption that those needs are known. Stakeholder needs turn into system-level requirements. Requirements lead to objectives and integrated models with performance measures for analysis. The framework uses the objectives, models, and design alternatives to assess the performance, cost, and time to develop the desired UGV system. Integrated trade-off analysis is used to assess the value, cost, and schedule of potential system designs. A few things to know about this diagram shown in the red ovals is the use of technology readiness levels that integrates with the system reliability methodology. Also, our analysis under a normal time frame would include a schedule model to show how decisions impact the system development timeline, but this case study does not consider this as a factor.

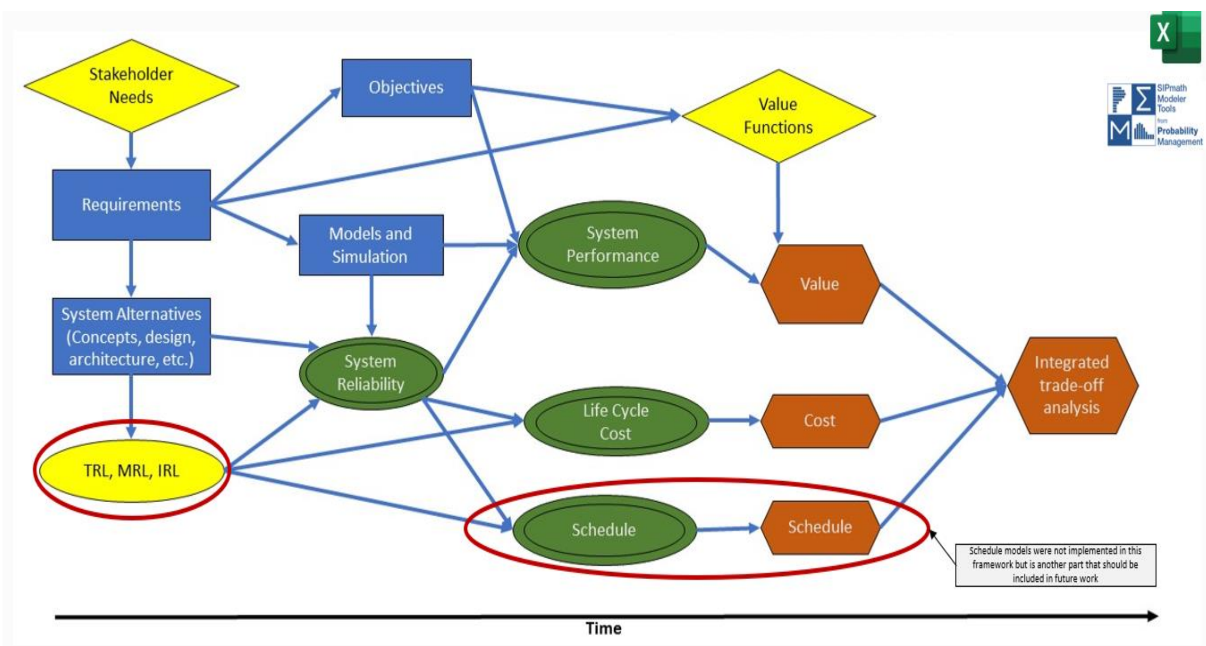

Figure 1. Unmanned Ground Vehicle Influence Diagram for Integrated Models

2.2 Assessment Flow Diagram for Integrated Models

We created an Assessment Flow Diagram (AFD) [4], shown in Figure 2, to illustrate the flow of information and the parametric models needed to calculate performance measures and the life cycle cost for a UGV. The AFD starts with design decisions such as mobility, power source, and sensor technology capabilities. Design and operational decisions are inputs to the parametric models shown in the model-based calculations section, impacting the design concept's performance measures and life cycle cost—the color-coding in the Figure describes the current modeling progress. In the legend, the blue color represents the modeling level is not implemented. The yellow color indicates we achieved a minimum level of modeling. The green color indicates the achievement of a more advanced level of modeling.

Performance measures in the UGV model include total vehicle weight, mission range, probability of detection, and endurance. Objectives of those performance measures include maximizing UGV transportability, maximizing survivability in operational environments, and maximizing the probability of enemy detection. The impact of design decisions on reliability and reliability on performance and cost are of significant interest.

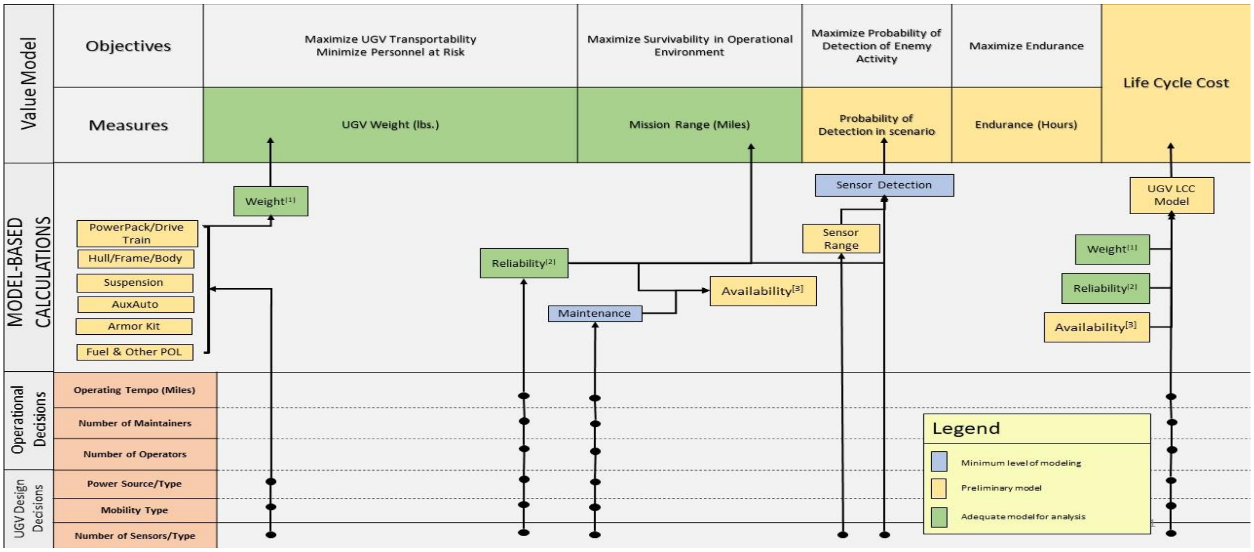

Figure 2. Assessment Flow Diagram for Integrated Models

3. Literature Review

The need for system reliability modeling and analysis in early conceptual design has increased as the industry tries to reduce the development time of complex technologies. The literature review focused on methodologies developed for the analysis of the reliability of complex systems in early conceptual design to understand existing approaches and identify opportunities for additional research. We used the Web of Science [5] core collection to find relevant papers for the research. This database was used due to its trusted sources of high-quality journals that include systems reliability. This provided a means to search thousands of papers within minutes using advanced keyword searches and additional features. To focus on the most recent research, the scope was narrowed to 2000-2021. The context of the literature review focused on system and subsystem reliability methodologies that did not require detailed information on subsystem components.

3.1 Literature Review Methodology

This section discusses our literature review methodology. The literature review process was tailored to find relevant papers, shown in Figure 1. We developed a set of research questions to screen the number of papers we reviewed, such as:

- Is reliability described early in the life cycle?
- Does the paper have a reliability model?
- Do they quantitatively estimate reliability in early system design?
- Do they assess the impact of reliability on system performance, cost, and schedule?

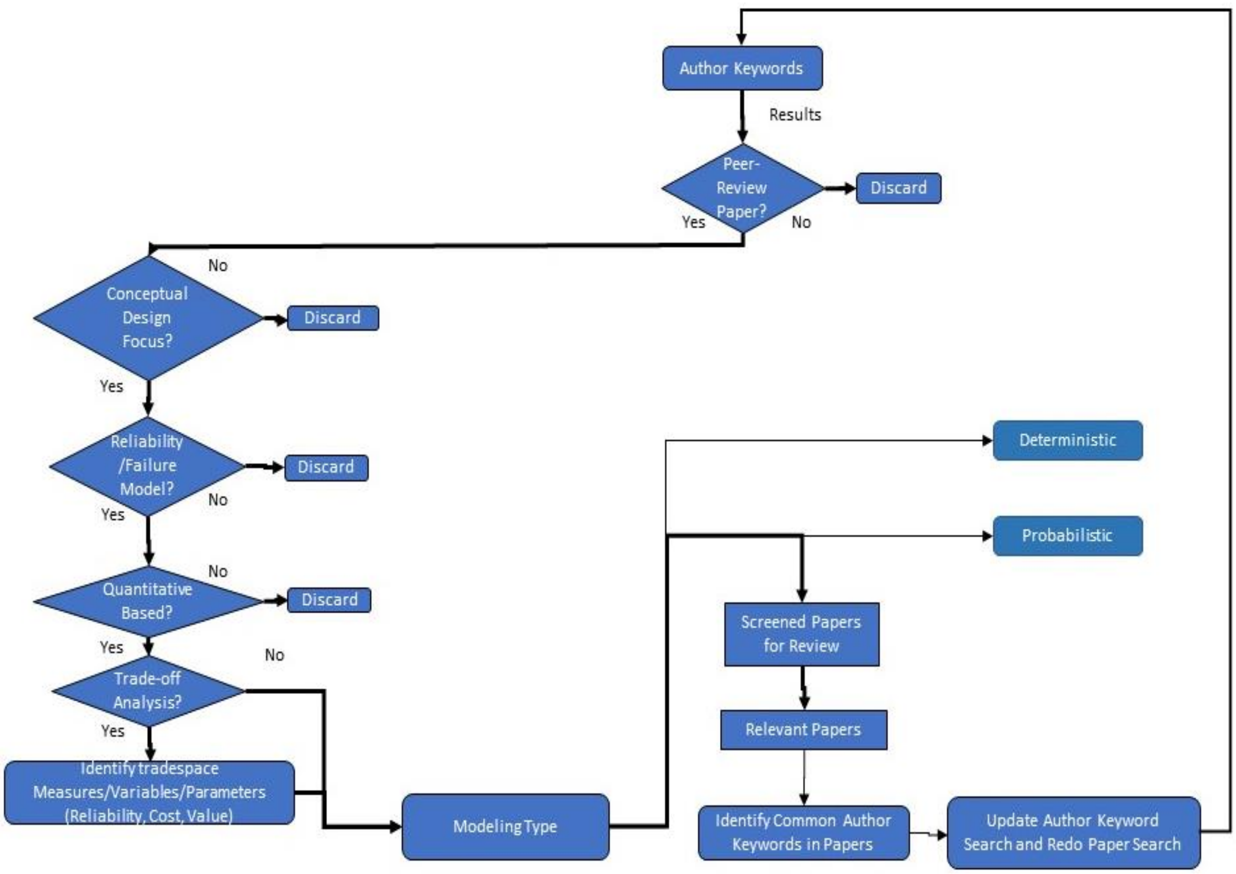

Figure 3. Literature Review Process

3.2 Literature Review Screening Process

To screen for the most useful papers, we used keyword words to search abstracts, author keywords, and titles to find relevant papers (Table 1). The initial keywords returned papers from a broad range of sources not focused directly on our research topic. We revised the keywords (as shown in Table 2) to search for papers more aligned with the research questions.

Table 1. Literature review keyword/phrase

Initial Keywords/Phrases	Conceptual design, early life cycle, reliability design, failure propagation, functional failure
Updated Keywords/Phrases	Failure propagation, functional modeling, failure modeling, failure flow decision-making, conceptual design, functional failure, failure analysis, failure prevention

Table 2 shows the keyword sets and the number of papers returned for each search iteration. As shown in the table, all sets were not included in the final analysis. After iterating through single and multiple combinations of keywords, the number of papers was reduced to a manageable 62 papers instead of a few thousand papers previously. Then, sets were combined to find a unique set of papers and eliminate duplicates. After this step, we found 50 unique papers to potentially review.

Table 2. Updated keyword/phrase result

Screening #	Keyword	# Of Papers	Duplicates
Not Used	"Failure Analysis"	15266	-
Not Used	"Failure Prevention"	772	-
Not Used	"Functional Failure"	613	-
Not Used	"Functional Modeling"	420	-
Not Used	"Failure Propagation"	391	-
Not Used	"Failure Modeling"	234	-

Table 2. Updated keyword/phrase result Cont.

Screening #	Keyword	# Of Papers	Duplicates
Not Used	"Failure Flow Decision-Making"	1	-
	Total Used	-	-
1	"Functional Modeling" AND "Conceptual Design"	30	-
2	"Failure Analysis" AND "Conceptual Design"	17	6
3	"Functional Failure" AND "Conceptual Design"	7	2
4	"Failure Propagation" AND "Conceptual Design"	4	1
5	"Failure Prevention" AND "Conceptual Design"	2	1
6	"Failure Flow Decision-Making" AND "Conceptual Design"	1	1
7	"Failure Modeling" AND "Conceptual Design"	1	1
	Total Used	62	12

Our next step of the process was separating peer-reviewed papers from non-peer-reviewed papers to reduce the number further. This process is shown in Figure 2. There were 30 peer-reviewed papers and 20 non-peer-reviewed papers. Non-peer-reviewed papers were removed from the review. The selection of high-quality peer-reviewed papers was included.

The screening of papers for reliability, failure, and conceptual design models was another part of the literature review essential for the methodology. We focused on papers with a conceptual design and quantitative models at this step. There were 10 with some conceptual design methodology/model and 20 papers without reliability models.

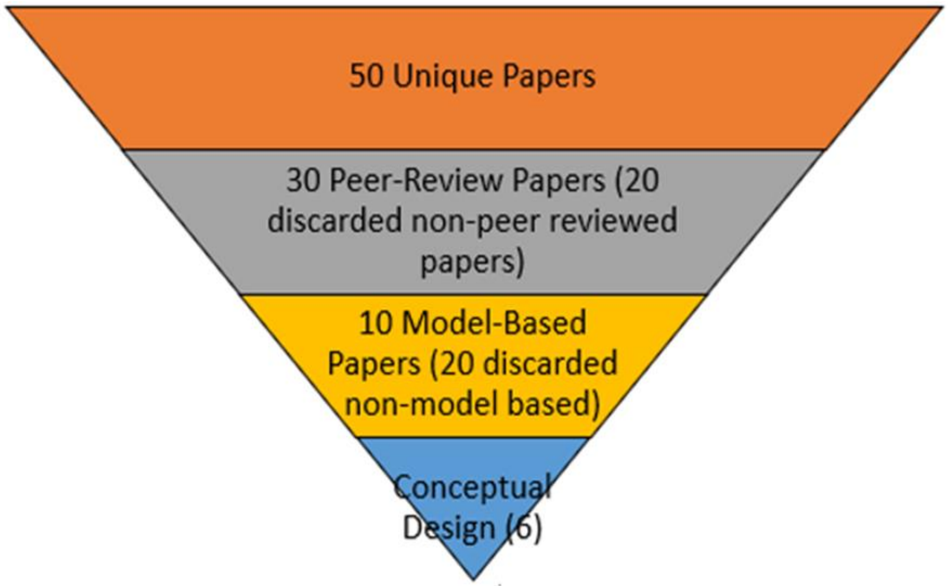

Figure 4. Reducing Literature Review Papers

Our review focused on 6 model-based papers that are reliability-related or use functional analyses of systems in early conceptual design. These papers were found from an iterative literature framework that used keywords from relevant papers to widen the review. The following section focuses on the review of the 6 papers.

3.3 Literature Review Summary of the Relevant Papers

Kurtoglu and Tumer [6] introduced a new framework called the function-failure identification and propagation framework to allow designers to analyze the functional structure of a system concept in the early stages of design. Using high-level models, a graph-based and simulation-based approach allow designers to understand how functions could fail and how the failure propagates throughout the system. This framework allows designers to assess the impact of a potential failure or failure path in the system early before making costly decisions.

Kurtoglu, Tumer, and Jensen [7] use a functional failure methodology for informed decision-making in the early conceptual design of complex systems. A simulation-based tool was used to develop a framework, enabling system architecture analysis in the early design stages. This work extends the efforts of Kurtoglu and Tumer [6], which introduced the Functional Failure Identification and Propagation (FFIP) analysis framework. The FFIP enables the analysis of functional failures and the impact made in early system design. In this paper, the authors extended the FFIP framework to a new framework called the Functional Failure Reasoning (FFR) framework. This framework represents failure as a functional element of the system not performing its designed task. The framework allows analyzing multiple design alternatives in different scenarios to assess the impact of functional failures propagating throughout the system. This framework also allows the assessment of risk and the reduction in risk between design alternatives. The noticeable difference between Kurtoglu and Tumer [6] is that this paper allows multiple concepts to be evaluated instead of a single concept.

A similar paper [8] uses the failure flow of information and failure propagation methodology to improve system survivability while aiding decision-making. The difference in this paper is the methodology that sacrifices non-critical subsystems and protects the functions and flow of information that enable the system to complete its primary objective. Short, Lai, Douglas, and Van Bossuyt [8] developed the failure flow decision function (FFDF) methodology to enable designers to model failure flow decision-making problems. When applied to specific scenarios, this framework can assess critical subsystems to inform decision-making. A case study in this paper is the Mars Exploration Rover (MER) platform. The FFDF framework was shown to effectively improve the survivability of the Rover by designing the system where the function is redirected to a different subsystem to reduce critical failures.

This paper [9] assesses the impact of failure propagation and the interaction of multiple failure modes in an integrated risk value model. Jing, Xu, Sun, Peng, Li, Gaom, and Jiang [9], produced a risk-based decision model to assess risk quantitatively using functional modeling. They generate a functional/graph-based model, assessing the severity of failure propagation by calculating the score of a potential design alternative and a risk value of a failure mode for conceptual design analysis. The principal solution weight is a factor that is used to calculate the severity of a failure mode when failure propagates.

Tumer and Smidts [10] also use the FFIP framework from Kurtoglu and Tumer [6] to assess the propagation of hardware, software, and hardware/software failures. This paper addresses how to evaluate the behavior of a combined software/hardware system. A focus is on software and hardware interaction that can lead to significant and costly failures.

Augustine, Yadav, Jain, and Rathore [11] propose a failure analysis technique to assess reliability issues in the early design stages. This approach is focused on higher-level interactions of subsystems rather than detailed component-level analysis. They use cognitive maps for system modeling and the use of simulation for failure analysis. This technique is used with various failure modes along with interaction failures.

The papers above have a similar objective focused on assessing reliability or functional failure early in conceptual design. Although there are various approaches researchers have taken or extended upon, there are missing elements for the research questions that are not addressed within these papers. When analyzing complex systems in the early life cycle, it is essential to look at different perspectives that impact decisions.

Throughout the literature review, only a few papers addressed the impact of reliability or failure analysis on performance, cost, and schedule. A significant literature gap in this research area, indicated by the red triangle (Figure 3), needs to be filled to develop integrated methodologies in the early life cycle design. It could be advantageous to apply integrated trade-off analysis to include all system design elements.

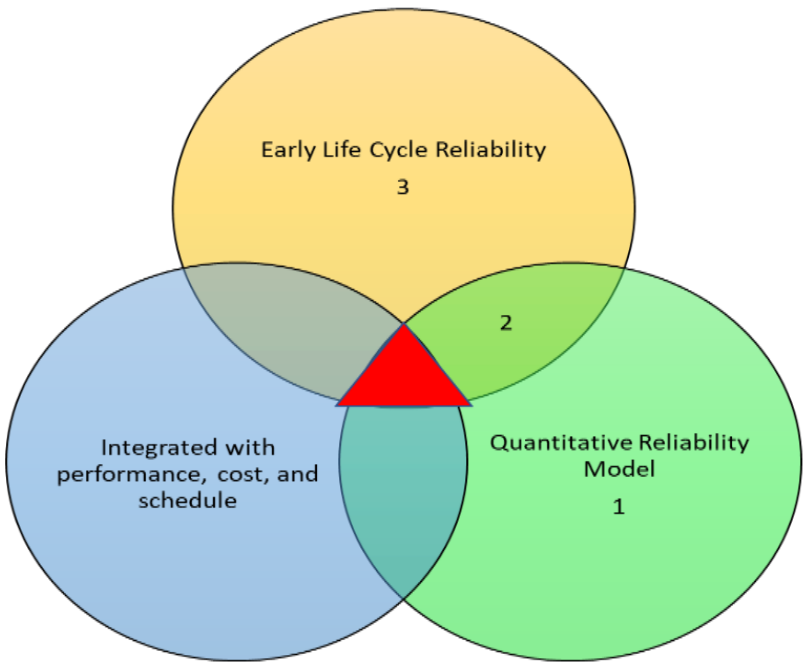

Figure 5. Literature Research Gap

Kurtoglu, Tumer, and Jensen [7] mentioned future work assessing trade-offs between the cost of the analysis vs. the benefits for more complex systems but did not mention the additional elements of trade-off analysis. Jing, Xu, Sun, Peng, Li, Gaom, and Jiang [9], assess cost, performance, and benefit, but decisions do not have cascading effects. These papers focused on failure propagation analysis in conceptual design, but there is an opportunity to integrate these methods with cost modeling, performance modeling, and schedule.

4. Methodology

As mentioned earlier, our work is focused on developing an integrated framework of performance models to assess the feasibility and evaluate design concepts. Our AFD and ID approach starts with fundamental design decisions such as the mobility platform, power source, and sensor types. Calculations of the system's reliability, performance measures, system value, and life cycle cost of all the alternatives are used to evaluate the design tradespace and perform trade-off analysis fully from the design decision.

4.1 Reliability Modeling

Traditionally, reliability is the probability that a component or system will perform its required function for a given time when used under stated operating conditions [12]. In this research, reliability is the probability that a component or system will satisfy a given function(s) over time, in which functional performance conditions on the current state of other interrelated functions. These definitions are the same theoretically, but there is an emphasis that the failure of a component or system is dependent on the current state of other system components. Although obtaining calculations can vary depending on the method chosen for analysis, the underlying structural analysis for reliability is the same.

There are two basic structures for system configuration when analyzing the reliability of a system: series and parallel. These two structures can be combined two create a series-parallel structure. This research only focuses on these types of structures. The equations for a series and parallel structure are in equations (1) and (2), respectively. This study uses the exponential life distribution to model the reliability of the critical components for the UGV (equation 3). An assumption is that failure is dependent on the function, represented by the failure rate, λ_i, where "i" denotes the function. The failure rate for the system is critical to calculating the number of systems required for the operations concept and the life cycle cost.

$$R_{sys}(t) = \prod_{i=1}^{n} R_i(t) \quad (1)$$

$$R_{sys}(t) = 1 - \prod_{i=1}^{n}(1 - R_i(t)) \quad (2)$$

$$R_i(t) = e^{-\lambda i * t} \quad (3)$$

Our research involves the prediction of reliability in the conceptual design stages of system development. Our approach for reliability analysis uses notional data and functional analysis to assess the reliability of a chosen design concept. Regarding functional analysis, a fundamental approach to the methodology is defining system functions that are used in conceptual design. In the case of a UGV, generic functions were defined that are used in the system analysis.

Table 3 is a list of UGV functions and their functional relationships. The term functional relationship can be loosely labeled functional dependencies, but due to the circular relationship of the functions, dependency is not the term used. For example, Function 8.0 depends on either function 9.0, 10.0, 11.0, 12.0 or 13.0. However, all those functions could depend on function 8.0. The interesting factor here is that we look at these functions as relationships instead of acyclic dependencies. These functions are ways of showing the flow of information. If we cannot process a signal (F8.0), how we can record any type of external data (F9.0, F10.0, F11.0, F12.0, F13.0). On the other hand, if we cannot record external data, we cannot process signals. We do not have any data to share due to a potential failure that could cascade and impact signal processing. A visualization of the functions is shown in Figure 6.

Table 3. Functional Analysis Relationships

Function	Functional Relationships
Function 1.0	-
Function 2.0	F1.0
Function 3.0	OR {F1.0, F2.0}
Function 4.0	F3.0
Function 5.0	F4.0
Function 6.0	F5.0, F7.0
Function 7.0	F3.0 AND F8.0 AND (OR {F10.0, F11.0, F12.0, F13.0})
Function 8.0	OR {F9.0, F10.0, F11.0, F12.0, F13.0}
Function 9.0	F8.0
Function 10.0	F8.0
Function 11.0	F8.0
Function 12.0	F8.0
Function 13.0	F8.0

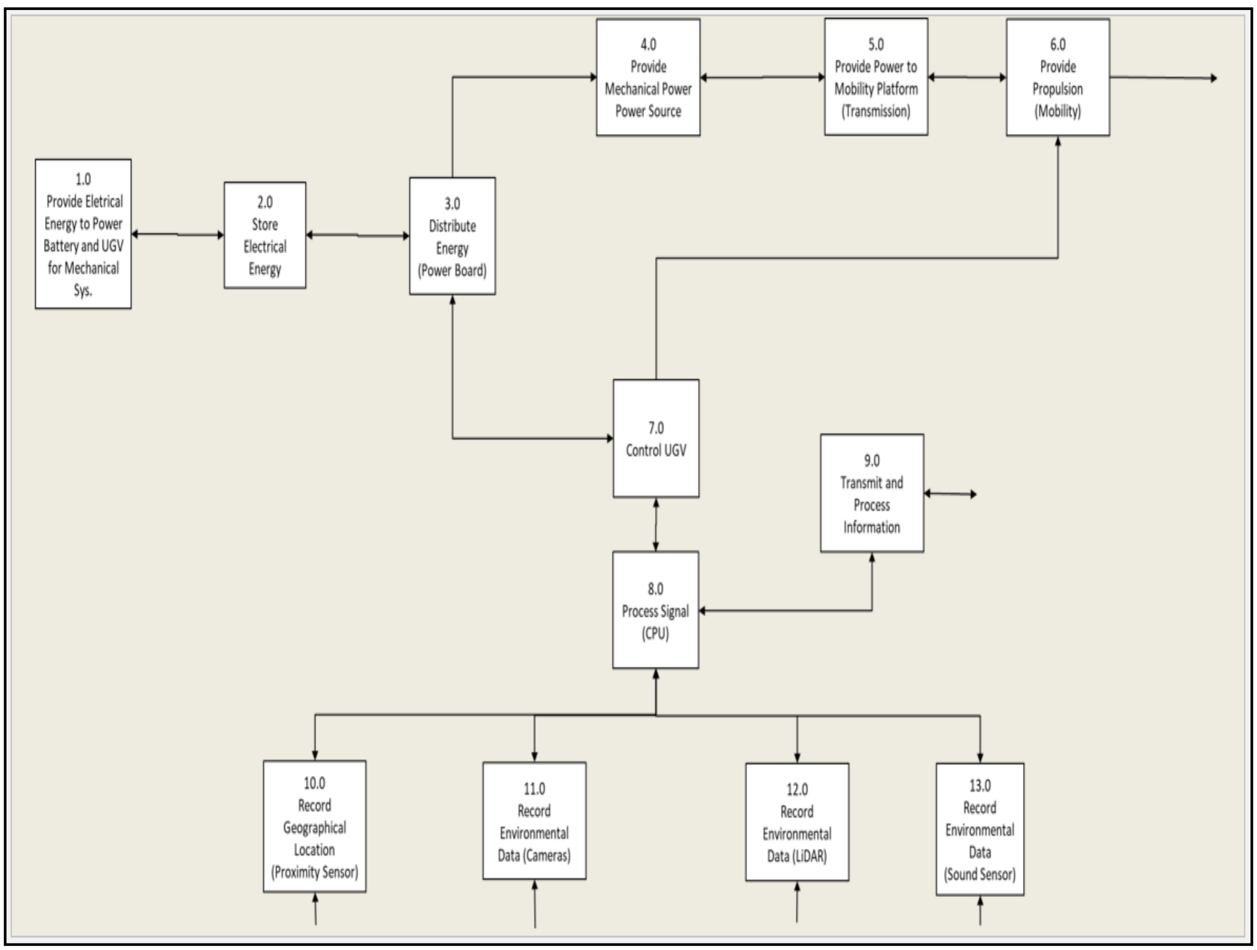

Figure 6. Functional Analysis Graph

In our analysis, we use the technology readiness levels that impact system design to represent the assumed minimum, baseline, and maximum values for reliability for a given system component. Table 4 represents a deterministic structure of decisions, reliability, and the three range levels of TRL used for indexing.

Table 4. Structure of Technology Readiness Level (TRL), Reliability, and Design Decisions

		Index		
		1	**2**	**3**
Function	**Reliability**	**TRL 5**	**TRL 6**	**TRL 7-9**
F1.0	Index {1,2,3}	0.7	0.8	0.97
F2.0	Index {1,2,3}	0.7	0.8	0.97
F3.0	Index {1,2,3}	0.7	0.8	0.97
F4.0	Index {1,2,3}	0.7	0.8	0.97
F5.0	Index {1,2,3}	0.7	0.8	0.97
F6.0	Index {1,2,3}	0.7	0.8	0.97
F7.0	Index {1,2,3}	0.9	0.95	0.99
F8.0	Index {1,2,3}	0.9	0.95	0.99
F9.0	Index {1,2,3}	0.9	0.95	0.99
F10.0	Index {1,2,3}	0.9	0.95	0.99
F11.0	Index {1,2,3}	0.7	0.9	0.99
F12.0	Index {1,2,3}	0.8	0.9	0.99
F13.0	Index {1,2,3}	0.8	0.9	0.99

As mentioned before, data in conceptual design can be hard to come by. Therefore, this functional analysis approach is adapted to work with technology readiness levels to indicate the potential reliability of a high-level function. This approach allows analysis of the relationships between functions and how they impact performance, value, and cost. The Excel index function is used for three readiness levels assumed for a given system component. The system reliability is then calculated based on the system's functional structure using equations 1 and 2. If a function depends on all functional relationships, it is indicated by AND logic. If it only depends on a minimum of one function, it is indicated by OR logic in the functional relationships table. The following equation is used to turn the logic into a reliability estimate based on the functional relationships. To indicate the best-case scenario of non-failure, the framework takes the max reliability value of the functional relationships. When calculating this value, we wanted an optimistic perspective for the case study given the design decisions. Instead of using MAX, one could simply use MIN to calculate the worst-case scenarios for reliability performance in the tradespace.

- Functional Reliability Estimate = MAX (SET{Functional Relationship Reliability}*(TRL Reliability of the Base Function))
- Functional Dependencies Reliability -> Different Reliability Estimates for Functional Relationships
- For example, function 3.0 depends on F1.0 or F2.0. Shown below is the method of calculating the reliability estimate.
    - F3.0_Reliability=MAX (SET {1.0_Reliability, 2.0_Reliability} * F3.0_Reliability)

Based on how we defined the reliability relationships, we can easily calculate function reliabilities. In the example above, we take the base reliability estimate of function 3.0 and use the other functions that 3.0 is dependent on as the likelihood that function 3.0 will fail given the probability that function 1.0 or 2.0 fails. This methodology is like series-parallel systems, but more emphasis should be placed on how failure propagates forwards and backward. Given the complexity of relationships, sufficient defining of relationships could be practical in conceptual design.

4.2 Life Cycle Cost

Life cycle cost assesses all relevant costs from conceptual development through production, deployment, operations, and retirement of a product or system; it is the total cost of ownership [13]. Part of our focus was integrating reliability into the life cycle cost. It is essential to account for the impact reliability has on the life cycle cost to make the best system design decisions early in the life cycle. We do this by assuming the reliability of the system will remain constant over the system life given regular maintenance. With this assumption, we can calculate the mean time to failure of the design life and approximate total failure costs. At this point in conceptual design, failure costs are unknown, but the use of subject matter experts and looking at similar systems could provide a great starting point. A cost analysis can be defined in many ways; this research uses the cost analysis structure from Ebeling [13]. From this structure, we calculate life cycle cost using equations (4) and (5). Life cycle cost categories in Table 5 and the inputs in Table 6 were used.

Table 5. Life Cycle Cost (LCC) Categories Used for UGV Cost Analysis

Acquisition	**Operations and Support Costs**	**Phase-Out (Retirement)**
Research and Development Design and Prototyping Production	Operations Support Failure Costs Training Technical Data	Salvage Value Disposal Costs

Table 6. Life Cycle Cost Inputs

Cost Model Inputs	
C_u	Unit Acquisition Cost
N	# Of identical units to produce
F_o	Fixed cost of operating
C_o	Annual operating cost per unit
F_s	Fixed Support Cost

Table 6. Life Cycle Cost Inputs Cont.

Cost Model Inputs	
C_s	Annual support cost per unit
C_f	Cost per failure
t_o	Operating hours per year per unit
t_d	Design life (years)
S	Unit salvage value
i	Discount rate
P_A (i, t_d)	Present Day Worth over design life
MTTF	Mean time to failure

$$\text{LCC} = \text{Acquisition Costs} + \text{Operations Costs} + \text{Failure Costs} + \text{Support Costs} - \text{Net Salvage Value} \tag{4}$$

$$\text{Net Salvage Value} = \text{Salvage Value} - \text{Disposal Cost} \tag{5}$$

4.2.1 Acquisition Costs

In Figure 4, acquisition cost covers research and development, design and prototyping, and production costs. Fixed costs were used for each design decision to capture the resource cost in the framework. In this approach, only need the cost per unit for acquisition cost and the total number of units to produce are needed, shown in equation (6).

$$\text{Acquisition Costs} = (C_u)(N) \tag{6}$$

4.2.2 Operations and Support Costs

Operations and support costs (O&S) cover operating, failure, support, training, and technical data costs. We only focus on the first three cost categories. For operating costs, the methodology includes a fixed cost of operating upfront and an additional element of annual operating cost in present-day dollars over the design life. Present-day dollars are calculated with a discount rate, where the discount rate is the difference between the assumed return on investment and the inflation rate [13]. To keep things simple for the case study we assumed the discount rate is constant over the system life. Equation (7) represents the operating costs.

$$\text{Operating Costs} = F_o + P_A\ (i, td)\ (C_o)(N) \tag{7}$$

Failure costs include the present worth of annual failure cost over the design life and the expected number of failures per year. This research addresses the failure cost of a design rather than focusing on the cost of improving reliability. Focusing just on this section allowed us to show how reliability impacts life cycle costs by isolating the failure costs. Equation 8 shows the failure cost calculation we used in our model.

$$\text{Failure Costs} = P_A\ (i, td)\ (C_f)\ (\frac{\text{to}}{\text{MTTF}})(N) \tag{8}$$

Support costs are another area impacting the tradespace for a UGV. Support is necessary for this system to ensure operational readiness and effectiveness for a complex unmanned system. Support costs include fixed and additional annual support costs over the design life in present-day dollars. Notional data was used as a static value for support cost over the set design life. Equation (9) was used to calculate support costs for the system.

$$\text{Support Costs} = F_s + P_A\ (i, td)\ (C_s)(N) \tag{9}$$

4.2.3 System Retirement Costs

When a system is retired, the net salvage value represents the system's anticipated salvage value minus the disposal costs. The research does not incorporate this cost, but the cost should be integrated into later stages of development. Equation (10) shows the calculation for the salvage value.

$$\text{Net salvage value} = P_F\ (i, td)\ (S)(N) \tag{10}$$

This section addressed the critical points of life cycle cost: acquisition, operations, failure, and support costs. The focus of the cost model was to integrate reliability in a meaningful way to aid in future decision-making. An important note is that all cost elements may not be feasible or make sense in conceptual design if there is limited information about the system.

4.3 Multiple-Objective Decision Analysis Value Model

An additional element of the tradespace is the value of a design alternative. Multiple objective decision analysis (MODA) quantitatively assesses the trade-offs between conflicting objectives by evaluating an alternative's contribution to the value measures and the importance of each value measure [14]. The MODA model is used to assess the alternative's value using the objectives and value measures (Table 7). The aggregate of each objective's value measure is shown vs. life cycle cost to define a value vs. cost tradespace

Table 7. MODA Model Objectives and Measures

Function			
Transport UGV	Survive in War Environment	Detect Enemy Activity	Detect Enemy Activity
Objectives			
Minimize UGV Transport Weight	Maximize Survivability in Operational Environment	Maximize Probability of Detection of Enemy Activity	Maximize Endurance
Value Measures			
UGV Weight (lbs.)	UGV Mission Range (miles)	Probability of Detection	Endurance (hrs.)

A feasible design meets the system requirements. Performance models are used to assess feasibility before displaying the feasible tradespace. Performance models are used to calculate the current ability of design choice, i.e., we use a sensor detection model to determine the probability of detecting enemy activity with given design choices. We use the model to determine if the design meets the minimum requirements gathered from stakeholders. If not, the model excludes the design from the tradespace.

4.3.1 Performance Models

Because design decisions vary in performance, we use performance models to assess the impact on performance, value, and cost. In the integrated modeling framework, we calculate the system reliability of subsystems based on design decisions. For a suite of sensors, the reliability of the sensor suite impacts the detection probability, directly impacting the objective of maximizing the probability of detection of enemy activity. We integrate reliability into system performance by multiplying the value of the system alternative value by the reliability value. For example, if the probability of detection is .90 and the system reliability is .70, the true probability of detection given the system capability is 0.63. However, if a system is near .99 in reliability it would be .89 for the probability of detection. This approach is integrated with other performance objectives as well.

4.3.2 System Performance

Since stakeholder input defines the functions, objectives, and value measures, we want to ensure that we meet the minimum acceptable level of performance for a given performance measure. In this context, if the detection probability were below a minimum threshold of 0.6, we would define this design alternative as infeasible.

4.3.3 Value Model

To ensure we capture the importance of a performance measure, we use the swing weights in the additive value function to calculate the total value of an alternative [15]. The model definition is in table 8, defining the elements of the additive model [16]. Shown in equation 11 is the additive value model. Equation 12 is another equation associated with the model to satisfy the normalization of swing weights. The model is used to assess alternatives and assign a value. Shown in Figure 8 are the value curves we are using currently. The x-axis indicates the level of the performance measure, and the y-axis is the score converted into a value.

$$v(x) = \sum_i^n w_i v_i(x_i) \tag{11}$$

$$\sum_i^n w_i = 1 \tag{12}$$

Table 8. Additive Value Model Definitions

Cost Model Inputs	
x	Vector of the alternative scores
v(x)	Alternative's value of x
i	1 ton is the index of the value measure
x_i	The alternative's score of the ith value measure
$v_i(x_i)$	Single-dimensional value of an x-axis score of x_i
w_i	The swing weight of the ith value measure

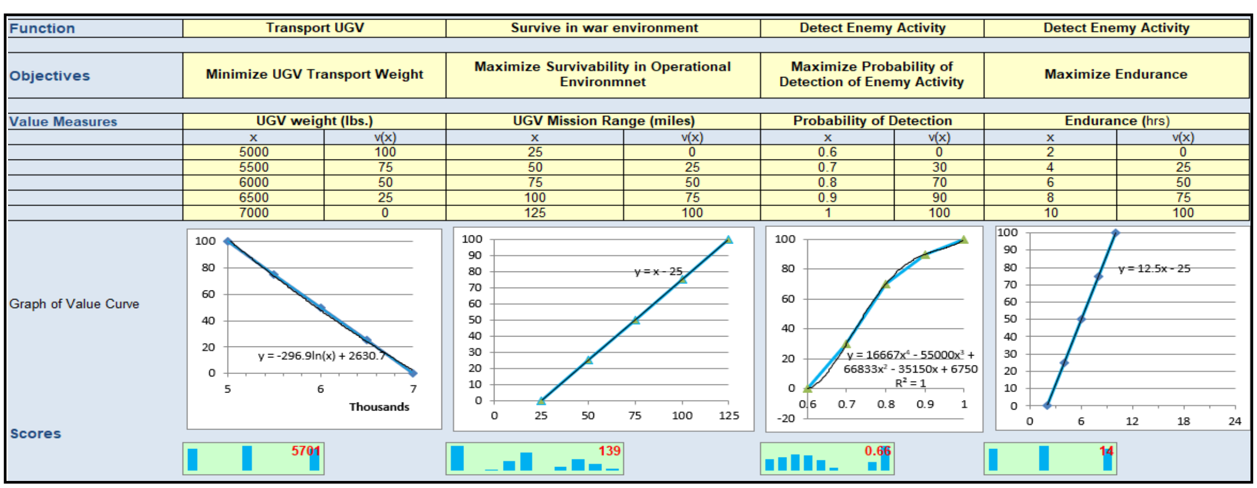

Figure 7. Preliminary Value Curves for a Notional UGV System

5. Trade-off Analysis

This paper addresses an approach to life cycle cost and value while incorporating a basic reliability model. In the integrated modeling framework, we highlight a few primary areas: reliability, value, and cost. The following section shows preliminary results in the cost vs. value tradespace using the technology readiness levels for the system functions.

The model allows us to index three TRLs and calculate an alternative's reliability, value, and cost for each level. We use integrated parametric models shown in Appendix I. The output of the integrated modeling framework is a tradespace that looks at the trade-offs between alternative value, cost, and reliability for a given design. A poorly designed system or system alternative would negatively impact dependent variables such as system design value and life cycle cost.

5.1 Deterministic Analysis of Integrated Models with Integrated Reliability

We sought to compare the deterministic analysis vs. uncertainty analysis of TRL levels. According to [17], the purpose of TRL is to “measure the maturity of technology components for a system. This measurement allows personnel to understand the progress on developing technology before being utilized.”

For deterministic analysis, each function was indexed by the same TRL level. The integrated framework would then calculate reliability, value, and cost for the 3 TRL levels. Below are the results of the deterministic analysis.

The first results are from a deterministic analysis using the integrated framework. In the chart below, we have a design space of 3 points. The blue point represents TRL 5, the orange represents TRL 6, and the green represents TRL 7-9. The chart shows the impact of reliability on the life cycle cost of a design. For our assumed parameters, when a system has very low reliability, the cost of poor performance is realized by the model methodology. When systems have improved reliability, the life cycle cost is lower due to not having associated maintenance, repair, and failure costs.

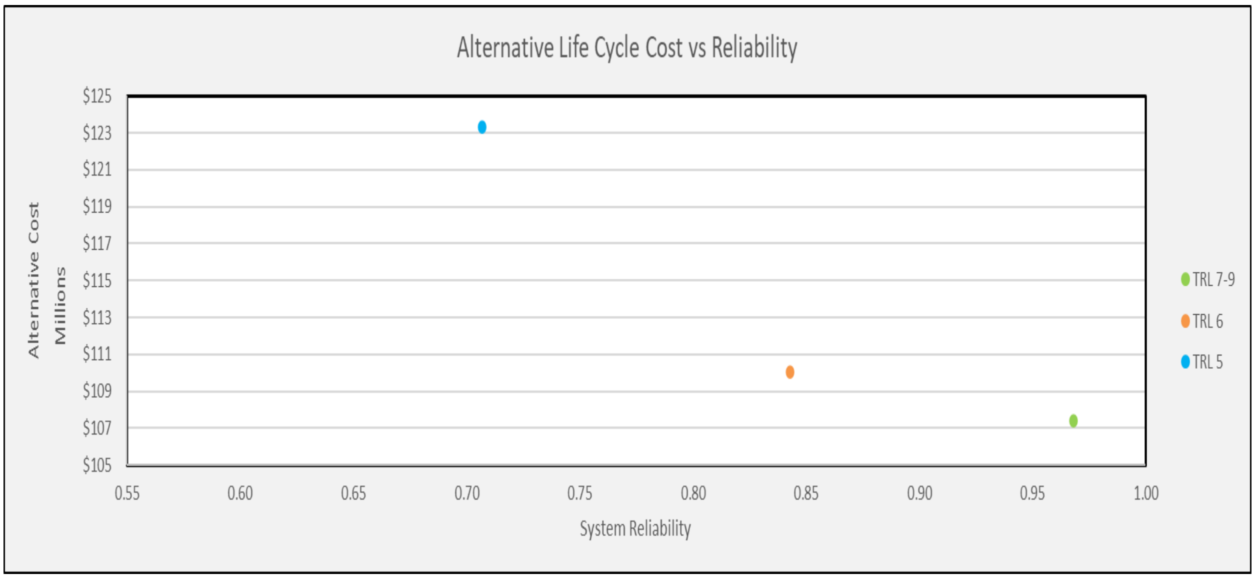

Figure 8. Deterministic Life Cycle Cost vs Reliability (Integrated)

The following figure shows the impact of reliability on the value of a system design. The way reliability is integrated, this graph clearly shows that reliability impacts the performance of a design alternative which impacts the value of the alternative. Another important takeaway is that there is only a marginal increase in value as reliability increases, this is because our framework is developed the be sensitive to poorly performing alternatives. As the reliability increases, the cost of failure will decrease significantly. Costs are likely marginal as reliability improves. The framework places emphasis on poor reliability.

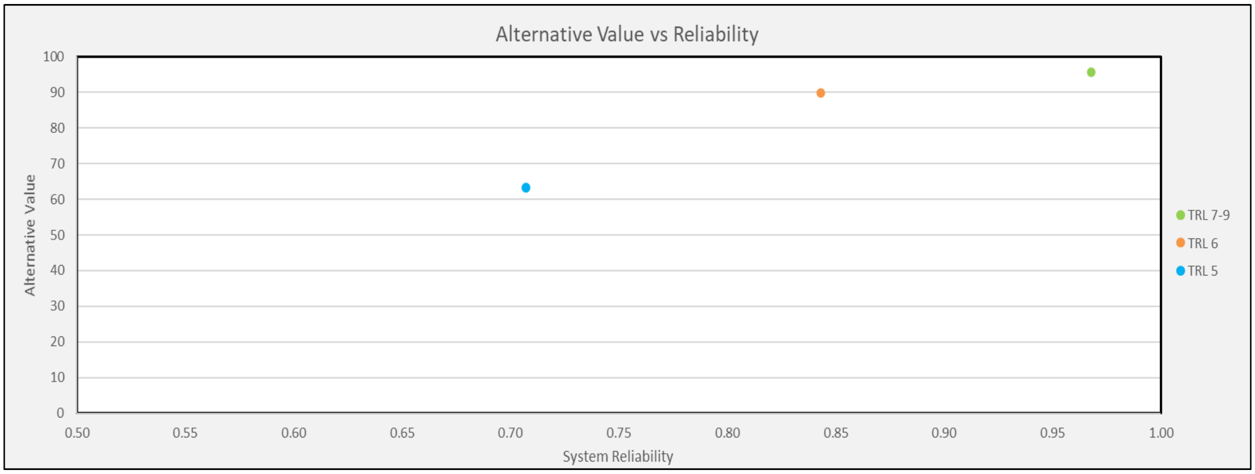

Figure 9. Deterministic Alternative Value vs. Reliability (Integrated)

The last figure in the deterministic analysis with integrated reliability shows the design space with alternative value vs. life cycle cost. Reliability (driven by TRL) has a significant impact on cost and value for low TRL. With the goal of this research being to show the impact of reliability in conceptual design, this graph indicates the impact failure costs can have on alternative development.

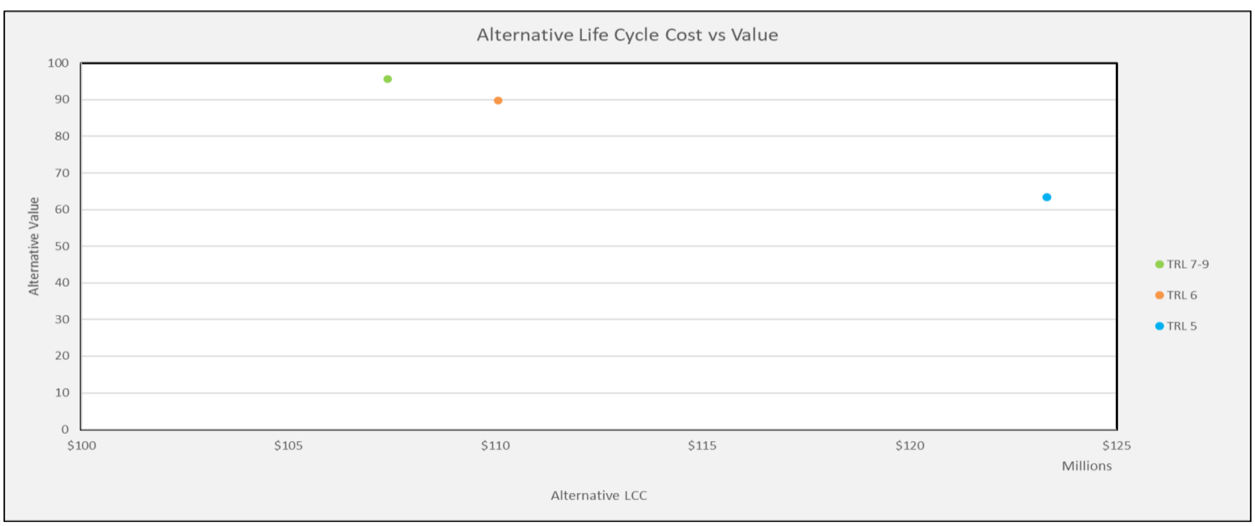

Figure 10. Deterministic Alternative Value vs. Life Cycle Cost

5.2 Deterministic Analysis of Integrated Models without Integrated Reliability

The next section discusses the results of the deterministic analysis when you do not integrate reliability values into the performance measures. First, we show it impacts the value alternative by not integrating the reliability measure into performance. Then we show how not integrating reliability impacts cost. Finally, we assess the value vs life cycle cost impact.

Shown below, we see that when you do integrate reliability to have an impact on the performance models, your preference for alternatives based on value is almost negligible. This result is saying regardless of the reliability estimation, the value will not be significantly different. If it were the case in our model where lower reliability was cheaper, decision-makers might prefer the cheaper alternative.

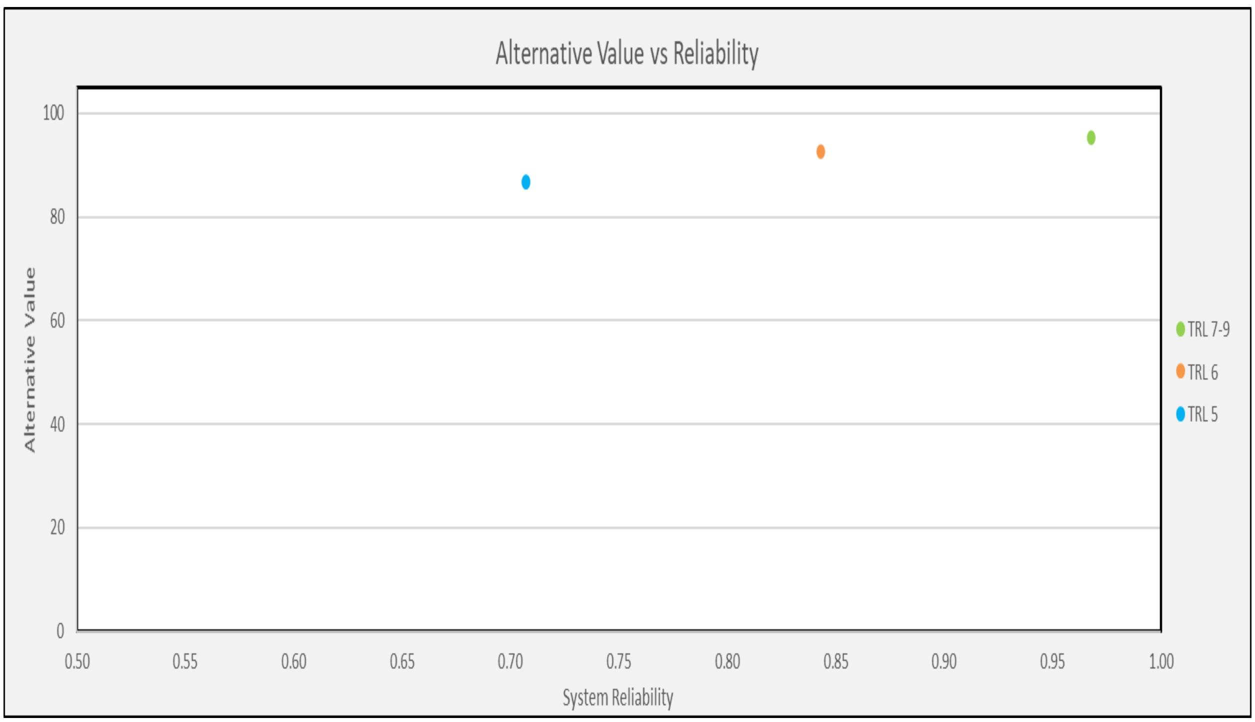

Figure 11. Alternative Value vs. System Reliability (Not Integrated)

Next, we see that alternative value is negligible for life cycle cost as well. This is because the failure costs associated with the reliability performance of the system no longer have an impact. These results show the impact of integrating reliability performance directly into the performance that impacts alternative value.

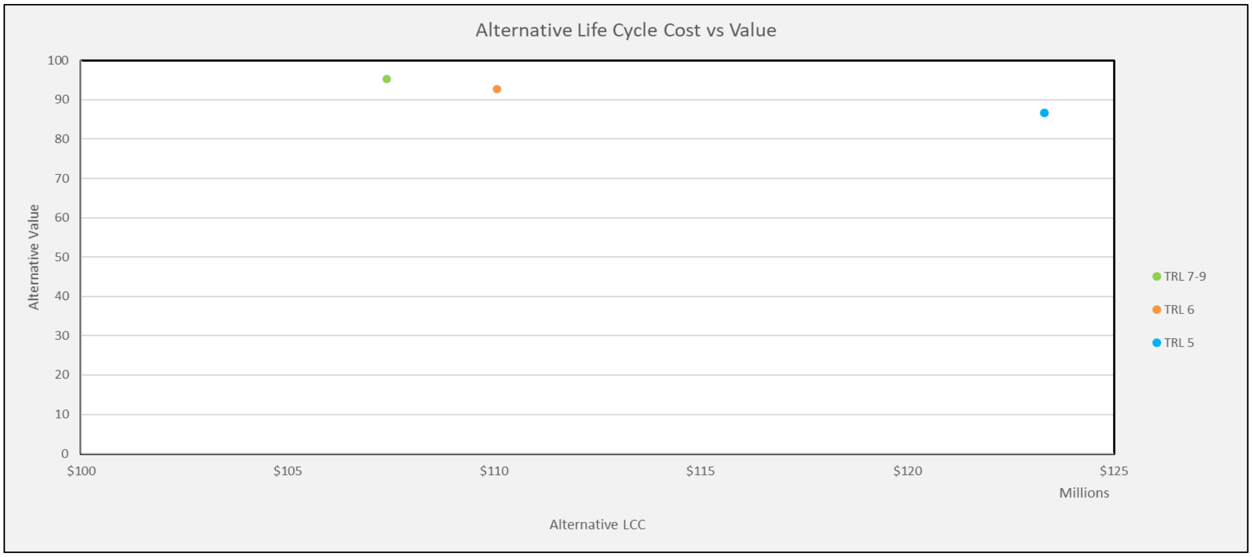

Figure 12. Alternative Value vs. Life Cycle Cost (Not Integrated)

5.3 Incorporating Uncertainty in the Analysis of Integrated Models

It was important to see the result deterministically when analyzing the systems, but it is also important to include uncertainty in the results. In this case, uncertainty was defined as the distribution of the TRL range that results in a design space that could be realistically compared to deterministic analysis. We may think a particular function is well developed, and we place a high level of TRL of 7-9 for that decision. On the other hand, another function might have technology where the best case is only TRL 5.

We used Monte Carlo simulation to create the mixture design using SIPmath tool the SIPmath tool from ProbabilityManagement.org [18]. According to Probability Management, “probability management is the representation of uncertainties as data arrays called Stochastic

Information Packets (SIPs) that obey laws of arithmetic and the laws of probability." SIPmath is an Excel-based add-in feature that allows anyone to conduct a Monte Carlo Simulation on the index value. The index value is used to obtain the values of a given design. To do this, a distribution is assigned to each function and a given TRL range. We used a discrete-uniform distribution to select the index values within this research. A discrete-uniform distribution was used because we are selecting from 3 different types of TRL ranges, and we want a uniform or equally likely selection of the TRL ranges. A triangular distribution was used to define the range of TRL values with the minimum, and maximum values, shown in Appendix II. Triangular distributions were used because they are useful if you are using notional data due to not having system data available. The index values for each function were defined as an "Input" for the modeler tool. Once selected, the SIPmath modeler tool simulates the index value for a set number of trials and automatically stores user-defined information. The reliability cells are defined as "output."

It is important to understand the designation of whether the point falls under TRL 5, TRL 6, or TRL 7-9. In this research, mixed design alternatives are labeled by the relative reliability range they fall in. For TRL 5 the range was [.67, .75], TRL 6 was (.75, .85], TRL 7-9 was (.85, .99]. These values were binned based on outputs from the Monte-Carlo simulation. You could see a distinct grouping of points. Another reason for binning is previous meetings with researchers indicated the approximate range of values that could be valid for further analysis. With these two points in my mind, we binned the values accordingly.

The analysis results have a similar story to the deterministic analysis. There is a grouping of points that dominate the tradespace by having significantly higher reliability, lower cost, and more value.

Shown below is the result of life cycle cost vs. system reliability, we can see that the points with TRL 7-9 range have higher reliability and significantly lower costs than the infeasible points shown in purple. The infeasible points are where reliability did not meet the minimum requirement threshold of .67 for the TRL 5 starting point. An interesting takeaway from the results shows there is a grouping of points where we get similar reliability values, but the cost could be higher. However, this is only marginal and at a program level, a couple of million dollars could be negligible.

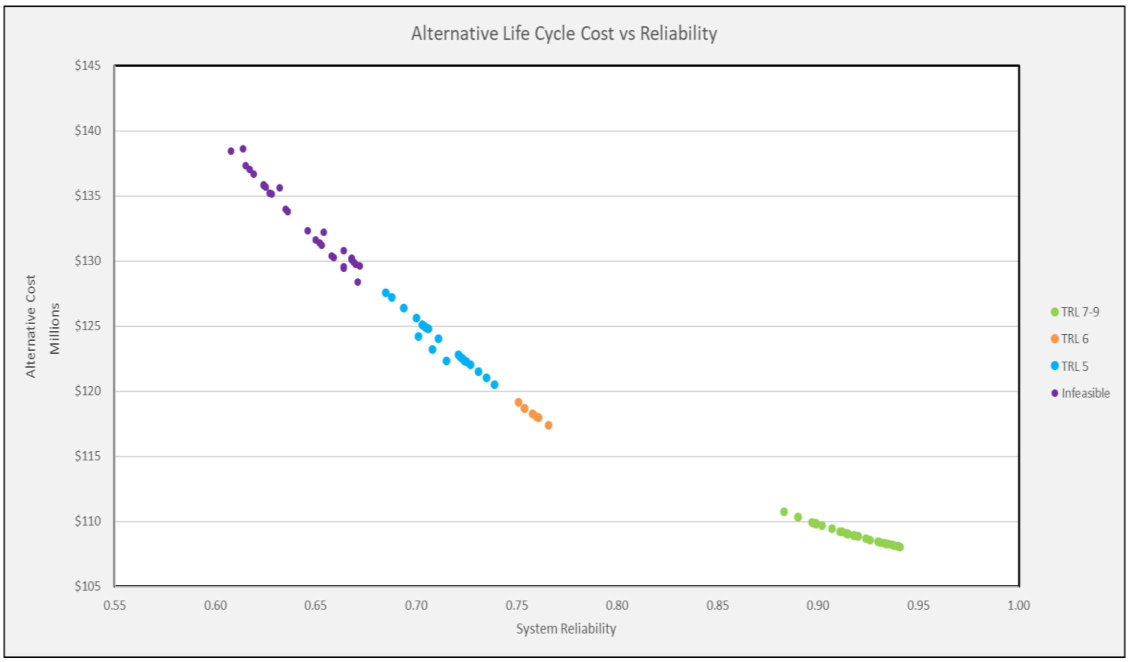

Figure 13. Monte Carlo Simulation Life Cycle Cost vs, Reliability (Integrated)

Alternative value vs. reliability for mixture designs present a different output than the deterministic analysis. We have the desired traits for higher reliability to a high alternative value score. However, there is an interesting gap for lower-level reliability values in the range [0.60, 0.75] that includes infeasible points and the lower TRL range. We have a tradespace where we can have the same reliability value and a significantly different outcome for the value model. This is purely based on the performance inputs for the models. If the TRL ranges have significantly different performance model outputs but the reliability of those functions is similar, you get the result shown below. Performance inputs impact calculations such as mission range which is used in the value model with significant weight. Alternatives could have the same calculated system reliability, but the impact of horsepower on mission range is what separates the alternatives.

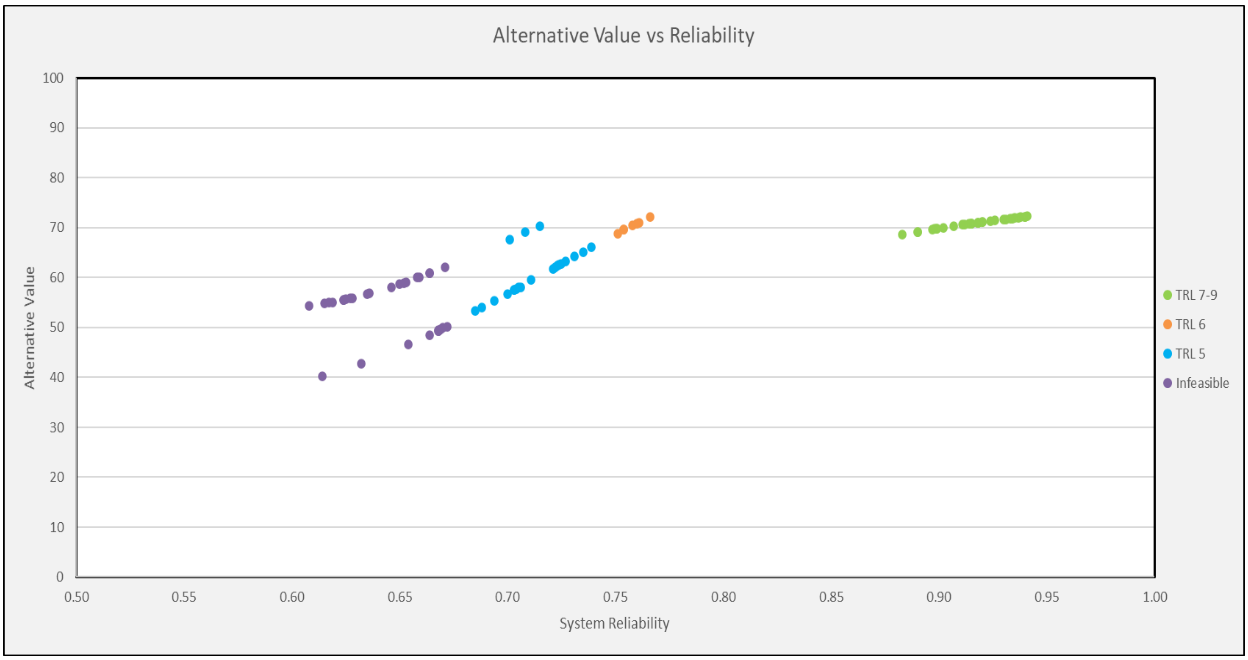

Figure 14. Monte Carlo Simulation Alternative Value vs. Reliability (Integrated)

When we look at alternative value vs. life cycle cost, we can see as alternative value increases, the life cycle cost decreases because failure impact is lower compared to a low value. However, when the life cycle cost is increased, we have a split in decision points because of the slight trade-offs between TRL 5 vs. TRL 6. Again, it is interesting to negligible costs have very different alternative values outputs. The emphasis on reliability and performance truly impacts the outcomes of the analysis.

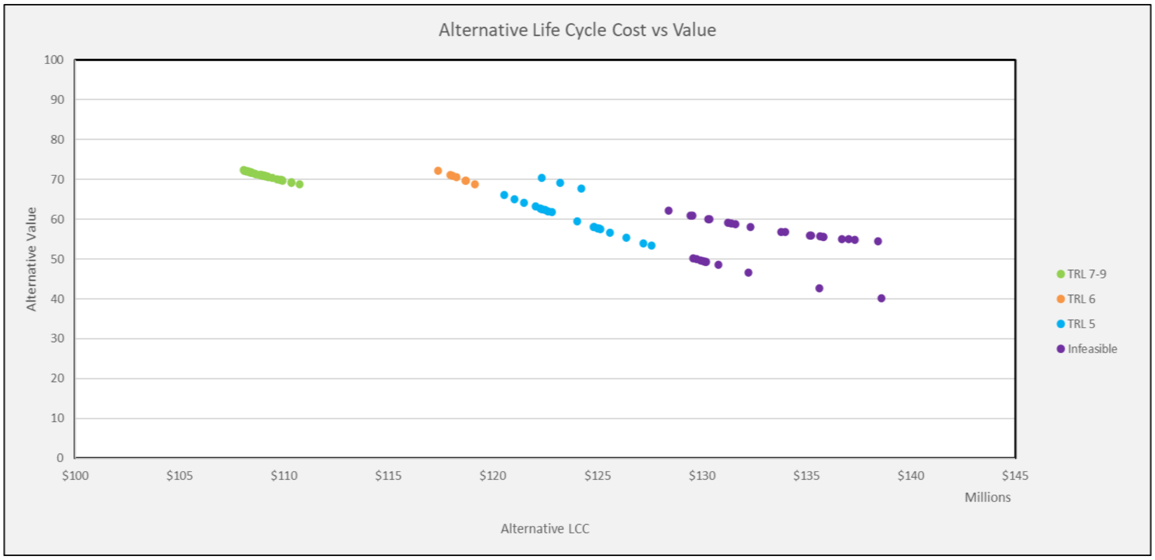

Figure 15. Monte Carlo Simulation Alternative Life Cycle vs. Value

6. Discussion of Results

For our illustrative UGV case study, the change in reliability versus the impact on value is significant. There is a greater sensitivity compared to the impact of reliability on cost. However, by analyzing the results, one can see the impact of 1) How reliability is estimated, 2) How reliability is integrated into performance models, and 3) How reliability is integrated into life cycle cost.

Emphasized earlier in this research was the lack of actual data to construct the models and obtain realistic results. While this research could produce reasonable reliability values, the impact it has on research efforts depends on the use case and how well constructed the models are. However, this research focused on the what-if scenario or how the tradespace looks without modeling failure into the cost and value model. The insights drawn from the analysis could be helpful in future work.

7. Conclusion

The current approach uses static values for reliability on a specific subsystem or component. This approach becomes dynamic when using Monte Carlo Simulation to index all static values for design decisions. Within this framework, design decisions were broad, and TRL levels were used to indicate the change in levels of reliability. This research generated a tradespace by enumerating combinations of design decisions by using the SIPmath tool. The final analysis is promising for continued work on reliability modeling methods using the high-level system trade-offs.

Areas for future work include parametric modeling and data availability. Much time was spent researching for general rules of thumb, and that information could be replaced with actual data. Other models such as system-level availability to determine the usage impacts on mission performance should be considered in future work. Also, implementing learning curves for the cost model could improve estimation performance over the design life as well. Without the proper resources, time, and knowledge to construct scalable parametric models this research falls under the category of being potentially significant when having the right information. Data availability was another problem that could be addressed in future work. Having a resource that can provide data to support detailed analysis would be useful in this framework.

Future work should construct higher fidelity models for cost, performance, and reliability. This is just a starting point on the methods that could be applied in early conceptual design. Other methods depending on the information readily available could include Bayesian Networks for estimating the impact of reliability with conditional probabilities, simulation modeling for time-based failure analysis of functions, and Monte Carlo simulation with higher fidelity parametric models that impact the functional analysis method.

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9. Appendix I

This appendix I includes the parametric model calculations that were not embedded within the body of the work. Parametric models for value and cost are included within the body of the work. Below are parametric equations that impact performance and lead to the value measures. Some of the parametric models are static (input value), and others are based on the outcome of another model. Calculations include system horsepower, power source weight, suspension weight, mobility platform weight, powerpack/drivetrain, hull weight, miles per gallon (MPG), UGV mission range, and UGV endurance, and probability of detection.

1. System HP = $(Fixed\ HP) * (Power\ Source\ Quantity)$
2. Power Source Weight = $(Power\ Source\ Weight) * (Power\ Source\ Quantity)$
3. Suspension Weight = $0.14 * BaseWeight$
4. Mobility Platform Weight=$(\text{Mobility Platform Weight}) * (\text{Mobility Platform Quantity})$
5. PowerPack/DriveTrain Weight = $9.86 * System\ HP$
6. Hull Weight = $0.5 * PowerPack\ Weight$
7. MPG Calculation = $-0.15 * System\ HP + 58$
8. Mission Range Calculation = $MPG * 30$
9. Endurance calculation = $\left(\frac{Total\ Vehicle Weight}{1000}\right) * 2.5$
10. Probability of Detection = $1 - (1 - SingleSensorDetectionProb)^{SensorRedundancy}$

10. Appendix II

Appendix II is an overview of the integrated framework within excel. The framework starts with identifying key functions of the system of interest, indicating the quantity needed of that function to support proper operations of the system, and the potential reliability performance of the system indicated by the TRL range. From there attributes are filled in for the given function that serves as inputs to the cost model, performance model, and value model.

Control UGV	Reliability	Index	TRL 5	TRL 6	TRL 7-9	Quantity Needed	Cost Per
CPU	0.9	1	0.9	0.95	0.99	1	$ 2,000.00
	$ 1,800		$ 1,800	$ 2,000	$ 2,200		
Process Signal	**Reliability**	**Index**	**TRL 5**	**TRL 6**	**TRL 7-9**	**Quantity Needed**	**Cost Per**
CPU	0.9	1	0.9	0.95	0.99	1	$ 2,000.00
	$ 1,800		$ 1,800	$ 2,000	$ 2,200		
Transmit/Process Information from External	**Reliability**	**Index**	**TRL 5**	**TRL 6**	**TRL 7-9**	**Quantity Needed**	**Cost Per**
GPS+Comms	0.9	1	0.9	0.95	0.99	2	$ 1,000.00
	$ 900		$ 900	$ 1,000	$ 1,100		
Record Geographical Location	**Reliability**	**Index**	**TRL 5**	**TRL 6**	**TRL 7-9**	**Quantity Needed**	**Cost Per**
Proximity Sensor	0.9	1	0.9	0.95	0.99	2	$ 2,000.00
	$ 1,800		$ 1,800	$ 2,000	$ 2,200		
Record Environmental Data	**Reliability**	**Index**	**TRL 5**	**TRL 6**	**TRL 7-9**	**Quantity Needed**	**Cost Per**
Camera	0.70	1	0.70	0.90	0.99	2	$ 200.00
	$ 180		$ 180	$ 200	$ 220		
Record Environmental Data	**Reliability**	**Index**	**TRL 5**	**TRL 6**	**TRL 7-9**	**Quantity Needed**	**Cost Per**
LiDAR	0.80	1	0.80	0.90	0.99	2	$ 500.00
	$ 450		$ 450	$ 500	$ 550		
Record Environmental Data	**Reliability**	**Index**	**TRL 5**	**TRL 6**	**TRL 7-9**	**Quantity Needed**	**Cost Per**
Sound Sensor	0.80	1	0.80	0.90	0.99	3	$ 500.00

Figure 16. Function Data Input (TRL, Cost, Resource Requirements)

			Index						
Provide Eletrical Energy for Mech. Sys	Reliability	Index	TRL 5	TRL 6	TRL 7-9	Quantity Needed	Cost Per		
Alternator	0.8	1	0.8	0.9	0.95	2	$ 200.00		
	$ 180		$ 180	$ 200	$ 220				
Store Electrical	Reliability	Index	TRL 5	TRL 6	TRL 7-9	Quantity Needed	Cost Per		
Batteries	0.7	1	0.7	0.85	0.99	2	$ 3,500.00		
	$ 3,150		$ 3,150	$ 3,500	$ 3,850				
Distribute Energy	Reliability	Index	TRL 5	TRL 6	TRL 7-9	Quantity Needed	Cost Per		
Power Control Board	0.85	1	0.85	0.9	0.99	4	$ 400.00		
	$ 360		$ 360	$ 400	$ 440				
Provide Mechanical Power	Reliability	Index	TRL 5	TRL 6	TRL 7-9	Quantity Needed	Cost Per	Weight	HP
Power Source	0.80	1	0.80	0.90	0.95	1	$ 4,500.00	550	350
	$ 4,050		$ 4,050	$ 4,500	$ 4,950				
	315		315	350	385				
	605		605	550	495				
Provide Power to Mobility Platform	Reliability	Index	TRL 5	TRL 6	TRL 7-9	Quantity Needed	Cost Per		
Transmission	0.8	1	0.8	0.9	0.95	1	$ 3,500.00		
	$ 3,150		$ 3,150	$ 3,500	$ 3,850				
						Cost Analysis Inputs		Weight Input and Performance	
Provide Propulsion	Reliability	Index	TRL 5	TRL 6	TRL 7-9	Quantity Needed	Cost Per	Needed Quantity	Weight
Mobility Platform	0.75	1	0.75	0.85	0.95	1	$ 3,200.00	1	600
	$ 2,880		$ 2,880	$ 3,200	$ 3,520				
	660		660	600	540				

Figure 17. Function Data Input (TRL, Cost, Resource Requirements)

	Function Reliability	Reliability Based on Dependencies	
Function 1.0	0.96	0.96	
		Reliability Function 1.0	
Function 2.0	0.91	0.87	
		Reliability Function 1.0	Reliability Function 2.0
Function 3.0	1.00	0.96	0.91
Function 4.0		Reliability Function 3.0	
	0.80	0.80	
Function 5.0		Reliability Function 4.0	
	0.80	0.80	
Function 6.0		Reliability Function 5.0	Reliability Function 7.0
	0.75	0.60	0.68
Function 7.0		Reliability Function 8.0 AND (10.0,11.0,12.0,13.0)	
	0.90	0.81	
Function 8.0		Reliability Function (9.0,10.0,11.0,12.0,13.0)	
	0.90	0.90	
Function 9.0		Reliability Function 8.0	
	0.99	0.89	
Function 10.0		Reliability Function 8.0	
	0.99	0.89	
Function 11.0		Reliability Function 8.0	
	0.91	0.82	
Function 12.0		Reliability Function 8.0	
	0.96	0.86	
Function 13.0		Reliability Function 8.0	
	0.99	0.89	

Figure 18. Reliability Calculation Values

Function Identifier	Function	Subsystem
1.0	Provide Eletrical Energy for Mech. Sys	Alternator
2.0	Store Electrical	Batteries
3.0	Distribute Energy	Power Control Board
4.0	Provide Mechanical Power	Power Source
5.0	Provide Power to Mobility Platform	Transmission
6.0	Provide Propulsion	Mobility Platform
7.0	Control UGV	CPU
8.0	Process Signal	CPU
9.0	Transmit/Process Information from External	GPS+Comms
10.0	Record Geographical Location	Proximity Sensor
11.0	Record Environmental Data	Camera
12.0	Record Environmental Data	LiDAR
13.0	Record Environmental Data	Sound Sensor

Figure 19. Function Definition

Sensors/Cameras				
9				
Multi-Sensor Detection	0.51			
Probability Detection w/ redundant systems	0.76			
			Quantity	Reliability
10.0	Record Geographical Location	Proximity Sensor	2	0.89
11.0	Record Environmental Data	Camera	2	0.82
12.0	Record Environmental Data	LiDAR	2	0.86
13.0	Record Environmental Data	Sound Sensor	3	0.89

Figure 20. Multi-Sensor Detection Probability

Horsepower (hp)
315
Miles Per Gallon(Energy)
105.3
UGV Mission Range
1614
Endurance
14

Figure 21. Horsepower, MPG, Mission Range, Endurance

Target Weight	Horsepower (hp)	Power Source Weight (lb)	Suspension Weight	Mobility Platform Base Weight	PP/DriveTrain Weight	AuxAuto Weight (lb)	ArmorKit_ArmorWeight	Fuel_POL_Weight	Hull Weight	Total Weight
4500	315	605	630	660	3106	400	200	100	1553	5701

Figure 22. UGV Weight

Life Cycle Cost	
$	-

Acquisiton Cost	$ 190,350
Operational Cost	$ 15,263,582
Failure Cost	$ 296,422
Support Cost	$0

Fixed Cost of Operating	$ 200,000.00
Effective Discount Rate	0.08
Design Life (Years)	20
Annual Operating Cost Per Unit	175000

Effective Discount Rate	0.08
Design Life (Years)	20
Cost Per Failure (anticipated)	$ 5,000
Operating Hr, Per Year, Per Unit	180
Mean Time to Failure (Anticipated) hrs	268

Fixed Support Cost	100000
Effective Discount Rate	0.08
Design Life (Years)	20
Annual Support Cost Per Unit	50000
Unit Salvage Value	0

System MTTR (Weighted Avg)	7	
System Availability	0.975	Inherent Availability Based on Failure distribution and repair time distribution

Figure 23. Life Cycle Cost Framework Part 1

Step 1: Calculate Unit Acquisition Cost - Per Function (Subsystem/Components)												
1.0	2.0	3.0	4.0	5.0	6.0	7.0	8.0	9.0	10.0	11.0	12.0	13.0
$ 180	$ 3,150	$ 360	$ 4,050	$ 3,150	$ 2,880	$ 1,800	$ 1,800	$ 900	$ 1,800	$ 180	$ 450	$ 450

Step 2: Calculate Lot Acquisition Cost	
Total Cost Per Unit	$ 21,150
Total Acquisition Costs	$ 190,350

Step 3: Calculate Operations Costs	
Present Worth at the end of Design Life Per Unit	($1,718,175.80)
Number of Units	9
Operations Cost	$15,263,582

Step 4: Calculate Failure Costs	
Present Worth at the end of Design Life Per Unit	($49,090.74)
Expected # of Failures Per Year	0.67
Number of Units	9
Failure Cost	$ 296,422

Step 5: Calculate Support Costs	
Present Worth at the end of Design Life Per Unit	($490,907.37)
Future Worth at the end of Design Life Per Unit	$0.00
Number of Units	9
Support Cost	$4,518,166

Figure 24. Life Cycle Cost Framework Part 2

Swing Weight Matrix

	Mission Critical			Important		
		fi	wi		fi	wi
Significant impact				Endurance (Hrs)	50	0.27
	Probability of Detection	100	0.54			
Some impact	UGV Mission Range	25	0.14			
				UGV Weight (lbs.)	10	0.05

sum of fi	185

f_i = swing weight

w_i = normalized swing weight

Figure 25. Value Model Swing Weight Matrix

Function	Transport UGV		Survive in war environment		Detect Enemy Activity		Detect Enemy Activity	
Objectives	Minimize UGV Transport Weight		Maximize Survivability in Operational Environmnet		Maximize Probability of Detection of Enemy Activity		Maximize Endurance	
Value Measures	UGV weight (lbs.)		UGV Mission Range (miles)		Probability of Detection		Endurance (hrs)	
	x	v(x)	x	v(x)	x	v(x)	x	v(x)
	5000	100	25	0	0.6	0	2	0
	5500	75	50	25	0.7	30	4	25
	6000	50	75	50	0.8	70	6	50
	6500	25	100	75	0.9	90	8	75
	7000	0	125	100	1	100	10	100

Graph of Value Curve

Scores

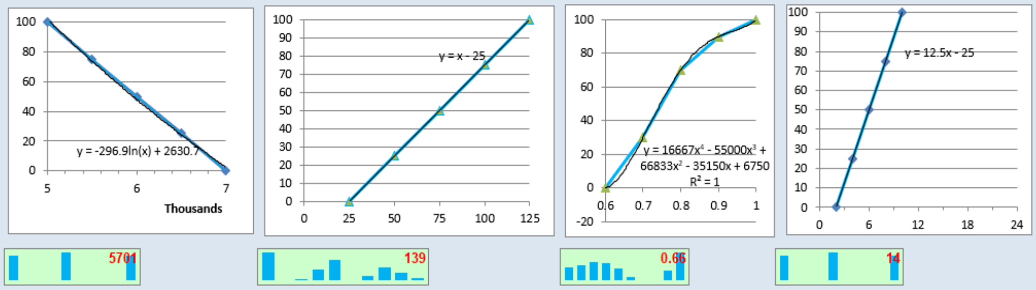

Figure 26. Value Curves

Function 1			
Triangular Distribution	TRL 5	TRL 6	TRL 7-9
Minimum Value	0.65	0.9	0.92
Most Likely Value	0.75	0.95	0.96
Maximum Value	0.8	0.97	0.98
Random Cell			

Function 2			
Triangular Distribution	TRL 5	TRL 6	TRL 7-9
Minimum Value	0.65	0.75	0.92
Most Likely Value	0.75	0.85	0.96
Maximum Value	0.8	0.9	0.98
Random Cell			

Function 3			
Triangular Distribution	TRL 5	TRL 6	TRL 7-9
Minimum Value	0.65	0.75	0.92
Most Likely Value	0.75	0.85	0.96
Maximum Value	0.8	0.9	0.98
Random Cell			

Function 4			
Triangular Distribution	TRL 5	TRL 6	TRL 7-9
Minimum Value	0.65	0.75	0.92
Most Likely Value	0.75	0.85	0.96
Maximum Value	0.8	0.9	0.98
Random Cell			

Function 5			
Triangular Distribution	TRL 5	TRL 6	TRL 7-9
Minimum Value	0.65	0.75	0.92
Most Likely Value	0.75	0.8	0.96
Maximum Value	0.8	0.9	0.98
Random Cell			

Function 6			
Triangular Distribution	TRL 5	TRL 6	TRL 7-9
Minimum Value	0.75	0.75	0.92
Most Likely Value	0.8	0.85	0.96
Maximum Value	0.9	0.9	0.98
Random Cell			

Function 7			
Triangular Distribution	TRL 5	TRL 6	TRL 7-9
Minimum Value	0.85	0.9	0.95
Most Likely Value	0.9	0.95	0.97
Maximum Value	0.95	0.97	0.99
Random Cell			

Function 8			
Triangular Distributior	TRL 5	TRL 6	TRL 7-9
Minimum Value	0.85	0.9	0.95
Most Likely Value	0.9	0.95	0.97
Maximum Value	0.95	0.97	0.99
Random Cell			

Function 9			
Triangular Distributior	TRL 5	TRL 6	TRL 7-9
Minimum Value	0.85	0.9	0.95
Most Likely Value	0.9	0.95	0.97
Maximum Value	0.95	0.97	0.99
Random Cell			

Function 10			
Triangular Distributior	TRL 5	TRL 6	TRL 7-9
Minimum Value	0.85	0.9	0.95
Most Likely Value	0.9	0.95	0.97
Maximum Value	0.95	0.97	0.99
Random Cell			

Function 11			
Triangular Distributior	TRL 5	TRL 6	TRL 7-9
Minimum Value	0.75	0.85	0.95
Most Likely Value	0.8	0.9	0.97
Maximum Value	0.95	0.95	0.99
Random Cell			

Function 12			
Triangular Distributior	TRL 5	TRL 6	TRL 7-9
Minimum Value	0.75	0.85	0.95
Most Likely Value	0.8	0.9	0.97
Maximum Value	0.95	0.95	0.99
Random Cell			

Function 13			
Triangular Distributior	TRL 5	TRL 6	TRL 7-9
Minimum Value	0.75	0.85	0.95
Most Likely Value	0.8	0.9	0.97
Maximum Value	0.95	0.95	0.99
Random Cell			

Figure 27. Triangular Distribution Table - TRL Values