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A Fuzzy Framework for the Air Force Mission Dependency Index

Devin M. DePalmer

A FUZZY FRAMEWORK FOR THE AIR FORCE MISSION DEPENDENCY INDEX

THESIS

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Abstract

The Air Force Installation Mission Support Center (AFIMSC) completed a Mission Dependency Index (MDI) modernization in 2019 to support better risk-based decision-making by utilizing tactical mission-owner knowledge to quantify the relationship between facilities and the missions they enable. The resulting facility-mission risk scores leave room for improvement for better use of their intended purposes, due to (1) the vulnerability of cognitive biases affecting survey responses due to the use of a traditional risk matrix, (2) the lack of resolution between scores from risk ties, and (3) the failure to include information from the operational and strategic organizational hierarchy level. This research addresses these concerns through the novel implementation of a fuzzy logic system that uses the existing assessment Interruptability and Replicability criteria. Fuzzy logic uses expert knowledge and logical rules, where insufficient or imprecise data is present, to produce meaningful results that are more precise and reliable than traditional risk matrices. The Air Force, and other similarly motivated organizations, can use the proposed framework to quantify a facility's MDI, prioritize projects, and authorize limited facility sustainment, maintenance, and restoration resources.

Acknowledgments

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I look forward to serving with you in the future, hopefully in-person.

Devin M. DePalmer

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I. Introduction

Background

Innovation in data collection and analysis techniques have improved facility managers' opportunities to understand facility life-cycle costs and make data-driven decisions, which are arguably more efficient than those based on decision-maker preferences. Facility managers can use this data to optimize sustainment resources and extend facilities or real property asset longevity. Executive Order 13327 mandated using identified best practices of asset management for all Federal real property to increase efficiencies and improve economic return (White House 2004).

When developing operational risk management strategies, the Navy identified the need for an objective process to compare and prioritize construction projects to mitigate consequences associated with facility failure. This process needed to ensure that leadership prioritized resources for facilities that support the Navy's most critical mission sets. The Navy researched the link between facilities and the missions they enable to develop the Mission Dependency Index (MDI) metric, which is used for decision support when prioritizing sustainment, restoration, and maintenance projects (Antelman et al. 2008). MDI was a novel concept within the Department of Defense. It was calculated through facility manager surveys using traditional risk matrices and quantifying the facility's Intra-Dependency, Inter-Dependency, and the number of subcomponents who depend on the facility for mission-critical support.

The MDI methodology was validated and deployed for naval facilities. Grussing et al. (2010) estimated that establishing a base's MDI values would cost between $40,000 and $75,000 and lead to an annual data maintenance cost between $2.5M and $6.9M for the Air Force (Grussing et al. 2010; Nichols 2015). To avoid the initial and recurring costs associated with the Navy's model, the Air Force modified the Navy's process to assign MDI based on asset type category codes (CATCODE). This low-cost solution required less data collection and led the Air Force to develop a simple, CATCODE-to-MDI model (Nichols 2015). The CATCODE is a six-digit identifier classifying the facility type for the Federal government's Real Property Categorization System (ASD 2020). Facility owners identified issues with the Air Force's CATCODE-to-MDI methodology when mission-critical facilities had inaccurate scores because of their facility type, rather than the importance to the mission they supported. When used to make decisions about operational risk management strategies, these score mismatches lead to sub-optimal results. Inaccuracies disproportionately affected some Air Force Major Command's (MAJCOM), like Air Force Global Strike Command (AFGSC) and Air Education and Training Command (AETC), because of AFGSC's unique mission focus on nuclear deterrence and AETC's reliance on traditionally less critical facilities such as classrooms, auditoriums and administrative offices (Blaess 2017). These score mismatches occurred most frequently when the primary or active duty mission of an installation was not aviation-focused (Smith 2016). These instances were widespread and resulted in critical projects remaining unfunded and led to wasted resources for sub-optimal assets (Blaess 2017).

To combat MDI score inaccuracy and disproportionality, the Air Force Civil Engineer Center (AFCEC) provided guidance for installations to adjudicate facility MDI scores (AFCEC 2015).

The adjudication process was complicated and required Air Force Civil Engineers at the base level to justify all identified discrepancies and manage approval coordination between six levels of authority. The additional human resources and management investments needed to assign a facility's MDI score accurately highlighted a significant inefficiency with AFCEC's process and further strained under-resourced base-level engineers (Smith 2016). Initially, AFCEC implemented a re-normalization of adjudicated MDI scores to keep the desired 100-point range for MDI. Eventually, the re-normalization process was abandoned and led to the MDI distribution shifting, becoming left-skewed due to bases only adjudicating facility MDI when scores were too low (Nichols 2015; Savatgy et al. 2019). Higher MDI scores were incentivized because a facility's MDI contributed to the final technical project score used to compete for funding against other sustainment, restoration, and maintenance facility projects. Because of these motivations, Air Force's MDI values became inflated, and the range of possible scores decreased by one-third, reducing the metric's decision-making value (Nichols 2015).

Researchers have conducted graduate-level research previously about the MDI. Nichols (2015) investigated the history of the MDI and performed a Delphi Study with CE Senior Leaders to determine how AFCEC can create a useable MDI metric that is not vulnerable to score inflation over time. Next, Smith (2016) integrated MDI and machine learning with a Knowledge Discovery in Database process to minimize the manual MDI adjudication efforts and better quantify the relationship between facilities and the mission they support. Additionally, Blaess (2017) investigated deviations between portfolios that used the CATCODE, NAVFAC, and adjudicated MDI scores. Each study identified opportunities for the MDI to be more accurately quantified. The researchers also identified issues with the existing adjudication process and the need to review scores to detect and prevent inflation periodically.

AFIMSC has recently modernized the Air Force's MDI metric to ensure installations can accurately assign a facility's MDI with information about the mission it enables and the facility's consequences of failure. This methodology represents a departure from the CATCODE-based methods and uses operational risk management concepts within a traditional risk matrix (Figure 1). Like the Navy's MDI, the Air Force uses survey responses from mission owners to identify a facility's Interruptability and Replicability to assign the MDI value. Interruptability gauges how quickly a facility failure would impact the installation's mission. Replicability determines how difficult it would be to relocate, replicate, or reconstitute the facility's mission-enabling functionality (Savatgy et al. 2019). Unlike the Navy, the Air Force's MDI does not consider the number of other missions dependent on the facility from within the installation level or across different functional levels of the Air Force mission sets. Additionally, the traditional risk matrix used does not incorporate operational or strategic level leadership opinions for a facility failure's consequence to the mission or capture uncertainties between the risk matrix categories. Furthermore, although a traditional risk matrix is easy to use and simple to produce, it is criticized for its mathematical analysis errors and sub-optimal results, along with their vulnerability to cognitive biases and subjective judgment (Cox 2008; Duijm 2015; International Electrotechnical Commission 2019; Li et al. 2018; Smith et al. 2009).

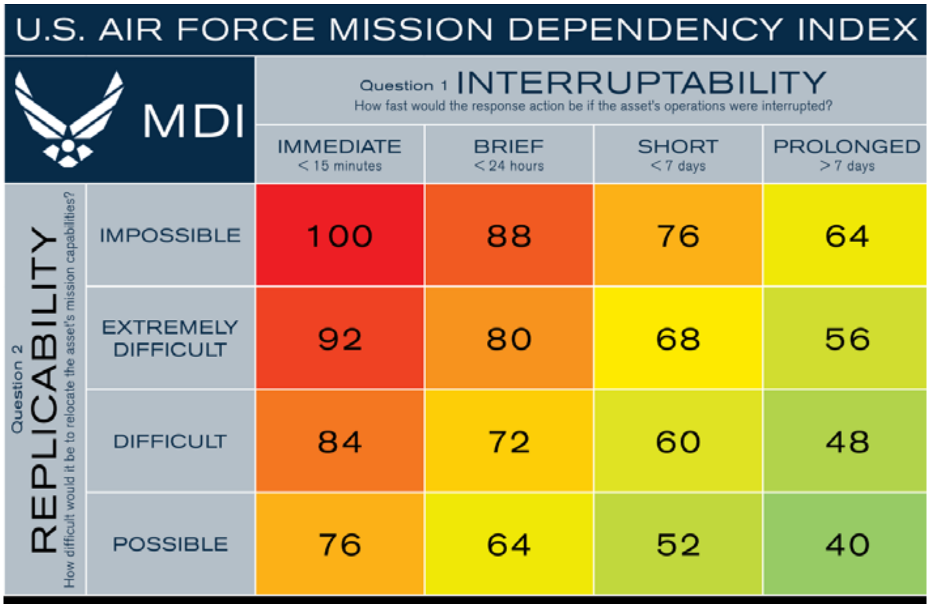


Figure 1. The tactical MDI risk matrix created by AFIMSC uses mission-owner responses of the facility's Interruptability and Replicability to determine the MDI score (Savatgy et al. 2019).

Because AFIMSC completed the MDI re-baselining with a 4 × 4 categorical risk matrix, many instances of score ties were produced (Figure 2). This result, which is a function of the limited discrete outcomes from the matrix, does not enable leadership to analyze risks in rank order, as facilities could only have 14 possible raw MDI scores. Over 45% of facilities had a "Prolonged" Interruptability and "Possible" Replicability, which resulted in a raw score of MDI equal to 40. In these instances, the MDI business rules triggered a re-ranking scheme based on two-digit facility type codes. Base Civil Engineer Squadrons would determine a priority order of the facility codes, which were then used by AFIMSC to assign these facilities scores below 40. This practice fails to remedy the previously identified issues with a CATCODE-based MDI scoring process and reduces the metric's decision-making value (Nichols 2015).

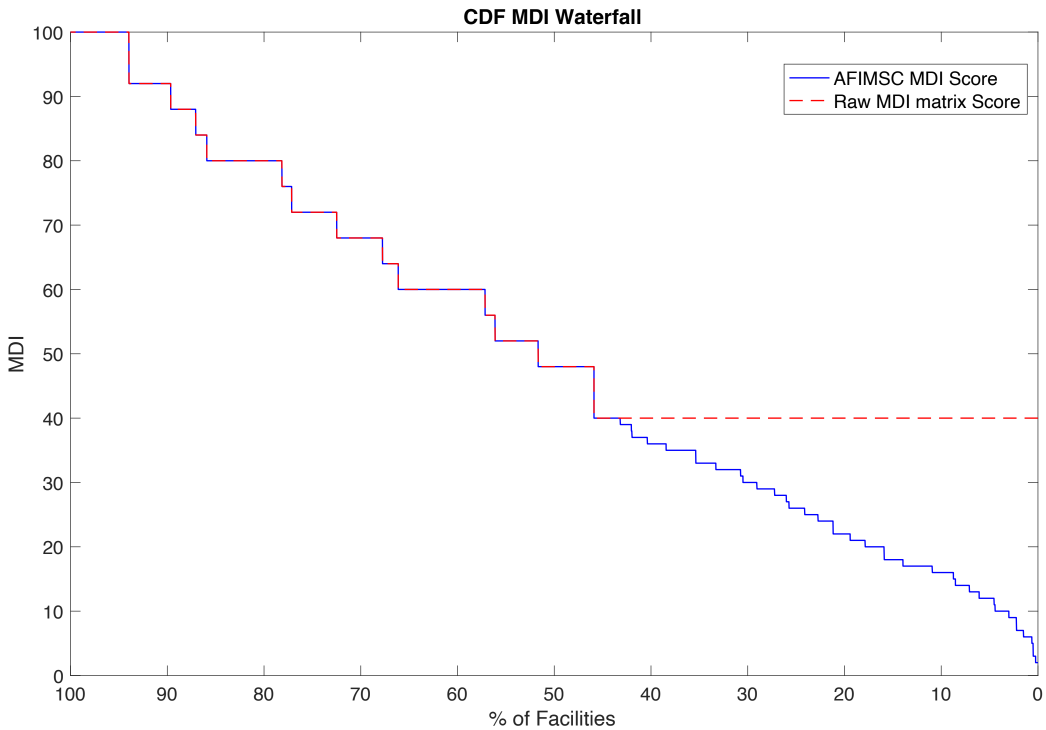


Figure 2. The cumulative density of AFIMSC's MDI survey results with the raw matrix score and the re-scored "Prolonged" and "Possible" classified facilities. This approach produces the inconsistent "step" in the density function.

Problem Statement

The Air Force wants a simple, repeatable process to quantify the relationship between facilities and the missions they enable. Though the second version of MDI is an upgrade over historical versions, this new methodology leaves room for improvements. Currently, the MDI methodology does not provide enough resolution to create meaningful prioritizations, is susceptible to cognitive biases and human decision-making differences, and re-introduces the potential for score mismatches and the adjudication issues identified using CATCODE-based MDIs. The system must be improved to include information from all management hierarchy levels and consider human decision-making differences to reduce bias. The system also needs to be easily adaptable to meet the Air Force's changing needs without additional complexities. These upgrades will result in a more accurate MDI methodology that the Air Force and similarly motivated organizations can use to make better risk-based decisions, prioritize limited resources, and avoid wasted efforts.

Research Objectives

This research demonstrates Fuzzy Logic's use to link the relationship between Air Force facilities and the missions they enable. This MDI metric can prioritize diverse project portfolios and help base leadership understand its' overall risk profile. To facilitate this objective, the author developed three investigative questions to guide the research:

1. Is fuzzy logic an appropriate methodology for calculating MDI?
2. What is an appropriate framework for a Fuzzy Inference System (FIS) that could enable mission risk assessments?
3. How can fuzzy logic be used to expand MDI to enable participation by stakeholders from all organizational hierarchy levels, e.g., operational and strategic level?

Methodology Overview

This research primarily focuses on using fuzzy logic as a methodology to determine MDI. It expands the system boundaries to include information from the operational and strategic levels of the Air Force. The use of value judgment and linguistics to categorize the likelihood and severity of events during a risk assessment introduces uncertainty due to fuzziness. Translating this uncertainty into fuzzy sets can allow users to solve problems where sharp boundaries may not exist (Zadeh 1965). Fuzzy logic is essentially an expert knowledge-driven methodology comparable to computing with words (Zadeh 1999). Human linguistics and analytical knowledge can conclude without the use of mathematical numbers. For example, if you say:

IF Justin lives *near* Steven.

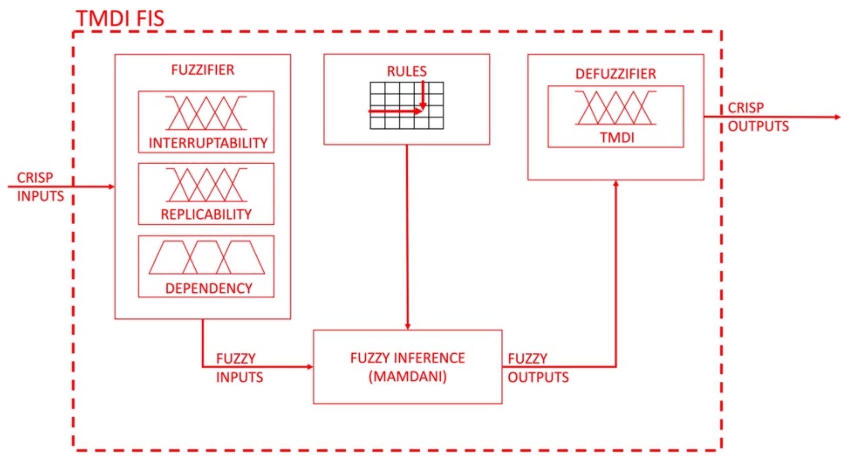
AND Steven lives *near* Chris.

You can answer the following question imprecisely: *How far is Justin from Chris?*

THEN, Chris lives *not far* from Justin.

When tolerance for imprecision can be exploited to achieve a result, computing with words can provide a low cost, realistic result that is easy to understand and provides a satisfactory conclusion (Zadeh 1999). Fuzzy logic and its beneficial substitution for traditional risk matrices have been researched for military operational planning in the past and adequately address common problems caused by knowledge uncertainties and linguistic inputs (Nelson 2019). Readers can learn more about the fuzzy logic in the literature review seen in Chapter 2.

The framework proposed in this research follows the basic setup seen in Figure 3. Each fuzzy system uses crisp inputs for a facility and fuzzifies them to a degree of truth within the system. This fuzzy input is translated to a fuzzy output by set rules determined with expert knowledge. This fuzzy output is then defuzzified with a determined inference methodology of defuzzification to produce a crisp output used for decision support as described in Chapter 2.



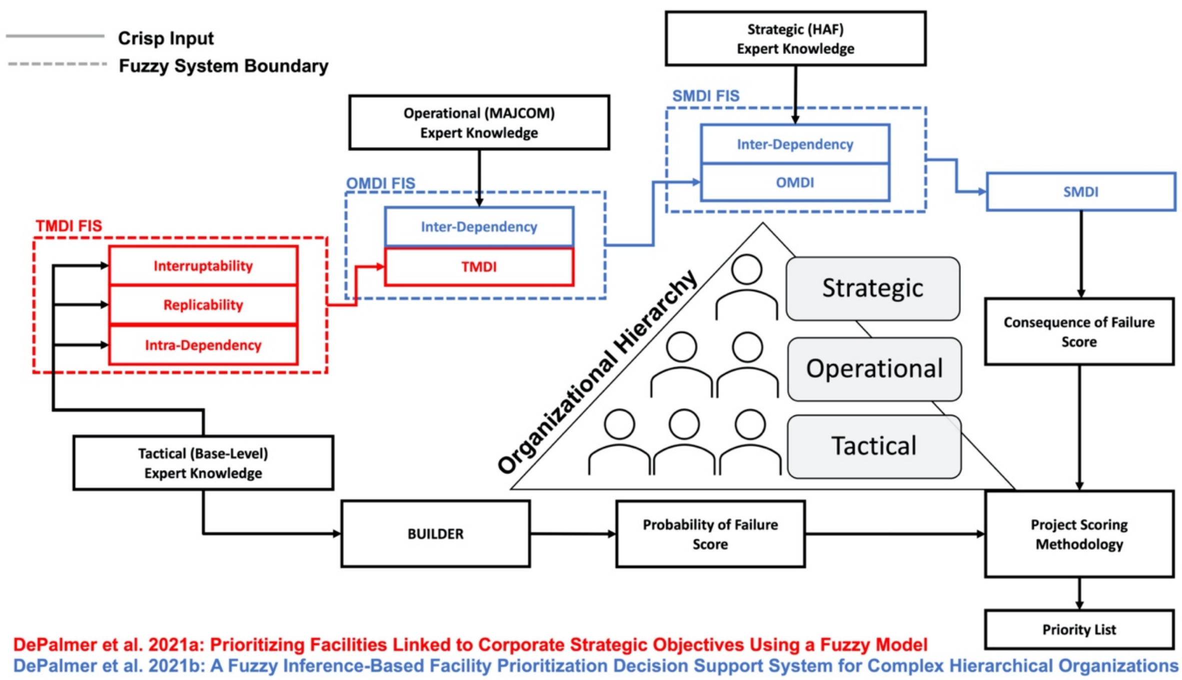


Figure 3. The basic fuzzy inference system (Figure 3a, top) and its role within the MDI framework proposed (Figure 3b, bottom). Chapter 2's focus is the red text, and Chapter 3 is the blue text sections of the framework.

AFIMSC is the sponsor for this research and owns the new tactical MDI methodology and re-baselining data. The authors used the tactical MDI re-baselining data from 13 January 2020 to simulate crisp input responses for the variables Interruptability and Replicability. These survey response distributions allow the simulated results to remain realistic but unspecific to protect any base or location's identities.

Thesis Organization

The remainder of this thesis follows the scholarly format. Chapters 2 and 3 serve as a stand-alone journal publication. Chapter 2, "Prioritizing Facilities Linked to Corporate Strategic Objectives Using a Fuzzy Logic Model," is a journal article submitted in January 2021 for publication in Emerald Publishing's *Journal of Facilities Management.* This publication builds the fuzzy inference system's foundation and integrates the existing AFIMSC tactical MDI matrix with fuzzy logic. These FIS results were used to create an ordinal list of projects to compete for project authorization and sustainment, maintenance, and restoration funding. A second journal article is prepared for submission in Chapter 3, "A Fuzzy Inference-Based Facility Prioritization Decision Support System for Complex Hierarchical Organizations," expands upon Chapter 2's foundation to include operational and strategic level inputs to the FIS. This manuscript also includes a sensitivity analysis to understand how risk attitude and cognitive biases in human decision-making for subjective inputs can affect the system's overall results. Prediction bounds were used to estimate expected outcomes and identify locations with extreme results. Sites with extreme results can be re-evaluated to validate scores and to mitigate inflation of the MDI metric. The literature review is dispersed between Chapters 2 and 3. Chapter 2 focuses on reviewing fuzzy logic applications with risk assessment and prioritization methodologies to determine if it is appropriate to integrate with the MDI. Chapter 3 focuses its literature review on human decision-making and fuzzy logic's application to hierarchical organizations. Finally, Chapter 4 summarizes the research's limitations, conclusion, significance, and contributions, as well as recommended future research areas.

II. Prioritizing Facilities Linked to Corporate Strategic Objectives Using a Fuzzy Logic Model

Devin DePalmer, Steven Schuldt, Justin Delorit

Abstract

A Mamdani fuzzy logic inference system is coupled with a traditional, categorical risk assessment framework to understand a facilities' consequence of failure and its effect on an organization's strategic objectives. Model performance is evaluated using the United States Air Force's facility portfolio, which has been previously assessed, treating facility Replicability and Interruptability as minimization objectives. The fuzzy logic inference system is built to account for these objectives, but as proof of ease-of-adaptation, facility Dependency is added as an additional risk assessment criterion. Limited facilities operating and modernization budgets require organizations to carefully identify, prioritize, and authorize projects to ensure allocated resources align with strategic objectives. Traditional facility prioritization methods using risk matrices can be improved to increase granularity in categorization and avoid mathematical error or human cognitive biases. These limitations restrict the utility of prioritizations, and if erroneously used to select projects for funding, they can lead to wasted resources. This paper proposes a novel facility prioritization methodology that corrects these assessment design and implementation issues. Results of the fuzzy logic-based approach show a high degree of consistency with the traditional approach, though the value of the information provided by the framework developed here is considerably higher, as it creates a continuous set of facility prioritizations that are unbiased. The fuzzy logic framework is likely suitable for implementation by diverse, spatially distributed organizations in which decision-makers seek to balance risk assessment complexity with output value.

Introduction

Portfolio and project management within facilities management departments are an important and complicated issue in the private and public sectors. Prioritization requires that companies identify, prioritize, and authorize projects that align with organizational objectives (Filho et al. 2018; Hannach et al. 2016). Large, geographically distributed organizations may require projects from subordinate locations or work centers to compete for centralized funding. Limited resources drive organizations to prioritize projects with the understanding that not all candidate projects submitted by subordinate locations will be selected for funding. Companies must, therefore, establish a standardized basis for comparing facilities to determine how each affects corporate objectives. The net effect of developing a prioritization framework has two beneficial outcomes. First, it ensures organizations can fund the right project at the right time and avoid funding a project for a facility when other facilities and projects could be more critical for satisfying strategic objectives. Second, it provides organizations with a translation of objectives to facilities, enabling the development of facility and organizational risk profiles. Each of these outcomes results in enhanced fiscal resource utilization and minimizes organization risk and decision-maker regret. However, a valuable methodology for prioritization should seek meaningful, robust results as simply as possible; decision-makers prefer this approach (Karlsson et al. 2006).

In general, project prioritization methodologies are organization specific. However, they should emanate from a generalized methodological approach to ensure prioritization outputs are valid and can be post-processed to meet decision-maker use requirements. Three main steps exist for methodological prioritization: (1) identification of factors affecting decision making, (2) valuation of identified factors, and (3) ranking of projects (Akgun et al. 2010; Andres et al. 2016; Bowles and Peláez 1995; Bozbura and Beskese 2007; Jamshidi et al. 2013; Markowski and Mannan 2008; Moazami et al. 2011; Shaygan and Testik 2019). Factors for prioritization should be identified that align with the organization's strategic objectives (Hannach et al. 2016), and the risk assessment performed should reflect how the loss of an asset places risk on these objectives.

Facilities are an "enabler" for work processes that support organizational goals or productivity and link the facilities to the organization's objectives (National Research Council 2004). There is a literature gap concerning prioritization methods that link facilities to strategic organizational objectives, particularly within non-profit-seeking organizations. Akgun et al. (2010) conducted a highly stylized and single objective vulnerability assessment for a small municipal airport. Educational campuses, like Massachusetts Institute of Technology (MIT), have used analytical hierarchy process (AHP) and multi-attribute utility theory (MAUT) to prioritize facility renewal projects that align with identified impact categories, e.g., impact on health safety and the environment, economic impacts, and coordination with policies, programs, and operations (Karydas and Gifun 2006). This process allowed MIT's facilities managers to align projects with strategic objectives by understanding the consequence of not funding a project.

Three significant limitations emerge from both the Akgun et al. and Karydas and Gifun analyses: 1) they are applied to a single location, with a limited set of organizational objectives; 2) the methods of risk assessment require extensive amounts of data and deliberation to categorize the desired performance metrics, and 3) the methods do not make use of generalized approaches to risk. The DoD and NASA created the Mission Dependency Index (MDI) to link facilities to their organization's objectives (Antelman et al. 2008; Antelman and Miller 2002). This methodology can be applied to diverse locations. It does not require extensive amounts of data or training for decision-makers, and the metric score produced is used to stratify and authorize facility projects. Antelman's research is the only large-scale application of this type of requirement; however, the mathematical transformation of ordinal results to calculate the MDI score leaves room for improvement to reduce errors, bias, and uncertainty (Kujawski and Miller 2009). This paper's research intends to integrate the Air Force's MDI methodology with fuzzy logic so that facilities can be linked to strategic objectives, and facility projects can be funded in an order that best supports the organization.

Facility Risk Management

Risk assessments require decision-makers to think strategically and to problem solve when comparing alternatives (Hertz and Thomas, 1982). Hertz and Thomas (1982) conclude risk assessments are "useful for understanding, formulating and resolving ill-structured, complex policy and planning problems." Private companies typically focus their risk assessments on identifying projects that maximize revenues using cost-benefit analysis (Hannach et al. 2016; National Research Council 2004). Although profits and losses may be a common metric of consequence for some private-sector organizations, organizational objectives cannot be measured monetarily for many public and private entities, e.g., education, healthcare, corporate, or government agencies (National Research Council 2004). Instead, these types of corporations often measure their utility through risk mitigation. Faber and Stewart (2003) defined risk as "the expected consequences associated with a given activity." Risk cannot be measured in nature and instead is *a priori*, and calculated by formulas of probability and consequence, most simply as the product of the two.

One way to establish a standard comparison for risk mitigation-oriented organizations is to measure facility failure by estimating the organization's consequence from reduced productivity. Estimating the consequence of failure is made difficult by the complex nature of comparing direct losses (building damage, production loss), indirect losses (inconvenience to users, unemployment, social perceptions, cascading failures), and non-monetary losses such as loss of life, injury to employees, environmental damage, or community disruption (Faber and Stewart 2003; Karydas and Gifun 2006; National Research Council 2004). Identifying and quantifying these losses can help portfolio managers mitigate the risks associated with facility failure.

Markowski and Mannan (2008) suggest that there are qualitative, quantitative, and semi-quantitative approaches to constructing risk assessment methodologies. Organizations must select the approach that provides the level of risk detail desired for decision making. Qualitative methods use only categorical values, such as low, medium, and high, to assign risk likelihood or severity levels. Qualitative methods are preferred for their simplicity and can be used when quantitative data is unavailable or inadequate, or under budget or time constraints (Radu 2009). Unfortunately, qualitative assessments frequently do not provide numerically robust outputs that enable advanced decision making, do not capture uncertainty at the edges of each category, and only produce relative measures of risk. Quantitative categorization gives numerical intervals to well-defined categories, such as "likely to interrupt operations," which might correspond to an interval of unfavorable events with a probability of [0.25, 0.4]. Similarly, a category of severity indicating "very high risk to operations" could result in economic losses between $4 and $5 million. These objective categories can be used to repeatably calculate precise risk assessments, but can be time or budget consuming due to the requirement for accurate and available data, and require that organizations can quantify risk categories (Radu 2009). Semi-quantitative methods use categorical values, which may either added or multiplied to create a risk score. The categorical value on the matrix will indicate more severity or risk probability by assigning higher values, which increases the output risk score (Markowski and Mannan 2008). Semi-quantitative assessments have many of the same advantages as qualitative risk assessments in terms of ease of implementation, though these methods have the added bonus of creating an ordinal list of results that can be used for better prioritization (Radu 2009). Semi-quantitative results are not preferred when prioritization must occur through objective measures, like cost-benefit-analysis, but are less time and data-intensive than quantitative methods. In general, semi-quantitative approaches represent an attractive blend of qualitative and quantitative assessments and may be preferred by organizations seeking to minimize time spent thinking about facilities while still achieving a robust prioritization that will ensure limited budgets are applied to the most critical facilities.

Risk matrices commonly use the basic properties of likelihood and severity, or variations such as probability and consequence of an event, to prioritize risks or aid in decision-making about accepting risk (Duijm 2015; International Electrotechnical Commission 2019). Despite their popularity, risk matrices are criticized for their design and mathematical analyses of risk (Cox 2008; Duijm 2015; International Electrotechnical Commission 2019; Li et al. 2018; Nelson 2019; Smith et al. 2009). Because of their relatively simple design, matrices are subject to decision-maker cognitive biases and subjectivity (International Electrotechnical Commission 2019). Hubbard and Evans (2010) reveal bias and subjectivity arise from individual experiences, optimism bias, confirmation bias, variability in understanding verbal descriptions, and subjective assessment, among many nurtured and natural traits. Smith et al. (2009) goes on to document centering bias and prospect theory (Kahneman and Tversky 1979; Tversky and Kahneman 1992) and their effects on risk matrix results. Subjective probability causes individuals to overestimate small probabilities and underestimate large probabilities (Kahneman and Tversky 1979). Personal ownership causes individuals who have more attachment to the asset (i.e., managers or facility owners) to overestimate the severity of consequences (Smith et al. 2009).

Qualitative and semi-quantitative categories, commonly seen in risk matrices, are primarily based on user experience and can result in subjective judgments rather than quantitative standards. Subjective judgment is when different survey participants assign the same situation to different risk categories (International Electrotechnical Commission 2019). Traditional risk matrices are not recommended for complex risk assessments because of the limitations associated with these methodologies (Cox 2008; Duijm 2015; International Electrotechnical Commission 2019; Nelson 2019; Smith et al. 2009). Though matrices may still underly a risk assessment process, they should be designed or hidden to eliminate bias and subjectivity concerns.

Large, multi-location and multi-objective organizations like the Department of Defense (DoD) and NASA have prioritized large project portfolios using traditional risk-based metrics to link facilities to strategic organizational objectives (Amekudzi and McNeil 2008). Each has chosen to implement semi-quantitative traditional risk matrices with discrete categories as a means of simplifying the complexity of consistently evaluating a large number of facilities across multiple operating locations with unique missions (Antelman and Miller 2002; Grussing et al. 2010; Savatgy et al. 2019). Semi-quantitative risk matrices produce ordinal numbers, which the DoD and NASA have arithmetically transformed to understand vulnerable facilities on their campuses and prioritize facility projects at multiple organizational levels (Amekudzi and McNeil 2008; Kujawski and Miller 2009). However, semi-quantitative ordinal outputs cannot be translated using parametric mathematical operations. Therefore, transformed consequence outputs for any subsequent use, e.g., prioritizations, are inaccurate. Furthermore, the discrete categories and verbal linguistics used to prioritize these facilities introduce uncertainty due to fuzziness, leading to missed opportunities and wasted resources.

Fuzzy Logic and Risk Management

Fuzzy logic can be used with semi-quantitative risk assessments to produce discrete ordinal outputs that can be used for prioritization (Akgun et al. 2010; Markowski and Mannan 2008; Moazami et al. 2011). Furthermore, this methodology also removes the confirmation bias associated with using a traditional risk matrix by obscuring the decision makers' view (Duijm 2015; Hubbard and Evans 2010). Fuzzy logic and fuzzy sets may also be utilized when uncertainty due to fuzziness exists, such as between categories in a traditional risk matrix (Duijm 2015; Markowski and Mannan 2008). The advantages of maximizing value for decision-makers while minimizing complexity make fuzzy logic an ideal choice for integration with risk assessments.

Fuzzy logic is one of the only methodologies that enable decision-makers to compute with words (Zadeh 1999). Prioritization and risk assessment methodologies commonly use verbal linguistics to organize or categorize requirements making fuzzy logic a complementary synthesis. Analytical hierarchy process (AHP), a common technique used by decision-makers for analysis of alternatives, has been integrated with fuzzy logic to prioritize human capital measurement indicators (Bozbura and Beskese 2007), pavement rehabilitation and maintenance projects (Moazami et al. 2011), and generalized project prioritization and selection (Shaygan and Testik 2019). Fuzzy logic has been blended with failure mode, effects, and criticality analysis (FMECA) since FMECA typically uses imprecise information and verbal linguistics to assess criticality (Bowles and Peláez 1995). Fuzzy sets have been used to prioritize safety issues by developing a fuzzy risk matrix and were discovered to be more precise and reliable than traditional risk matrices (Markowski and Mannan 2008). Vulnerability assessments have used fuzzy logic to study facility risk against terrorist attacks, which specifically considered interdependencies among facilities for small-scale airports (Akgun et al. 2010). Fuzzy logic has been integrated with existing pipeline risk assessment methodologies to create a more precise and more robust model for controlling risks associated with pipelines (Jamshidi et al. 2013). An advantage of using fuzzy logic inference systems is that the system can be easily manipulated to add additional components without additional complexities to the modeler or decision-makers.

Facilities Risk Management and Fuzzy Logic

Despite the significant contributions of the aforementioned literature, no formalized prioritization method exists that links an organization's strategic objectives to its built assets. Decision-makers need a simple solution that limits data collection and deliberation time while providing actionable outputs without the use of a risk matrix. In this paper, a semi-quantitative risk assessment methodology used by the United States Air force to determine the consequence of failure for facilities, and as a component of capital improvement project prioritization, is adapted with a fuzzy logic inference system to improve the fidelity and granularity of facility prioritization process. The existing risk methodology used by the Air Force, which possesses many of the same risk-matrix design and implementation flaws discussed above, is described in Section 2. A semi-quantitative method is used because of the ordinal nature of events and the desire for a simple, repeatable process that can be applied to large, diverse organizations with hierarchical structures (Antelman and Miller 2002; National Research Council 2004). Fuzzy logic has been widely used in asset and organizational prioritization methodologies (Akgun et al. 2010; Jamshidi et al. 2013; Markowski and Mannan 2008; Moazami et al. 2011), but this is the first application where it has been used for large-scale, diverse organizations with hierarchical structures to link facilities to an organization's strategic objectives. The flexible nature of fuzzy logic systems allows modelers to add components without adding complexity, making it a superior choice for integration with the Air Force's project prioritization method and consequence of failure calculations (Nelson 2019).

Background Data and Methodology: Linking United States Air Force Objectives to Project and Facility Prioritization

Diverse, spatially distributed organizations are plentiful and form the backbone of many industries. The United States Department of Defense (DoD) is one of the world's largest industrial complexes. Like many U.S. government agencies, which possess many of the same risk matrix design and implementation flaws discussed above, the DoD developed the Mission Dependency Index (MDI) as the risk-based metric to link facilities to an organization's strategic objectives (Antelman et al. 2008; Antelman and Miller 2002). While each military service within the DoD uses a different methodology to calculate MDI, each version of MDI is calculated using some combination of Interruptability, Replicability, and Dependency as surrogates for organizational objectives (Antelman and Miller 2002; Nichols 2015). The Air Force Installation Mission Support Center (AFIMSC) focused its MDI on the tactical, or installation, level. AFIMSC implemented the

Tactical Mission Dependency Index (TMDI) to link local facilities or assets to local operational objectives in order to support risk-based decision making and provide leadership a risk profile view of their campus (Weniger 2020). The survey results categorized 54,000 facilities at 79 campus locations across the globe. TMDI was calculated with a traditional risk matrix (Figure 4) and used the following Replicability and Interruptability survey questions to elicit facility-by-facility responses from mission owners:

1) Interruptability: How fast would the campus's mission capabilities be impacted if the functional capabilities in building $x$were interrupted? (Assumes complete unavailability due to long term deferred maintenance).
2) Replicability: How difficult would it be for the campus to relocate or replicate functional capabilities if this facility's operations were interrupted? (Non-fixed equipment could be moved).

CONSEQUENCE OF FAILURE SCORE

Severity / Likelihood		Q1: Interruptability			
		Immediate < 15 Minutes	Brief < 24 Hours	Short < 7 Days	Prolonged 7 Days <
Q2: Replicability	Impossible	100	88	76	64
	Extremely Difficult	92	80	68	56
	Difficult	84	72	60	48
	Possible	76	64	52	40

Figure 4. Traditional TMDI Risk Matrix **(Savatgy et al. 2019)**

Mission owners and facility occupants answered the survey questions to determine the risk of facility loss on strategic objectives (Savatgy et al. 2019). The traditional risk matrix implemented by the Air Force for the TMDI framework is problematic because it only allows for 14 unique outcomes due to risk ties and discrete categories usage. These outcomes and ties can be seen by the large "stairs" or "step" results above TMDI = 40 in a cumulative density plot of the Air Force's facility portfolio (Figure 5). Assets that received a TMDI score less than 40 were automatically reassigned a score less than or equal to 40, based on the significant administrative function housed in the facility. This rescoring process affected nearly 45% of the Air Force's portfolio. It was mostly undertaken to quickly score assets that are unlikely to compete well for funds against those facilities with higher TMDI scores. However, rescoring in this way does not link specific facilities to strategic objectives. Instead, the rescoring linearly distributes scores based on facility type. By increasing the range of categories, portfolio managers and campus leadership can accurately capture campus risk profiles and prioritize projects by the organization's strategic objectives.

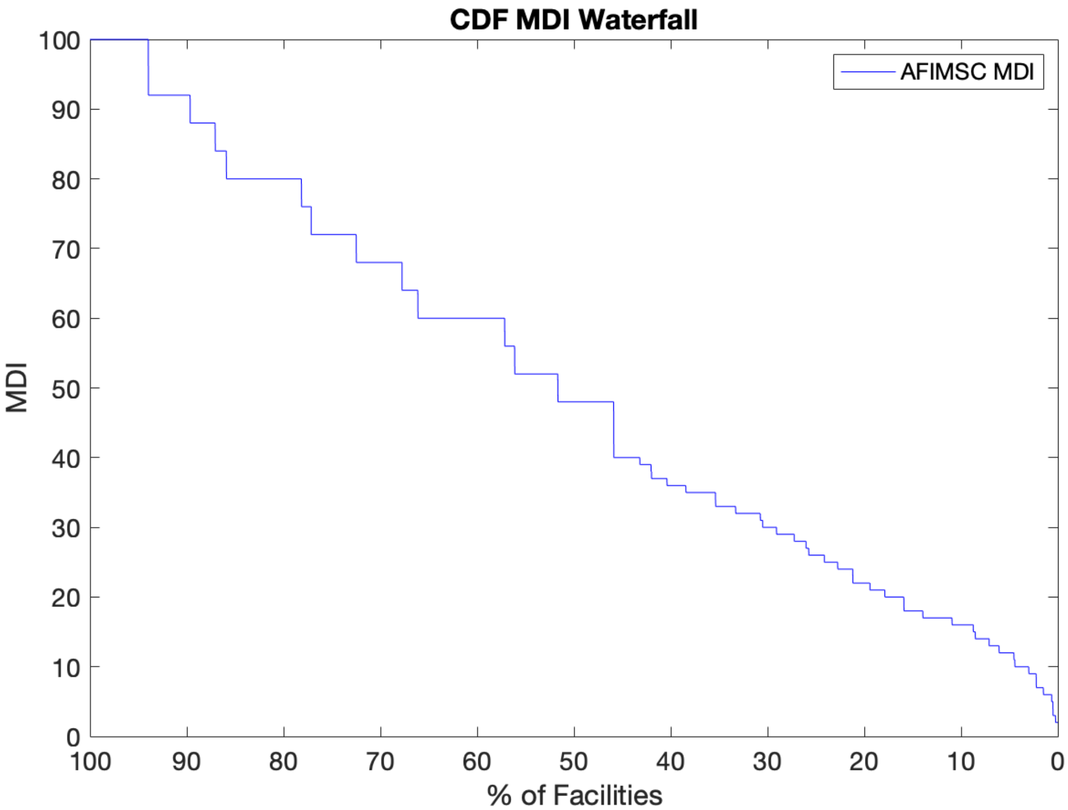


Figure 5. Cumulative density of AFIMSC's TMDI original survey results. Note, facilities with scores greater than 40 retain a matrix-based score. Those facilities receiving a matrix score of 40 are rescored. This approach produces the inconsistent "step" in the density function.

Furthermore, risk ties force prioritizations to be determined by the facility's probability of failure and do not provide campus leadership an accurate representation of their campus's risk profile. Another limitation of the current methodology is that Dependency was not used as a variable to determine consequences. Omitting Dependency is problematic when similar facility types exist at different campuses when multiple facilities with varying usage levels on a single campus are compared, or when a failure in one facility creates failure in others. Dependency should be evaluated to ensure cascading effects are considered when determining the consequence of failure. The coloring of the matrix in Figure 4 makes risk tolerance levels impossible to discern and adds no value to the matrix due to its equivalence with a risk score. The linguistic variables used to categorize facilities invite subjective judgment from all survey participants, and the fuzzy identity between categories is not captured within the matrix.

While TMDI is used primarily in the creation of installation and service-level risk profiles, Air Force civil engineers at each of the Air Force's 89 installations use a unique project scoring methodology to create an annual Integrated Priority List (IPL) of candidate facility improvement projects that compete for funding distributed by the Air Force Civil Engineer Center (AFCEC) (DoD 2017). The IPL is a list of projects prioritized by a technical score, which indicates a level of risk to the organization if the project goes unfunded. A project's technical score is calculated using TMDI. Because the Air Force's methodology to calculate TMDI is laden with substantive deficiencies in design and execution, project funding decisions are likely suboptimal.

The subjective probability introduced by mission owners and facility occupants when answering TMDI questions adds bias to the results from their perceptions or personal ownership (Hubbard and Evans 2010; Kahneman and Tversky 1979; Smith et al. 2009). This bias affects the accuracy and utility of TMDI, which manifests itself in both risk profiles and project outcomes. While literature shows general risk assessment design and implementation issues are pervasive across organizations, the authors suspect these issues extend to facilities prioritization. This study provides a path forward, illustrating an adaptation methodology that integrates a fuzzy logic inference system for bias-reduced facilities prioritization. While the methodology is calibrated to the Air Force, any organization that can define its objectives can benefit from a fuzzy logic-based approach.

Methodology: Fuzzy Logic for Facility Risk Assessment

Zadeh (1965) proposed classes of objects called fuzzy sets with "continuous grades of membership." Natural human linguistics is frequently used to describe fuzzy sets (Zadeh 1965). A fuzzy logic system takes a crisp input value from a decision-maker and fuzzifies it into a fuzzy input set (Figure 6). This facilities prioritization problem translates crisp inputs for Interruptability, Replicability, and Dependency to fuzzy inputs. The fuzzy input sets become a fuzzy output set based on a set of rules, which are discussed below. The fuzzy outputs from the inference system are defuzzified through weightings and averages of the outputs from all the rules, and a deterministic, crisp output is calculated.

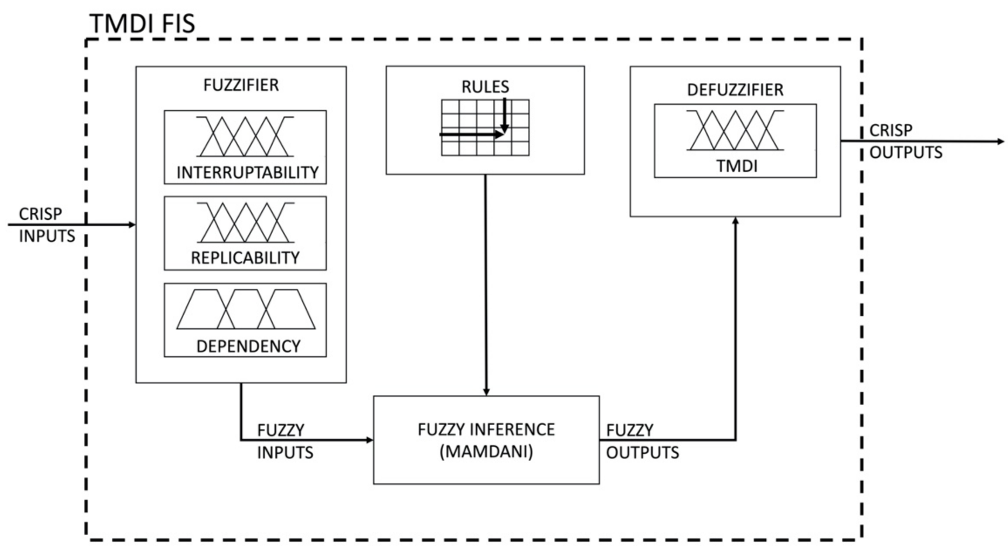


Figure 6. Generalized fuzzy inference system adapted from Larguech et al. 2015

A fuzzy inference system can provide additional information with similar utility and meaningful results using less time and resources for analysis (Mitchell and Carter III 1993). Verbal linguistics' popularity provides fuzzy logic a seamless integration with established risk analysis methods, reducing bias, and capturing additional dimensionality. Although the initial system must be constructed, the outputs are more valuable for decision-makers. They can easily be used to link facilities to organizational objectives for the allocation of prioritized resources.

The fuzzy logic integration framework proposed here is adapted to the TMDI risk assessment and follows a four-step process: (1) membership functions are created to enable continuous input for Interruptability, Replicability, and Dependency; (2) membership functions are developed for outputs to calculate the Consequence of Failure, which produces a TMDI score; (3) rules for the risk-based-matrix and fuzzy system are established; (4) outputs are evaluated graphically to ensure the prioritization of facilities is consistent with decision maker priorities.

Step 1. Establish membership functions for inputs

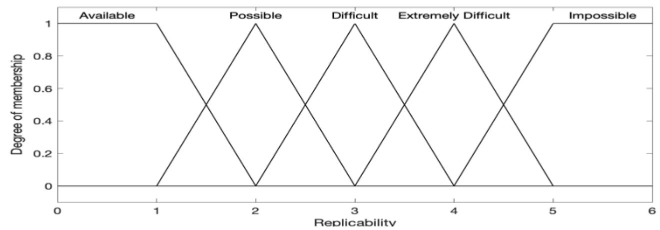
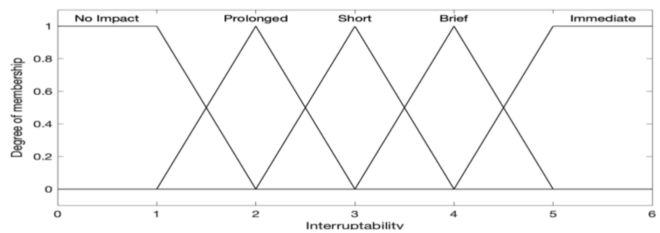
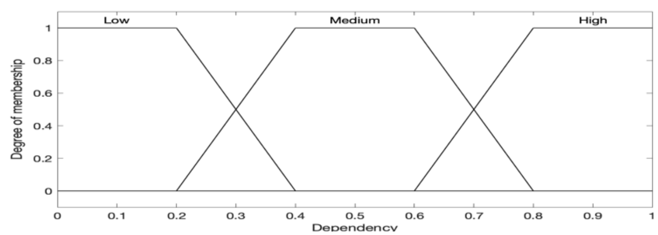
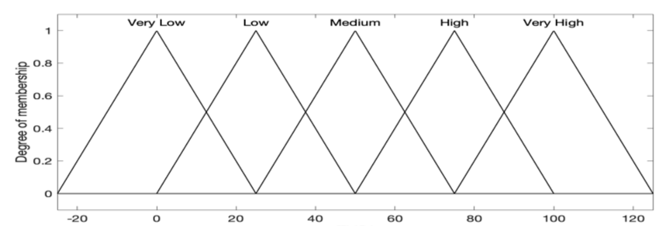
The fuzzy logic system used Interruptability, Replicability, and Dependency as input categories. The TMDI survey established by AFIMSC previously defined Interruptability and Replicability, but Dependency was added to reflect the best practices identified by NASA, the DoD, and focused mission Dependency index Delphi studies (Antelman and Miller 2002; Nichols 2015). Dependency is defined here by the number of facilities, expressed as a percent of total operations on campus, that depend on the operation of the facility in question. Dependency was divided into three levels of high, medium, and low. Clearly, Dependency can be redefined by an organization, and it is kept purposefully simple here to maintain the interpretability of results.

To overcome the rescoring requirement for facilities rated at TMDI = 40, and to achieve an output range of 0 to 100 for congruence with the Air Force's project scoring model, additional categories of likelihood and severity were added to the Air Force's basic matrix. Though this increases the matrix's size, it adds little in the way of complexity for the decision-maker, as the matrix is not revealed. As mentioned above, the membership functions for inputs were determined to be triangular and trapezoidal. Replicability and Interruptability membership functions were set to have equal boundary size with the range of all crisp input values set from [0, 6]. The range was determined by aligning each category's peak such that equal spacing is achieved between each of the positive integers starting at 1. Dependency was divided into three trapezoidal membership functions and had a range of [0, 1]. The range for Dependency was set with the intent that there was a maximum value of 100 and a minimum value of 0. This range was set to indicate the percentage of other facilities on an installation that relied on the operations within a facility. The membership function limits for low, medium, and high were determined with realism and practicality in mind. Fuzzy degrees of truth had equal rates of change between Low - Medium and Medium - High Dependency levels. Input fuzzy set ranges and linguistic terms are summarized in Table 1. These membership function ranges and limits can be easily calibrated to match an organization's leadership or decision-maker opinions, and they allow the establishment of a clearly defined evaluation process with common terminology (National Research Council 2004). The cumulative effect reduces bias while maximizing the use of risk assessment best practices described in the previous sections.

Step 2. Establish membership functions for outputs

The fuzzy logic system used the consequence of failure as the output category. The output category was divided into five membership functions to match the commonly classified MDI risk categories established by the Navy and Army (Amekudzi and McNeil 2008; Grussing et al. 2010). The risk levels determined each category's boundaries, and the range of values was set from [0,100] to match the existing TMDI score range. Triangular membership functions were used to simplify the model and for their effectiveness representing uncertainty between categories. All membership functions were equally spaced from 0 to 100 and can be calibrated to fit leadership and decision-maker opinions. Table 1 displays the output fuzzy set ranges and established terms.

Table 1. Fuzzy Sets for Fuzzy Risk Matrix

Linguistic Variable	Linguistic Terms (Fuzzy Set)	Description range	Universe of Discourse	Membership Function
Replicability (Likelihood) L	I: Impossible II: Extremely Difficult III: Difficult IV: Possible: V: Available	$(4 < \mathrm{I} \leq 6)$ $(3 < \mathrm{II} < 5)$ $(2 < \mathrm{III} \leq 4)$ $(1 < \mathrm{IV} \leq 3)$ $(0 \leq \mathrm{V} \leq 2)$	$X_L \in (0,6)$	
Interruptability (Severity) S	A: Immediate B: Brief C: Short D: Prolonged E: No Impact	$(4 < \mathrm{A} \leq 6)$ $(3 < \mathrm{B} < 5)$ $(2 < \mathrm{C} \leq 4)$ $(1 < \mathrm{D} \leq 3)$ $(0 \leq \mathrm{E} \leq 2)$	$X_S \in (0,6)$	
Dependency D	Low Medium High	$(0 \leq \mathrm{D} \leq 0.4)$ $(0.2 \leq \mathrm{D} \leq 0.8)$ $(0.6 \leq \mathrm{D} \leq 1)$	$X_D \in (0,1)$	
Consequence of Failure C	VH: Very High H: High M: Medium L: Low VL: Very Low	$(75 < \mathrm{VH} \leq 100)$ $(50 < \mathrm{H} < 100)$ $(25 < \mathrm{M} \leq 75)$ $(0 < \mathrm{L} \leq 50)$ $(-25 \leq \mathrm{VL} \leq 25)$	$X_C \in (0,100)$	

Step 3. Establish rules for the fuzzy system

The fuzzy inference system maps fuzzified Interruptability, Replicability, and Dependency inputs to outputs to create a crisp TMDI result. The rules established for the inference system determine the actions of the system and are presented simply:

$$IF\ x_1\ is\ A_{i1} and\ x_2\ is\ A_{i2}\ and\ ...\ x_r\ is\ A_{ir}\ THEN\ y\ is\ B_i\ (for\ i = 1,2,3\ ...\ k) \quad (1)$$

Where x_i is the input variable; A_{ir} and B_i are linguistic terms; y is the output variable; and k is the number of rules. This structure is simple compared to other approaches, and it simulates the complexity of human decision making (Lee 1990).

Rules for the fuzzy logic system were determined based on the risk levels (Figure 7). Seventy-five Boolean-logic rules were created that correspond to all the possible outcomes of Dependency, likelihood, and severity within the fuzzy system. Risk scores were created based on the semi-quantitative methodology similar to the original TMDI matrix (Figure 4). Since the categories were determined to follow a logarithmic scale of classification, addition was used to combine the risk scores, which was a best practice identified by Duijm (2015). A Medium Dependency matrix was created first. This matrix is intended to most closely represent the original TMDI matrix and provides a point-of-departure for High and Low Dependency simulations. Beyond adding an extra category for Interruptability and Replicability, as discussed above, the score differences between each category were adjusted to achieve an even categorical distribution, which is consistent with the original TMDI matrix. In the original TMDI matrix, Interruptability and Replicability scores had a gradient of twelve and eight, respectively (Figure 4). The matrix proposed here is updated such that Replicability has a gradient of ten to avoid risk ties and expand the scores range. Rules were determined by the prevailing membership function of the resulting score. The Low Dependency rules were created by subtracting six from both Interruptability and Replicability category values for medium Dependency. The High Dependency rules were created by adding six to both the Interruptability and Replicability values for Medium Dependency. The addition and subtraction presented here is arbitrary but is provided as an illustration of the ease with which additional dimensionality can be added to risk assessments through fuzzy logic and the degree to which TMDI scores are sensitive to a range of Dependency assumptions.

LOW DEPENDENCY					
Severity / Likelihood	Q1: Interruptability				
Q2: Replicability	-4	8	20	32	44
44	40	52	64	76	88
34	30	42	54	66	78
24	20	32	44	56	68
14	10	22	34	46	58
4	0	12	24	36	48

MEDIUM DEPENDENCY					
Severity / Likelihood	Q1: Interruptability				
Q2: Replicability	2	14	26	38	50
50	52	64	76	88	100
40	42	54	66	78	90
30	32	44	56	68	80
20	22	34	46	58	70
10	12	24	36	48	60

HIGH DEPENDENCY					
Severity / Likelihood	Q1: Interruptability				
Q2: Replicability	8	20	32	44	56
56	64	76	88	100	112
46	54	66	78	90	102
36	44	56	68	80	92
26	34	46	58	70	82
16	24	36	48	60	72

Very High	100 to 87.5
High	87.5 to 62.5
Medium	62.5 to 37.5
Low	37.5 to 12.5
Very Low	12.5 to 0

LOW DEPENDENCY					
Severity / Likelihood	Q1: Interruptability				
Q2: Replicability	E	D	C	B	A
I	M	M	H	H	VH
II	L	M	M	H	H
III	L	L	M	M	H
IV	VL	L	L	M	M
V	VL	VL	L	L	M

MEDIUM DEPENDENCY					
Severity / Likelihood	Q1: Interruptability				
Q2: Replicability	E	D	C	B	A
I	M	H	H	VH	VH
II	M	M	H	H	VH
III	L	M	M	H	H
IV	L	L	M	M	H
V	VL	L	L	M	M

HIGH DEPENDENCY					
Severity / Likelihood	Q1: Interruptability				
Q2: Replicability	E	D	C	B	A
I	H	H	VH	VH	VH
II	M	H	H	VH	VH
III	M	M	H	H	VH
IV	L	M	M	H	H
V	L	L	M	M	H

Figure 7. Dependency levels (top row) and corresponding fuzzy rules (bottom row)

Fuzzy inference requires a database of all possible linguistic control outcomes for the fuzzy system. Mamdani fuzzy models are the most widely used inference method in risk assessments (Jamshidi et al. 2013; Markowski and Mannan 2008). A Mamdani inference system uses each membership function combination triggered by crisp inputs to map the minimum degree of freedom to the output rule membership function. The Mamdani model applies the minimum operator for the "AND" method and the maximum operator for the "OR" method of rules. The fuzzy output set was aggregated for each rule. The final step was the defuzzification of the result, which was calculated using the centroid method to produce a crisp consequence value. There are many defuzzification methods, and the most popular approach uses centroid defuzzification, which returns the center of gravity of the fuzzy set along the x-axis (Equation 2).

$$x = \frac{\sum_i \mu(x_i) x_i}{\sum_i \mu(x_i)} \tag{2}$$

Where $\mu(x_i)$ is the degree of truth for point x_i on the universe of discourse U. The advantage of using the centroid method is that all activated rules contribute to the defuzzification process (Jamshidi et al. 2013). The centroid method of defuzzification is used in this methodology due to its simplicity and widespread use for prioritization methods (Akgun et al. 2010; Jamshidi et al. 2013; Moazami et al. 2011)

The final fuzzy risk surface is produced to show the difference in consequence (TMDI) as Dependency, Interruptability, and Replicability change (Figure 8). The different Dependency levels allow for further understanding of consequence and better prioritization when the success or failure of facilities are linked.

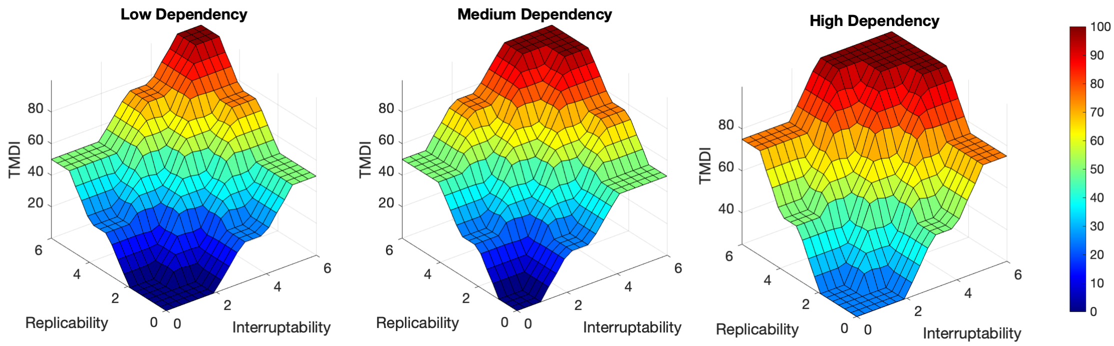


Figure 8. Fuzzy risk surfaces

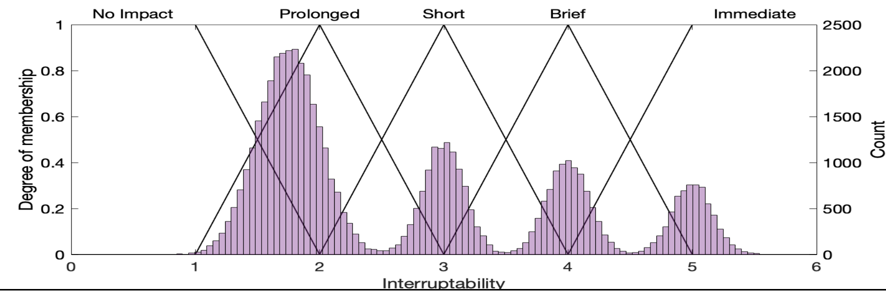
Step 4. Evaluate outputs graphically

The crisp inputs used for the fuzzy logic system were simulated using the original TMDI survey responses. A Gaussian distribution was used to approximate responses from survey takers and translate the discrete traditional risk matrix into the continuous, crisp input responses required for the fuzzy inference system (Smith et al. 2009). Crisp inputs for the categories of "Immediate," "Brief," "Short," "Impossible," "Extremely Difficult," and "Difficult," used the maximum degree of membership for each membership function as value μ. The average value μ was shifted down by 0.2 to simulate crisp inputs for "Prolonged" and "Possible" responses. It was assumed that survey responders would have to pick between the "Prolonged – No Impact" and "Possible – Available" answer combinations, but that the responses would be skewed towards "Prolonged" and "Possible." This assumption reflects the likelihood that most assets are realistically unlikely to have "No Impact" or be immediately available for use. A standard deviation was determined, so less than 1% of the Gaussian-shaped, simulated crisp inputs would fall outside the selected survey category's membership function. For example, a survey taker who classified a facility to have "Possible" Replicability should have a crisp input value less than 2.5 or "Extremely Difficult" Replicability to have a crisp value within [3.5, 4.5]. Dependency was assumed to be higher at the campus (tactical) level due to similar geographic location and the intentional independent operations of each campus location. Dependency was modeled using a Pearson distribution to translate the skew of the results (Table 2). These input parameters only show the additional dimensionality of the proposed methodology. The crisp inputs were translated into outputs using the fuzzy inference system, and the resulting cumulative distribution of the fuzzy inference system's outputs of consequence is shown in Figure 9.

Table 2. Simulated response distribution parameters

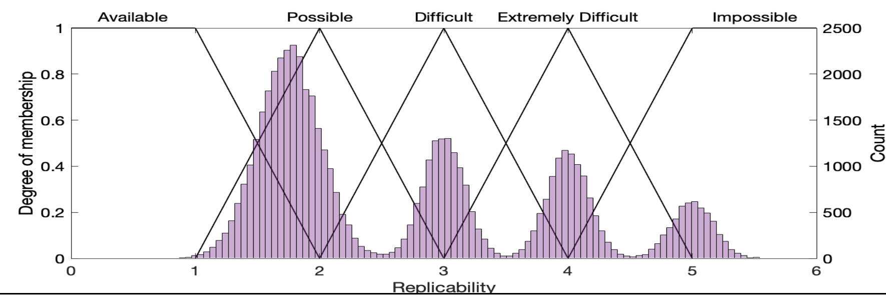
Interruptability

	μ	σ
Immediate	5	0.167
Brief	4	0.167
Short	3	0.167
Prolonged	1.75	0.25



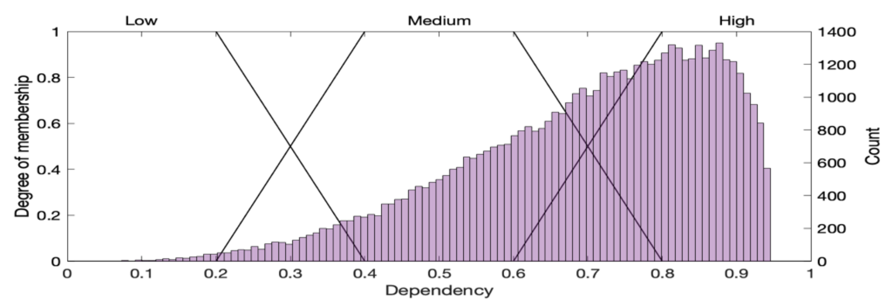
Replicability

	μ	σ
Impossible	5	0.167
Extremely Difficult	4	0.167
Difficult	3	0.167
Possible	1.75	0.25



Dependency

μ	σ	kurtosis	skew
1	0.167	3	-0.75



Results and Discussion

The resulting consequence of failure scores in Figure 9 are more continuous than the previously seen "Steps" in Figure 5. The distribution of results allows campus leadership to effectively prioritize facilities due to fewer risk ties and ensures the funding limit falls between clear distinctions in facilities consequence of failure scores. That is, decision-makers will now be able to distinguish between facilities close to the funding boundaries or create 1-n facility priority lists. The TMDI consequence scores from the fuzzy logic system are slightly higher than AFIMSC's results due to the Dependency metric's addition and the assumption that Dependency is higher at the local campus level. Still, the consistency between the original and modeled TMDI results suggests that the framework produces useful results that do not materially change the output but add dimensionality without increasing the decision maker's complexity. These similar results ensure a simple and repeatable process can be implemented to determine the consequence of failure that links facilities to the organization's strategic objectives.

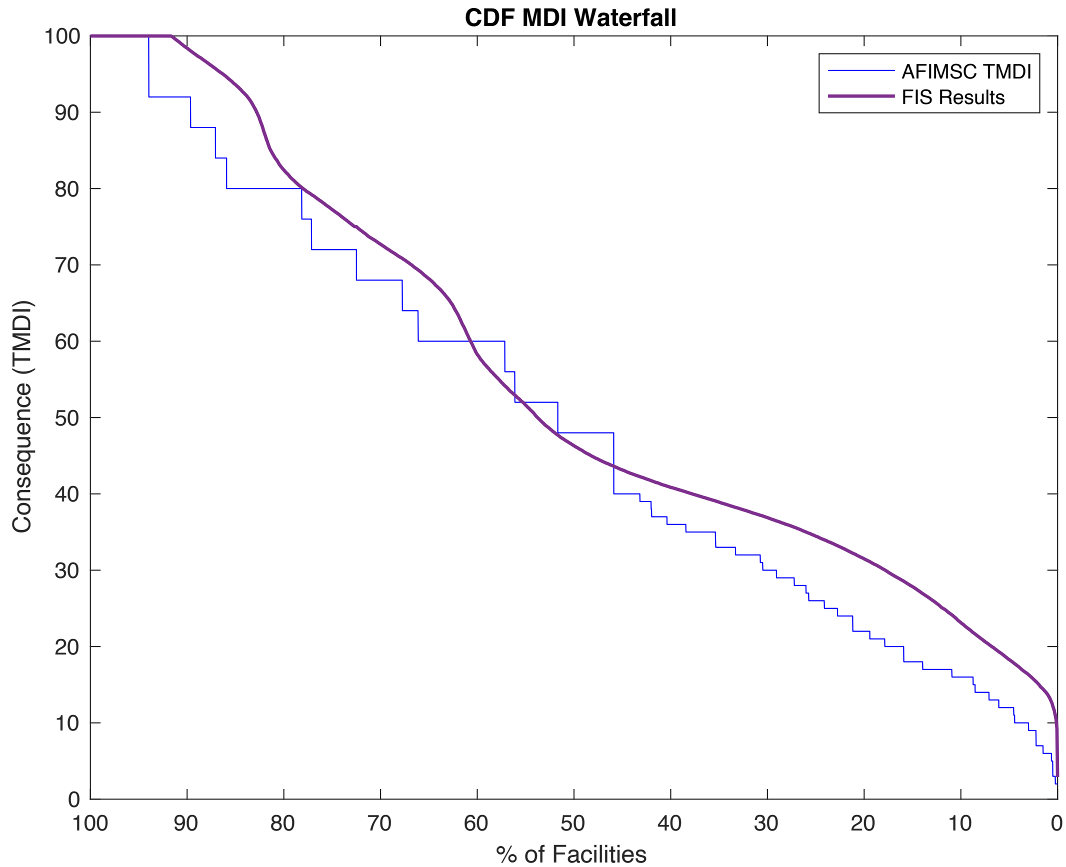


Figure 9. Cumulative distribution waterfall of fuzzy results plotted with the original AFIMSC TMDI scores.

A review of fictional facilities reveals the value of the proposed framework at the facility-scale. Ten fictional example facilities were examined with the fuzzy logic inference system. The use of Dependency was identified as a necessary variable to determine TMDI. The need for Dependency is made clear by comparing scenarios A and B, which detail different campus Child Care Centers (Nichols 2015). Each example facility may support the needs of the larger organization similarly. Still, scenario A should have a higher consequence of failure since over 60% of other campus operations depend on its services. This difference in score reflects lower availability or quality of childcare resources in the local economy, which drives users and the campus's mission to rely on uninterrupted childcare. Facilities that previously existed on the edges of the same category, such as those possessing an Interruptability of one day or six days, are both considered "Short." These were previously indistinguishable using the traditional risk matrix (Figure 4). Including the fuzzy logic framework clarifies scenarios A and C, which were previously treated as identical due to the Air Force TMDI matrix's categorical nature, and are now accurately distinguished within the membership functions. Utilizing Dependency also allows facilities to be accurately prioritized in extreme situations such as scenario F. This special use facility would have previously had the highest score using the traditional risk matrix but can now be accurately prioritized against similarly vulnerable and specialized operations. Even though the change (TMDI = 100 becomes 96.7), it provides the distinguishment necessary to make difficult funding or emergency response decisions. Dependency also enables positive TMDI change, specifically for facilities that may be identified as having lower Replicability or Interruptability. Such is the case for scenario H, which receives a higher prioritization post-fuzzy logic due to the inclusion of cascading failure in other facilities. Clearly, if a hospital becomes inoperable other facilities are affected, like fire stations and facilities

Table 3. Example Scenarios Fuzzy vs. Traditional Methodology

Example Scenarios		Inputs						Output			Priority	
		Traditional			Fuzzy			Traditional	Fuzzy	Risk Level	Traditional	Fuzzy
		L	S	D	L	S	D					
A	Child Care Center	Brief	Difficult	Medium	3.8	3.2	0.62	72	72.3	High-Medium	3	5
B	Child Care Center	Brief	Difficult	Low	3.8	3.2	0.2	72	56	Medium-High	3	8
C	Family Housing Center	Brief	Difficult	Medium	3.1	3.8	0.62	72	69	High - Medium	3	6
D	Flight Simulator	Short	Impossible	Medium	3.8	4.8	0.62	76	94	High - Medium	4	3
E	Passenger Terminal	Immediate	Possible	Low	4.5	3.55	0.2	76	63.1	High - Medium	4	7
F	Special Use Facility	Immediate	Impossible	Low	5	4.9	0.1	100	96.7	Very High- High	1	2
G	Religious facility	Short	Ex. Difficult	Medium	3.8	3.2	0.62	68	72.3	High-Medium	5	5
H	Hospital	Immediate	Ex. Difficult	High	5.5	4	0.85	92	100	Very High	2	1
I	Heritage Monument	No Impact	Impossible	High	1	5.3	0.8	40	75	High	6	4
J	Secondary Runway	Short	Available	Low	3.8	1	0.15	40	25	Very Low- Low	6	9

Score ties are seen in the traditional TMDI methodology for assets classified like scenario D; "Short" and "Impossible," or scenario E; "Immediate" and "Possible." These score ties make prioritization impossible and may result in wasted efforts and resources by portfolio managers. Using crisp inputs for Interruptability, Replicability, and Dependency reduces risk ties, and organizations can more accurately and more precisely prioritize their facilities based on their strategic objectives. When score ties do appear, such as scenario A and scenario G, it can be determined that there is no subjectivity due to the linguistic or discrete categories, and the risk associated with funding one or the other is equal.

The requirement to prioritize facility types for assets with a TMDI less than 40 was an additional step implemented by the Air Force that did not link the specific facility with the organization's strategic objectives. Instead, the original methodology tied the facility type with the organization's strategic goals. Over 45% of the Air Force's facilities were initially scored below 40. Due to the limited resolution, both scenarios I and scenario J earned the same score of 40 and would need to be rescored when using the traditional risk matrix. Risk ties lead to inaccurate prioritization levels when two of the same facility types have different impacts on the organization's strategic objectives. A heritage monument (scenario I) may be seemingly unimportant to an organization's goals by its operations; however, when over 80% of the other organizations on campus use this location for events or promotions, it may have a social impact that needs to be considered when prioritizing funds. A redundant facility such as a secondary runway (scenario J) might seem extremely important for the Air Force. Still, when found in a location that does not have flying objectives or the risk of losing the primary runway is negligible, it should be given a low MDI score and identified as obsolete.

From a project funding perspective, TMDI is 30% of the Air Force's multiplicative facility project scoring model. Even though a majority of facility cases presented here have a minimal difference between original and fuzzy logic-based TMDI, centralized project funding decisions at the margin will benefit from this framework. For any large organization, capital improvement funds will be limited, and there will be a final project funded and a first project not selected for funding. Using a categorical approach, like the one the Air Force used, creates situations where many projects have the same priority, making these marginal decisions difficult. The fuzzy logic approach rectifies conflicts and makes it such that discerning between projects is simplified.

The relative consistency between the original and fuzzy logic-based outputs should be viewed positively. The purpose of this study was not to meaningfully change the outcomes but to provide a framework that 1) eliminates biases and risk ties; 2) creates distinguishment between facilities; and 3) enables the addition of additional risk assessment parameters (Dependency) without adding significant complexity for the decision-maker. To that end, the framework presented here is simple and repeatable and can be used to link facilities to an organization's strategic objectives. The fuzzy inference system presented can be easily calibrated to an individual organization's leadership or decision-maker objectives.

Still, the vast majority of the fuzzy logic inference system parameters for the triangular and Gaussian distributions are arbitrarily assigned, which is a significant limitation of this work. In the Air Force case, AFCEC would likely be responsible for defining and calibrating the number of risk categories, linguistic terms, distribution types, distribution interactions, and boundary conditions for each objective-oriented question. While this up-front work is not simple, the value of the information contained in the outputs is significantly higher than that of a traditional approach.

Another limitation of this work is that it only assesses local risk. Echelons within the organizational hierarchy between the installation and AFCEC have no input on TMDI scores. Although the installation is most familiar with local conditions and local Dependency, higher authority levels often have a broader perspective, which should also be included in a holistic, organizational-level facilities risk assessment. Future research should investigate the inclusion of a reassessment of risk at higher levels within the hierarchy.

Conclusion

Viewing facilities through the lens of organizational objectives is essential for portfolio managers to accurately prioritize facilities and projects when resources are limited. Traditional risk matrices can lead to ambiguous results, uncertainties, and inaccurate prioritizations, but they are commonly used due to their simplicity and ease (Cox 2008; Nelson 2019; Smith et al. 2009). The fuzzy logic-based consequence of failure framework proposed in this work can be used by campus leadership to link facilities to an organization's objectives when success or failure is not necessarily measured monetarily. This framework is simple and repeatable and can be used to better prioritize resources, understand the risk profile of a diverse campus, and identify organizational objective vulnerabilities tied to facilities. While the framework presented here is calibrated to the United States Air Force, non-military, hierarchically equivalent organizations, like a spatially distributed university or hospital campuses that are part of a more extensive system, could benefit from its implementation.

A key benefit of the fuzzy logic approach is that objectives or assessment criteria can be added without precipitously compounding complexity for the decision-makers. Here, facility Dependency is added to Replicability and Interruptability as an example of expanding the risk assessment criterion. In the implementation, the Dependency is manifested as simply another question for a decision-maker to answer for each facility. However, the nature of the question is identical to that of Replicability and Interruptability.

Decision-makers are likely to favor consistent and straightforward frameworks that expedite the prioritization process and limit the degree to which bias can influence results. Another benefit of a fuzzy logic-based approach is that the traditional risk matrix is absconded from the decision maker's view, limiting the degree to which the decision-maker can "game," or match, the desired score to their responses. While it is not addressed in this research, a user interface such as slider bars for each question could replace the matrix interface. Not only would an implementation such as this reduce gaming, but it would also expedite the facility risk assessment process.

Lastly, the purpose of a facility risk assessment and prioritization effort is to distinguish between the importance or consequence of failure of facilities. The fuzzy logic-based approach reduces the occurrence of identical score outcomes that plague categorical risk matrices. Achieving a continuous order of merit for facilities enables decisive action concerning project funding at the margins, and emergency response decisions, both when resources are constrained.

Portfolio managers and campus leaders need to ensure limited resources are allocated appropriately to campus construction and sustainment projects. Decision-makers need to understand how facilities play a role in an organization's objectives while maximizing the value of information collected and minimizing the time, resources, and complexity required to compare and prioritize projects. This novel framework integrates fuzzy logic with a risk assessment methodology to produce a facility prioritization that meets the needs of decision-makers, portfolio managers, and campus leadership.

III. A Fuzzy Inference-Based Facility Prioritization Decision Support System for Complex Hierarchical Organizations

Devin DePalmer, Steven Schuldt, Justin Delorit

Abstract

Safeguarding limited resources for an organization's most critical assets can be difficult when decision-makers at different corporate hierarchy levels have different objectives and needs. Prioritizing resources in a manner that aligns with the organization's strategic goals requires expertise and knowledge at all corporation levels. DePalmer et al. (2021) explored the opportunity to quantify the relationship between facilities and the operations they support using a Mamdani fuzzy inference system. This research extends the previous work by incorporating multi-level perspectives of the facilities and the operations they support outside of the tactical campus. Additionally, the authors simulated various risk attitudes to investigate how subjective inputs at the tactical level can affect strategic-level outputs. This research produces a framework that aggregates junior-level facility knowledge depth with the breadth of senior-level operational and strategic knowledge to support decision-making for facility project prioritization. An additional prediction boundary is created from the risk attitude variance and can give portfolio managers data-driven tools for quality control of risk profiles at individual campus locations.

Introduction

Authorizing facilities and infrastructure projects in a manner that aligns with organizational objectives can be difficult when the organization has a multi-level, hierarchical structure (Hafezalkotob and Hafezalkotob 2017). The leaders of these complex organizations are responsible for many dispersed operating locations and or facilities and face the arduous task of making decisions for a built asset portfolio for which they may rarely have physical oversight. To ensure facility prioritizations reflect both the organizational objectives and local operational realities, company leadership should rely on a mixture of both local facility manager input and corporate influence. Regardless of the organization's hierarchical management structure, e.g., functional, divisional, or matrix, a multi-level framework that targets bottom-up prioritization could more accurately reflect the value generated by facilities, provided the organization clearly represents its objectives in the organizational framework (DePalmer et al. 2021). This research aims to expand previous research by DePalmer et al. (2021) to account for multi-level input in prioritizing facilities by assessing Dependency and analyzing various risk attitudes among decision-makers participating in the prioritization process.

Corporate hierarchy refers to the layers of vertical authority within a company based on job function and status (Kenton 2020; Reitzig and Maciejovsky 2015). Typically pyramid shaped with the most influential positions located towards the top, a corporate hierarchy can represent a chain of command of decision-making authority and scope of responsibility for organizational goals (Kenton 2020). Each level of hierarchy may have different organizational objectives and expertise areas. For example, the corporation's strategic level sets the company's direction or goals but is blind to a single facility's operations at the tactical level. Conversely, a facility manager understands how the facility enables the operations at the tactical level, but not its role at the strategic level. The corporation's value of the facility is determined with information from all levels. When facilities must compete at higher levels of the organization for funding, their value must be accurate and comparable. The organization can represent these hierarchy levels in many ways such as local, regional, and national; tactical, operational, and strategic; city, county, and state; etc. Incorporating expert facility information from each hierarchy level ensures the corporation can prioritize the most critical sustainment and maintenance projects within an extensive and diverse project portfolio.

Facility project prioritization methodologies focus on three necessary steps for project prioritization: (1) identifying factors important to decision-making, (2) evaluating these factors, and (3) ranking the projects (Akgun et al. 2010; Andres et al. 2016; Bowles and Peláez 1995; Bozbura and Beskese 2007; Jamshidi et al. 2013; Markowski and Mannan 2008; Moazami et al. 2011; Shaygan and Testik 2019). The essential factors used for project prioritization and their respective weighting should align with the organization's strategic objectives (Hannach et al. 2016). However, this previous research identified by DePalmer et al. (2021) failed to incorporate information for corporations with an organizational hierarchy of decision-making for facility operation. It also fails to quantify how external influences of human decision-making from subjective inputs affect the results.

Realistically, project prioritization methodologies can expand across multiple levels of the corporate hierarchy. Decision-maker input value may depend on the company's structure and the decision-makers' expertise level or position (Hafezalkotob and Hafezalkotob 2017; Yazdi et al. 2020). Corporations may value junior-level decision-maker inputs equally to senior-level inputs, using a democratic-style decision-making process, or they could favor a more autocratic style, giving final judgment to the senior decision-maker. Few studies have incorporated hierarchical decision-making and the effect on final prioritizations. Hafezalkotob and Hafezalkotob (2017) was the first study focused on this topic by incorporating fuzzy best-worst method to create an optimal weighting system model for integrating senior and junior decision-maker opinions during decision making. More recently, Yazdi et al. (2020) developed a model for prioritizing system failures for a supercritical water gasification system using Failure Mode Effects Analysis (FMEA), which is flexible for autocratic and democratic decision-making processes.

Technology-oriented decision tools, such as decision support systems (DSS), are commonly used to enhance the quality of human decision-making, encourage rational thinking, reduce bias, and avoid errors (Phillips-Wren et al. 2019). Decision-making is useful when a proposed solution is related to desired goals and relevant to the decision in question (Power et al. 2019). However, cognitive biases, individual decision styles, and risk attitudes are all internal influences for human decision-making that allow decision-makers to believe their choices are rational when in reality, these factors influence them towards a sub-optimal decision (Phillips-Wren et al. 2019). Cognitive processing limitations cause people to rely on heuristics to reduce complexity when asked to determine subjective judgments (Tversky and Kahneman 1974). Tversky and Kahneman identified three significant heuristics commonly used in decision-making to predict values and assess probabilities: representativeness, availability, and anchoring. These heuristics can influence how individual decision styles and cognitive biases affect decision-makers and how they interact with the decision support tool. Additionally, the personal risk attitudes of the decision-makers can influence rational decision-making. Decision-makers are typically modeled as risk-taking, risk-neutral, or risk-averse to determine the degree to which risk attitudes can impact the way agents will interact with the technology-based DSS (Delorit and Block 2020; Holt and Laury 2002; Phillips-Wren et al. 2019). Risk-averse individuals may overestimate subjective inputs, while risk-taking attitudes may underestimate these same variables. Improving the quality of decisions can be accomplished when the DSS considers the influences seen on the decision-makers. System architects should build tools with the constraints of human decision-making in mind (Kahneman and Tversky 2012; Phillips-Wren et al. 2019; Power et al. 2019; Tversky and Kahneman 1974). The researchers included a sensitivity analysis to understand how subjective input variance in human decision-making can affect the operational and strategic consequence of failure scores determined in this methodology.

Rational decision-making for portfolio prioritization requires quantifying risk to understand alternative outcomes (Kaplan and Garrick 1981). Since the 1980s, researchers have studied risk. Researchers have yet to establish a standardized risk formula due to the diverse risk analysis applications and the complex relationships between identifying direct and indirect risk variables (Karimpour et al. 2016). The linguistic terms used to categorize and estimate risk invite uncertainty and bias into the risk assessment (Akgun et al. 2010; Jamshidi et al. 2013; Karimpour et al. 2016; Markowski and Mannan 2008; Nelson 2019). Many assessment methodologies like analytical hierarchy process (AHP) (Bozbura and Beskese 2007; Moazami et al. 2011; Shaygan and Testik 2019); failure mode, effects, and criticality analysis (FMECA) (Bowles and Peláez 1995); risk matrices (Markowski and Mannan 2008); and vulnerability assessments (Akgun et al. 2010) have used fuzzy logic to capture uncertainty in risk assessments. Karimpour et al. (2016) determined the benefits for integrating fuzzy logic with risk assessments include: expressing the possibility rather than the likelihood of an outcome; using logical rules rather than complex arithmetic formulas; using insufficient, vague, or imprecise data; and the ease for managers to understand results. Some of the disadvantages of fuzzy logic are the need for subjective inputs and the expert knowledge required to establish rules and calibrate membership functions (Karimpour et al. 2016; Zadeh 1965). These benefits suggest that fuzzy logic is a tool that DSS designers can use to improve human decision-making quality with technology-oriented decision tools.

Despite the significant contributions of the aforementioned topics, there are gaps in the literature about fuzzy prioritization methods for organizations with a hierarchical structure. This paper addresses those gaps by aggregating lower-level expert information of a system's Interruptability, Replicability, and Intra-Dependency with higher-level Inter-Dependency inputs utilizing a fuzzy inference system. This system architecture provides information for how a single facility failure can affect the corporation's overall strategic objectives by determining a consequence of failure metric at each hierarchical level of the company for prioritizing resources. The authors expanded DePalmer et al. (2021) 's research to the company's operational and strategic organizational hierarchy level. Organizations value senior-level expertise for its broader scope of responsibility and knowledge about the system in which each facility operates. Junior-level expertise is valued because of their in-depth understanding of the facility and its link to tactical objectives. A sensitivity analysis is performed on the junior-level results to show how subjective judgment can affect overall results. Corporate leadership can use this information to ensure a bias-reduced decision-making process is used to calculate the consequence of facility failure for corporate strategic objectives.

Case Study and Background: The United States Air Force Mission Dependency Index

The Air Force is a large, complex, and diverse corporation that could benefit from a repeatable risk assessment methodology to prioritize facility construction and sustainment projects. Like many other private and public corporations, the Air Force's strategic objectives are not profitmotivated and will need to assess risk and prioritize projects without using a cost-based analysis (Hannach et al. 2016; National Research Council 2004). Corporations with similar objectives and organizational structure of the Air Force also need a simple, repeatable process that can help them assess the consequence of failure across individually operated and spatially distributed campuses or assets. Additional operational and strategic decision-maker input is essential to organizations whose tactical operations are independently run to focus momentum and ensure proper direction towards its strategic objectives. The methodology currently used by the USAF to prioritize their portfolio is risk-based and can be integrated with fuzzy logic to improve decision-making and optimize resource allocation (DePalmer et al. 2021). The improvements to the methodology proposed in this paper apply to other hierarchical organizations that use a consequence of failure metric to make risk-based decisions or prioritizations.

The Air Force Civil Engineer Center (AFCEC) currently requires Air Force Civil Engineers to create an annual Integrated Priority List (IPL) of candidate facility improvement projects that must compete for approval and funding (AFCEC 2020). The IPL is a list of facility projects ordered by highest to lowest technical score. The technical score indicates to decision-makers a level of risk to the organization if the project goes unfunded. Engineers calculate the technical score by multiplying the project's Probability of Failure (PoF) with its Consequence of Failure (CoF). PoF is determined using historical data from the Air Force's Sustainment Management System BUILDER. PoF represents the facility's condition on a scale of 1 to 100, with one being the best condition (lowest PoF) and 100 being the worst (highest PoF). The CoF is a measurement of facility importance and also measured on a scale of 1 to 100, with one being the least important and 100 being the most important (the highest consequence of failure). Engineers calculate the

CoF by combining the facility's Mission Dependency Index (MDI) and the project's priority ranking from senior-level decision-makers. MDI is a metric used by the DoD other similar government agencies like NASA to quantify the importance of the relationship between facilities and the mission they enable (Antelman et al. 2008; Antelman and Miller 2002; Savatgy et al. 2019). The project's priority ranking by senior-level decision-makers is valuable to the Air Force to ensure leadership perspective remains an important factor in determining the final project approval scores. AFCEC combines all installation's IPL to make funding authorization decisions from highest to lowest technical project score. This order ensures the Air Force allocates funds to the highest-scoring projects across the enterprise first, due to limited resources available each year (AFCEC 2020).

Presently, Air Force Civil Engineers calculate tactical MDI with a traditional risk matrix constituted by a likelihood and severity analysis of Replicability and Interruptability. Each variable is broken into four categories, producing a possibility of 16 combinational outcomes. Although traditional risk matrices are low-cost to assemble and simple to use, they are heavily criticized for their sub-optimal mathematical analysis and are easily prone to errors through user cognitive biases or subjective categories (Cox 2008; Duijm 2015; International Electrotechnical Commission 2019; Li et al. 2018; Siefert and Smith 2011). The logarithmic scale and additive scoring combination used for the MDI variables result in risk score ties, reducing granularity further, and providing 14 unique MDI matrix scores between 100 and 40. To increase the range of possible MDI scores, the Air Force re-scores all assets with an MDI of 40 based on the facility type (Savatgy et al. 2019). This methodology is problematic because it inaccurately links the MDI score to the facility's type rather than its function. The re-scoring process can lead to mismatched MDI scores and the need for an additional score adjudication process (Blaess 2017; Nichols 2015; Smith 2016).

DePalmer et al. (2021) investigated the MDI prioritization methodology. They integrated the process with a fuzzy logic inference system (FIS) that used the inputs of Interruptability, Replicability, and Dependency to output a CoF score, identified as tactical MDI (TMDI). This methodology builds upon the TMDI FIS to include senior-level Inter-Dependency information at the organization's operational and strategic levels. Senior-level decision-makers currently determine priority ranking points with only qualitative data. Qualitative data is simple and can be used when quantitative data is unavailable, inadequate, or under a limited budget and time constraints (Radu 2009). Unfortunately, qualitative assessments do not provide enough information for extensive evaluations, do not capture uncertainty, and are incredibly subjective data points (International Electrotechnical Commission et al. 2019). Senior-level decision-makers can use priority points to manipulate the final technical score of projects and tarnish the risk assessment's validity and objectivity, project prioritization methodology, and approval process. This research does not include changing the PoF metric. Instead, it focuses on integrating fuzzy logic as a risk-assessment methodology at all of the organization's hierarchy levels to eliminate the need for senior-level priority ranking in the CoF metric and simultaneously create a more accurate and less biased project prioritization methodology.

The MDI's operational and strategic value goes beyond project prioritization for AFCEC's IPL. Corporate leadership and facility planning teams can use this metric to understand how specific facilities enable operations at their location and how each facility is linked to other critical infrastructure or mission sets throughout the organization. Additionally, MDI can be used to differentiate between primary or secondary operations within a facility or installation, link operations to space needs, or model dynamic mission needs at the operational or strategic level (Heron et al. 2017). Every level of the organization can use the tactical, operational, or strategic level information this system produces to understand how a facility failure may have cascading effects, allowing decision-makers to make better choices for the organization as a whole.

Methodology

The authors expanded the fuzzy logic methodology used in DePalmer et al. (2021) to account for multi-level input for prioritizing facilities with an assessment of Inter-Dependency and an analysis of how a variety of risk attitudes from decision-makers can affect the prioritization process. The system is shown in Figure 2 and specifies this research's scope compared to DePalmer et al. (2021). This study makes use of the initial results from AFIMSC's TMDI re-baselining survey. For this survey, local facility managers used a traditional risk matrix to quantify their facility's Replicability and Interruptability for over 54,000 facilities at 79 installation (campus) locations worldwide.

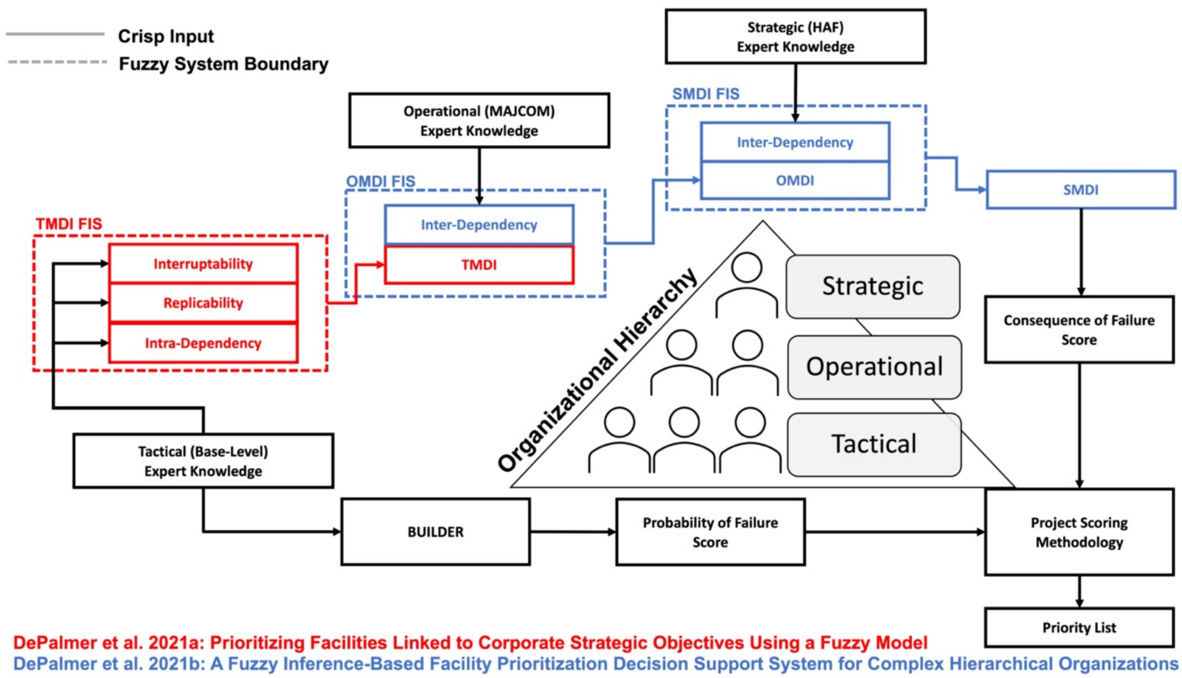


Figure 10. Paper scope and methodology for Strategic Mission Dependency Index (SMDI) creation. The blue text is the focus of this research, and the red text indicates research completed by DePalmer et al. (2021). Fuzzy system boundaries and input variables are marked with a dashed line, while solid lines indicate a crisp input value.

The tactical level MDI score provides information about the Interruptability, Replicability, and Intra-Dependency of a facility (DePalmer et al. 2021). Interruptability indicates how fast the impact to campus's overall operations would be if functional capabilities of the facility were interrupted. Survey responders assume the interrupted facility is completely unavailable due to some disruption caused by deferred preventative maintenance. Replicability indicates how difficult it would be for the campus to relocate or replicate its functional capabilities if the facility were interrupted (Savatgy et al. 2019). Intra-Dependency shows the percent of other mission sets at the tactical level that relies on the facility's operations for success. This paper introduces additional hierarchy-levels and information about Inter-Dependency. Inter-Dependency is distinguished from Intra-Dependency as it indicates the percent of other mission sets at the operational and strategic level that rely on the facility's operations for mission success. The Operational Mission Dependency Index (OMDI) score and Strategic Mission Dependency Index (SMDI) score use the outputs of the score produced at the subordinate hierarchical level as crisp inputs to their fuzzy inference system (FIS). Each FIS runs in series to one another to provide separate output results at each hierarchy level. Information from each tier is independent of one another since the fuzzy system hides the fuzzified subordinate level's inputs. The resultant CoF outputs of TMDI, OMDI, and SMDI indicate the risk to different hierarchical levels from a facility's outage or failure.

Building the Operational and Strategic Dependency FIS

The FIS used in this work follows the same four-step process as the previous research of DePalmer et al. (2021): (1) membership functions are designed to enable continuous input; (2) membership functions are developed for outputs; (3) rules for the risk-based-matrix and fuzzy system are established; (4) outcomes are evaluated graphically to ensure the prioritization of facilities is consistent with decision-maker priorities. It is essential that the system designers accurately calibrate the membership functions to fit the expert's logical rules because each component of the fuzzy logic system influences the outcome.

Step 1. Establish membership functions for inputs

The operational FIS used TMDI and operational Inter-Dependency as inputs. The Tactical FIS, previously established by DePalmer et al. (2021), output a crisp TMDI score is re-fuzzified into the Operational FIS. Inter-Dependency is defined here by the number of facilities, expressed as a percent of total missions at the operational level, that depends on the success of the facility in question. Inter-Dependency is divided into three membership functions of High, Medium, and Low, and is the other half of the input for OMDI. The Strategic FIS operates identically to the Operational FIS, though it uses OMDI and strategic Inter-Dependency as input categories.

The authors determined membership functions for all inputs to be triangular and trapezoidal for the system's simplicity. Triangular membership functions were used to simplify the model and for their effectiveness representing uncertainty between categories. TMDI and OMDI were divided into five membership functions to simulate the commonly classified MDI risk categories established by the Navy and Army (Amekudzi and McNeil 2008; Grussing et al. 2010). The risk levels determined each category's boundaries, and the range of values was set from [0,100], similar to the existing MDI score range. All membership functions for TMDI and OMDI inputs were equally spaced from 0 to 100. System designers can calibrate these functions to fit leadership and decision-maker needs. The authors determined the membership function's range by aligning each category's peak with equal spacing between categories to achieve a maximum score of 100 and a minimum score of 0. Inter-Dependency was divided into three trapezoidal membership functions and had a range of [0, 1]. The Inter-Dependency range was set with the intent that there was a maximum value of 100% and a minimum value of 0%. This range was set to indicate the percentage of other facilities at the operational or strategic level that relied on a facility's success.

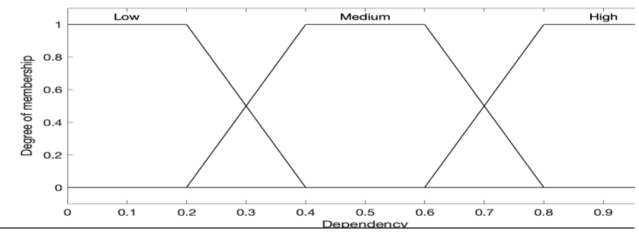
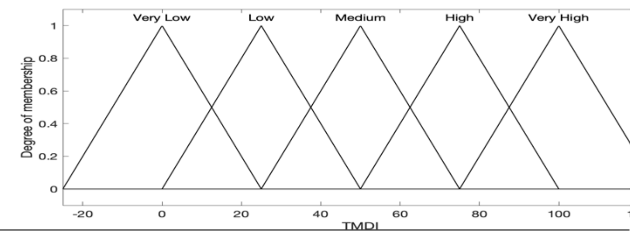
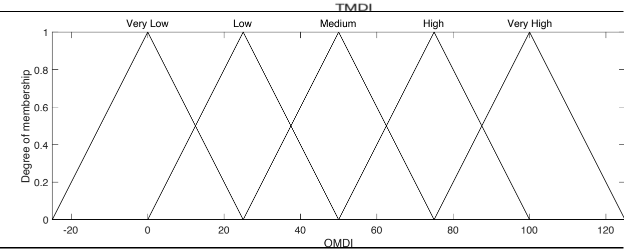
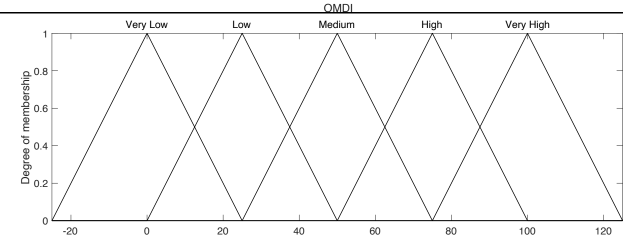
The authors determined Low, Medium, and High membership function limits with realism and practicality in mind. Fuzzy degrees of truth had equal rates of change between Low - Medium and Medium - High Dependency levels. Input fuzzy set ranges and linguistic terms are summarized in Table 4. These membership function ranges and limits can be easily calibrated to match an organization's leadership or decision-maker opinions. This fuzzy system establishes a clearly defined evaluation process with common terminology (National Research Council 2004). For additional detail on the construction and function of the FIS, readers are directed to DePalmer et al. (2021).

It is important to note that a corporation's leadership can re-define Inter-Dependency, or set a different analysis metric based on organizational objectives. Inter-Dependency links tactical, operational, and strategic levels based on Air Force stakeholders' communications. It is purposefully simplified here to maintain the interpretability of results, aligning with the Air Force's strategic purpose for its MDI framework. Dependency assessment is modeled as independent at the tactical, operational, and strategic levels and is determined by an unbiased analysis of connections between facilities. That is, TMDI inputs and outputs are hidden from operational level assessors when assigning inter-dependencies, as well as OMDI, during the strategic assessment. This blind input system was intended to limit influence from the human decision-making biases but could be eliminated based on decision-maker preferences.

Step 2. Establish membership functions for outputs

The operational level FIS outputs the OMDI value, and the strategic level FIS outputs the SMDI value. The OMDI and SMDI fuzzy inference systems are identical in function and therefore are described as one system in this section. The output was divided into five membership functions to match the commonly classified MDI risk categories established by the Navy and Army (Amekudzi and McNeil 2008; Grussing et al. 2010). The risk levels determined each category's boundaries, and the range of values was set from [0,100] to match the existing TMDI score range. Triangular membership functions were used to simplify the model and for their effectiveness representing uncertainty between categories. All membership functions were equally spaced from 0 to 100 and can be calibrated to fit leadership and decision-maker opinions. The output fuzzy set ranges and established terms are displayed in Table 4. For additional detail on the construction and function of the FIS, readers are directed to DePalmer et al. (2021).

Table 4. FIS Membership functions and input ranges for each hierarchy level MDI score

Linguistic Variable	**Linguistic Terms (Fuzzy Set)**	**Description range**	**Universe of Discourse**	**Membership Function**
Inter-Dependency (D)	Low Medium High	$(0 \leq \mathrm{D} \leq 0.4)$ $(0.2 \leq \mathrm{D} \leq 0.8)$ $(0.6 \leq \mathrm{D} \leq 1)$	$X_D \in (0,1)$	
TMDI (T)	VH: Very High H: High M: Medium L: Low VL: Very Low	$(75 < \mathrm{VH} \leq 100)$ $(50 < \mathrm{H} < 100)$ $(25 < \mathrm{M} \leq 75)$ $(0 < \mathrm{L} \leq 50)$ $(-25 \leq \mathrm{VL} \leq 25)$	$X_T \in (0,100)$	
OMDI (O)	VH: Very High H: High M: Medium L: Low VL: Very Low	$(75 < \mathrm{VH} \leq 100)$ $(50 < \mathrm{H} < 100)$ $(25 < \mathrm{M} \leq 75)$ $(0 < \mathrm{L} \leq 50)$ $(-25 \leq \mathrm{VL} \leq 25)$	$X_O \in (0,100)$	
SMDI (S)	VH: Very High H: High M: Medium L: Low VL: Very Low	$(75 < \mathrm{VH} \leq 100)$ $(50 < \mathrm{H} < 100)$ $(25 < \mathrm{M} \leq 75)$ $(0 < \mathrm{L} \leq 50)$ $(-25 \leq \mathrm{VL} \leq 25)$	$X_S \in (0,100)$	

Step 3. Establish rules for the fuzzy system

The fuzzy inference system maps fuzzified hierarchy-level MDI and Inter-Dependency inputs to hierarchy level outputs to create a crisp CoF score. The rules established for the inference system determine the actions of the system and are presented simply as:

$$IF\ x_1\ is\ A_{i1} and\ x_2\ is\ A_{i2}\ and\ \ldots x_r\ is\ A_{ir}\ THEN\ y\ is\ B_i\ (for\ i = 1,2,3\ldots k) \quad (3)$$

Where x_i is the input variable; A_{ir} and B_i are linguistic terms; y is the output variable; and k is the number of rules. This structure is simple compared to other approaches, and it simulates the complexity of human decision-making (Lee 1990).

Rules for the fuzzy logic system were determined for applicability of the system and shown in Figure 11. The authors created 15 Boolean-logic rules for each department-level FIS to correspond to all the possible Inter-Dependency and department-level MDI outcomes within the fuzzy systems. The Medium Inter-Dependency level was used as the baseline for the operational-level FIS, and outputs were either increased or decreased for High and Low Inter-Dependency. The strategic-level FIS started with the Low Inter-Dependency as the expected baseline response and increased or decreased the final consequence output accordingly. These rules were set as examples for building the system architecture and need to be calibrated and established by the organization's correct asset management experts. The fuzzy system's rules link inputs and outputs and must reflect the system owner's needs.

Operational MDI		Inter-Dependency		
		Low	Medium	High
TMDI	Very High	H	VH	VH
	High	M	H	VH
	Medium	L	M	H
	Low	VL	L	M
	Very Low	VL	VL	L

Strategic MDI		Inter-Dependency		
		Low	Medium	High
OMDI	Very High	H	H	VH
	High	M	H	VH
	Medium	M	M	H
	Low	L	M	H
	Very Low	VL	L	M

Figure 11. Boolean logic rules established for the Operational (a, left) and Strategic (b, right) level FIS.

This system continues the fuzzy inference methodology from DePalmer et al. (2021) using a Mamdani fuzzy model. This Mamdani model applies the minimum operator for the "AND" method and the maximum operator for the "OR" method of rules. The defuzzification method used for the operational and strategic level was the centroid method. Centroid defuzzification returns the center of gravity of the fuzzy set along the x-axis (Equation 4).

$$x = \frac{\sum_i \mu(x_i)x_i}{\sum_i \mu(x_i)} \tag{4}$$

Where $\mu(x_i)$ is the degree of truth for point x_i on the universe of discourse U. For additional detail on the construction and function of the FIS, readers are directed to DePalmer et al. (2021).

Step 4. Evaluate outputs graphically

The FIS's outputs for Operational MDI and Strategic MDI were evaluated by reviewing the surface plots produced. The final fuzzy risk surfaces show the difference in output consequence as the department-level MDI and Inter-Dependency change (Figure 12). As expected, the rules and membership functions of the system determine the final fuzzy surface. It is paramount that corporate experts choose the appropriate rules for each FIS's calibration to ensure the final surface reflects the organizational objectives and the linkages between different organizational levels of input. For this research, both surfaces must have positive or zero slopes for the Z-axis. This slope ensures that as the inputs increase, the CoF at each department-level does not decrease as their inputs increase.

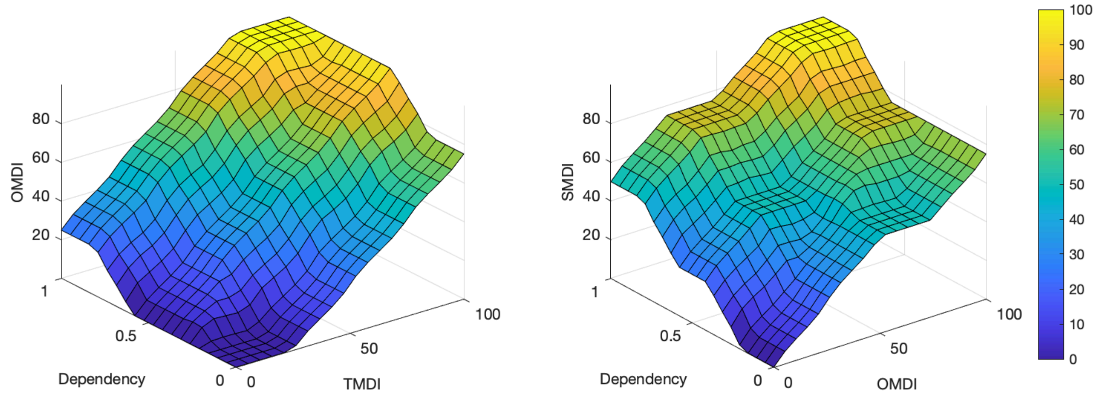


Figure 12. Risk surface plot for a (left) Operational MDI, and b (right) Strategic MDI.

Since the framework has each hierarchy in series, it is essential to recognize that the resulting outputs are re-fuzzified for inputs at the higher level and only reflect the department's crisp consequence score. For example, the OMDI will equal 100 when the TMDI is held at 100, and operational Inter-Dependency increases from Medium to High. A facility classified as [100, 0.5] at the Operational level will have the same OMDI score of 100 as a facility classified as [100, 0.90]. When both of these output OMDI consequences are used in the Strategic FIS, they have an equal opportunity to change. The SMDI FIS does not see the Inter-Dependency difference at the operational level; it only sees the resulting OMDI score of 100. While the system's primary goal is to create an overall prioritization method, leadership can use CoF's crisp outputs at each level for better strategic decision-making in other portfolio management areas besides competing for project authorization funds. Additional details are provided in the discussion.

Sensitivity Analysis and Simulating Data

Decision-makers at all levels can be tricked into believing they are making rational decisions when, in reality, they are influenced by their cognitive biases and personal risk attitudes (Kahneman and Tversky 2012; Phillips-Wren et al. 2019; Power et al. 2019; Siefert and Smith 2011). When resources are limited, these sub-optimal decisions lead to wasted efforts. System architects should analyze these influences and uncertainties and put protection measures in place to mitigate them. System architects can use fuzzy logic in semi-quantitative risk assessments to capture the uncertainty between classes of objects (Duijm 2015; Markowski and Mannan 2008; Zadeh 1965). Once this uncertainty is analyzed, acceptable tolerances can be determined by the organization's leadership to quality control the system. Additionally, the scaling or descriptions used for the universe of discourse for inputs can be adjusted and calibrated to avoid ambiguity or subjectivity of crisp inputs.

A sensitivity analysis was performed with the subjective inputs of Replicability and Interruptability to analyze the effect of risk attitudes and cognitive biases on MDI. It was assumed that simulated crisp inputs would closely mirror the actual TMDI survey responses for all facilities, and simulated responses would have a degree of membership greater than 0.5 for the original category chosen. This range ensures the crisp inputs vary only between the uncertainty between categories. For example, if the TMDI survey response for Replicability was "Extremely Difficult", the distribution of simulated crisp inputs would range from [3.5, 4.5]. A triangular membership function was used because of the simplicity of setting maximum, minimum, and peak location for each simulated response's crisp input. Figure 13 shows the simulated response ranges for results within the membership functions, and Table 5 identifies maximum and minimum values used for crisp input simulations. The maximum and minimum values of each triangular distribution were set for all survey responses, and the peak location varied between these limits. Because the Available and No Mission Impact categories were not part of the original TMDI survey, the authors assumed no more than 25% of assets would be identified to have Replicability or Interruptability crisp inputs of less than 1 (less than 0 degrees of membership of Prolonged or Possible). The range for the Prolonged and Possible responses between [0.75, 2.5] was set with this limit in mind. The triangular distributions were varied with Equation 5.

$$b = a + D(i)(c - a) \tag{5}$$

Where a is the minimum limit to the triangular distribution, b is the peak value of the triangular distribution, and c is the maximum limit to the triangular distribution. D represents the decision maker's personal attitudes and ranges from 0 to 1. A decision-maker's i, risk attitude of $D = 0$ indicates the maximum level of risk-taking, and $D = 1$ indicates the maximum level of risk-aversion. A decision-maker with $D = 0.5$ means a risk-neutral attitude. When decision-makers have a D = 0 value, the distributed results have a peak value (b) at the minimum value (a) for the subjective input. This would indicate that the decision-makers have a risk-taking attitude, and the crisp inputs belong closer to the category below, reducing the crisp input of the subjective variable and potentially the final consequence of failure score.

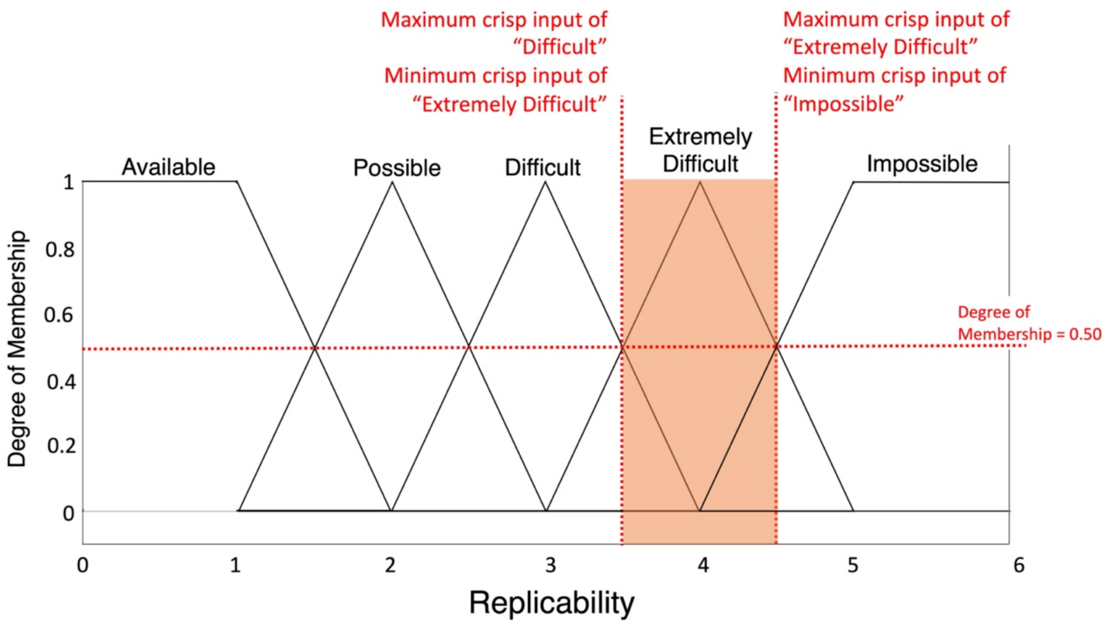


Figure 13. How maximum and minimum limits for triangular distribution were established to simulate crisp inputs for TMDI survey results

Table 5. Maximum and minimum values used for simulating triangular distributions for crisp inputs to TMDI survey responses of Interruptability and Replicability.

Variable	**Category**	**Minimum *a***	**Maximum *b***
Interruptability	Immediate	4.5	5.5
	Brief	3.5	4.5
	Short	2.5	3.5
	Prolonged	0.75	2.5
Replicability	Impossible	4.5	5.5
	Extremely Difficult	3.5	4.5
	Difficult	2.5	3.5
	Possible	0.75	2.5

The tactical, operational, and strategic level Dependency responses were simulated to validate the fuzzy logic system's architectural framework. Crisp input values of Dependency ranged from 0 to 1 and were determined using a Pearson distribution. Each department level's distribution values can be seen in Table 6. The cumulative distribution of simulated Dependency inputs can be seen with the membership functions overlayed in Figure 14, showing the difference between the tactical, operational, and strategic level distributions. Other distributions would affect the overall results of the sensitivity analysis.

Table 6. Simulated Dependency values for tactical, operational, and strategic level

Department Level	**Mean μ**	**Standard Deviation σ**	**Skewness**	**Kurtosis (Normal = 3)**
Tactical	0.6	0.166	-0.75	3
Operational	0.5	0.166	0	3
Strategic	0.4	0.166	0.75	3

These values were determined with the assumption that facilities become less Inter-Dependent as they increase in managerial level. This assumption is because facilities should be highly Intra-Dependent at the tactical level due to their geographic proximity and the need for entire operating locations to function independently. Conversely, as the hierarchy level increases, the facility is less likely to be unique or provide services across the entire department's responsibility scope. For example, each tactical-level location may have a facility that has a high Inter-Dependency at their campus. This facility is useful at the tactical level and commonly found at every location. Because this requirement is satisfied at multiple campuses, the operational level may not classify the need for a high Inter-Dependency between that specific facility and other campuses since their needs are being met locally.

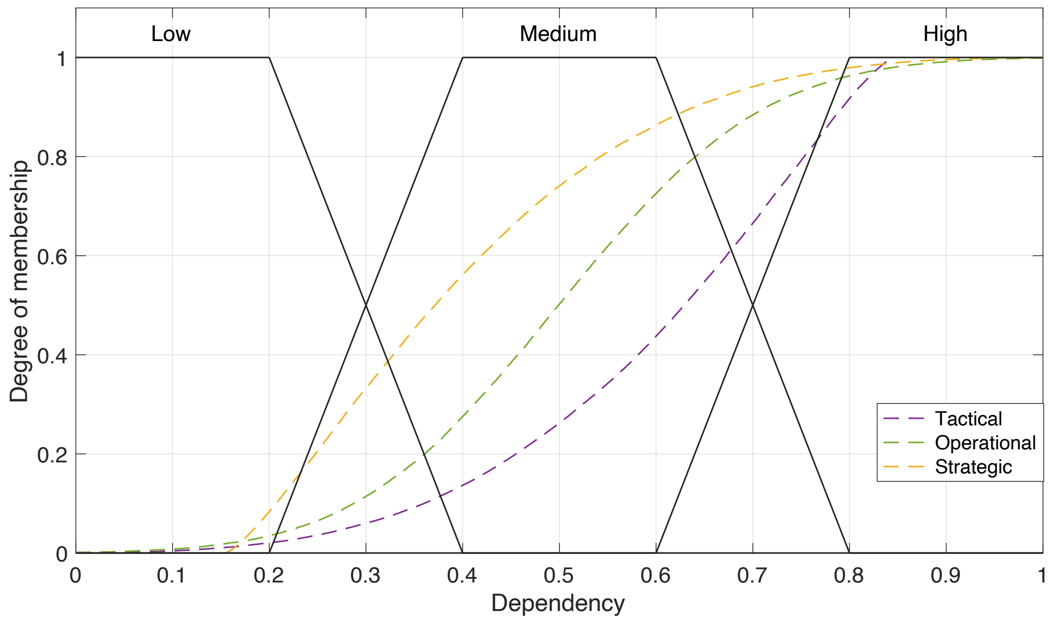


Figure 14. Dependency Cumulative Distribution Function plot, describing the density of each department level's simulated crisp Dependency input

Results

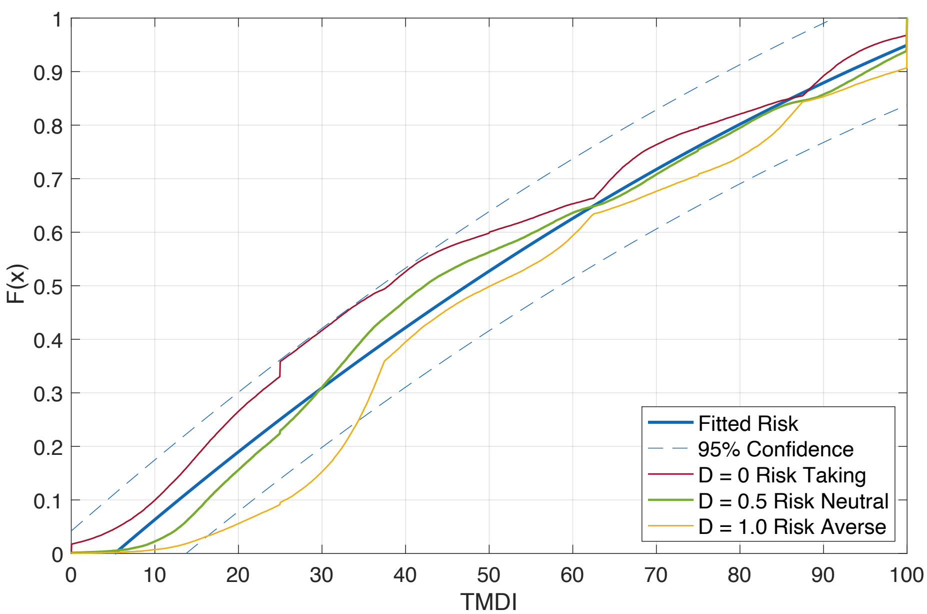
The fuzzy system was successfully implemented to produce the consequence of failure scores at each department level with simulated response inputs. These results are specific to the simulation inputs, and true results will be dependent on the verified responses from decision-makers at the tactical, operational, and strategic department levels. Simulated results were used to determine the final fit parameters of the polynomial regression. Although stylized, this process can be repeated with true results, and multi-level influence can be analyzed at a low computational cost. This analysis can inform future investments and serve as quality control for locations with unacceptable risk tolerance.

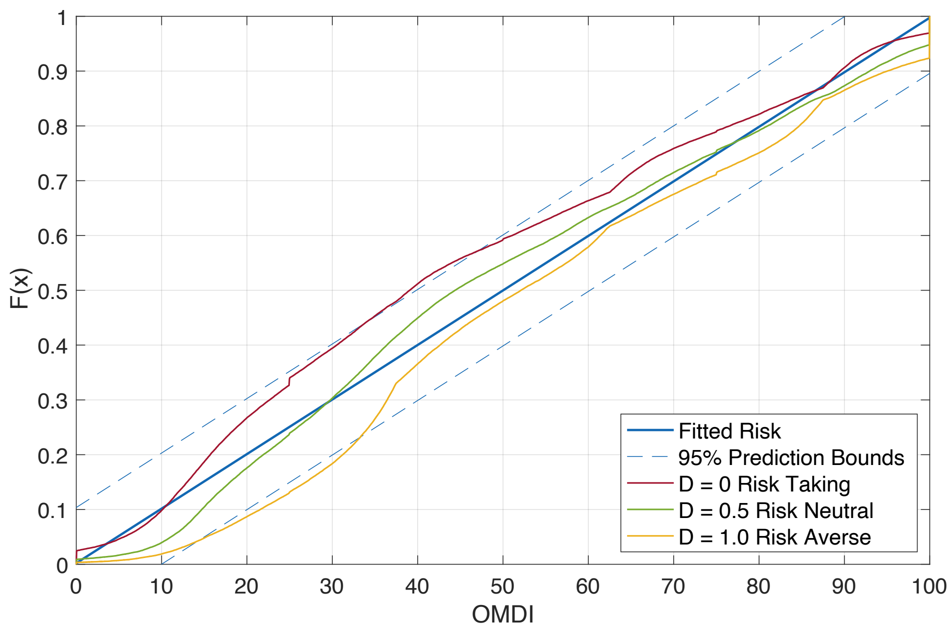
The cumulative distribution function percentiles were plotted and fit with a polynomial regression line to quantify the effect of decision-maker risk attitudes on MDI variability across the range of possible scores. The polynomial regression coefficients and goodness of fit statistics can be seen in Table 7, and the results of the expected MDI and the 95% prediction bounds for each hierarchy level can be seen graphically in Figure 15. These results will change as the membership functions and rules are calibrated by decision-makers and serve the purpose of creating an acceptable risk attitude boundary for the proposed prioritization framework.

Table 7. Polynomial Regression Coefficients and Goodness of Fit Statistics for Tactical, Operational, and Strategic level Risk Attitudes

Generalized Fit Model $f(x) = p_1x^2 + p_2x + p_3$					
Department Level	**Coefficients (95% confidence bounds)**	**R-square**	**Adj R-Square**	**SSE**	**RMSE**
Tactical	$p_1 = -3.52 \times 10^{-5}$ $(-4.19 \times 10^{-5}, -2.83 \times 10^{-5})$ $p_2 = 1.37 \times 10^{-2}$ $(1.30 \times 10^{-2}, 1.45 \times 10^{-2})$ $p_3 = -7.04 \times 10^{-2}$ $(-8.79 \times 10^{-2}, -5.29 \times 10^{-2})$	0.96	0.96	1.60	0.06
Operational	$p_1 = -2.64 \times 10^{-5}$ $(-3.20 \times 10^{-5}, -2.09 \times 10^{-5})$ $p_2 = 1.28 \times 10^{-2}$ $(1.22 \times 10^{-2}, 1.34 \times 10^{-2})$ $p_3 = -5.07 \times 10^{-2}$ $(-6.46 \times 10^{-2}, -3.68 \times 10^{-2})$	0.97	0.97	1.14	0.05
Strategic	$p_1 = 3.26 \times 10^{-5}$ $(1.95 \times 10^{-5}, 4.57 \times 10^{-5})$ $p_2 = 1.20 \times 10^{-2}$ $(1.06 \times 10^{-2}, 1.34 \times 10^{-2})$ $p_3 = -0.23$ $(-0.27, -0.20)$	0.94	0.94	2.46	0.07

Although specific to the assumptions made for this simulation, these types of quantifications give senior-level quality control managers data-driven tools to ensure responses fall within expected or acceptable ranges and can be used to identify outlier locations or assess whether categorical risk behavior exists within sections of the MDI range. Like upper and lower control limits, the 95% prediction bounds serve as the threshold for acceptable risk attitude behavior. The width of the bounds indicates the uncertainty associated with the fitted risk curve. Non-simultaneous observation bounds measure with 95% confidence that a new observation will lie within the interval specified given the predicted inputs of CDF percentile and department-level MDI (MathWorks, Inc 2020). The prediction bounds are useful for a case-by-case analysis of a base's overall risk profile and for company leadership to understand the expected variance of results. If a campus's results are within the boundaries, their responses are within the expected risk tolerance threshold. If an operating location's risk profile is outside of these thresholds, the location's responses may require a manual review. This review can identify if locations need supplementary education about properly using the system or if there are assets that need redistribution or additional redundancies to ensure each portfolio has a balanced risk profile. Additionally, this review can reveal extreme risk attitudes that may warrant extreme risk-aversion due to security concerns at the campus location.





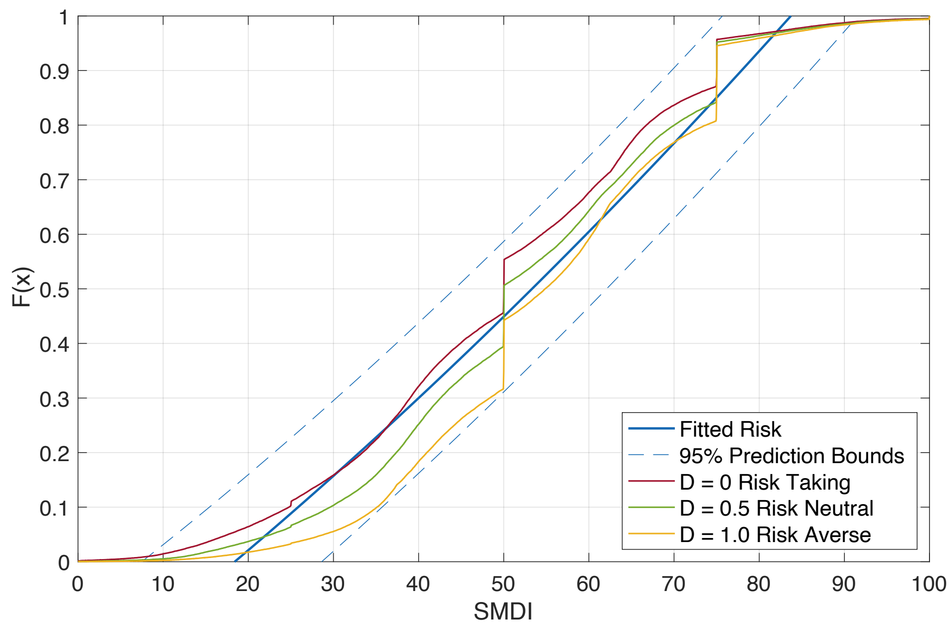


Figure 15. Cumulative Distribution Plot for tactical (a, top), operational (b, middle), and strategic (c, bottom) department levels showing the change in cumulative distribution as decision-maker attitude is altered. The blue dashed lines indicate the 95% prediction bounds for the fitted risk curve.

In the final results for SMDI (Figure 15c), there are two prominent vertical asymptotes at SMDI 50 and SMDI 75. These asymptotes are due to the large percentage of flat surface area on the FIS's produced risk surface (Figure 12b). The risk surface is a visual translation of the determined fuzzy rules for the FIS. These asymptotes can be avoided by adjusting the rules or adding more granularity to the framework through additional membership functions for possible outputs. These vertical asymptotes indicate MDI score ties and can make determining the order to fund facilities a challenge for leadership if the financial funding limit were to fall between multiple assets with equal SMDI. The rules and membership functions for the true system should be calibrated to minimize risk score ties.

Discussion

In addition to adding dimensionality, Inter-Dependency from the operational and strategic levels of a corporation can help facility management teams better understand a facility failure's overall impact. These inputs are valuable for facilities that enable organizational goals beyond the department-level. Figure 16 shows a Low-Medium TMDI score that is transformed into a High-Very High consequence score through the OMDI and SMDI evaluations due to a high degree of operational and strategic Dependency on the facility's mission. This example demonstrates how multiple department-level consequence scores should be taken into consideration during corporate facility prioritization. This example also demonstrates the limitation of the prioritization methodology if it only takes into account the tactical level of knowledge about a facility and the operations it enables. Creating crisp MDI outputs at each hierarchical level within the organization reveals how the risk value differentiation affects the score, enables better risk-based decisions, and increases the understanding of the non-linear impact facility failure may have on the various levels of the organization.

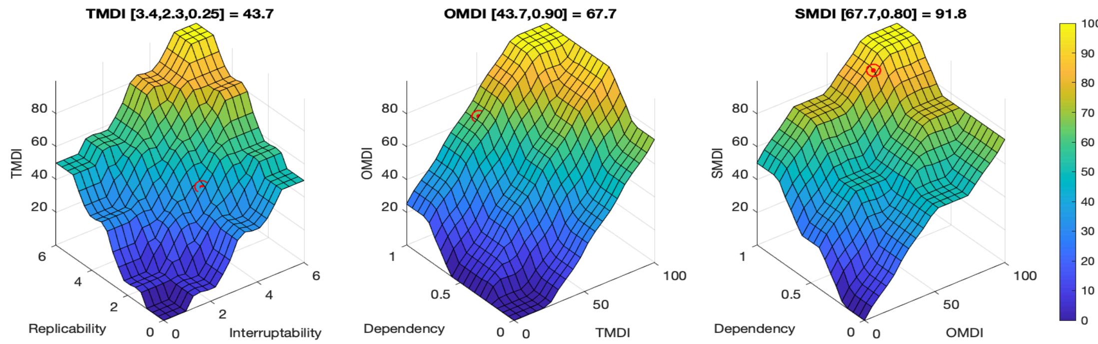


Figure 16. Example of how a facility's tactical MDI score changes when senior-level experts evaluate it. This may indicate the facility operations are secondary to other facilities at the tactical level but critically important to the organization as a whole. This information must be captured for decision-makers to effectively prioritize projects and analyze risk.

The prediction bounds established in the risk attitude sensitivity analysis create a boundary of acceptable risk tolerance for department levels or responding groups. By establishing these boundaries, quality control managers can ensure users are interacting with the system appropriately and portfolio risk profiles are balanced to an acceptable level across operating location and facility type. The resulting prediction bounds were examined at the tactical level for five different Air Force Base locations seen in Figure 17. Base A's resulting cumulative distribution indicates that responses may be too risk-taking for the organization's risk preference, while Base B and Base C may be too risk-averse. The results suggest these three locations require additional review of their responses. After investigation, it was found that Base A had the lowest average TMDI value of all 79 locations in the survey. Base A may be under-valuing its facilities compared to other similar campus locations and may benefit from facility disposal or asset redistribution. For example, Base A is geographically located such that many of the community support functions, e.g., lodging, childcare, grocery, and gym facilities, are replicated off-base by private entities. Divesting these asset types could remedy the graphical result and lower the total operating costs of the base.

Base B and Base C are located in geographically similar locations outside of the United States and require additional critical infrastructure due to their required independence from the local community and proximity to kinetic threat. These points alone may justify the categorial risk aversion, and decision-makers should look for opportunities to re-balance base B and C's risk profile with system redundancies or look to redistribute critical assets to locations within geographic proximity of Bases B and C to mitigate risk-aversion. Base D and E are both within the 95% prediction bounds and suggest that although Base D seems more risk-taking than Base A, the difference in risk attitude is acceptable given the organization's thresholds and the Bases' have a balanced risk profile.

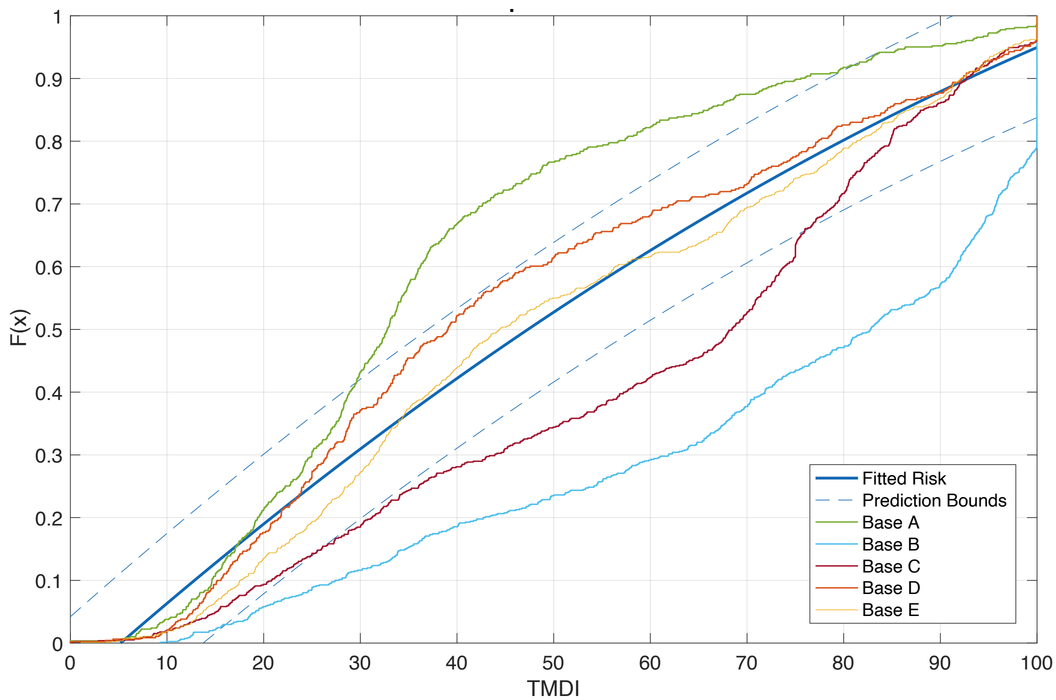


Figure 17. Example of five unique bases TMDI results with the risk boundaries for the cumulative distribution function.

This research's limitations are the multiple assumptions made to simulate data at different corporate hierarchy levels is a significant limitation of this work. Although the system's membership functions and rules were estimated with realism and simplicity in mind, it is the responsibility of the using organization to calibrate the system so results fit their need. These assumptions make it possible to create a consequence of failure risk assessment framework that considers higher hierarchical level objectives. Weighting each hierarchical level is possible to change leadership influence but was not investigated for this research due to the added complexity of inclusion and the formulation's theoretical nature. Future research is needed for different types of organizational hierarchy templates and democratic-autocratic weighting changes.

Due to the application of this methodology within national defense, the protection of SMDI and OMDI data is a necessary requirement and limitation of this research. When directly linking specific assets to an operational or strategic priority, this information can be used not just for the benefit of the organization but also to the benefit of an adversary when looking for system vulnerabilities. This can cause additional costs from security measures needed to protect information and clear access to vetted individuals only.

This framework can prioritize facility projects and identify risk profiles at the tactical, operational, or strategic level. This framework links facilities to the organizational objectives they enable without the use of monetary objectives or profits and can benefit similarly organized public and private entities who have a hierarchical structure, e.g., education, healthcare, corporate, or government agencies. An advantage of using fuzzy logic for the risk assessment is that the system can be easily manipulated to add or change components without additional complexities to the system architect or decision-makers.

Conclusion

Different department levels within a corporation provide valuable information needed to properly quantify a facility's consequence of failure (CoF). This CoF metric can be used to ensure organizations are funding the most critical projects to support their overall objectives (Savatgy et al. 2019). The fuzzy logic-based architecture proposed here is an extension of DePalmer et al.'s framework and case study of the U.S. Air Force's Mission

Dependency Index (MDI) metric (DePalmer et al. 2021). This research is intended to improve the previous project prioritization methodology and aid with risk-based decision support. The inter-Dependency values added to the methodology create openings for the CoF score to change as risk information is aggregated from senior-level departments. These additions eliminate the need for the Air Force's subjective priority point ranking as part of the CoF metric while simultaneously improving the project prioritization methodology to be more accurate and less biased.

Cognitive biases, individual decision styles, and risk attitude can all plague technology-oriented methodologies used for decision support (Phillips-Wren et al. 2019; Power et al. 2019; Tversky and Kahneman 1974, 1992). These individual influences can cause users to choose sub-optimal decisions, which lead to wasted resources or unnecessary facility failure of vulnerable, unfunded projects. The previous methodology was improved by considering these individual biases and determining the possible effects personal risk attitude can have on desired results. These results established acceptable risk thresholds that can identify increased education needs, flag extreme responses, or identify portfolio groups with unbalanced risk profiles.

Portfolio managers and campus leaders need to ensure limited resources are allocated appropriately to campus construction and sustainment projects. Decision-makers need to understand how a facility plays a role in an organization's objectives at all department levels while maximizing the value of information collected and minimizing the time, resources, and complexity required to compare and prioritize projects. The tactical, operational, and strategic MDI metric produced by this system is simple and repeatable and can be used for applications other than project prioritization like balancing the overall risk profile of a location. Decision support tools need to consider how personal biases and attitudes can affect the responses, and quality control specialists must create simple methods to quickly vet responses. This novel framework integrates senior-level department knowledge with a previously created risk assessment methodology to produce a facility prioritization method that meets the needs of decision-makers, portfolio managers, and campus leadership.

IV. Conclusions and Recommendations

Assumptions/Limitations

Fuzzy logic enables computing with words, and this methodology creates an algorithm that converts linguistic variables into realistic results with imprecise data and expert's logical inferences (Lee 1990; Zadeh 1999). Therefore, the FIS results are heavily dependent on the expert opinions used to calibrate the FIS. There is an assumption that the system, as parameterized in this thesis, is built to the organization's satisfaction (Nelson 2019). Although the authors designed the membership functions and risk levels of this framework with realism in mind, AFIMSC must determine the tactical, operational, and strategic level inputs needed to determine the MDI. An MDI focus group of stakeholders with various facility management, risk, and tactical, operational, or strategic mission experience can quickly validate assumptions and determine requirements for the system.

Table **8** shows the steps needed to replace the assumptions made for this framework.

Table 8. Table of Assumptions

Framework Step	**Assumption**	**AFIMSC Determines**
Establish membership functions for inputs	Input Variables	Linguistic Variable Linguistic Terms Universe of Discourse
	Input Membership Functions	Fuzzy Set Range Function Shape
Establish membership functions for outputs	Output Variables	Linguistic Variable Linguistic Terms Universe of Discourse
	Output Membership Functions	Fuzzy Set Range Function Shape
Establish rules for the fuzzy system	Rules	Inference Type Expert Rules

		Defuzzification Method
Evaluate outputs graphically	Validate Fuzzy Risk Surface	System Surface Accurately Represents MDI
	Validate Response	Responses Fit Required Need -True Responses/Data or Expected Distribution of Responses

AFIMSC provided survey results from the four-by-four TMDI matrix (Figure 1); however, the actual crisp inputs used in the FIS are unknown, and chosen distributions were assumed to simulate risk attitude. In Chapter 2, a neutral risk attitude was assumed for the subjective inputs Interruptability and Replicability. These responses were varied in Chapter 3 using triangular distributions to show how different risk attitudes can affect system outputs. These assumptions could be limiting if the true responses do not match the simulated responses used to validate the outputs and build the system. Actual survey responses would be used as crisp inputs to and change the results of this research. AFIMSC's focus group can use these simulated responses or risk attitude distributions to test the system and ensure the outputs align with their objectives or identify unacceptable thresholds for their process.

An additional limitation identified by this research is the need to protect SMDI and OMDI data for national security reasons. Directly linking specific assets to an operational or strategic priority may provide an adversary a list of critical nodes. This threat can incur additional costs from the added security needed to protect data and clear access to vetted individuals for use. A classified military information status may limit the MDI metric's wide-spread application and useability (AFIMSC 2020).

Conclusions of Research

This research investigated the new tactical MDI re-baselining effort by AFIMSC and the opportunities for improvement by applying fuzzy logic. Three investigation questions were studied in this research:

Investigative Question 1: Is fuzzy logic an appropriate methodology for calculating MDI?

Although the Air Force's current process to quantify the MDI is valid, it can be improved to reduce the imprecision, uncertainty, and bias by integrating the existing traditional risk matrix with a modernized fuzzy inference system. Fuzzy logic can combine the MDI's descriptive linguistic terms and imprecise data with the Air Force's value and respect for expert knowledge to create tangible results. A fuzzy system can capture the uncertainty between the risk matrix categories and can be customized to fit the user's needs. The products of a fuzzy inference system can be used for prioritization and risk assessments, with the opportunity to expand the system boundaries and include new inputs for computing operational and strategic level MDI. Assessing the viability of using fuzzy logic for risk assessment was further investigated in Chapter 2. The literature review in Chapter 2 revealed fuzzy logic as an appropriate methodology to integrate with risk assessments, prioritization methodologies, and risk matrices because of their imprecise nature and use of linguistic variables for better understanding of results. Fuzzy logic has also been explicitly applied to military operational risk planning (Nelson 2019). The benefits of using fuzzy logic include the system's customizability to reflect the Air Force's needs and flexibility to changing operational priorities without additional complexities for decision-makers.

Investigative Question 2: What is an appropriate framework for a Fuzzy Inference System (FIS) that could enable assessments of mission risk?

The fuzzy tactical MDI framework was built with AFIMSC's original MDI re-baselining matrix as the foundation to determine the rules, variables, and membership functions, as seen in Chapter 2. The original four-by-four matrix was expanded to increase the range of possible MDI scores and eliminate the need for re-scoring assets below 40. Dependency was added as an input variable to show the ease of flexibility and add dimensionality to the system. Initial MDI survey results were normally distributed to capture the uncertainty between categories and produce realistic results for system validation. The different risk surfaces can be compared in Figure **18**, which shows the additional resolution able to be achieved when using a fuzzy inference system rather than a traditional risk matrix.

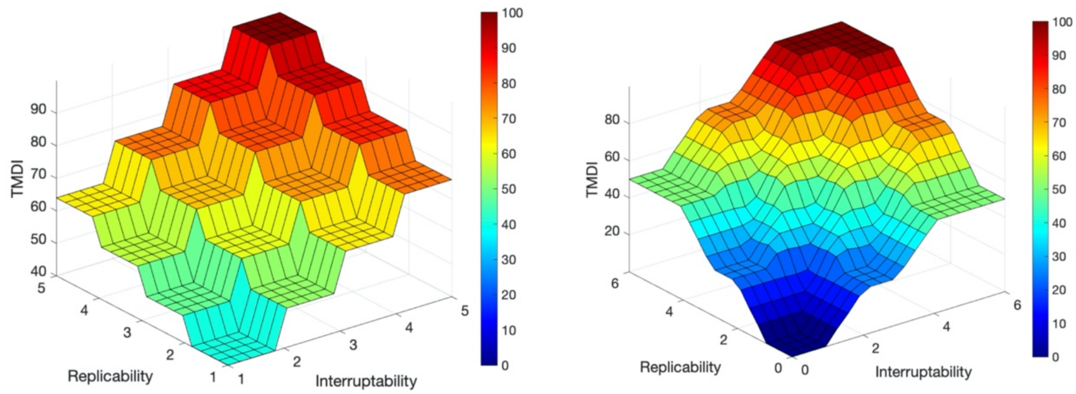


Figure 18. a (left) AFIMSC's TMDI risk matrix surface as compared to b (right) the proposed fuzzy TMDI surface at Dependency = 0.5

In Chapter 3, the authors expanded the MDI metric beyond the original matrix to explore the opportunities to quantify MDI at the operational and strategic levels. This framework produced a series of FISs that used Interruptability, Replicability, and Dependency to output TMDI, OMDI, and SMDI scores. Although Chapter 2 and Chapter 3 propose a framework that assesses a facility's failure risk to mission, the framework must be calibrated by AFIMSC to produce realistic results. Calibration requirements can be seen in **Table 8** and should be determined by Air Force facility management, risk, and mission experts. The calibrated system requirements should be included in future research on this topic.

Investigative Question 3: How can fuzzy logic be used to expand MDI to enable participation by stakeholders from all levels of the organizational hierarchy, e.g., operational and strategic level?

Chapter 3 investigates the opportunity to expand the MDI to include operational and strategic level influence. The research suggests that fuzzy logic is a methodology that is capable of adding assessment criteria without increasing the complexity of understanding the results to decision-makers. This research illustrates this by increasing the informational depth at the tactical level with Inter-Dependency in Chapter 2 and increasing the breadth with Intra-Dependency information at the strategic and operational level in Chapter 3. These additional variables were quickly incorporated into the system, expanding MDI's dimensionality without complicating the results for decision-makers. The framework in Chapter 3 includes operational and strategic knowledge to produce OMDI and SMDI results. Still, these variables could all be independent input variables for a single system merging tactical, operational, and strategic facility data to produce one MDI metric. The authors did not research this single-output-architecture due to stakeholder requests for individual MDI scores at each hierarchy level. The ability to include additional meaningful information without further taxation of decision-maker resources is vital to keep the process simple and repeatable across the entire Air Force or similarly motivated organizations. A significant limitation to the operational and strategic expansion in the Air Force is the need to protect the operational and strategic level data from adversaries.

Significance of Research

Air Force operational risk managers need a reliable methodology to accurately assess the consequence of a facility's failure to strategic objectives and ensure resources are prioritized for the highest-risk projects. The procedure should be a simple and repeatable process that takes into account tactical, operational, and strategic level knowledge about the facility and the mission it enables. The process needs to be resilient to human decision-making biases and risk attitude as well as MDI inflation. This research provides a novel framework for using fuzzy logic to assess risk and quantify the relationship between a facility and the enabled functions.

Unlike traditional risk matrices, fuzzy logic can capture the uncertainties between categorical input classes and use them to determine a low-cost, robust solution. Without capturing uncertainty between categories, the traditional risk matrix produces risk ties that do not provide the resolution needed to distinguish between facilities when decision-making differences exist. For example, if two facilities have a Replicability of "Extremely Difficult", but Facility A has an Interruptability requirement of a 30-minute response, and Facility B needs just under a 24-hour response, both facilities fall within the "Brief" category. The risk matrix (Figure 1) would give both of these facilities an MDI of 80 when clearly, Facility A requires a more critical response than Facility B. Although this example is highly simplified, the complexity is increased if a decision-maker is forced to choose between many facilities with the same risk score. This process becomes even more difficult or impossible without the tactical-level knowledge needed to differentiate multiple facilities.

This framework can be implemented into Air Force asset management practices as a technical backbone for a prioritization methodology or a decision support system. Because the MDI is part of AFIMSC's technical project score, risk score ties can cause zones of uncertainty when it comes to project authorization. By using a fuzzy logic system, these risk ties can be reduced, and the remaining risk ties can be assumed to have an equal consequence to the mission. Reducing risk ties and capturing uncertainty allows the organization to use the methodology to create meaningful prioritizations with ordinal results. This system can be built using MathWork's Fuzzy Logic Toolbox (MathWorks, Inc 2021) and fed crisp inputs employing data collection from existing Real Property databases or mission owner survey responses.

The additional information from the senior-leadership levels and the capture of uncertainty within the categories can allow the Air Force to eliminate the use of CATCODE-based MDI scores. This update ensures there is no need for an adjudication process due to mismatched CATCODE-to-MDI scores. The MDI accurately reflects the facility's consequence to the mission at all levels, based on the function rather than the facility type. This can also be useful when a location's objectives are changed, such as when a new mission is beddown at a base or an old mission is relocated. Previously, these changes would require Base Civil Engineers to re-prioritize their facility type codes to align with the base's new objectives and re-distribute scores for facilities categorized as "Prolonged" Interruptability and "Possible" Replicability. By eliminating the use of CATCODEs within the system, the Air Force can eliminate this need for large-scale re-prioritization.

The value of an MDI score goes beyond a centralized project prioritization for large scale portfolio management. This metric can be used by organization leadership to determine the best use of their resources in many different situations. For example, base defense experts can use MDI to determine which facilities need additional hardening and threat protection. Civil Engineers and communication technicians can use MDI to decide which facilities require redundant systems (such as generators or servers) and in what order to distribute these resources. Tactical leadership can use MDI to authorize or advocate for decentralized funding to sustain, repair, or modernize facilities.

Recommendations for Future Research

Primarily, this research was limited by the availability of expert knowledge about the true MDI membership functions and translating linguistic rules. The resulting framework can be calibrated to fit the Air Force's needs after future research determines the real membership function class, range, and shape of all input and output variables. Additionally, the linguistic rules that translate these inputs to outputs must be attuned to fit the organization's desired results. Once the system is calibrated, products can be created to update a variable's information in the system easily. Crisp inputs can be collected by a graphical user interface (GUI) with tools like a slider bar for subjective values or direct database links to Real Property Inventory Data values, as seen in Figure 19. This interface can be customized to fit the organization's needs and reduce the influence from human decision-making biases or risk attitudes with personalizations such as hiding the final MDI score or junior level Dependency values at higher organizational echelons.

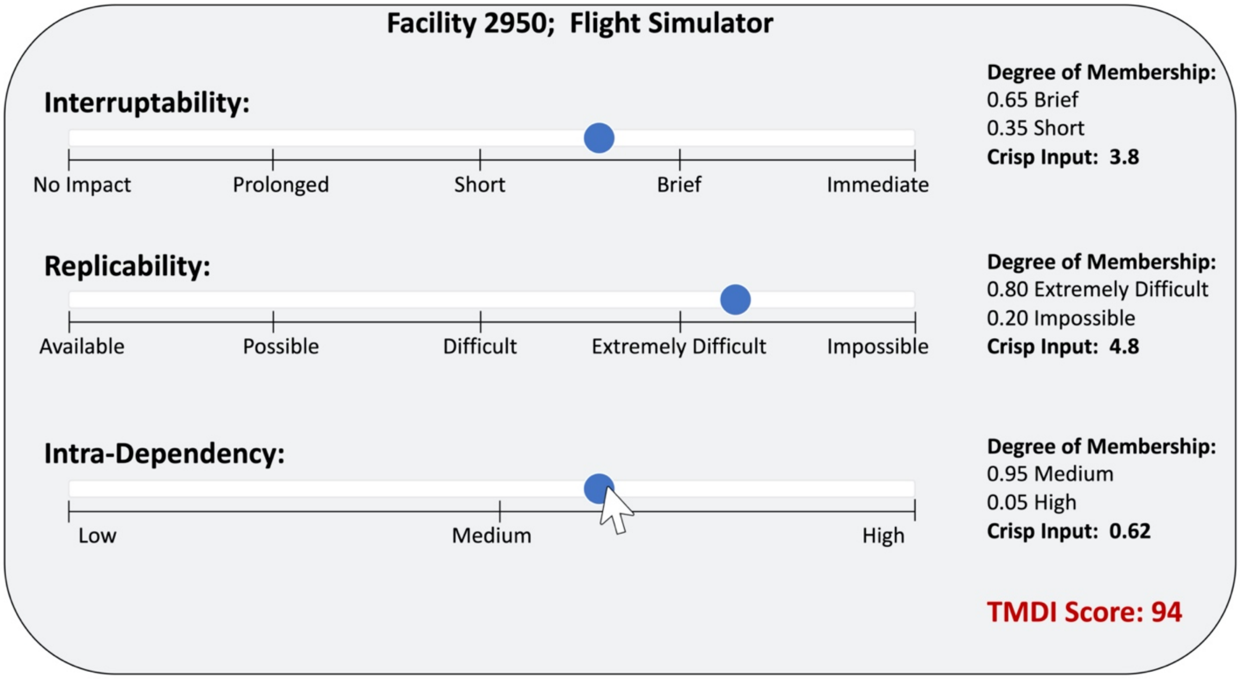


Figure 19. Example graphical user interface to collect crisp inputs for the Fuzzy MDI methodology.

Secondly, additional research is needed for different organizational hierarchy frameworks. The proposed method of a three-tiered organization will not work in all instances. Other hierarchical structures with multiple management levels or shared assets will require additional future research.

Finally, the Air Force should expand the TMDI metric beyond facilities to other infrastructure types such as roads and utilities. These additional infrastructure assets are essential to mission success, and facilities are highly dependent on their operations. Future researchers should determine if Interruptability, Replicability, and Dependency are still appropriate variables for quantifying the MDI of infrastructure. With these future research topics, the Air Force can expand the MDI metric to support better risk-based decision-making and asset management practices.

Appendix A. MATLAB Fuzzy Inference System Code

```
[System]
Name='TMDI'
Type='mamdani'
Version=2.0
NumInputs=3
NumOutputs=1
NumRules=75
AndMethod='min'
OrMethod='max'
ImpMethod='min'
AggMethod='max'
DefuzzMethod='centroid'

[Input1]
Name='Interruptability'
Range=[0 6]
NumMFs=5
MF1='No_Impact':'trapmf',[-1 0 1 2]
MF2='Prolonged':'trimf',[1 2 3]
MF3='Short':'trimf',[2 3 4]
MF4='Brief':'trimf',[3 4 5]
MF5='Immediate':'trapmf',[4 5 6 7]

[Input2]
Name='Replicability'
Range=[0 6]
NumMFs=5
MF1='Available':'trapmf',[-1 0 1 2]
MF2='Possible':'trimf',[1 2 3]
MF3='Difficult':'trimf',[2 3 4]
MF4='Ex._Difficult':'trimf',[3 4 5]
MF5='Impossible':'trapmf',[4 5 6 7]

[Input3]
Name='Dependency'
Range=[0 1]
NumMFs=3
MF1='Low':'trapmf',[-0.3 0 0.2 0.4]
MF2='Medium':'trapmf',[0.2 0.4 0.6 0.8]
MF3='High':'trapmf',[0.6 0.8 1 1.3]

[Output1]
Name='TMDI'
Range=[-25 125]
NumMFs=5
MF1='Very_Low':'trimf',[-25 0 25]
MF2='Low':'trimf',[0 25 50]
MF3='Medium':'trimf',[25 50 75]
MF4='High':'trimf',[50 75 100]
MF5='Very_High':'trimf',[75 100 125]

[Rules]
1 1 2, 1 (1) : 1
```

```
1 2 2, 2 (1) : 1
1 3 2, 2 (1) : 1
1 4 2, 3 (1) : 1
1 5 2, 3 (1) : 1
2 1 2, 2 (1) : 1
2 2 2, 2 (1) : 1
2 3 2, 3 (1) : 1
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[System]
Name='OMDI'
Type='mamdani'
Version=2.0
NumInputs=2
NumOutputs=1
NumRules=15
AndMethod='min'
OrMethod='max'
ImpMethod='min'
AggMethod='max'
DefuzzMethod='centroid'

[Input1]
Name='TMDI'
Range=[0 100]
NumMFs=5
MF1='Very_Low':'trimf',[-25 0 25]
MF2='Low':'trimf',[0 25 50]
MF3='Medium':'trimf',[25 50 75]
MF4='High':'trimf',[50 75 100]
MF5='Very_High':'trimf',[75 100 125]

[Input2]
Name='Dependency'
Range=[0 1]
NumMFs=3
MF1='Low':'trapmf',[-0.1 0 0.2 0.4]
MF2='Medium':'trapmf',[0.2 0.4 0.6 0.8]
MF3='High':'trapmf',[0.6 0.8 1 1.2]

[Output1]
Name='OMDI'
Range=[-25 125]
NumMFs=5
MF1='Very_Low':'trimf',[-25 0 25]
MF2='Low':'trimf',[0 25 50]
MF3='Medium':'trimf',[25 50 75]
```

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MF4='High':'trimf',[50 75 100]
MF5='Very_High':'trimf',[75 100 125]

[Rules]
1 1, 1 (1) : 1
2 1, 1 (1) : 1
3 1, 2 (1) : 1
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4 2, 4 (1) : 1
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5 3, 5 (1) : 1

[System]
Name='SMDI'
Type='mamdani'
Version=2.0
NumInputs=2
NumOutputs=1
NumRules=15
AndMethod='min'
OrMethod='max'
ImpMethod='min'
AggMethod='max'
DefuzzMethod='centroid'

[Input1]
Name='OMDI'
Range=[0 100]
NumMFs=5
MF1='Very_Low':'trimf',[-25 0 25]
MF2='Low':'trimf',[0 25 50]
MF3='Medium':'trimf',[25 50 75]
MF4='High':'trimf',[50 75 100]
MF5='Very_High':'trimf',[75 100 125]

[Input2]
Name='Dependency'
Range=[0 1]
NumMFs=3
MF1='Low':'trapmf',[-0.1 0 0.2 0.4]
MF2='Medium':'trapmf',[0.2 0.4 0.6 0.8]
MF3='High':'trapmf',[0.6 0.8 1 1.2]

[Output1]
Name='SMDI'
Range=[-25 125]
NumMFs=5
MF1='Very_Low':'trimf',[-25 0 25]
```

```
MF2='Low':'trimf',[0 25 50]
MF3='Medium':'trimf',[25 50 75]
MF4='High':'trimf',[50 75 100]
MF5='Very_High':'trimf',[75 100 125]

[Rules]
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2 1, 2 (1) : 1
3 1, 3 (1) : 1
4 1, 3 (1) : 1
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1 3, 3 (1) : 1
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AFIMSC completed an MDI modernization to support better risk-based decision-making by utilizing tactical mission-owner knowledge to quantify the relationship between facilities and the missions they enable. The resulting facility-mission risk scores leave room for improvement for better use of their intended purposes due to (1) the vulnerability of cognitive biases affecting survey responses due to the use of a traditional risk matrix (2) the lack of resolution between scores from risk ties and (3) the failure to include information from the operational and strategic organizational hierarchy level. This research addresses these concerns through the novel implementation of a fuzzy logic system that uses the existing assessment Interruptability and Replicability criteria. Fuzzy logic uses expert knowledge and logical rules, where insufficient data is present, to produce meaningful results more precise and reliable than traditional risk matrices. The Air Force, and other similar organizations, can use the proposed framework to quantify a facility's MDI, prioritize projects, and authorize limited facility sustainment, maintenance, and restoration resources.

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Fuzzy Logic, Mission Dependency Index, Risk Analysis

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