Research Article

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

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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.

1.0 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). In this paper, the authors will refer to the tactical, operational, and strategic level of an organization and the mission it supports. Mission, although typically used in a military or government context, can be interpreted by civilian institutions as the tasks, job, or goals of the company ("Mission" 2021). The tactical level refers to the lowest level of the organization responsible for day-to-day facility operations and the local decision making required to accomplish the mission. The operational level is a higher level of corporate hierarchy, usually responsible for the coordination, definition, and direction of the tactical level, or multiple tactical mission sets. The strategic level is the highest level or corporate hierarchy, with the responsibility of establishing and defending the mission of the organization as a whole and may be responsible for multiple operational missions. In simplistic terms tactical, operational, and strategic levels of management can be used to define the "how" (tactical), "what" (operational), and "why" (strategic) of an organization's mission (White

2009). 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. Interruptability indicates how fast the impact to campus's overall operations would be if functional capabilities of the facility were interrupted. 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 lower 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 higher levels of operation that rely on the facility's operations for mission success. 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) 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.

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

The United States 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 profit-motivated 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 United States Air Force 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). This quantitative method of risk assessment works well with accurate numerical values but can be misleading if engineers are using qualitative and biased data to estimate the PoF or CoF. PoF is determined using historical data from the Air Force's Sustainment Management System BUILDER. BUILDER is a web-based database used to track and project an asset's physical condition using local inspections and typical degradation curves of equipment. The inspection and equipment data are used to create a 1-100 Condition Index (CI) score for each asset in a facility, with a CI of 1 representing significantly degraded, and a CI of 100 indicating an asset in perfect condition. Project justification may include the condition of multiple assets, which are aggregated by a cost-weighted calculation to create an overall condition of the project. This CI score of the project is inversely related to the PoF used in technical scoring. PoF represents the current 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 semi-qualitative metric used by the Department of Defense and other similar government agencies like NASA to quantify 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 a subjective ranking, but 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. Without considering a facility's function, comparing two identical storage facilities by type would result in both receiving the same mission dependency score. This is an inaccurate representation of mission dependency since the first storage building houses necessary and expensive medical equipment and the other houses excess office furniture. Even though both are categorized as conditioned storage warehouses, the function of the facility is necessary to identify an accurate MDI score. The re-scoring by function 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 mission dependency index's operational and strategic value goes beyond project prioritization for AFCEC's integrated priority list. 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.

3.0 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 1 and specifies this research's scope compared to DePalmer et al. (2021). This study makes use of the initial results from the Air Force'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. The tactical mission dependency index output by the initial fuzzy system, was combined with operational level knowledge (Inter-Dependency) and used as crisp (non-fuzzy) inputs for the Operational Mission Dependency Index (OMDI) score. The output OMDI score was then combined with strategic level knowledge (Inter-Dependency) and used as crisp inputs to the Strategic Mission Dependency Index (SMDI) score.

The tactical level MDI score provides information about the Interruptability, Replicability, and Intra-Dependency of a facility (DePalmer et al. 2021). 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

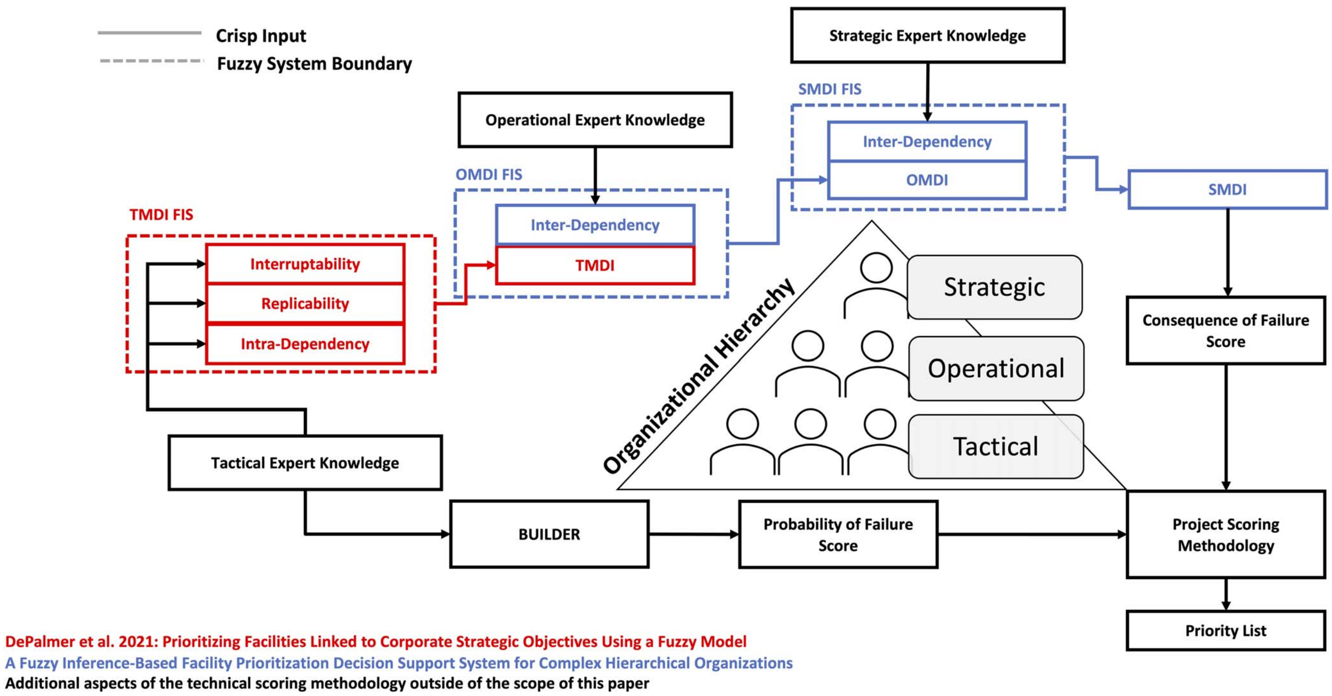


FIGURE 1.—Paper scope and methodology for Strategic Mission Dependency Index (SMDI) creation. The blue text is the focus of this research, and the red text indicates research completed by DePalmer et al. (2021). The black text indicates important aspects of the project technical scoring methodology but is not specifically researched in depth. Fuzzy system boundaries and input variables are marked with a dashed line, while solid lines indicate a crisp input value.

different hierarchical levels from a facility's outage or failure.

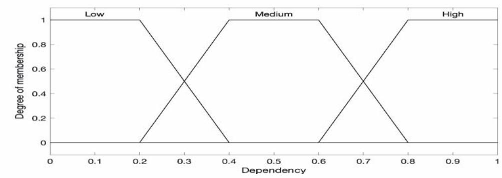
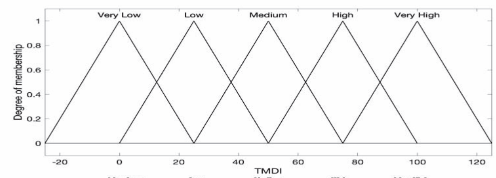
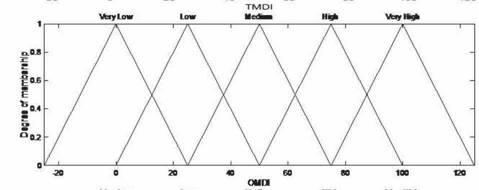
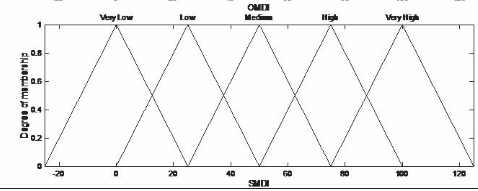
3.1 Building the Operational and Strategic Dependency FIS

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), outputs a crisp TMDI score that 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. Trapezoidal membership functions were used on the boundaries of the system indicating all values above or below this range exist at the highest degree of membership. TMDI and OMDI were divided into five membership functions (Very Low, Low, Medium, High, Very High) 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

TABLE 1.—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	$(75 < \mathrm{VH} \leq 100)$ $(50 < \mathrm{H} < 100)$ $(25 < \mathrm{M} \leq 75)$ $(0 < \mathrm{L} \leq 50)$ $(-25 \leq \mathrm{VL} \leq 25)$	$X_S \in (0,100)$	

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. 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 outer boundaries of Very Low and Very High were set beyond this range so that the centroid method of defuzzification's minimum and maximum values of TMDI would be 0 and 100. The output fuzzy set ranges and established terms are displayed in Table 1. For additional detail on the construction and function of the FIS, readers are directed to DePalmer et al. (2021).

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:

a

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

b

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

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

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 for applicability of the system and shown in Figure 2. 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.

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 2).

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

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 3). 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.

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] (TMDI = 100, Operational Inter-Dependency = 50%) at the Operational level will have the same OMDI score of 100 as a facility classified as [100, 0.90] (TMDI = 100, Operational Inter-Dependency = 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.

3.2 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

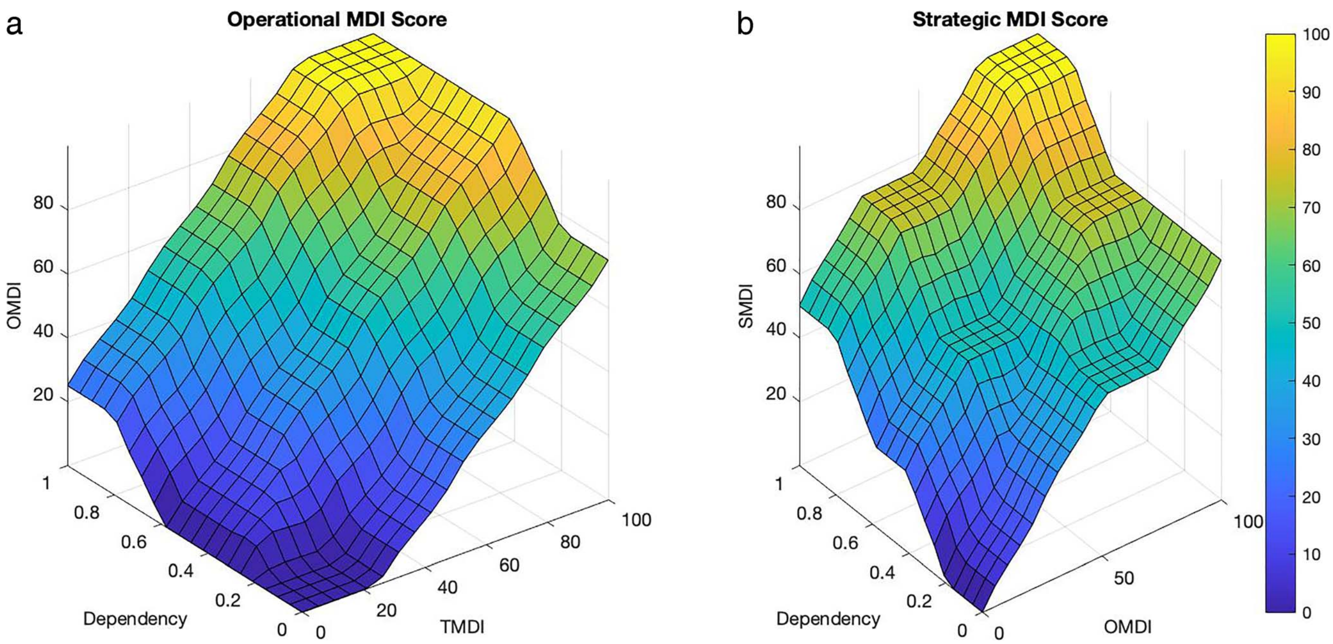


FIGURE 3.—Risk surface plot for a (left) Operational MDI, and b (right) Strategic MDI.

adjusted and calibrated to avoid ambiguity or subjectivity of crisp inputs.

His is correct, thank you for 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 4 shows the simulated response ranges for results within the membership functions, and Table 2 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 3.

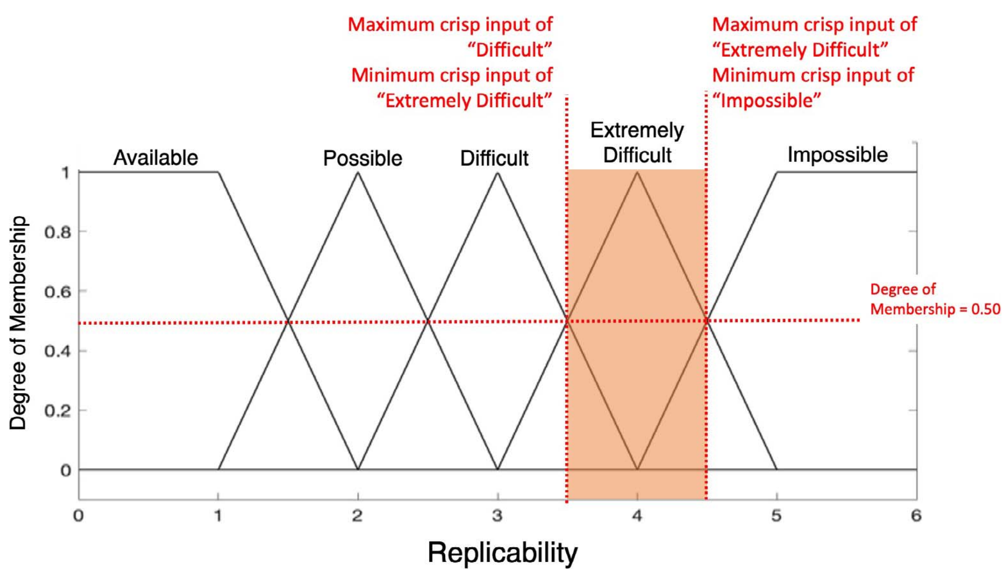


FIGURE 4.—How maximum and minimum limits for triangular distribution were established to simulate crisp inputs for TMDI survey results

TABLE 2.—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
	No Mission Impact	0	0.75
Replicability	Impossible	4.5	5.5
	Extremely Difficult	3.5	4.5
	Difficult	2.5	3.5
	Possible	0.75	2.5
	Available	0	0.75

$$b = a + D(i)(c - a) \tag{3}$$

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.

TABLE 3.—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

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 3. The cumulative distribution of simulated Dependency inputs can be seen with the membership functions overlayed in Figure 5, showing the difference between the tactical, operational, and strategic level distributions. Other distributions would affect the overall results of the sensitivity analysis.

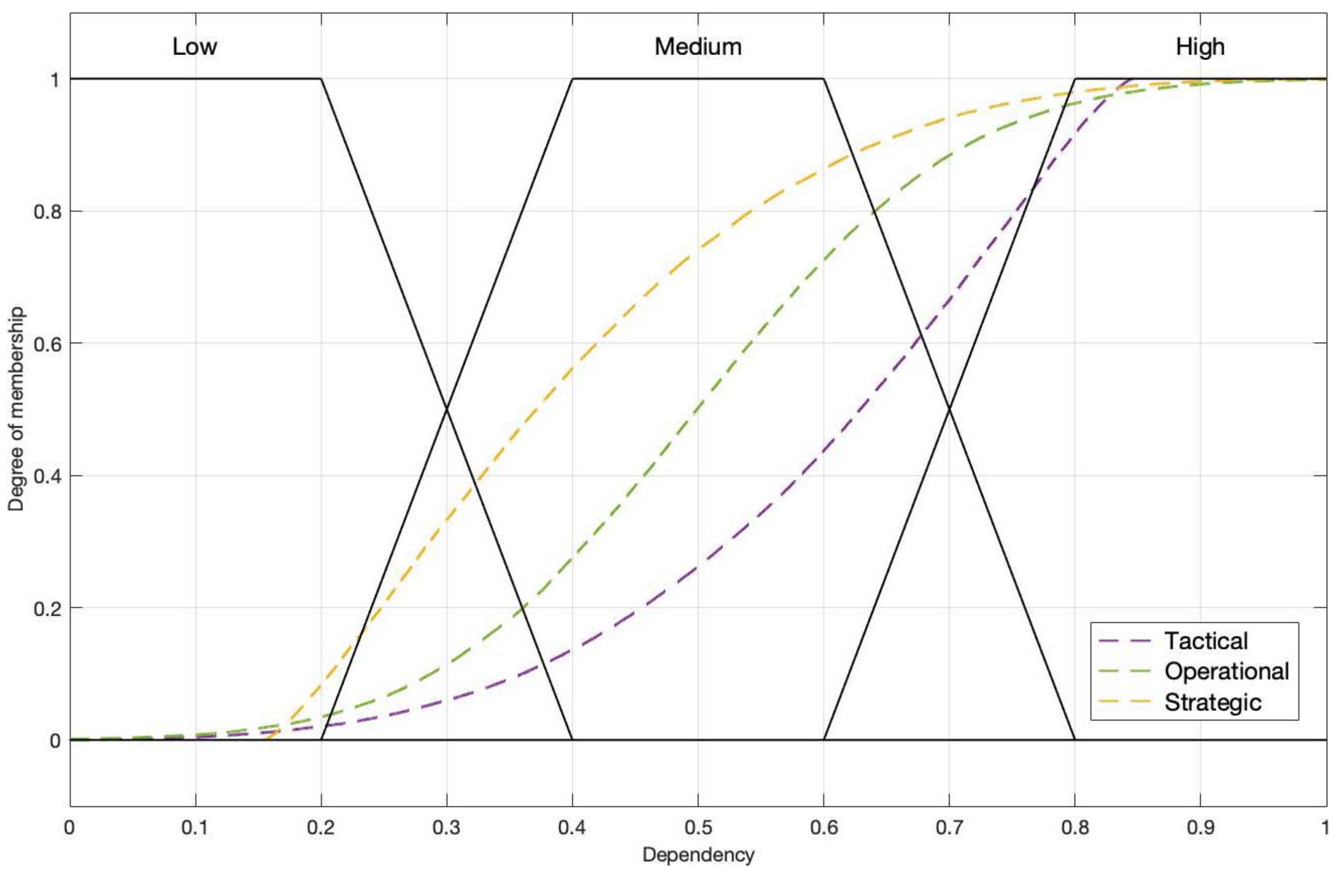


FIGURE 5.—Dependency Cumulative Distribution Function plot, describing the density of each department level's simulated crisp dependency input.

TABLE 4.—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	$p_1 = -3.52\times10^{-5}$ $(-4.19\times10^{-5}, -2.83\times10^{-5})$ $p_2 = 1.37\times10^{-2}$ $(1.30\times10^{-2}, 1.45\times10^{-2})$ $p_3 = -7.04\times10^{-2}$ $(-8.79\times10^{-2}, -5.29\times10^{-2})$	0.96	0.96	1.60	0.06
Operational	$p_1 = -2.64\times10^{-5}$ $(-3.20\times10^{-5}, -2.09\times10^{-5})$ $p_2 = 1.28\times10^{-2}$ $(1.22\times10^{-2}, 1.34\times10^{-2})$ $p_3 = -5.07\times10^{-2}$ $(-6.46\times10^{-2}, -3.68\times10^{-2})$	0.97	0.97	1.14	0.05
Strategic	$p_1 = 3.26\times10^{-5}$ $(1.95\times10^{-5}, 4.57\times10^{-5})$ $p_2 = 1.20\times10^{-2}$ $(1.06\times10^{-2}, 1.34\times10^{-2})$ $p_3 = -0.23$ $(-0.27, -0.20)$	0.94	0.94	2.46	0.07

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.

4.0 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 4, and the results of the expected MDI and the 95% prediction bounds for each hierarchy level can be seen graphically in Figure 6. 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.

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.

In the final results for SMDI (Figure 6c), 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 3b). 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.

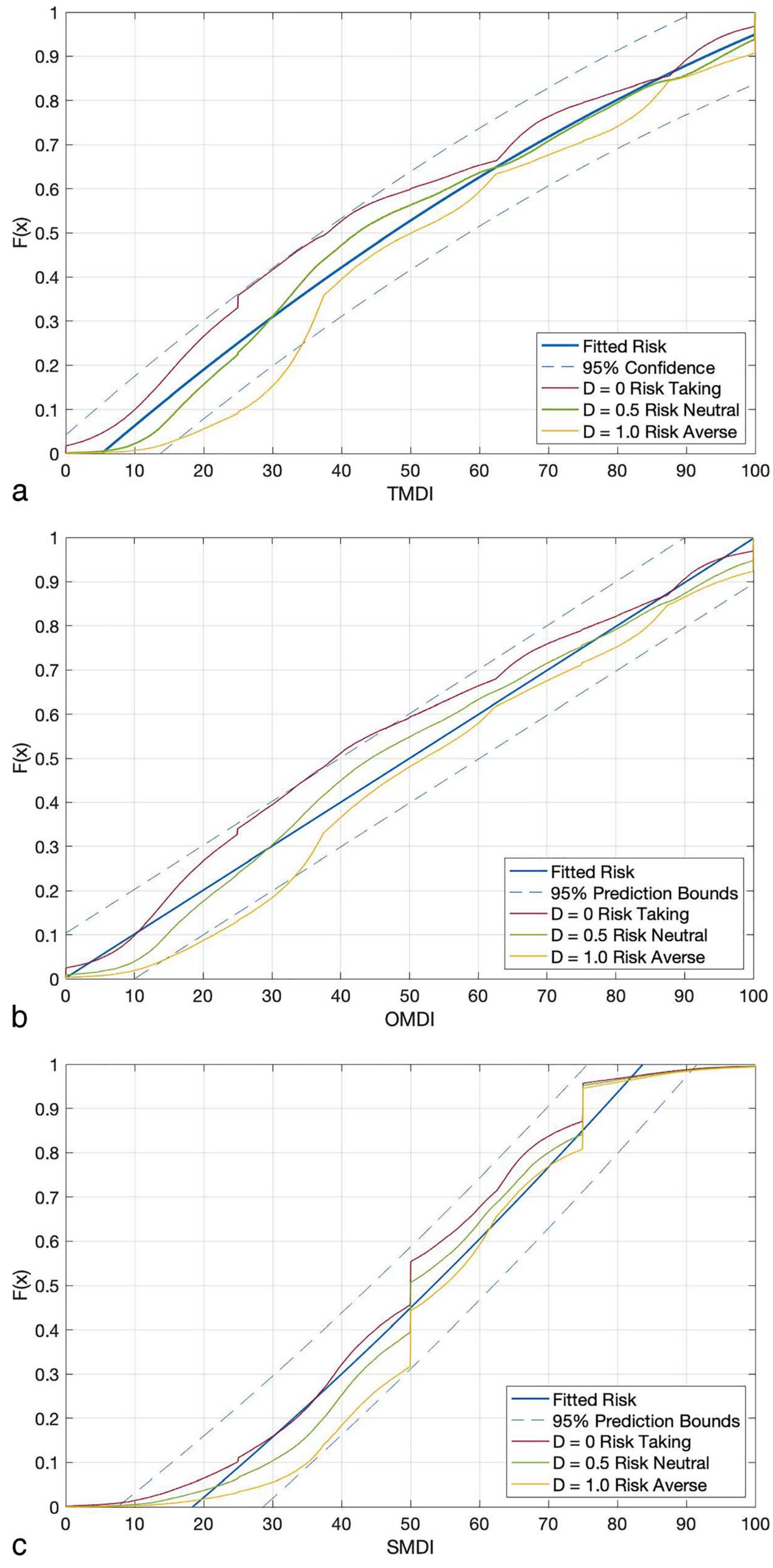


FIGURE 6.—Cumulative Distribution Plot for tactical (a, top), operational (b, middle), and strategic (c, bottom) department levels showing the change in cumulative distribution as decision-maker attitude is altered. The blue dashed lines indicate the 95% prediction bounds for the fitted risk curve.

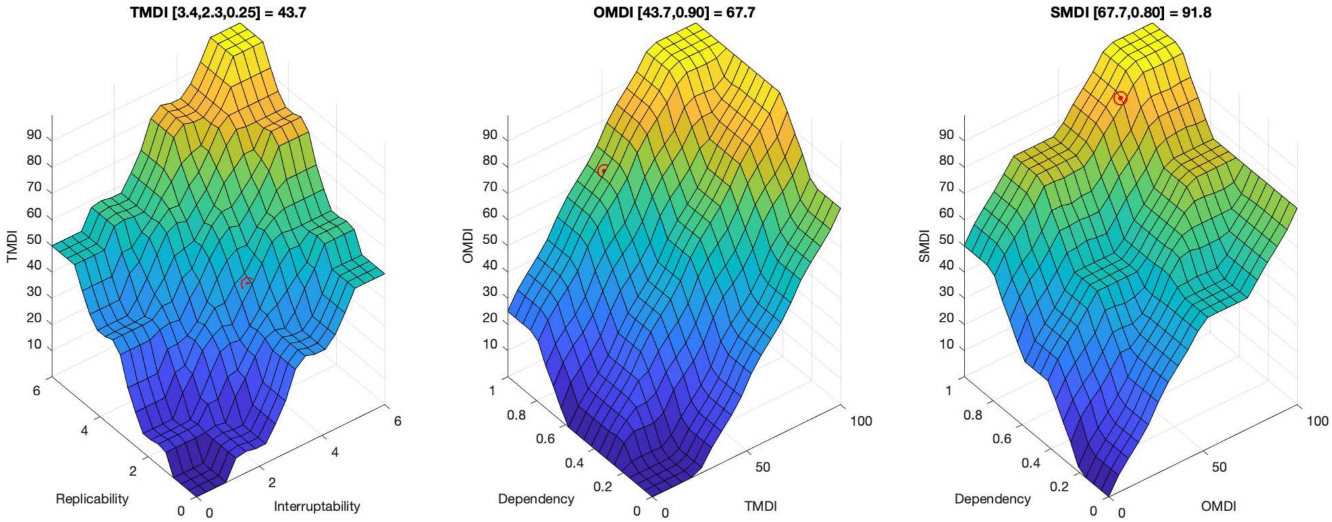


FIGURE 7.—Example of how a facility's tactical MDI score changes when senior-level experts evaluate it. This may indicate the facility operations are secondary to other facilities at the tactical level but critically important to the organization as a whole. This information must be captured for decision-makers to effectively prioritize projects and analyze risk.

5.0 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 7 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.

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 8. 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 E, the difference in risk attitude is acceptable given the organization's thresholds and the Bases' have a balanced risk profile.

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

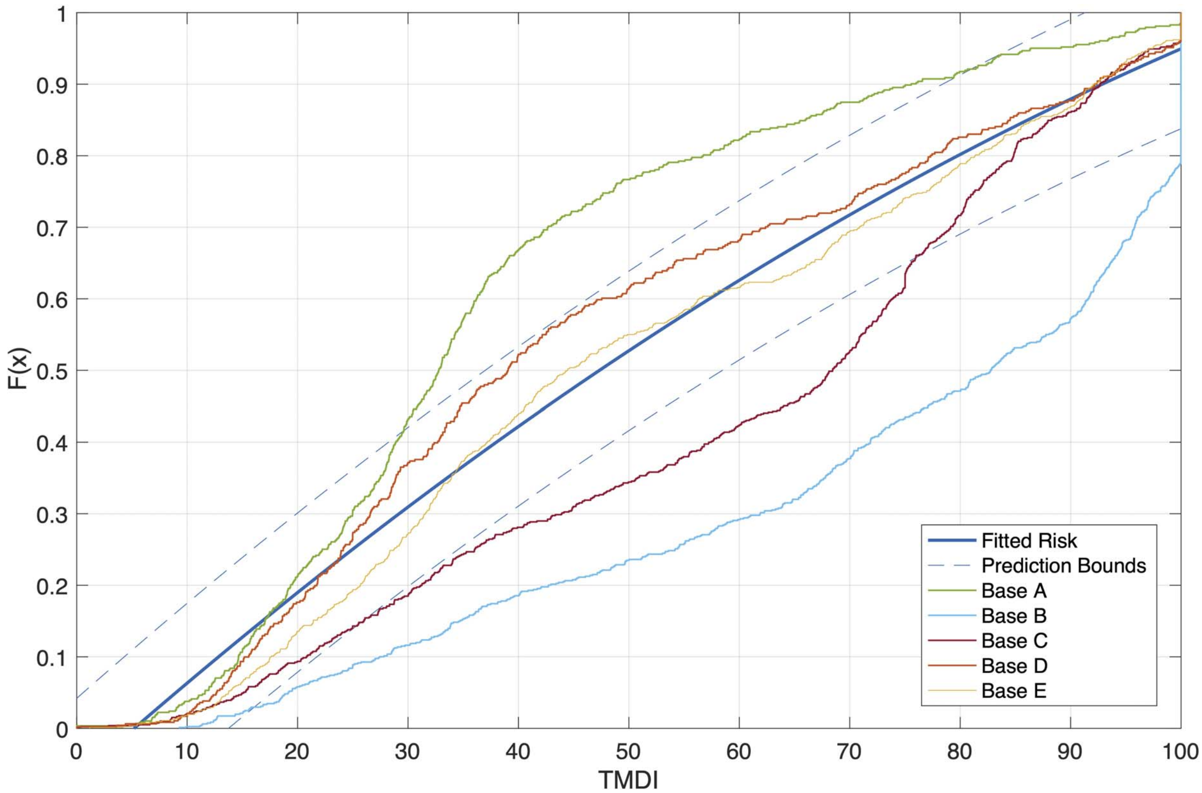


FIGURE 8.—Example of five unique bases TMDI results with the risk boundaries for the cumulative distribution function.

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.

6.0 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. 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 on large- and small-scale facility networks 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 consequence of failure assessment methodology to produce a facility importance metric that meets the needs of decision-makers, portfolio managers, and campus leadership and helps prioritize limited resources.

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