

Prioritizing facilities linked to corporate strategic objectives using a fuzzy model

Devin DePalmer

*Department of Systems Engineering, Air Force Institute of Technology,
Wright-Patterson AFB, Ohio, USA, and*

Steven Schuldt and Justin Delorit

Air Force Institute of Technology, Wright-Patterson AFB, Ohio, USA

Abstract

Purpose – 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 aims to propose a novel facility prioritization methodology that corrects these assessment design and implementation issues.

Design/methodology/approach – 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 US 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.

Findings – 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 an output value.

Originality/value – This paper fills the identified need for portfolio management strategies that focus on prioritizing projects by risk to organizational operations or objectives.

Keywords Fuzzy logic, Facility management, Risk assessment, Prioritization, Consequence, Operational objectives, Mission dependency index, Tactical

Paper type Research paper

1. Introduction

Portfolio and project management within facilities management departments are important and complicated issues in the private and public sectors. Prioritization requires that companies identify,

© Devin DePalmer, Steven Schuldt and Justin Delorit. Published by Emerald Publishing Limited. This article is published under the Creative Commons Attribution (CC BY 4.0) licence. Anyone may reproduce, distribute, translate and create derivative works of this article (for both commercial and non-commercial purposes), subject to full attribution to the original publication and authors. The full terms of this licence may be seen at <http://creativecommons.org/licences/by/4.0/legalcode>

This work was supported by the Air Force Civil Engineer Center [grant number AFIT2020-104].



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 the 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 such as the 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.

1.1 Facility risk management

Risk assessments require decision-makers to think strategically and to problem solve when comparing alternates (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, health-care, 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 and production loss), indirect losses (inconvenience to users, unemployment, social perceptions and 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 \$5m. 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) go 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 such as 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.

1.2 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 used 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 alternates, 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), as 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.

1.3 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 US 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 the 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).

2. Background data and methodology: Linking US air force objectives to project and facility prioritization

Diverse, spatially distributed organizations are plentiful and form the backbone of many industries. The US Department of Defense (DoD) is one of the world's largest industrial complexes. Like many US 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 1) and used the following replicability and interruptability survey questions to elicit facility-by-facility responses from mission owners:

- *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).
- *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).

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

CONSEQUENCE OF FAILURE SCORE					
Severity		Q1: Interruptability			
		Immediate	Brief	Short	Prolonged
Likelihood		< 15 Minutes	< 24 Hours	< 7 Days	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 1.
Traditional TMDI
risk matrix (Savatgy
et al., 2019) describing
the relationship
between
interruptability and
replicability with the
MDI score

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 2). 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.

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 1 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

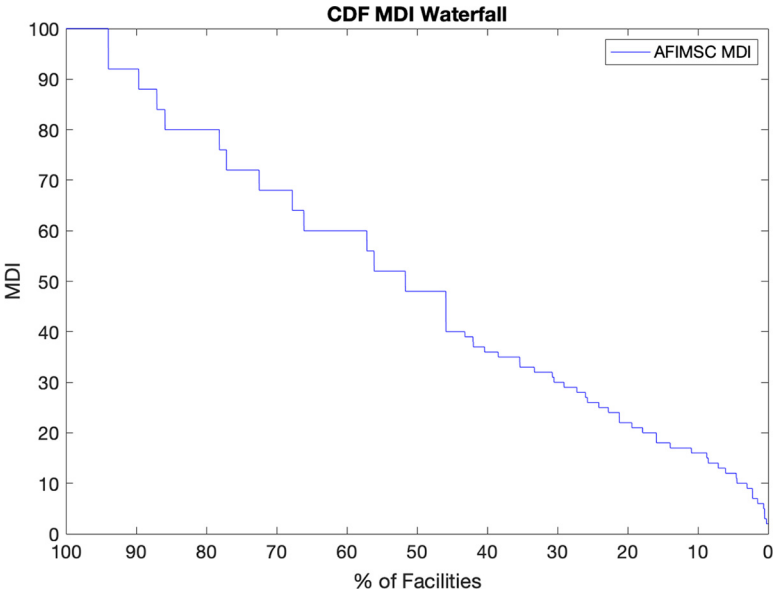


Figure 2. Cumulative density of AFIMSC’s TMDI original survey results. Note, facilities with scores greater than 40 retain a matrix-based score. Those facilities receiving a matrix score of 40 are rescored. This approach produces the inconsistent “step” in the density function

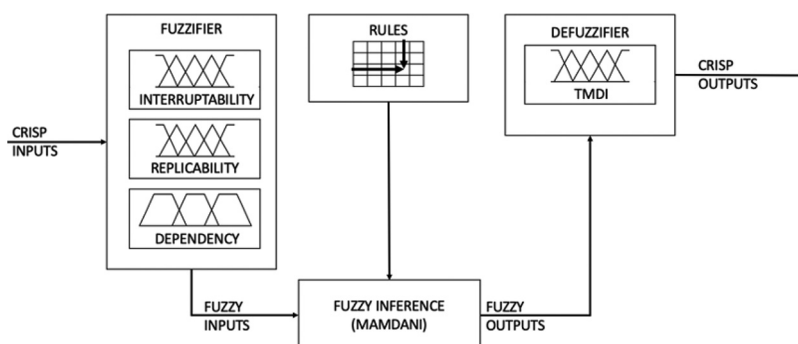
facility improvement projects that compete for funding distributed by the Air Force Civil Engineer Center (AFCEC) (DoD, 2017). The IPL is a list of projects prioritized by a technical score, which indicates a level of risk to the organization if the project goes unfunded. A project's technical score 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.

3. 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 3). 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.

A fuzzy inference system can provide additional information with similar utility and meaningful results using less time and resources for analysis (Mitchell and Carter, 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.



Source: Adapted from Larguech *et al.* (2015)

Figure 3.
Generalized fuzzy
inference system

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; and
- (4) outputs are evaluated graphically to ensure the prioritization of facilities is consistent with decision-maker priorities.

3.1 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 depends 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 Figure 4. 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.

3.2 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

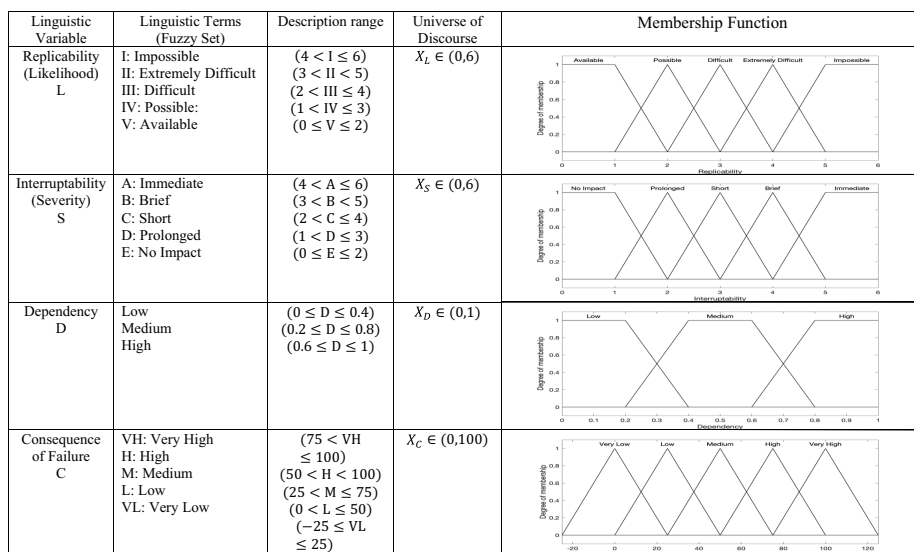


Figure 4.
Fuzzy sets for fuzzy
risk matrix

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. Figure 4 displays the output fuzzy set ranges and established terms.

3.3 Step 3. Establish rules for the fuzzy system

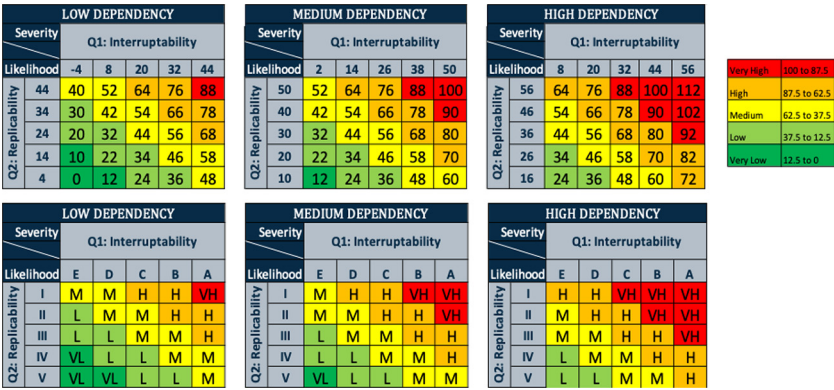
The fuzzy inference system maps fuzzified interruptability, replicability and dependency inputs to outputs to create a crisp TMDI result. The rules established for the inference system determine the actions of the system and are presented simply:

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

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 5). In total, 75 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 1). As the categories were determined to follow a logarithmic scale of classification, an 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

Figure 5.
Dependency levels
(top row) and
corresponding fuzzy
rules (bottom row)



matrix. In the original TMDI matrix, interruptability and replicability scores had a gradient of 12 and 8, respectively (Figure 1). The matrix proposed here is updated such that replicability has a gradient of 10 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.

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)]:

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

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 a dependency, interruptability and replicability change (Figure 6). The different dependency

levels allow for further understanding of consequence and better prioritization when the success or failure of facilities are linked.

3.4 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 toward “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 (Figure 7). 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 8.

4. Results and discussion

The resulting consequence of failure scores seen in Figure 8 are more continuous than the previously seen “steps” in Figure 2. 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

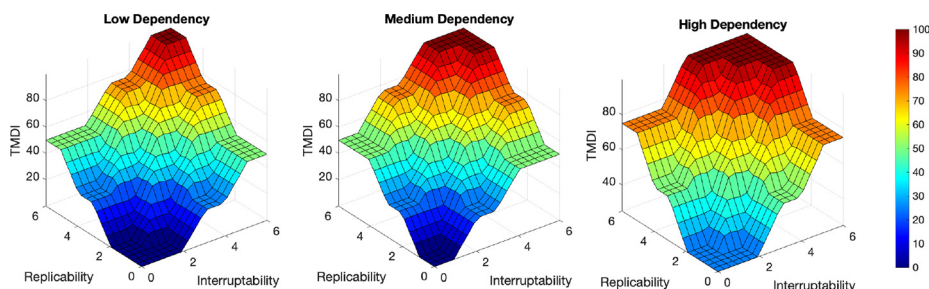
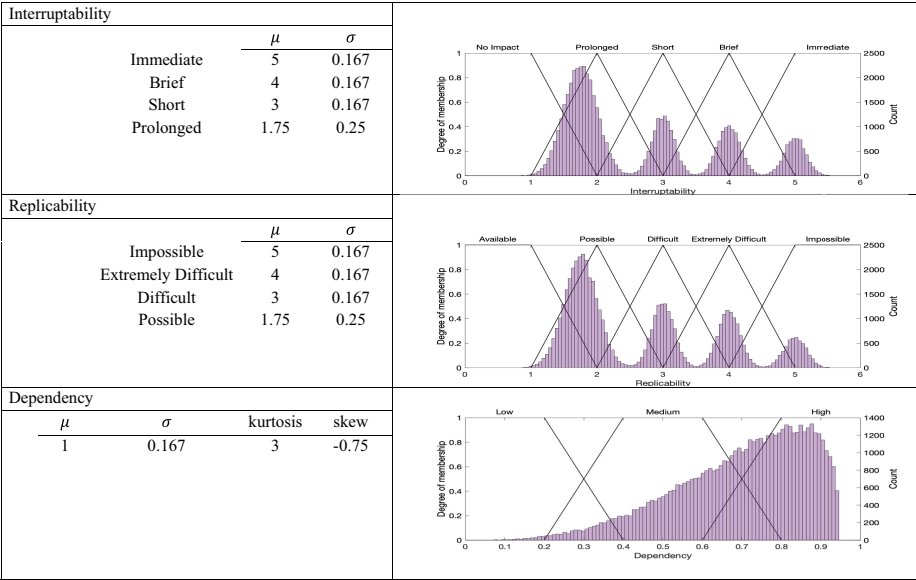


Figure 6.
Fuzzy risk surfaces
for low dependency
(left), medium
dependency (middle),
high dependency
(right)

Figure 7.
Simulated response
distribution
parameters



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.

A review of individual facilities reveals the value of the proposed framework at the facility-scale and 10 example facilities were examined with the fuzzy logic inference system in Table 1. 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, as 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 1). Including the fuzzy logic, the 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. Using 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

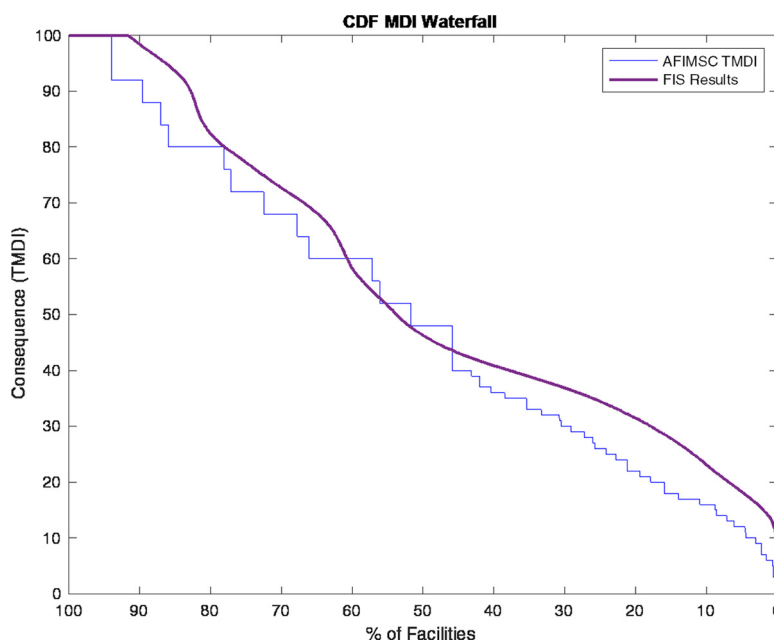


Figure 8.
Cumulative
distribution waterfall
of fuzzy results
plotted with the
original AFIMSC
TMDI scores

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 that must be within a certain distance or response time of medical personnel.

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 reduce 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.

Table 1.
Example scenarios
fuzzy vs traditional
methodology

Example scenarios														
Inputs			Traditional						Fuzzy		Output		Priority	
L	S	D	L	S	D	Fuzzy	Traditional	Fuzzy	Risk level	Traditional	Fuzzy	Traditional	Fuzzy	
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		

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.

5. 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 US 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.

Finally, the purpose of a facility risk assessment and prioritization effort is to distinguish between the importance or consequence of the 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.

References

- Akgun, I., Kandakoglu, A. and Ozok, A.F. (2010), "Fuzzy integrated vulnerability assessment model for critical facilities in combating the terrorism", *Expert Systems with Applications*, Vol. 37 No. 5, pp. 3561-3573, doi: [10.1016/j.eswa.2009.10.035](https://doi.org/10.1016/j.eswa.2009.10.035).
- Amekudzi, A. and McNeil, S. (2008), *Infrastructure Reporting and Asset Management: Best Practices and Opportunities*, American Society of Civil Engineers, Reston, VA, doi: [10.1061/9780784409589](https://doi.org/10.1061/9780784409589).
- Andres, L., Biller, D. and Dappe, M.H. (2016), "A methodological framework for prioritising infrastructure investment", *Journal of Infrastructure Development*, Vol. 8 No. 2, pp. 111-127, doi: [10.1177/0974930616667886](https://doi.org/10.1177/0974930616667886).
- Antelman, A. and Miller, A. (2002), Mission Dependency Index Validation Report NFESC Special Publication SP-2113-SHR.
- Antelman, A., Dempsey, J. and Brodt, B. (2008), "Mission dependency index – a metric for determining infrastructure criticality", *Infrastructure Reporting and Asset Management: Best Practices and Opportunities*, American Society of Civil Engineers, Reston, VA, pp. 141-146, doi: [10.1061/9780784409589](https://doi.org/10.1061/9780784409589).
- Bowles, J.B. and Peláez, C.E. (1995), "Fuzzy logic prioritization of failures in a system failure mode, effects and criticality analysis", *Reliability Engineering and System Safety*, Vol. 50 No. 2, pp. 203-213, doi: [10.1016/0951-8320\(95\)00068-D](https://doi.org/10.1016/0951-8320(95)00068-D).
- Bozbura, F.T. and Beskese, A. (2007), "Prioritization of organizational capital measurement indicators using fuzzy AHP", *International Journal of Approximate Reasoning*, Vol. 44 No. 2, pp. 124-147, doi: [10.1016/j.ijar.2006.07.005](https://doi.org/10.1016/j.ijar.2006.07.005).
- Cox, A. (2008), "What's wrong with risk matrices?", *Risk Analysis*, Vol. 28 No. 2, pp. 497-512, doi: [10.1111/j.1539-6924.2008.01030.x](https://doi.org/10.1111/j.1539-6924.2008.01030.x).

- DoD (2017), Base Structure Report, Fiscal Year 2018 Baseline, Office of the Deputy Assistant Secretary of Defense, p. 204.
- Duijm, N.J. (2015), "Recommendations on the use and design of risk matrices", *Safety Science*, Vol. 76, pp. 21-31, doi: [10.1016/j.ssci.2015.02.014](https://doi.org/10.1016/j.ssci.2015.02.014).
- Faber, M.H. and Stewart, M.G. (2003), "Risk assessment for civil engineering facilities: critical overview and discussion", *Reliability Engineering and System Safety*, Vol. 80 No. 2, pp. 173-184, doi: [10.1016/S0951-8320\(03\)00027-9](https://doi.org/10.1016/S0951-8320(03)00027-9).
- Filho, M.S., Gomes, U.R.P. and Pinheiro, P.R. (2018), "Project portfolio prioritization aided by verbal decision analysis", *2018 13th Iberian Conference on Information Systems and Technologies (CISTI)*, pp. 1-6, doi: [10.23919/CISTI.2018.8399312](https://doi.org/10.23919/CISTI.2018.8399312).
- Grussing, M.N., Gunderson, S., Canfield, M.F., Falconer, E., Antelman, A. and Hunter, S.L. (2010), *Development of the Army Facility Mission Dependency Index for Infrastructure Asset Management*, Construction Engineering Research Laboratory, doi: [10.21236/ada552791](https://doi.org/10.21236/ada552791).
- Hannach, D.E., Marghoubi, R. and Dahchour, M. (2016), "Project portfolio management towards a new project prioritization process", *2016 International Conference on Information Technology for Organizations Development (IT4OD)*, pp. 1-8, doi: [10.1109/IT4OD.2016.7479281](https://doi.org/10.1109/IT4OD.2016.7479281).
- Hertz, D. and Thomas, H. (1982), "Evaluating the risks in acquisition", *Long Range Planning*, Vol. 15 No. 6, pp. 38-44, doi: [10.1016/0024-6301\(82\)90005-X](https://doi.org/10.1016/0024-6301(82)90005-X).
- Hubbard, D. and Evans, D. (2010), "Problems with scoring methods and ordinal scales in risk assessment", *IBM Journal of Research and Development*, Vol. 54 No. 3, pp. 2:1-2:10, doi: [10.1147/JRD.2010.2042914](https://doi.org/10.1147/JRD.2010.2042914).
- International Electrotechnical Commission (2019), *Risk Management: Risk Assessment Techniques*, International Electrotechnical Commission.
- Jamshidi, A., Yazdani-Chamzini, A., Yakhchali, S.H. and Khaleghi, S. (2013), "Developing a new fuzzy inference system for pipeline risk assessment", *Journal of Loss Prevention in the Process Industries*, Vol. 26 No. 1, pp. 197-208, doi: [10.1016/j.jlp.2012.10.010](https://doi.org/10.1016/j.jlp.2012.10.010).
- Kahneman, D. and Tversky, A. (1979), "Prospect theory: an analysis of decision under risk", *Econometrica*, Vol. 47 No. 2, p. 263, doi: [10.2307/1914185](https://doi.org/10.2307/1914185).
- Karlsson, L., Höst, M. and Regnell, B. (2006), "Evaluating the practical use of different measurement scales in requirements prioritisation", *Proceedings of the 2006 ACM/IEEE International Symposium on International Symposium on Empirical Software Engineering – ISESE '06, Rio de Janeiro*, ACM press, p. 326, doi: [10.1145/1159733.1159782](https://doi.org/10.1145/1159733.1159782).
- Karydas, D.M. and Gifun, J.F. (2006), "A method for the efficient prioritization of infrastructure renewal projects", *Reliability Engineering and System Safety*, Vol. 91 No. 1, pp. 84-99, doi: [10.1016/j.res.2004.11.016](https://doi.org/10.1016/j.res.2004.11.016).
- Kujawski, E. and Miller, G. (2009), "The mission dependency index: fallacies and misuses", *INCOSE International Symposium*, Vol. 19 No. 1, pp. 1565-1580, doi: [10.1002/j.2334-5837.2009.tb01035.x](https://doi.org/10.1002/j.2334-5837.2009.tb01035.x).
- Larguech, S., Aloui, S., Pagès, O., El Hajjaji, A. and Chaari, A. (2015), "Fuzzy sliding mode control for turbocharged diesel engine", *Journal of Dynamic Systems, Measurement, and Control*, Vol. 138 No. 1, doi: [10.1115/1.4031913](https://doi.org/10.1115/1.4031913).
- Lee, C.C. (1990), "Fuzzy logic in control systems: fuzzy logic controller. I", *IEEE Transactions on Systems, Man, and Cybernetics*, Vol. 20 No. 2, pp. 404-418, doi: [10.1109/21.52551](https://doi.org/10.1109/21.52551).
- Li, J., Bao, C. and Wu, D. (2018), "How to design rating schemes of risk matrices: a sequential updating approach: how to design rating schemes of risk matrices", *Risk Analysis*, Vol. 38 No. 1, pp. 99-117, doi: [10.1111/risa.12810](https://doi.org/10.1111/risa.12810).
- Markowski, A.S. and Mannan, M.S. (2008), "Fuzzy risk matrix", *Journal of Hazardous Materials*, Vol. 159 No. 1, pp. 152-157, doi: [10.1016/j.jhazmat.2008.03.055](https://doi.org/10.1016/j.jhazmat.2008.03.055).
- Mitchell, H.A. and Carter, J.C. III (1993), "Applications of fuzzy ranking methods to risk-management decisions", in Bosacchi, B. and Bezdek, J.C. (Eds). *Applications of Fuzzy Logic Technology*, International Society for Optics and Photonics, Boston, MA, doi: [10.1117/12.165029](https://doi.org/10.1117/12.165029).

- Moazami, D., Behbahani, H. and Muniandy, R. (2011), "Pavement rehabilitation and maintenance prioritization of urban roads using fuzzy logic", *Expert Systems with Applications*, Vol. 38 No. 10, pp. 12869-12879, doi: [10.1016/j.eswa.2011.04.079](https://doi.org/10.1016/j.eswa.2011.04.079).
- National Research Council (2004), *Investments in Federal Facilities: Asset Management Strategies for the 21st Century*, National Academies Press, Washington, DC, doi: [10.17226/11012](https://doi.org/10.17226/11012).
- Nelson, C.B. (2019), "Fuzzy inference systems for risk appraisal in military operational planning", The Air Force Institute of Technology, The Air Force Institute of Technology, available at: <https://scholar.afit.edu/etd/2311>
- Nichols, M.J. (2015), "A delphi study using value-focused thinking for United States air force mission dependency index values", The Air Force Institute of Technology, Wright Patterson Air Force Base, OH, available at: <https://scholar.afit.edu/etd/159>
- Radu, L.D. (2009), "Qualitative, Semi-Quantitative and, quantitative methods for risk assessment: case of the financial audit", *Analele Stiintifice Ale Universitatii "Alexandru Ioan Cuza" Din Iasi – Stiinta Economice*, Vol. 56, pp. 643-657.
- Savatgy, D. Brown, M. Reimann, M. Witherspoon-Rivera, D. and Heron, J. (2019), "USAF MDI sustainment playbook".
- Shaygan, A. and Testik, Ö.M. (2019), "A fuzzy AHP-based methodology for project prioritization and selection", *Soft Computing*, Vol. 23 No. 4, pp. 1309-1319, doi: [10.1007/s00500-017-2851-9](https://doi.org/10.1007/s00500-017-2851-9).
- Smith, E.D., Siefert, W.T. and Drain, D. (2009), "Risk matrix input data biases", *Systems Engineering*, Vol. 12 No. 4, pp. 344-360, doi: [10.1002/sys.20126](https://doi.org/10.1002/sys.20126).
- Tversky, A. and Kahneman, D. (1992), "Advances in prospect theory: cumulative representation of uncertainty", *Journal of Risk and Uncertainty*, Vol. 5 No. 4, pp. 297-323.
- Weniger, R. (2020), "Interview with russ weniger".
- Zadeh, L.A. (1965), *Information and Control*, Vol. 8 No. 3, pp. 338-353, doi: [10.1016/S0019-9958\(65\)90241-X](https://doi.org/10.1016/S0019-9958(65)90241-X).
- Zadeh, L.A. (1999), "Fuzzy logic = computing with words", in Lotfi, A.Z. and Kacprzyk, J. (Eds), *Computing with Words in Information/Intelligent Systems 1: Foundations*, Physica-Verlag HD, Heidelberg, pp. 3-23, doi: [10.1007/978-3-7908-1873-4_1](https://doi.org/10.1007/978-3-7908-1873-4_1).

Corresponding author

Devin DePalmer can be contacted at: Devin.depalmer@gmail.com

For instructions on how to order reprints of this article, please visit our website:

www.emeraldgroupublishing.com/licensing/reprints.htm

Or contact us for further details: permissions@emeraldinsight.com