Proceedings Paper:
Proma, Nawshin Mannan, Bin Firoz, Hasan, PATERSON, Colin et al. (2026) Fuzzifying the Operational Design Domain: A Scalable Situation Hyperspace Generation. In: 2026 IEEE International Conference on Fuzzy Systems (FUZZ-IEEE). Proceedings of the IEEE International Conference on Fuzzy Systems. IEEE. (In Press)

Fuzzifying the Operational Design Domain: A Scalable Situation Hyperspace Generation

Nawshin Mannan Proma , Hasan Bin Firoz, Colin Paterson, Richard Hawkins, Victoria Hodge and Rob Alexander
Department of Computer Science
University of York
York, United Kingdom
{nawshinmannan.proma, hasan.binfiroz, colin.paterson, richard.hawkins, victoria.hodge, rob.alexander}@york.ac.uk

***Abstract*—Underground mine environments present complex conditions for autonomous systems, including narrow tunnels, variable lighting, and dynamic obstacles. In the design phase, ensuring the safety of critical drone systems under the vast and uncertain Operational Design Domain (ODD) of an underground mine is practically impossible through exhaustive testing alone. Our work proposes a fuzzy logic-based approach to focus testing by constructing a hyperspace from the ODD that prioritizes high-risk situations to test at the design phase efficiently. We demonstrate how this approach prioritizes critical test cases and minimizes redundant evaluations of low-risk situations. The resulting framework enhances safety testing in mining operations and can be extended to other safety-critical systems facing similar challenges of scale and uncertainty. The proposed fuzzy-logic-based approach reclassifies many test cases that would be labeled as high risk under a disjoint method into medium-risk categories by allowing gradual transitions between risk levels, enabling more fine-grained risk assessment and more effective risk-based test prioritization while maintaining coverage of hazardous situations.**

***Index Terms*—fuzzification, situation hyperspace, verification, safety testing, critical systems**

I. INTRODUCTION

Mining operations represent one of the most hazardous industrial environments, where dynamic and unpredictable conditions such as unstable geological structures, limited visibility, moving equipment, and environmental constraints pose significant risks to both personnel and infrastructure. In the literature, the complexity of these complex operating conditions for autonomous road vehicles is typically captured through Operational Design Domain (ODDs) [1]–[3]. The international driving automation standard SAE J3016 [1] defines ODD as *"Operating conditions under which a given driving automation system or feature thereof is specifically designed to function, including, but not limited to, environmental, geographical, and time-of-day restrictions, and/or the requisite presence or absence of certain traffic or roadway characteristics"*. While much of the existing literature focuses on road-based autonomous vehicles and the associated ODDs for on-road driving, comparatively little research has addressed ODD specification for other domains [4], such as autonomous drones operating within underground mining environments. Our work addresses this gap by extending the ODD concept to an underground mine setting.

In our case, the ODD for the underground mine environment (for the full ODD, see [5]) integrates multidimensional parameters, including structural features (e.g., corridor width, ceiling height), environmental factors (e.g., lighting, air quality), and operational elements (e.g., static and dynamic obstacles). However, the sheer scale and combinatorial nature of ODDs make exhaustive safety testing impractical, if not impossible [6], [7].

Rigorous testing of these ODDs is vital for ensuring safety and functional reliability. Traditional testing methodologies, particularly those derived from Hazard and Operability studies (HAZOP) [8], [9] and Failure Mode Effect Analysis (FMEA) [10], are fundamentally limited in this context. While invaluable for initial hazard identification, HAZOP based testing is inherently qualitative and struggles with the combinatorial explosion of states within a large ODD [7], [11], [12]. It relies on experts brainstorming potential failures using guide words (e.g.,"No," "More," "Less," "Part of") applied to system parameters. HAZOP becomes overwhelmingly complex for high dimensional systems. HAZOP and FMEA have long been criticized for their inability to predict emerging risks in complex, high-dimensional systems. These approaches rely heavily on inductive reasoning from past accidents and incidents, meaning they are often "trapped" in historical data and struggle to anticipate novel or unforeseen hazards [12], [13]. Moreover, their binary classifications (e.g., safe/unsafe, valve open/closed) and rigid formalism limit their capacity to capture real-world ambiguity and the graded nature of risk [13]. HAZOP typically deals in binary states. A valve is either "open" or "closed." A corridor is either "narrow" or "not narrow." It struggles with partial or degraded states (e.g., "mostly dark" or "somewhat narrow").

Our work proposes a move towards a systematic, quantitative, and automated approach for risk-based test case selection by constructing a situation hyperspace [14]–[16] through fuzzy logic [17]. In [18], 'situation' is defined as '*the entirety of circumstances which are to be considered by a robot for its selection of an appropriate behavior pattern in a particular moment.*' Building on this definition of situation, we aim to operationalize it by generating a fuzzy-powered situation hyperspace that quantifies and structures the ODD into a systematic, parameterized form.

We adopt ISO 34504:2024's tag-based scenario categorization [19], which transforms the often abstract ODD into a concrete, parameterized model. In ISO 34504:2024, scenario categorization (SC) is presented not only as a way to organize test cases for autonomous driving system but also as an essential bridge between an ODD's high-level definition and the vast combinatorial space of possible operating conditions. This scenario categorization is conceptually equivalent to our 'situation hyperspace' [20], as both systematically organize environmental factors, system states, and external influences to represent the combinatorial space of possible autonomous system situations.

In our case, we extended the ALOFT testbed [21] which simulates a PX4-based drone [22] flying inside a mine environment simulated using the Gazebo classic simulator [23]. ALOFT testbed is derived from scans of a representative mock-mine environment that features narrow passageways, hanging ropes, and various static obstacles inside the mine. In this scenario, the PX4 drone is deployed and manually piloted to perform a surveying task inside the mine, where both corridor width and lighting conditions can vary. Given a PX4 drone with dimensions of approximately $0.47\,\mathrm{m}$ (width) $\times$ $0.47\,\mathrm{m}$ (length) $\times$ $0.11\,\mathrm{m}$ (height), inspecting inside a corridor of $1.8\,\mathrm{m}$ width may be classified as "narrow" in certain operational contexts and "acceptable" in another, depending on lighting, obstacle presence, or operator experience. In contrast, a fuzzy approach can represent such variations naturally. For example, rather than assigning a corridor of 1.5 m width to a binary category ("narrow" = 1, "not narrow" = 0), fuzzy logic assigns a degree of membership, i.e., "narrow" with 0.7 confidence and "not narrow" with 0.3. If lighting is poor, the "narrow" membership might increase to 0.9, automatically reflecting higher perceived risk. This gradation allows the system to deal with uncertainty in a way that mirrors human judgment but scales computationally across thousands of situations.

Fuzzy-powered situation hyperspace excels on high-dimensional data. The fuzzy inference engine evaluates all parameter interactions simultaneously based on the pre-defined rules (detailed in the next section). Based on the rule-based evaluation, the hyperspace construction then identifies the most critical combinations without manual effort. In contrast to HAZOP, which provides a static snapshot of hazards at a given point in time, a fuzzy situation hyperspace has the potential to function as a dynamic and evolving safety model. As new sensor data from the mine is collected, the membership functions and rules can be refined. The hyperspace can then be updated to reflect real world measured conditions, making the model smarter over time.

Our approach is not without limitations, as its effectiveness depends on the quality and completeness of the expert-defined membership functions and rule base, and like other formalized methods, it may miss entirely novel hazards lying outside the scope of the modeled ODD. Thus, the fuzzy hyperspace should be seen not as a replacement but as a complementary methodology that extends and strengthens traditional risk analysis and safety testing of critical systems.

The main contributions of this paper are as follows:

- We introduce a novel approach to transform ODD parameters into linguistic fuzzy sets, enabling fine-grained reasoning about risk in situations where disjoint and binary classifications (e.g., safe/unsafe) are insufficient.
- We propose the construction of a situation hyperspace that systematically maps ODD parameters to risk values, allowing scalable identification of high-risk regions while avoiding combinatorial explosion.
- We evaluate the effectiveness of the fuzzy-powered situation hyperspace by comparing it against a disjoint sampling-based hyperspace, demonstrating improved efficiency and risk-sensitive test case selection.[1]

The next sections detail the overall framework for constructing the fuzzy-based situation hyperspace, followed by an evaluation of its effectiveness against the disjoint model.

II. FUZZY-POWERED SITUATION HYPERSPACE

This research develops a methodology for constructing a *situation hyperspace* from an *ODD* model to support systematic, risk-informed safety testing of an autonomous drone in a mine environment. Figure 1 presents the overall strategy. To make the process concrete, we illustrate it with an initial and simple example of a corridor navigation task where a drone (0.47m in width in this case) must operate safely under varying corridor widths and lighting levels inside a mine. For clarity and ease of understanding, the proposed framework is divided into two subsections, each of which is briefly described below.

A. ODD Knowledge and Risk Factor Identification

In this example, we identify corridor width and lighting level as representative risk factors derived from the ODD. We focus on these two factors for simplicity in this initial work, but the framework can be extended in future work to include additional parameters or a more detailed set of conditions. These factors directly influence the drone's perception reliability and maneuvering safety during indoor navigation. Corridor width defines the available free space for lateral movement. Narrow corridors reduce the drone's clearance margin relative to its width, thereby increasing the likelihood of wall proximity, collision, or instability due to air turbulence near surfaces. Additionally, low light levels can degrade feature extraction, delay obstacle recognition, and that leads to safety violations. Although multiple other factors such as the drone's speed, sensor noise, air flow disturbances, or presence of dynamic obstacles might increase risk, we restrict our focus here to corridor width and light level for ease of understanding. The same reasoning and modeling process can be systematically extended to other risk factors (i.e., dust/wind) in future work.

B. Situation Hyperspace and Fuzzy Inference Framework

To manage uncertainty and imprecision in environmental parameters, sensor readings, given as precise numerical values

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[1] https://github.com/uoy-research/FuzzyODD.git.

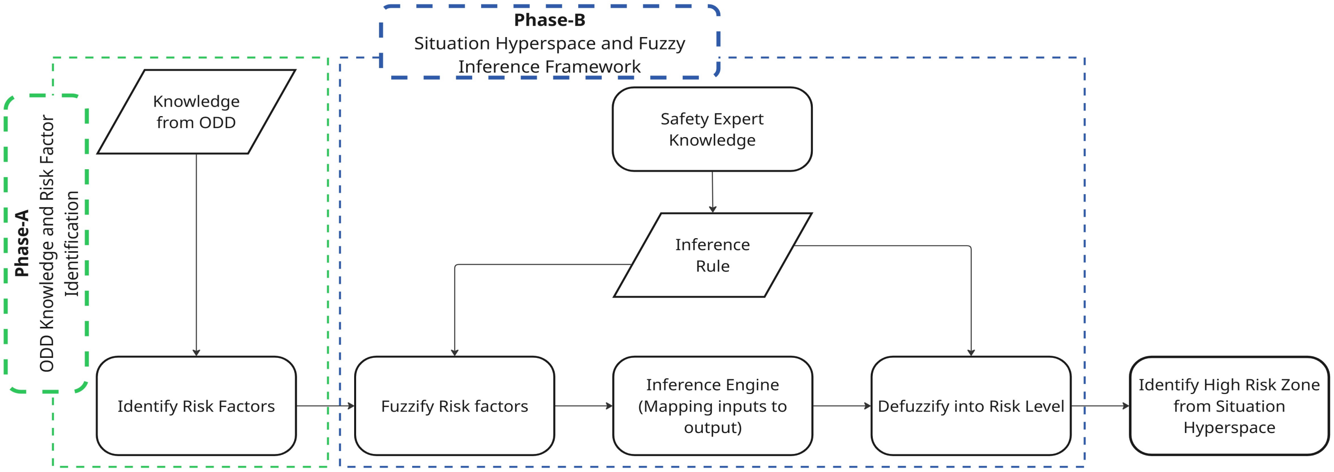

Fig. 1: Overall framework for fuzzy-based situation hyperspace construction.

are quantised into fuzzy sets that capture graded degrees of membership across multiple linguistic categories (e.g., *narrow*, *medium*, *wide* for corridor width) using MATLAB [24].

For each linguistic label, a *membership function* is designed which converts a crisp input value into a degree of membership in the range $[0, 1]$. These functions are typically defined using expert knowledge, observations, or design heuristics. In this example, corridor width and lighting intensity are modeled using fuzzy linguistic variables. As there is limited prior work on defining fuzzy membership functions and rules for drones operating in underground mining environments, our design is inspired by established practices in mobile robot perception, where fuzzy modeling is commonly used to handle sensory uncertainty [25], [26]. Indoor lighting levels below 40 lux are generally considered low for robotic perception, motivating the selected low-light membership functions here [27].

For example, let us assume membership functions for corridor width defined as follows (See figure 2):

- *Narrow*: trapezoidal spanning 0–2.5 m, peak from 0–1 m.
- *Medium*: triangle spanning 1–4 m, peak at 2.5 m.
- *Wide*: trapezoidal spanning 2.5–5 m, peak from 4 m.

When the input is 1.5 m, the intersection with these membership functions yields:

$$\mu_{\text{Narrow}}(1.5) = 0.7, \quad \mu_{\text{Medium}}(1.5) = 0.3, \quad \mu_{\text{Wide}}(1.5) = 0.$$

This indicates that the corridor is mostly characterized as *narrow* but also partially *medium*.

Similarly, for lighting intensity with trapezoidal membership functions in figure 2:

- *Dark*: trapezoidal spanning 0–40 lux, peak from 0-8 lux.
- *Dim*: trapezoidal spanning 20–140 lux, peak from 40-80 lux.
- *Wide*: trapezoidal spanning 80–200 lux, peak from 140 lux.

This fuzzification process enables the system to represent real-world conditions more flexibly than disjoint classification, supporting reasoning under imprecise or overlapping conditions.

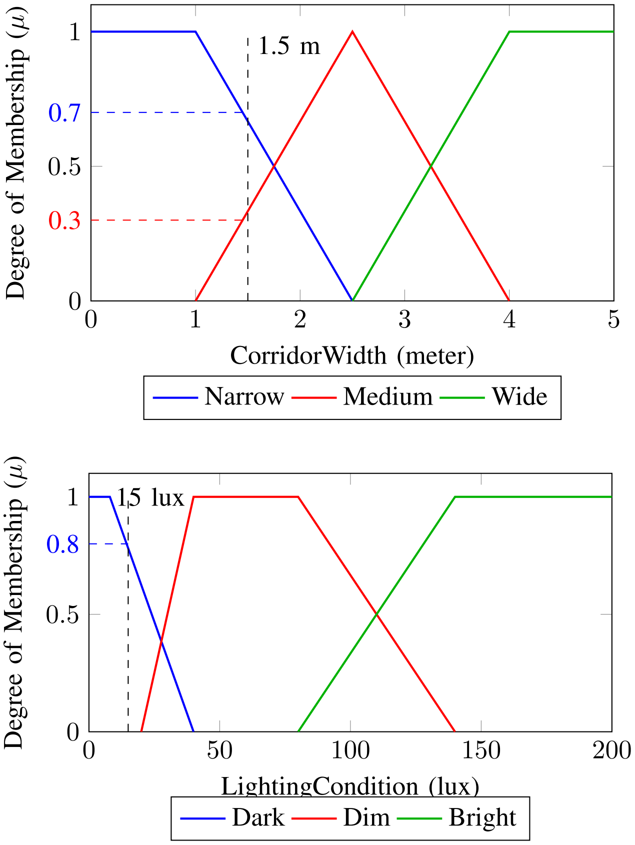

Fig. 2: Membership function plots for fuzzy-powered situation hyperspace (corridor width (top) and lighting conditions (bottom)).

A fuzzy rule base, defined with expert knowledge, encodes safety-related reasoning in IF–THEN form (see TABLE I). The fuzzy inference engine evaluates and aggregates these rules to

TABLE I: Fuzzy inference Rules for risk score evaluation (CW = CorridorWidth, LC = LightingCondition)

ID	Rule
R1	LC: Dark → Risk: High
R2	CW: Narrow, LC: Dim →Risk: High
R3	CW: Medium, LC: Dim →Risk: Medium
R4	CW: Wide, LC: Dim →Risk: Low
R5	CW: Narrow, LC: Bright → Risk: High
R6	CW: Medium, LC: Bright → Risk: Low
R7	CW: Wide, LC: Bright → Risk: Low

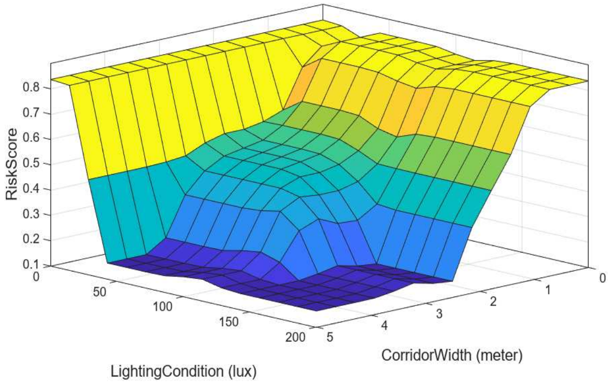

Fig. 3: Fuzzy-powered situation hyperspace. The color gradient represents a gradual risk transition (the yellow zone indicates high-risk situations, the cyan region corresponds to medium risk, and the blue region denotes low-risk situations).

assess the risk associated with parameter combinations. The aggregated fuzzy output is then converted into a numerical risk value using defuzzification (e.g., the centroid method). To get clear context, again considering the 1.5m corridor is "narrow" (0.7) and 15 lux lighting is "dark" (0.8), Rule 1 (R1) strongly activates, producing a high-risk outcome. After aggregation and defuzzification, the crisp risk value is calculated as 0.83 here. In this manner, the combinations of input parameters and corresponding risk values define a three dimensional *fuzzy powered-situation hyperspace* (e.g., x: width, y: lighting, z: risk) (see figure 3). This hyperspace captures the structure of the operational space with risk evaluations. Within this space, regions with higher and medium risks are typically highlighted and prioritized for safety testing.

The system identifies that situations with corridor widths $< 2.5m$ and lighting $< 40\ lux$ consistently produce high risk. These areas are marked as *priority zones* (plotted as yellow zone in figure 3) for safety testing. Instead of randomly testing well-lit, wide corridors, the system generates multiple variations of *narrow + dimly lit corridors*, since they may cause safety violations.

This methodology enables systematic exploration of operational conditions by combining fuzzification, fuzzy inference, and hyperspace construction. By embedding expert knowledge into the risk evaluation process and prioritizing high-risk regions, the approach provides a principled way to focus safety testing on the most critical situations.

III. PERFORMANCE ANALYSIS

To evaluate our fuzzy-powered situation hyperspace approach, we plan to generate a disjoint situation hyperspace based on the same two key factors. We then examine the performance of the fuzzy approach in comparison with the disjoint hyperspace. Building on this, we will explore the following research questions (RQ):

RQ1: To what extent does a fuzzy situation hyperspace reduce combinatorial explosion by limiting the number of test cases classified as strictly high- or low-risk, while maintaining coverage of safety-relevant situations, compared to a disjoint hyperspace model?

RQ2: Can a fuzzy situation hyperspace improve the detection of safety-critical edge cases in a mine environment, in terms of missed hazardous situations and misclassification severity, compared to a disjoint classifier?

RQ3: How does the granularity of risk assessment differ between fuzzy powered and disjoint hyperspace modeling approaches?

In section III-A, we briefly describe how the disjoint hyperspace is generated and how the membership function is defined using MATLAB [24].

A. Disjoint Situation Hyperspace Construction

Unlike fuzzy powered situation hyperspace, where membership can vary gradually between 0 and 1, this disjoint situation hyperspace assigns each input to exactly one class (e.g., narrow, medium, wide; dark, dim, bright) (see figure 4). Each region in the 3D disjoint situation hyperspace (figure 5) corresponds to a unique pairing of corridor width and lighting class, and each pairing is associated with a fixed risk value. Because the sets are disjoint, there is no overlap between categories. Because the categories are binary and disjoint, the hyperspace is composed of flat, block-like surfaces where each block corresponds to a single, fixed risk level. There are no gradients or smooth transitions, as risk changes abruptly whenever an input crosses from one category into another. While this binary representation is simple and easy to interpret, it also leads to a large number of discrete test combinations for both high priority and safe zones. In contrast, a fuzzy-powered hyperspace allows continuous membership and smooth transitions, which might reduce the number of required test cases and handle the otherwise infinite exploration space of real-world conditions more efficiently.

B. Fuzzy vs. Disjoint Situation Hyperspace

We evaluate our approach by simulating situations common to both hyperspaces in the ALOFT testbed [21] to assess each hyperspace's ability to characterize risk and prioritize test cases. For mismatched situations, corridor widths were set identically across hyperspaces, while lighting was mapped abstractly to Gazebo Classic's diffuse color parameter [23], rather than calibrated illuminance.

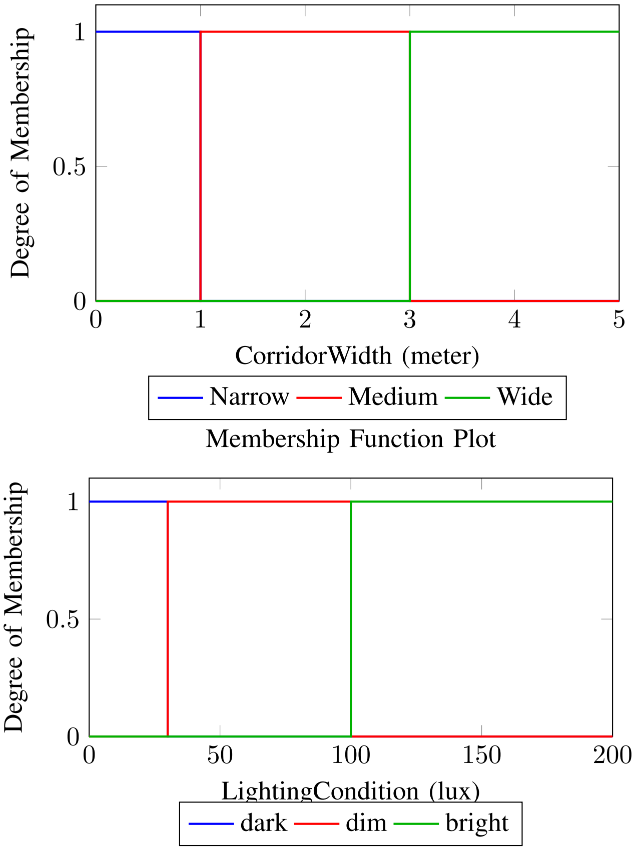

Fig. 4: Membership function plots for disjoint situation hyperspace (corridor width (top) and lighting conditions (bottom)).

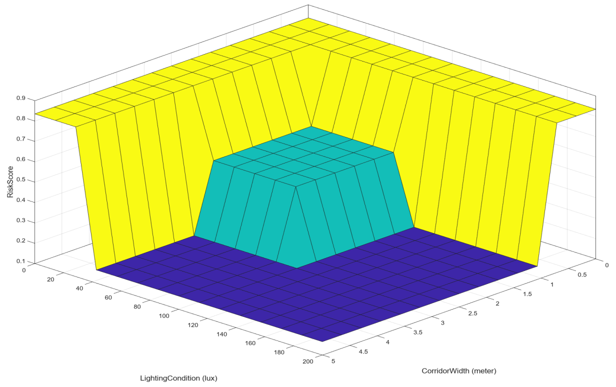

Fig. 5: Disjoint situation hyperspace. Risk is represented using discrete regions with sharp boundaries (yellow denotes high-risk situations, cyan indicates medium risk, and blue corresponds to low-risk conditions).

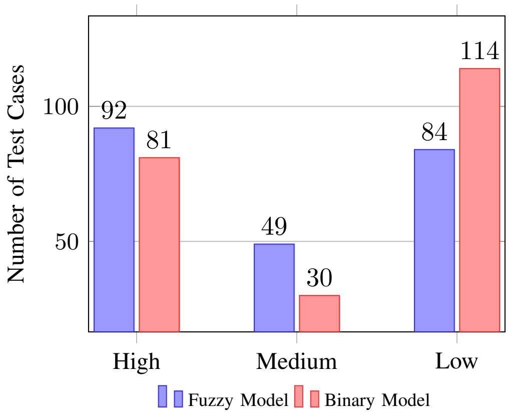

Fig. 6: Risk distribution comparison between fuzzy and disjoint situation hyperspace.

The comparative results reveal clear differences in risk characterization, as summarized in Fig. 6. We observe that the disjoint hyperspace produces a highly polarized risk distribution: out of 225 test cases, 114 are classified as low risk and 81 as high risk, with only 30 cases assigned to the medium-risk category. In contrast, the fuzzy hyperspace produces a more graded risk distribution, identifying 49 medium-risk cases; nearly two-thirds more than the disjoint model while still maintaining substantial coverage of high-risk (92 cases) and low-risk (84 cases) situations. This more balanced distribution indicates that fuzzy modeling captures gradual variations in risk rather than forcing situations into binary extremes (RQ3). More importantly, the disagreement analysis (Fig. 7) highlights safety-relevant limitations of the disjoint classification strategy when compared against the fuzzy hyperspace, which is treated here as the reference risk assessment within the ALOFT testbed. Among the 52 mismatched cases, the disjoint model assigns a lower risk category than the fuzzy model in a total of 42 situations (35 mild + 7 severe underestimations). These underestimations, in which situations assessed as high risk by the fuzzy model are labeled as low or medium risk by the disjoint model. Under this comparative framing, such discrepancies represent the most critical failure mode for safety-oriented testing, as potentially hazardous situations may receive insufficient testing priority (RQ2). As summarized in Table II, these 42 severe and mild risk underestimations correspond to nearly 19% of all evaluated test cases, indicating a substantial likelihood that the disjoint model would fail to adequately flag potential hazards. At the same time, by distributing situations across multiple intermediate risk levels rather than concentrating them at extremes, the fuzzy hyperspace supports more effective risk-based test prioritization without sacrificing coverage of hazardous conditions (RQ1).

Overall, these results demonstrate that the proposed fuzzy situation hyperspace enables more fine-grained risk assessment (RQ3) and more reliably identifies safety-critical edge cases compared to the disjoint model (RQ2). At the same time, it maintains comprehensive test coverage through effective risk prioritization (RQ1).

IV. CONCLUSION

By constructing a fuzzy-powered situation hyperspace, this work represents a novel application of fuzzy logic to system-level safety testing of critical systems, where risk is assessed continuously rather than through discrete pass/fail judgment.

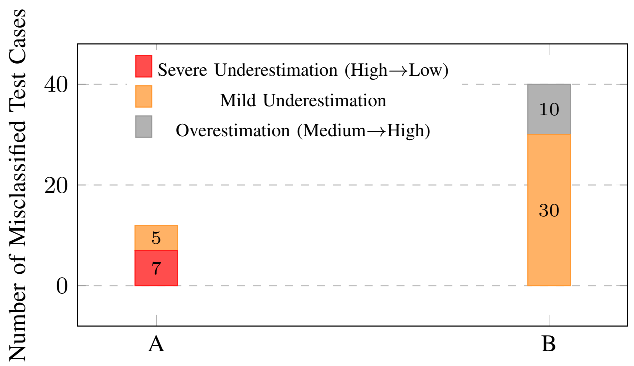

Fig. 7: Safety-critical errors in the disjoint model, showing severe underestimations, mild underestimations, and overestimations.

TABLE II: Safety impact summary of disjoint model discrepancies relative to the fuzzy hyperspace

Error Type	Cases	Safety Impact	RQ Relevance
Severe Underestimation *(High→Low)*	7	**Critical** *Misses dangerous situations*	RQ2
Mild Underestimation *(High→Med:5, Med→Low:30)*	35	**Problematic** *Underestimates severity*	RQ1, RQ2
Overestimation *(Medium→High)*	10	**Conservative** *Overly cautious, inefficient*	RQ3
Total Mismatches	52		All RQs
Matched Correctly	173	**Agreement**	

The resulting automated process produces objective, continuous risk scores for test case prioritization, reducing reliance on subjective expert judgment while offering improved scalability. However, the approach still relies on expert-defined membership functions and inference rules.

Moreover, although fuzzy modeling scales better than the disjoint model, designing and maintaining a robust rule base for very high-dimensional operational design domains still remains challenging.

ACKNOWLEDGEMENTS

VH's work was supported by the Centre for Assuring Autonomy (CfAA), a partnership between Lloyd's Register Foundation and the University of York (https://www.york.ac.uk/assuring-autonomy/).

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