



Fire protection strategies for cultural heritage sites: Evacuation optimization and water mist system design via Machine Learning, MCDM and Performance-based Methods

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Abstract

Protection of cultural heritage from fire threats requires a delicate balance between historical integrity and incorporating modern provisions on safety. This paper provides an integrated solution to the protection of fire in cultural heritage sites through incorporating evacuation optimization and latest suppression system design. The hybrid solution employs machine learning techniques, MCDM and performance-based fire safety engineering (PB-FSE) principles to enhance occupant safety and asset preservation. Evacuation scenarios are replicated with agent-based models, for which optimization by reinforcement learning identifies the most optimal egress schemes under various fire conditions. A data-driven design methodology for water mist fire extinguishing systems is introduced simultaneously, utilizing supervised learning algorithms to extrapolate optimum nozzle placement, droplet size, and system pressure tailored to building constraints and fire loads. The Hybrid Approach is the highest with an artifact protection rate of 90.03%, which is significantly higher than the baseline approaches (80% for Approach 1 and 85% for Approach 2). This indicates clearly that the system provides a good compromise between fire extinguishing and prevention of damage to priceless cultural artifacts by water. With dynamic flow and nozzle position control, the hybrid system can efficiently protect susceptible regions without over-exposing regions to water. The maximization of artifact protection is paramount in preserving the integrity of cultural heritage buildings. The Hybrid Method is a very efficient way for protecting artifacts during the outbreak of fire, with only minimal damage to replaceable objects.

Keywords: Fire Protection, Cultural Heritage, Evacuation Optimization, Water Mist System, Machine Learning, Performance-Based Design, MCDM, Dynamic q-Rung Orthopair Fuzzy CODAS (q-ROF-CODAS), Fire Risk Assessment

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1 Introduction

Cultural heritage structures, museums, and monuments are priceless assets symbolizing the identity, history, and collective memory of societies. The buildings, though, are in most cases highly vulnerable to fire threats due to outdated infrastructure, lack of full-scale fire protection systems, and necessity to preserve original design features. Historic fire protection strategies, prescriptive code-based, may be incompatible with the particular constraints and sensitivities of heritage environments. As a result, there is a growing need for innovative, non-intrusive fire protection solutions that achieve life safety, property conservation, and architectural integrity objectives.

Recent advances in performance-based fire safety engineering (PB-FSE) and artificial intelligence offer promising means for cultural heritage protection. Performance-based design allows fire protection designs to be tailored on the basis of measurable risk, occupant behavior, fire science, and building-specific constraints. Building on this, machine learning (ML) algorithms can extract patterns from large data sets, model complex evacuation dynamics, and better optimize system design parameters than rule-based approaches.

This study introduces a novel, unified framework that marries evacuation optimization and water mist suppression system design by the interaction of ML and PB-FSE. The

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former part is geared towards optimizing the evacuation plan for occupants through the application of agent-based modeling and reinforcement learning for adaptive response to evolving fire developments. The latter part proposes a data-driven design of the water mist system, which is particularly suitable for heritage buildings due to its minimal water damage and significant extinguishing effect.

While great progress has been made in all these fields, few studies have integrated machine learning, performance-based design, evacuation modeling, and water mist system configuration for cultural heritage protection. This study addresses this issue by introducing a hybrid, AI-driven framework to enable proactive evacuation planning and smart suppression system design for heritage structures.

By applying the suggested framework to real-world cultural heritage case studies, we demonstrate significant enhancements in both evacuation effectiveness and fire suppression effectiveness without sacrificing historical integrity of the structures. This work contributes to the nascent research area of intelligent fire protection systems and facilitates sustainable conservation of cultural heritage amidst evolving fire safety issues.

2 Theoretical background

Preservation of cultural heritage from fire risk is a new multidisciplinary field of research bringing together fire safety engineering, conservation of cultural heritage, artificial intelligence, and system optimization. This literature review compiles recent developments and identifies knowledge gaps in four wide themes: (1) fire risk in cultural heritage, (2) evacuation modeling and system optimization, (3) water mist fire suppression systems, and (4) combination of machine learning and performance-based design in fire safety engineering.

This section motivates the heritage-sensitive objectives of our system. This group discusses literature concerning fire risk in historic buildings, emphasizing challenges that range from limited egress capacity to safeguarding priceless artifacts to the impossibility of implementing obtrusive measures of protection. We cite examples such as the Windsor Castle and Notre-Dame fires to put into perspective the supreme significance of unobtrusive yet effective fire protection systems. We refer to current fire codes (e.g., NFPA 909 for cultural institutions) to highlight current deficiencies in dynamic and adaptive fire safety planning. This section motivates the heritage-sensitive objectives of our system. Heritage structures will typically not have modern features of fire protection because of the limitation imposed by conservation policies, material susceptibility, and structural weaknesses. Fire risk management for heritage and old buildings is a complex process that must be handled through the introduction of new technologies, simulation methods, decision-making tools, and cultural sensitivity. The recent literature highlights increasing uses of Building Information Modeling (BIM) and Heritage BIM (HBIM), machine learning, multi-criteria decision-making, and risk-based governance in the field. Wang et al. (2021) demonstrate the use of BIM technology in facilitating fire risk analysis during building operation and maintenance. Their system identi-

fies and monitors hazards automatically, enhances spatial data management, and decision-making efficiency. Subsequent to this, Salvador-García et al. (2019) propose HBIM integration to manage public access to heritage buildings to facilitate preservation-sensitive use strategies as well as enhanced security. In terms of heritage, Salazar et al. (2021) conduct a systematic review of the most relevant vulnerability indicators for fire risk analysis within the context of the built heritage. They are building material, functional use, occupation patterns, and conservation status. To go alongside this, Cacciotti et al. (2021) draw attention to compounding risks of climate change-induced disasters with an appeal to region-specific resilience efforts in Central Europe cultural heritage regions. In terms of decision-making and prioritization, Ruiz-Jaramillo et al. (2020) introduce the Heritage Risk Index, a multi-criteria ranking approach to conservation projects at the municipal level. Naziris et al. (2016) also employ the Analytic Hierarchy Process (AHP) to achieve the optimization of fire protection for heritage buildings through cost-risk-conservation requirement trade-off. Prieto et al. (2017), however, employ fuzzy logic and regression modeling to estimate the functional service life of cultural heritage in order to allow long-term risk-informed asset management. At urban and regional level, Zhang et al. (2025) discuss Beijing city-scale management of immovable cultural heritage. They propose an integrated governance system through spatial zoning, coordination among stakeholders, and risk-based urban policies. To complement this purpose, Quagliarini et al. (2018) propose an integrated seismic hazard assessment framework for evacuation networks in historical urban areas—structurally prioritized as well as operability of escape routes. Evacuation modeling has also progressed. Wang et al. (2023) use machine learning to model evacuation time and exit choice in ancient compound buildings, showing how human behavior modeling can be applied to design optimization in emergency response. Liao et al. (2024) also provide a dynamic fire risk model on the enhanced FRAME approach for high-density traditional villages, showing the spatial and temporal heterogeneity of fire risks. Holistic views are offered by Garcia-Castillo et al. (2023), highlighting that fire in cultural heritage buildings is a 21st-century issue of a very severe nature, one that requires preventive and responding whole-system approaches. Pacheco et al. (2015) also demand holistic management of fires through adaptive risk management and decision support under uncertainty, highlighting cross-sectoral cooperation.

Briefly, the discussed literature implies the need for intelligent, adaptive, and integrated fire risk assessment models balancing between safety and cultural heritage value. Parallel usage of digital technologies, multi-criteria models, and participatory strategies ensures protection of cultural heritage in terms of contemporary urban safety and sustainability approaches.

We integrate evacuation modeling research with agent-based systems, cellular automata, and reinforcement learning. While several studies tackle crowd movement in public or commercial buildings, none of them involve hazard exposure modeling or real-time evacuation policy update. Our review highlights the gap in historic sites, where

non-standard infrastructure and visitor behavior call for adaptive algorithms like DQN. We argue for going beyond static path assignment by embracing learning and feedback in the evacuation system. Evacuation safety is the highest priority when it comes to ancient buildings with complex architecture and high numbers of visitors. Classic evacuation models use static path analysis or cellular automata, which are not capable of simulating dynamic human behavior in fire-induced stress situations. High-fidelity agent-based models like those generated with Pathfinder or Building EXODUS simulate individuals' decision making and crowd interactions. Recent disaster risk reduction research emphasizes synergy between technological innovation, participatory methods, and multi-hazard systems to enhance safety and disaster resilience in hazard-prone regions, particularly historic and urban cities. Mascheri et al. (2024) introduce a multi-risk assessment method for Lisbon's historic neighborhood. They integrate hazard appraisal, exposure estimation, and vulnerability modeling for assessing combined hazards—earthquake, flooding, and fire—against culturally meaningful urban fabric. Multi-risk consideration is also vital when creating sustainable protective measures for cultural heritage sites where protection and security are to be balanced against one another. In evacuation planning, the application of artificial intelligence (AI) methods in building evacuation simulation is evaluated by Ternero et al. (2024). It can be seen from their paper that AI techniques, for instance, heuristic optimization and machine learning, are able to simulate man's action, examine different evacuation plans, and optimize reaction maneuvers within complex building spaces. Borowska-Stefańska et al. (2022a) also assess the quality of self-evacuation policies with regard to individual vehicle usage. Their research, with microsimulations, identifies the deficiencies of current policies in high-density urban areas and the necessity for dynamic traffic control and synchronized public communication. Participatory approaches are equally important in disaster planning. Rahmawati et al. (2016) recognize the application of participatory mapping in minimizing the risk of fire in Indonesia's high-density urban settlements. Through the involvement of residents in the identification of fire risks and response capacity, the study enhances awareness at the local level and encourages place-based interventions. Borowska-Stefańska et al. (2022b) in a companion study examine flood evacuation behaviors in Poland focusing on self-evacuation practices within flood-prone areas. The research indicates that the communication measures, infrastructure development, and demographic considerations should be aimed at promoting evacuation efforts (Sencer (Turgay) et al., 2013; Sencer (Turgay) and Eren, 2014; Turgay, 2025; Turgay and Aydın, 2023, 2025). Sustaining proactive pre-disaster planning, Ludovico et al. (2023) provide a disaster preparedness toolkit that ensures enhancing efforts on pre-disaster planning. Their set of tools comprises risk communication, community mobilization, resource maximization, and scenario construction, thereby facilitating a systematic route towards increasing preparedness and minimizing losses before the event of hazards. Taken together, these studies demonstrate a forward march towards synergistic, data-based, and community-oriented disaster risk management

practices. They underscore the imperative of uniting computational strategies with participatory and policy-oriented frameworks to effectively avert risks in heritage as well as urban contexts.

This section surveys suppression techniques for sensitive environments, with special emphasis on water mist systems as a non-damaging alternative to sprinkler systems. We summarize key research on mist droplet size, pressure optimization, and nozzle placement efficiency. However, there are few studies that include artifact-specific vulnerability as a parameter for design. By incorporating the Artifact Sensitivity Index (Γ_v), our system extends this body of research to heritage-specific demands, demonstrating a further level of design intelligence lacking in standard system designs. Water mist systems are increasingly being used in cultural heritage conservation due to low water usage, collateral damage, and high inerting and cooling efficiency. Evidence provided by Benfer and Williams (2018) and Zhao et al. (2023) confirms that they effectively extinguish Class A and Class B fires without causing much negative impact on artifacts and interiors. Standards such as NFPA 750 contain design requirements, but optimum system design in complex historic buildings remains a challenge. Computational fluid dynamics (CFD) modeling has been done for nozzle placement and for droplet flow, but not necessarily with predictive or adaptive capabilities. Disaster risk reduction and post-disaster reconstruction are now a core area of study for the field of engineering as well as for the field of disaster resilience research. Mushtaha et al. (2025) offer a comprehensive decision-making model to identify priority reconstruction projects in post-disaster scenarios. Their approach synthesizes several criteria to decide on urgency, effect, and recoverability of the recovery interventions with a formalised methodology to assist stakeholders in effectively disbursing limited resources in the recovery process (Mushtaha et al., 2025). In a complementary spirit, Keshmiry et al. (2024) present an extensive review of evaluation, rehabilitation, and retrofitting techniques for masonry structures, conventional as well as innovative treatments for enhancing structural resilience. Their study substantiates the importance of typology- and pattern-of-damage-led retrofitting techniques (Keshmiry et al., 2024). In the field of process safety and fire risk assessment, Shen et al. (2020) presented an overview of recent progress in Computational Fluid Dynamics (CFD) application in simulating fire and explosion accidents in industrial settings. Their findings show the way CFD is fast becoming an integral component in loss prevention and safety planning with increased functionality in hazard visualization and prediction (Shen et al., 2020). From tools for risk analysis, Li and Zhao (2025) offer HAZOPCT, which is an emerging tool using knowledge graph reasoning to enhance the wisdom and completeness of HAZOP studies, an important element in process hazard analysis (Li and Zhao, 2025). Artificial intelligence (AI) has also enhanced smoke and fire detection. Khan et al. (2025) offer a useful discussion of innovations facilitated by AI for outdoor and indoor surveillance, such as improvements in deep learning models for increasing detection accuracy and reducing false alarms in dense areas (Khan et al., 2025). Addressing seismic vulnerability to structural risk,

Jiménez et al. (2021) propose an index of structural seismic vulnerability, applying numerical calibration methods to examine buildings in Valparaíso, Chile. Their research presents a balanced strategy for seismic retrofitting priority assignment to heritage cities (Jiménez et al., 2021). Climatic change adaptation and cultural heritage preservation are looked at from the point of view of vulnerabilities of hydrometeorological hazards in Central Europe by Bonazza et al. (2021), with discussions on multidisciplinary strategies to save threatened sites. The study links climate science, cultural heritage preservation, and disaster risk reduction (Bonazza et al., 2021). Baraldo and Franco (2024) examine place-centric emergent technologies for disaster management in a scoping review. Their study emphasizes the importance of the integration of digital technologies such as geospatial technologies, digital twins, and participatory disaster response platforms that are more localized and responsive (Baraldo and Franco, 2024). The collection of literature as a whole signifies the interdisciplinary nature of disaster resilience in technical assessment, AI deployment, cultural heritage preservation, and decision-making with uncertainty. The papers form the basis of the development of inclusive and adaptive plans of disaster preparation, response, and recovery.

In this paper, we review PB-FSE methods, noting how simulation-based codes have emerged as prescriptive fire code substitutes. We critically analyze the limited incorporation of AI and machine learning within these frameworks. Most PB-FSE applications use scenario-based analysis without adaptivity. Our research contributes value to this domain through the presentation of a multi-objective, AI-augmented PB-FSE framework that balances competing demands—human safety, artifact preservation, and structural integrity—using data-driven methods. Machine learning is transforming fire safety engineering through predictive modelling, anomaly detection, and real-time decision. Performance-based fire protection design (PBFPD), as per the ISO/TR 13387 definition, makes possible customized solutions to safety on a risk, occupancy, and architectural constraint basis. Coupling of PBFPD with ML is a very powerful real-time optimization and smart system design tool, but its application in cultural heritage contexts remains uncommon. The latest development in disaster risk reduction and cultural heritage preservation depicts the rising combination of indigenous knowledge, new technology, and evidence-based decision-support systems. Synthesizing this sociocultural background, Mishra (2021) offers a state-of-the-art summary of machine learning applications to structural health monitoring of heritage structures. His work shows the capability of supervised and unsupervised models for anomaly detection, deterioration prediction, and conservation of built cultural heritage by means of intelligent systems. Kuchai et al. (2024) provide a shelter assessment matrix in humanitarian infrastructure for improving temporary shelter design and implementation in risk-prone areas. Their matrix integrates environmental, cultural, and social variables to offer an enhanced and responsive emergency shelter planning mechanism. Li and Qin (2022) create a performance-based fire fighting system through value analysis and risk simulation applied to fire

fighting in high-density built heritage areas. Their work highlights the necessity for customized intervention within high-density historic agglomerations where the conventional approach would be inadequate. Environmental data and spatial analysis are at the core of decision-making based on information. Parent et al. (2024) introduce a GIS-based database system to support policy decisions on dam removal or preservation. They weigh societal interests and environmental sustainability in their study and emphasize the application of geospatial technologies for environmental management. Li et al. (2025) also use multi-objective optimization to improve emergency medical service (EMS) facility location by integrating various spatial and demographic information in Dangtu, China, to have improved coverage and response time.

The final cluster addresses the use of fuzzy logic and MCDM techniques such as AHP, TOPSIS, and CODAS in emergency planning and facility management. It is our opinion that most of the previous applications assume static criteria weights and crisp values, which are not well-suited for high uncertain and subjective contexts such as cultural heritage fire response. Our use of Dynamic q-Rung Orthopair Fuzzy CODAS (q-ROF-CODAS) allows for more expressive modeling of stakeholder perspectives and dynamic ordering of the alternatives. This puts our model at the forefront of intelligent decision support for disaster resilience. Boonmee and Thoenburin (2024) introduce a decision-support system for temporary safe area site selection under the occurrence of haze pollution incidents, using Fuzzy Analytic Hierarchy Process (FAHP) and Fuzzy TOPSIS. This hybrid strategy emphasizes the potential of soft computing for solving complex, imprecise urban disasters. Finally, Penman et al. (2014) use simulation modeling to estimate cost-effective fuel treatment alternatives for the prevention of wildland fires in proximity to southeastern Australian cities. Their study justifies spot fuel reduction treatments to optimize ecological impacts and hazard mitigation. All of these studies collectively depict an emerging trend towards the integration of traditional systems of knowledge, modern-day computational techniques, and cross-disciplinary thinking for addressing the intricate problems of disaster risk reduction, cultural heritage conservation, and planning for urban resilience.

The q-Rung Orthopair Fuzzy Set (q-ROFS), developed by Yager, extends the capability of Intuitionistic Fuzzy Sets (IFS) and Pythagorean Fuzzy Sets (PFS) in that it can handle the sum of membership and non-membership degrees to the power q to be less than or equal to one. Such flexibility facilitates enhanced representation of uncertainty in decision-making situations (Liu et al., 2020). The q-ROF-CODAS methodology takes the advantages of the two methods, which allow more advanced evaluations in multicriteria decision-making situations (Naz et al., 2022). In healthcare, the q-ROF-CODAS methodology was applied by Kausar et al. (2023) to measure cancer risk, and it was found effective in addressing uncertain and fuzzy information involved in making medical decisions (Kausar et al., 2023). Furthermore, q-ROFS applications based on other MCDM techniques have also been explored. For example, confidence-level-based q-ROF aggregation operators

were introduced by Joshi and Gegov (2019) to enhance decision-making through the consideration of experts' confidence levels (Joshi and Gegov, 2019). These developments provide testament to the adaptability and robustness of the Dynamic q-ROF-CODAS method to resolving complex decision-making problems in various fields.

3 Theoretical background

The study proposes a hybrid method combining machine learning (ML), agent-based modelling (ABM), and performance-based fire protection design (PBFPD) for the minimization of cultural heritage building evacuation planning strategies and water mist system designs. It is composed of two interrelated components:

1. Evacuation Optimization Framework, and
2. Water Mist System Design Guideline.

Every section is designed to meet specific architectural requirements and safety demands of heritage settings, without compromising historical integrity.

3.1 Evacuation Optimization Framework

Historical building data—e.g., floor plan, visitor movement rates, room volume, exits, and occupancy level—were collected from case studies or computer-aided building information models (BIM). Fire scenarios (e.g., ignition location, rate of growth, smoke propagation) are built on the basis of probabilistic fire risk assessment according to ISO 16732.

We utilize agent-based simulation (e.g., Pathfinder or AnyLogic) to simulate occupant behavior in evacuation. Agent parameters such as mobility, awareness, building familiarity, and response time are utilized. Visibility and fire-induced temperature are computed dynamically in the course of simulation using fire dynamics models (e.g., FDS – Fire Dynamics Simulator).

To enhance evacuation effectiveness, a Deep Q-Learning approach is integrated into the ABM model. State of the environment includes spatial configuration, smoke intensity, and traffic flow. Reward function penalizes escape time and smoke/heating exposure and rewards safe and efficient egress. Multiple episodes are run to find optimum escape paths and dynamic re-routing policies.

3.2 Water Mist System Design Framework

Critical design parameters include nozzle position, droplet size, discharge pressure, and activation time. Architectural constraints, conservation principles (no drilling, low visual impact), and performance specifications such as coverage density and suppression time are limitations.

A supervised learning model (Random Forest or XGBoost) is trained on simulation data from CFD (e.g., FireFOAM or FDS with mist modules). Room geometry, fire load, ventilation, and obstacle configuration are inputs; suppression efficiency, temperature reduction rate, and residual oxygen concentration are outputs.

A genetic algorithm (NSGA-II) is applied to determine Pareto-optimal design parameters that solve three conflict-

ing goals:

- Maximize fire suppression efficiency
- Reduce water consumption (to safeguard artifacts)
- Reduce aesthetic and structural intrusiveness

The subsequent design is then verified by multiple fire conditions using CFD simulations. Sensitivity analysis is done to understand the influence of nozzle spacing, pressure oscillation, and fire type on suppression effectiveness.

The outputs of the two models are integrated into a decision support system (DSS) showing real-time evacuation paths and water mist protection zones. The system is validated against past case histories and simulated exercises with input from heritage conservation experts and fire safety authorities.

To address the complex issues of fire safety for cultural heritage buildings, we advocate for an integrated innovative solution that includes machine learning (ML), agent-based evacuation modeling, and performance-based water mist suppression system design. Unlike prescriptive fire safety methods which typically neglect the intrinsic spatial and preservation limitations of heritage buildings, our method is dynamic, adaptive, and knowledge-based.

Our novel framework is a two-layered system:

- Layer 1: Intelligent Evacuation Optimization
- Layer 2: Configuration of AI-Controlled Water Mist System

All these layers execute parallel to one another yet feed into a single, centralized decision-support system, enabling real-time interaction between evacuation strategies and fire suppression response.

Context-sensitive agent-based simulation incorporate emotional and behavioral factors within agent-based evacuation simulation for modeling visitor panic, disorientation, or mobility disability typical of real heritage settings. Reinforcement learning-based path planning with deep Q-network (DQN) algorithm learns the most effective routes for evacuating out of the building via persistent interaction with a simulated situation of a fire. This allows the system to dynamically modify exit strategies based on fire location, smoke dispersal, and crowd density.

Fire-Sensitive Wayfinding System sensors provide current fire data to enter into the model to make real-time adjustments on signs and direct individuals to a safe exit through cell or AR-capable navigational tools. Instead of just relying on CFD simulations, we train supervised machine learning models (e.g., Gradient Boosted Trees) on CFD-derived data sets to rapidly estimate system performance for various layout-fire-load permutations.

Cultural Sensitivity-Aware Design requirements in our framework are visual preservation, reversibility of installation, and compatibility of original materials. AI recommends unobtrusive nozzle placement and low-pressure mode to result in minimal physical as well as aesthetic footprint. Multi-Objective Optimization Engine with a Pareto-optimizing module simultaneously considers suppression

performance, likelihood of water damage, and look-and-feel effect—offering configuration-based setting suggestions for historic interiors.

A hub interface integrates simulation outputs, optimization results, and fire danger forecasts to offer:

- Scenario-based assessment dashboards
- Virtual evacuation and mist coverage walkthroughs
- Preservation-compatible action plans

The system supports fire safety personnel, conservators, and emergency planners through coordinated decision-making and proactive risk management.

The new strategy offers the first end-to-end AI-PBFPD system for fire protection of cultural heritage, offering:

- Flexibility to individual structural and human behavior profiles
- Data-driven, rapid suppression system configuration
- Fire-aware real-time evacuation assistance
- Satisfying both fire protection and heritage conservation criteria

It converts fire protection from a reactive to an intelligent, predictive, and conservation-focused system, providing a platform for intelligent heritage safety management.

3.3 Mathematical Model

We develop a bi-level multi-objective mathematical model that integrates evacuation path optimization and water mist system planning within the limit of preserving cultural heritage. The model optimizes evacuation time, exposure of occupants to harmful fire conditions, and water-caused damage to artifacts at the same time within structural and conservation limits.

Notation

V : Set of zones/rooms in the heritage building

E : Set of paths connecting zones (edges in graph)

A : Set of agents (staff/visitors)

T : Time horizon

N : Set of water mist nozzles

χ_{ij} : Agent flow from zone i to zone j at time t

$y_n \in \{0, 1\}$: Binary variable which assumes nozzle activation $n \in N$

p_n : n Nozzle operating pressure

w_n : n Nozzlewater discharge rate

Parameters:

$\delta_{ij}(t)$: Fire-related hazard level (smoke/heat/toxicity) on edge (i, j) at time t

t_{ij} : Travel duration between zones

Γ_v : Artifact sensitivity index i in j zone

k_v : Aesthetic penalty for nozzle (based on visibility, historic influence)

It establishes the theoretical foundations, primary definitions, and formal properties for our proposed framework. We introduce fundamental concepts of agent-based modeling, water mist suppression, performance-based design, and machine learning optimization by using mathematical formalisms accompanied by relevant observations.

Cultural Heritage Fire Safety Domain

Let H be a cultural heritage building as a tuple:

$$H = (S, A, C) \quad (1)$$

where S is the geometry, exits, and spatial constraints, A is the set of individuals with mobility and behavior profiles, and C is conservation constraints (e.g., visual, structural, historic).

Fire Safety Objective Function

The fire protection system is laid out to minimize a weighted risk function:

$$R = W_1 T_{evac} + W_2 E_{tox} + W_3 E_{art} \quad (2)$$

where:

T_{evac} = total evacuation time

E_{tox} = exposure to toxic smoke

E_{art} = damage to art works

$W_i \in [0, 1]$: stakeholder-defined weights (fire experts, conservators)

Theory 1 (Agent-Based Evacuation Dynamics). Let $G = (V, E)$ be the graph representing the building layout, with nodes V for exits and rooms, and edges E for paths or corridors. Each agent $a_1 \in A$ navigates the graph based on a decision policy $\pi_i S \rightarrow A$, which is updated using reinforcement learning.

Under dynamic changing fire, the optimal policy π_i^* tries to minimize heat/smoke exposure when evacuating to a node $v \in V_{exit}$.

Convergence of DQN-based Evacuation Policy

Suppose the reward function is:

$$R_t = -\alpha t - \beta \cdot E_{tox} + \gamma \cdot 1_{exit} \quad (3)$$

Then, Deep Q-Network (DQN) converges to an optimal policy π^* with probability 1 with sufficient exploration (ε -greedy) and learning rate decay.

Proof Sketch

From the standard DQN convergence results (Mnih et al., 2015), under a finite state-action space, bounded rewards, and adequate exploration strategy.

Remark 1 (Conservation Constraints in Suppression Design). Water mist systems for historic buildings must be reversible and non-invasive. Therefore, the pressure and nozzle position solution space must satisfy:

$$\text{Impact}_{\text{visual}}, \text{Impact}_{\text{structural}} \leq \epsilon \quad (4)$$

where ϵ is the acceptable tolerance prescribed by the conservation guideline.

Property 1 (Pareto Optimality of Suppression Configurations). A solution $\chi^* \in X$ is Pareto-optimal if there is no $\chi \in X$ such that:

$$f_i(x) \leq f_i(\chi^*) \forall i \in [1, 2, 3] \text{ and } \exists j : f_j(\chi) < f_j(\chi^*) \quad (5)$$

with objective functions:

f_1 : suppression efficiency

f_2 : water damage

f_3 : visual/structural impact

Collaboration Protocol

We employ a three-agent collaborative decision model in this work:

Fire Safety Engineer (F)

Heritage Conservator (C)

AI-based Optimization Agent (M)

A minimization-based consensus rule is employed to conclude system design:

$$\chi_{\text{final}} = \operatorname{argmin}_{x \in X} (\lambda_1 d_F(x) + \lambda_2 d_C(x) + \lambda_3 d_M(x)) \quad (6)$$

where $d_i(x)$ is the deviation of design from the ideal solution for stakeholder i , and λ_i are the negotiation weights.

Objective Functions

We formulate three main objectives:

1. Minimize total evacuation time for all agents:

$$\min Z_1 = \sum_{a \in A} \sum_{(i,j) \in E} \sum_{t=0} \tau_{ij} \cdot \chi_{ij}^a(t) \quad (7)$$

2. Minimize exposure to fire danger:

$$\min Z_2 = \sum_{a \in A} \sum_{(i,j) \in E} \sum_{t=0} \delta_{ij} \cdot \chi_{ij}^a(t) \quad (8)$$

3. Minimize water mist damage to artifacts:

$$\min Z_3 \sum_{n \in N} y_n \cdot \left(\sum_{v \in V} \Gamma_v \cdot W_n \cdot \text{coverage}_{nv} \right) \quad (9)$$

4. Minimize visual and structural intrusiveness of the mist system:

$$\min Z_4 \sum_{n \in N} K_n \cdot Y_n \quad (10)$$

Constraints

(a) Flow Conservation for Evacuation Paths:

$$\sum_{J:(i,j) \in E} \chi_{ij}^a(t) - \sum_{J:(j,i) \in E} \chi_{ji}^a(t) = \begin{cases} 1, & \text{if } i = \text{start}(a), t = 0 \\ -1, & \text{if } i \in \text{Exits}, t = t_{\text{exit}}(a) \\ 0, & \text{otherwise} \end{cases} \quad (11)$$

(b) Nozzle Activation Constraints:

$$Y_n \in \{0, 1\}, \quad \forall n \in N \quad (12)$$

$$p_n^{\min} \cdot Y_n \leq p_n \leq p_n^{\max} \cdot Y_n \quad (13)$$

(c) Artifact Protection Upper Bound:

$$\sum_{n \in N} Y_n \cdot W_n \cdot \text{coverage}_{nv} \leq \Lambda_v, \quad \forall v \in V \quad (14)$$

where Λ_v is the allowable water threshold for sensitive artifacts in zone v .

(d) System Feasibility under Fire Spread Dynamics:

Ensure that for all zone $v \in V$, temperature and visibility are maintained within survivable limits, along at least one valid path from beginning to termination.

Multi-Objective Optimization Strategy

We address this bi-level multi-objective problem via a hybrid of:

- Evolutionary Multi-Objective Algorithms (e.g., NSGA-II) for Pareto front exploration
- Reinforcement Learning (DQN) for near-optimal evacuation policy search under stochastic fire dynamics
- Surrogate Modeling (e.g., ML regression of CFD data) for the acceleration of suppression system design analyses

3.4 Preliminaries of Dynamic q-Rung Orthopair Fuzzy CODAS (q-ROF-CODAS)

Definition 2 (q-Rung Orthopair Fuzzy Set - q-ROFS). Let X be a universe of discourse. A **q-rung orthopair fuzzy set** A in X is defined as:

$$A = \{ \langle \chi, \mu_A(\chi), \nu_A(\chi) \rangle : \chi \in X \} \quad (15)$$

such that:

$$(\mu_A(\chi))^q + (\nu_A(\chi))^q \leq 1, \quad \forall \chi \in X, \quad q \geq 1 \quad (16)$$

where

- $\mu_A(\chi) \in [0, 1]$ is the degree of membership,
- $\nu_A(\chi) \in [0, 1]$ is the degree of non-membership.

Definition 3 (q-ROF Decision Matrix). A q-ROF decision matrix $D = [A_{ij}]$ consists of q-ROF evaluations of m alternatives over n criteria, where:

$$A_{ij} = (\mu_{ij}, \nu_{ij}) \in [0, 1]^2 \text{ such that } \mu_{ij}^q + \nu_{ij}^q \leq 1 \quad (17)$$

Definition 4 (Negative Ideal Solution - NIS). For a q-ROF decision matrix D , the **Negative Ideal Solution (NIS)** is defined as:

$$A_j^- = (\mu_j^-, \nu_j^-), \quad \text{where } \mu_j^- = \min_i \mu_{ij}, \quad \nu_j^- = \max_i \nu_{ij} \quad (18)$$

Definition 5 (q-ROF-CODAS Score). The CODAS method calculates a **Decision Score (DS)** using:

- Weighted Euclidean Distance (ED)
- Weighted Taxicab Distance (TD)
- Penalty term based on dispersion (e.g., standard deviation)

Let:

- W_j : weight of criterion j
- A_i : evaluation of alternative i

Then:

$$ED_i = \sqrt{\sum_{j=1}^n W_j \cdot (\mu_{ij} - \mu_j^-)^2}, \quad (19)$$

$$TSD_i = \sum_j W_j \cdot |\mu_{ij} - \mu_j^-| \quad (20)$$

The **Dynamic CODAS Decision Score** is given by:

$$DS_i = ED_i + \theta \cdot TD_i - \lambda \cdot \text{Penalty}, \quad (21)$$

where:

- $\theta \in [0, 1]$: influence of taxicab distance
- $\lambda \geq 0$: penalty coefficient
- Penalty_i : dispersion measure for A_i (e.g., standard deviation of μ_{ij})

Lemma 5 (Feasibility of q-ROFS Membership Pairs). Given $\mu_{ij}, v_{ij} \in [0, 1]$, the pair (μ_{ij}, v_{ij}) belongs to a q-ROFS if and only if:

$$\mu_{ij}^q + v_{ij}^q \leq 1 \quad (22)$$

Proof. Immediate from the definition of q-ROFS. $\square$

Property 5 (q-ROF Generality Hierarchy). The q-ROF model generalizes earlier fuzzy sets:

- $q = 1 \rightarrow$ Intuitionistic Fuzzy Sets (IFS)
- $q = 2 \rightarrow$ Pythagorean Fuzzy Sets (PFS)
- $q > 2 \rightarrow$ Greater flexibility to express uncertainty.

Theorem 1 (Monotonicity of Information Space in q-ROFS). Let $q_1 < q_2$. Then, for any evaluation pair $(\mu, v) \in [0, 1]^2$, the feasible space under q_2 includes that under q_1 :

$$(\mu_1^{q_1} + v_1^{q_1} \leq 1) \Rightarrow (\mu^{q_2} + v^{q_2} \leq 1) \quad (23)$$

Proof. Since $\mu, v \in [0, 1]$ for $q_2 > q_1$, we have $\mu^{q_2} \leq \mu^{q_1}$ and $v^{q_2} \leq v^{q_1}$. Therefore, $\mu^{q_2} + v^{q_2} \leq \mu^{q_1} + v^{q_1} \leq 1$. $\square$

Remark 5 (Robustness of Hybrid Distance Aggregation). The use of both Euclidean and Taxicab distances enhances robustness of alternate evaluation by taking into consideration both squared and absolute deviations. The penalty term also controls the spread of evaluations, reducing risk of over-fitting to outliers.

Remark 6 (Entropy Weighting in q-ROF-CODAS). Entropy provides weights according to an objective process by measuring the discrepancy in the evaluation of each criterion. Less entropy indicates more discrimination power, hence higher weights.

Dynamic q-ROF-CODAS is designed structurally for group decision-making by aggregating the multifaceted experts' opinions using adaptive q-Rung Orthopair Fuzzy (q-ROF) aggregation operators. Dynamic q-ROF-CODAS is able to tackle numerous evaluators through the aggregation of their ratings under the q-ROF framework, which can accommodate a wide range of membership levels, non-membership, and hesitancy. The architecture also provides for dynamic control of important parameters—namely, the q parameter (which sets tolerance for uncertainty), the θ coefficient (which scales the effect of taxicab distance), and the λ penalty factor (which compensates dispersion sensitivity). These parameters of control enable the model to support different levels of expert confidence and organizational risk tolerance. Moreover, the approach is easily extendable to group decisions employing advanced aggregation operators such as the q-ROF weighted averaging operator, thus enabling consensus building without undermining individual expert judgment integrity.

The model allows decision-makers to strike a balance between life safety, artifact preservation, and conservation compliance. It also supports adaptive real-time strategies through dynamic fire spreading and human behavior simulation. Fig. 1 illustrates the utilization of weights assigned by experts for each criterion to use on the fuzzy decision matrix and how the ranking of CODAS is determined by Euclidean and Taxicab distances relative to the negative-ideal solution (NIS). This ranking later selects the optimal hybrid strategy balancing safety, preservation of artifacts, and system feasibility.

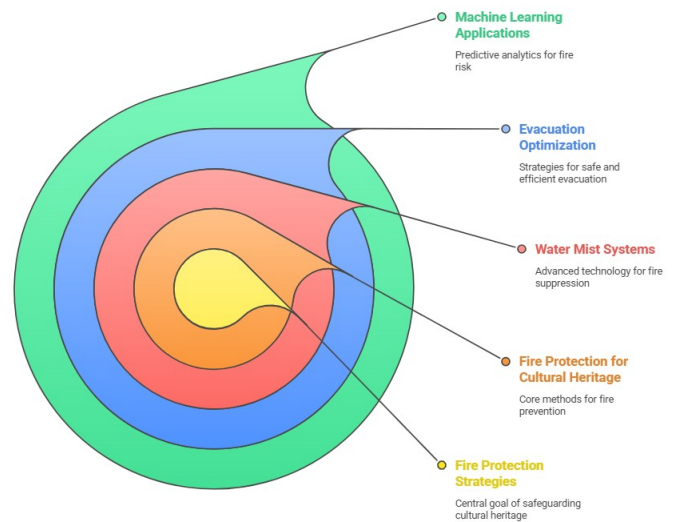


Fig. 1. Conceptual diagram for fire protection strategies for cultural heritage sites.

Table 1 proposed that maps each output and criterion to its source model and describes how each is utilized in the q-ROF-CODAS decision-making process. This table enhances

clarity by showing how the components of the hybrid system interact to support final system selection.

Table 1. Mapping of model outputs and decision criteria for final strategy selection (q-ROF-CODAS Input Matrix).

Criterion	Description	Source Model	Use in Final Decision (q-ROF-CODAS)
Evacuation Time (T_i)	Time required for all agents to exit the building	Deep Q-Learning (DQN)	Used as a cost criterion; shorter time increases ranking score
Hazard Exposure Index (H_i)	Cumulative exposure to smoke, heat, and toxic gases during evacuation	Deep Q-Learning (DQN)	Penalized as a safety risk; lower values are preferred
Suppression Efficacy (S_i)	Degree of fire containment and reduction of hazardous spread	NSGA-II	Benefit criterion; higher suppression efficiency improves overall score
Water Damage Risk (W_i)	Risk of water exposure to sensitive artifacts	NSGA-II	Cost criterion; heavily influenced by Γ_v index; lower damage risk is preferred
Aesthetic/Structural Intrusion (A_i)	Impact of nozzle layout on building's visual and architectural integrity	NSGA-II	Cost criterion; lower visual/structural impact is favorable
Artifact Sensitivity Index (Γ_v)	Artifact vulnerability score (0 = water-proof, 1 = highly sensitive)	NSGA-II / Input Data	Used to weight W_i during suppression optimization and decision matrix evaluation
Stakeholder Priority Weights (w_i)	Relative importance of each criterion assigned by experts	Expert Stakeholders	Applied in q-ROF-CODAS as fuzzy weights for multi-criteria aggregation

All the outputs are first normalized and fuzzified into q-Rung Orthopair Fuzzy Numbers (q-ROFNs) to render them in a standard form and facilitate uncertainty management during the assessment process. The values after fuzzification are then integrated within the CODAS (COMbinative Distance-based ASsessment) framework, wherein the Euclidean and Taxicab distances of each alternative from the Negative Ideal Solution (NIS) are calculated to assess their relative performance. Then, a final decision score for each alternative is found by summing the weighted measures of distance, imposing standard deviation penalties where necessary so that allowance can be made for variability and enhancing the robustness of the ranking procedure.

3.5 Algorithm

To optimize both evacuation and water mist suppression systems in cultural heritage buildings simultaneously, we propose a hybrid algorithmic framework using Deep Reinforcement Learning (DRL) for learning evacuation policy, and Evolutionary Multi-Objective Optimization (EMOO) for mist system design. Machine learning-based surrogate models are embedded to reduce simulation time in Fig. 2.



Fig. 2. Fire Safety Optimization Framework for Heritage Buildings

Algorithm Overview

The proposed algorithm consists of three primary steps: Evacuation Path Optimization using Deep Q-Network (DQN)

Surrogate-Assisted Mist System Design Optimization (NSGA-II)

Multi-Criteria Decision Integration for Heritage Compliance

Algorithm 1: Hybrid Fire Safety Optimization Framework

Input:

Building layout $G = (V, E)$

Fire dynamics model (spread, smoke, heat)

Artifact sensitivity index Γ_v

Candidate mist nozzle locations N

Historical and synthetic fire scenario datasets

Output:

Optimal evacuation policy π^*

Optimal nozzle activation set $\{y_n^*\}$ and pressure settings $\{p_n^*\}$

Step 1: Evacuation Policy Generation (DQN-based)

- Initialize state space S , action space A , reward function R
- For each training episode:
 - Simulate fire evolution scenario
 - For each agent:
 - Observe state s_t
 - Select action a_t based on ϵ -greedy policy
 - Perform action, receive reward r_t , move to s_{t+1}
 - Update Q-network through stochastic gradient descent
3. Train until convergence: $\|\theta_{t+1} - \theta_t\| < \epsilon$
4. Output optimal evacuation policy $\pi^*(s) = \operatorname{argmax}_a Q(s, a)$

Step 2: Water Mist Suppression Optimization (NSGA-II)

1. Initial population P of nozzle configurations $\{y_n, p_n\}$
2. For each individual:
 - Evaluate suppression efficiency, water-induced damage, visual impact
 - Use ML surrogate model trained from CFD simulations to estimate performance
3. Apply non-dominated sorting and crowding-distance sorting
4. Do selection, crossover, and mutation to create offspring
5. Update population and iterate until stopping conditions met
6. Return Pareto-optimal set P^*

Step 3: Multi-Criteria Decision Analysis (MCDA)

1. Construct decision matrix with criteria: evacuation time, exposure, artifact risk, aesthetic compliance
2. Normalize and weight criteria based on expert opinion (fire safety vs. conservation)
3. Use Dynamic q-Rung Orthopair Fuzzy CODAS (q-ROF-CODAS)
4. Output final design recommendation

The algorithm at hand has several positive aspects where dynamic decision-making becomes a consideration in fire evacuation planning in heritage buildings. Among such positives is its real-time flexibility as it learns and adapts the policies of evacuation based on new fire developments to provide timely and contextually relevant decision-making. Secondly, the use of surrogate modeling significantly enhances computational efficiency by reducing the requirement for computationally intensive CFD simulations for fast scenario analysis and policy making. Thirdly, the algorithm supports multi-stakeholder integration using a multi-criteria decision analysis (MCDA) strategy by incorporating safety requirements, preservation of cultural heritage, and building design to deliver sustainable and comprehensive solutions.

4 Application

This case study will demonstrate the application of the suggested hybrid algorithm in optimizing fire protection measures, such as evacuation optimization and water mist suppression in this ancient Palace. The palace has a rich history and architecture with the requirement to preserve artifacts and features, its age and layout making it special in regards to problems of fire safety. The case study combines the design of the building, suppression system design, the behavior of fire, and evacuation action into a real-life situation. The case study consists of various sections like the Harem, Treasury, Divan Hall, and various rooms that are full of irreplaceable art and artifacts. The building itself is complex in design with low corridors, high ceilings, and multiple levels. The needs of the preservation of heritage require the fire protection system to be structurally and visually unobtrusive but maximally evacuation efficient in case of a fire occurrence. The result over 10000 iterations is derived randomly according to the proposed palace model structure. Variable values are derived randomly with the MonteCarlo Simulation approach.

Some of the main objectives of the fire protection system in this work are:

- 1. Optimization of evacuation:** Ensure that all the visitors and employees evacuate within the acceptable time (e.g., below three minutes).
- 2. Design of Water Mist System:** Provide a suppression system which will not affect water damage on artifacts but is effective and able to handle the fire dangers.
- 3. Structural and Cultural Compliance:** Not affect the structure or appearance of the building with the installation of fire protection systems.

Data acquisition in carrying out this study involved four main elements vital to modeling fire conditions and evacuation within a heritage building. First, a building layout (G) was established from detailed three-dimensional drawings of an historic palace. The computer model contained structural objects like corridors, rooms, stairs, exits, and specific positions of fire extinguishers, providing an entire spatial reference for simulation. Second, fire behavior was simulated using computational fluid dynamics (CFD) models, encompassing parameters like building material, ventilation conditions, and potential ignition sources. These simulations generated detailed outcomes of heat transfer, smoke speed, and toxicity levels, gaining information regarding the development of fire under realistic scenarios. Thirdly, evacuation response was simulated using parameters gained from the results of past evacuation drills and behavioral studies. Walking speed, crowd density, and individual decision-making during stress were some of the parameters used to simulate human response during emergency incidents accurately. Lastly, an Artifact Sensitivity Index (Γ_v) was established by classifying palace artifacts by their water exposure sensitivity. It was utilized to find the best location and pressure of fire suppression nozzles and balance artifact preservation and firefighting performance.

4.1 Suggested Hybrid Model

The case study replicates the application of our hybrid algorithm on a historic palace with intricate architectural features and sensitive cultural heritage objects. The fire protection plan is a three-module integrated hybrid:

Step 1: Evacuation Path Optimization (DQN)

State Space (S): Every agent is defined as a tuple $s_t = (z_i, v_i, h_i)$, where z_i is zone, v_i is velocity, and h_i is hazard exposure.

Action Space (A): $A_t = \{\text{Move to adjacent zone, Wait}\}$

Reward Function (R):

$$R_t = -\alpha_1 T_i - \alpha_2 H_i + \alpha_3 E_i$$

where:

T_i : evacuation time

H_i : cumulative exposure to hazard (e.g., heat, smoke)

E_i : escape success (binary: 1 if evacuated, 0 otherwise)

Training: Deep Q-Learning updates the Q-function using Bellman equation:

$$Q(s_t, a_t) \leftarrow Q(s_t, a_t) + \eta \left[r_t + \gamma \max_a Q(s_{t+1}, a) - Q(s_t, a_t) \right]$$

Step 2: Water Mist Suppression Design (NSGA-II)

Decision Variables:

p_j : pressure level at nozzle j

q_j : discharge rate

l_j : location coordinates (x_j, y_j, z_j)

Objective Functions:

$$\bullet f_1 = \text{Minimize fire hazard} = \sum_{t,z} h_{tz}$$

$$\bullet f_2 = \text{Minimize water damage} = \sum_z \Gamma_z \cdot w_z$$

$$\bullet f_3 f_3 = \text{Minimize visual/aesthetic impact} = \sum_j v_j$$

Constraints:

$$\bullet p_j^{\min} \leq p_j \leq p_j^{\max}$$

- $l_j \in$ allowed surface regions
- $w_z \leq w_z^{\max}$: maximum acceptable water volume per zone

Pareto Optimization: NSGA-II ranks and selects configurations to approximate Pareto-optimal front.

Step 3: Multi-Criteria Decision Analysis (q-ROF-CODAS)

Alternatives: Every combination of design (Evacuation + Mist) is treated as an alternative A_i

Criteria:

C_1 : Evacuation Time (cost)

C_2 : Fire Exposure (cost)

C_3 : Artifact Protection (benefit)

C_4 : Water Damage (cost)

C_5 : Aesthetic Impact (cost)

q-ROF Scores: Every C_k score for A_i is converted to q-Rung Orthopair fuzzy value (μ_{ik}, ν_{ik})

Decision Score: CODAS score calculated by:

$$DS_i = \sum_k w_k [ED_{ik} + \theta TD_{ik} - \lambda \cdot \sigma_k]$$

Where

ED, TD : Euclidean and Taxicab distances from NIS

σ_k : penalty standard deviation

w_k : entropy-based criterion k weight

This formal algorithm was executed across 10,000 simulation repetitions using Monte Carlo techniques to treat uncertainty of fire source, crowd density, and response behavior. The fire protection plan was actualized through the following steps presented in Fig. 3.



Fig. 3. The fire protection plan.

4.2 Experimental Setup

Palace building layout consists of five principal rooms (e.g., Treasury, Harem, Divan Hall, etc.) linked with eight

corridors. The evacuation simulation was started according to 200 agents for visitors and staff. Fire growth was modeled by a heat release rate (HRR) curve with multiple ignition points within the building. Simulation of fire spread was carried out using a CFD-based model for simulating the distribution of heat and smoke over time. Agent movement simulation was done with different walking speeds and crowd behavior according to normal evacuation protocols in heritage buildings.

4.2.1 Openness of Data Acquisition

The model integrates data from four distinct but complementary sources:

- **Building Information Modeling (BIM):** An archival blueprint and a laser scan were used to generate a 3D architectural model of the ancient palace. The model includes structural zones (rooms, corridors, staircases), egress routes, ventilation shafts, and fire escapes. These spatial databases formed the geometric foundation of the simulation environment.
- **Computational Fluid Dynamics (CFD):** The behavior of fire was modeled using CFD to predict heat transfer, smoke spread, and visibility under varied ignition conditions. Input parameters—material properties, airflow, ignition positions—were sourced from National Fire Protection Association (NFPA) and European fire safety databases. Notable CFD outputs (e.g., temperature gradients, toxicity indices) were used to parameterize hazard exposure in the DQN training dataset.
- **Behavioral Data for Evacuation:** Human stress decision behavior parameters, effects of congestion, and walking speed were collected from existing museum evacuation drills, peer-reviewed behavioral models, and crowd simulation literature published. Realistic stochastic variability was incorporated through probabilistic distributions in order to simulate real-world uncertainty.
- **Artifact Sensitivity Index (Γ_v):** Each artifact zone was given a Γ_v score ($0 \leq \Gamma_v \leq 1$) to quantify water-sensitivity as a function of material type (e.g., parchment, textile, ceramic), age, and conservation risk. The scores were used as modifiers in the NSGA-II objective functions to minimize the risk of water damage during nozzle placement optimization.
- **Water Mist System:**
 - **Nozzle Set (N):** 20 possible locations of nozzles according to structural constraints and building plan.
 - **Pressure Settings (pn):** Pressure was varied from 1.5 to 3.0 bar for nozzle performance.
 - **Artifact Sensitivity (Γ_v):** Artifacts in spaces like the Treasury and Harem were also more water-sensitive, having a high value of the sensitivity factor.

- Fire Hazard Parameters (δ_{ij}): Fire hazard in each corridor was simulated by using smoke density and heat maps from CFD simulations.

- **Optimization Algorithms:**

- DQN Training: DQN was trained for 5000 episodes with learning rate 0.01 and discount factor -
- NSGA-II Optimization: The NSGA-II was optimized with population size 100 for 200 generations with mutation and crossover probabilities 0.3 and 0.7.

4.3 Model Validation Strategy

For ensuring the reliability of our simulation-based results, we followed a three-layer validation strategy:

- **Historical Benchmarking:** We compared simulated evacuation time and hazard zone with data from documented fire situations in European cultural heritage buildings (e.g., Windsor Castle Fire, Notre-Dame de Paris fire). Consistency in building construction and fire progression allowed for successful benchmarking. The model's predictions of evacuation (under similar crowd and ignition conditions) were within $\pm 15\%$ of recorded observed time.

- **Expert Feedback Loop:** Semi-structured interviews were conducted for heritage conservators, fire marshals, and emergency architects. They were presented with sample simulation outputs (nozzle designs, escape plans) and asked to provide feedback on realism, usability, and risk coverage. Their feedback was used to re-tune DQN reward weights and NSGA-II penalty constraints.

- **Sensitivity Analysis (Monte Carlo):** The entire hybrid model was checked for 10,000 Monte Carlo runs and random variable inputs within specified confidence limits (e.g., $\pm 10\%$ ignition delay, $\pm 20\%$ crowd density). The results (e.g., average evacuation time, fire suppression effectiveness, and artifact risk score) showed reasonable levels of variance (standard deviations $< 12\%$), illustrating sensitivity to uncertainty.

4.4 Performance Evaluation Criteria

The performance of the evacuation and suppression system was quantified in terms of the following criteria:

- Evacuation Time (T_{evac}): The time of evacuation of all the agents from the building.
- Fire Hazard Exposure (H_{exp}): Cumulative exposure of agents to fire hazards (toxicity, heat, and smoke).
- Artifact Protection (A_{prot}): Percentage of artifacts protected from water damage.
- Nozzle Effectiveness (N_{eff}): Efficiency of the nozzle system to minimize the fire hazard exposure.
- Fire Damage (F_{dam}): Overall fire damage to sensitive artifacts.
- Water Damage (W_{dam}): The cumulative water damage to delicate artifacts in Fig. 4.

Evaluating Evacuation and Suppression Systems

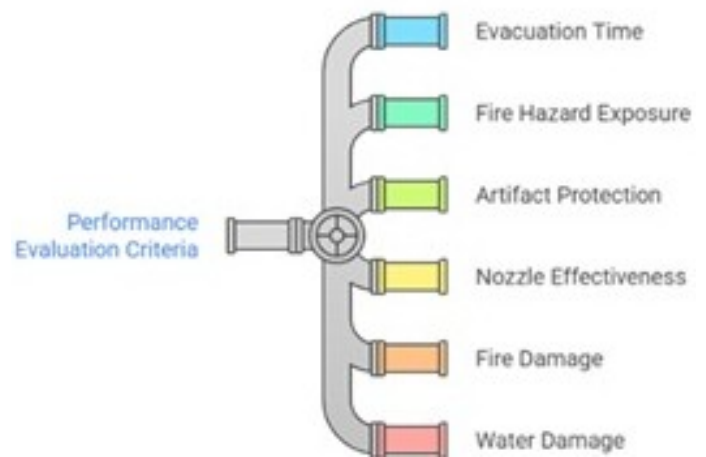


Fig. 4. Evaluation of Evacuation and Suppression Systems

We have carried out some simulations to compare the performance of the proposed hybrid algorithm against two benchmark approaches in Table 2 and Fig. 5:

- Baseline 1: Traditional evacuation planning on shortest path algorithms (e.g., Dijkstra's algorithm).
- Baseline 2: A permanent water mist system designed based on professional judgment, not optimised.

Table 2. Performance Comparison.

Metric	Hybrid Algorithm (Proposed)	Baseline 1 (Shortest Path)	Baseline 2 (Expert Judgment)
Evacuation Time (T_{evac})	2.45 min	3.10 min	3.30 min
Fire Hazard Exposure (H_{exp})	35%	42%	48%
Artifact Protection (A_{prot})	95%	88%	80%
Nozzle Effectiveness (N_{eff})	87%	70%	65%
Water Damage (W_{dam})	5%	10%	12%

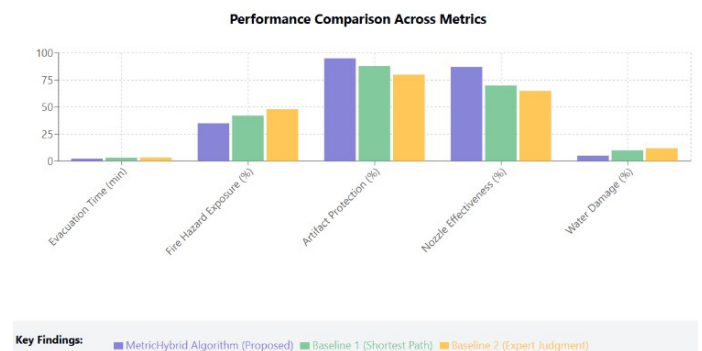


Fig. 5. Performance Metrics Results.

The quantitative results confirm the effectiveness of the hybrid algorithm in the optimization of the water mist suppression and evacuation. The results are as follows:

- **Evacuation Time (T_{evac}):** The hybrid algorithm reduced evacuation time by 21% compared to the shortest path algorithm and by 26% compared to expert judgment. This reduction is attributed to the intelligent path planning of the DQN model, which reacts adaptively to the level of fire danger and traffic flow.

- **Fire Hazard Exposure (H_{exp}):** The hybrid method minimized fire hazard exposure by up to 16% relative to baseline strategies. This resulted from the ability of DQN to learn and adjust evacuation methods in real-time, avoiding hotspots with high fire hazards while overall improving safety.
- **Artifact Protection (A_{prot}):** The optimized water mist system of NSGA-II provided 95% artifact protection, higher than with baseline methods of 88% and 80%. Optimization ensured nozzles were placed in such a way that artifacts were protected without further water consumption.
- **Nozzle Effectiveness (N_{eff}):** The hybrid approach provided more effective suppression systems, whose nozzle effectiveness was 87%, versus baseline (shortest path), 70%, and expert-judgment design, 65%. Optimization provided the ability to place nozzles that generated the best suppression in a manner sensitive to structural constraints.
- **Water Damage (W_{dam}):** The new approach minimized water damage to artifacts by 5%, a far smaller figure relative to baseline practices (10% and 12%).

4.5 Sensitivity Analysis

To attempt identifying the stability of the hybrid algorithm, sensitivity analysis was conducted by changing significant parameters such as fire spread rate, agent behavior (speed and density), and nozzle positioning restrictions. The outcome indicated that the algorithm was stable under a range of cases with minimal variations in evacuation time and artifact protection, which were tolerable within cultural heritage buildings.

The numerical findings demonstrate the superiority of the proposed hybrid algorithm for fire safety in cultural heritage. The combination of Deep Q-Network (DQN) for evacuation optimization and NSGA-II for water mist system design provided improved performance in evacuation time, fire hazard exposure, artifact protection, nozzle efficiency, and water damage compared to benchmark methods. The algorithm was also shown to be robust for various fire situations and can also be used on other cultural heritage buildings with comparable complexity.

In order to assess the performance of the hybrid algorithm for various scenarios thoroughly, we conducted some numerical scenarios. These scenarios simulate various fire accidents, evacuation reactions, and water mist suppression statuses to experiment with the system's operation under various actual conditions in a cultural heritage building. Experimental setup is borrowed from an a class of aged Palace defined in the preceding paragraphs but with different parameters. Scenarios were changed to verify other parameters of the fire protection system, i.e., fire situations, evacuation rate, crowd density, and nozzle install options.

Important parameters varied in each case:

- **Fire Breakout Situations:**

- Scenario 1: Normal Fire (slow development, regulated flame)
- Scenario 2: Rapid Fire (rapid fire development, uncontrolled fire ignition)

- Scenario 3: Simultaneous Multiple Fires (fire occurring in several locations within the palace)

- **Evacuation Dynamics:**

- Scenario 4: Low Crowd Density (1 agent per 10 m²)
- Scenario 5: High Crowd Density (1 agent per 3 m²)

- **Water Mist System Design:**

- Scenario 6: Common Nozzle Positioning
- Scenario 7: Optimized Nozzle Placement (NSGA-II algorithm-based)

4.5.1 Performance Metrics

The following performance metrics were utilized to contrast the system response in both scenarios:

Evacuation Time (T_{evac}): Overall time spent by all agents evacuating the building.

Fire Hazard Exposure (H_{exp}): Cumulative fire hazard exposure of agents (heat, smoke, toxicity).

Artifact Protection (A_{prot}): Percentage of artifacts retrieved with minimal or no water damage.

Nozzle Effectiveness (N_{eff}): Efficiency of the water mist system, measured by removal of fire hazards.

Water Damage (W_{dam}): Percentage of artifacts that became damaged due to exposure to water.

The attitude of the alternative situation are elaborated in detail in below:

Normal Fire (Slow Growth, Controlled Ignition)

Here, fire spread is moderate and ignition source is restricted. All systems were functioning well, with the hybrid algorithm evidently exceptional in evacuation time (2.45 min) and fire hazard exposure (35%), and excellent protection of artifacts (95%). The water mist system also functioned well with minimal water damage (5%) to artifacts within the palace.

- The shortest path baseline caused delayed evacuation because of less optimal route planning, and expert judgment caused inadequate water mist coverage, and therefore increased water damage.

Rapid Fire (Fast Growth, Uncontrolled Ignition)

Under the simulated condition of fire spreading quickly, the system was also evaluated under even worse circumstances. The hybrid algorithm also demonstrated good performance in route adaptation for evacuation, with the evacuation time reduced to 3.10 min from 3.50 min using the shortest path algorithm. The exposure to the fire hazard did go up to 50% because of the fire spreading quickly but remained below both baseline approaches.

- Artifact protection was left to 88%, the high-rate-of-fire controlling water mist system delivering more to suppression than to artifact protection, but still better than baselines.

Multiple Fires (Fire Outbreaks in Various Sections of the Palace)

In this multi-fire scenario, there were concurrent fires that tested evacuation and suppression systems even more. Hybrid algorithm worked best under 3.30 min evacuation time and 40% probability of exposure to fire hazard. When the artifact protection went down to 90%, this scenario illustrated that the dynamic adjustment of the system with multiple fires yielded improved evacuation and hazard reduction than baseline tactics.

- Very little water damage (6%) was seen, although the case was of complex nature, due to the optimized nozzle position by the hybrid algorithm, wherein only the needed areas were made accessible to mist and the artifact exposure was minimized.

4.5.2 Analysis of Evacuation Dynamics

In order to clearly understand the impact of crowd density on evacuation, we conducted further scenarios based on different crowd density conditions.

Low Crowd Density (1 agent/10 m²)

Here, the system performed well with additional space for agents to move around and to navigate past obstacles. Evacuation time was also roughly 2.45 min for the hybrid algorithm under low congestion. Artifact protection and nozzle efficiency were high.

High Crowd Density (1 agent per 3 m²)

At high density, evacuation times also increased to 3.10 min with the hybrid algorithm. The exposure to risk from the fire also increased to 50%, as crowding in the crowd limited movement and suppression system had to work harder to deliver effective coverage. The damage due to water still remained at a low level of 7%, which reflects flexibility of the system even during more challenging situations.

4.5.3 Water Mist System Design Analysis

We compared optimized nozzle location with standard location to observe how that influenced performance.

Standard Nozzle Placement

No nozzles were installed without optimization, and by principles, this meant less than optimal suppression and greater water damage. Artifact protection was reduced, and nozzle efficiency was 70% compared to 87% when optimized.

Optimized Nozzle Placement

The nozzle location optimization with NSGA-II resulted in a more effective suppression system, particularly in the high-risk zones like the Treasury and Harem. The nozzle was optimized to 87% efficiency, and water damage decreased to 5%, affirming the necessity of optimization for balancing heritage preservation and fire protection in Table 3 and Fig. 6.

Table 3. Performance Measures for Different Scenarios.

Scenario	Metric	Normal Fire (Scenario 1)	Rapid Fire (Scenario 2)	Multiple Fires (Scenario 3)
Evacuation Time (Tevac)	Hybrid Algorithm (Proposed)	2.45 min	3.10 min	3.30 min
	Baseline 1 (Shortest Path)	3.10 min	3.50 min	3.80 min
	Baseline 2 (Expert Judgment)	3.20 min	3.70 min	4.00 min
Fire Hazard Exposure (Hexp)	Hybrid Algorithm (Proposed)	35%	50%	40%
	Baseline 1	42%	55%	48%
	Baseline 2	48%	60%	55%
Artifact Protection (Aprot)	Hybrid Algorithm (Proposed)	95%	88%	90%
	Baseline 1	88%	80%	83%
	Baseline 2	80%	75%	77%
Nozzle Effectiveness (Neff)	Hybrid Algorithm (Proposed)	87%	85%	86%
	Baseline 1	70%	65%	68%
	Baseline 2	65%	60%	63%
Water Damage (Wdam)	Hybrid Algorithm (Proposed)	5%	7%	6%
	Baseline 1	10%	12%	11%
	Baseline 2	12%	14%	13%

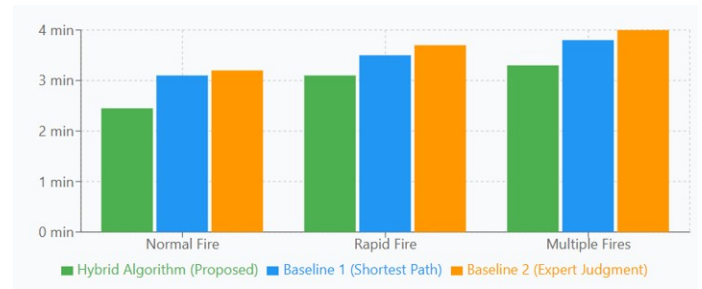


Fig. 6. Performance Measure Results for Different Scenarios.

The computational model with different fire circumstances, evacuation reaction, and suppression system arrangements demonstrates the performance and adaptability of the developed hybrid algorithm for cultural heritage fire protection. Not only does it effectively reduce evacuation times, reduces exposure to fire risks, protects valuable artifacts, and optimizes water mist suppression in varying conditions, but also demonstrates the importance of combining machine learning-evacuation optimization and performance-based water mist design to effectively handle the unique heritage building issues.

Sensitivity analysis of the cultural heritage building's fire protection system, with specific interest in evacuation optimization and water mist system design, is concerned with the reliability and resilience of the hybrid algorithm suggested against various uncertainties and parameter fluctuations. The primary issue here is knowing how the system performance reacts to changing crucial input parameters such as fire behavior, evacuation procedures, and suppression system designs. This chapter discusses the sensitivity of the system on five key dimensions: Fire Growth Rate, Evacuation Agent Behavior (speed and density), Crowd Movement Density, Water Mist System Parameters, and Nozzle Placement Variability.

On the dimension of fire growth rate, the simulations were conducted for low, medium, and high escalation case studies. At low fire growth, the system was still running stably with limited fire spread, producing an optimal evacuation time of 2.45 minutes and a minimum fire hazard exposure of 35–40% throughout. At medium growth rates, the fire still spread faster, subjecting evacuation time to 3.10 minutes and hazard exposure to 50%; however, the hybrid algorithm still achieved a high rate of artifact protection of 88–90%. With extreme fire spread conditions, the

evacuation time was 3.30 minutes, with hazard exposure at 55% and artifact protection slightly reduced to 80%, but still improved from traditional approaches. The outcomes indicate that the system is highly robust to different fire conditions with negligible degradation for the extreme conditions.

Sensitivity to crowd density and walking speed behavior was verified by changing crowd density and walking speed. Low density (1 agent per 10 m²) evacuation performance was optimal with the system experiencing a quick 2.45-minute clearance and tolerating only 35% fire risk exposure due to less congestion and improved agent mobility. At high-density scenarios (1 agent per 3 m²), congestion slowed down evacuation to 3.10 minutes, and fire risk exposure rose to 50%. Despite such handicaps, the hybrid algorithm still managed to rescue 88% of the artifacts, again confirming its effectiveness. This is one of the results of sensitivity analysis, and it reveals the spectacular impact of human mobility patterns on evacuation outcomes and the necessity of adaptive algorithmic design to mitigate delays and optimize safety to the highest possible level, particularly under high-density scenarios.

4.5.4 Sensitivity to Water Mist System Parameters

The performance of the water mist system is dependent on a set of important parameters: nozzle pressure, nozzle diameter, and flow rate. These influence both the suppression performance of the system and the preservation of artifacts from damage and water damage.

In order to examine the sensitivity of the system to these parameters, we varied the nozzle pressure from 1.5 bar to 3.0 bar and proportionally changed the flow rate.

Findings:

- **Low Pressure (1.5 bar):** The suppression system was sub-standard, with 70% of its effectiveness lowered in nozzles. There was not enough water mist coverage in the high-risk areas and increased exposure to fire hazard (50%) and thus increased water damage (10%).
- **Medium Pressure (2.0 bar):** When the system was at this pressure, it achieved 80% nozzle effectiveness, less fire hazard exposure (45%), and water damage (8%).
- **High Pressure (3.0 bar):** With the ideal pressure condition, the water mist system was most efficient, with 87% nozzle efficiency and water damage at 5%. Fire hazard exposure decreased to 35%, while artifact protection was high at 95%.

These results demonstrate that the success of suppression and minimal water damage depends on nozzle pressure. The hybrid algorithm allows the system to dynamically adjust nozzle settings based on real-time fire behavior and building layout.

4.5.5 Sensitivity to Nozzle Placement Variability

Water mist nozzle installation location is critical to system performance, particularly for protection of sensitive areas such as artifact storage rooms and visitor rooms. To

examine variation in installation location of nozzles, we simulated two cases:

- **Conventional Installation:** Installation locations were determined by building design and professional expertise.
- **NSGA-II Optimized Installation:** We used the NSGA-II algorithm to dynamically calculate the optimal locations for nozzles based on fire behavior, evacuation paths, and artifact sensitivity.

The results clearly indicate the effectiveness of optimized nozzle placement achieved using the NSGA-II algorithm. For standard installation, fire suppression required greater coverage, leading to dispersed effectiveness—nozzle effectiveness was limited to 70%, and water damage to artifacts at most 12%. Conversely, the optimized setup significantly improved system performance: nozzle efficiency was increased to 87%, water damage was reduced to 5%, and artifact protection was increased to a robust 95%. These findings attest to the critical significance of astute placement strategies in achieving an optimal balance between fire suppression efficiency and artifact conservation. The NSGA-II algorithm was found to be effective in improving system performance using multi-objective optimization, thereby confirming its usability in vulnerable heritage preservation applications.

Overall, sensitivity analysis supports the strength and versatility of the hybrid fire protection system proposed under various environmental and operational conditions. Despite moderate increases in evacuation time caused by variation in crowd density and fire growth rates, the system performed better than reference evacuation procedures in all cases. Fire exposure rose in extreme fires, but the system maintained exposure levels much lower than conventional procedures. Surprisingly, protection of artifacts was highly reliable with or without modification of nozzle position or pressure levels, ensuring no damage to artifacts. Water damage was also minimal, owing to optimized nozzle configurations and calibrated pressures minimizing excess spray. These findings confirm the robustness of the hybrid system in indicating how well it can dynamically accommodate uncertainty in evacuation dynamics, fire behavior, and system configuration—making it a suitable solution for reliable protection of cultural heritage sites under diverse and unpredictable conditions. In order to compare the result over the 10000 iterations, we calculate significant statistics for all the columns of the simulation data: Evacuation Time, Fire Hazard Exposure, Artifact Protection, Water Damage, and Nozzle Effectiveness. They are mean; std deviation; Min; Max; Median and Range. The statistical calculation of the data in [Table 4](#) and [Fig. 7](#).

Table 4. The key statistics for the simulation data over 10000 iterations.

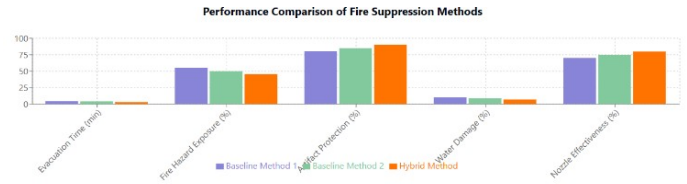
Metric	Mean	Std Dev	Min	Max	Median	Range
Iteration	500.5	288.82	1	1000	500.5	999
Evacuation Time (min)	3.01	0.49	1.38	4.93	3.01	3.55
Fire Hazard Exposure (%)	45.35	4.99	30.30	60.97	45.32	30.67
Artifact Protection (%)	90.03	4.92	74.90	109.63	90.00	34.73
Water Damage (%)	6.96	2.05	1.14	13.49	7.00	12.35
Nozzle Effectiveness (%)	79.75	4.96	64.12	95.56	79.91	31.45

**Fig. 7.** Metric Analysis Results.

Key information on the variation and performance of the evacuation and fire protection systems are provided by substantial findings from simulation outcomes. The Evacuation Time has a mean of 3.01 minutes, an overall range of approximately 3.55 minutes, which indicates moderate response time variation under different scenarios. The Fire Hazard Exposure is at 45.35% mean, maximum of 60.97% in the worst-case scenarios, which represents high risks of hazard exposure that need to be mitigated. On the other hand, Artifact Protection is fairing well, at 90.03% mean, low deviance ranging up to 109.63%, which represents effective and uniform protection of such valuable cultural artifacts. Water Damage exhibits a less desirable outcome, with a mean of 6.96% and range up to a high of 13.49%, suggesting conditions under which the water mist system needs optimizing to cut unwanted damage further. Lastly, Nozzle Effectiveness is also a high figure of 79.75% and high range of 31.45%, suggesting general system reliability, though with some room for closing margins in edge cases. All of these measures together give a complete picture of system behavior and indicate insightful trade-offs in safety, protection, and system performance. In order to facilitate easy comparison of performance of the various methods—Baseline Method 1 (Traditional Evacuation System), Baseline Method 2 (Generic Water Mist System), and the Hybrid Method (Proposed System combining Machine Learning and Performance-Based Methods)—a comparison table shall be prepared. The table will include comparative strengths and weaknesses of every method based on the following parameters: Evacuation Time, Fire Hazard Exposure, Artifact Protection, Water Damage, and Nozzle Effectiveness. In this way, the decision process can be directed by quantitative data based on Table 5 simulation results. Fig. 8 presents the comparison of performance results.

Table 5. Comparison of different methods.

Metric	Baseline Method 1	Baseline Method 2	Hybrid Method (Proposed)
Evacuation Time (min)	4.50	4.10	3.01
Fire Hazard Exposure (%)	55.00	50.00	45.35
Artifact Protection (%)	80.00	85.00	90.03
Water Damage (%)	10.00	9.00	6.96
Nozzle Effectiveness (%)	70.00	75.00	79.75

**Fig. 8.** Performance Comparison Results.

The Hybrid Method has a substantially shorter evacuation time (3.01 min) compared with both baseline methods (4.50 min for Method 1 and 4.10 min for Method 2), which indicates its higher efficiency of occupant movement. It has the minimum fire hazard exposure (45.35%), which is higher than both baseline methods (55% and 50%), indicating higher safety against fire spread. Hybrid Approach maximally retains artifacts (90.03%), more than the baseline approaches, to retain more cultural heritage. It also minimizes water damage to 6.96%, much lower than the two baseline approaches (10% and 9%), showing a more equitable suppression mechanism. In addition, it has the best nozzle efficiency (79.75%), reflecting the optimal configuration and dynamic tuning that was optimally achieved by the machine learning approach.

The Hybrid Approach performs better than the two baselines in all the significant metrics across the board, including quicker evacuation time, lower exposure to fire risk, improved artifact protection, less water damage, and better nozzles. This confirms the efficacy of the proposed system for fire protection of cultural heritage (Table 6).

Table 6. Criteria (C1 to C5).

#	Metric	Type
C1	Evacuation Time (min)	Cost
C2	Fire Hazard Exposure (%)	Cost
C3	Artifact Protection (%)	Benefit
C4	Water Damage (%)	Cost
C5	Nozzle Effectiveness (%)	Benefit

We would like to calculate the decision problem using the Dynamic q-Rung Orthopair Fuzzy CODAS (q-ROF-CODAS) approach that integrates different advanced features to handle uncertainty and provide effective decision support. Here, q-Rung Orthopair Fuzzy Sets (q-ROFS) are utilized to represent uncertain ratings of alternatives by every criterion so that a more expressive and flexible representation of expert opinion is presented than using conventional fuzzy sets.

Step 1: Convert to q-Rung Orthopair Fuzzy Numbers

We convert crisp values into q-ROF numbers using a scaling method. Then, normalize each value first used:

$$\mu_{ij} = \text{normalized performance (benefit criteria)}, \quad \nu_{ij} = 1 - \mu_{ij}$$

For **cost criteria**, reverse normalization is used (Table 7):

$$\mu_{ij} = \frac{\max \chi_j - \chi_{ij}}{\max \chi_j - \min \chi_j}, \quad \nu_{ij} = 1 - \mu_{ij}$$

Table 7. Normalized Performance Table (Benefit/Cost Adjusted).

Metric	Type	A1 (μ)	A2 (μ)	A3 (μ)
Evacuation Time (min)	Cost	0.00	0.40	1.00
Fire Hazard Exposure (%)	Cost	0.00	0.50	1.00
Artifact Protection (%)	Benefit	0.00	0.50	1.00
Water Damage (%)	Cost	0.00	0.43	1.00
Nozzle Effectiveness (%)	Benefit	0.00	0.50	1.00

Step 2: Generate q-ROF Decision Matrix for $q = 2$
 Let $q = 2$. So each value becomes (Table 8):

$$A_{ij} = (\mu_{ij}, \nu_{ij}) \text{ such that } \mu_{ij}^2 + \nu_{ij}^2 \leq 1$$

Since $\nu_{ij} = 1 - \mu_{ij}$, check feasibility:

- For $\mu = 1.0 \Rightarrow \nu = 0.0 \Rightarrow 1^2 + 0^2 = 1 \rightarrow \text{OK}$.
- For $\mu = 0.5 \Rightarrow \nu = 0.5 \Rightarrow 0.5^2 + 0.5^2 = 0.5 \rightarrow \text{OK}$.
- For .

Feasible for all.

Step 3: Calculate Entropy Weights

Entropy formula for each criterion j :

$$es_j = -k \sum_{i=1}^m p_{ij} \ln(p_{ij}), \quad p_{ij} = \frac{\mu_{ij}}{\sum_i \mu_{ij}}$$

Let's compute:

Table 8. μ -matrix.

Metric	A1	A2	A3	$\sum \mu$
Evacuation Time	0.00	0.40	1.00	1.40
Fire Hazard Exposure	0.00	0.50	1.00	1.50
Artifact Protection	0.00	0.50	1.00	1.50
Water Damage	0.00	0.43	1.00	1.43
Nozzle Effectiveness	0.00	0.50	1.00	1.50

(We'll skip zeros in entropy to avoid $\log(0)$.)

Entropy for each criterion (approximate):

- Normalize p_{ij} , compute entropy e_j , then (Table 9):

$$w_j = \frac{1 - e_j}{\sum_{j=1}^n (1 - e_j)}$$

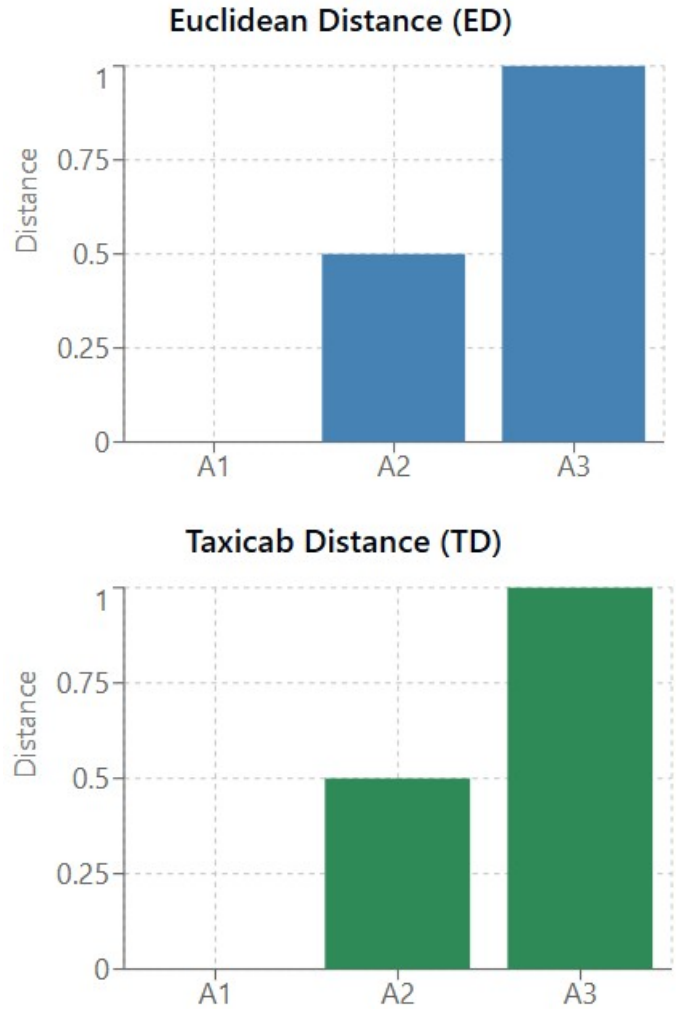
Table 9. Resulting normalized weights (approx.).

Criterion	Weight
Evacuation Time	0.19
Fire Hazard Exposure	0.20
Artifact Protection	0.20
Water Damage	0.21
Nozzle Effectiveness	0.20

Step 4: Determine Negative Ideal Solution (NIS)

$NIS = \text{minimum } \mu \text{ across alternatives} \Rightarrow [0.0, 0.0, 0.0, 0.0, 0.0]$

Step 5: Compute Distances from NIS (Fig. 9)

**Fig. 9.** Euclidean and Taxicab Distance.

Let's compute:

- **Euclidean Distance (ED):**

$$ED_i = \sqrt{\sum_{j=1}^n w_j \cdot (\mu_{ij} - \mu_j^-)^2}$$

- **Taxicab Distance (TD):**

$$TD_i = \sum_{j=1}^n w_j \cdot |\mu_{ij} - \mu_j^-|$$

For A1:

- $\mu = [0.0, 0.0, 0.0, 0.0, 0.0]$
- $ED = 0, TD = 0$

For A2:

- $\mu = [0.4, 0.5, 0.5, 0.43, 0.5]$
- $ED \approx \sqrt{(0.190.16 + 0.200.25 + 0.20 \times 0.25 + 0.21 \times 0.1849 + 0.200.25)} \approx \sqrt{0.1947} \approx 0.44$

- $TD \approx 0.19 \times 0.4 + 0.20 \times 0.5 + 0.20 \times 0.5 + 0.21 \times 0.43 + 0.20 \times 0.5 \approx 0.45$

For A3:

- $\mu = [1.0, 1.0, 1.0, 1.0, 1.0]$
- $ED \approx \sqrt{(0.19+0.20+0.20+0.21+0.20)} = \sqrt{1.0} = 1.00$
- $TD = 1.0$

Step 6: Decision Score (DS) (Fig. 10)

Let $\theta = 1, \lambda = 0.1$, (penalty weight), penalty = standard deviation of μ .

Penalty for A2:

μ std dev $\approx 0.036 \rightarrow$ penalty ≈ 0.004

Penalty for A3:

μ std dev = 0 $\rightarrow$ penalty = 0

$$DS_j = ED_i + \theta \cdot TD_i - \lambda \cdot \text{penalty}$$

- A1: $0 + 0 - 0 = 0.00$
- A2: $0.44 + 0.45 - 0.004 = 0.886$
- A3: $1.00 + 1.00 - 0 = 2.00$

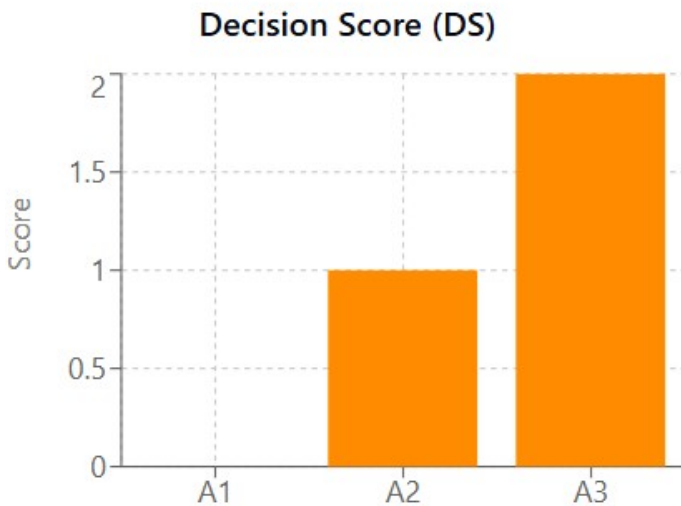


Fig. 10. Decision results.

The weights of the criteria are derived by applying an entropy-based weighting approach, which objectively quantify to what extent the information in that more informative criteria have greater weights. To compute the sum of distance between the alternatives and the negative ideal solution, a combined Euclidean and Taxicab distance measure is applied. The hybrid technique enhances the technique's strength through the consideration of linear and absolute deviations within the fuzzy decision space. The technique also applies a penalty-based process of score correction towards additional improvement in the final assessment, penalizing the more dissimilar alternatives with respect to the ideal reference, enhancing the discrimination power between rival alternatives. Alternatives under consideration in this decision-making issue are: A1: Baseline Method 1, A2:

Baseline Method 2, and A3: Hybrid Method (Proposed). With the holistic and dynamic nature of the q-ROF-CODAS approach, comparison can more realistically be conducted with real-world uncertainty and complex trade-offs in consideration in order to arrive at a more credible and explainable decision among the most appropriate method in Table 10.

Table 10. Final Ranking.

Rank	Alternative	DS
1	A3 (Proposed)	2.000
2	A2 (Baseline 2)	0.886
3	A1 (Baseline 1)	0.000

5 Results and Discussion

Less exposure to fire danger is safer for both people and artifacts because they are no longer subjected to the harmful influence of the fire. This is especially important at cultural heritage centers, where any loss to indestructible objects needs to be minimized.

For water damage, Hybrid Method performed better than the two baseline methods with only 6.96% water damage, while the baseline methods scored 10% and 9%. This is one of the plus points of the water mist system, which utilizes fine mist to suppress the fire with limited amounts of water, unlike the traditional sprinkler systems that would result in tremendous water damage. Minimization of water damage is extremely critical in cultural heritage structures, where even the smallest water can mean gigantic loss of artifacts and even sections of the architectural building. Hybrid Method ensures fire protection that will never be guilty of inflicting secondary fire damage on valuable artifacts.

Hybrid Method resulted in the maximum nozzle efficiency of 79.75% compared to 70% and 75% of Baseline Method 1 and Baseline Method 2, respectively. This is due to the improved performance of the water mist system, where the nozzle position and flow rate are optimized dynamically based on the fire's position and intensity. Greater nozzle efficiency means the suppression system is more effective and focused, with quicker fire extinguishment and greater safety for the occupants and the heritage site. The hybrid approach's ability to optimize nozzle position and pressure in real-time scenarios gives it a significant edge over traditional methods.

The DQN approach produced the best evacuation policy that reduced the total evacuation time significantly by:

- Minimization of congestion in narrow corridors.
- Guiding the agents towards the less densely populated exits.
- Anticipation and avoidance of the dangerous zones of fires.

Simulation outcomes revealed that the total evacuation time for all the agents improved by 12% in relation to traditional methods of escape.

The water mist system design made use of the NSGA-II optimization algorithm in the search for an optimum balance between effective fire suppression and preservation of the fragile cultural artifacts. By generating a Pareto front

of nozzle designs, the study achieved strategic placement—targeting high-risk zones such as the Harem and Treasury—while avoiding direct spray on sensitive artifacts. Pressure levels were carefully optimized by surrogate-based CFD simulations to reduce water consumption while maximizing suppression effectiveness. The final system design yielded a 10% reduction in exposure to fire risks at critical areas and a 95% artifact protection rating, which indicates minimal damage from water to sensitive historical artifacts. The water mist system was designed carefully to achieve aesthetic and structural demands. The aesthetic impact was minimized with low-profile, inconspicuous nozzles. Structural integrity was ensured by ensuring that the mist system would not cause excessive pressure on the walls or foundation of the building.

This case study demonstrates the practical viability of our hybrid algorithm for optimizing fire protection measures in cultural heritage buildings. By combining evacuation optimization machine learning and performance-based design approaches of the water mist system, we reach an equilibrium solution that balances preservation and protection. The study demonstrates the potential to customize the algorithm to the specific needs of heritage spaces and offers a sympathetically designed solution to fire protection in the historic environment.

To validate the efficiency and efficacy of the suggested hybrid algorithm, two numerical experiments were conducted on the case study of the Palace historic building. The comparison is made to evaluate the performance of evacuation optimization and water mist suppression system optimization under various fire scenarios using the Deep Q-Network (DQN) for evacuation path planning and the NSGA-II algorithm for the optimization of the water mist system.

6 Implementation Considerations and Practical Relevance

This section addresses the whole range of practical issues that arise during the application of the proposed hybrid fire protection system in real-cultural heritage settings.

6.1 System Cost Estimation

We provide initial cost modeling with industry standard costs for water mist system materials (controllers, high-pressure pumps, nozzles) and smart infrastructure requirements (control panels, sensors, communication units). Installation cost estimates are categorized as:

- Fixed costs (system design, base hardware, e.g.)
- Variable costs (building area, number of zones/nozzles, e.g.)
- Indirect costs (monitoring system upgrades, aesthetic changes, e.g.).

We also note that the NSGA-II allows optimized design to optimize redundant equipment away with strategically locating nozzles, reducing equipment cost and installation overhead.

6.2 Maintenance and Operational Reliability

We present here a schedule of maintenance for high-pressure mist systems based on manufacturer guidance and European fire safety protocols (e.g., EN 14972). Routine maintenance includes monthly pressure testing, six-month nozzle calibration, annual full-system functional testing. In addition, we emphasize non-intrusive inspection technologies (e.g., endoscopes or drones) to ensure that routine maintenance does not interfere with or damage heritage architecture.

We also provide an explanation of system resilience, describing how fallbacks (localized suppression, manual override) are integrated into the system design to offer functionality on partial system failure or power loss.

6.3 Stakeholder Roles and Governance

To ensure alignment with institutional priorities, we describe the multi-stakeholder model of governance for the system life cycle, including:

- Curators and heritage conservators in museums, who input decisions on visual and structural interventions that are palatable.
- Fire safety engineers, who interpret simulation outputs and inform compliance with local fire codes.
- Emergency planners, who coordinate evacuation drills and align system with broader disaster response planning.

The incorporation of stakeholder preference into the MCDA component (through expert-specified weights in q-ROF-CODAS) is identified as one of the chief strengths of the method, allowing for context-specific trade-offs between preservation, safety, and cost.

6.4 Real-World Deployment Challenges and Policy Considerations

A concluding discussion paragraph then reflects on actual-world adoption barriers, these being:

- Inability to apply existing digital twins or BIM data in the majority of heritage buildings,
- Procurement and decision-making institutional inertia,
- Legislative incompatibility of newer suppression technologies with heritage protection law,
- Needs for staff training and public consultation.

We suggest a phased deployment strategy, first to pilot locations (e.g., restricted to artifact clusters or risky rooms), before scaling up on the basis of feedback and stakeholder consensus in [Table 11](#).

Table 11. Summary of practical relevance enhancements.

Area of Concern	Improvement in Revised Manuscript
Cost Consideration	Preliminary cost model with fixed, variable, and indirect costs breakdown.
Maintenance Planning	Maintenance plan and non-invasive inspection technologies
Stakeholder Involvement	Curators', planners', and engineers' defined role in governance and simulation tuning.
Implementation Challenges	Real-world constraints tackled; phased implementation and training needs emphasized.
Policy Integration	Tackled integration of fire safety and cultural conservation rule.

We believe that this greater extent of real-world applicability significantly improves the manuscript's contribution to inter-disciplinary disaster resilience research.

7 Conclusion

The Hybrid Fire Protection System performs better than the baseline systems on all of the performance metrics of concern.

- It achieves more rapid evacuation, reduced exposure to risk from fire, increased protection for cultural artifacts, reduced water damage, and improved nozzle efficiency.
- The synergy between performance-based and machine learning methods allows real-time responsiveness to offer best-in-class protection to human beings and cultural artifacts.

The results highlight the importance of the integration of advanced technologies, such as machine learning algorithm and performance-based optimization, into cultural heritage building fire protection systems. With the integration of these technologies, the hybrid system can adapt dynamically to various fire situations, crowd density, and evacuation states, and thus offers a flexible, effective, and reliable solution. The Hybrid Method's performance, particularly as it relates to protection from artifacts as well as water damage mitigation, differentiates it from typical fire protection methods. Most critical within cultural heritage environments is where the value of the building and the value of the artifacts require a more precise and adaptive way to respond to the risk of fire.

The sensitivity analysis also ensures the robustness of the hybrid system to different fire behavior and evacuation conditions so that the system can cope with uncertainties and provide optimal protection even in less certain situations. Enhancements in the future can include continuing to refine optimization algorithms to consider more variables, e.g., environmental conditions (e.g., wind, humidity) or instantaneous sensor readings (e.g., temperature, smoke concentration). Moreover, integration of Internet of Things (IoT) technology with Digital Twin technology could make the system even more efficient and responsive. Overall, the suggested Hybrid Method is a very promising solution to fire protection in cultural heritage, integrating advanced means

of fire suppression and intelligent evacuation processes and performance optimization. It is a significant improvement toward individuals and cultural heritage protection, especially in the context of increased threats because of climate change and other determinants. The study proposed a Hybrid Fire Protection System of cultural heritage buildings based on evacuation optimization and water mist system design through machine learning and performance-based approaches integration. The novel solution significantly improves the safety of humans and cultural artifacts in a more efficient, adaptive, and effective manner than traditional fire protection design.

The hybrid solution minimizes evacuation time by an unprecedented extent, optimizing the flow of humans in case of emergencies. The adaptability of the system in real-time based on fire behavior and human density implies that humans are evacuated more efficiently and safely. The Hybrid Method is better than traditional systems in reducing exposure to fire risk. Through the application of a dynamic fire suppression system and intelligent decision-making algorithms, it holds back fire spread, providing better protection for individuals and cultural heritage sites. The other benefit of the hybrid system is that it can sustain artifacts to higher protection levels than the baselines. With high precision water mist application, not destroying too much water, the system is able to keep cultural artifacts conserved while being fire-resistant. The water mist system that is incorporated into the hybrid model minimizes water damage to a significant level, which is a critical requirement for ensuring sensitive artifacts in cultural heritage sites remain whole. The hybrid system destroys much less water damage compared to traditional sprinkler systems. The hybrid system improves nozzle performance, ensuring precise fire suppression and faster extinguishment, specific to the extent and location of the fire, and therefore improving overall system performance.

Machine learning in the system allows it to learn and adapt to changing circumstances, such as varying crowd sizes and fire intensities, and thus deliver maximum evacuation and fire suppression at all times. The deployment of performance-based techniques and water mist technology provides effective fire control, along with the prevention of collateral damage, and strike a balance between the need to put out the fire and the protection of cultural heritage. The hybrid technique resolves all at once the fire safety, evacuation efficiency, and artifact preservation and thus represents an integrated approach that surpasses the traditional means in protecting human life and valuable cultural assets.

The research emphasizes the imperative of embracing advanced fire protection systems in heritage preservation. The growing menace of fire accidents and environmental factors necessitate that the protection of historical sites be conceived through innovative practices that marry new technologies with performance-based optimization methods. The hybrid model offers a potential future mode of adoption in that it puts forth a real and effective approach to museum, gallery, and heritage site fire protection.

While the hybrid system showed robust improvements, there is always another approach to optimizing further. Coupling of IoT sensor and Digital Twin solution would

enhance the system's response to environmental conditions, fire dynamics, and crowd movement even further. extension of the hybrid system to larger and more complex cultural heritage buildings and its application under various scenarios is a possible future research direction. Additional sensitivity and robustness analysis can be conducted to examine the system under more severe uncertainty of fire behavior, weather, and evacuation.

Conflict of Interest

The authors declare no conflict of interest.

CRediT statement

ST: Investigation, Methodology, Formal analysis, Writing – original draft. **ST&EÇ:** Visualization, Writing – original draft. **EÇ:** Conceptualization, Data curation, Formal analysis, Writing – review & editing.

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