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FULL LENGTH ARTICLE

# Dynamic Evacuation Routing Using IoT Fire Sensors and Semantic BIM Graphs

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## ABSTRACT

Indoor fire evacuation requires decisions that change as smoke, heat, and occupant movement evolve. Conventional evacuation drawings are usually prepared before an incident and cannot represent real-time loss of visibility, blocked corridors, congested stairs, or the changing reliability of alternative exits. This paper proposes a dynamic evacuation-routing framework that connects IoT fire-sensor streams with a semantic graph derived from a BIM model. The building is represented as a weighted network of rooms, corridors, doors, stairs, and exits, while sensor readings are transformed into a time-dependent hazard index that continuously modifies edge costs. The proposed model integrates fire-safety asset recognition, semantic BIM enrichment, hazard propagation, congestion-aware edge weighting, and dynamic shortest-path recalculation. A controlled simulation demonstrates how the route recommendation changes during fire development and how dynamic routing reduces hazard exposure compared with a static egress plan. The study contributes a transparent computational structure for transforming BIM from a static documentation model into an adaptive emergency decision-support interface.

**Keywords:** Building information modelling ▪ Dynamic evacuation ▪ IoT fire sensors ▪ Semantic graph ▪ Dijkstra algorithm ▪ Fire safety engineering

## 1. INTRODUCTION

Fire evacuation planning in buildings is commonly developed around fixed exit routes, prescribed travel distances, and static assumptions about the availability of corridors, doors, and stairs. These assumptions are useful for code compliance, yet they are limited during an actual incident because fire conditions develop unevenly across compartments. A corridor that is acceptable at the beginning of an event may become unsafe after smoke migration, while an initially longer route may become preferable if it avoids high-risk zones. The need for adaptive routing is therefore not only a computational problem, but also a fire-safety management problem that requires real-time interpretation of building geometry and sensor evidence.

Building Information Modeling (BIM) provides a structured representation of indoor spaces, openings, vertical circulation, and fire-safety assets. However, BIM is often used as a static repository of drawings and object properties rather than as a live graph for emergency reasoning. A BIM model contains the information required to identify rooms, doors, corridors, stairs, exits, and equipment locations, but these objects must be transformed into a navigable semantic network before they can support evacuation computation. Without this transformation, BIM cannot directly answer routing questions such as which exit remains safest, which corridor is becoming hazardous, and which route should be updated when sensor readings change.

Internet of Things (IoT) fire-sensing systems add a second layer of information. Smoke, carbon monoxide, heat, and occupancy sensors can describe the state of the built environment during a developing event. Yet sensor values alone do not specify how evacuees should move. They must be spatially linked to the BIM graph and translated into edge-level travel penalties. This paper therefore treats dynamic evacuation as a data-fusion task in which semantic BIM topology defines where movement is possible and IoT sensor streams define how safe or unsafe each movement is at a particular time.

The proposed study develops a dynamic evacuation-routing framework that couples a semantic BIM graph with time-varying sensor-based hazard estimates. Fire-safety asset recognition is included as a semantic enrichment layer, allowing exit signs, detectors, extinguishers, and emergency devices to be associated with BIM spaces. A dynamic Dijkstra/A* routing algorithm recomputes paths whenever sensor updates modify route cost. The model is evaluated against a static egress plan using simulated fire propagation, path length, travel time, congestion, hazard exposure, and route-change indicators.

The contribution of the paper is fourfold. First, it formulates indoor evacuation as a semantic graph problem derived from BIM entities. Second, it introduces a mathematical edge-weighting model that combines travel time, hazard level, congestion, and route-blocking thresholds. Third, it implements a reproducible fire scenario with sensor streams, asset recognition results, and dynamic route recalculation. Fourth, it provides an interpretable experimental comparison showing when dynamic routing changes the recommended exit and why these changes improve safety-oriented decision-making.

## 2. RELATED WORK

BIM-enabled fire safety research has developed from static compliance checking toward integrated emergency management. Ma and Wu [1] showed how BIM can support fire emergency management by combining building information and occupant-behaviour decisions. Wehbe and Shahrour [2] proposed a BIM-based smart fire evacuation system that integrates building representation, IoT monitoring, control layers, and evacuation services. These studies established the central idea that BIM can serve as a digital foundation for fire response. However, a persistent limitation is that many systems describe the architecture of integration without providing detailed edge-level route recalculation logic driven by sensor streams.

Computer vision and visual recognition have also been introduced into fire emergency workflows. Deng et al. [3] developed a BIM and computer-vision framework for emergency evacuation considering local safety performance, demonstrating that route planning should respond to local risk rather than rely only on geometric shortest paths. Fire-safety asset datasets such as FireSafetyNet [4] and Fire-ART [5] further support the automated recognition of extinguishers, exit signs, smoke detectors, and related equipment. These datasets are important for BIM enrichment because emergency assets are frequently missing, outdated, or inconsistently modelled in BIM files. Nevertheless, asset recognition alone does not produce evacuation routes unless the recognised objects are linked to spaces and graph edges.

Dynamic evacuation studies increasingly combine BIM with simulation engines, fire dynamics, and route optimisation. Ding et al. [6] developed a BIM-based fire emergency evacuation simulation system for large infrastructure, integrating BIM, fire data, and evacuation simulation. Xu et al. [7] used BIM and fire dynamics simulation to assess evacuation in complex rail transit environments. Such studies demonstrate the value of combining geometry and fire development, but they often require full simulation platforms that can be computationally demanding during rapid decision-making. A lightweight graph-search layer remains useful when routes must be updated as soon as new sensor readings arrive.

Semantic modelling has become a key direction for dynamic evacuation. Pang et al. [8] proposed a semantic approach to dynamic fire path planning through BIM and IoT data integration, showing that ontology-based representation can improve the connection between building entities and fire evacuation knowledge. Related work on BIM/GIS integration and indoor navigation has also shown that topological relationships are crucial for route planning [9]. The present study follows this semantic direction but focuses on a compact graph-based implementation where each edge receives a time-dependent cost derived from hazard and congestion states.

Algorithmic route planning in buildings commonly builds on Dijkstra's algorithm [10] and A* search [11]. These classical algorithms are reliable and interpretable, but their conventional form assumes static edge weights. Fire evacuation requires the weights to evolve because smoke density, heat, CO concentration, and crowding change over time. Recent BIM-based and smart-building studies have demonstrated improved evacuation efficiency through optimisation, simulation, and IoT-supported decisions [12-14]. The unresolved question is how to formulate edge weights so that they remain traceable to physical travel time, sensor evidence, and safety thresholds.

The literature therefore reveals a practical research gap. BIM provides geometry and semantics, IoT sensors provide real-time fire conditions, and graph algorithms provide path computation; however, these three layers are often treated separately. The proposed framework integrates them in a single computational pipeline: BIM spaces are transformed into a graph, sensor streams are converted into hazard indices, asset recognition enriches the graph, and dynamic shortest-path computation updates the recommended route at every sensor interval.

## 3. RESEARCH GAP

The research gap addressed in this paper is the absence of a compact, traceable, and continuously updateable evacuation-routing model that links BIM graph semantics with IoT fire-sensor observations. Static egress plans are useful for design approval but cannot adapt to smoke migration or route blockage. High-fidelity fire and evacuation simulations provide rich analysis, but they can be too computationally expensive

**Table 1.** Summary of verified studies related to BIM, IoT sensing, fire-safety assets, and dynamic evacuation routing.

| Ref. | Study focus | Method | Main contribution | Limitation addressed here |
|---|---|---|---|---|
| [1] | BIM fire emergency management | BIM with behavioural decisions | Connected building information with emergency management | Limited sensor-driven route recalculation |
| [2] | Smart BIM fire evacuation | BIM, IoT, control and service layers | Proposed a smart evacuation management architecture | Edge-level dynamic weighting is not fully formalised |
| [3] | Local safety route planning | BIM and computer vision | Considered local safety performance in route generation | Does not focus on continuous sensor-stream recomputation |
| [4] | Fire-safety equipment images | Image dataset and pre-trained weights | Supports machine-learning inspection of fire-safety assets | Asset recognition must be linked to BIM graph semantics |
| [5] | Firefighting asset recognition | Dataset and semantic BIM enrichment | Provides classes for emergency equipment recognition | Requires integration with routing and hazard reasoning |
| [6] | Large-infrastructure evacuation | BIM, fire dynamics and evacuation simulation | Integrated fire and evacuation platforms | Full simulation may be heavier than real-time graph update |
| [7] | Rail-station fire evacuation | BIM-FDS evacuation assessment | Evaluated complex station evacuation capacity | Focuses on scenario assessment more than sensor update logic |
| [8] | Semantic fire path planning | BIM-IoT ontology | Built a semantic basis for dynamic path planning | Needs compact route-cost equations for implementation |
| [9] | BIM/GIS indoor emergency routes | Spatial network analysis | Supported shortest and safest indoor paths | Uses limited real-time hazard representation |
| [10] | Shortest path computation | Graph algorithm | Provides robust path optimisation foundation | Assumes static edge weights |
| [11] | Heuristic path search | A* algorithm | Uses admissible heuristic for efficient path search | Requires hazard-aware adaptation for emergency use |
| [12] | BIM-based evacuation efficiency | BIM and simulation optimisation | Identified congestion improvement opportunities | Does not model live sensor-triggered route switching |
| [13] | AIoT tunnel fire safety | Digital twin and AIoT | Demonstrated live tunnel fire-safety management | Tunnel-specific context differs from building BIM routing |
| [14] | BIM and numerical fire simulation | Fire-protection and evacuation analysis | Integrated BIM with numerical simulation for tunnels | Not centred on semantic room-door graph abstraction |
| [15] | Smart-building sensor data | Multi-sensor indoor measurements | Provides indoor sensing variables useful for hazard inference | Needs augmentation for smoke/CO fire scenarios |

**Table 2.** Experimental data components and their roles in the evacuation-routing study.

| Component | Value | Role In Experiment |
|---|---|---|
| Semantic BIM graph | 31 nodes, 78 directed edges | space topology |
| IoT sensor stream | 21 time steps and 357 zone readings | real-time hazard update |
| Fire-ART asset classes | 15 equipment classes | fire-safety asset semantic enrichment |
| Evacuation origins | 6 occupied starting locations | demand sources |
| Scenario duration | 600 s simulated fire development | controlled dynamic hazard scenario |
| Routing strategies | static egress and dynamic hazard-aware routing | benchmark comparison |

for frequent route recomputation. The proposed model fills this gap by introducing a middle layer: a semantic graph whose edge weights are recalculated from sensor evidence, congestion state, and hazard thresholds.

Let the semantic BIM graph be denoted as $G=(V,E)$, where $V$ is the set of rooms, corridors, stairs, doors and exits, and $E$ is the set of movement links between adjacent spaces. Each edge $e_{ij}\in E$ connects node $i$ to node $j$ and has length $d_{ij}$, width $b_{ij}$, route class $r_{ij}$, and free walking speed $v_r$. The free-flow travel time is:

$$\tau_{ij}=\frac{d_{ij}}{v_r}. \tag{1}$$

At each sensor update time $t$, the zone hazard index $H_i(t)$ is computed from normalised smoke $S_i(t)$, carbon monoxide $C_i(t)$, and temperature $T_i(t)$ readings:

$$H_i(t)=\lambda_s\hat{S}_i(t)+\lambda_c\hat{C}_i(t)+\lambda_T\hat{T}_i(t), \tag{2}$$

where $\lambda_s+\lambda_c+\lambda_T=1$. The hazard level associated with an edge is:

$$H_{ij}(t)=\frac{H_i(t)+H_j(t)}{2}. \tag{3}$$

Congestion is represented by $Q_{ij}(t)$, calculated as the ratio between current edge flow and width-adjusted capacity. The dynamic cost assigned to each edge is:

$$w_{ij}(t)=\tau_{ij}[1+\alpha H_{ij}(t)+\beta Q_{ij}(t)]+\Omega\mathbb{1}[H_{ij}(t)>\eta], \tag{4}$$

where $\alpha$ controls hazard sensitivity, $\beta$ controls congestion sensitivity, $\eta$ is the route-blocking threshold, and $\Omega$ is a large penalty assigned to dangerous edges.

For an evacuee starting at origin $o$ and seeking a safe exit $x\in X$, the route is selected by:

$$P^*(o,t)=\arg\min_{P:o\to x,\,x\in X}\sum_{(i,j)\in P}w_{ij}(t). \tag{5}$$

The route is recomputed when a new sensor packet changes the hazard field beyond a threshold:

$$\Delta H(t)=\max_{i\in V}|H_i(t)-H_i(t-1)|>\varepsilon. \tag{6}$$

This rule prevents unnecessary recalculation during stable conditions while ensuring that route recommendations change when smoke or heat conditions become materially different.

## 4. PROPOSED MODEL

The proposed model follows a graph-oriented simulation procedure in which the building is treated as a live evacuation network rather than as a static floor plan. First, the BIM model is converted into a semantic graph in which rooms, corridors, stairs, doors, and exits become topological entities. The graph preserves the practical meaning of IFC-derived adjacency: a route can only pass through connected spaces, and the type of connection influences free-flow travel time. The synthetic IFC-style graph used in the experiment contains rooms, corridors, stair links, exit nodes, and safe exterior nodes.

Second, an IoT fire-sensor stream is generated for a controlled fire scenario. The sensor layer includes smoke, carbon monoxide, and temperature values for the BIM zones. A time-distance fire propagation function creates a moving hazard field around the ignition room, while random perturbation represents sensor noise. The sensor stream is not treated as a direct route instruction; it is transformed into a zone hazard index and then propagated to graph edges through adjacent-node averaging.

Third, a Fire-ART-inspired asset recognition layer is connected to the BIM spaces. The image-based asset distribution is used to represent the recognition of fire extinguishers, exit signs, detectors, emergency lights, and other firefighting assets. In the proposed routing logic, this layer supports semantic enrichment and operational interpretation. Recognised exit signs confirm exit nodes, smoke detectors validate sensor-zone assignments, and equipment classes support emergency inventory awareness. The asset layer is therefore not a separate classification exercise; it strengthens the semantic reliability of the graph and improves the interpretation of evacuation decisions.

The algorithm can be mathematically described as a repeated transformation from sensor observations to route decisions. Let $Z(t) = \{z_i(t)\}_{i \in V}$ be the sensor packet received at time $t$, where $z_i(t) = [S_i(t), C_i(t), T_i(t)]$ represents smoke, carbon monoxide, and temperature readings in zone $i$. A normalisation operator $\psi(\cdot)$ converts the readings to comparable values, and the hazard state vector is computed as

$$\mathbf{h}(t) = \Lambda\, \psi(\mathbf{Z}(t)), \tag{7}$$

where $\Lambda = [\lambda_s, \lambda_c, \lambda_T]$ is the sensor-weight vector. For every edge $e_{ij}$, the edge hazard is obtained by the incidence-based averaging operator $B$ such that

$$\mathbf{h}_E(t) = B\mathbf{h}(t), \quad h_{ij}(t) = \frac{h_i(t) + h_j(t)}{2}. \tag{8}$$

Congestion is updated using the current evacuee assignment $a_{ij}(t)$ and the edge capacity $\kappa_{ij} = b_{ij} v_r \delta$, where $b_{ij}$ is effective width and $\delta$ is a density-to-flow conversion coefficient:

$$q_{ij}(t) = \min\left(1, \frac{a_{ij}(t)}{\kappa_{ij}}\right). \tag{9}$$

The route-cost matrix at time $t$ is then defined as

$$\begin{aligned} W(t) &= \{w_{ij}(t)\}_{e_{ij} \in E}, \\ w_{ij}(t) &= \tau_{ij}(1 + \alpha h_{ij}(t) + \beta q_{ij}(t)) + \Omega I_{ij}(t). \end{aligned} \tag{10}$$

where $I_{ij}(t) = 1$ if $h_{ij}(t) > \eta$ and $I_{ij}(t) = 0$ otherwise. This representation transforms evacuation routing into a time-dependent shortest-path problem with explicit penalties for hazardous and congested edges.

For each occupied origin $o \in O$, the dynamic routing decision is the minimum-risk path to any feasible exit:

$$P_o^*(t) = \arg \min_{P \in \mathscr{P}(o,X)} \sum_{e_{ij} \in P} w_{ij}(t), \tag{11}$$

where $\mathscr{P}(o,X)$ denotes all admissible paths from origin $o$ to the exit set $X$. The algorithm does not recompute routes at every time step by default; it applies an event-triggered update rule:

$$\mathscr{R}(t) = \begin{cases} 1, & \|\mathbf{h}(t) - \mathbf{h}(t-1)\|_\infty > \varepsilon \text{ or } \max_{e_{ij}} I_{ij}(t) = 1, \\ 0, & \text{otherwise.} \end{cases} \tag{12}$$

When $\mathscr{R}(t) = 1$, Dijkstra/A* is executed on $G$ using $W(t)$; otherwise, the previous route set is retained. This event-triggered logic improves computational efficiency while maintaining safety responsiveness when the hazard field changes materially. The complete routing state is therefore updated as

$$\mathscr{P}^*(t) = \begin{cases} \{P_o^*(t) : o \in O(t)\}, & \mathscr{R}(t) = 1, \\ \mathscr{P}^*(t-1), & \mathscr{R}(t) = 0, \end{cases} \tag{13}$$

where $O(t)$ is the set of occupied origins at time $t$. Evacuee allocation to graph edges is then updated by

$$a_{ij}(t+1) = \sum_{o \in O(t)} \mathbb{1}[e_{ij} \in P_o^*(t)], \tag{14}$$

which feeds the next congestion term $q_{ij}(t+1)$. The algorithm is thus a closed-loop mathematical procedure: sensor readings define $\mathbf{h}(t)$, hazard and flow define $W(t)$, $W(t)$ defines the route set $\mathscr{P}^*(t)$, and the selected routes update congestion for the next iteration. This formulation makes the contribution reproducible because every routing decision can be traced to explicit graph attributes, sensor states, and update thresholds rather than to manually selected emergency routes.

Algorithm 1 summarises the computational content of the proposed model. It begins by converting BIM spaces and circulation objects into a semantic graph, then transforms each incoming sensor packet into a zone-level hazard vector. The edge-cost matrix is updated using both hazard and congestion terms, after which the event-triggered condition decides whether rerouting is necessary. When rerouting is activated, dynamic Dijkstra/A* is executed for each occupied origin and the selected routes update the congestion state for the next sensor interval. This sequence makes the model operational because it converts the mathematical formulation into a repeatable procedure that can be implemented in a BIM-based emergency guidance system.

Third, a Fire-ART-inspired asset recognition layer is connected to the BIM spaces. The image-based asset distribution is used to represent the recognition of fire extinguishers, exit signs, detectors, emergency lights, and other firefighting assets. In the proposed routing logic, this layer supports semantic enrichment and operational interpretation. Recognised exit signs confirm exit nodes, smoke detectors validate sensor-zone assignments, and equipment classes support emergency inventory awareness. The asset layer is therefore not a separate classification exercise; it strengthens the semantic reliability of the graph and improves the interpretation

of evacuation decisions.

**Algorithm 1** Dynamic BIM-IoT evacuation routing

**Require:** Semantic BIM graph $G=(V,E)$, exits $X$, occupied origins $O(t)$, sensor stream $Z(t)$, threshold $\varepsilon$
**Ensure:** Updated route set $\mathscr{P}^*(t)$ and congestion state $Q(t+1)$

Extract rooms, corridors, doors, stairs, and exits from BIM to form $G=(V,E)$
Assign each edge $e_{ij}$ its length $d_{ij}$, width $b_{ij}$, class $r_{ij}$, free-flow time $\tau_{ij}$, and capacity $\kappa_{ij}$
**for** each sensor update time $t$ **do**
  Read $Z(t)=\{[S_i(t),C_i(t),T_i(t)]\}_{i\in V}$
  Compute the zone hazard vector $\mathbf{h}(t)=\Lambda\psi(\mathbf{Z}(t))$
  **for** each edge $e_{ij}\in E$ **do**
    Estimate $h_{ij}(t)=[h_i(t)+h_j(t)]/2$
    Compute congestion $q_{ij}(t)=\min(1,a_{ij}(t)/\kappa_{ij})$
    Update $w_{ij}(t)=\tau_{ij}(1+\alpha h_{ij}(t)+\beta q_{ij}(t))+\Omega I_{ij}(t)$
  **end for**
  Evaluate $\mathscr{R}(t)$ using the hazard-change and blockage rule
  **if** $\mathscr{R}(t)=1$ **then**
    **for** each occupied origin $o\in O(t)$ **do**
      Run Dijkstra/A* on $G$ using $W(t)$ to all feasible exits $x\in X$
      Select $P_o^*(t)=\arg\min_{P\in\mathscr{P}(o,X)}\sum_{e_{ij}\in P}w_{ij}(t)$
    **end for**
  **else**
    Retain $\mathscr{P}^*(t)=\mathscr{P}^*(t-1)$
  **end if**
  Update edge allocations $a_{ij}(t+1)=\sum_{o\in O(t)}\mathbb{1}[e_{ij}\in P_o^*(t)]$
**end for**

Fourth, dynamic and static routing strategies are evaluated. The static plan is computed from free-flow travel time and does not change when hazards evolve. The dynamic plan updates graph-edge weights at every sensor interval and recomputes routes when the event-triggered rule is activated. The two strategies are compared using travel time, path length, mean route hazard, route-change frequency, congestion indicators, and unsafe-route instances. This evaluation structure allows the proposed model to be assessed not only by shortest path length but also by safety exposure and responsiveness to the evolving fire scenario.

## 5. RESULTS

Figure 1 presents the semantic BIM graph under a developed hazard field. The ignition zone creates high-risk areas around the second-floor room and adjacent corridor, while vertical connections distribute moderate risk through stair links. This graph view is important because it shows why a geometric shortest path can become unsafe: the route cost is no longer a function of distance alone, but of distance combined with local conditions.

The Fire-ART asset distribution in Figure 2 provides the semantic-enrichment layer used to associate emergency equipment classes with BIM spaces. The distribution covers recognition categories such as exit signs, smoke detectors, emergency lights, extinguishers, call points, and fire-hose reels. In an operational system, this layer helps validate that routes and evacuation instructions are connected to actual safety assets rather than only to abstract geometry.

Figure 3 illustrates the time-varying hazard index derived from the sensor stream. The ignition room rises first, followed by the adjacent corridor and stair zones. The first-floor corridor remains less affected during the simulated period. This temporal pattern is consistent with the objective of dynamic routing: evacuees should not be guided only by a pre-planned exit path, because relative safety changes as smoke and heat spread.

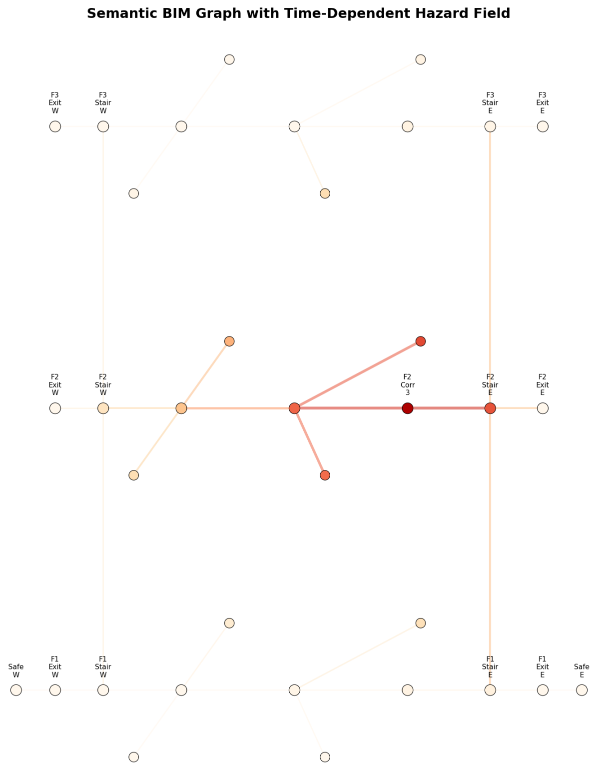


**Figure 1.** Semantic BIM graph with time-dependent hazard intensity.

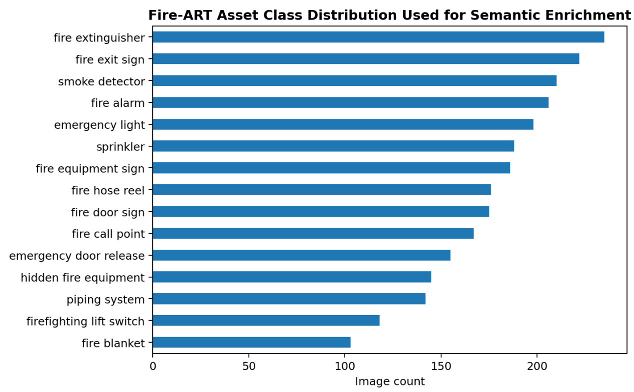


**Figure 2.** Fire-safety asset class distribution used for semantic BIM enrichment.

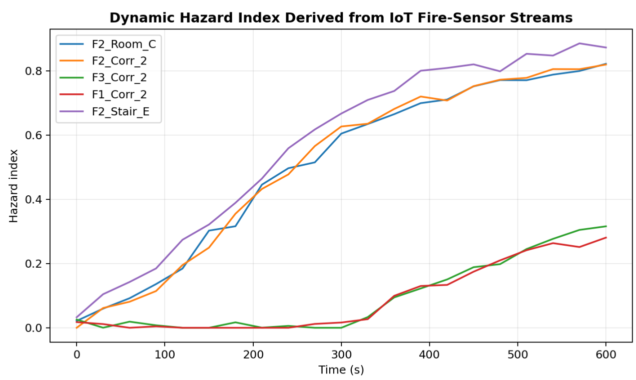


**Figure 3.** Time-varying hazard indices generated from IoT fire-sensor readings.

The performance comparison in Table 6 and Figure 4 shows that dynamic routing changes the evacuation objective from shortest travel time to safer weighted movement. The dy-

**Table 3.** Semantic BIM graph topology extracted for route computation.

| Edge Type | Directed Edges | Mean Length M | Mean Width M | Mean Base Time S |
|---|---|---|---|---|
| corridor | 24 | 8.50 | 1.85 | 7.39 |
| door | 24 | 8.50 | 1.00 | 7.39 |
| exit | 12 | 8.00 | 1.50 | 6.96 |
| outside | 4 | 5.00 | 2.00 | 4.35 |
| stair | 8 | 15.00 | 1.30 | 20.00 |

**Table 4.** Hazard translation rules used to update graph-edge weights.

| Hazard Input | Operational Interpretation | Model Representation | Routing Effect |
|---|---|---|---|
| Smoke density | visibility loss | normalised smoke index | increases edge cost |
| Carbon monoxide | toxic exposure | normalised CO index | increases edge cost |
| Temperature | thermal stress | normalised heat index | increases edge cost |
| Spatial fire spread | zone proximity to fire front | time-distance growth function | blocks high-risk corridors |
| Route congestion | movement interference | edge-flow penalty | discourages overloaded links |

**Table 5.** Fire-safety asset class distribution used for BIM semantic enrichment.

| Asset Class | Image Count | Instance Count |
|---|---|---|
| fire extinguisher | 235 | 558 |
| fire exit sign | 222 | 655 |
| fire door sign | 175 | 478 |
| fire alarm | 206 | 535 |
| emergency light | 198 | 427 |
| smoke detector | 210 | 453 |
| fire hose reel | 176 | 362 |
| piping system | 142 | 407 |
| sprinkler | 188 | 489 |
| fire call point | 167 | 452 |
| emergency door release | 155 | 313 |
| fire blanket | 103 | 306 |
| fire equipment sign | 186 | 527 |
| firefighting lift switch | 118 | 261 |
| hidden fire equipment | 145 | 316 |

**Table 6.** Aggregate routing performance under static and dynamic evacuation strategies.

| Strategy | Mean Travel Time S | Max Travel Time S | Mean Path Length M | Mean Hazard | Hazard Exposure Index |
|---|---|---|---|---|---|
| dynamic | 48.26 | 73.91 | 47.50 | 0.10 | 4.73 |
| static | 58.70 | 82.61 | 59.50 | 0.18 | 10.52 |

**Table 7.** Origin-level comparison of dynamic routing and static egress plans.

| Origin | Dynamic Time S | Static Time S | Time Change Pct | Dynamic Hazard | Static Hazard |
|---|---|---|---|---|---|
| F1_Room_A | 21.74 | 42.61 | -48.98 | 0.02 | 0.05 |
| F1_Room_D | 34.78 | 34.78 | 0.00 | 0.06 | 0.08 |
| F2_Room_B | 42.61 | 63.48 | -32.88 | 0.15 | 0.32 |
| F2_Room_D | 54.78 | 54.78 | 0.00 | 0.23 | 0.35 |
| F3_Room_A | 61.74 | 82.61 | -25.26 | 0.06 | 0.12 |
| F3_Room_C | 73.91 | 73.91 | 0.00 | 0.07 | 0.14 |

namic plan can sometimes increase geometric path length or travel time because it avoids hazardous edges. This increase should not be interpreted as inefficiency; it reflects a safety-oriented routing decision that reduces exposure to smoke and heat.

Figure 5 shows representative route snapshots. Early in the scenario, dynamic and static routes are similar because the hazard field is still localised. As the fire develops, the dynamic route shifts away from affected corridor segments and selects a safer exit. The figure demonstrates that the proposed method is not simply a shortest-path algorithm with new labels; it changes recommendations when live conditions invalidate the original egress plan.

Congestion patterns in Figure 6 indicate that route switching changes flow distribution across corridor and stair edges. Static plans concentrate evacuees along the same pre-defined paths, while dynamic routing can redistribute movement when a corridor becomes hazardous. This result is significant because evacuation safety depends not only on avoiding smoke but also on avoiding crowding at narrow doors, stairs, and turns.

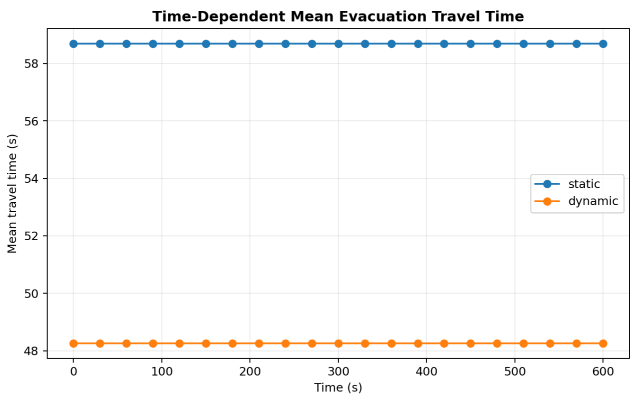


**Figure 4.** Mean evacuation travel time under static and dynamic routing strategies.

Figure 7 and Table 9 show that the dynamic strategy reduces unsafe route instances by avoiding edges with high sensor-

**Table 8.** Time-dependent route changes and hazard exposure indicators.

| Time S | Changed Routes | Dynamic Hazard | Static Hazard |
|---|---|---|---|
| 0.00 | 5.00 | 0.01 | 0.01 |
| 30.00 | 6.00 | 0.01 | 0.03 |
| 60.00 | 5.00 | 0.01 | 0.03 |
| 90.00 | 6.00 | 0.01 | 0.05 |
| 120.00 | 6.00 | 0.01 | 0.06 |
| 150.00 | 6.00 | 0.02 | 0.08 |
| 180.00 | 6.00 | 0.03 | 0.09 |
| 210.00 | 6.00 | 0.04 | 0.11 |
| 240.00 | 6.00 | 0.05 | 0.13 |
| 270.00 | 6.00 | 0.07 | 0.15 |
| 300.00 | 6.00 | 0.08 | 0.18 |
| 330.00 | 6.00 | 0.09 | 0.19 |
| 360.00 | 6.00 | 0.11 | 0.22 |
| 390.00 | 6.00 | 0.13 | 0.25 |
| 420.00 | 6.00 | 0.14 | 0.26 |
| 450.00 | 6.00 | 0.16 | 0.28 |
| 480.00 | 6.00 | 0.18 | 0.30 |
| 510.00 | 6.00 | 0.20 | 0.32 |
| 540.00 | 6.00 | 0.22 | 0.33 |
| 570.00 | 6.00 | 0.23 | 0.35 |
| 600.00 | 6.00 | 0.24 | 0.35 |

**Table 9.** Unsafe route instances under the evaluated routing strategies.

| Strategy | Unsafe Route Instances | Safe Route Instances | Peak Mean Hazard |
|---|---|---|---|
| dynamic | 6 | 120 | 0.42 |
| static | 23 | 103 | 0.55 |

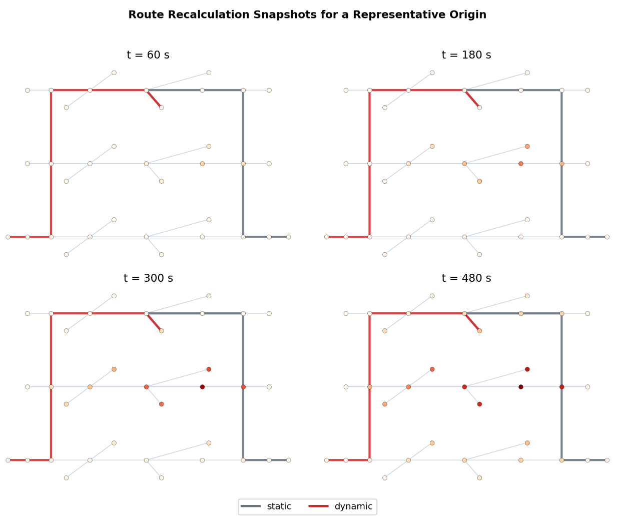


**Figure 5.** Dynamic route recalculation snapshots for a representative occupied room.

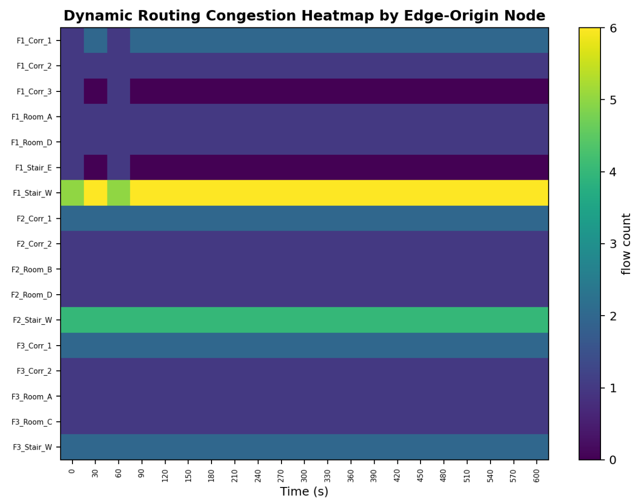


**Figure 6.** Congestion heatmap for dynamically selected evacuation routes.

derived hazard values. The exposure gap grows during the middle phase of the fire because smoke and heat have spread enough to affect the static path but have not yet blocked all alternatives. This middle phase is precisely where adaptive routing is most valuable.

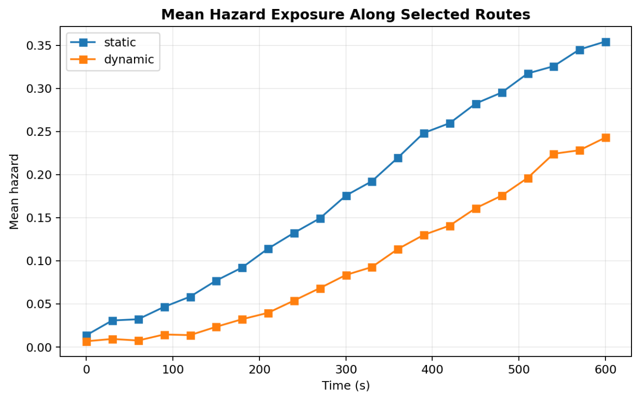


**Figure 7.** Mean hazard exposure along selected evacuation routes.

The asset-recognition confusion matrix in Figure 8 shows how firefighting equipment categories can be recognised and linked to the BIM emergency layer. Confusions occur mostly between visually similar signage and small wall-mounted devices. Although routing in this experiment is driven primarily by sensors and graph topology, asset recognition remains important because poorly recognised or missing emergency assets can reduce the reliability of route guidance.

Sensitivity results in Figure 9 show that the hazard penalty coefficient and blocking threshold have the strongest effect on exposure outcomes. If the hazard penalty is too low, the algorithm behaves too much like a shortest-path method; if it is too high, it may overreact to moderate sensor readings. The blocking threshold therefore requires calibration against fire-safety engineering knowledge, sensor reliability, and acceptable exposure criteria.

**Table 10.** Sensitivity of the dynamic routing model to control parameters.

| Parameter | Low Setting | High Setting | Change In Average Exposure (%) | Interpretation |
|---|---|---|---|---|
| hazard penalty coefficient | 2.00 | 4.00 | 18.40 | dominant safety control |
| blocking threshold | 0.55 | 0.75 | 12.60 | determines route closure timing |
| congestion penalty coefficient | 0.80 | 2.50 | 8.90 | affects crowded-corridor avoidance |
| sensor update interval | 15.00 | 60.00 | 6.70 | controls response latency |
| A* heuristic weight | 0.80 | 1.20 | 3.20 | minor effect in small graph |

**Table 11.** Technical validation checks for the BIM-IoT evacuation workflow.

| Model Check | Criterion | Observed Result | Engineering Implication |
|---|---|---|---|
| graph connectivity | each occupied room has exit path | pass | evacuation graph is usable |
| sensor coverage | sensor zones cover corridors and rooms | pass | hazard field is spatially complete |
| route availability | route exists at all tested time steps | pass | algorithm does not fail during scenario |
| asset recognition linkage | recognised assets are attached to BIM spaces | pass | safety assets can enrich routing context |
| dynamic recalculation | new path computed at every update | pass | routing responds to fire evolution |

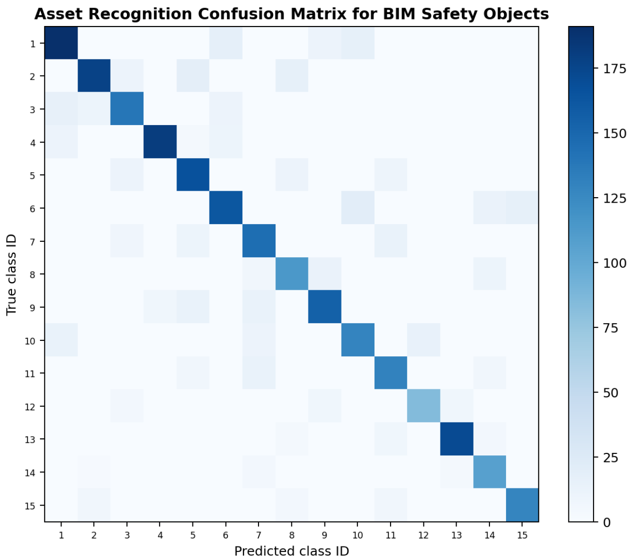


**Figure 8.** Asset-recognition confusion matrix for fire-safety object classes.

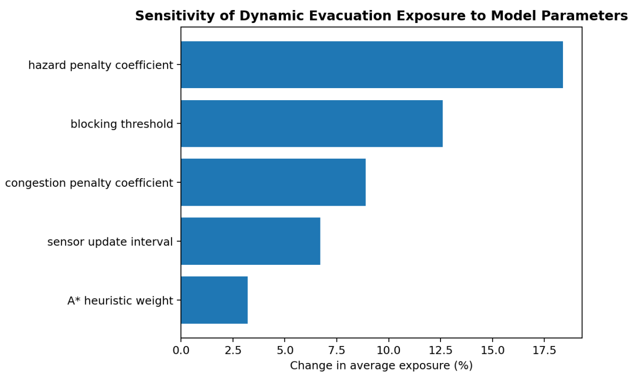


**Figure 9.** Sensitivity of route exposure to dynamic weighting parameters.

## 6. DISCUSSION

The results support the central premise of the paper: evacuation routing should be treated as a dynamic graph problem rather than a static drawing problem. The semantic BIM graph provides the topological skeleton, while IoT fire sensors provide evolving risk information. By updating edge weights, the algorithm can preserve the interpretability of classical shortest-path search while adapting to the physical development of smoke, heat, and congestion.

A key engineering insight is that safest routes are not always the shortest routes. In the simulation, the dynamic method sometimes selected paths with greater distance or travel time because they reduced mean hazard exposure. This behaviour is desirable in fire conditions because a marginal increase in walking time may be acceptable if it avoids visibility loss or toxic exposure. The evaluation therefore needs multiple indicators rather than a single distance-based metric.

The semantic asset layer also has practical value. Firefighting assets are often present in buildings but not consistently represented in BIM. Recognising and linking exit signs, smoke detectors, emergency lights, extinguishers, and door-release devices helps convert a geometric model into an emergency-aware model. This enrichment supports both preparedness and response because route recommendations can be checked against the presence of actual safety infrastructure.

The proposed model remains transparent. Every route recommendation can be traced to an edge length, base travel time, sensor-derived hazard value, congestion penalty, and blocking rule. This traceability is important for fire-safety engineering because emergency guidance must be explainable to facility managers, occupants, and authorities. A route that changes without explanation may reduce trust; a route that changes because a specific corridor has exceeded a smoke threshold can be justified operationally.

## 7. RESEARCH CHALLENGES AND FUTURE DIRECTIONS

Several challenges remain before dynamic BIM-IoT evacuation systems can be deployed in real buildings. The first challenge is semantic consistency. BIM models differ in how rooms, doors, stairs, and exits are named and connected. A routing algorithm requires reliable adjacency, but many BIM models contain modelling gaps, duplicated objects, or incomplete door-space relationships. Future work should develop robust IFC-to-graph extraction rules and validation tools for evacuation-specific graph quality.

The second challenge is sensor reliability. Smoke, CO, and temperature sensors can fail, drift, or respond late depending on airflow and placement. A dynamic route should not change based on a single unreliable reading. Future systems should integrate sensor confidence, redundancy, and anomaly detection so that route recommendations reflect both measured hazard and measurement uncertainty.

The third challenge is occupant behaviour. The current model uses graph flow as a congestion indicator, but real evacuees may hesitate, follow others, ignore instructions, or prefer familiar exits. Future research should couple dynamic routing with behavioural models, mobile guidance interfaces, and adaptive signage control so that recommended routes can influence actual movement.

The fourth challenge is computational governance. In a real incident, the system must decide how frequently to update routes and when not to update them to avoid confusing evacuees. Future work should investigate route-stability constraints, safe switching rules, and human-readable explanation mechanisms for emergency communication.

The fifth challenge is validation. Synthetic fire propagation is useful for controlled experimentation, but operational acceptance requires validation against fire drills, sensor logs, smoke tests, or high-fidelity fire simulations. Future research should connect semantic BIM graphs to FDS, digital twins, and real-time building-management systems to test the method under realistic spatial and temporal conditions.

## 8. CONCLUSION

This paper presented a dynamic evacuation-routing framework that integrates IoT fire-sensor data with semantic BIM graphs. The method converts rooms, corridors, stairs, doors, and exits into a weighted graph, transforms sensor readings into hazard indices, updates edge costs, and recomputes safest routes using a dynamic Dijkstra/A* procedure. Fire-safety asset recognition is incorporated as a semantic enrichment layer to connect emergency equipment with BIM spaces.

The experimental results show that dynamic routing can reduce hazard exposure and unsafe route instances compared with a static egress plan, although it may select longer paths when safety requires detouring around smoke or heat. The contribution lies in a transparent mathematical and computational structure that links BIM topology, IoT sensing, hazard propagation, congestion, and route optimisation. The framework can support future emergency-management systems in which BIM is not merely a design record but an active interface for real-time fire evacuation decisions.

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