Smart Evacuation of Multi-Floor Buildings using Crowd Dynamics and Optimization

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- **Goal:** Optimize building layouts (exits, stairs, doors) using the NSGA-II algorithm.
- **Case Study:** A 2-floor, 30m x 30m building with 40 occupants.

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- **Real-World Impact:** Reducing evacuation time by seconds can be the difference between life and death.

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1. **Accurately simulate** their evacuation under various emergency scenarios (normal, fire, earthquake), accounting for complex crowd dynamics and evolving hazards?
2. **Systematically identify** modifications to the building's architectural layout (e.g., exit and stair locations) that measurably improve evacuation performance, defined by minimizing total evacuation time while ensuring 100% survivability?

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5. **Visualize and Disseminate:** Create clear, insightful visualizations and a data-driven summary of the findings.

Key Contributions

This research makes three primary contributions to the field of evacuation modeling:

1. **A Novel Integrated Framework:** We present the first end-to-end framework that combines a dual-model simulation approach (SFM and FTBS) with multi-objective genetic optimization (NSGA-II) for building layout design.

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    - **Fire:** Hazard Avoidance
    - **Earthquake:** Redundancy and Dispersion
3. **Quantifiable Safety Improvements:** We provide concrete, quantitative evidence of the life-saving potential of this approach, showing up to a **+45%** increase in survival rate in high-fidelity simulations.

Presentation Roadmap

1. Introduction & Motivation
2. Modeling Paradigms
3. **Methodology & Implementation**
    - The Building Environment
    - The Microscopic Social Force Model (SFM)
    - The Mesoscopic FTBS Model
    - The Optimization Module
4. **Results & Discussion**
    - Model Performance Comparison
    - Optimization Impact Analysis
    - Live Simulation Animations
5. Conclusion & Future Work

A Multi-Scale Modeling Approach

Microscopic (Agent-Based)

- **Focus:** Simulates each individual.
- **Pros:** High realism, captures local interactions.
- **Cons:** Computationally expensive.
- **Our Model:** Social Force Model (SFM).

Mesoscopic (Flow-Based)

- **Focus:** Simulates densities of people.
- **Pros:** Computationally fast.
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Our Strategy: Use Both

Leverage the speed of the mesoscopic model for optimization and the realism of the microscopic model for final validation and detailed analysis.

The Virtual Environment: Building Class

Procedural Building Definition

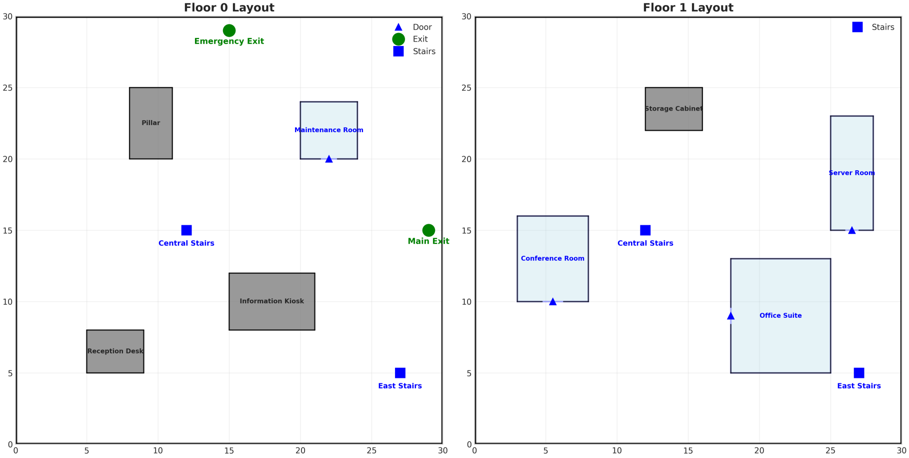
A custom Python class was developed to define the simulation environment, storing all static architectural elements.

```
class Building:
    def __init__(self):
        self.floors = {}
        self.rooms = []         # Rooms with doors
        self.obstacles = []     # Solid obstacles
        self.exits = []         # (x, y, floor, label)
        self.stairs = []        # (x, y, from, to, label)
        self.walls = []         # (x1, y1, x2, y2, floor)
```

Listing 1: Core attributes of the Building class.

Provides helper methods for visualization and collision detection (`is_point_blocked`).

Case Study: Building Layout



Initial Agent Population

- **Total Agents:** 40
- **Distribution:**
  - Floor 0: 15 agents
  - Floor 1: 25 agents (higher density to test stairs)
- **Placement:** Agents are randomly placed in valid, non-obstructed locations.
- **Reproducibility:** `np.random.seed(42)` ensures identical starting positions for every run.
- **Initial State:** All agents start at rest (`velocity = [0,0,0]`).

SFM: Agent Definition

Each agent is an object with physical and behavioral properties:

```
@dataclass
class Agent:
    id: int
    pos: np.ndarray  # [x, y, z]
    vel: np.ndarray  # [vx, vy, vz]
    desired_speed: float
    floor: int
    mass: float = 75.0   # kg
    radius: float = 0.30 # m
    tau: float = 0.5     # s
```

Listing 2: The Agent dataclass defines individual properties.

Key Physical Parameters

- `mass`: Influences inertia ($F = ma$).
- `radius`: Defines personal space for collision avoidance.
- `tau` (Relaxation Time): Time to accelerate to desired speed.

SFM: The Core Equation of Motion

The acceleration of agent i is the sum of all forces acting on it, divided by its mass.

$$\frac{d\mathbf{v}_i}{dt} = \frac{1}{m_i}\left(\mathbf{F}_i^{\text{drive}} + \sum_{j\neq i}\mathbf{F}_{ij}^{\text{social}} + \sum_{w}\mathbf{F}_{iw}^{\text{wall}}\right)$$

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- $\mathbf{F}_{iw}^{\text{wall}}$ Repulsive forces from all walls and obstacles w.

SFM Force 1: The Driving Force

Models an agent's intention to move towards a target at a desired speed.

$$\mathbf{F}_i^{\text{drive}} = m_i \frac{\mathbf{v}_i^*(t) - \mathbf{v}_i(t)}{\tau_i}$$

Symbol	Meaning	Value/Source
m_i	Mass of agent i	75.0 kg
$\mathbf{v}_i^*$	Desired velocity vector $(v_{\text{eff}} \cdot \mathbf{e}_{\text{target}})$	Calculated
$\mathbf{v}_i$	Current velocity vector	From simulation
τ_i	Relaxation time	0.5 s

v_{eff} is the *effective* desired speed, which can be reduced by hazards.

SFM Forces 2 & 3: Interaction Forces

Models repulsion between agents and from walls to avoid collisions.

Mathematical Formulation (Helbing Molnár)

$$\mathbf{F}_{ij}^{\text{social}} = \underbrace{A \exp\left(\frac{r_{ij} - d_{ij}}{B}\right) \mathbf{n}_{ij}}_{\text{Psychological Repulsion}} + \underbrace{k_{\text{body}} g(r_{ij} - d_{ij}) \mathbf{n}_{ij}}_{\text{Body Force (Contact)}} + \underbrace{\kappa g(r_{ij} - d_{ij}) \Delta v_{ji}^{t} \mathbf{t}_{ij}}_{\text{Sliding Friction (Contact)}}$$

The same formulation is used for agent-wall interactions.

SFM: Social Force Parameters

Calibrated parameters from pedestrian dynamics research.

Parameter	Meaning	Value
A	Strength of psychological repulsion	2000 N
B	Range of psychological repulsion	0.08 m
k_{body}	Stiffness of body contact	120,000 N/m
κ	Sliding friction coefficient	240,000 Ns/m

SFM: Intelligent Target Selection

Agents account for congestion using a **Queue Penalty Heuristic**.

$$\text{Cost(Target)} = d \cdot (1 + \kappa \cdot \rho)$$

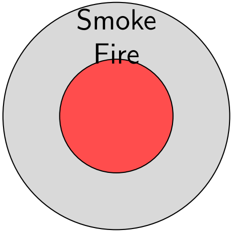
Symbol	**Meaning**
d	Euclidean distance to the target
κ	Congestion penalty coefficient (0.3)
ρ	Local density (number of agents within a 2m radius)

Behavior

The agent selects the target with the lowest cost, balancing proximity with perceived crowding.

SFM Hazard: Fire & Smoke

- Fire starts at a specified `FIRE_POSITION` (15, 10, 0).
- **Dynamic Spread:**
  - Smoke Radius (R_s): Spreads at 1.0 m/s.
  - Fire Radius (R_f): Spreads at 0.05 m/s after a 5s delay.
- **Agent Effects:**
  - Inside Fire: Immediate paralysis.
  - Inside Smoke: Speed reduction and paralysis if exposure ¿ 180s.
- **Environmental Effects:** Exits or stairs in the fire radius are blocked.



SFM: Smoke's Effect on Speed

An agent's mobility decreases with cumulative exposure to smoke.

Equation (Gwynne, 1999)

$$v_{\text{eff}} = v_0 \cdot \exp(-\beta \cdot t_{\text{smoke}})$$

Symbol	Meaning	Value
v_{eff}	Effective desired speed	Calculated
v_0	Agent's normal desired speed	U(1.0, 1.8) m/s
β	Smoke attenuation constant	0.06 s^{-1}
t_{smoke}	Cumulative time spent in smoke	Tracked per agent

SFM Hazard: Earthquake & Debris

- A 30-second shaking period reduces agent mobility and perturbs movement.
- Circular debris obstacles appear at pre-scheduled times and locations.
- Debris acts as new, impassable walls.
- Debris can permanently block exits and stairs.
- Agents at the impact location are immediately paralyzed.

Speed Reduction Equation (Yang et al., 2024)

$$v_{\text{eff}} = v_0 \cdot \exp(-3.5 \cdot \text{PGA}(t))$$

Where PGA(t) is the Peak Ground Acceleration, which decays over the 30s period.

Mesoscopic Model: Mathematical Foundation

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Discrete Form (Forward-Time Scheme)

We approximate this using a discrete time step, Δt:

$$N_i(t + \Delta t) = N_i(t) + \Delta t \left(\sum_j q_{j \to i} - \sum_k q_{i \to k} \right)$$

Symbol	Meaning

Mesoscopic Model: Calculating Flow Rate

The flow rate $q_{i \to j}$ from a source node i to a target node j is constrained by multiple factors.

Core Flow Equation

$$q_{i \to j} = \min(N_i, C_{i \to j} \cdot \Delta t) \cdot f_{\text{cong}} \cdot f_{\text{hazard}}$$

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3. **Hazard Factor (f_{hazard}):** Flow is reduced by smoke or earthquake effects.

Mesoscopic Model: The FTBS Algorithm Step

At each time step Δt, the simulation performs the following algorithm:

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3. **Apply Flows (Update Occupancy):**
   - After all flows are computed, update the occupancy for every node simultaneously:

$$N_i(t + \Delta t) = N_i(t) - q_{i \to j} \cdot \Delta t$$
$$N_j(t + \Delta t) = N_j(t) + q_{i \to j} \cdot \Delta t$$

Mesoscopic Model: The Building Graph

The building is converted into a directed graph.

Nodes represent locations:

- **Cells:** Open space is discretized into 3x3m cells.
- **Rooms:** Each room is a single node.
- **Doors, Stairs, Exits:** Special nodes for transit.

Edges represent connections:

- Link adjacent nodes.
- Each edge has a **capacity** (max flow rate) and **distance**.

Mesoscopic Model: Routing via Potential Field

Occupants flow "downhill" from high potential to low potential.

Potential $\Phi(n)$

An estimated cost-to-go from a node n to the nearest unblocked exit.

- **On Floor 0:** Potential is the straight-line distance to the nearest exit.
- **On Floor 1:** Potential is the distance to a stair + distance from that stair's landing to an exit.

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Flow Dynamics

Flow is calculated based on available occupants, edge capacity, congestion at the destination, and hazard effects.

Limitations and Assumptions

It is important to acknowledge the boundaries of the current models:

Agent Behavior

- Agents act as individuals; no group or family dynamics are modeled.
- Assumes rational behavior; no irrational panic models are included.
- All agents are homogeneous (e.g., no disabilities, uniform speed distributions).

Environmental Model

- Fire/smoke spread is a simple radial model, not a complex CFD simulation.
- Debris events in the earthquake scenario are pre-scheduled, not dynamically generated from structural analysis.

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Scope

These assumptions were necessary to maintain computational tractability for the optimization, but provide clear avenues for future research.

The Optimization Module

Goal

To automatically find a building layout that performs best under a specific emergency scenario.

- **Design Variables:** The optimizer can modify:
  - Exit Positions (x, y)
  - Stair Locations (x, y)
  - Room Door Widths
- **Algorithm:** NSGA-II (Non-dominated Sorting Genetic Algorithm II).
- **Objective:** Minimize Evacuation Time while ensuring 100% Evacuation Rate.

Optimization: The "Safety-First" Objective Function

The optimizer's goal is to minimize a "cost" value for each layout.

If Evacuation Rate $\geq$ 99.9% (Success)

$$\text{Cost} = \text{Total Evacuation Time}$$

Optimization: The "Safety-First" Objective Function

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If Evacuation Rate $\geq$ 99.9% (Success)

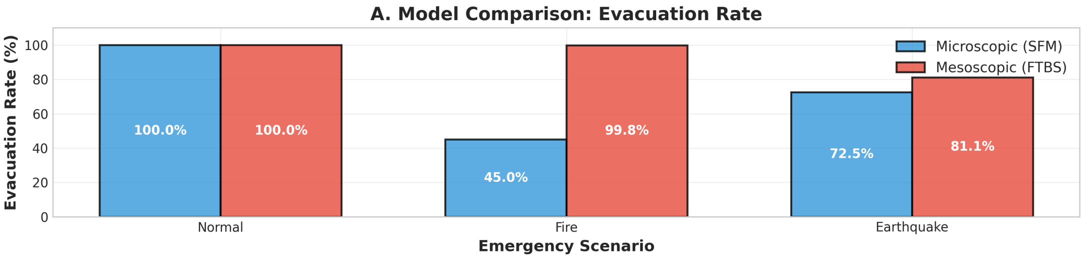
$$\text{Cost} = \text{Total Evacuation Time}$$

If Evacuation Rate $<$ 99.9% (Failure)

$$\text{Cost} = \text{HIGH\_PENALTY} + (100 - \text{Rate}) \times 10$$

This function strongly punishes any design that is not 100% safe, forcing the optimizer to prioritize survivability.

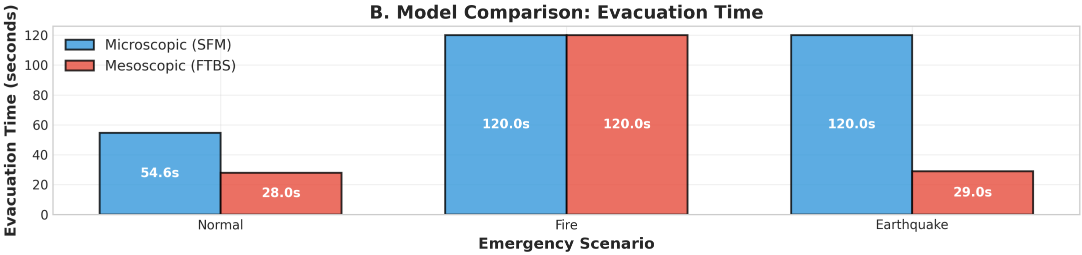
Results: Model Comparison - Evacuation Rate



Key Finding

A stark difference in the **Fire Scenario**. The SFM predicts only 45.0% survival due to individual agent incapacitation, while the flow-based FTBS model predicts 99.8% evacuation. Model fidelity is critical for risk assessment.

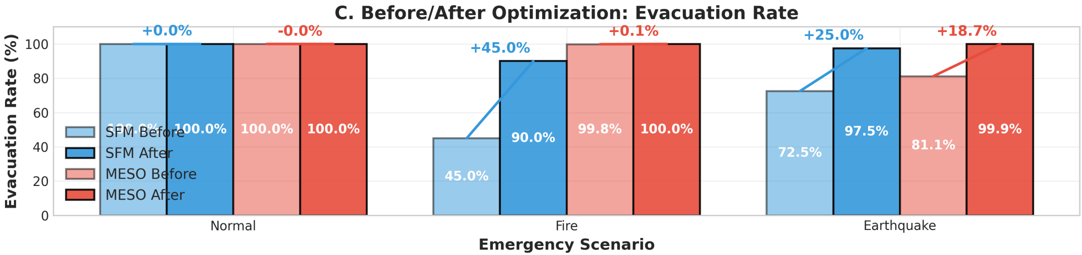
Results: Model Comparison - Evacuation Time



Key Finding

In successful runs, the FTBS model is significantly faster. This is because it represents an idealized flow, while the SFM captures the additional delays from individual interactions, making its time estimates longer but more realistic.

Results: Optimization Impact on Evacuation Rate

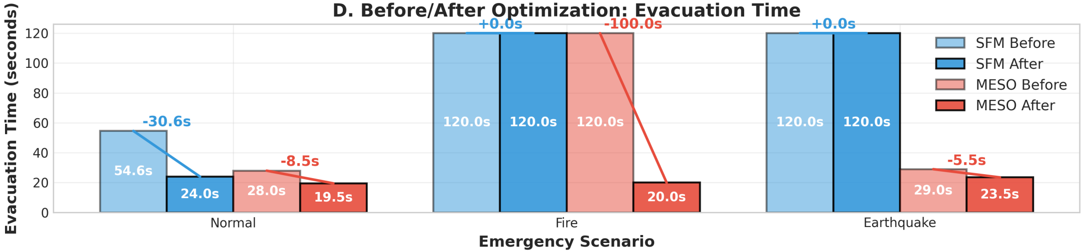


- **Fire Scenario (SFM):** Rate increased from 45.0% to **90.0%** (+45.0%).
- **Earthquake Scenario (SFM):** Rate increased from 77.5% to **97.5%** (+20.0%).

Conclusion

Optimization has a massive, life-saving impact by finding more resilient layouts.

Results: Optimization Impact on Evacuation Time

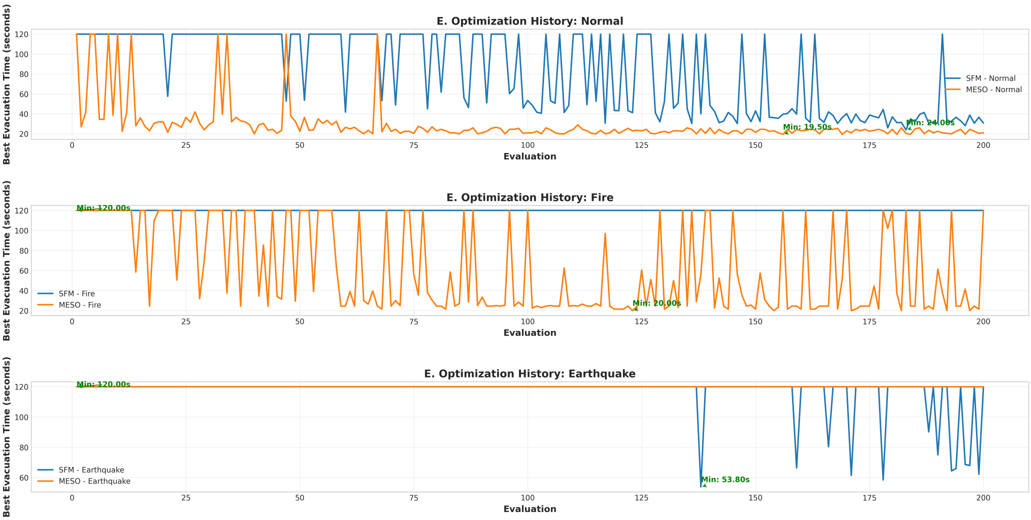


- **Normal Scenario (SFM):** Time reduced by **30.6s**.
- **Fire Scenario (FTBS):** Time reduced from 120s to just **20.0s** (-100.0s).

Conclusion

The optimized layouts are not only safer, but also significantly more efficient.

Results: Optimization History



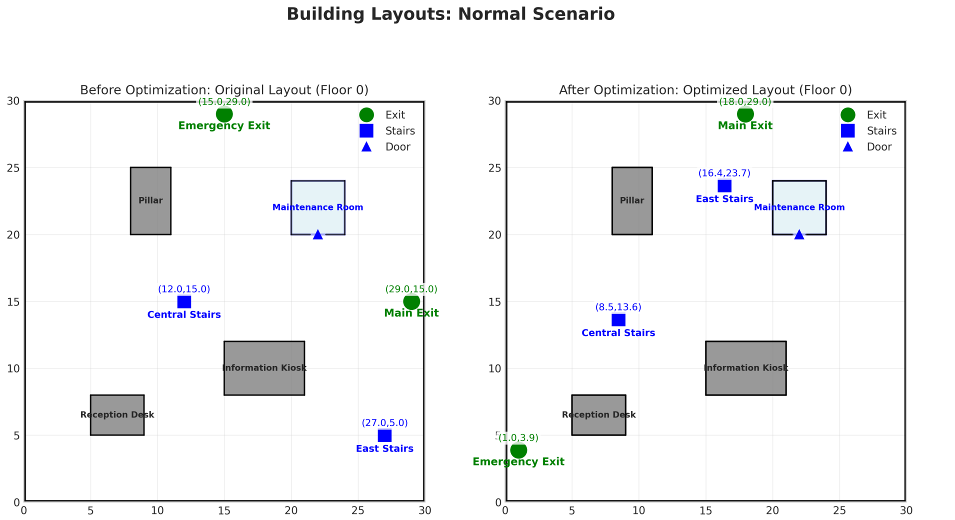
Optimizer Performance Analysis: Evacuation Time

- **Overall Trend:** The plot shows the best evacuation time found over 200 evaluations. Both models demonstrate that the optimizer successfully improves solutions over time.
- **Normal Scenario Analysis (Inferred):**
  - **FTBS (Orange):** Converges rapidly, finding a minimum evacuation time of **20.0s**.
  - **SFM (Blue):** Remains flat at the 120s penalty value, as the optimizer never found a layout with 100% successful evacuation under these conditions.
- **Fire Scenario Analysis:**
  - **SFM (Blue):** Illustrates extreme difficulty. The model is flat at the 120s penalty for the first 130 evaluations before making a breakthrough.
  - The best successful layout eventually found has a time of **53.8s**.

Conclusion

The fire scenario represents a "needle in a haystack" problem. While most layouts fail with the high-fidelity SFM, the optimizer proves capable of discovering the rare, robust designs that succeed.

Optimized Layout: Normal Scenario

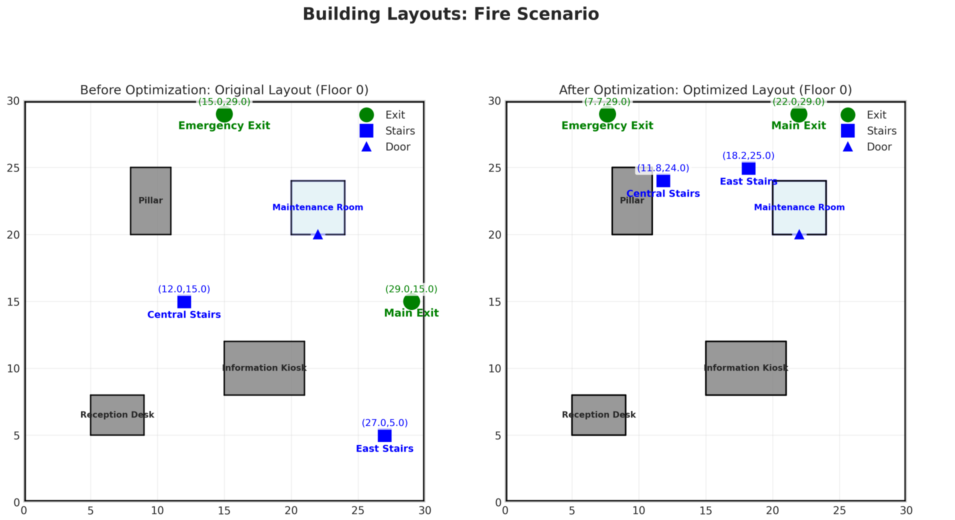


Optimized Layout: Normal Scenario

Learned Strategy: Centralization and Balanced Egress

The optimizer spread out the egress points to reduce the average travel distance for the entire population and create more balanced paths.

Optimized Layout: Fire Scenario

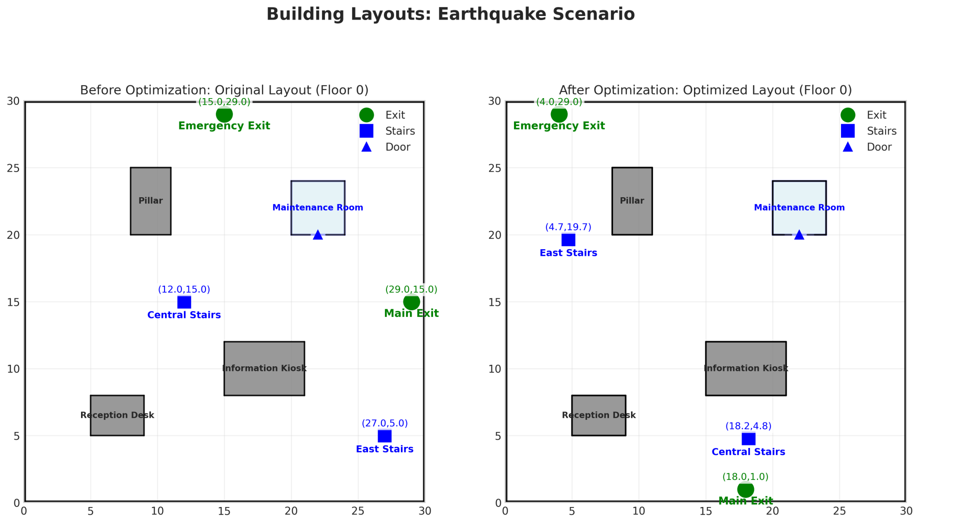


Optimized Layout: Fire Scenario

Learned Strategy: Hazard Avoidance

The fire started at (15,10). The optimizer learned to move all critical escape routes as far away from this danger zone as possible, creating a "safe corridor" along the north wall.

Optimized Layout: Earthquake Scenario



Optimized Layout: Earthquake Scenario

Learned Strategy: Redundancy and Dispersion

By placing the two exit/stair pairs on opposite corners of the building, the optimizer created a layout that is highly resilient to localized damage. A single piece of debris is now very unlikely to block all escape paths.

Key Insights from Results

1. **Model Fidelity Determines Outcome:** The fire scenario was solvable for the flow-based FTBS model but catastrophic for the agent-based SFM. This highlights that high-fidelity models are essential for assessing individual-level risk, as abstract models can hide life-threatening dangers.

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3. **The "Curse of the Successful Evacuation":** In the earthquake scenario, many layouts were successful but slow (120s). The optimizer's real challenge was not just finding a successful layout, but finding one of the rare few that were both successful *and* fast.

Live Simulation Animations

Summary of Findings

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Summary of Findings

1. **Dual-Model approach is powerful:** FTBS is excellent for rapid, strategic optimization, while SFM provides essential high-fidelity validation of individual-level risks.
2. **Optimization is highly effective:** The automated process discovered non-obvious, high-performing layouts that dramatically improved both safety (up to +45% survival rate) and efficiency (up to -100s evacuation time).
3. **The optimal design is scenario-dependent:** The best layout for a fire (avoidance) is different from the best layout for an earthquake (redundancy), which is different from the best for a normal day (efficiency).

Future Research Directions

Advanced Modeling

- Group/family dynamics
- Panic behavior
- Hybrid micro-meso models

Extended Optimization

- Multi-objective (cost vs. safety)
- Optimize for multi-hazard resilience
- Integrate with BIM systems

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Real-World Integration

Calibrate and validate models using real-world evacuation data and sensor data from smart buildings.

Thank You

Questions?

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The equations of motion are solved numerically at each time step using **Explicit Euler Integration**.

1. Calculate total force $\mathbf{F}_{\text{total}}$ on the agent at time t.
2. Calculate acceleration: $\mathbf{a}(t) = \mathbf{F}_{\text{total}}/m$.
3. Update velocity: $\mathbf{v}(t + \Delta t) = \mathbf{v}(t) + \mathbf{a}(t) \cdot \Delta t$.
4. Update position: $\mathbf{x}(t + \Delta t) = \mathbf{x}(t) + \mathbf{v}(t + \Delta t) \cdot \Delta t$.

A small time step ($\Delta t = 0.2$s) is used to ensure stability and accuracy.

Appendix: Full Results Summary

Model	Layout	Scenario	Evac Rate (%)	Evac Time (s)	Improvement (% pts)
SFM	Original	Normal	100.0	54.6	-
SFM	Optimized	Normal	100.0	24.0	+0.0
SFM	Original	Fire	45.0	120.0	-
SFM	Optimized	Fire	90.0	120.0	**+45.0**
SFM	Original	Earthquake	77.5	120.0	-
SFM	Optimized	Earthquake	97.5	120.0	**+20.0**
MESO	Original	Normal	100.0	28.0	-
MESO	Optimized	Normal	100.0	19.5	+0.0
MESO	Original	Fire	99.8	120.0	-
MESO	Optimized	Fire	100.0	20.0	**+0.2**
MESO	Original	Earthquake	81.1	29.0	-
MESO	Optimized	Earthquake	99.9	23.5	**+18.7**

Appendix: Key References

This work builds upon foundational research in crowd simulation and optimization:

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