

# SUMO Pedestrian Traffic Model: Sensitivity and Scenario Analysis

Damien Castro (dcastr18), Dom Evans (devan137), Eric Legostaev (elegosta)

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## 1 Introduction

This milestone builds upon the foundation established in Milestone 5 by applying sensitivity and scenario analysis techniques to evaluate the robustness and responsiveness of a pedestrian traffic simulation model of the KSU Marietta campus. The objective is to assess how the system reacts to changes in key input parameters—such as building occupancy levels and pedestrian routing strategies—and to understand the implications of those changes on travel time, congestion, and throughput.

Since Milestone 5, the SUMO model has been enhanced to include dynamic pedestrian route adjustments based on real-time congestion conditions. Rather than following a fixed path from origin to destination, pedestrians can now modify their route during the simulation in response to localized density on their current path. This behavior adds realism to the model and allows for more accurate analysis of how routing strategies and occupancy loads affect overall system performance.

Through a series of controlled experiments, this milestone evaluates the system under varying conditions, including isolated parameter changes (sensitivity analysis) and combined input variations (scenario analysis). The findings offer insight into both the strengths and limitations of the current model and provide recommendations for future improvements.

## 2 Definitions and Terms

This section defines key terms and concepts used throughout the sensitivity and scenario analysis. These definitions establish a shared technical vocabulary and clarify the scope of analysis for both model configuration and interpretation of results.

### 2.1 Sensitivity Analysis

A method used to determine how variation in the output of a model can be attributed to different variations in its input parameters. Sensitivity analysis helps identify which variables have the most influence on system behavior, allowing modelers to prioritize calibration and data accuracy for those inputs.

- **Local Sensitivity Analysis:** A technique that varies one input parameter at a time while holding others constant to isolate its individual effect on output metrics.

### 2.2 Scenario Analysis

An evaluation of how a model responds under different sets of simultaneous input conditions. Scenarios are constructed to represent alternative futures—such as peak demand or behavioral shifts—and help assess model performance under uncertainty.

- **Baseline Scenario:** A control configuration representing current or expected normal conditions.
- **High-Load Scenario:** A stress-test condition involving increased input volume (e.g., pedestrian demand).
- **Dispersed Routing Scenario:** A configuration where routing behavior is diversified to simulate realistic, non-optimal pedestrian choices.

### 2.3 Occupancy Estimate

An estimate of the number of individuals present in a building at a given time. In this study, occupancy varies dynamically over the course of the day based on modeled hourly schedules, reflecting campus-specific usage patterns.

### 2.4 Routing Strategy

The logic or probability model that governs how pedestrians select their paths through the network:

- **Shortest Path Routing:** All pedestrians choose the most direct route from origin to destination.
- **Mixed Routing (70/30):** A probabilistic strategy where 70% of pedestrians follow the shortest path and 30% are assigned alternative, non-optimal routes.

## 2.5 Key Performance Metrics

- **Average Travel Time:** The mean time taken by pedestrians to reach their destinations.
- **Maximum Wait Time:** The longest delay experienced by any pedestrian at congested areas, typically crosswalks.
- **Max Density:** The highest pedestrian density observed on any path segment during simulation.
- **Throughput:** The total number of pedestrians who successfully completed their trips.

## 3 Methodology

### 3.1 Sensitivity Analysis Approach

#### 3.1.1 Selection of Parameters

The sensitivity analysis focused on two categories of input parameters:

1. **Building Occupancy Estimates:** specifically for the Atrium and Academic Building. These buildings were selected due to their central role in generating pedestrian traffic on campus.
2. **Pedestrian Routing Strategy:** representing decision-making variability in route selection.

These parameters were selected based on their expected impact on traffic density, crosswalk congestion, and average pedestrian travel time.

#### 3.1.2 Variation Methods

- **Occupancy Estimates** varied over time, reflecting real-world usage patterns. The base occupancy values were extracted from a schedule simulating hourly changes in building usage. For each sensitivity case, occupancy values were adjusted  $\pm 20\%$  at every time step to preserve the temporal dynamics of foot traffic. For example, if the Atrium was scheduled to have 200 occupants at 9:00 AM, the adjusted scenarios tested values of 160 and 240 at that time.
- **Routing Strategy** was tested in two configurations:
  - 100% shortest-path routing (baseline)
  - 70% shortest-path routing with 30% randomly assigned alternative routes

This variation introduced a realistic stochastic routing behavior, simulating pedestrians who do not always follow the most direct path.

#### 3.1.3 Simulation Execution Plan

The sensitivity analysis was conducted using the SUMO (Simulation of Urban Mobility) framework. Each parameter variation was tested in isolation, while all other simulation inputs were held constant to ensure clear attribution of effects. Simulations were performed using dynamic pedestrian routing and building occupancy values across the network.

Each variation scenario was executed with 30 independent runs. This threshold was selected based on guidance from the Central Limit Theorem, which states that for sample sizes  $n \geq 30$ , the sample mean approximates a normal distribution regardless of the underlying distribution of the data. This supports valid use of confidence intervals and statistical comparisons.

#### Sample Sufficiency Justification:

To validate the adequacy of 30 simulation runs per scenario, the following analyses were performed:

- **Confidence Intervals:** For each key output metric, the 95% confidence interval was computed across the growing number of simulation runs. Figures 1 through 4 show that these intervals narrow and stabilize, indicating sufficient sampling for reliable estimation.
- **Standard Error:** The standard error of the mean decreased with the number of runs, confirming reduced variability and increased precision in the aggregated metrics.

- **Convergence Analysis:** The progression of sample means was tracked over successive runs. All metrics exhibited stable convergence before the 30th run, confirming that additional simulation iterations would yield only marginal refinement of output estimates.

**Key performance metrics logged for each run included:**

- Average pedestrian travel time
- Maximum crosswalk wait time
- Maximum pedestrian density (per edge)
- Total throughput (completed trips)

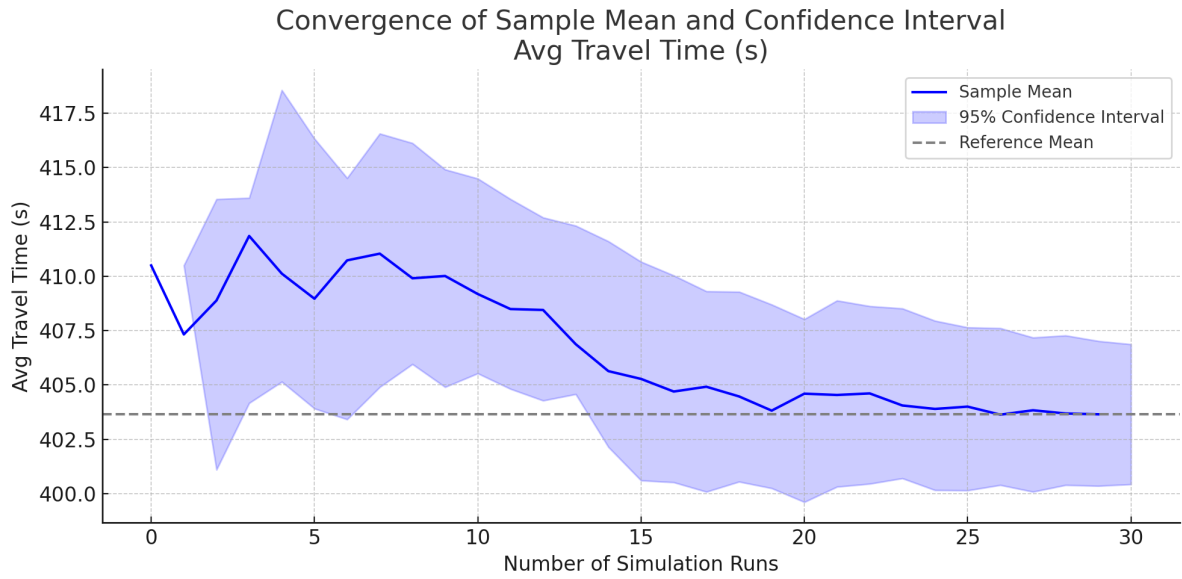


Figure 1: Convergence of Sample Mean and 95% Confidence Interval: Average Travel Time

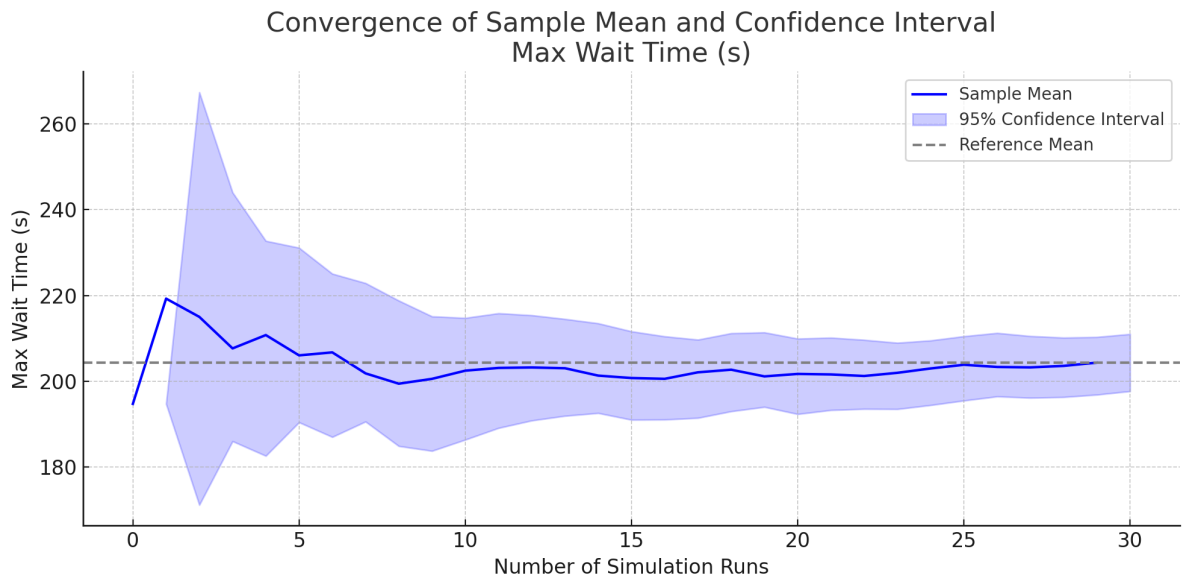


Figure 2: Convergence of Sample Mean and 95% Confidence Interval: Maximum Wait Time

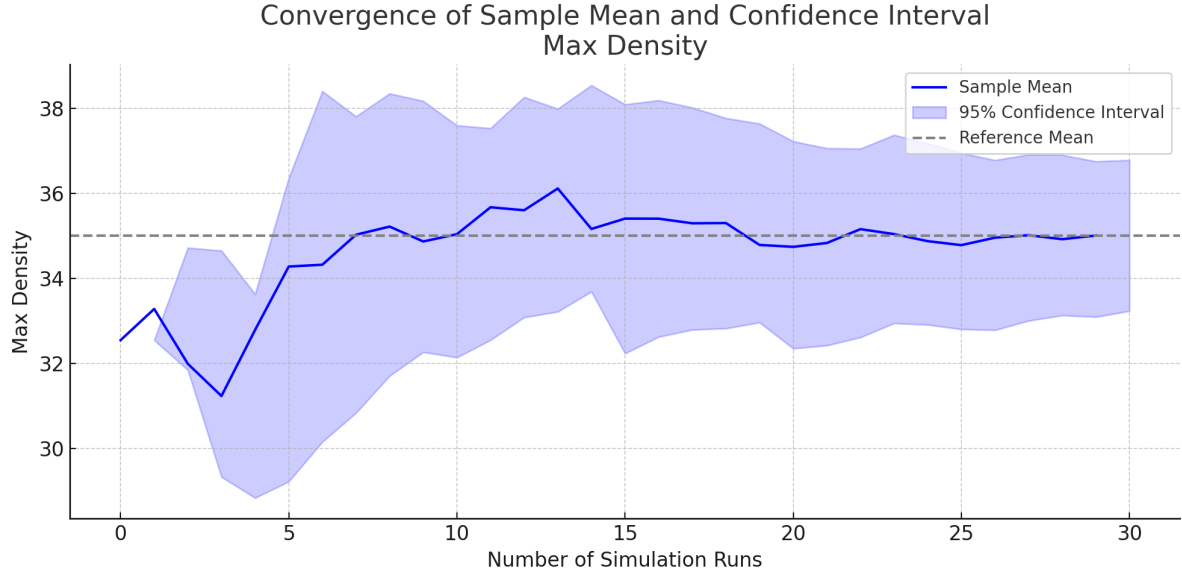


Figure 3: Convergence of Sample Mean and 95% Confidence Interval: Maximum Pedestrian Density

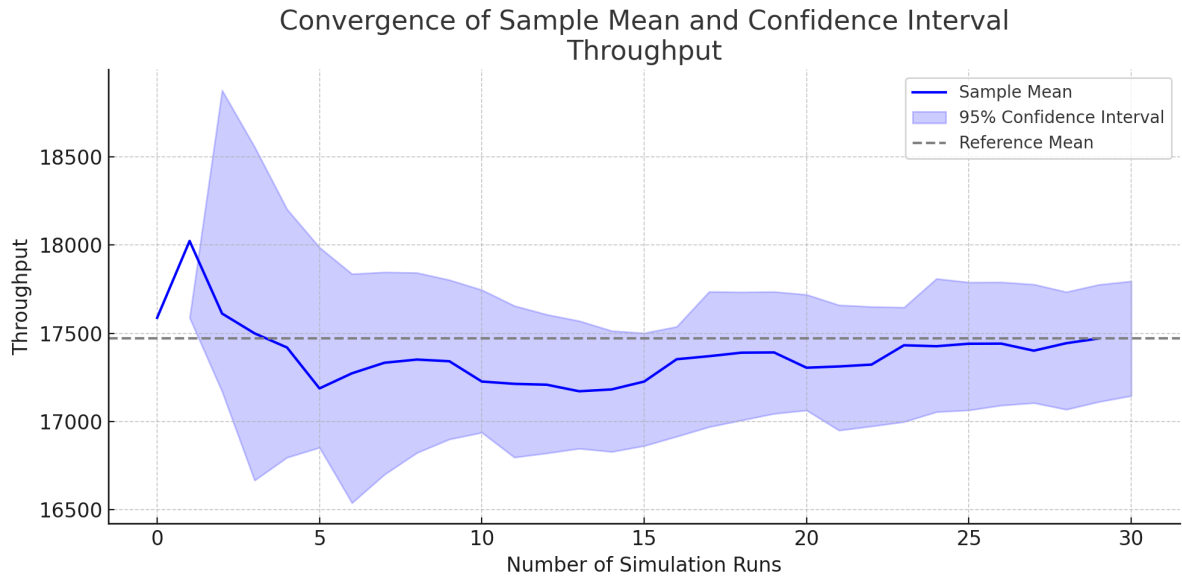


Figure 4: Convergence of Sample Mean and 95% Confidence Interval: Throughput

These outputs formed the basis for both the sensitivity and scenario analysis comparisons in later sections.

## 3.2 Scenario Analysis Approach

### 3.2.1 Description of Scenarios

Four scenarios were developed to evaluate how the pedestrian simulation model performs under varying demand and behavioral assumptions:

1. Baseline Scenario – Represents typical conditions using scheduled building occupancy and 100% shortest-path routing.
2. High-Load Scenario – Simulates increased pedestrian demand by raising Atrium and Academic building occupancy by 20%, maintaining shortest-path routing.

3. Low-Load Scenario – Models reduced campus activity by lowering both building occupancies by 20%, with shortest-path routing unchanged.
4. Dispersed Routing Scenario – Keeps occupancy at baseline levels but introduces routing variability, with 70% of pedestrians taking the shortest path and 30% using alternative routes.

### 3.2.2 Parameter Settings

Table 1: Scenario Parameter Settings

Scenario	Atrium Occupancy	Academic Occupancy	Routing Strategy
Baseline	Scheduled	Scheduled	100% Shortest Path
High-Load	+20% of Schedule	+20% of Schedule	100% Shortest Path
Low-Load	−20% of Schedule	−20% of Schedule	100% Shortest Path
Dispersed Routing	Scheduled	Scheduled	70% Shortest / 30% Alternative

### 3.2.3 Justification for Choices

The selected scenarios were designed to explore the model’s performance under varying demand levels and behavioral assumptions:

- The **Baseline Scenario** establishes a reference point for evaluating the effects of changes to inputs. It reflects typical pedestrian traffic using schedule-based occupancy and deterministic routing.
- The **High-Load Scenario** represents a stress-test condition, such as midday peak or campus events, where increased occupancy stresses walkways and crosswalks. This scenario helps identify potential congestion bottlenecks under realistic routing behavior.
- The **Low-Load Scenario** serves as a counterpoint to the high-load condition, modeling periods such as early morning, summer semesters, or holidays. It provides insight into how pedestrian flow behaves in underloaded situations, helping confirm model responsiveness at low traffic volumes.
- The **Dispersed Routing Scenario** isolates the effect of pedestrian behavior by altering route selection strategy. This reflects real-world behavior where not all individuals take the shortest path, especially when responding to visible congestion, signage, or personal preference.

By holding routing constant in the High and Low Load scenarios and varying only occupancy, the analysis ensures clear attribution of observed effects. The Dispersed Routing scenario complements this by holding occupancy constant, isolating the behavioral factor. Together, these scenarios offer a balanced and rigorous exploration of system dynamics.

## 4 Results

This section presents the outcomes of the sensitivity and scenario analyses performed on the pedestrian simulation model for the KSU Marietta campus. The goal was to assess the impact of varying building occupancy estimates and pedestrian routing strategies on key performance metrics including travel time, wait time, density, and throughput.

### 4.1 Sensitivity Analysis Results

The sensitivity analysis involved independently adjusting occupancy values for the Atrium and Academic Buildings by  $\pm 20\%$ , while holding all other parameters constant. Each configuration was run a minimum of 30 times to ensure statistical reliability.

#### Key Observations:

- **Atrium Occupancy Variations** had the most significant impact on system behavior. A +20% increase led to greater congestion (Max Density = 41.06) and higher wait times (212.29 s). Conversely, a -20% reduction significantly reduced congestion (Max Density = 28.84).

- **Academic Building Occupancy Variations** produced more modest changes in system performance, suggesting it has less influence on overall pedestrian flow. Both +20% and -20% scenarios showed minimal difference in congestion and travel time, suggesting the Academic Building's effect on overall pedestrian flow is less pronounced compared to the Atrium.

Table 2: Sensitivity Analysis Results: Impact of Occupancy Variation

Scenario	Avg Travel Time (s)	Max Wait Time (s)	Max Density	Total Pedestrians	Throughput
Atrium +20%	409.57	212.29	41.06	148,549	18,283
Atrium -20%	409.29	198.06	28.84	133,751	16,713
Academic +20%	407.41	207.61	34.86	145,818	18,118
Academic -20%	409.04	207.83	35.05	136,370	16,877

Figures 5–7 provide a visual comparison of these results. Travel time and congestion rise with increasing occupancy in the Atrium, while the Academic Building's influence is more subdued.

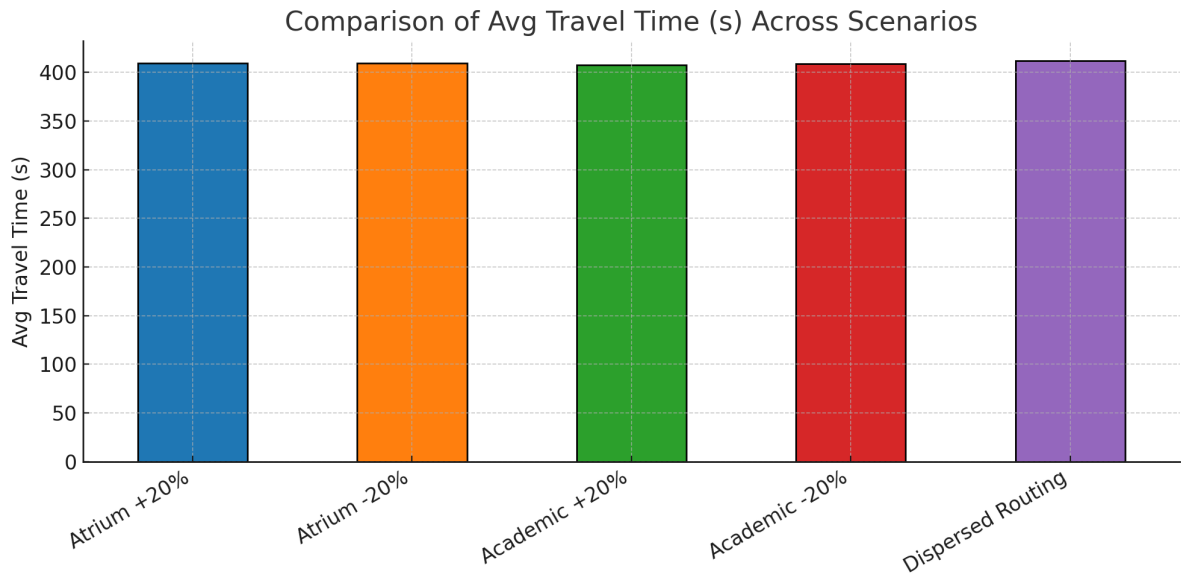


Figure 5: Comparison of Average Travel Time Across Scenarios



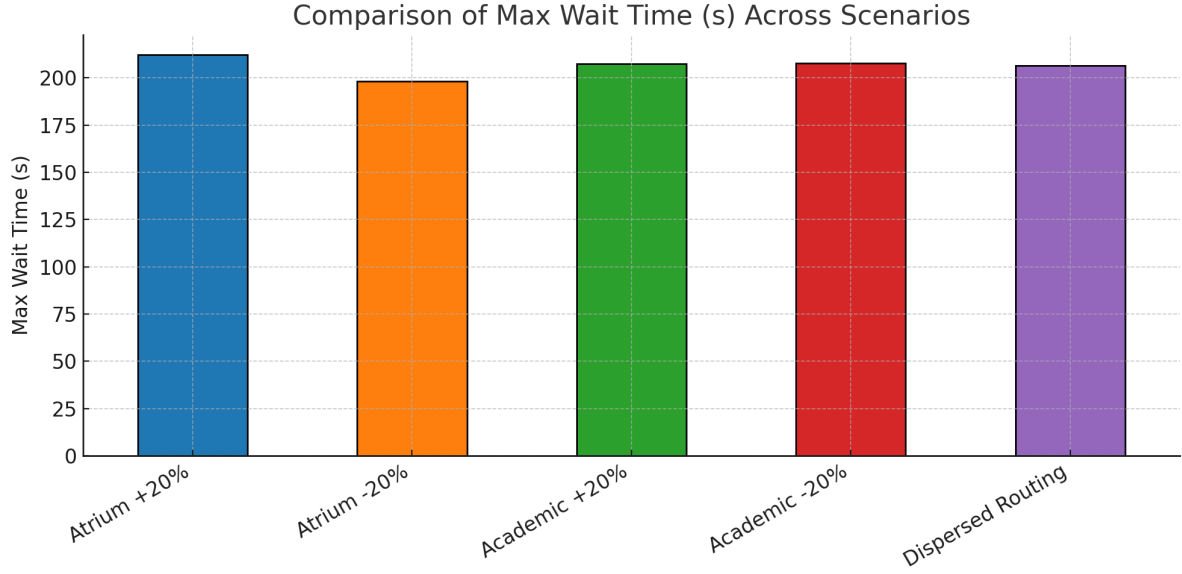


Figure 6: Comparison of Max Wait Time Across Scenarios

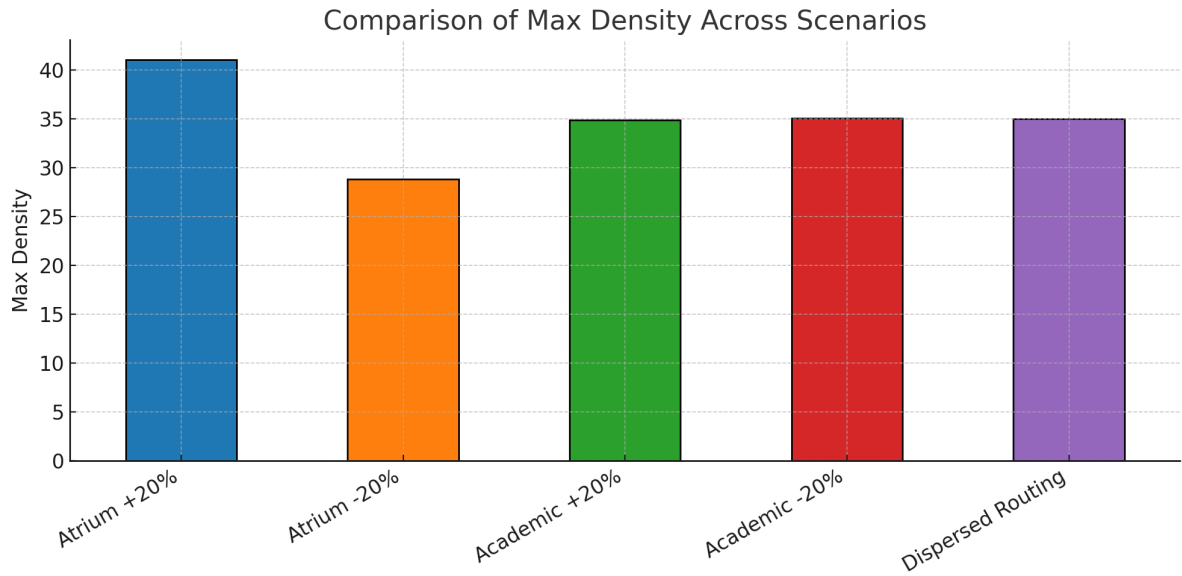


Figure 7: Comparison of Max Pedestrian Density Across Scenarios

The sensitivity analysis focused on evaluating the impact of  $\pm 20\%$  changes in occupancy for the Atrium and Academic Buildings. Key performance metrics—average travel time, maximum wait time, maximum pedestrian density, and throughput—were monitored to determine how the system responds to varying pedestrian demand at these major traffic-generating buildings.

To quantify the relative impact of input variation on output performance, **elasticity** was computed for each metric using the formula:

$$\text{Elasticity} = \frac{\Delta Y/Y}{\Delta X/X}$$

Where:

- $Y$  is the output metric (e.g., travel time)
- $X$  is the input parameter (e.g., occupancy)

- $\Delta Y$  and  $\Delta X$  are the changes from baseline

Elasticity provides a normalized measure of model sensitivity, indicating the proportional response of outputs to changes in a given input. Positive values indicate direct sensitivity, while negative values reflect inverse relationships.

Table 3: Elasticity of Output Metrics to  $\pm 20\%$  Occupancy Changes

Scenario	Avg Travel Time	Max Wait Time	Max Density	Throughput
Atrium +20%	0.050	0.133	0.874	0.226
Atrium -20%	-0.046	0.211	0.874	0.222
Academic +20%	0.023	0.020	-0.013	0.179
Academic -20%	-0.043	-0.025	-0.014	0.175

#### Interpretation:

The results show that:

- **Max Density** exhibited the highest elasticity in response to changes in Atrium occupancy (0.874), confirming its central role in campus congestion. Travel time and wait time also showed moderate sensitivity.
- **Throughput** was positively elastic in all cases, confirming that increased demand results in higher volume completion—though at the cost of increased congestion.
- The **Academic Building** showed much lower elasticity values across all metrics. In fact, its max density and wait time metrics showed near-zero or slightly negative elasticity, suggesting minimal system-wide impact.
- Interestingly, **wait time** under Atrium -20% exhibited higher elasticity (0.211) than under +20%, suggesting that removing pedestrian load from critical hubs yields greater marginal benefit than increasing it adds cost.

These findings confirm that the model is significantly more sensitive to occupancy variations in the Atrium Building than in the Academic Building. This aligns with the Atrium’s geographic centrality and the density of intersecting pedestrian flows. Elasticity values offer a concise way to communicate not just statistical significance, but practical relevance, supporting targeted interventions in high-impact areas.

## 4.2 Scenario Analysis Results

The scenario analysis explored system-level behavior under varying combinations of demand and pedestrian routing strategies. Each scenario was designed to isolate the effects of either occupancy fluctuation or behavioral variation.

Table 4: Scenario Analysis Result: Dispersed Routing Impact

Scenario	Avg Travel Time (s)	Max Wait Time (s)	Max Density	Total Pedestrians	Throughput
Dispersed Routing	412.03	206.57	34.98	140,839	17,491

The dispersed routing scenario resulted in a slight increase in travel time but maintained comparable levels of wait time and density to the baseline scenario (see Figures 5–8). This suggests that introducing moderate behavioral variability does not negatively impact overall throughput and may offer improved flow distribution across the network.

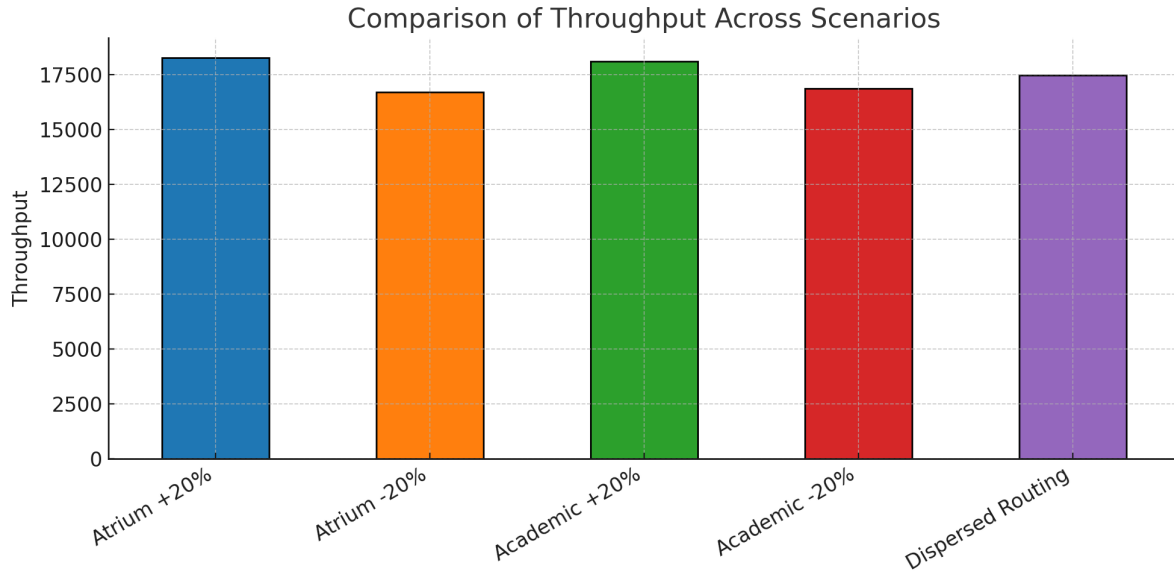


Figure 8: Comparison of Pedestrian Throughput Across Scenarios

### 4.3 Interpretation of Findings

- Sensitivity Results confirmed that the Atrium Building has a stronger influence on system congestion than the Academic Building.
- Throughput correlates with total pedestrian input, but congestion levels and wait times are disproportionately affected by localized demand in the Atrium.
- Scenario Results show that introducing a degree of non-optimal routing does not drastically degrade performance, and may help balance flow across the network—important for crowd resilience and natural human behavior modeling.

Together, these results validate the simulation’s ability to represent realistic pedestrian dynamics and identify critical pressure points on campus.

## 5 Discussion

### 5.1 Implication of Findings

The model demonstrated a clear sensitivity to variations in Atrium Building occupancy, affirming its role as a central pedestrian hub. A +20% increase in occupancy resulted in a substantial rise in both maximum density and wait times, suggesting that even moderate overcapacity can lead to congestion bottlenecks, particularly near crosswalks and major thoroughfares.

In contrast, changes to the Academic Building’s occupancy had less pronounced effects on system-wide performance metrics. While throughput and pedestrian counts changed proportionally with input, congestion indicators such as wait time and density remained relatively stable. This suggests the Academic Building, while important, does not exert the same centralizing influence on foot traffic as the Atrium.

The routing strategy scenario revealed that incorporating a degree of behavioral variability (70% shortest path, 30% alternative routing) had only a minor effect on performance. While average travel time increased slightly, congestion was more evenly distributed, and system throughput remained nearly unchanged. This indicates that allowing for stochastic or adaptive routing behavior can be beneficial in reducing localized strain on popular paths without compromising overall efficiency.

### 5.2 Insights into Model Behavior

The results reinforce the validity of key model assumptions:

- Temporal variation in occupancy effectively captures realistic fluctuations in campus activity.
- Shortest-path routing produces predictable pedestrian flows but can concentrate traffic unrealistically in high-occupancy scenarios.
- Introducing non-deterministic routing yields more distributed flows, improving resilience without major efficiency losses.

These insights confirm that the simulation accurately models both structural and behavioral factors in pedestrian movement and can serve as a valuable tool for planning infrastructure improvements or policy adjustments (e.g., class scheduling, signage, or crowd control during events).

### 5.3 Limitations and Assumptions

Despite the model's utility, several limitations should be acknowledged:

- Simplified pedestrian behavior: Real pedestrians respond to visual cues, social behavior, and environmental changes, which are only approximated here.
- Occupancy estimates are modeled, not observed: The  $\pm 20\%$  variations are hypothetical and based on assumed schedules, not live sensor data or field counts.
- Static network assumptions: The simulation assumes that infrastructure remains constant across runs; dynamic features like construction or weather were not considered.
- Uniform routing probabilities: The 70/30 routing split does not account for individual decision-making based on congestion perception or destination type.

### 5.4 Opportunities for Model Refinement

Future improvements could address these limitations by:

- Incorporating empirical occupancy data from sensor feeds or access logs to better calibrate pedestrian generation.
- Enhancing behavioral realism using agent-based decision models with peer influence.
- Testing the impact of temporary constraints (e.g., blocked paths, emergency detours) to evaluate system adaptability.

## 6 Pitfalls and Resolutions

During the development and analysis of the pedestrian simulation model, several challenges were encountered. These pitfalls were both technical and conceptual. The following summarizes key issues and their resolutions:

- **Pitfall: Routing Congestion Oversimplification**

Initial routing logic relied exclusively on shortest-path calculations, which led to unrealistic congestion buildups at major nodes like the Atrium crosswalk. Pedestrians funneled into single paths regardless of load.

*Resolution:* A probabilistic routing strategy was introduced, where 30% of pedestrians were assigned to alternate viable paths. This improved congestion distribution and better reflected real-world variability in pedestrian behavior.

- **Pitfall: Unrealistic Pedestrian Spawning Timing**

Pedestrian agents were initially generated uniformly over the simulation duration, which did not capture real-world spikes during class change intervals.

*Resolution:* Occupancy schedules were implemented with time-based spawning tied to expected building use patterns, leading to realistic peak congestion and more accurate performance metrics.

- **Pitfall: Output Variability and Lack of Confidence**

Early performance results were based on a small number of runs, resulting in unstable averages and wide variance across scenarios.

*Resolution:* 30 simulation runs per configuration was adopted, with statistical justification through confidence intervals and convergence analysis to ensure reliable outcome interpretation.

- **Pitfall: Incomplete Edge Connectivity and Invalid Routes**

Early versions of the pedestrian network contained disconnected or improperly linked path segments, leading to simulation errors and missing agents.

*Resolution:* The SUMO network was debugged using NetEdit and TraCI inspection tools to identify and fix non-traversable links and ensure complete edge connectivity.

These issues highlight the iterative nature of simulation modeling and the importance of aligning system behavior with both real-world logic and technical constraints.

## 7 Conclusion

This study applied sensitivity and scenario analyses to a pedestrian traffic simulation model of the KSU Marietta campus to evaluate how variations in building occupancy and routing behavior affect system performance. The analyses provided a data-driven foundation for understanding how localized changes—particularly at high-traffic nodes like the Atrium—can lead to substantial changes in congestion, travel time, and throughput.

Through controlled  $\pm 20\%$  variations in occupancy for the Atrium and Academic Buildings, it was determined that the Atrium is a significant driver of pedestrian congestion, while the Academic Building has a more limited impact. Scenario testing with probabilistic routing behavior revealed that even modest deviations from strict shortest-path logic can improve the distribution of pedestrian flow without significantly degrading system efficiency.

Overall, the model demonstrated robustness and responsiveness to input changes, validating its utility as a decision support tool for pedestrian infrastructure planning. These findings highlight the importance of both spatial demand distribution and pedestrian behavior in urban mobility systems. Future model refinements could incorporate more detailed behavior modeling, real-time data integration, and additional environmental constraints to further enhance predictive power and practical applicability.

## 8 Model Validation

Model validation ensures that simulation outputs are consistent with real-world expectations and behaviors. The following multi-method validation approach was applied to assess the credibility and robustness of the pedestrian simulation model:

- **Face Validation:** Output patterns were reviewed and qualitatively compared to known campus dynamics. For example, observed congestion near the Atrium during class change intervals was consistent with simulation behavior under high-occupancy conditions.
- **Conceptual Validation:** The model was evaluated for logical soundness in its routing logic, occupancy schedules, and time sequencing. Occupancy input values were applied dynamically to capture fluctuating pedestrian loads throughout the day.
- **Sensitivity Validation:** As documented in Section 4, the model exhibited appropriate and interpretable responses to variations in key input parameters. Increasing occupancy in high-traffic buildings such as the Atrium led to increases in congestion and travel time, while changes in the Academic Building had minimal system-wide impact. This confirmed the internal consistency and behavioral realism of the simulation.
- **Empirical Validation (Future Direction):** Future validation efforts could include the use of sensor-based pedestrian counting or video analytics to calibrate model parameters and verify outputs empirically.

This multi-level validation approach supports the conclusion that the model is both conceptually sound and operationally robust, offering valuable insight for pedestrian planning and infrastructure analysis for KSU Marietta campus.

## References

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## Appendices

### Appendix A: Simulation Configuration

The simulation was implemented using the SUMO (Simulation of Urban Mobility) framework with the following configuration details:

- **Network Source:** Custom-built KSU Marietta pedestrian path network
- **Simulation Tool:** SUMO 1.x
- **Time Resolution:** 1-second timestep
- **Pedestrian Types:** Dynamic pedestrians with real-time routing updates
- **Runs per Scenario:** 30
- **Metrics Logged:**
  - Total pedestrians per timestep
  - Average travel time
  - Maximum waiting time
  - Maximum density per edge
  - Throughput (completed trips)

Routing adjustments were applied using SUMO's TraCI API to enable dynamic rerouting based on real-time congestion indicators.

### Appendix B: Parameter Definitions and Ranges

Table B.1: Simulation Parameters and Variation Ranges

Parameter	Base Value	Variation Range	Notes
Atrium Occupancy	Varies hourly (avg ~190)	$\pm 20\%$ per timestep	Based on schedule estimates
Academic Occupancy	Varies hourly (avg ~150)	$\pm 20\%$ per timestep	Modeled similarly to Atrium
Routing Strategy	100% shortest path	70% shortest / 30% alternative	Applied at simulation initialization

### Appendix C: Example Output Schema

Below is an example of the output CSV format used to log simulation statistics during each timestep:

Table C.1: CSV Output Schema

Time	Total Pedestrians	Mean Speed	Waiting Pedestrians	Avg Route Time	Throughput	Max
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