

## **DATA-DRIVEN AGENT-BASED PEDESTRIAN MODELING AND SIMULATION IN INDOOR ENVIRONMENTS**

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### **ABSTRACT**

Modeling pedestrian behavior in diverse environments presents a complex challenge that requires a nuanced and adaptable approach. Our research aims to develop a comprehensive framework for pedestrian dynamics through Agent-Based Modeling and Simulation, guided by data-driven insights. The framework specifically addresses challenges related to design validation and space utilization in indoor environments, with a focus on data-driven initialization, deep learning-assisted model calibration, and incorporating agent heterogeneity to enhance realism. By integrating deep learning with traditional parameter search methods such as Particle Swarm Optimization, the framework also emphasizes establishing a robust model validation process to ensure confidence in its accuracy and applicability for real-world scenarios.

### **1 INTRODUCTION**

With rising urban populations and increased demands on indoor spaces, understanding pedestrian dynamics has become crucial for effective urban planning, transportation design, and crowd management. Traditional methods, including field experiments and observational studies, provide valuable insights but often lack the adaptability and accuracy required for complex scenarios.

The authors of "Agent-Based Simulation for Pedestrian Evacuation" note that while rule-based models are common, advancements in behavioral frameworks, high-performance computing, and machine learning offer better solutions. Thus, our research aims to address these limitations by developing a comprehensive framework that integrates these advanced methods.

### **2 PROPOSED APPROACH AND CHALLENGES**

Our framework focuses on data-driven initialization, which utilizes real-world data collected at intervals to initialize the framework. It also includes deep learning-assisted model calibration, accelerating the calibration process by leveraging pre-trained deep learning surrogate models. Furthermore, the framework enhances simulation realism by incorporating agent heterogeneity through diverse agent profiles.

Microscopic-level modeling with heterogeneity increases calibration complexity but allows for rapid adaptation to data changes, balancing complexity with realism.

### **3 IMPLEMENTATION AND RESULTS**

#### **3.1 Model Calibration using Particle Swarm Optimization**

Particle Swarm Optimization (PSO) is used as the main algorithm for parameter optimization in our Agent-Based System. PSO is a metaheuristic search technique that mimics the movement of a swarm of particles in a multidimensional space to identify optimal solutions for optimization problems.

If we denote the number of agents as  $M$  and the number of optimizing parameters per agent as  $K$ , the dimensionality of the optimization problem in PSO becomes  $M \times K$ .

Given this high-dimensional space, PSO can incur substantial computational costs due to the direct evaluation of the fitness function. To avoid these costs, we incorporate a Surrogate Model approach.

### 3.2 Deep Learning assisted PSO

To avoid the high costs of direct fitness function evaluation, we utilize a pre-trained Deep Learning Model (TabNet). We set  $learning\_rate = 0.001$  and  $num\_epochs = 1000$ . Challenges include determining “how” pedestrians move rather than “where,” and extracting relevant features from the environment, such as distances to walls, corners, spots, and surrounding agents. We extract features such as local and global speeds, acceleration/deceleration percentages, and turning angles, aiming to optimize parameters for heterogeneous agents in various local environments with corresponding velocity and orientation.

### 3.3 Experimental Setup and Results

We use the ATC Pedestrian Tracking dataset recorded in shopping mall in Osaka, which is divided into calibration (model training/testing and PSO calibration) and validation sets. The dataset includes time, person ID, position (x, y, z), velocity, and angles of motion and facing.

We evaluated the calibration module using two model calibration techniques: standard PSO and DL-assisted PSO. In standard term, PSO directly evaluates the objective function at each step, adjusting all agent parameters and executing model regularly. We set PSO parameters  $\{c1': 0.5, c2': 0.3, w': 0.9, k': 3, p': 2\}$  and  $num\_iterations=100$ .

In DL-Assisted PSO, a pre-trained deep learning model approximates the fitness function to save calibration time. The Agent-Based System’s overall quality was assessed using Dynamic Time Warping (DTW), comparing the validation (real) trajectory with the model output per agent and summing the results.

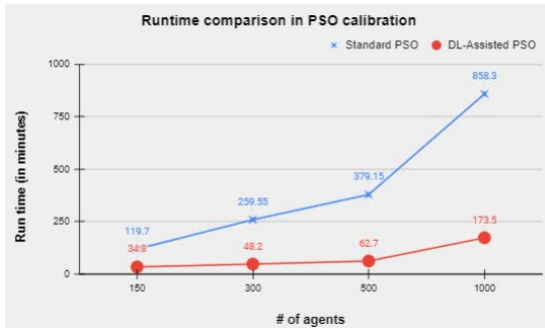


Figure 1: Run time comparison in PSO process.

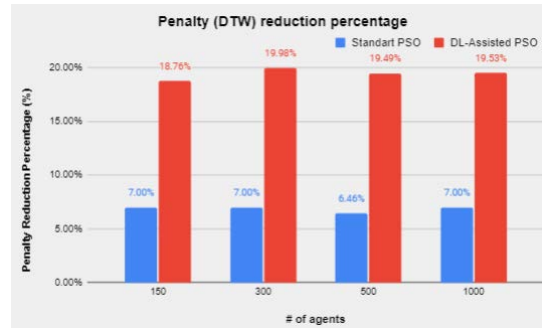


Figure 2: Penalty reduction percentage.

Figure 1 shows that DL-assisted PSO is approximately five times faster than standard PSO. Additionally, as shown in Figure 2, the penalty has significantly decreased compared to baseline values (generated using reference parameters), with a significant reduction of approximately 20%.

## 4 CONCLUSION

The proposed approach is effective for large datasets, with Deep Learning-assisted PSO significantly reducing calibration runtime and achieving our initial goal. The penalty (DTW value) is reduced by 18-20% compared to reference values. The system’s quality relies on the Deep Learning model’s accuracy and can be extended to model group dynamics by distinguishing pedestrian groups with its size.

## REFERENCES

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