26th International Congress on Modelling and Simulation, Adelaide, SA, Australia, 30 Nov–4 Dec 2025
mssanz.org.au/modsim2025

Using machine learning to emulate physics-inspired agent-based models: a case study in emergency evacuations

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Abstract: Agent-based models are powerful tools for simulating complex systems, but their high computational cost limits their use in real-time decision support and sensitivity analysis. To address this, we develop a neural network surrogate to accelerate emergency evacuation simulations generated with the PiXIE (ProXimity toolkit for Interacting Entities) pedestrian flow simulator. The surrogate achieves high accuracy in reproducing evacuation times and crowd density metrics with respect to in-distribution, interpolation, and extrapolation testing regimes.

Keywords: *Agent-based models, Neural Networks, Evacuations, Surrogate modelling.*

1. INTRODUCTION

Agent-based models (ABMs) simulate interactions of autonomous agents in complex systems and are widely used in areas such as evacuation modelling, transportation, and epidemiology. They capture individual heterogeneity and emergent behaviours but at high computational cost. As agent numbers, spatial scale, duration, and interaction resolution grow, runtimes can become prohibitive, restricting ABM use in near real-time decision support, calibration, sensitivity analysis, uncertainty quantification, and optimisation.

To address this bottleneck, this study explores machine learning (ML) as a surrogate approach to accelerate ABM analysis. A deep neural network emulator for the PiXIE (ProXimity toolkit for Interacting Entities) pedestrian flow simulator [1] is developed. PiXIE uses the physics-inspired Social Force Model (SFM) [2] to capture microscopic pedestrian dynamics, which requires very fine temporal integration of its continuous differential equations leading to a very high number of simulation steps, in the order 10^3 steps for every simulated second. The neural network emulator bypasses this by directly learning the mapping from simulation inputs to outputs, achieving orders-of-magnitude speedups and enabling exploration of parameter spaces that are far larger than is feasible with ABMs.

2. METHODOLOGY AND RESULTS

Figure 1 presents the proposed neural network surrogate for the evacuation simulator. The experimental dataset comprised 30000 PiXIE simulations of evacuations from a 20 × 20 m room through a single doorway leading to a 2 × 4 m exit corridor (Figure 2). Three parameters were varied systematically: door width (1-2m), population size (20-600), and desired walking speed (1.2-1.8ms). For feature extraction (Figure 2), the domain was discretised into 10 rectangular cells $c_i,\ i \in \{0, 9\}$ each defined by its geometry (height (h_i), width (w_i)) and proportional accessibility along its boundaries $b_{i,u}, u \in \{T, L, B, R\}$. Agent features included population size, the density function of initial positions $(p(0) \dots p(9))^T$, the desired walking velocity, and the normal distributions of agent mass and radius. The neural network was designed to emulate the simulations by estimating (i) percentiles of the agent evacuation time distribution (50th, 65th, 75th, 90th, 98th) and the (ii) temporal distribution of the crowd density around the entrance to the exit corridor.

The emulator was evaluated under three regimes: (i) within-distribution testing using an 80%-20% training-test split of the simulation data set; (ii) interpolation, with an unseen medium corridor door width (1.5 m) when trained on corridor door widths above and below it; and (iii) extrapolation, on unseen corridor widths at either the lower or upper bounds (1 m or 2 m) when trained on widths that are above or below, respectively.

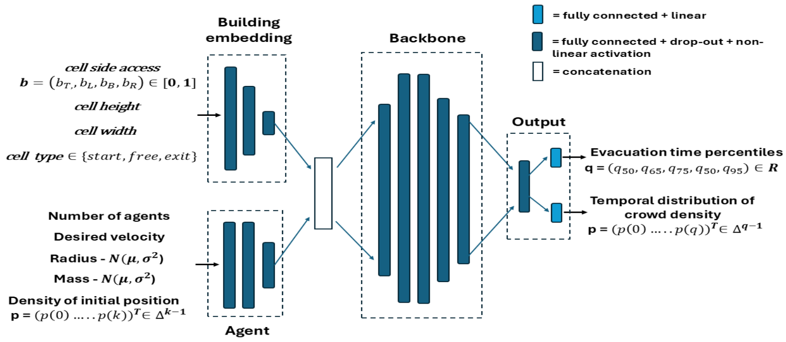

Figure 1 Neural network architecture used for evacuation emulation

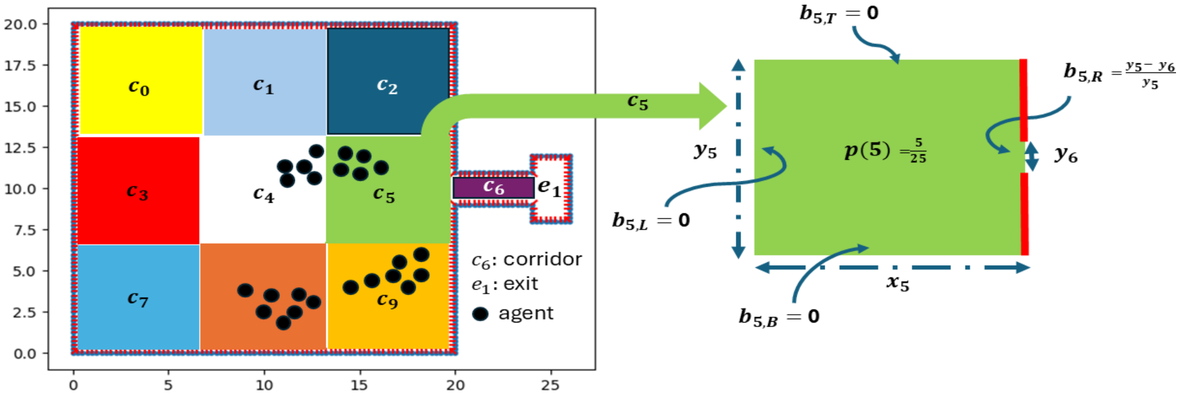

Figure 2 Evacuation scenario involving a large room and narrow exit corridor. A demonstration of the input features computed in each of the partitioned spatial cells c_i (in this case, c_5) of the evacuation domain.

Table 1 Performance of the neural network surrogates for in-distribution, interpolation and extrapolation tests.

			Evacuation time	Crowd density distribution		Running time
Regime	**Train**	**Test**	**MAE (s)**	**KLD**	**MAE (%)**	**Mean (s)**
In distribution	80%	20%	2.6	0.02	1.6	PiXIE = 11.1 Surrogate = 0.013
Interpolation	{1, 2}m	1.5m	4.6	0.019	1.8	
Interpolation	{1,1.25, 1.75, 2}m	1.5m	3.0	0.016	1.5	
Extrapolation	{1.75, 2}m	1m	3.3	0.021	2.0	
Extrapolation	{1.5, 1.75, 2}m	1m	2.0	0.019	1.5	
Extrapolation	{1,1.25}m	2m	4.0	0.025	1.9	
Extrapolation	{1,1.25,1.5}m	2m	2.4	0.014	1.5	

Table 1 reports the performance of the three test regimes in terms of the Mean Absolute Error (MAE) of evacuation time percentiles and the MAE and Kullback–Leibler Divergence (KLD) of the crowd density distribution. The emulator demonstrated strong accuracy in reproducing evacuation time and crowd density metrics, with performance declining as the interpolation and extrapolation gap increased. Furthermore, the average simulation time of PiXIE and the average inference time of the neural surrogate were evaluated across 6,000 test simulations of regime (i), with the surrogate achieving an average inference approximately three orders of magnitude faster.

To demonstrate its practical utility, the neural surrogate model was then applied to a case study comparing evacuation strategies. The strategy involved evacuating 700 agents uniformly distributed in the 20 × 20 m room (shown in Figure 2) with a 2 m-wide exit. A baseline single-stage evacuation was evaluated against multi-stage strategies, where agents in different subsets of cells c_i were evacuated sequentially until the room was empty. Leveraging the emulator's efficiency, all cell permutations were emulated in a couple of seconds, enabling rapid exploration of multi-stage design alternatives. Analysis of evacuation times and crowd density metrics revealed that well-designed two-stage strategies can substantially reduce periods of dangerous congestion (~ 95%) compared to the single-stage baseline, with smaller increases (~ 20%) in overall evacuation time.

3. CONCLUSIONS

In conclusion, the proposed neural emulators were shown to be an accurate and efficient surrogate for Physics-inspired ABMs in evacuation modelling. By delivering three orders of magnitude reduction in run-time, they enable large-scale sensitivity analyses, real-time scenario evaluation, and optimisation of evacuation strategies. Future work will investigate the transferability of the surrogate models across different building designs, supporting the rapid deployment of an emulator across a range of evacuation scenarios.

4. REFERENCES

[1] Andrés-Thió N., Ras C., Bolger M., Lemiale V. (2021) A study of the role of forceful behaviour in evacuations via microscopic modelling of evacuation drills, Safety Science, 134

[2] Helbing D., Molnar P. (1995) Social force model for pedestrian dynamics, Phys. Rev. E, 51(5), pp. 4282

