Simheuristics for Indoor Crowd Evacuation Optimization

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Context

According to OECD data, people actively working spend around 1750 hours a year at their jobs, which represents approximately 30% of their waking hours.

Adding up leisure, shopping, and other activities, we may spend about half of our lifes in public indoor spaces.

Motivation

Rapid and orderly evacuation of crowds from enclosed spaces is essential to minimize casualties and ensure public safety.

It is essential to understand:

- The features of the environment
- the behavior of the crowd
- their interplay

General Problem

Evacuation Problem

Given an environment $\mathcal{E}$ hosting a crowd $\mathcal{C}$, ensure the best possible evacuation in time T.

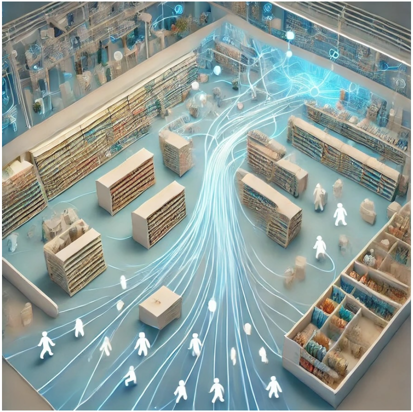
Key questions:

Q1 What can be optimized?

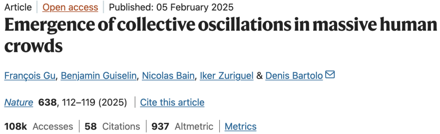
Q2 How will success be measured?

Q3 By which means can the problem be optimized?

Why is it Hard?



The crowd dynamics are non-linear, with emergent behaviors and local interactions.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Emergence of collective oscillations in massive human crowds

François Gu, Benjamin Guiselin, Nicolas Bain, Iker Zuriguel & Denis Bartolo

Nature **638**, 112–119 (2025) | Cite this article

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Watch Video

Analytic models are not available.

We need to resort to simulations.

What are Simheuristics?

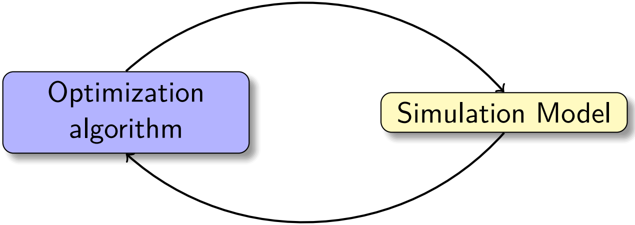
Simheuristics

Simheuristics are a specialized class of simulation-optimization algorithms that integrate simulation into a metaheuristic-driven framework to solve large-scale optimization problems.

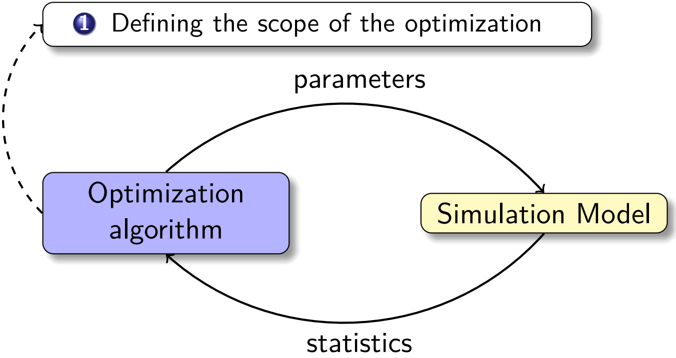
Simulation

Simulation is the process of designing a model of a real system and conducting experiments with this model for the purpose of either understanding the behavior of the system and/or evaluating various strategies for the operation of the system.

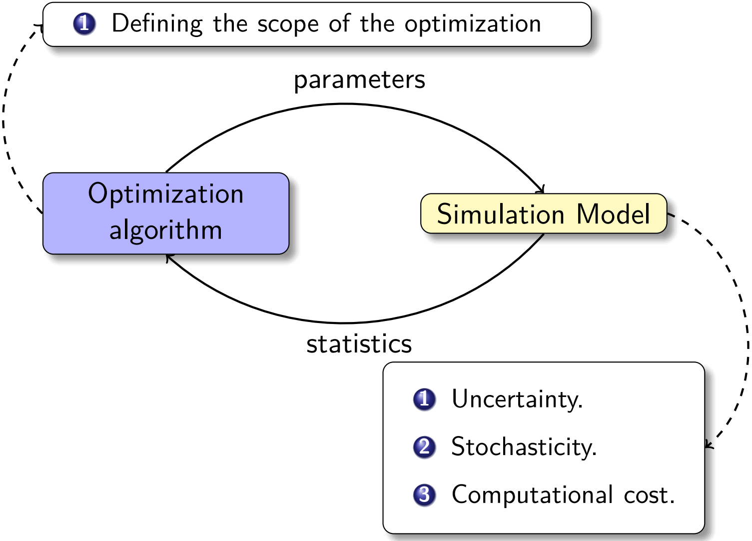
Simheuristic Architecture



Simheuristic Architecture



Simheuristic Architecture



Uncertainty vs Stochasticity

They are related but are different:

- Stochasticity captures an inherent variability of the results.
- Uncertainty captures epistemic limitations of the model.

	Stochasticity	Uncertainty
Objective	$f : \mathcal{V} \times \mathbb{R} \to [0,1]$	$f : \mathcal{V} \to \mathbb{R} \in \mathcal{U}(\hat{f}(\mathcal{V}))$
Evaluation	multiple replicas	a value with (locally variable) uncertainty $\sigma^2(x)$
Selection	estimator statistical test	$f'(x) = f(x) + \kappa\sigma(x)$

Computational Cost

Evaluating solutions is expensive.

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Review

A review of surrogate-assisted evolutionary algorithms for expensive optimization problems

Chunlin He[a], Yong Zhang[a,*], Dunwei Gong[b,*], Xinfang Ji[a]

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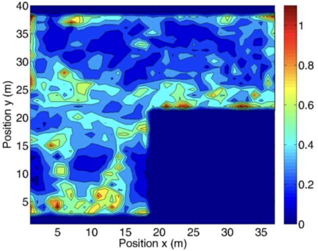
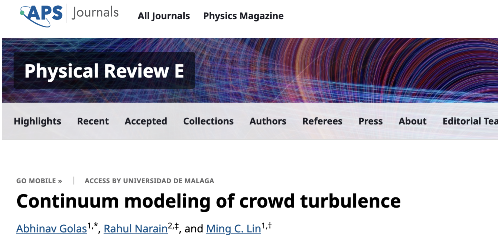
Or ensure fast convergence to near-optimal solutions.

Modeling Approaches

There are two large categories:

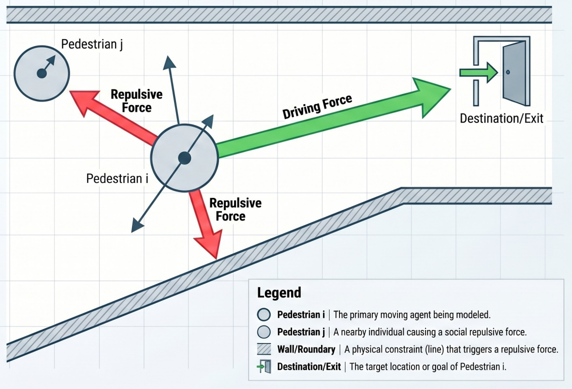
1. Macroscopic: crowd as a whole. Model pedestrian density, velocity, and flow using differential equations.
2. Microscopic: each pedestrian is an agent with its own behavioral rules, that interacts with other pedestrians.





Agent-based modeling

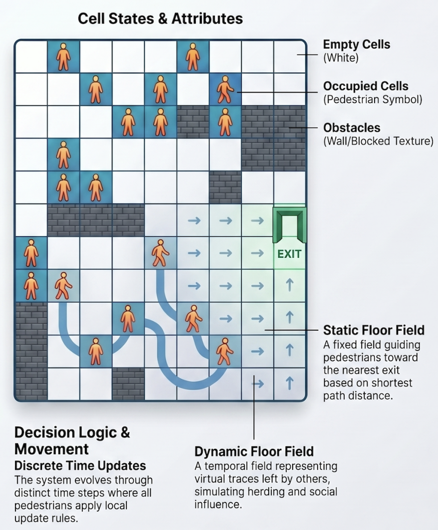
Social Forces



Individuals are modeled as particles subject to attractive forces toward destinations and repulsive forces from obstacles and nearby pedestrians.

Continuous modeling required.

Agent-based Cellular Automata



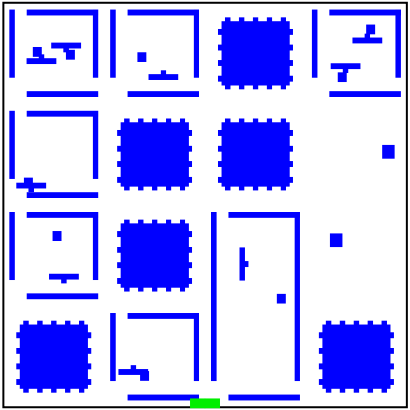
The environment is discretized into a grid of cells.

Pedestrians are agents moving between neighboring cells according to probabilistic or rule-based transition mechanisms.

Spatial discretization.

Computationally efficient.

Environment

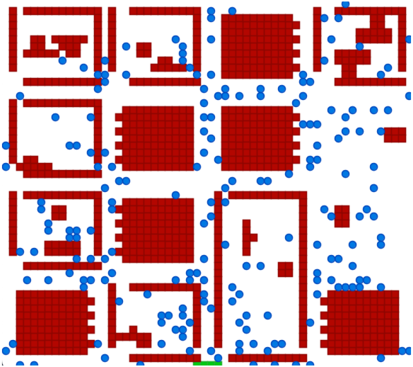


The environment $\mathcal{E}$ is a tuple (w, h, A, O), where:

- w and h are the width and height of $\mathcal{A}$ respectively.
- $A = \{\alpha_1, \ldots, \alpha_k\}$ is a collection of accesses.
- $O = \{o_1, \ldots, o_m\}$ is a collection of obstacles.

This environment $\mathcal{E}$ is populated with n pedestrians who will try to evacuate when an emergency is declared.

Pedestrians

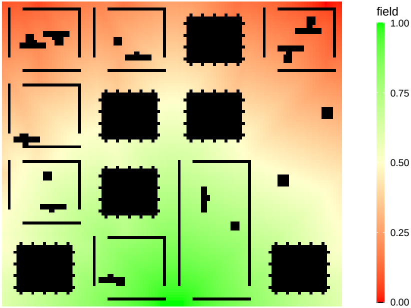


The initial configuration S is $S = \{(x_1, y_1), \ldots, (x_n, y_n)\}$, where (x_i, y_i) are the coordinates of the i-th pedestrian.

The environment is discretized into a grid of square cells of side length c.

Cellular Automaton

Attraction Field



A static attraction field is defined on the CA:

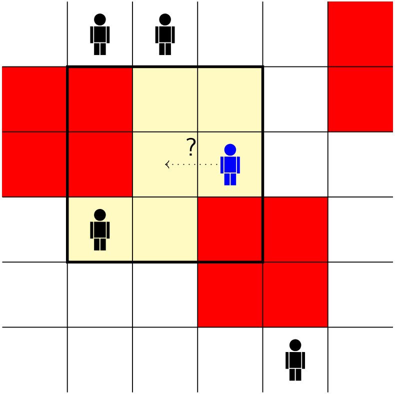
$$\mathcal{A}_{ij} = 1 - \frac{d_{ij}}{\max_{rs} d_{rs}},$$

where d_{ij} is the distance from cell (i, j) to the nearest exit according to Dijkstra's algorithm.

The static attraction field represents the rational behavior of pedestrians, who will attempt to evacuate as quickly as possible.

Cellular Automaton

Repulsion Field



Each cell has a dynamic repulsion value:

$$\mathcal{R}_{ij} = \frac{1}{1+\omega_{ij}},$$

where ω_{ij} is the number of accessible neighbors of cell (i, j).

The repulsion field represents the subjective crowd aversion of pedestrians.

Cellular Automaton

Crowd Dynamics

The two fields are integrated into a desirability measure:

$$\mathcal{D}_{ij} = \exp(\phi \cdot \mathcal{A}_{ij} - \psi \cdot \mathcal{R}_{ij}),$$

where ϕ, ψ are two coefficients weighting the contribution of each field.

Each pedestrian will attempt to move to an adjacent empty cell with probability proportional to the excess desirability with respect to the least desirable neighbor.

Demo

Performance Metrics

Let $\sigma(\mathcal{A}, S)$ be the result of simulating the CA on environment $\mathcal{A}$ with initial pedestrian configuration S.

Let ξ^+ (resp. ξ^-) be the set of pedestrians that evacuate $\mathcal{A}$ (resp. pedestrians that did not evacuate $\mathcal{A}$). For each $i \in \xi^+$, t_i is the time at which evacuation was done, and for each $i \in \xi^-$, d_i is the distance of an exit at which they ended up.

The performance of the evacuation is measured as:

$$
\begin{aligned}
f(\sigma(\mathcal{A}, S)) &= |\xi^-| + \quad [\xi^- = \emptyset] \quad \left(\tfrac{1}{T}\max_{1 \leqslant i \leqslant n} t_i + \tfrac{1}{nT^2}\textstyle\sum_{1 \leqslant i \leqslant n} t_i\right) + \\
&+ \quad [\xi^- \neq \emptyset] \quad \left(\tfrac{1}{D}\min_{i \in \xi^-} d_i + \tfrac{1}{nD^2}\textstyle\sum_{i \in \xi^-} d_i\right)
\end{aligned}
$$

where T is the maximum simulation time and D is the environment diameter.

Problem Formulation

Optimal Evacuation Problem (OEP)

An OEP instance is defined as a tuple $(\mathcal{A}, \mathbb{S}, k, \lambda)$, where

- $\mathcal{A} = (w, h, A, O)$ is the environment.
- $\mathbb{S}$ is a collection of initial configurations of n pedestrians.
- $k \in \mathbb{N}^+$ is the number of emergency exits.
- $\lambda > 0$ is the width of emergency exits.

The solution sought is $E = \{e_1, \ldots, e_k\} \subset [0, 2(w + h)]$, where each e_i represents the location of an emergency exit, such that

$$\rho(E) = \frac{1}{|\mathbb{S}|} \sum_{S_i \in \mathbb{S}} f(\sigma(\mathcal{A}_E, S_i))$$

is minimal.

A Greedy Approach

Algorithm 1: Greedy Algorithm

Data: an instance OEP$(\mathcal{A}, \mathbb{S}, k, \lambda)$

$E \leftarrow \emptyset$;
$\eta \leftarrow \lceil 2(w+h)/\omega \rceil$;
for $i \leftarrow 1$ **to** k **do**
  $p \leftarrow \text{rand}(0, 2(w+h))$;
  $best \leftarrow \infty$;
  for $j \leftarrow 1$ **to** η **do**
    $cur \leftarrow \rho(E \cup \{p\})$;
    if $cur < best$ **then** $best \leftarrow cur$; $e \leftarrow p$;
    $p \leftarrow p + \lambda$;
    if $p > 2(w+h)$ **then** $p \leftarrow p - 2(w+h)$;
  end
  $E \leftarrow E \cup \{e\}$;
end
return E

Starting from a random position in the perimeter, tentative exits are placed side to side, and the one providing the best results is kept.

The best one is kept and the procedure is repeated for the next exit, until all exits are placed.

An Evolutionary Algorithm

Solutions are encoded as a k-dimensional floating point vector $E = \{e_1, \ldots, e_k\}$.

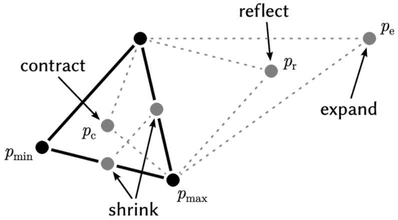
Recombination is done using a discrete procedure:

Algorithm 2: Set-based recombination

Data: two sets $E = \{e_1, \ldots, e_k\}$ and $E' = \{e'_1, \ldots, e'_k\}$
$C \leftarrow E \cup E'$; $S \leftarrow \emptyset$;
for $i \leftarrow 1$ **to** k **do**
    $e \leftarrow$ PICK (C); `// makes random selection`
    $S \leftarrow S \cup \{e\}$; $C \leftarrow C \setminus \{e\}$;
end
return S

Mutation is done by adding a Gaussian perturbation of zero mean and amplitude σ.

Nelder-Mead Algorithm

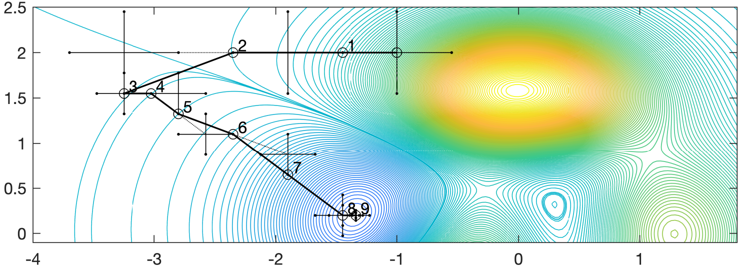


The Nelder-Mead method optimizes a k-dimensional continuous function by keeping a polytope of $k+1$ tentative solutions.

New vertices a repeatedly picked to replace the worst vertex of the polytope, until all vertices in the polytope have converged to very similar values of the objective function or a maximum number of iterations is reached.

Advance

Hooke-Jeeves Algorithm



The Hooke-Jeeves algorithm optimizes a continuous *k*-dimensional function by moving a search pattern throughout the solution space.

When better solutions are found, the search direction is updated; when no improvement is found, a contraction of the search pattern takes place.

Memetic Algorithm

A memetic algorithm (MA) is defined by combining the EA with the Hooke-Jeeves local search method.

Local search is incorporated as an additional mutation operator.

Due to its computational cost, a partial Lamarckism strategy is employed, i.e., the local search operation is applied with probability p_{LS}.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Harnessing memetic algorithms: a practical guide

Original Paper | Open access | Published: 03 February 2025

Volume 33, pages 327–356, (2025) Cite this article

Results

Instance Generation

Attributed Grammars

We consider procedurally generated instances resembling office areas. We use attribute grammars for this purpose.

An attribute grammar is an extension of standard generative grammars that captures semantic information by defining attributes of terminal/nonterminal symbols:

$$\phi(\alpha_A) : A[\alpha_A] \rightarrow_w X_1[f_1(\alpha_A)] \ldots X_m[f_m(\alpha_A)]$$

where $A \in N$ is a nonterminal, $X_i[\alpha_{X_i}]$ denotes a terminal/nonterminal symbol $X_i \in N \cup T$ with attributes $\alpha_{X_i} = \alpha_1, \ldots \alpha_{n_X}$, $f_i(\cdot)$ is a function indicating how to compute the attribute values of X_i, w is the weight of the rule, and $\phi(\cdot)$ is a logical predicate stating a precondition for the application of the rule.

Instance Generation

L-Grammar Considered

The nonterminal symbols are $N = \{E, R, O\}$, where

- E represents a generic subspace that can be recursively subdivided. This symbol is also the initial axiom.
- R represents a virtual room (a specific subspace).
- O represents an office, that is, a space surrounded with walls (accessible from all sides) and containing some furniture.

The terminal symbols are $T = \{solid, table, office_{1,2}\}$, where

- *solid* represents a small solid object of square shape.
- *table* represents a conference table with chairs around it.
- $office_1$, and $office_2$ represent the particular arrangement of furniture within an office, with desks aligned horizontally or vertically respectively.

Instance Generation

L-Grammar Considered

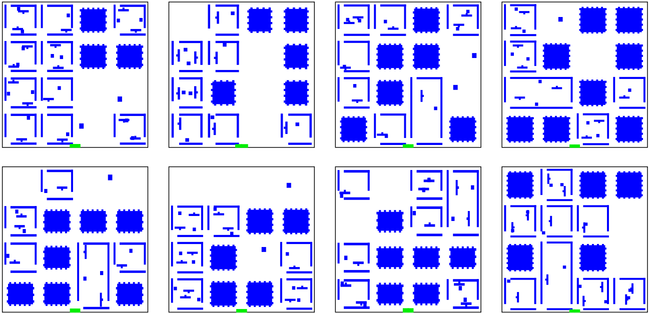
All symbols have four attributes defining a bounding rectangle.

$$
\begin{array}{rlll}
w > 8: & E[x,y,w,h] & \to_3 & E[x,y,w/2,h]E[x+w/2,y,w/2,h] \\
h > 8: & E[x,y,w,h] & \to_3 & E[x,y,w,h/2]E[x,y+h/2,w,h/2] \\
w > 8 \wedge h > 8: & E[x,y,w,h] & \to_4 & E[x,y,w/2,h/2]E[x+w/2,y,w/2,h/2] \\
 & & & E[x,y+h/2,w/2,h/2]E[x+w/2,y+h/2,w/2,h/2] \\
w \leqslant 8 \vee h \leqslant 8: & E[x,y,w,h] & \to_1 & R[x+2\zeta,y+2\zeta,w-4\zeta,h-4\zeta] \\
\text{true}: & R[x,y,w,h] & \to_3 & O[x,y,w,h] \\
\text{true}: & R[x,y,w,h] & \to_1 & solid[x+\zeta+\rho\cdot(w-5\zeta),y+\zeta+\rho\cdot(h-5\zeta),3\zeta,3\zeta] \\
w < 8 \wedge h < 8: & R[x,y,w,h] & \to_2 & table[x,y,w,h] \\
w > h: & O[x,y,w,h] & \to_1 & office_1[x,y,w,h] \\
w \leqslant h: & O[x,y,w,h] & \to_1 & office_2[x,y,w,h]
\end{array}
$$

where ζ is used as a reference unit for object sizes and ρ is a random ephemeral constant uniformly distributed in [0,1).

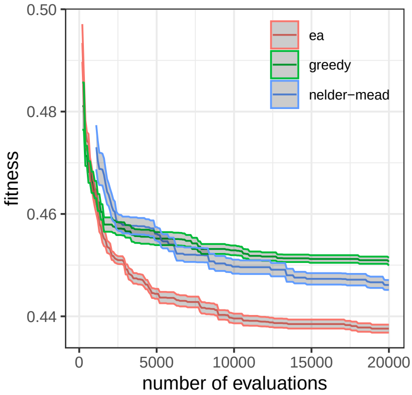
Experimental Setting

We consider a benchmark composed of eight instances generated by the L-grammar:



We consider a number of exits $k = 4$, $\lambda = 2$m, $c = 0.5$m, $n = 50$, reference velocity $v = 0.77$m/s, field attraction bias $\phi = 4$, crowd repulsion bias $\psi = 0$, $T = 60$s.

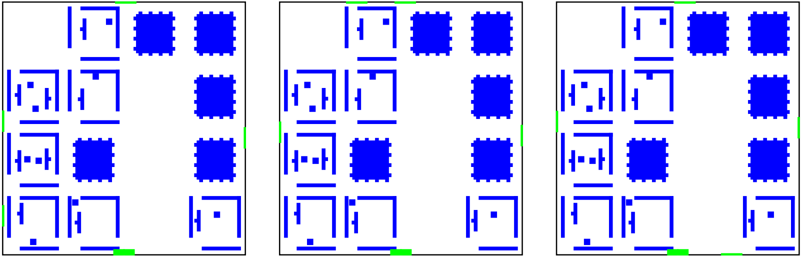
Numerical Results



The EA provides the best training results in 7/8 instances (with statistical significance over Nelder-Mead in 7/7 instances, and over the greedy method in 4/7 instances).

The EA provides the best test results in 5/8 instances (3/5 against Nelder-Mead and 4/5 against greedy), and Nelder-Mead is the best in 3/8 (3/3 against the EA and 2/3 against greedy).

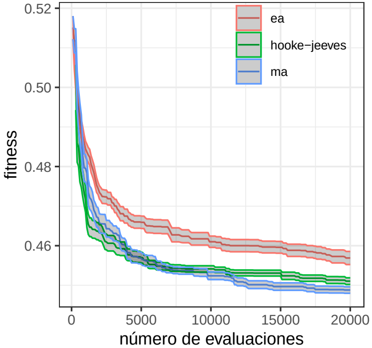
Solutions Attained

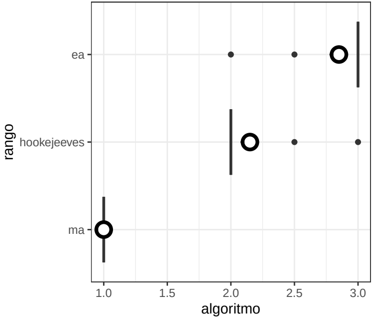


EA greedy Nelder-Mead

Memetic Approaches

Resultados Numéricos





Hooke-Jeeves is generally better than the EA and both are outperformend by the MA.

Quade test (p-value $<$ 1e-5) and Holm-Bonferroni using MA as the reference algorthm (p-value $=$ 0.01013) are passed.

Take Home Messages

1. Crowd behavior is emergent and non-linear.
2. It is inherently simulation-driven.
3. Simheuristics are thus the natural framework.
4. Memetic approaches are particularly effective.

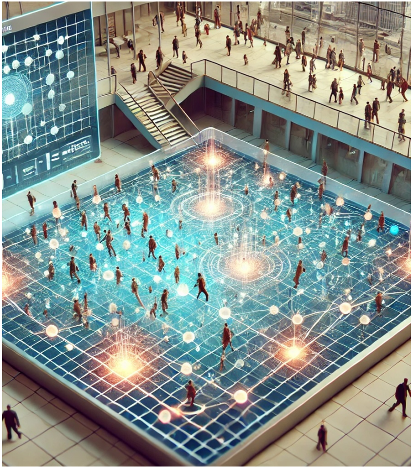
Future Directions

Larger training sets may be required. Thus, efforts must be directed towards parallel computing and surrogate models.

There is plenty of room to enrich the simulation model and the algorithmic approaches.

Future Directions

Enriching the Model



Enriching the behavior of the pedestrians:

- Stratification
- Heterogeneous behaviors
- ...

Enriching the environment:

- Signage
- Dynamic maps
- ...

And many more!

Thank You!

Novel Bioinspired Optimization Techniques for Resilience and Sustainability

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