# Artificial neural networks predicting pedestrian dynamics in complex buildings

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**Abstract** The prediction of pedestrian movements in complex buildings is a difficult task. Recent experiments have shown that the behaviour of pedestrians tends to depend on the type of facility. For instance, flows at bottlenecks often exceed the maximal rates observed in straight corridors. This makes pedestrian behaviours geometry-dependent. Yet the types of geometries are various, and their systematic identification in complex buildings is not straightforward. Artificial neural networks are able to identify various types of patterns without supervision. They could be a suitable alternative for forecasts of pedestrian dynamics in complex architectures. In this paper, we test this assertion. We develop, train and test artificial neural networks for the prediction of pedestrian speeds in corridor and bottleneck experiments. The estimations are compared to those of an elementary speed-based model. The results show that neural networks distinguish the flow characteristics for the two different types of facilities and significantly improve the prediction of pedestrian speeds.

**Keywords** Pedestrian Dynamics, Prediction, Complex Geometry, Artificial Neural Network, Training and Testing

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# 1 Introduction

Traffic engineers frequently use pedestrian simulation models to predict crowd dynamics. This may be to manage large events (e.g. sports events) or in the planning phases of complex buildings (e.g. train stations). Classical operational approaches are microscopic. They are decision-based, velocity-based or again acceleration-based models (see [4, 24] and references therein). Such models consider physical, social or psychological factors. They are specified by few parameters which generally have physical interpretations. Before making predictions, the physics-based models have to be calibrated and validated experimentally or statistically.

Despite their relative simplicity, microscopic physics-based models can describe realistic pedestrian flows and observed self-organization phenomena [13, 23]. However, accurate predictions of pedestrian dynamics in complex spatial structures remain difficult. Observations show that pedestrians adapt their behaviour according to the facilities [5]. For instance, the flow significantly increases at bottlenecks [19, 25, 27]. This leads to geometry-dependent behavior. Yet the types of geometries are various and not precisely defined. Their systematic identification in complex buildings is ambiguous.

Artificial neural networks (ANN) represent an alternative modelling approach for prediction of pedestrian dynamics. The high plasticity of the networks allows identifying various types of patterns without supervision. Neural networks have already proven their efficiency for motion planning of robots and autonomous vehicles (see e.g. [15, 22]). Researchers started to use ANN for pedestrian dynamics as well, e.g. in complex geometries [6] or for the motion of robots moving in a crowd [3]. Simplest approaches are feed-forward neural networks (see [6, 17]), while the most sophisticated prediction algorithms lie in long-short-term memory networks [1] and deep reinforcement learning techniques [3].

The objective of the article is to evaluate whether neural networks could accurately describe pedestrian behaviors for two different types of facilities, namely a corridor and a bottleneck. We develop and test feed-forward networks for prediction of pedestrian's speed based on the relative positions of the closest neighbours. A physics-based model commonly used in traffic engineering is used for comparison as a benchmark. The performances significantly differ according to the geometry. We investigate the ability of neural networks to identify the specific patterns of each geometry, and evaluate the prediction enhancement.

# 2 Speed model and artificial neural networks

Our aim is to predict the speed of pedestrians according to the relative positions of the $K = 10$ closest neighbours. One denotes in the following $(x, y)$ as the position of the considered pedestrian, $v$ as its speed, and $\big((x_i, y_i), i = 1, \dots, K\big)$ as the positions of the $K$ closest neighbours.

### Speed-based model

The physics-based modelling approach is the Weidmann fitting model for the fundamental diagram [26]. In the Weidmann's model, the speed of a pedestrian is a non-linear function of the mean spacing with the closest neighbours:

$$\mathrm{FD}(\bar{s}_K, v_0, T, \ell) = v_0 \left(1 - \exp\left(\frac{\ell - \bar{s}_K}{v_0 T}\right)\right). \tag{1}$$

Here

$$\bar{s}_K = \frac{1}{K} \sum_i \sqrt{(x - x_i)^2 + (y - y_i)^2} \tag{2}$$

is the mean spacing distance to the $K$ closest neighbours that we use to approximate the local density. The Weidmann's model has three parameters: The time gap $T$, corresponding to the following time gap with the neighbor in front; The pedestrian speed in a free situation, also called the desired speed and denoted $v_0$; The physical size of a stopped pedestrian $\ell$. In the following, we use the Weidmann's model (Eq. (1)) and its parameters as a benchmark.

### Artificial neural networks

The data-based modelling approach for prediction of the pedestrian speed are feed-forward neural networks with hidden layers $h$. We test two networks with different inputs :

- In the first network, the inputs are the relative positions to the $K$ closest neighbours ($2K$ inputs)

$$\mathrm{NN}_1 = \mathrm{NN}_1\big(h, (x_i - x, y_i - y, 1 \le i \le K)\big). \tag{3}$$

- In the second network, the speed is predicted as function of the relative positions and the mean distance spacing $\bar{s}_K$ to the $K$ closest neighbours ($2K + 1$ inputs)

$$\mathrm{NN}_2 = \mathrm{NN}_2\big(h, \bar{s}_K, (x_i - x, y_i - y, 1 \le i \le K)\big). \tag{4}$$

The hidden layers $h$ describe the complexity of the network. The number of parameters of the algorithm depends on the number of artificial neurons in the hidden layers. They have in general no physical interpretation.

## 3 Empirical data

Two experiments are used to calibrate, train, test and compare the physics-based model and the artificial neural networks. In the first experiment, the pedestrians walk through a corridor while in the second they pass a bottleneck. The experiments were performed in 2009 in Düsseldorf, Germany, as part of the Hermes research project [14]. The trajectories of pedestrians are obtained by video analysis. Roughly $N =$

2100 pseudo-independent observations of pedestrian speeds and relative positions to the $K$ closest neighbors are extracted by experiment. The data and their description are available online, see [8].

## Corridor and bottleneck experiments

The first dataset, denoted by C for "corridor experiment", comes from a uni-directional experiment done in a corridor of length 30 m and width 1.8 m with periodic boundary condition (see Fig. 1, top panel). The trajectories were measured on a straight section of length 6 m. Eight experiments were carried out with $N = 15$, 30, 60, 85, 95, 110, 140 and 230 participants (i.e. for density levels ranging from approximately 0.25 to 2 ped/m$^2$). The second dataset, denoted B, is an experiment at bottlenecks (see Fig. 1, bottom panel). The width of the corridor in front of the bottleneck is 1.8 m while the width of the bottleneck varies from 0.70, 0.95, 1.20 to 1.80 m in 4 distinct experiments involving 150 participants each.

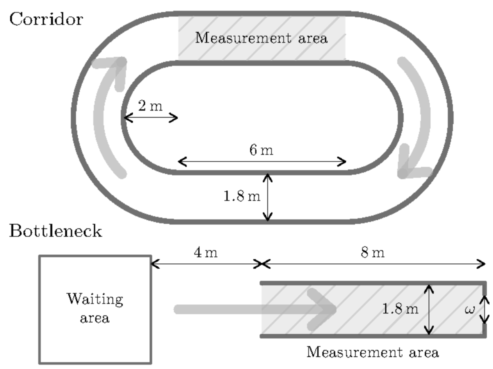


**Fig. 1** Top panel: Scheme for the corridor experiment (C). Several experiments were carried out for different density levels (ranging from 0.25 to 2 ped/m$^2$). Bottom Panel: Scheme for the bottleneck experiment (B). Four experiments were carried out for the different bottleneck widths $\omega$ = 0.70, 0.95, 1.20 and 1.80 m.

## Data analysis

The speed/mean spacing data sets in the corridor and at the bottleneck describe two slightly different interaction behaviours (see Fig. 2). The speed for a given mean spacing is in average higher in the bottleneck than in the corridor experiment. Estimations by least squares of the time gap $T$ and the desired speed $v_0$ for Weidmann's model (Eq. (1)) significantly differ according to the experiment (resp. around 0.85 s and 1.50 m/s for the corridor, and 0.49 s and 1.64 m/s for the bottleneck, see Table 1). The pedestrian size $\ell$ remains approximately constant (resp. 0.64 and 0.61 m). Note that the mean spacing is around 10% smaller in the corridor (resp. 1.03 and 1.14 m for the bottleneck). However, the mean speed is more than two times larger in the bottleneck (resp. 0.35 and 0.72 m/s).

**Fig. 2** Pedestrian speeds as function of the mean distance spacing with the $K = 10$ closest pedestrian neighbors for the corridor and bottleneck experiments and their respective fitting with Weidmann's model (Eq. (1)). Two distinct relationships can be identified.

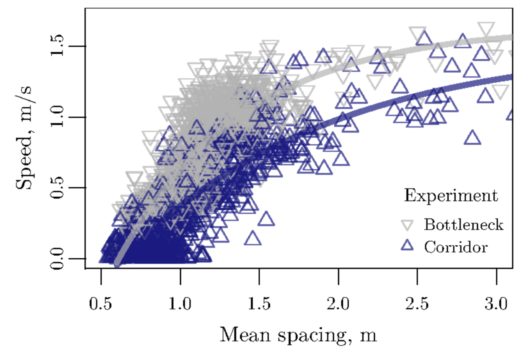


**Table 1** Mean value and standard deviation for the speed and the spacing, and least squares estimations for the pedestrian size $\ell$, the time gap $T$, and the desired speed $v_0$ parameters of Weidmann's model (Eq. (1)) for the corridor and bottleneck experiments.

| Experiment | Spacing (m) | Speed (m/s) | $\ell$ (m) | $T$ (s) | $V_0$ (m/s) |
|---|---|---|---|---|---|
| Corridor | 1.03 ± 0.40 | 0.35 ± 0.33 | 0.64 | 0.85 | 1.50 |
| Bottleneck | 1.14 ± 0.37 | 0.72 ± 0.34 | 0.61 | 0.49 | 1.64 |

## 4 Predictions for the speed

We predict the pedestrian speeds with the artificial neural networks Eqs. (3) and (4), and use as a benchmark the speed-based model by Weidmann (Eq. (1)). The coefficients of the neural networks and the three parameters of the physics-based model are estimated by minimising the mean square error

$$\mathrm{MSE} = \frac{1}{N}\sum_{i=1}^{N}\left(v_i - \tilde{v}_i\right)^2. \tag{5}$$

Here $v_i$ are the observed speeds, while $\tilde{v}_i$ are the predicted speeds and $N$ is the number of observations. The training phase of the neural networks is carried out with the back-propagation method [21] on the normalised dataset. The bootstrap method is used to evaluate the precision of estimation [16, 18]. Fifty bootstrap sub-samples are carried out for each training and testing phase. The computations are done with R [20] and the package `neuralnet` [9]. We use in the following feed-forward recursive neural networks to describe the monotonic relationship described in Fig. 2. Note that alternative data-based prediction methods such as nearest-neighbor regression or again hidden Markov chain could be used as well [7].

## Setting the network complexity

We determined the complexity (hidden layer $h$) of the neural networks through training and testing phases (cross-validation). Eight different hidden $h$ are tested: (1), (2), (3), (4,2), (5,2), (5,3), (6,3) and (10,4). The simplest network is composed of a single neuron, while the more complex neural network contains two layers with respectively 10 and 4 neurons. The training and testing MSE for the full dataset combining the corridor and bottleneck experiments are presented in Fig. 3. As expected, the training error systematically decreases as the complexity of the network increases, while the testing error presents a minimum before overfitting. This minimum is reached for the single hidden layer $h$ = (3) for the network $NN_2$ based on mean distance spacing and relative positions. While it is reached for $h$ = (5,2) for the networks $NN_1$ solely based on the relative positions. The information provided by the mean spacing, even if resulting from the relative positions, allows to reduce the required complexity of the networks.

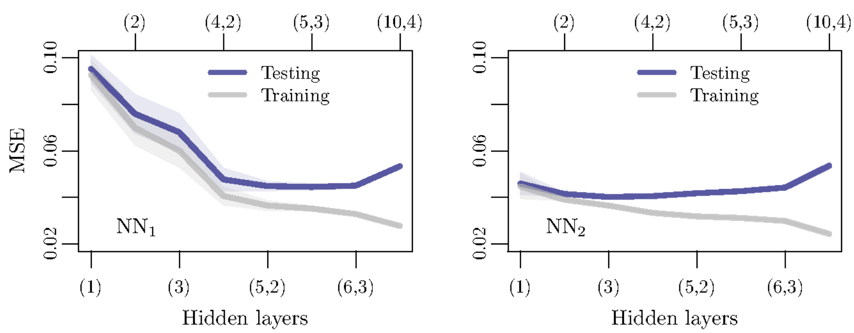


**Fig. 3** Training and testing errors according to different hidden layers in the networks. The curves correspond to the mean of 50-bootstrap estimates while the bands describe 0.99-confidence interval.

## Predictions for the speed

The neural networks $NN_1$ and $NN_2$ (see Eqs. (3) and (4)) are trained and tested for combinations of the corridor (C) and bottleneck (B) experiments. In the following, the first argument X in the notation 'X/Y' corresponds to the dataset of the training phase, while the second argument Y corresponds to the dataset used for the testing phase. For instance B/C corresponds to prediction for the corridor experiments with a network trained on the bottleneck experiment. Seven combinations are analysed:

- B/B and C/C.
  Here a single dataset is used for both training and testing.
- B/C and C/B.
  Such cases are used to test the prediction ability in new situations.

- C+B/B, C+B/C and C+B/C+B.
  Such combinations are used to test prediction in heterogeneous situations.

The testing errors are presented in Fig. 4. The prediction for the network $NN_1$ solely based on relative positions is, due to a lack of data, worth than those of the speed model for any combination of single experiments (i.e. scenarios C/C, B/B, C/B and B/C). The network $NN_2$ based on mean spacing is comparable to Weidmann's model for the corridor experiment C/C, and better for the bottleneck B/B (around 10%) or when the network deals with unobserved situations, i.e. for the datasets C/B and B/C (around 15%). All the networks improve the prediction in case of mixed dataset, i.e. the scenarios C/C+B, B/C+B and C+B/C+B, with enhancement up to 20%. The orders of improvement are similar to the ones obtained in [1] with the social LSTM neural network and the social force pedestrian model [12] or in [6] for traffic flow with a feed-forward ANN with 4 layers and 20 neurons and the classical Greenshield [11] and Greenberg [10] models.

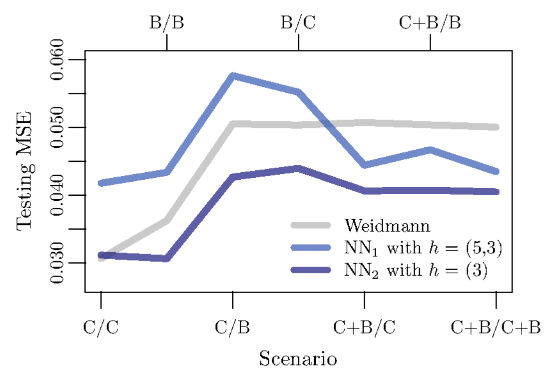


**Fig. 4** Testing error for the neural networks $NN_1$ and $NN_2$ (see Eqs. (3) and (4)) and Weidmann's model (Eq. (1)) for combinations of the corridor (C) and bottleneck (B) experiments. The argument X in the notation 'X/Y' corresponds to the dataset used for the training, while the argument Y is the dataset used for the testing.

## Quality of the fit

The prediction residuals

$$z_i = v_i - \tilde{v}_i, \qquad i = 1, \dots, n \tag{6}$$

$v_i$ being the observed and $\tilde{v}_i$ the predicted speeds can be considered independent and normally distributed (see Fig. 5). The Akaike Information Criterion (AIC) for normal data is (see, e.g., [2])

$$\text{AIC} = 2k + n\ln(\text{MSE}) + n\big(1 + \ln(2\pi)\big), \tag{7}$$

with $k$ the number of parameters of the algorithm. The parametric Weidmann's model has $k_W = 3$ parameters. Each neuron of the neural networks contains $I + 1$

parameters, $I$ being the number of inputs. We have $I_1 = 2K$ and $I_2 = 2K + 1$ inputs for the neural networks $\mathrm{NN}_1$ and $\mathrm{NN}_2$, $K$ being the number of neighbours for the interaction. The optimal numbers of neurons are 9 and 4. Since $K = 10$, the number of parameters for $\mathrm{NN}_1$ and $\mathrm{NN}_2$ are respectively $k_1 = 189$ and $k_2 = 88$.

The AIC differences of the neural networks to the AIC of the Weidmann's model are presented in Fig. 6. Relatively to the parameter number, the networks better describe the observations than the Weidmann speed model when the AIC difference is negative. We observed that the Weidmann's model systematically better perform that the networks for simple scenarios (c.f. scenarios C/C and B/B). Yet, the data-based algorithm $\mathrm{NN}_2$ based on the relative positives and mean distance spacing better performs than the Weidmann's model for heterogeneous walking situations (i.e. for the scenarios C+B/C, C+B/B and C+B/C+B).

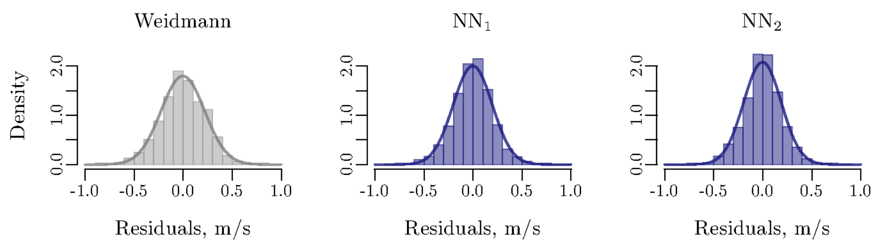


**Fig. 5** Histogram of the speed residuals $z_i = v_i - \tilde{v}_i$, $v_i$ and $\tilde{v}_i$ being respectively the observed and predicted speeds and the empirical normal distribution (continuous curves) of the Weidmann's model and the neural networks $\mathrm{NN}_1$ and $\mathrm{NN}_2$ for the heterogeneous scenario C+B/C+B.

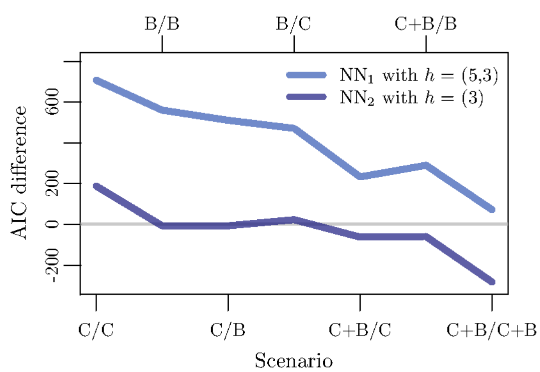


**Fig. 6** AIC differences of the neural networks $\mathrm{NN}_1$ and $\mathrm{NN}_2$ (see Eqs. (3) and (4)) to the AIC of the Weidmann's model Eq. (1). The networks better describe the data than the Weidmann speed model relatively to the parameter number when the AIC difference is negative.

# 5 Conclusion

We develop artificial neural networks for the prediction of pedestrian dynamics in two different walking situations, namely a corridor and a bottleneck. The data-driven approach is able to distinguish pedestrian behaviors according to the facility. The predictions for mixed data combining both the corridor and bottleneck experiments are improved by a factor up to 20% compared to a classical physics-based model. Furthermore, predictions in case of new situations, i.e. predictions of the speed in a bottleneck for networks trained on the corridor experiment or inversely, are also significantly improved (by a factor up to 15%), attesting for the robustness of the networks. Adding the mean spacing in the input of the networks, even if it is calculated by the relative positions, significantly increases the quality of the prediction. It allows to reduce the complexity of the algorithm, and therefore the amount of data necessary for the training.

The results are first steps suggesting that neural networks could be robust algorithms for the prediction of pedestrian dynamics in complex architectures including different types of facilities. The setting of the network complexity has to be experimentally tested for various geometries. Simulation of the networks remains to be carried out over full trajectories, and compared to the performances obtained with other existing microscopic models, and notably anisotropic models and multi-agent systems. This will be the topic of future work.

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