# A Comparison of Microscopic Pedestrian Simulation Models based on RiMEA Test Cases

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**Abstract.** Simulations enable to predict pedestrian flows for the evaluation of architectural designs and operational plans. In order to assess the strength and weaknesses of different pedestrian simulation models, their performance has to be evaluated in a qualitative and quantitative manner. The RiMEA-Guideline aspires to define a minimum standard for evacuation analysis based on different test cases for evaluating implementations of pedestrian simulation models. This paper provides a comparison of three different pedestrian simulation models, i.e. Social Force, Cellular Automaton and Optimal Reciprocal Collision Avoidance, based on selected test cases from the RiMEA-Guideline. The results provide model developers and practitioners valuable insights into the major differences between the evaluated pedestrian simulation models.

## Introduction

Over the last years, microscopic pedestrian simulation models have proven to be a valuable tool for the prediction of pedestrian flows to evaluate architectural designs and operational plans. These models can simulate detailed behaviour of individual humans and represent collective phenomena such as emergent behaviour.

In order to objectively compare different implementations of microscopic pedestrian simulation models, their performance has to be assessed qualitatively with respect to emerging spatial-temporal patterns (e.g. lane formation) and quantitatively based on evaluation measures with respect to accuracy (e.g. reproducibility of pedestrian densities). As of now, several evaluation measures have been described and used in the literature.

One recent attempt to define a minimum standard for evacuation analysis is stated by the development of the RiMEA-Guideline [1] which includes fourteen test cases for evaluating implementations of pedestrian simulation models. In addition the United States' National Institute of Standards and Technology (NIST) recommended a set of seventeen verification tests in order to verify building fire evacuation models [2].

The contribution of this paper is to provide a comparison of three different microscopic pedestrian simulation models based on selected test cases from the RiMEA-Guideline. Therefore, we implemented a Social Force model [3], a Cellular Automaton [4] and an Optimal Reciprocal Collision Avoidance model [5]. The results give valuable insights into the major differences between the evaluated pedestrian simulation models which are important for model developers as well as for practitioners.

The remainder of this paper is structured as follows: Section 1 provides an overview of the related work. Section 2 describes the test cases that were used in this work. Section 3 outlines the models for pedestrian simulation. Section 4 presents the evaluation results from applying the modelling approaches to the test cases. Section 5 summarizes the results and discusses the main outcomes. Section 6 concludes the findings and provides recommendations for future work.

## 1 Related Work

The RiMEA-Guideline (in German: RiMEA-Richtlinie, Richtlinie für Mikroskopische Evakuierungs Analysen – Guideline for Microscopic Evacuation Analyses; RiMEA-Guideline) is a guideline for German-speaking authorities to evaluate the quality of evacuation analyses for complex buildings. Based on the RiMEA-Guideline expert reports are written to ensure that the fundamental questions of an evacuation analysis are answered.

The RiMEA-Guideline has been used in several scientific contributions for the demonstration and evaluation of pedestrian simulation models: In [6] a dynamic distance potential field method for route choice on the operational level of pedestrian dynamics has been described and was applied in a simulation of a RiMEA test case. In [7] a cellular automaton based on a hexagonal grid was calibrated and the simulation results were evaluated according to a test provided by RiMEA. Furthermore, the results of different commercial simulation tools (e.g. Viswalk, PedGo, ASERI) with respect to the RiMEA test cases are published on the RiMEA Website [8].

In [9] the tests recommended by NIST were simulated using the PEDFLOW tool, which lead to the identification of several shortcomings and modifications for further improvements of the tool.

## 2 Description of Test Cases

The RiMEA-Guideline [8] includes a description of different test cases for evaluating implementations of pedestrian simulation models to reproduce a set of requirements for an evacuation analysis. As of now, 14 test cases are defined in total. In this paper we used the following three test cases for the model comparisons:

- *Test Case 4*: Specific flow through an opening
- *Test Case 6*: Moving around a corner
- *Test Case 12*: Effects based on bottlenecks

The comparison in this work has put the focus on the core functionality of the investigated models only. Hence, we selected test cases which do not include aspects of dynamic routing (e.g. selection of exits). In the following the three test cases used in this study are described in detail.

### 2.1 Test Case 4

Based on a periodic boundary system with a width of 4 m the specific flow (in persons/ms) should be measured for different densities (in persons/m²) inside the system. The results of this test case should reveal the relation between specific flow and density in a so-called *Fundamental Diagram* [10] as shown in Figure 1.

Since periodic boundaries are hard to implement in a simulator, we use an approximation for this test case by modelling a corridor 60 m in length and 10 m in width as illustrated in Figure 2.

Over the available area, we equally distributed pedestrians and varied their total number in different simulation runs in order to generate average densities of 1, 2, 3, 4 and 5 persons/m². Each pedestrian should move towards the same end of the corridor.

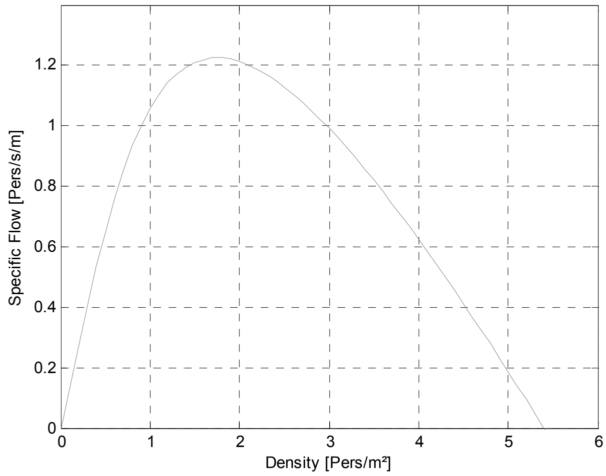



**Figure 1**. Fundamental diagram representing specific flow
(y-axis) and density (x-axis) based on [10].

The averages of density and velocity are measured in an interval of 1s inside an area of 2 x 2m (see blue rectangle in **Figure 2**) and an area of 4 x 4m (see orange rectangle in **Figure 2**) located at the centre of the corridor. Size and location of the measurement areas have been chosen in order that no boundary effects from walls are measured.

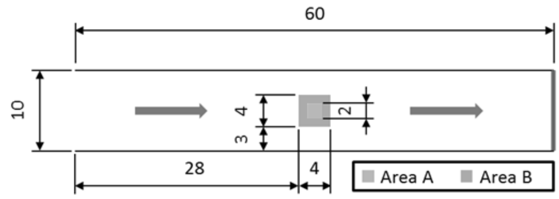



**Figure 2**. Test Case 4 - Pedestrians are equally distributed over the available area and move towards the right end (red line) of the corridor (red arrows denote walking direction). All measures are in m.

### 2.2 Test Case 6

In this test case 20 pedestrians should move around a 90° corner without "crossing" walls. The layout of the corner in this test case is illustrated in **Figure 3**. Furthermore, the walking time for each pedestrian is measured between $\mathrm{L_{Start}}$ and $\mathrm{L_{End}}$.

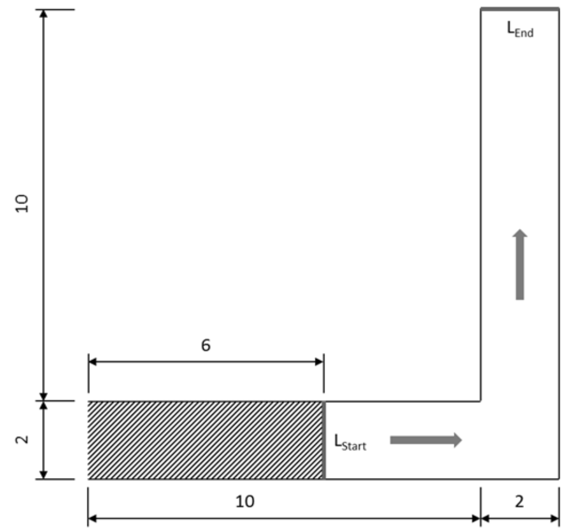



**Figure 3.** Test Case 6 - Pedestrians are placed in the crosshatched area and walk around the corner (red arrows denote walking direction) without crossing walls and corner. All measures are in m.

### 2.3 Test Case 12

In this test case 150 pedestrians should be placed in the crosshatched area of the first room (see **Figure 4**) and should move immediately towards the exit in the second room using the connecting corridor. The results should reveal if congestion appears at the exit. Since the pedestrian flow is limited by the bottleneck in the first room, it is expected that congestion only appears at this location and not at the exit in the second room. Therefore, the density is measured for each room in two different areas (see **Figure 4**): Area A (blue) covers a 1x1m region directly in front of each bottleneck and Area B (orange) covers a region of 5m² in the vicinity.

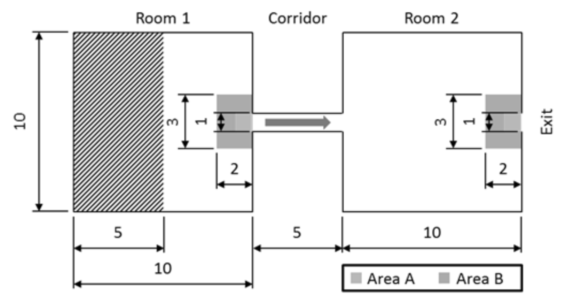



**Figure 4.** Test Case 12 - The bottleneck in Room 1 should lead to congestion while this should not occur in Room 2. All measures are in m.

## 3 Modelling Approaches

For the comparisons in this paper, we selected three different microscopic modelling approaches for pedestrian simulations, namely:

- *Social Force* from [3] and [11]
- *Cellular Automaton* from [4]
- *Optimal Reciprocal Collision Avoidance* from [5]

The choice was mainly motivated by the fact that these approaches are widely used within commercial tools and the scientific community.

### 3.1 Social Force

The Social Force approach introduced by [11] defines attraction and repulsion forces with respect to other humans and the environment, thus representing individual walking behaviour as a sum of different accelerations as

$$f_\alpha(t) = \frac{v_\alpha^0 e_\alpha - v_\alpha}{\tau_\alpha} + \sum_{\beta \neq \alpha} f_{\alpha\beta}(t) + \sum_i f_{\alpha i}(t). \quad (1)$$

The acceleration $f_\alpha$ at time $t$ of an individual $\alpha$ towards a certain goal is defined by the desired direction of movement $e_\alpha$ with a desired speed $v_\alpha^0$. Here, the current velocity $v_\alpha$ is adapted to the desired speed $v_\alpha^0$ within a certain relaxation time $\tau_\alpha$. The movement of a pedestrian $\alpha$ is influenced by other pedestrians $\beta$ which is modelled as a repulsive acceleration $f_{\alpha\beta}$. A similar repulsive behaviour for static obstacles $i$ (e.g. walls) is represented by the acceleration $f_{\alpha i}$. For notational simplicity, we omit the dependence on time $t$ for the rest of the paper.

In this work we use a Java implementation of the definition of an elliptical repulsive force from [3] formulated by

$$f_{\alpha\beta} = a_\alpha e^{-\frac{w_{\alpha\beta}}{b_\alpha}} \frac{d_{\alpha\beta}}{\|d_{\alpha\beta}\|}, \quad (2)$$

where the semi-minor axis $w_{\alpha\beta}$ of the elliptic formulation is defined by

$$w_{\alpha\beta} = \frac{1}{2}\sqrt{\left(\|d_{\alpha\beta}\| + \|d_{\alpha\beta} - (v_\beta - v_\alpha)\Delta t\|\right)^2 - \|(v_\beta - v_\alpha)\Delta t\|^2}. \quad (3)$$

Here, the velocity vectors $v_\alpha$ and $v_\beta$ of pedestrians $\alpha$ and $\beta$ are included allowing to take into account the step size of pedestrians. Furthermore, we take into account that pedestrians have a higher response to other pedestrians in front of them by including an anisotropic behaviour, as described in [3].

### 3.2 Cellular Automaton

In [4] a two-dimensional cellular automaton model is presented for simulating pedestrian movement. Each cell has a size of 40 × 40 cm² and can either be empty or occupied by exactly one pedestrian. The probabilities for moving a pedestrian are encoded in a 3×3 matrix where the central element describes the probability for the pedestrian not to move at all, while the remaining 8 correspond to a move to the neighbouring cells. If a cell is occupied, the probability is set to zero. The update is performed in parallel for all pedestrians and conflicts are resolved according to the following rules: If no other pedestrian targets the desired cell, the move is executed. If more than one pedestrian share the same target cell, one is chosen according to the relative probabilities based on which each pedestrian has chosen the target. The first ranked pedestrian moves while its rivals for the same target keep their position.

Long-range interactions between pedestrians are modelled using a floor field which modifies the transition probabilities to neighbouring cells. This field can be discrete or continuous and is subject to diffusion and decay (e.g. to model the behaviour of following other pedestrians). Furthermore, it is modified by the motion of the pedestrians. Therefore, the model uses an idea similar to chemotaxis, but with pedestrians following a virtual rather than a chemical trace. The results of [4] show that their Cellular Automaton approach is able to model collective and self-organization effects such as lane formation in counterflow through a large corridor.

### 3.3 Optimal Reciprocal Collision Avoidance

The approach of the Optimal Reciprocal Collision Avoidance (ORCA) model as described in [5] implies that each individual takes into account the observed velocity of other individuals in order to avoid collisions. Individuals are reciprocally collision-avoiding (they "share the responsibility") and it is guaranteed that two particular individuals are collision-free for at least a fixed amount of time into the future.

Thus, for each other individual the model derives a half-plane (in velocity-space) of velocities that are allowed to be selected in order to guarantee collision avoidance. The individual then selects its optimal velocity from the intersection of all permitted half-planes, which can be done efficiently using linear programming.

Under certain conditions with high densities, the resulting linear program may be infeasible, in which case the ORCA model selects the "safest possible" velocity using a three-dimensional linear program.

In this work we use the RVO2 C++ library [12] as the implementation of the ORCA algorithm.

## 4 Results

We simulated the three test cases as described in Section 2 using the three modelling approaches presented in Section 3. For the Social Force model, we defined the desired speed $v_\alpha^0$ according to [10] from a normal distribution with mean value $\mu = 1.34\, m/s$ and standard deviation $\sigma = 0.26$. All other parameters were set according to [13]. In order to have a maximum pedestrian speed in the Cellular Automaton model corresponding to the 95% percentile of this distribution we set the time step to 1/4.65s. To achieve variations in speed the probability for non-movement steps is set to 28%. Using this parameter set trajectories can be produced with an average velocity of 1.34 m/s. We implemented the long-range interactions between pedestrians by a continuous floor field. For the ORCA model the default parameters were used [5]. Note, that the parameter sets of the three models are left unchanged during all simulation runs.

In the test cases 6 and 12 the final goal is not visible from every point in the starting zone. Therefore an intermediate goal is placed manually to guarantee validity of all trajectories. The changeover to the final goal takes place when a pedestrian has approached to the intermediate goal nearer than one meter.

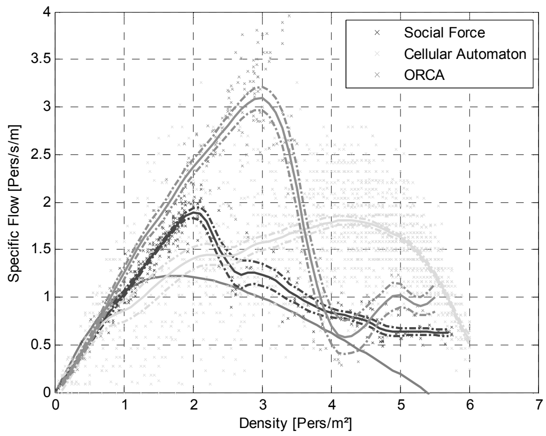
In this section we demonstrate and discuss the results of our model comparisons.

### 4.1 Results for Test Case 4

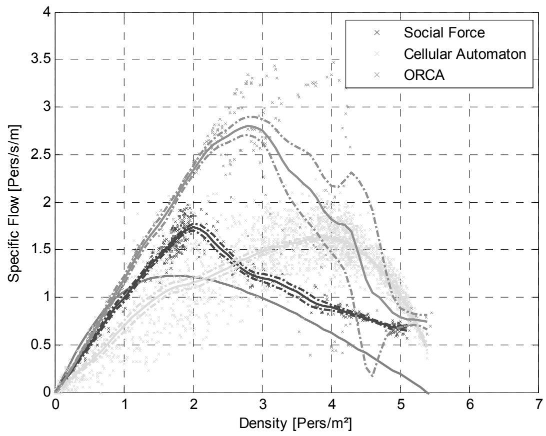
We performed five simulation runs for each average density ranging from 1 to 5 persons/m². All of the tested models were able to simulate pedestrian movement in the defined corridor setting as demanded in the description of the test case in Section 2.1. The resulting Fundamental Diagrams are shown in Figure 5.

Highly localized measurements maintain the homogeneity of density. Hence, we first used a measurement area of 2x2m for this test case (see Figure 5a). However, the results of the Cellular Automaton reveal unrealistic high deviations of flow: at higher densities the average flow is not decreasing as expected.

The implementation of the Cellular Automaton defines speed variations by a certain probability of keeping a position or moving to a neighbouring cell. While on a global perspective the average velocities can be derived correctly, it generates high errors for local measurements. This strong influence of the measurement method was already discussed in [14].




(a)




(b)

**Figure 5.** Fundamental Diagrams as result from the three tested models using a measurement area of (a) 2x2m and (b) 4x4m from Test Case 4. The red line corresponds to the fundamental diagram given in [10].

When switching to a larger measurement area of 4x4m (see Figure 5b) also higher heterogeneity in the local densities is introduced.

The effects from the smaller measurement area are reduced for the Cellular Automaton and the shape of the typical flow over density relationship is apparent. Also the results from the Social Force and the ORCA model reproduce a similar shape of the flow-density curve. Both models generate higher flow rates than given in [10] and in case of the ORCA model the maximum is shifted to a higher density.

## 4.2 Results for Test Case 6

In this test case, we have performed 10 simulation runs for each model. Our results confirm that all tested models are able to replicate movement around a corner without stepping through the walls. A qualitative evaluation of the simulation for walking around a corner is illustrated in Figure 6. It has to be noted that we defined a sub-goal, which is located one meter away from the inner corner on a line connecting the vertices of the inner and outer corner. Thus, pedestrians do not steer directly to the vertex of the inner corner. Figure 7 shows the empirical cumulative distribution function of the walking times from all simulation runs.

The resulting average and extreme values of the walking times from the 10 simulation runs are shown in Table 1. These results show that the three tested models simulate significant different walking times in this test case. The average walking times are more than twice as large for the Cellular Automaton than for the Social Force model. Pedestrians simulated with the Social Force model can move smoothly around the corner which results in the fastest average walking times. In contrast, the ORCA model creates congestions in the area of the corner which slow down the pedestrian flow. The pedestrians in the Cellular Automaton choose lower individual velocities than in the other two models as the densities in this test case are relatively low.


**Figure 6.** Simulation results from the three tested models at time t = 10s for Test Case 6.

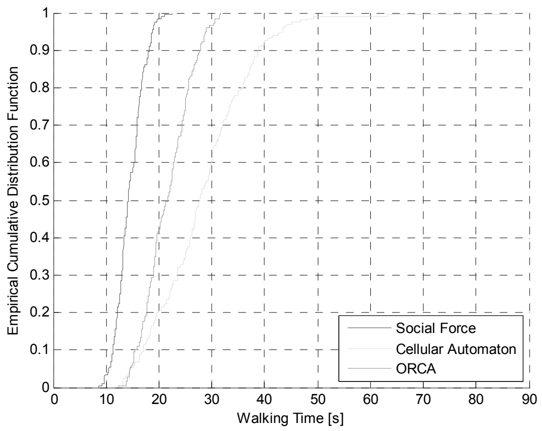



**Figure 7.** Empirical cumulative distribution of walking times from Test Case 6.

### 4.3 Results for Test Case 12

We have performed 10 simulation runs for each model in this test case. Again, we have defined a sub-goal at the centre of the entrance to the bottleneck in Room 1. The qualitative results shown in **Fehler! Verweisquelle konnte nicht gefunden werden.** reveal the differences in the pedestrian behaviour in conjunction with bottlenecks: the Social Force model creates congestions in front of the bottleneck in Room 1 which forms a half circle. At the beginning there is almost no congestion in front of the bottleneck in Room 2, but over time the density increases too. In contrast, the Cellular Automaton generates two walking lanes inside the corridor most of the time. As a consequence, the throughput is significantly higher than in the two other models. The ORCA model creates strong turbulences in the movement of pedestrians in front of the bottleneck in Room 1. This restricts the pedestrians from walking into the bottleneck and creates unrealistic high waiting times in front of the bottleneck in Room 1.

These qualitative observations are also confirmed by the empirical cumulative distribution function of the walking times shown in **Figure 9**. While the cumulative distribution of walking times for the Social Force model and the Cellular Automaton show a similar trend, these times are significantly longer for the ORCA model.

**Figure 10** illustrates the densities which were measured for the three tested models in the two areas of both rooms. As expected, all models reveal higher densities in Room 1 for Area A. For Area B, the Social Force model and the Cellular Automaton reach densities of over 4 persons/m² while the ORCA model stays below this value.

In Room 2, the Social Force model and the Cellular Automaton show both higher densities in Area A which is directly in front of the bottleneck. In the surrounding area (i.e. Area B) these two models produce higher densities for short time periods only.

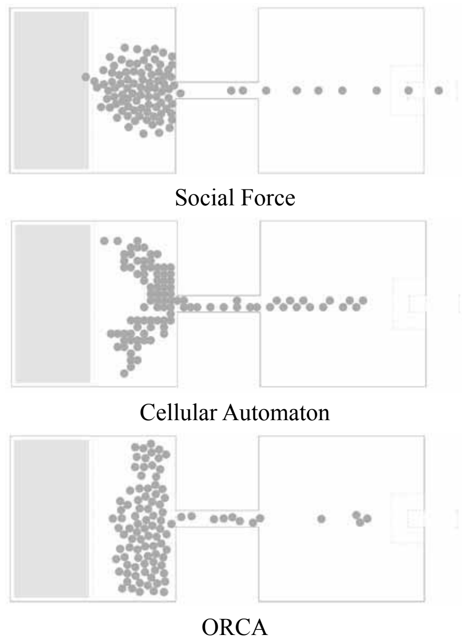



**Figure 8.** Simulation results from the three tested models at time t = 15s for Test Case 12.

In contrast, the ORCA model creates no congestions in neither of the two areas within Room 2. It can be seen that this is a result of the inflow restrictions into the bottleneck of Room 1. The original hypothesis of Test Case 12, namely, that congestion only appears at the exit of the first room and not at the exit of the second room is satisfied only by the ORCA model.

The resulting average and extreme values of the walking times from the 10 simulation runs are shown in Table 1. For the Cellular Automaton and the Social Force model, the average walking times are in the same range whereas the values for the ORCA model are twice as large as for the other two tested models.

| | Average Walking Times (Min,Max) [s] | |
|---|---|---|
| | Test Case 6 | Test Case 12 |
| **Social Force** | 19.1 (16.0,22.5) | 185.0 (129.2,347.1) |
| **Cellular Automaton** | 50.6 (38.9,86.7) | 161.1 (121.9,269.5) |
| **ORCA** | 29.8 (25.6,31.7) | 394.7 (338.3,456.7) |

**Table 1**. Walking times from Test Case 6 and Test Case 12.

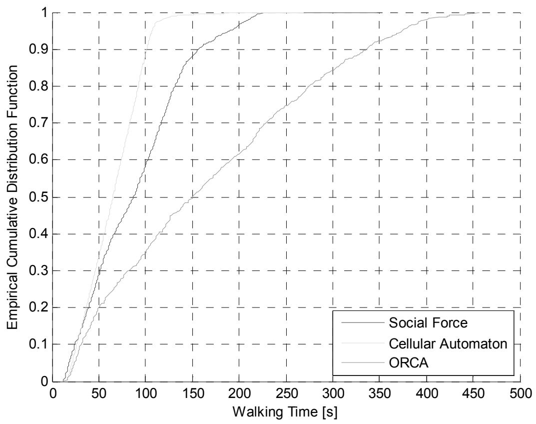



**Figure 9.** Empirical cumulative distributions of walking times from Test Case 12.

## 5 Summary

Based on the comparison of the three modelling approaches in Section 4 it is hard to infer systematic behaviour for each individual model.

For instance, the Cellular Automaton revealed the longest average walking time in Test Case 6. However, in Test Case 12, it had the least average walking time among the tested models. An explanation for this behaviour can be found in the Fundamental Diagram from Figure 5: compared to the other two models, the Cellular Automaton keeps a higher average flow rate at high densities and a lower average flow rate at low densities. A further reason are wall effects in Test Case 12 which keep the pedestrians in the Social Force and the ORCA model in single lanes walking through the corridor whereas in the Cellular Automaton model the pedestrians are walking in double lanes (see Figure 8).

The used implementation of the ORCA model shows strong turbulences in the pedestrian flow in front of bottlenecks (see [15]) which explains the long evacuation times in Test Case 12.

Furthermore, our results of Test Case 4 have underlined the importance of suitable methods for measuring and evaluating fundamental diagrams [14].

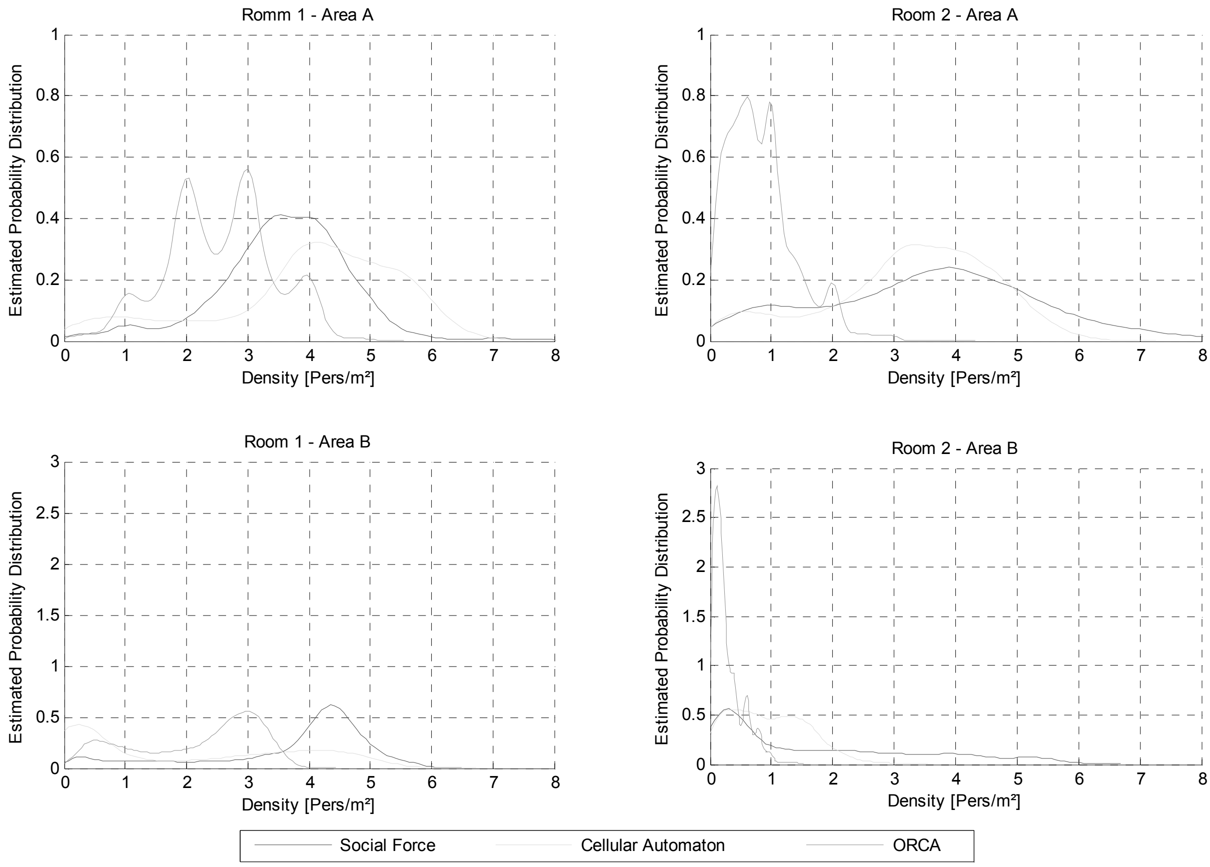



**Figure 10.** Densities measured for the three tested models from Test Case 12.

## 6 Conclusion and Perspectives

The presented work compared implementations of the Social Force model, Cellular Automaton and Optimal Reciprocal Collision Avoidance model based on three selected test cases from the RiMEA-Guideline. This comparison showed differing results of the three modelling approaches in all three test cases but did not provide identifiability of systematic behaviour for each individual model.

From our results of the test cases we cannot disprove any of the three tested models. An explanation for this is that the encoded criteria to successfully fulfil the tests are not strict (with the exceptions that pedestrians must reach their goal and must not walk through walls) and lack of quantifiable measures, such as minimum and maximum boundaries for average walking times in Test Case 6 and 12.

Currently, empirical data from experimental or real-world observations are not included in the RiMEA test cases. Since the effects described in the test cases are therefore rather based on assumptions or human observations, there is a strong need for empirical underpinning of these effects. This goes along with an extension of quantitative evaluation metrics for pedestrian movement characteristics beyond, for instance, the Fundamental Diagram.

In particular, three points need further discussion: 1) investigating which procedures are most suitable to measure and evaluate pedestrian movement characteristics, 2) including real world data into the test cases and 3) providing empirical data and well studied methods for model calibration. We understand this work as a further step towards making different microscopic pedestrian simulation models comparable and accelerating the development of benchmark and validity tests of such models.

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