# Multi-Agent Simulations as a tool for the assessment of urban microclimate and its effect on pedestrian behaviour

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**Abstract:** The urban canopy layer is characterised by a specific climate which significantly differs from the average regional climate conditions. Especially inside urban structures such as street canyons, shopping malls or public places, the local microclimate depends directly on the physical properties of the surrounding surfaces and objects, producing well-known effects such as wind speed decrease, local jets, increased turbulence or increased thermal loads. These phenomena can have a strong influence on the comfort of pedestrians using these areas for different tasks of urban life or leisure activities. Assessing urban climate means to answer the question, how the citizens feel under the given circumstances and to decide, whether the urban design, the usage of urban structures and the needs of the pedestrians fit together or not. This complex assessment process requires a queue of different methods starting with numerical climate models that provide the meteorological parameters ending up with a set of models that simulate the comfort level or the behaviour of citizens acting inside the structure.

In this paper, the Multi-Agent model climBOT is presented which aims to simulate the interactions between local climate and pedestrian behaviour. The different modules needed for that task are outlined and the general perception-decision approach for the agents is shown.

**Keywords:** Multi-Agent Simulation, Urban Climate, Pedestrian behaviour, Micro-modelling, Biometeorology

## 1 INTRODUCTION

According to studies of the UNSECO, more than 60 percent of the worlds population will live in cities with more than 5000 inhabitants by the beginning of the 21st century. Building up houses and paving the surfaces changes the climate in urban areas significantly, leading to well-known effects such as the urban heat island, increased air pollution or modified wind situations. Especially inside urban structures such as street canyons or shopping malls, we observe that the local microclimate directly depends on the physical properties of the surrounding surfaces and objects, which can lead to both pleasant and uncomfortable climate situations.

Assessing the urban climate basically means to answer the questions

- how the citizens feel under the given circumstances (in particular thermal comfort, wind comfort etc),
- how those feelings will affect their behaviour within the urban structures, and
- if the urban design, thermal preferences and behaviour of the citizens fit together or not.

If we neglect extreme situations, in which the hostility of the environment is obvious, it is clear that urban climate itself does not posses properties making it a *good* or *bad* climate. The question, whether someone is pleased by local climate or not, is basically a question about what this single person expects from the climate he/she is walking in. These expectations are, of course, a mixture of general preferences and short-term needs that may vary with respect to the actual physical (heat balance), physiological (thermoregulatory strain), and psychological (e.g. work or leisure) states of the subject. This circumstance produces a number of difficulties and uncertainties in the search of objective assessment parameters, adding to the already complex climate conditions themselves.

Several methods and models have been developed in the past, to help planners and researches in finding the link between urban climate and human comfort, most of then specialised in the thermal component of the reaction complex (see e.g. Mayer and Höppe, 1987; ASHRAE, 1992; ISO 7730, 1994).

Keeping in mind, that the assessment of urban climate depends on the opinions of individual subjects, it seems to be a promising approach to start the evaluation process focusing on a single pedestrian rather than starting with the meteorological conditions. Numerical models that are based on the simulation of individual microscopic components (”agents”) posses a number of benefits compared to traditional simulation concepts which use formal laws to describe the aggregated (macroscopic) interactions between the different model components:

- non-local and non-stationary effects are implicitly considered as they are transported with the agent,
- macroscopic effects develop automatically through the iterative application of microscopic rules (e.g. tendency to self-organisation),
- dependencies and relationships between model variables can be discovered and simulated although they are not included explicitly in the model equations

In this paper, the model climBOT is presented, which aims to simulate the interactions between urban climate and pedestrian behaviour using Multi-Agent modelling techniques. The different modules needed for that task are outlined and the general perception-decision approach for the agents is presented. The purpose of the model is to learn about the interactions between urban environmental factors, here especially microclimate and pedestrian behaviour. Also, it might serve as a tool for predicting pedestrian traffic or optimizing urban design.

## 2 OVERVIEW OF THE CLIMBOT MODEL SYSTEM

The climBOT model system consists of several submodels simulating different aspects of the behaviour of the single agent (climBOT) as shown in Figure 1. The model environment consists of a two-dimensional horizontal grid domain with a typical resolution between 0.5 and 2 m. Data, that are provided from external models (grayed boxes in Fig. 1) are either directly calculated in the spatial resolution of the climBOT model domain or interpolated from the provided data. The positions of the agents inside the domain are calculated in non-discrete coordinates for an accurate simulation of dynamical aspects, but the agents are always assigned to a ”home” grid point, which is closest to the recent location and occupied by the agent. The time step of the simulation depends on the velocity of the fastest agent as well as on the grid box size and is typically between 0.5 and 2 s. The assessment of grid points is expressed using resistances whereby the agents tries to move only towards grid points with lower resistances than the one he is standing on.

From the architectural point of view, the climBOT is a horizontal layered agent. The different sensory input data are connected to their responsible assessment modules, which independently produce suggestions in terms of resistances. Although horizontal layered agents may suffer from non-coherent behaviour if different modules produce contradicting suggestions, the heterogeneous character of the different environmental input data and the complexity of the assessment modules themselves would make other agent structures (e.g. vertically layered agents) hardly designable.

The **urban environment** is represented by the environmental situation and by the morphological data (buildings, roads,trees,...) that are needed in the climBOT model. The selection of variables describing the environmental situation depends on the different assessment and decision models that are implemented in the system. For the microclimate complex to those parameters are for example wind speed, air temperature, humidity and shortwave radiation. In our model, the data are supplied by the microscale climate model ENVI-met (Bruse and Fleer, 1998), but any other source could be used too.

Based on the potential targets of pedestrian traffic, a set of target positions is created for each agent and a **general routing** taking into account the urban structure is calculated. The final way to the target is constructed just in time using orthogonal segments connecting the centers of each grid cell.

The internal state of the agent ($ST$) describes the level of comfort or discomfort corresponding to the different modules the agent consists of. For example, the **dynamical comfort module** describes the

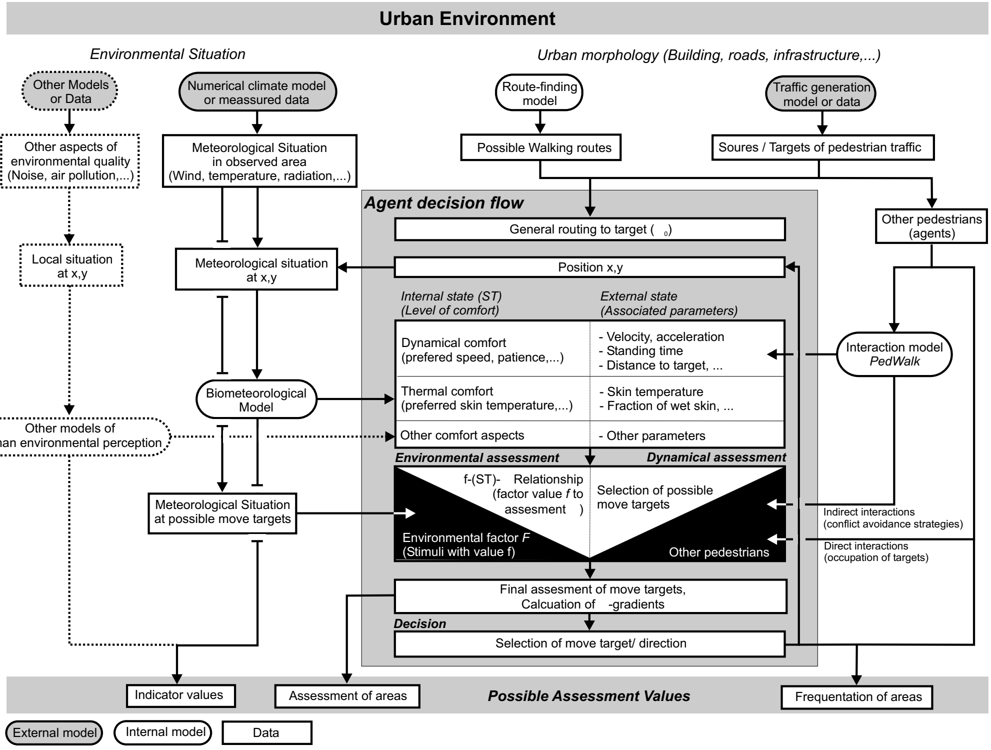

Figure 1: Schematic overview of structure and data flow in the climBOT model

agents comfort concerning dynamical aspects such as actual velocity versus desired one or conflicts with other pedestrians.

The **assessment section** of the climBOT agent consists of several parallel sub-modules expressing the agents assessment of an environmental factor ($F$) in terms of a resistance value ($\Omega$). Finally, the overall assessment of a target grid can be calculated as the sum over the all resistances provided by the sub-modules and the grid point with the lowest resistance is chosen as best move target.

## 3 BASIC ASSESSMENT CONCEPT: DEFINITION OF RESISTANCES AS REFERENCE SYSTEM

Before any assessment process can take place, it is necessary to define a global reference system in which the different assessment values are defined. The special difficulty in the context of this model is, that contrary to physically motivated models that relate to existing variables, the available information here has an extreme heterogeneous structure. To overcome this problem and in order to give the different layers of information a manageable structure, the concept of **resistance fields ($\Omega$-fields)** was created.

In this idea, different $\Omega$-values are assigned to each grid point which represent levels of ”attractiveness” of the point with respect to the goals and the internal state of the agent. The higher the sum of the resistance values is, the more unattractive the grid point is for the agent. The absolute values of $\Omega$ depend on two factors: the local situation on the grid point and the agents attitude towards this situation. Consequently, each agent has a personal ”voting” for each grid point, that might change during the simulation, when the internal state of the agent changes and might be different to other agents opinions.

The overall resistance of a grid point $i, j$ is composed of a base value $\Omega^0$ plus different additional values which represent a specific aspect of the agents perception and its assessment:

$$\Omega = \Omega^0_{i,j} + \Omega^1_{i,j} + \Omega^2_{i,j} + ... + \Omega^N_{i,j} \qquad (1)$$

The **base resistance** $\Omega^0$ is a general property of the grid and equal to the walk-able distance to the target grid of the agent (see section 4.1). The additional values $\Omega^1 ... \Omega^N$ are the outcomes of the different assessment modules and might be positive or negative (see Section 4.4).

As reference unit for the resistance model we have chosen the distance to a target in meter. Hereby we also fix the interpretation of the assessment of a grid point: negative assessments will increase the virtual distance to the target, positive ones will shorten it. The concept of resistances makes the model open to other influencing factors. Anything that has an attractive effect might either serve as an additional traffic target (e.g. scenic places) or as a local attractor by lowering the resistances of grid points close to the attractor (e.g. shopping windows).

## 4 INTEGRATED SUB-MODELS AND DECISION PROCESS

### 4.1 Route-finding model

The most important goal of pedestrians, except some kind of tourists, is to reach their targets using the shortest available routing. Here, the meaning of ”shortest” is not restricted to the real distance, it also includes comfort and dynamical aspects. The route-finding model provides the MA simulation with the shortest walk-able route from any grid point in the model domain to a specified target grid as basic information. This includes the consideration of unpassable structures (buildings) as well as the consideration of less-walkable areas (e.g. roads).

The route-finding model is based on a modified flooding algorithm know as ”Bellmann Flooding”, in which the flooding value (=base resistance $\Omega^0$) is increased by the distance between the grid poit centers each time a new grid point is entered. From each grid point of the model domain, the shortest way to the target can be found by simply moving towards the adjacent grid with the lowest resistance (”BOTs best way” in Fig. 2). Grid points that are less walk-able will increase the flooding value by a specific resistance (+2 in the example shown in Fig. 2) and grids with un-passable structures will stop the flooding process (black grids in Fig. 2). Although the flooding algorithm is only 4-point connected, it is accurate enough to allow also diagonal agent moves and less time-consuming than the 8-point connected version.

### 4.2 Pedestrian Interaction Model *PedWalk*

Pedestrians can only follow their personal optimal route, if no conflicts with other persons exists. As this is a rather unlikely case in an urban environment, it is necessary to include a realistic behaviour model of pedestrian movement in the simulation.

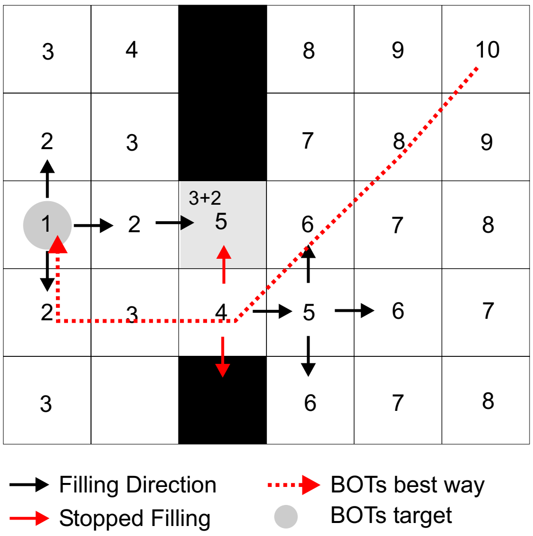

Figure 2: Example of route-finding algorithm showing the $\Omega_0$ resistance field and resulting shortest way

Looking at a group of pedestrians, one might get the impression, that their movement decisions are chaotic and cannot be reproduced by numerical models. In fact, this is not true and it was shown that pedestrian movement can be realistically simulated in many ways, for example by using fluid dynamic equations (Henderson, 1971) or by potential-field driven particles models (”social force models”, Helbing and Molnar, 1995) .

The intention of the *PedWalk* model is to simulate different behavioral strategies that can be observed in pedestrian motion based on a microscopic (agent-to-agent) interaction modelling. This part of interaction modelling is called ”indirect interactions” in the diagram shown in Fig. 1. Direct interactions between agents (e.g. blocking of grids or competing for grids) are solved directly in the moving decision step. *PedWalk* includes **spatial strategies** (e.g. deviation process, trail formation), **dynamical strategies** (acceleration and deceleration to avoid conflicts) as well as **mixed strategies** (combination of both such as overtaking decisions or walking in groups). To be compatible with the rest of the model, all situations that might have an effect on the routing decision must be expressed as additional resistances that are added to the resistance field.

### 4.3 Biometeorological model

The biometeorological model is responsible for the simulation of the effects of urban microclimate on the thermal comfort level of the pedestrians. The exposure to uncomfortable climate conditions can lead to thermophysiological stress situations, from which the heat stress caused by direct sun and high temperatures is the most frequent one in urban areas (see e.g Fanger, 1972; Mayer and Höppe, 1985).

Different models and standards have been developed in the past, that relate the outdoor climate condition to the average thermal comfort of pedestrians moving in the environment (e.g *Predicted Mean Vote PMV*, *Effective Temperature ET**, see ASHRAE, 1992, ISO7730, 1994). The disadvantage of these models is, that they do not take into account the different assessment of local climate depending on thermal situations the individual has experienced before. Sunny areas will be regarded as comfortable locations after walking through a shady street, even if the climate conditions would lead to a thermal discomfort after some time. To avoid this problem, the thermoregulatory system of each agent is calculated with a 2-node model of the human energy balance similar to those presented by Gagge (1986) or Mayer and Höppe (1985). This model predicts several thermal relevant parameters of the human thermal complex such as skin temperature, fraction of wet skin or the sweat rate for each time step and each location of the agent. These parameters are then used in the assessment process as indicators for the internal state ($ST$) of the agent.

### 4.4 Assessment Process

The assessment process must transform the different environmental and dynamical aspects into resistance values that can be used to calculate the final resistance of a possible move target. In the model we can distinguish between **dynamical assessment**, which handles the different interactions with other agents and **environmental assessment** that is responsible for the assessment of the environmental conditions found in the model area. In this section, we will only focus on the environmental assessment, as it is the more complex one.

The general procedure of the assessment process, is to transform an environmental factor $F$ respectively its value $f$ into a resistance value $\Omega$. If the observed $F$ is assessed positive, the resulting value $\Omega$ will be smaller than zero, if assessed negative, it will be above zero. For $\Omega < 0$, the overall resistance of a grid point $i, j$ will be decreased (see (1)), in the other case it will be increased[1]. As agents try to move towards the lowest resistance, a positive assessment of a grid cell $i, j$ will increase the probability, that the agent selects this cell as next way point.

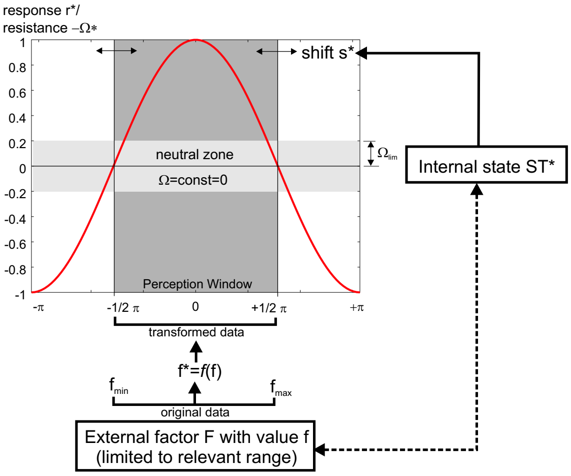

Figure 3: Link between environmental factor $F$, internal state $ST$ and assessement value $\Omega^*$

The relationship between $f$ (or normalized $f^*$) and its assessment $\Omega$ (or normalized $\Omega^*$) is established inside the so called *perception window*, which, depending in its position, shows different segments of the cosinus function (see Fig. 3):

$$\Omega^* = -\cos\left(f^* + s^*\right) \tag{2}$$

The assessment of any factor depends of course the agents personal attitude towards this factor. This attitude is expressed using the *internal state* $ST$ of the agent which shifts the perception window either to the left or to the right. In the middle position, the agent feels neutral towards $f$ (e.g. for assessing the factor ”sun”, the skin temperature calculated by the biometeorological model might be used as the relevant state $ST$). The link between the relevant internal state and the shift of the window ($s^*$ in (2)) depends on the personal type of the agent. For sensible agents, the perception window will shift quickly when $ST$ is non-neutral, for more tolerant agents, it will shift slower.

Although the assessment procedure is based on simple geometrical functions such as the cosinus curve shown in Figure 3, there are still three critical transformations in the model: scaling $f$ to a normalized $f^*$, converting the internal state $ST$ to the normalized $ST^*$ and then into the window shift $s^*$ and finally the re-scaling of the normalized resistance $\Omega^*$

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[1] Note that in the graph, the resistance value has the opposite sign to the response to allow a more clear assignment between positive values and positive assessment

to a meter-based resistance that is compatible to the rest of the model. Finding the correct parameters for these operations could be based on empirical observations or theoretical models. For the moment being, just simple ad-hoc values that seem to give realistic results are used.

### 4.5 Final move-decision process

After assessing all relevant aspects, a final overall resistance is calculated for each move target after (1). With respect to the resistance value of the grid cell the agent is recently standing on, the $\Omega$-gradients to all eight neighbor cells are calculated and the grid which offers the highest resistance decrease is chosen as optimal move. However, due to the presence of other pedestrians occupying grid cells this optimal move cannot always be performed, so that sub-optimal options may be taken, including the decision not to move at all, or to move to grid points with a higher resistance value.

## 5 RESULTS OF THE MODEL

It is typical for Multi-Agent systems that they produce a huge number of interpretable information instead of a few obvious results. For the climBOT model, this is not different. Depending on the questions asked to the model and the aspects the user is interested in, there is a huge band of possible insights than can be taken from the different model variables. Some possible ideas are:

- Frequentation of areas as a result of pedestrian behaviour including the level of comfort of passing pedestrians,
- Analysing areas of high discomfort and high frequentation to optimise planning decisions,

At the recent stage, this model is only able show qualitative effects of urban microclimate on pedestrian behaviour. Empirical observations such as video observations or surveys are needed to adjust the different model parameters and validate the model in order to achieve quantitative reliable data. First results show obvious differences between static assessment methods such as PMV (ASHRAE 1992) and those obtained with the MA simulation. For example, areas for which the PMV indicates high thermal discomfort turned out to be less problematic as the majority of pedestrians have passed shady areas before and feel comfortable back in the sun.

Due to the complexity of the model and the restricted place in this paper, it is not possible to present results of the model. The author regarded it more useful to present the climBOT model in a complete form rather than leaving it incomplete for the benefit of some result pictures.

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