Urban energy micro-simulation

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University of Nottingham (UK).
Macro-simulation (1970s +)
Typological sampling: EEP (1998 +)
Image processing of DEMs (late 90s)
Passive zone

Non passive zone

Orientation

LT-Urban (1999-2000)

Urban horizon angle
MATLAB / LT coupling: processing

Urban 3-D database (DEM) → Image processing → LT Model → Energy consumption
Energy use @ 50% GR

Energy use @ optimal GR

Difference

Optimal GR
• EU Target: 80% GHG reductions by 2050; cities will be crucial
• Cities are complex self-organising systems: firms + individuals
• Buildings & infrastructural networks: increased interconnectivity
• But to transform cities in this complex landscape we need:
  – Integrated models where behaviour is central
    • Investment probability
    • (Activity-dependent) behaviours
  – Better understanding of how this behaviour can be influenced
  – Better energy conservation: reinforces behaviour sensitivity
• Approach: Multi-Agent Stochastic Simulation (MASS)
• **CitySim**: a *detailed* decision support tool to support sustainable urban planning and design

• **Micro-simulation** for flexibility; breadth of scenarios

• Based on modelling of *urban energy and matter flows*

• Accounting for:
  – Occupants’ *behaviour*
  – Urban climate
  – Synergetic energy & matter exchanges

• Applicable at the *range of scales*

• Productive and intuitive

*Robinson et al, BS 2009; Robinson, 2011.*
1) Create or import 3D model and its clones
2) Describe envelope composition
3) Describe occupancy and equipment schedules
4) Describe HVAC and ECS systems
5) Simulate and analyse

CitySim workflow
Scene file (XML) → Climate file (ascii) → CitySim scene creation → Rad model pre-process → Rad model → Thermal model → HVAC models → ECS models → Behavioural profiles → HVAC characteristics → ECS characteristics → Fuel characteristics

- XML data exchange: GUI to solver
- ASCII data exchange: solver to GUI
- Solver coded in C++

CitySim solver: current version
• Step 1 – Calculate energy distribution throughout a discretised sky vault.
• Step 2 – Determine patch / obstruction view factors and identify dominant obstruction
• Step 3 – Determine solar view factors
• Step 4 – Build matrices and determine energy contribution from sun, sky and reflections

Robinson and Stone (2004), Solar Energy 77(3)
SRA verification

SRA verification

Annual irradiation, MWh/m²

Napier-Shaw Medal, CIBSE 2007

Difference plot: green is within 10%
Robinson and Stone (2006), Solar Energy 80(3)
Good dynamic behaviour compared to ESP-r

Ideal Heating and Cooling Loads reasonable dispersion
Heating Ventilation and Air Conditioning Model

Mixture of Ideal Gases (Air and Vapour)
• enthalpy changes
Solar collectors (PV + thermal)
Wind turbines
Boilers and co-generation systems
Heat pumps (air + ground: hoz / vert)
Sensible + latent heat storage

Co-generation of heat and electricity

Energy Conversion Systems
Occupants’ presence
Energy & Buildings 40(2), 2007

- Production of internal metabolic heat gains and “pollutants”
- Position of blinds (solar gains; daylight)
- Use of electrical lighting (associated electricity consumption and internal heat gains)
- Use of windows and doors (ventilation rate and associated heat gains and losses)
- Use of appliances (associated electricity and hot and cold water consumption, internal heat gains and production of grey- and waste-water)

Key behavioural models (2001 - 2011)
Tables, line graphs & results export
From deterministic to multi-agent stochastic simulation
We want **stochastic** models that will account for:

- the **variety of behaviours** (investments, occupants’ presence, appliance use, comfort adaptations: personal & envelope)
- the **variation over time** of these behaviours,
- the **variation between individuals** of these behaviours.

To test **scenarios** to improve urban system performance

And to provide more precise **inputs** to our simulations.

- better **load profiles** for the sizing and control of energy conversion systems and the design of supply networks: building-embedded and district-wide.
1) Create synthetic population of N agents

2) Assign parameters to each agent of population

3) Assign appliances to household / workplace

4) Long workplace absences & destination

5) Presence chains (arrivals / departures)
Basic hypotheses:
- Independence of occupants
- Markov condition:

\[ P(X_{t+1} = j \mid X_t = i) =: T_{ij}(t) \]

From the profile of probability of presence:

\[ P(t + 1) = P(t) \cdot T_{11}(t) + (1 - P(t)) \cdot T_{01}(t) \]

Parameter of mobility: \[ \mu(t) := \frac{T_{01}(t) + T_{10}(t)}{T_{00}(t) + T_{11}(t)} \]

Determination of probabilities of transition:

\[ T_{01}(t) = \frac{\mu - 1}{\mu + 1} \cdot P(t) + P(t + 1) \]

\[ T_{11} = \frac{1 - P(t)}{P(t)} \cdot T_{01} + \frac{P(t + 1)}{P(t)} = \frac{1 - P(t)}{P(t)} \cdot \left[ \frac{\mu - 1}{\mu + 1} \cdot P(t) + P(t + 1) \right] + \frac{P(t + 1)}{P(t)} \]

And closing the loop:

\[ T_{00} = 1 - T_{01} \quad T_{10} = 1 - T_{11} \]

Occupant presence: theory
Cumulated probability function

Draw a number \( n \) uniformly between 0 and 1.

\( X_t = 0 \begin{bmatrix} 1-T_{01}(t) & T_{01}(t) \\ 1-T_{11}(t) & T_{11}(t) \end{bmatrix} = X_{t+1} \)

\( n1 = 0.71 \)
\( n2 = 0.18 \)
\( n3 = 0.52 \)
\( T_{01} = 0.34 \)

In addition to this we simply need to account for long absences… this we do as a pre-process
Duration of a single presence
Cumulative presence over a whole week - office no.1

Cumulated presence over a whole week - office no.2

Cumulated presence over a whole week - office no.3

Cumulated presence over a whole week - office no.4

The University of Nottingham

Cumulative presence
Option 2: Transport model
1) Create synthetic population of N agents

2) Assign parameters to each agent of population

3) Assign appliances to household / workplace

4) Long workplace absences & destination

5) Presence chains (arrivals / departures)

6) Presence-dependent activities
- Activity probability distributions $p_i(t)$ for a typical day.

- **Modelling approach 1:** Bernoulli process: activity is drawn from the current distribution. Requires $N_{act} [52] \times N_{ts} [24] = 1248$ parameters.
The probability of changing activity varies according to time of day and the activity.
$P_{\text{trans}}(\text{Activity}, t)$
• **Modelling approach 2:**
  
  – Monte-Carlo simulation of activity changes with \( p_{\text{trans}}(t) \), \( p_{\text{trans}}(\text{Act}) \) or \( p_{\text{trans}}(t, \text{Act}) \)
  
  – Choice of new activities based on their probability distribution
  
  – \( \text{Nts} \cdot \text{P}_{\text{trans}}(t) \) + \( \text{Nact} \times \text{Nts} = 1272 \) parameters

• **Modelling approach 3:**
  
  – Use of time-dependent transition probabilities \( p_{ij}(t) \)
  
  – \( \text{Nact}^2 \times \text{Nts} = 64,896 \) parameters
• The distribution of the durations of activities is easily modelled by standard functions, eg. Exponential (1 parameter), Weibull (2 parameters),…

• To efficiently model dynamics:
  – When an activity starts, predict its duration.
  – When this time elapses, choose a new activity, either from $p_i(t)$ or $p_{ij}(t)$.
  – Requires (min): $2 \times N_{act}$ [Weibull] + $N_{act} \times N_{ts} = 1352$ parameters.

![Activity duration (min) Frequency](image)
Fitted duration distributions
Efficient aggregate model: \( P_i(t) + \text{Weibull} \)
Proposed MAS platform

1) Create synthetic population of N agents

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7) Activity location

8) Thermal / gaseous emissions

9) Environmental solver

10) Behavioural actions on:
   - windows
   - shading devices
   - lights
   - personal characteristics
   - appliances
   - HVAC systems

\[ S(t) \quad \text{and} \quad \text{Action}(t) \]
Actions on windows may be modelled in at least three ways:

- **Bernoulli process** (using observed window states).
- Discrete-time **Markov process** (using observed actions on windows).
- **Continuous-time random process** (using observed delays between actions).

\[ \begin{array}{c}
\text{Arrival} \\
\text{Closed} \quad \text{Open} \\
\text{During presence} \\
\text{Closed} \quad \text{Open} \\
\text{Departure} \\
\text{Closed} \quad \text{Open}
\end{array} \]

\[ P_{01, \text{arr}} \quad P_{10, \text{arr}} \]

\[ T_{\text{closed}} \quad T_{\text{open}} \]

\[ P_{01, \text{dep}} \quad P_{10, \text{dep}} \]

Haldi and Robinson (2009), Building and Environment, 44(12).
**Best Paper: Building and Environment, 2009**
• Probability $p$ that we observe the window to be open; which may depend on one or several predictors $x = (x_1,...,x_p)$.

• Binomial family of **generalised linear models**, using the **logit** link:

$$p(x_1,...,x_p) = \frac{\exp(a + b_1x_1 + ... + b_px_p)}{1 + \exp(a + b_1x_1 + ... + b_px_p)}$$

• Select the best univariate model, followed by examination of the usefulness of adding further variables (**forward selection**).

• **Disadvantage**: Poor simulation of the **dynamics** of opening and closing behaviour (reset at each time step).
• Here we consider the current state of the system using a **Markov process** (transitions).

• **Occupancy transitions** are a crucial factor.

• Realistic **dynamic description** of the states of windows.

---

2): Markov process predicting actions
Indoor temperature is the most influential environmental variable in both cases.

$$P_{01}(\theta_{in}, \theta_{out}) = \frac{\exp(-13.88 + 0.312\theta_{in} - 0.0433\theta_{out} + 1.862T_{abs, prev} - 0.45f_k)}{1 + \exp(-13.88 + 0.312\theta_{in} + 0.0433\theta_{out} + 1.862T_{abs, prev} - 0.45f_k)}$$

$$P_{10}(\theta_{in}, \theta_{out}) = \frac{\exp(3.97 - 0.286\theta_{in} - 0.0505\theta_{out})}{1 + \exp(3.97 - 0.286\theta_{in} - 0.0505\theta_{out})}$$

Actions on arrival
For openings, indoor temperature is the most influential predictor, while it is outdoor temperature for closings.
Outdoor temperature (expectations) is the most influential predictor, along with some other related variables.
• Treating windows as a Markov process leads to redundant Monte-Carlo simulation (low transition probabilities).

• Alternative approach: directly simulate the durations that states will remain unchanged.

• More efficient, independent of time step and offers more general results.

• Survival analysis: we can fit parametric distributions, such as Weibull distribution:
Both indoor and outdoor conditions influence the durations for which windows are left closed.

Weibull distribution with shape \( \alpha < 1 \) with scale \( \lambda(\theta_{\text{in}}, \theta_{\text{out}}) \).
• Opening durations vary mainly with outdoor temperature (more differentiated curves).
• Weibull distribution with shape $\alpha < 1$ with scale $\lambda(\theta_{\text{out}})$. 
Recommended model:

- Discrete-time Markov process for opening actions and a Weibull distribution for opening times.
- Efficient modelling of airflows on a time step independent basis.

Hybrid algorithm
The hybrid model offers the best trade-off between sensitivity and specificity.

The true positive rate (or sensitivity, or hit rate): \( TPR = \frac{TP}{TP+FN} \)
The false positive rate (or fallout): \( FPR = \frac{FP}{FP+TN} \)
Finally, we compare the observed total number of windows open with simulations. The **hybrid model** again offers the most reliable predictions.
**Conventional behaviour**

- Actions increase with $\theta_{\text{in}}$ and $\theta_{\text{out}}$.

**Predictive thermal behaviours**

- Similar, but decreased actions for high $\theta_{\text{out}}$ to avoid overheating.

**Non-thermal behaviours**

- Almost independent of thermal stimuli.

*Pre-process: random behaviour assignment*
• Probability of lowering:

\[
P_{\text{lower}}(E_{\text{in}}, B_{\text{low}}) = \frac{\exp(-6.708 + 0.000845 E_{\text{in}} + 2.380 B_{\text{low}})}{1 + \exp(-6.708 + 0.000845 E_{\text{in}} + 2.380 B_{\text{low}})}
\]

\[
P_{\text{lower}}(E_{\text{in}}, B_{\text{low}}) = \frac{\exp(7.501 + 0.000767 E_{\text{in}} + 1.085 B_{\text{low}})}{1 + \exp(7.501 + 0.000767 E_{\text{in}} + 1.085 B_{\text{low}})}
\]

• Probability of raising:

\[
P_{\text{raise}}(E_{\text{in}}, B_{\text{low}}) = \frac{\exp(-0.787 - 0.000272 E_{\text{in}} - 4.119 B_{\text{low}})}{1 + \exp(-0.787 - 0.000272 E_{\text{in}} - 4.119 B_{\text{low}})}
\]

\[
P_{\text{raise}}(E_{\text{in}}, B_{\text{low}}) = \frac{\exp(3.571 - 0.000205 E_{\text{in}} - 2.607 B_{\text{low}})}{1 + \exp(3.571 - 0.000205 E_{\text{in}} - 2.607 B_{\text{low}})}
\]

\[\text{Robinson and Haldi, JBPS (in press).}\]
• In case of action, we determine whether full lowering or raising takes place (based on initial shaded fraction and outdoor illuminance).

• For partial lowering / raising, the lower unshaded fraction is well described by a Weibull distribution (scale $\lambda$ proportional to the initial blind position)
Check occupancy status

Does blind lowering occur?

Blinds status

Arrival

Check occupancy status

Does blind lowering occur?

Climate data: outdoor illuminance

Daylight model

Intermediate

Does blind lowering occur?

Indoor illuminance

Draw shaded fraction

Does blind raising occur?

Daylight model

Indoor illuminance

Shading behaviour algorithm
• Comparison of repeated simulations \((B_{\text{lower, sim}}, B_{\text{upper, sim}})\) with measurements: predicted distribution close to reality, albeit with a slight over-estimation of shading.
• The total unshaded fraction for the whole building is well reproduced.
On arrival switch-on probabilities

**Hunt**

Within-day switch-on probabilities

**Reinhart**

Measured switch-off probabilities as a function of absence duration

**Pigg**

\[ P(I_{\text{min}}) = \left\{ \begin{array}{ll} 0.0027 + 0.017/(-64.19(\log_{10}E_{\text{min}} - 2.41)) \text{ for } E_{\text{min}} \neq 0 \\ 1 \text{ for } E_{\text{min}} = 0 \end{array} \right. \]

**Lights: Lightswitch 2002**
Indoor temperature (°C)
Proportion of cold drinks consumption
18 20 22 24 26 28 30
0.0 0.2 0.4 0.6 0.8 1.0
Proportion of hot drinks consumption
-5 0 5 10 15 20 25
0.0 0.2 0.4 0.6 0.8 1.0
Running mean outdoor temperature (°C)
Proportion of cold drinks consumption
18 20 22 24 26 28 30
0.0 0.2 0.4 0.6 0.8 1.0
Proportion of hot drinks consumption
-5 0 5 10 15 20 25
0.0 0.2 0.4 0.6 0.8 1.0
Running mean outdoor temperature (°C)
Metabolic activity level (met)
20 22 24 26 28
0.0 0.2 0.4 0.6 0.8 1.0
1.0 met
1.2 met
1.6 met
Metabolic activity level (met)
0 5 10 15 20 25
0.0 0.2 0.4 0.6 0.8 1.0
1.0 met
1.2 met
1.6 met
Metabolic activity level (met)
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1.6 met
Metabolic activity level (met)
0 5 10 15 20 25
0.0 0.2 0.4 0.6 0.8 1.0
1.0 met
1.2 met
1.6 met
Bottom-up stochastic model:

1. appliance allocation
2. activity-dependent switch-on
3. duration of use
4. varying demand whilst in use
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1. appliance allocation
2. activity-dependent switch-on
3. duration of use
4. varying demand whilst in use
Bottom-up stochastic model:
1. appliance allocation
2. activity-dependent switch-on
3. duration of use
4. varying demand whilst in use

\[ T_{ij}(P(t+1) = l_j \mid P(t) = l_i) \]
Micro-simulation: Appliance → Person → Vehicle → Building → City

Towards smart grid simulation...
Proposed MAS platform

1) Create synthetic population of N agents

2) Assign parameters to each agent of population

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10) Behavioural actions on:
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    - lights
    - shading devices
    - windows
    - HVAC systems
    - personal characteristics

11) Environmental perception

Action(t)
Adaptive algorithms v Comfort models
• Proposition: a linear model accounting for the effects of actions, individuals and season: \[ \theta_{\text{conf,ijk}} = \mu + \alpha_i + \beta_j + \gamma \theta_{\text{out,rm}} + \varepsilon_{ijk} \]

• Compared to the model with \( \theta_{\text{out,rm}} \) only, \( R^2 \) increases from 0.226 to 0.574, with a strong decrease of \( \gamma \), the slope of \( \theta_{\text{out,rm}} \).

• This also provides a measure of the comfort feedback of actions: \( \theta_{\text{ad}} = \theta_{\text{in}} - \sum \beta_i p_i(\theta_{\text{in}}) \).
• In addition to comfort temperature, the **probability distribution of thermal sensation** completes the assessment of indoor environment. This can be described by an ordinal logistic model.

• **Comfort probability** is generally of more direct interest. We model $p_{\text{cold}}$ and $p_{\text{hot}}$ through logistic functions which determines $p_{\text{comf}} = (1-p_{\text{cold}})(1-p_{\text{hot}})$
Linking actions and comfort

Dynamic building simulation program

Adaptive increments

Action(t)

Adaptive actions (probabilistic / stochastic models)

Sensation, comfort & overheating probability

$\theta^i(t)$

$\theta_i'(t)$

$(\theta_i' - \Delta \theta)(t)$

$\theta_i(t)$

Action(t)
For constant charging of overheating probability (tolerance discharge)

\[ P_{OH}(t) = 1 - \exp(-4.75 \cdot 10^{-4} DH_{10,t}) \]

JBPS 1(1), p43-55, 2008
Energy and Buildings, 40 p1240-1245.

\[ T \in [0,1] \quad P_{OH} = 1 - T \]
Proposed MAS platform

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10) Behavioural actions on:
    • appliances
    • lights
    • shading devices
    • windows
    • HVAC systems
    • personal characteristics
11) Environmental perception
12) t + 1?, b + 1?, g + 1?
From single results to distributions...
Proposed MAS platform

1) Create synthetic population of N agents

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    - personal characteristics

11) Environmental perception

12) $b + 1$, $g + 1$

13) destroy synthetic population of N agents

$t + 1$?
MASS of activity & subsequent behaviour:

- **Presence**: long absences; calibration parameters: data
- **Activity**: location + pollutants: data
- **Windows**: IAQ stimuli; simplified airflow model; calibration parameters: data (Vienna+)
- **Blinds**: calibration parameters: data (Vienna+)
- **Lighting**: calibration parameters: data (residential!)
- **Appliances**: testing of core hypotheses / simplified activity-based model; calibration: data
- **Comfort**: coupling behaviour and dynamic human thermo-regulation modelling; more detailed adaptive model: data

*Oh, and did I mentioned we need more data ;-)*

Further work…
Some CitySim Applications...
A district: Neuchâtel

440 buildings
4,700 residents
Cadastral and LIDAR data: Visual survey:

Buildings / inhabitants register data; energy use data:

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Data processing

- 2.5D model creation
- Data harmonisation
- Managing conflicts / errors / missing data
A *clumsy* first solution for district energy modelling:

- Import tools
- Climate file
- Geometry file (.kml)
- Parameters files
- Citysim model

Input files for model
Some first results
We need a DBMS that supports:
- Multi-user remote access
- Full 3D modelling
- Spatio-temporal data management
- Interconnectivity
A City: Zürich (2kW City)

- Climate
- LIDAR
- Census
- Visual observations
Visual observations: glazing ratio
Q-GIS interface to PostgreSQL database

Kreis 3 – Alt-Wiedikon
Pre-renovation: old buildings dominate
Post-renovation: 8% total heating reduction
Urban energy simulation has advanced considerably:

- Core deterministic models
- Basic behavioural models

Decision modelling is the way forward:

- Investments and activities
- Activity-dependent behaviours

We still have a long way to go:

- Development & validation of a core MASS platform
- Coupling of complementary modules (climate, transport, space...)

But isn’t it exciting?
CONTENTS

1. Introduction

Part I  Climate and Comfort

2. The Urban Radiant Environment

3. The Urban Climate

4. Pedestrian Comfort

Part II  Metabolism

5. Building Modelling

6. Transport Modelling

Part III  Measures and Optimisation of Sustainability

7. Measures of Urban Sustainability

8. Optimisation of Urban Sustainability

Part IV  An Eye to the Future

9. Dynamics of Land-Use Change and Growth

10. Conclusions
Thank you!