CITYSIM: COMPREHENSIVE MICRO-SIMULATION OF RESOURCE FLOWS FOR SUSTAINABLE URBAN PLANNING

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ABSTRACT

In this paper we describe new software "CitySim" that has been conceived to support the more sustainable planning of urban settlements. This first version focuses on simulating buildings' energy flows, but work is also under way to model energy embodied in materials as well as the flows of water and waste and inter-relationships between these flows; likewise their dependence on the urban climate. We discuss this as well as progress that has been made to optimise urban resource flows using evolutionary algorithms. But this is only part of the picture. It is also important to take into consideration the transportation of goods and people between buildings. To this end we also discuss work that is underway to couple CitySim with a micro-simulation model of urban transportation: MATSim.

INTRODUCTION

It is estimated that over half of the global population is now living in urban settlements (UN, 2004), in which three quarters of global resources are consumed (Girardet, 1999). Energy derived from fossil fuels is key amongst these resources, so that urban settlements are responsible for the majority of greenhouse gas emissions. It is thus important that existing urban settlements are adapted and that proposed settlements are designed to minimise their net resource consumption. Software for simulating and optimising urban resource flows will play an essential role in this process. In this paper we describe progress that is being made in one such initiative: the development of CitySim. We also describe work that is underway to add further functionality to CitySim and to couple CitySim with a microscopic transport simulation model MATSim to resolve for all key urban resource flows.

Achieving this would provide an invaluable platform for the testing of planning interventions to improve urban sustainability.

CITYSIM STRUCTURE

In common with its predecessor SUNtool (Robinson et al, 2007) the use of CitySim's Java-based GUI to simulate and optimise building-related resource flows proceeds according to four key steps:

- Definition of site location and associated climate data.
- Choice and adjustment of default datasets for the types and age categories of buildings to be studied.
- Definition of 3D form of buildings; definition of energy supply and storage systems to be modelled; refinement of building and systems attributes.
- Parsing of data in XML format from the GUI to the C++ solver for simulation of hourly resource flows; analysis of results streamed back to the GUI.

The scale of analysis may vary from a neighbourhood of just a few buildings, though a district of several hundred to an entire city of tens of thousand. But in each case the core modelling capability and the data needs of these models is similar. In the following we describe this modelling capability and how this is being extended to facilitate thoroughly comprehensive simulations of urban resource flows and how these might be optimised.

CITYSIM: CORE MODELS

For the purposes of urban scale simulation, it is important to achieve a good compromise between modelling accuracy, computational overheads and data availability. In all cases these have been the criteria applied in the selection of an appropriate modelling methodology.

Thermal Model

From the above criteria it was decided to develop a model based on analogy with an electrical circuit; more specifically based on a resistor-capacitor network. In this case a conducting wall can be represented by one or more temperature nodes (Lefebvre, 1997). The heat flow between a wall and the outside air can be represented by an electric current through a resistor linking the two corresponding nodes and the wall's inertia can be represented by a capacitance linked at that node.

In our model (Kämpf and Robinson, 2007), which is a refinement of that due to Nielsen (2005), an external air temperature node T_{ext} is connected with an outside surface temperature node T_{os} via an external film conductance K_e, which varies according to wind speed and direction (Figure 1). T_{os}, which also experiences heat fluxes due to shortwave and longwave exchange, is connected to a wall node T_w of capacitance C_w via a conductance defined by the external part of the wall. In fact this node resembles a mirror plane, so that we have similar connections to an internal air node T_a of capacitance C_i via an internal surface node T_{is}. T_{is} may also experience shortwave flux due to transmitted solar radiation and a longwave flux due to radiant heat gains from internal sources (people and appliances) and T_a may experience convective gains due to absorbed shortwave radiation, internal casual gains and heating / cooling systems. Finally, our internal air node may be connected with our external air temperature node via a variable resistance due to infiltration and ventilation.

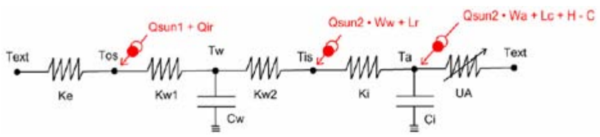

Figure1: Monozone form of the CitySim thermal model.

For a whole building with many subspaces, the air nodes of each zone are linked via the separating wall conductance. Interzonal airflow can also be handled through this conductance. To account for the corresponding inertia the capacitance of the separating wall is subdivided and allocated to the neighbouring zone's capacitance (Figure 2).

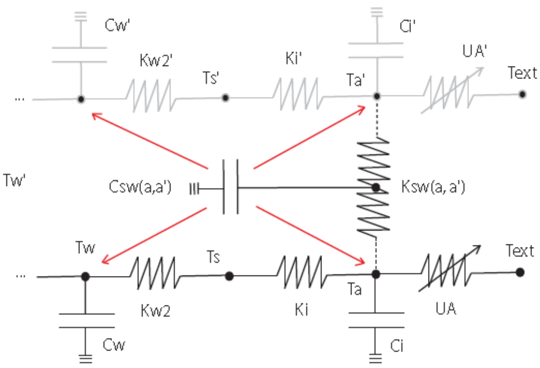

Figure 2: Interzonal connection between zones represented by the two-node thermal model

In general, an n-node model may be represented by the following differential equation:

$$C \cdot \vec{T}'(t) = A(t) \cdot \vec{T}(t) + \vec{u}(t) \qquad \ldots(1)$$

Where $\vec{T}(t)$ represents the temperature vector at the n-nodes $\vec{T}'(t)$ denotes its derivative with respect to time and $\vec{u}(t)$ represents the source terms of each node. C is the positive diagonal thermal capacity matrix and *A(t)*is the symmetric heat transfer matrix. In the particular case of our two-node multi-zone model eq(1) can be expressed as follows:

$$\begin{pmatrix} C_1 & 0 \\ 0 & C_2 \end{pmatrix} \cdot \begin{pmatrix} \vec{T}_a'(t) \\ \vec{T}_w'(t) \end{pmatrix} = \begin{pmatrix} D & E \\ F & G \end{pmatrix} \cdot \begin{pmatrix} \vec{T}_a(t) \\ \vec{T}_w(t) \end{pmatrix} + \begin{pmatrix} \vec{u}_a'(t) \\ \vec{u}_w'(t) \end{pmatrix} \qquad \ldots(2)$$

Where for the ith zone C_1 and C_2 are internal (air and the wall separating zones i and j) and wall (external and separating) capacitances. D, E, F and G correspond to combined conductances for external and separating walls.

Predictions from this simplified model compare well with those of ESP-r (Clarke, 2001) for a range of monozone and multizone scenarios.

Radiation models

In common with CitySim's predecessor "SUNtool", the Simplified Radiosity Algorithm (SRA) of Robinson and Stone (2004) is used to solve for the shortwave irradiance incident on the surfaces defining our urban scene. For some set of p sky patches, each of which subtends a solid angle Φ (Sr) and has radiance R ($Wm^{-2}Sr^{-1}$) then, given the mean angle of incidence ξ (radians) between the patch and our receiving plane of slope β together with the proportion of the patch that can be seen σ ($0 \leq \sigma \leq 1$), the direct sky irradiance (Wm^{-2}):

$$I_{d\beta} = \sum_{i=1}^{p} (R \Phi \sigma \cos \xi)_i \qquad \ldots(3)$$

For this the well known discretisation scheme due to Tregenza (1993) is used to divide the sky vault into 145 patches of similar solid angle and the Perez all weather model (Perez, 1993) is used to calculate the radiance at the centroid of each of these patches. The direct beam irradiance $I_{b\beta}$ is calculated from the beam normal irradiance I_{bn} which is incident at an angle ξ to our surface of which some fraction ψ is visible from the sun, so that:

$$I_{b\beta} = I_{bn} \psi \cos \xi \qquad \ldots(4)$$

Now the direct sky and beam irradiance contributes to a given surface's radiance R which in turn influences the irradiance incident at other surfaces visible to it, so increasing their radiance and vice versa. To solve for this a similar equation to that used for the sky contribution gives the reflected diffuse irradiance. In this case two discretised vaults are used, one for above and one for below the horizontal plane, so that:

$$I_{\rho\beta} = \sum_{i=1}^{2p} (R^* \Phi \omega \cos \xi)_i \qquad \ldots(5)$$

where ω is the proportion of the patch which is obstructed by urban (reflecting) surfaces and R^* is the radiance of the surface which dominates the obstruction to this patch (in other words, that which contributes the most to ω). As noted earlier, R^* depends on reflected diffuse irradiance as well as on the direct sky and beam irradiances. For this a set of simultaneous equations relating the beam and diffuse sky components to each surface's irradiance, which itself effects the reflected irradiance incident at other surfaces, may be formulated as a matrix and solved either iteratively or by matrix inversion (Robinson and Stone, 2004).

The principle complication in the above algorithm lies in determining the necessary view factors. For obstruction view factors, views encapsulating the hemisphere are rendered from each surface centroid, with every surface having a unique colour. Each pixel is then translated into angular coordinates to identify the corresponding patch as well as the angle of incidence. For sky view factors then, $\Phi\sigma\cos\xi$ is treated as a single quantity obtained by numerical integration of $\cos\xi \cdot d\Phi$ across each sky patch. Likewise for $\Phi\omega\cos\xi$, for which the dominant occluding surface is identified as that which provides the greatest contribution. A similar process is repeated for solar visibility fractions for each surface, for which a constant size scene is rendered from the sun position.

In addition to using the above view information to calculate incident shortwave irradiance, this may also be used to calculate longwave irradiance; given the corresponding surface and sky temperatures (see Robinson and Stone 2005). Eq (3-5) may also be solved using luminance / illuminance as an input to model the external luminous environment. Additional renderings may be then computed to determine the view information necessary to calculate the direct and reflected contributions to internal illuminance (at known points) as well as the incoming luminous flux for internal reflection calculations (Robinson and Stone, 2005; 2006).

Behavioural models

One of the key sources of uncertainty in building / urban simulation relates to occupants' behaviour, which is inherently stochastic in nature. Key types of behaviour and their main impacts on urban energy flows are as follows:

<u>Presence</u>: metabolic heat gains and pollutants.

<u>Windows</u>: infiltration rates.

<u>Blinds</u>: illuminance and transmitted irradiance.

<u>Lights</u>: heat gains and electrical power demand.

<u>Electrical appliances</u>: heat gains and electrical power demand.

<u>Waste</u>: production of combustible and recyclable solids.

The central behavioural characteristic relates to occupants' presence, which of course determines whether they are available to exercise any other form of influence on resource flows. Based on the hypotheses that all occupants act independently and that their actions at time *t+1* depend only upon the immediate past (*t*), we model transitions in occupants' presence (present to absent (T_{10}) or present (T_{11}) and vice versa) based on the Markov condition that:

$$P\left(X_{t+1} = i \middle| X_t = j, X_{t-1} = k, \ldots, X_{t-N} = l\right) = P\left(X_{t+1} = i \middle| X_t = j\right) =: T_{ij}(t) \quad \ldots(6)$$

For this we take as input a profile of the probability of presence at each time *t* and a mobility parameter μ – the ratio of the probability of changing state to not changing state, so that the transition absent to present is found from:

$$T_{01}(t) = \frac{\mu - 1}{\mu + 1} \cdot P(t) + P(t+1) \quad \ldots(7)$$

And that of present to present from:

$$T_{11} = \frac{1 - P(t)}{P(t)} \cdot T_{01} + \frac{P(t+1)}{P(t)} = \frac{1 - P(t)}{P(t)} \cdot \left[\frac{\mu - 1}{\mu + 1} \cdot P(t) + P(t+1)\right] + \frac{P(t+1)}{P(t)} \quad \ldots(8)$$

The remaining transitions are simply: $T_{10} = 1 - T_{11}$ and $T_{00} = 1 - T_{01}$. In addition to this we also need to consider long absences, for example due to illnesses or vacations. For this we use a daily profile of the probability of starting a long absence and a further profile for the cumulative probability of the duration of this absence. This takes precedence over the short time step transitions in presence, described above. For further details, we refer the reader to Page et al, (2007a).

Although this occupancy model has been integrated with CitySim, it is currently disabled. Rather, and as an intermediate step, use is currently made of deterministic rules / profiles describing occupants' presence and behaviour. In the near future however, the possibility will be provided to switch between deterministic representations and stochastic models. For this we will also use the models of: Haldi and Robinson (2009a, b) for window openings and the corresponding ventilation exchanges; Haldi and Robinson (2009c) for interactions with blinds and the impacts on solar radiation and daylight transmission; Page et al (2007b) for electrical appliances use and their associated power consumption and heat gain production. In the first instance the simplified model of Page (2007) will be used for solid waste production.

For interactions with lights we will initially use the same models as those integrated with Lightswitch-2002 (Reinhart et al, 2004). In particular, the probability of switching on lights at arrival as a function of minimum internal workplane illuminance ($E_{i,min}$) will be predicted by the expression due to Hunt (1979). Switching on lights at intermediate times is also predicted as a function of $E_{i,min}$, but by the expression of Reinhart and Voss (2003) whereas switching off at departure will be modelled as a function of expected duration of absence (Pigg et al, 1996). Note that interactions with blinds will be resolved before those with lights.

Plant and equipment models

This category of model includes both heating, ventilating and cooling (HVAC) systems and energy conversion systems (ECS).

The HVAC model is based on the psychrometry of humid air, considering an ideal mixture of two perfect gases: air and vapour. It computes the psychrometric state (temperature and moisture content and hence the enthalpy *h*) of the air at each *i*th stage in its supply (e.g. outside, heat recovered, cooled and de-humidified, re-heated, supply). Given the required mass flow rate $\dot{m}$ (which may be defined by the energy to be delivered or the room fresh air requirement) the total delivered sensible and latent loads for all stages in the heating and/or cooling of air q can then be calculated:

$$q = \sum_i^n \dot{m}_i \Delta h_i \quad \ldots(9)$$

The family of ECS models comprise a range of technologies that provide/store heat and/or electricity to buildings. These include a thermal storage tank model for hot/cold fluids, boilers, heat pumps, cogeneration systems, combined cogeneration and heat pump systems, solar thermal collectors, photovoltaic cells and finally wind turbines. These ECS models are in general based on performance curve regression equations whereas a simplified thermal model simulates the sensible / latent heat storage (so that phase change materials are also accounted for).

If the ECS models have insufficient capacity to satisfy the HVAC demands then the supply state is adjusted and the predicted room thermal state is corrected (using the thermal model).

Integration

The conceptual structure of CitySim is presented in Figure 3 below. The GUI produces an XML file which contains a geometric description of our urban scene together with numerous attributes that relate to each of the models influencing urban resource flows. This XML file also contains pointers to a climate file as well as to the appropriate entries in databases relating to building constructions, occupatants' behaviour and plant and equipment characteristics as well as the fuels combusted. This data is parsed to the CitySim solver, which creates instances of the objects describing our scene. Each of the models are then called in turn and are parsed the necessary data.

Shown in black are each of the functions that have been developed within CitySim and shown in grey are those that are either under development or are planned to be developed in the near future. These are described in the remaining sections of this paper.

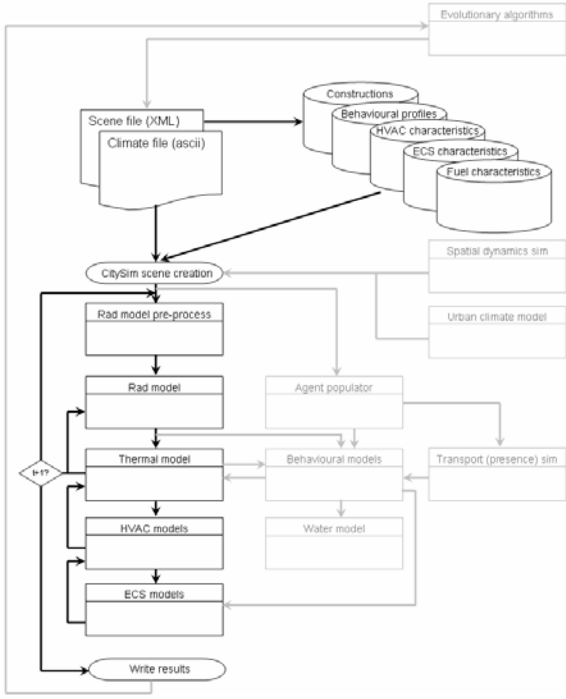

Figure 3: Conceptual structure of CitySim

CITYSIM: EXAMPLE APPLICATION OF CORE MODELS

We have applied CitySim's core models to a group of buildings in the district of Matthäus in Basel (Switzerland). For this, we used a 3D model provided by the city's Cadastral Office, and completed the physical description of the buildings by means of the national census data for the year 2000 and results from a recent visual field survey of the district.

Figure 4 shows a projected view of the group of buildings simulated, in which we have represented for one particular day and hour in the year the surface averaged irradiance at its centroid by coloured points. The colour map used represents the intensity in irradiance, from red to blue, calculated by the SRA model.

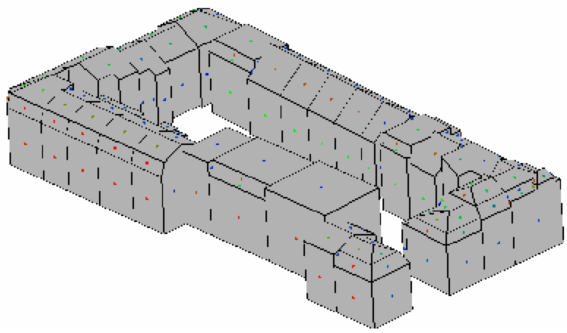

Figure 4: A projection of the group of buildings simulated in Matthäus district, Basel, Switzerland.

Using the buildings' construction date, renovation status and with the help of renovation specialists (EPIQR Rénovation), we attributed the physical characteristics relating to the walls, roofs and windows. See Kämpf and Robinson (2009) for a fuller description of this scene and the means for its attribution.

By way of example, figure 5 shows the averaged internal building temperature and the ideal heating and cooling demands for a selected building in the group, throughout the year on an hourly basis. The temperature set-points were chosen to be 21°C for heating and 26°C for cooling.

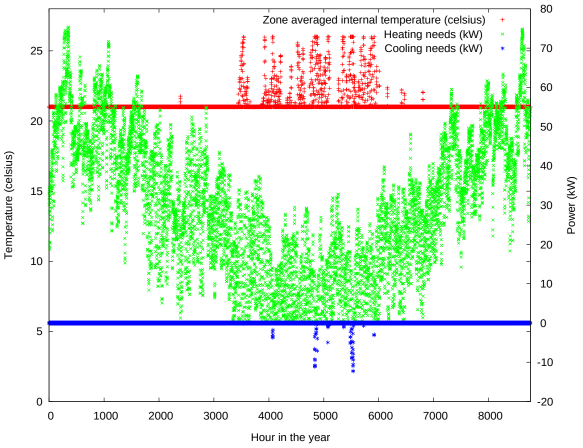

Figure 5: Internal volume-averaged temperature and heating and cooling demands for one of a group of buildings.

CITYSIM: FURTHER MODULES

In parallel with the above work in developing the core solver for CitySim, we have also been active in developing a range of complementary modelling capabilities to enhance CitySim's scope. These as well as some planned models (on which work will start shortly) are described below, to give a flavour of what CitySim's capabilities are expected to be in the near future.

Further object attribution

The energy flows during the operation of an urban development are just part of the story. It is also of interest to consider the embodied energy content of materials, to facilitate life cycle energy analysis. Related to this is an issue of primordial importance to the urban designer and developer – that of cost (both capital and running). Realistically speaking, this typically outranks environmental performance as a fitness function to optimise. Work is thus underway to add these additional attributes (cost and embodied energy) to the properties of the objects that comprise a CitySim urban scene. This is straightforward. Less straightforward is the compilation of databases that are rich enough to describe the attributes of the most commonly used construction / servicing products for potentially any users' location, including the costs of their acquisition and the local labour involved in their utilisation (construction labour). Likewise, the time-varying local energy purchase and feed-in tariffs.

Clearly much of the onus here will need to be placed upon the user (although the ETHZ EcoInvent database would be of use for embodied energy content). However, one way of maximising the re-use of this effort would be the use of an on-line open data respository – providing open access to users' data.

Further resource flows

The appliance model which is currently under development for integration within CitySim has thus far been calibrated exclusively to model electrical appliances. It does not currently model water consumption from appliances that consume exclusively water or both water and electricity.

It is thus planned to develop a simplified model of water flows, including:

- The consumption of water in buildings, distinguishing the quality of water required to support the activity concerned as well as the quality of output waste water.
- Evapotranspiration from vegetated surfaces and the associated consumption of water for irrigation.
- Harvesting and storage of rainwater and recycling of consumed water.
- Supply of water from recycled, harvested and mains sources.

Modelling of surface water drainage is currently considered to be beyond the scope of CitySim.

As part of this water processing module the anaerobic digestion of human waste will also be modelled in a simplified way. Combustible biogas and solid waste (predicted using the simplified solid waste model mentioned under 'core models') will then be available for input to the ECS models.

In the longer term, as we increase our scale of analysis as well as the diversity of building types that are modelled, it will be of special interest to model possible synergetic exchanges of energy and matter between buildings or the activities accommodated within them. In this way it will be possible to test hypotheses inspired by industrial ecology regarding ways of minimising net urban resource use, through improved circularity in their flows.

Consider the industrial park on the outskirts of the town of Kalundborg in Denmark for example. Amongst the numerous synergetic exchanges, the waste heat produced by the power station meets the space heating and hot water demands of the town's buildings and a fish-farm as well as the process heat needs of a bioplant and an oil refinery. The bioplant produces yeast for pig farmers as well as fermentation sludge for local farmers. Gypsum from the power station's flue gas desulphurisation plant is a key raw material of a plasterboard manufacturer…and so on. The reduction in resource imports and exports are considerable. These principles are readily applicable to urban developments, which tend to accommodate rich sets of energy and matter flows.

Since the processes involved may be represented in an aggregate way (as is typical with mass flow analysis), representing the potential exchanges need should not be difficult; provided of course that the necessary data is available.

Urban climate modelling

Compared with rural settings, in the urban context more shortwave radiation is absorbed, less longwave radiation is emitted and the mean wind speed is lower, so that the mean air temperature is higher. This urban heat island is exacerbated by anthropogenic heat sources and the relative lack of evapotranspiration due to vegetated surfaces. Due to inertial differences, urban and rural temperature profiles also tend to be out of phase, so that whilst the mean urban temperature is higher, afternoon temperatures may be lower, particularly in summer. These urban-rural temperature differences can have significant implications for predicted resource demands and so needs to be account for in our simulations.

Although the influencing mechanisms are reasonably well understood, predicting the urban climate is complicated by the scales involved: from buildings within the urban canopy (the size of a few meters) to large topographical features such as nearby water bodies or mountains (the size of a few kilometres). These scales cannot be satisfactorily resolved in a computationally tractable way using a single model. Our solution to this problem has been to couple different models which each address different spatial scales.

Firstly, freely available results from a global (macro) model are input to a meso-model at a slightly larger scale than that of our city. This meso-model is then run as a pre-process to interpolate the macro-scale results at progressively finer scales until the boundary conditions surrounding our city are resolved at a compatible scale. The meso-model may then be run in the normal way. In the rural context this may simply involve associating topography and average land use data with each cell, the former affecting temperature as pressure changes with height the latter affecting temperature due to evapo(transpir)ation from water bodies or vegetated surfaces. In the urban context however, it is important to account for the energy and momentum exchanges between our built surfaces and the adjacent air, which implies some representation of 3D geometry. For this we use a new urban canopy model in which the velocity, temperature and scalar profiles are parameterised as functions of built densities, street orientation and the dimensions of urban geometric typologies. These quantities are then used to estimate the sources and sinks of the momentum and energy equations.

Thus, a completely coupled macro, meso and urban canopy model can be used to predict the temperature, wind and pressure field in a city taking into account not only the buildings from which it is composed but also the scales which are bigger than the city itself.

This new modelling capability, which is described in Rasheed et al (2009), may be run as a pre-process to modify the climatic inputs to CitySim.

Evolutionary algorithms

For a new urban development, even with a relatively limited number of variables (geometry, type of use, occupancy and constructional characteristics, plant and energy supply technologies), the number of permutations is very large. The probability of identifying an optimal configuration of these variables by manual trial and error or simple parametric studies is thus correspondingly small. Moreover the response function computed by CitySim may exhibit a non-linear, multi-modal and discontinuous behaviour. Therefore heuristic methods such as Evolutionary Algorithms are needed to overcome possible local optima, keeping in mind that we can never be sure of finding the global optimum in a finite time frame.

Following from a review of available evolutionary algorithms (EAs), we have developed a hybrid of two algorithms (Covariance Matrix Adaptation – Evolutionary Strategy [CMA-ES] and Hybrid Differential Evolution [HDE]) which offers improved robustness over its individual counterparts for a larger range of optimisation problems (Kämpf and Robinson, 2009a,b).

After having applied this new algorithm to a range of solar radiation optimisation problems, we have recently coupled this with CitySim and deployed it to explore ways of optimising the energy performance of part of a district of the City of Basel in Switzerland, called Matthäus (see Kämpf and Robinson, 2009c). Work will shortly start on the integration of an interactive tool within CitySim with which users will be able to select parameters to optimise, together with the constrained range of values they may take and the criteria with which overall fitness is to be judged.

Uncertainty analysis

Finally, it is likely that the uncertainty in some of the inputs to urban models, particularly in relation to the conceptual design of new developments, may have a significant impact on performance predictions and the conclusions reached from these predictions.

To be able to accommodate these uncertainties in urban scale predictions, we intend to borrow techniques developed for the simulation of individual buildings (e.g. De Witt (2001) and Macdonald (2002)). A facility should then be provided within the interface to define the uncertainties of the parameters to which predictions are found to be particularly sensitive, and to select these parameters for simulation purposes.

MULTI- AGENT TRANSPORT SIMULATION (MATSIM)

Resources in urban settlements are consumed principally by buildings and the activities accommodated with them and by the transport of goods and people to and between them. To account for this transport related energy use, we use the Multi-Agent Transport Simulation Toolkit MATSim-T (1990).

MATSim-T simulates the sub-hourly transport of individual people within a given urban scene.

For this a geometric description of the scene is required, consisting primarily of the transport network nodes and the links between them as well as the locations of activities (work, home, education etc) located at or adjacent to these nodes / links. Using geo-coordinated census data a population of households may then be created which is then populated with individuals and associated with attributes such as ID, driving licence ownership, car availability, etc. Activity chains[1] such as home-work-leisure-work-home and the locations and preferred timing of these activities are then associated with these agents. With this initialisation complete the scene may be simulated (Figure 6).

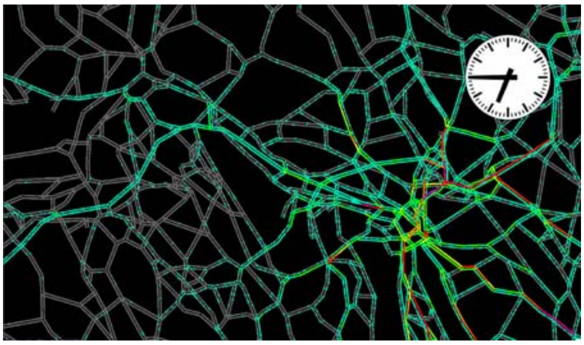

Figure 6: MATsim-T simulation of traffic results fo Zürich, Switzerland (from: www.matsim.org).

First the travel time of alternative plausible routes between the origin and destination of each journey is calculated to determine the least cost routes. This is carried out for all activity chains of all agents until all journey plans have been deduced. A stochastic queue-based traffic simulation then simulates each agent's journeys throughout the network. The actual arrival time at each destination then depends on the degree of network congestion.

Next a score is associated with the utility of the achieved daily travel plan, considering the utility of the time spent performing the required activities, the time spent in travel and whether or not these activities were started late. Using an evolutionary algorithm in which each member of a given generation corresponds to a new travel plan the next travel plan in line is then simulated. The success of these plans are then ranked. The worst performing ones are discarded and those that are retained are used to create the next generation. This process continues for a defined number of iterations until a daily plan of near optimal utility has been identified for each agent. This corresponds to the way in which humans learn from experience what is the most efficient time to leave one destination for another and according to what route. For example we may choose to leave home rather early in the morning to arrive at work quickly and also leave earlier to avoid heavy afternoon traffic.

With agents' daily travel plans chosen, their journeys may be simulated and the associated fuel consumption calculated, using empirical performance data.

Now to couple CitySim and MATSim all that is required is that the two tools share a common XML file holding (amongst other variables) building IDs and the characteristics of the occupants. By running MATSim as a pre-process to CitySim the means for data exchange will be the arrival and departure time of occupants – in effect replacing the current stochastic occupancy model.

As noted earlier, MATSim's initialisation process associates a range of attributes to each individual agent. These include age, gender and salary. To these we may add other attributes such as environmental preferences. In a CitySim pre-process we may then divide apartment buildings into households of appropriate size and allocate appliances to these households. We may refine our stochastic models so that behaviour is predicted as a function of say preferred summertime temperature or indoor illuminance…etc. In short, a coherent way for integrating MATSim and CitySim is through the multi-agent stochastic simulation of behaviour.

Work has recently started in developing this new MAS behavioural modelling environment. It is hoped that this modelling utility will be integrated into future single building as well urban simulation programs.

CONCLUSIONS AND OUTLOOK

Considerable progress has been made in recent years to simulate the availability of renewable energy within the urban context as well as the more general demand for and consumption of resources (energy, water and waste); culminating in the recent development of CitySim, to which this paper relates.

But their remains a great deal of work to do if we are to model urban resource flows, due to both buildings and transport, in a truly comprehensive way, together with means for optimising them. This is however a very exciting challenge and one which, should we succeed, would produce a model of acute value to future planners of urban settlements, both new and existing!

[1] e.g. derived from Swiss microcensus data

ACKNOWLEDGEMENT

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