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Use of Agent Based Modelling to Investigate the Dynamics of Slum Growth

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Abstract

Informal settlements arise as a result of the urgent need for shelter by the urban poor. Urban planners and policy makers face challenges in effective management of slum settlements as they do not fully understand their dynamics and extents. Advances in Geomatics research have recently offered growing results in identifying slum characteristics using various remote sensing and artificial intelligence approaches. The main objective of this research is to propose a conceptual model for the implementation of an empirically informed agent based prototype that can simulate future patterns and trends in land occupation change over time specifically with a focus on informal settlement proliferation in the city of Cape Town in South Africa. The study incorporates physical, environmental, social and economic factors specific to Cape Town in structuring behavioural rules for agents in a predictive environment. Input data is extracted from demographic, statistical and administrative datasets. The resulting concept model incorporates a static model, a dynamic and an interactive behaviour model that collectively form a combination for successful implementation of the physical agent based model. On implementation the model is expected to simulate city wide slum growth patterns and trends in Cape Town over time. Urban planners can use pattern information for proactive slum management and in preventing risk prone settlement especially in some low lying coastal areas that are flood prone.

1. Introduction

The rapid growth of informal settlements is one of the biggest challenges faced by modern developing cities. The United Nations (UN) Habitat defines an informal settlement as a collection of households living in close proximity to one another in a number of buildings such that the households share one or more deprivations of: access to improved water, access to improved sanitation facilities, sufficient living area, structural quality/ durability of living areas and security of tenure (UN-Habitat, 2003a).These settlements often arise as a response to the urgent need for shelter by migrants who move in search of better services and opportunities against an environment of weak statutory planning on the part of the receiving city (Augustijn-Beckers, 2008). According to the Millennium Development Goals (MDGs) a global declaration was made to seek to significantly improve the lives of at least 100 million slum dwellers by the year 2020 (UN-Habitat 2003b).One of the main setbacks to achieving this goal has been lack of adequate information on the dynamics of the informal settlements in terms of growth and expansion parameters of these unorganised layouts. Sluizas (1988) pointed out that regardless of appearing haphazard, the growth of such settlements is in itself not a random process but is geometry of distinct spatial patterns that are influenced by a number of physical, cultural, and economic factors. Modelling the dynamics of growing urban environments can be very difficult in the absence of tools that embrace the complexities of such expansion which arise from the fact that their growth is generally different from that of a planned settlement (Vincent, 2009).

Traditional approaches of predicting the complexities of urban growth have included the application of equation based systems, expert studies and statistical modelling using information extracted from remotely sensed imagery (Hoffman et al., 2001). Recently however, cellular automata and agent based modelling have displayed significant strength in their ability to simulate complex environments including uncontrolled land use/cover changes that result from human interactions with their surroundings (Flacke et al., 2010). An increasing number of Geomatics scholars have been exploring the potential of agent-based or multi-agent system tools for modelling informal settlement growth patterns and subsequent land-cover changes (Berger et al., 2005).

2. Related Work: Modern urban growth modelling

Current trends in urban modelling show a shift toward two main techniques: Cellular Automata (CA) and Agent Based Modelling (ABM). CA is a discrete dynamic system in which space is divided into regular spatial units called cells and time progresses in discrete steps (Lui et al., 2007). Each cell in the system has one of a finite number of states that are updated according to local rules dependent on its own state and the states of its nearby neighbours at the previous time step. Several researchers have shown the strength of CA in modelling urban growth such as Alkheder et al., 2005; Batty et al., 1999; Clarke et al., 1997.However ABM’s still shows strong advantages over CA especially in their ability to represent individual decision-makers and their interactions and to dynamically link social and environmental processes (Matthews et al., 2007).ABM is a powerful, computational simulation technique for modelling phenomenon as dynamic systems of agents living in an environment (Useya, 2011). Agent Based Models are simulation models in which the main decision makers or agents are humans or exhibit human like behaviour (animals or non-living objects can be agents if they exhibit intelligent behaviour in simulation). Figure 1 below shows a basic example of a raster based urban sprawl ABM in progress. The blue units at the periphery represent most recent settlements and the darker pixels are older settlement.

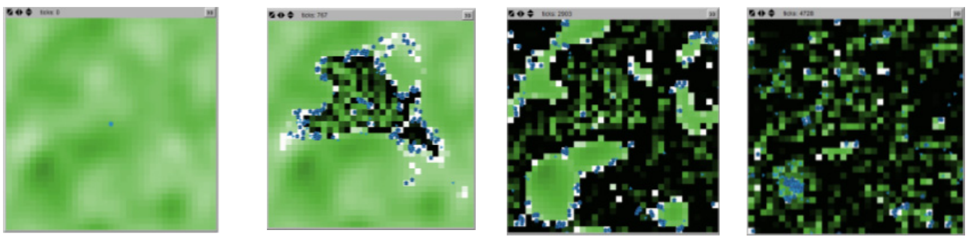

Figure 1. Raster based urban sprawl ABM in progress (Source: Felsen et al., 2007)

ABM simulation is conducted with three main components namely: agents, environment and a framework for simulating agent behaviours or interactions (Useya, 2011).

- Agents refer to components of the model, human or not, that are able to interact with their environment by following a set of rules which collectively characterize the behaviour of the agent within its environment (Berger et al., 2001). These entities have a memory, exhibit mobility and can reproduce. They are also communicative and interdependent on other agents.

- The environment can be static or dynamic. It is a discrete space in a virtual world in which agents inhabit and interact with other agents (Castiglione, 2000). In the case of the current study it is representative a specific geographic space i.e. Cape Town city hence it is referred to as being spatially explicit (Bonabeau, 2002). It is in the modelling and storage of environment based data that a strong coupling with Geographic Information Systems (GIS) is present. A spatially intelligent representation of the city as discussed in detail in section 4 forms a base map for the simulation. This representation is geographically referenced to the layout of Cape Town such that each point on the base map has a unique X,Y coordinate and stores unique thematic data about the administrative area to which it belongs. As the model transcends, mobile agents visit targeted locations guided by the coordinate identity of that location and they make settlement decisions. At each refreshing time step, new spatial data is created based on statistics gathered from the latest agent settlements and this updates a GIS data base. Output from the model is then visualised as cartographic layout e.g. thematic maps and charts on changing land use and demographic distributions. In addition GIS analysis functionality is strongly employed to calculate proximity variables, area computations and a general cost-service analysis of locations for agents against changing land uses.

- The framework for simulating agent behaviour or interactions is often achieved through scripting platforms or toolkits / software. Interactions within this framework can be agent-agent based, agent-environment or environment-environment based.

Model implementation is based on the assigning of entities to rules through the harnessing of a programming framework. Software toolkits for ABM include Net logo, Star logo, Mac-Star-Logo and Open-Star-Logo which are examples of open source options common in research work (Useya, 2011).The platforms are often Java, Python, Visual basic or C++ programming based and compile commands that assign character to agents in the simulation environment (Bonabeau, 2002). In ABM time is modelled in discrete time steps each being equivalent to a period in real time. A time step can be defined as the length of time it takes for an interval event to occur after which the system is updated (Hoffman et al., 2003). The output from both CA and ABM is ideally validated to ensure that the results yielded are as close as possible to scenarios on an independent reference. Proposed methods of validation include empirical calibration of the model as well as use of statistical measurements such as kappa statistic, goodness of fit, chi-square, spatial metrics, etc. (Bonabeau, 2002). The conceptual model referred to in this study will not focus on validation methods as those are of greater relevance on implementation of the model than its theoretical design.

3. An overview of the model concept architecture

The main objective of this research is to propose a conceptual model for the implementation of an empirically informed (predictive) agent based prototype that can reveal patterns and trends in informal settlement growth in the city of Cape Town in South Africa. The study breaks down the simulation problem into two distinct phases: the conceptual phase discussed in this paper and then later implementation phase that actions the concept. The building of an accurate ABM is dependent of the strength of its conceptual model (Useya, 2011). However, designing a concept model for a system based on human behaviour or choices can be a very complex subject (Berger et al., 2001).Often it will involve agents with potentially irrational behaviour, subjective choices, and complex psychology (Castle et al., 2006). These factors alone make it difficult to quantify, calibrate and justify certain parameters thus complicating the implementation and development of such a model. The purpose of a model however, including an ABM, is not necessarily to faithfully capture all aspects of a system; but to solely enrich the understanding of a process that is present within a system through controlled computational experimentation (Castle et al., 2006).

ABM conceptual model architecture comprises a three tier design as used and proposed by researchers such as Useya, 2010; Augustijn, 2008. Augustijn (2008) propose the following as components of a concept model for ABM:

- A static model which should show the mobile and non-mobile actors as entities. It is conceptually modelled as a class diagram as seen in Figure 3. Examples of class entities for this case study include migrants, households, services, utilities etc.

- A behaviour model which should define the behaviour of the settling agent's e.g. their rules, what to store in agent memory, actions for decision making. It is conceptually modelled as a flow chart (or agent activity chart) discussed in Figure 4.
- A dynamic interactive model which is based on the sequence with which events occur e.g. simulation timers, events list. It is conceptually modelled as sequence diagram (or agent time spending table) shown in Table 2 of section 5.1

These three tiers are combined through a programming platform on implementation as shown in Figure 2 below. They do not stand as independent pieces but are interlinked such that one feeds into the other to enable the model to be successfully implemented.

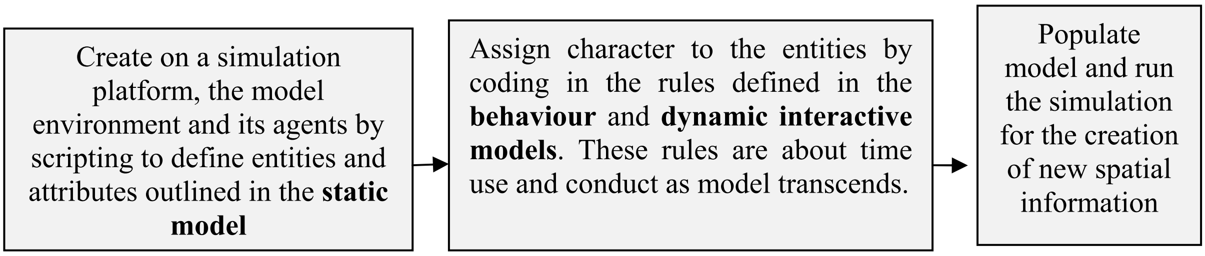

Figure 2. Combined diagram relating the three tiers of the concept architecture

4. Research Methodology based on the Cape Town, South Africa case

Councils and governments require information ahead of time in order to take preventative and adaptive stances to human settlement development, especially in low-lying coastal Cape Town where some land is likely to be flood prone. The Western Cape Province is divided into five District Councils (DC's) that are made up of 24 municipalities with an estimated over 1,369,180 households, 66.3% of which are situated within the Cape Town Metropolitan Municipality (Statistics South Africa, 2011). As of the 2011 census, Cape Town had an estimated population of 3,740,026 distributed on a land area of 2,461 square kilometres (Statistics South Africa, 2011). It is a rapidly growing urban centre with over 129 918 slum settlements within its frame (City of Cape Town, 2012). In 1994, the new government of South Africa inherited a housing crisis with an estimated 7.7 million residing in slums across the country (Fieuw, 2011). The government then proposed amongst other things, a Reconstruction Development Programme (RDP) aimed at providing low cost housing to the poor masses to alleviate the housing crisis. To date over 2,376,675 have been built at national level in an effort to improve urban poverty yet informal settlements continue to grow and pose a challenge to city developer's regardless (National Department of Human Settlements, 2011).

As highlighted above, Cape Town faces challenges with the problem of informal settlements. Several actors play significant roles in the 'theatre' of Cape Town settlement. Apart from settlers themselves, land developer and owners influence patterns as they not only expand housing options but can also shift rentals in or out of favour of the possible tenants from time to time. Different statutory bodies such as government and councils as well as community representation groups are also key actors in the equation as they have the power to influence developer's decisions or developmental factors. Ordinarily one must seek to settle on the most "attractive" space by considering whether it is affordable, within reasonable proximity to services of interest, safe, secure and familiar to the settler in terms of a connection with the surroundings. Therefore the decision to settle informally is motivated by choices between more "attractive" and less "attractive" locations with the given environs (Augustijn-Beckers et al., 2011) as guided by the aforementioned factors.

The main output of this study is a model of informal settlement growth patterns in concept; hence significant effort has been committed to identifying and gathering empirical data for use in the predictive model. This conceptual model will be motivated on social, economic and physical factors:

- Physical factors to be incorporated have to do with proximity to important services, closeness to family or peers, as well as nearness to employment opportunities, terrain suitability. Environmental factors are also important and can be considered under physical factors. These include e.g. presence of swampy areas, slopes, or nature of rugged terrain .
- Socio-economic factors include tenure regimes and costs, demographics, household incomes, etc.

Potential data has been compiled as part of the preparatory work for the model. Table 1 below is a summary of quantitative attribute data that include demographic data obtained from recent population census results and other data custodians that will be used as parameters in the predictive model.

Table 1 Demographic data for input parameters (Data Source: Human Sciences Research Council South Africa[2]and Statistics South Africa Census 2011[1])

Demographic Attribute	Value
Gender distribution; Male: Female ratio[1]	48,2% male : 51,7% Female
Average Household Size[1]	3,6 persons per household
Dwelling Tenure Ratios; Formal: Informal: Traditional / Other[1]	77.6% : 16.2%:6,2%
Total Number of Households, N_0[1]	1 068 572
Population growth rate based on comparison with 2007 data, G[2]	1.1%
% Informal upgraded to RDP in W/Cape[2]	15,7%
% Housing Development annual growth rate X[2]	4,06%
% Living below poverty datum of < R3,500/month/household [2]	42.8%
% National Unemployment[1]	43%

One limitation of compiling the demographic data of Table 1 above is that it is available at various temporal and spatial scales as it is housed at different organisations. So for the purposes of model building some generalisation is adopted in order to best represent the Cape Town case. The Spatial Development Framework (SDF) in vector format for the City of Cape Town (CoCT) is also required as the simulation base map. It is available at (CoCT) in numerous scales of representation. Appropriate scales for the current study would be 1:100,000 or more as there is minimal need for absolute detail. The SDF shows current land uses and future expansion plans for Cape Town. The city also has detailed digital elevation model (DEM) data generated from aerial photography (and recently Lidar) which have been used to interpret and identify settlement and service (electricity, sewage and bulk water) risk areas. In this model risk on the part of an informal settler can also refer to current or competing land uses as well as inhabitable areas. Risk maps are available at the CoCT and will be used to translate spatial risk into risk ratings as discussed in Figure 3 and Section 5.3.

From Table 1, two main income groups are classified as the Low/Unemployed and Medium/High Income. This is based on the poverty ratio set at 42, 8%: 57, 2% of agents, below and above the datum of R3, 500 incomes respectively. These two main groups show different choices regarding settling patterns. However there are several similarities as well between the income groups. For example, generally social relations like blood relations and friendships play a very important role in South African culture. Hence for the purposes of the model and because of certain clauses common in most lease agreements and real estate legalities in the country, the behaviour model discussed in section 5.2, assumes that adult agents can opt to settle with relatives / friends on a temporary basis (set at a maximum of 3 years or 156 weeks). Thereafter they must move as there is a settling cost implication on the household head. Real life scenarios may differ from household to household; this is merely a generalised approach to modelling 'temporary' accommodation.

The ultimate goal of each agent as an entity is to have their own dwelling, so they must seek their own settlement until they have "found" settlement. It is assumed that medium to high income earners will not at any point settle informally in the model. They will settle in planned dwellings and some will move from time to time where necessary but within planned residential areas. There are several residential buildings within Cape Town that have more than one dwelling unit in them hence the inclusion of the *Maximum Occupancy* criteria as a tool for modelling some multi-unit accommodation in Cape Town. The contribution of the RDP is also modelled through upgrading 15.7% of informal dwellings per annum on the model into formal dwelling units depicted in the simulation by a change in dwelling colour (for cartographic clarity) and an update of the *RDP status* under the *House /Dwelling* entity discussed in section 5.3. The model generally assumes that children will settle under the choices of older agents so they are incorporated into a *household*.

5. Concept architecture in detail

Section 3 above described an overview of the conceptual architecture combining static, dynamic interactive and behaviour models. This section then discusses each component in greater detail for clarity. Examples and narratives are given to provide a foundation for the physical implementation phase of the model under discussion and application in future research endeavours.

5.1 Dynamic interactive model: activity diagram

A dynamic interactive model conceptualises how agents will behave as spatial entities during transition over time as the simulation iterates. All agents regardless of income group are simulated to spend their day in a similar manner, with differences only coming in how they make settlement choices where they are then assigned different behaviour rules per income group. In the simulation a "week" is represented as a combination of three time components T_0 (Initialisation: runs for 5 minutes in real time), T_1 (Income generation: runs for 5 minutes) up to and including T_t during which the agents seek settlement for 10minutes in real time. This makes a 20minute slot in real time be equivalent to one week in the model time. After such a complete 20minute run , the time step moderated by a counter increases by 1/52 of a unit to signify increase in weeks until a specified time *n* is reached that is user defined as the time of termination of the particular experimental run as illustrated in Table 2 below. The table is a summary of the activities allocated to the groups of agents , describing how they would spend each model "day" (equivalent to a week or 1/52 year in real time).

Table 2 Daily activities of agents

Time	**Agents**	**Corresponding graphic action of agent in simulation environment**
T_0	Start agent day (allocated 5minutes)	Initiates day. Agent must locate a service centre closest to their dwelling. Agents are seen in motion towards centres.
T_1	Income generating activities or idle time (allocated 5 minutes in real time)	All agent including unemployed ones must maintain an X, Y position for this time space clustered around the service centre. This simulates or represents participation in income related activity including non-formal activity e. g vending, crime and idle time.
T_t	Seeking settlement (allocated10 minutes in real time)	All settled agent relocate to their settlement location while unsettled agents begin to navigate environment seeking settlement, guided by the rules outlined in behaviour model on Figure 2.

We chose to focus on a week's counter because of the rapid nature of growth of informal settlements potentially bringing large change over shorter time scales..

$$T_n = \sum T_i + 1/52 \qquad [1]$$

Where T_n is the time count in weeks or equivalent years at termination and T_i is the time at initiation of the simulation. These can be controlled by the user if desired.

Within the time steps there are other parameters that upgrade in line with demographic data to keep the representation true to reference.These include the number of agents N which increases or decreases based on annual population growth rates modelledas below:

$$N_t = N_0 * (1+G) \quad \text{where } N_t \text{ updates annualy} \qquad [2]$$

N_t is the new number of agents following an increase of G set at 1.1% which is the nett population growth rate of Cape Town that accomodates births, deaths, emigration, migration, relocations and any factors affecting human movement into and out of the city for a year. This rate G% is applied such that it increases the total population by 1.1% per annum, but within that 1.1% growth the ratio of agents is weighted as 42.8%:57.2% Lower and Higher income earners respectively based on demographic data.

In addition the model initiates with a specific number of formal *dwellings* H_0 made up of H *dwellings* per administrative area which together constitute planned settlements based on statistics of current housing unit counts in Cape Town by area. However the numbers of *dwelling*s modelled in the simulation will only be a sample representation and not the actual figures.The model should terminate once available space for formal housing expansion is exhausted based on rates of horizontal sprawl year on year, though in reality vertical sprawl is now also in progress.Vertical sprawl can be accomodated if a value for the planned rate of vertical expansion is known.Increases can be made on the *maximum occupancy* of the *household* entity discussed in 5.3 in the static model to accomodate multi units per *dwelling* . The equation describing increase in number formal dwellings units annually:-

$$H_t=H_0\ (1+X) \quad \text{where } H_1 \leq H_{max} \qquad [3]$$

where H_t is housing units at time t in a a given administrative area, H_0 is housing units at previous time step, H_{max} is maximum number of housing units for a specific area calculated by dividing available space by average parcel size for that area . X is a developmental growth rate factor quoted at 4,06% per annum.

A different approach is adopted in non-formal settlements. Open spaces are initially set at a settling cost value of zero meaning settling on them is at no cost. However as the model runs and informal settling has begun in an area the value increases by an abitrary value of 0.01 per time step just to show that the attractiveness of that space increases as other settlers have started settling informally in the area .The number of locations for informal dwellings in open spaces are modelled as finite and directly propotional to the unit area of the space. Average informal dwelling dimension is set at 16 square metres per unit as revealed in a research by Barry et al, 2005 on Cape Town slum charectaristics . Hence :-

$$U_{max}= Area_{max}/16 \qquad [4]$$

where $Area_{max}$ is the maximum area covered by a specific open space and U_{max} represents the maximum possible number of informal households who can settle in that area.

5.2 Agent behaviour model: flow chart

The behaviour model in Figure 4 shows the flow of settling decisions by agents. Low income/unemployed individuals will first opt for a stay with a relative / friend (set at a 3 year maximum stay, then agent is seen searching again). If not "successful" by virtue of failing to match agent attributes with favourable housing attributes such an agent either finds an affordable low cost house in formal areas or opts for informal settlement on available prime open spaces of lowest settling cost. Higher income earners simply settle at the first "favourable" formal unit they encounter as they navigate the spatial environment. "Favourable" is decided by the first match of agent to household attributes that agent encounters.

5.3 The static model: Class and relationships diagram

The static model in Figure 3 shows a representation of key entities identified for the slum growth model including mobile (settlers) and non-mobile agents (increasing households) in the simulation. A total of 13 entities as well as the parity of their relation one to another are identified. The nature of relationships between these entities are also indicated in the format one to one (1*1), one to many (1*m) and many to many (m*m). 1*1 is where there exists for any single entity a corresponding link of a related entity. 1*m is for that one entity, several examples of another related entity exist, and m*m is where an entity can have several examples of another entity and vice versa. Entities are made up of a collection of descriptive attributes that can be integer, Boolean, or text in nature amongst other. The relationships between different entities are shown in Figure 3 as linking arrows with a descriptive e.g. an agent <u>is part of</u> a household. This class diagram is important in highlighting not only the entities but also all attributes that will be modelled around each entity in the simulation.

Agent refers to inhabitants of Cape Town who make settling decisions. The *agent* is unique with a unique identifier, they have gender, race, and a specific X, Y location within the spatial framework at time t. *Agents* are part of a *household* (1:1) which is family with a relation identity that is useful for settlers seeking a relative. A *house dwelling* regardless of whether it is formal or informal, has a one or more households living in it and is assigned a settling cost (1:*). The *house/dwelling* is housed in a unique land parcel collectively under a community (*:1) where several communities are part of a *zone/administrative* boundary (*:1). Different *zones* have assorted *land uses* that are housing and non-housing related (1:*). An *unoccupied land parcel* is a unit without a building on it and one or more such units form an *open space* (*:1) that is a possible site for informal settling. It has an important attribute defined as the *risk rating* which the agent considers in making a settlement decision. The higher the risk rating the less "attractive" an *unoccupied parcel* becomes. *Occupation cost* is different from the risk rating as this is an arbitrary value that increases as the surrounding areas become occupied in the case of informal settling. In the case of planned areas *occupation cost* takes a value equivalent to the rental or living costs of the unit under discussion. *Transport/Utility networks* and *employment centres* are part of the *services* (* :*) whose proximity settlers consider in their choices to occupy a unit. All these entities collectively make up the Cape Town *environment* (*:1).

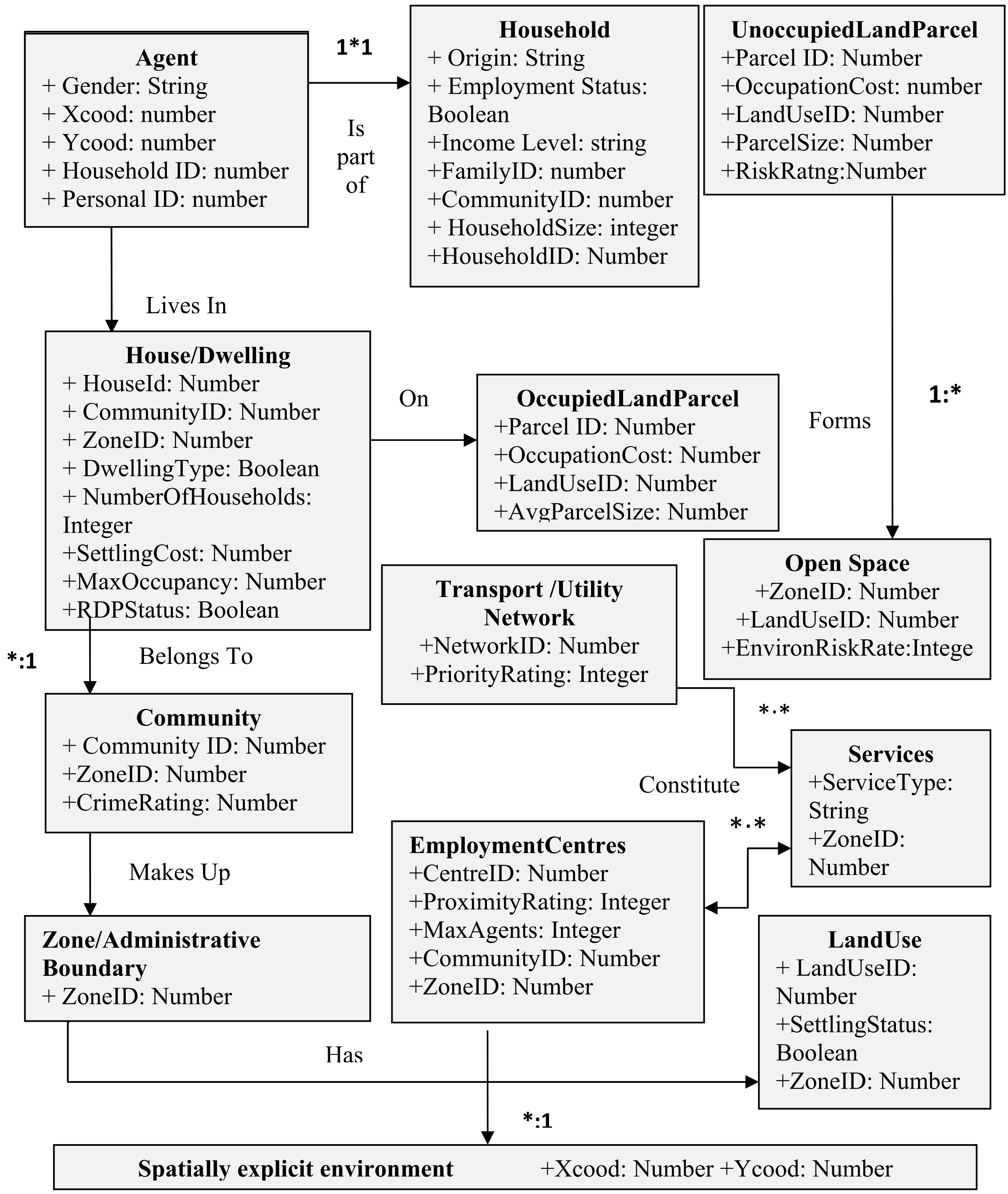

Figure 3. Class diagram of slum growth concept model

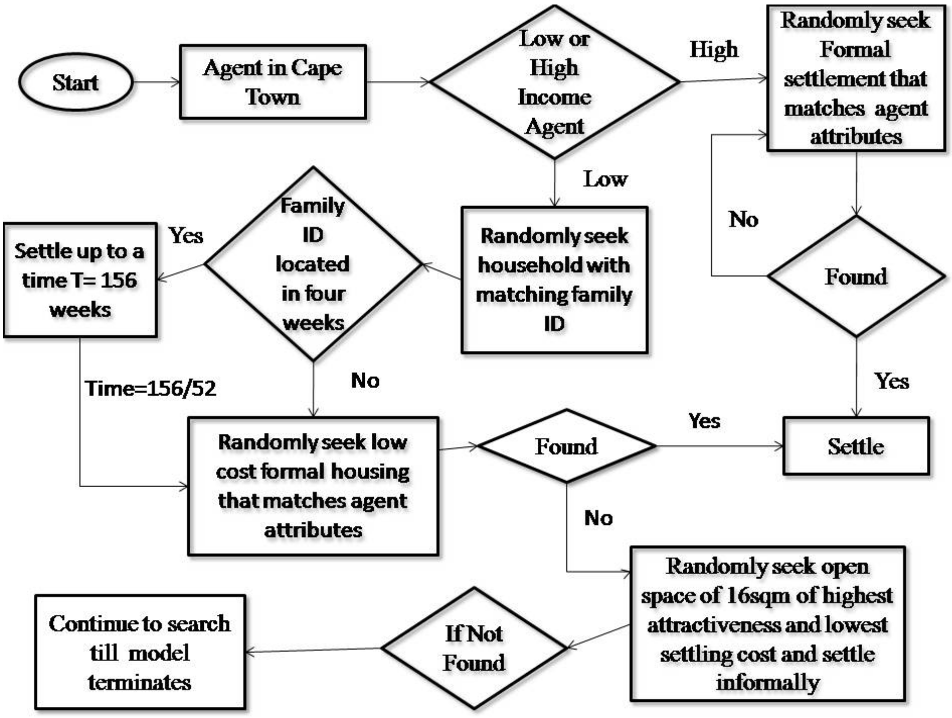

Figure 4. Behaviour of agent seeking settlement

6. Discussion

This study is part of some ongoing PhD research work on modelling pattern and trend information on informal settlements in Cape Town. It is anticipated that the concepts put together for this paper will be a foundation for further experimentation where the model will be physically implemented. Although much effort has been made to fully capture the important details of the settlement scenarios, some limitations do arise that create room for further experimentation and research growth.

Limitations of such a model structure may arise due to the fact that though efforts have been made to source the most recent demographics data on the city, a lot of spatial and temporal generalisation is inevitable in how the data is collected and kept. However mathematical tools such as a "sensitivity analysis" can be used in testing the final model for the extent to which increasing or decreasing particular variables of interest may affect the final result. Where a significant shift is noted then further research on improving the effect of that variable in the model is recommended, whereas low significance of a variable on result is likely to indicate it negligible compatibility. Weighting or use of preference indices based on survey results for choice entities such as service proximity in influencing settlement choice are valid multi-criteria decision making approaches that may yield interesting and perhaps improved results in models of this nature. However the choice of an appropriate statistical approach to multi-criteria scenarios is also dependent on who the audience of the result is and what is of criticality to them. It is difficult to fully model all complexities of human life e.g. some higher income earners in isolated cases may choose to live in slum, not all relatives may accommodate agent, and mixed income families are common in Cape Town. The proposed model is therefore one paradigm of dealing with the slum pattern challenge and can be developed further to fully address new viewpoints. It is hoped that on implementation interesting trends can be revealed that will be useful to planners and policy makers for the alleviation of some of the challenges that informal settlements bring to urban dynamics.

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