Multi-Agent GIS System for Improved Spatial Load Forecasting

(Demonstration)

Cruz E. Borges, Oihane Kamara Esteban, Ander Pijoan, and Yoseba K. Penya

Deusto Institute of Technology, University of Deusto

Bilbao, Spain

cruz.borges@deusto.es, oihane.esteban@deusto.es, ander.pijoan@deusto.es,
yoseba.penya@deusto.es

ABSTRACT

We present here a demo of a multi-agent-system-based GIS application to model human house choosing behaviour. More accurately, this application foresees future energy consumption in order to issue spatial load forecasts and help utilities to resize and adapt electrical infrastructures to cope with committed loads in the middle and long term. We have tested our application with real data of an Spanish city with more than 32 000 customers. The application is fully customisable and presents a friendly user interface.

Categories and Subject Descriptors: I.2.11 Distributed Artificial Intelligence: Multiagent systems.

General Terms: Algorithms, Human Factors.

Keywords: Spatial load forecasting; Agent-based modelling; Agent-based simulation.

Online Material: `http://youtu.be/TszTaNV3ih0`

1. LONG TERM LOAD FORECASTING

The advances in Geographic Information Services (GIS) have paved the way that drives to the world of Multi Agent System (MAS), providing a much easier and tighter coupling. Therefore, it is not surprising to see a Renaissance in GIS applications that address the MAS paradigm (or the other way round). There is an impressive work on agent-based simulations of geographic phenomena, ranging from several aspects of urban modelling [1] to housing choice [3].

Still, further than urban planning simulation, there are several *terrae incognitae* that deserve a closer look and deeper attention. One of the principals among these *El Dorado*, according to its economic importance, is Spatial Load Forecasting, which is the discipline that studies the evolution of electric consumption on a certain place over the years. To our knowledge, the only attempt to address this challenge was our contribution at [2].

Indeed, network planning is crucial, since utilities must be sure that they will be able to cope with the committed energy

supply in the future. The cornerstone to this end is to be able to foresee changes in the consumption behaviour of the clients. Usually, electric demand varies in two axes: vertically, when already existing clients increment or decrement their consumption (e.g. think of new gadgets appeared only in the last decade in each household), and horizontally, when new customers join the system (e.g. the utility gets new clients or the construction of a new industrial area).

Specifically, we deal here with horizontal long-term forecasting (aka *spatial forecasting*), in which as the development turns usually positive (i.e. the consumption grows), tackling this increment means high infrastructures investment. Otherwise, failing to resize the grid according to future demands leads to the inability to cope with load peaks, brownouts, blackouts and, generally, low-quality supply.

Spatial load forecasting is an area that, despite of IT advances, has not evolved much in the last decades: the forecast is roughly based on key socio-economic indicators (e.g. the Gross Domestic Product (GDP)), the expected population growth and sparse computer-aided calculations.

Needless to say, spatial load forecasting addresses simultaneously forecasting of these socio-economic key indicators as well as urban planning. One of the classical hurdles has been that the data needed for calculations has always been released in a proprietary format (if it was in an electronic support at all). Initiatives such as Open Data are closing this gap, enabling to take advantage of all this information in an automated way.

Against this background, we advance the state of the art by illustrating the integration of GIS into MAS and its application to spatial load forecasting with actual data of a real European city.

2. MAS DESCRIPTION

The MAS system presented hereby is able to simulate the variation in the load of the Transformers and electrical substations that a city experiences. To this end, we have modelled human behaviour when choosing a new place to live with two sorts of agents:

Infrastructure agents: These agents mainly represent the plots where a new building can be constructed. Every agent in this category owns a list of the features that its neighbourhood presents, such as the distances d_i to several public facilities (e.g. green zones, public transports, parking spaces, and the like). Table 1 shows a comprehensive list. Moreover, infrastructure agents also know which is

the electrical infrastructure that feeds its needs (in case it does not need a new one) and unitary price of the plot.

Human agents: These agents represent people looking for a new house. Since every person has different preferences about the presence of (or distance to) a particular public facility, we have encoded them in a vector a_i that describes how important each infrastructure is to that particular agent. Moreover, human agent have an individual budget limit. Further, we have identified three primary target groups sharing a common preference pattern: Elderlies, Families and Singles. The accurate values of the preference vector have been issued randomly following the distribution described in Table 2.

After both types of agents have been created, the human agents select the number of infrastructure agents that will be asked for information and then selects the best plot based on the following function f:

$$f(a,d) := \begin{cases} -1 & \text{if plot price} > \text{agent budget} \\ \sum_{i \in I} \dfrac{a_i}{d_i} & \text{in other case,} \end{cases}$$

where a is the preference vector of the human agent, d is the distance vector of the infrastructure and I are the categories in Table 1.

Next, the human agent will try to buy the best ranked plot. In the case that it has already been bought, the agent will try to get the next best one until the plots reach the minimum quality set for this agent. Please note that it may be possible for an agent not to get a plot. Finally, the load generated by this agent is added to the corresponding electrical infrastructure following the function l:

$$l(a,d) := E + I \cdot S \cdot A \cdot P_c$$

where E is the previous load in that particular electrical infrastructure, I is the electrical intensity of agent a, S is the simultaneity factor of the loads in that particular infrastructure, A is the area covered by this plot, and P_c is the power intensity of the area, measure as:

$$P_c := \frac{|B_{300}| \sum_{c \in C_{300}} c_i}{|C_{300}| \sum_{b \in B_{300}} b_s}$$

where B_{300} is the set of buildings within 300 meter radius, C_{300} is the set of clients within a 300 meters radius, $|\cdot|$ denotes the set cardinality, c_i is the contracted power by client c, and b_s is the total surface of the building (measured as the constructed area times the floor count).

Table 1: Factors considered

Factor	Infrastructures considered
HEALTH	Hospitals, clinics
EDUCATION	Schools, colleges, kindergartens, universities
SPORTS	Public swimming pools, pitch, stadiums
CULTURAL	Art centres, theatres, community centres, conference centres, museums, libraries, cinemas
FOOD SHOPS	Food and convenience shops, department stores, supermarkets

Table 2: Agents types and their preferences

Type	HEALTH	EDUCATION	SPORTS	CULTURAL	FOOD	AFFORD
ELDERLIES	1	0.2	0	0.7	0.8	€ 1800
FAMILIES	0.9	1	0.7	0.3	0.5	€ 1750
SINGLES	0.2	0.2	1	1	0.8	€ 1700

3. PROBLEM SCENARIO

This demo present the the run of this model over the city of Ciudad Real, in the south of Spain, using non-realistic conditions. The city is the capital of its region, with around 75 thousand citizens and presents a typical concentric zone model [4]. Moreover, the plot data comes from the national cadestre conflated with the information already provided in OpenStreetMap. The corresponding Utility (a Distribution System Operator) has provided us with client information. There are $\sim 32\,000$ clients, ~ 800 Transformers (feeding an average of 40 clients), and two main primary substations (with 400 Transformers each).

4. IMPLEMENTATIONS ASPECTS

The whole system has been built using a large set of frameworks and tools. The datasets needed are stored and calculated using a PostGIS geographical database. Written in Python, a forecasting program fetches all the needed data, creates and manages the execution flow of all the different agents. These agents are registered in a SPADE platform, which allows them to ask for information and react in accordance to it. On top of these, a Django web server is deployed using Leaflet for dynamic maps, and NodeJS with Socket.IO for pushing asynchronous messages to the web interface in real time.

The video shows the forecasting system trying to predict new settlements in one of the neighbourhoods of the chosen city. The users can define any area from the city, as well as the amount of agents the system will create. When launched, the system retrieves the electric layout and infraestructures inside said area, creates the agents and registers them. Then, the human agents start asking a variable number of infraestructure agents (new construction plots) for their characteristics, in order to select which one fits best their vector of preferences. After finishing the simulation, the demo depicts which agents have bought which plots, whether that was their best choice, and how these new settlements affect the electric grid.

5. ACKNOWLEDGMENTS

6. REFERENCES

[1] T. Baynes and S. Heckbert. Micro-scale simulation of the macro urban form: Opportunities for exploring urban change and adaptation. In 10th *international conference on Multi-agent-based simulation*, pages 14–24, 2009.

[2] C. Borges, Y. Penya, and A. Pijoan. Agent based spatial load forecasting. In *Proceedings of 3rd International Workshop on Agent Technologies for Energy Systems (ATES 2012- AAMAS 2012)*, pages 107–108, Valencia (Spain), 5th June 2012. ACM press.

[3] R. Jordan, M. Birkin, and A. Evans. Agent-based simulation modelling of housing choice and urban regeneration policy. In 11th *International Conference on Multi-agent-based simulation*, pages 152–166, 2010.

[4] J.-P. Rodrigue. *The Geography of Transport Systems, Third Edition*. Routledge, New York, 2013.