GIS and MAS tight coupling for Spatial Load Forecasting

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

Deusto Institute of Technology – DeustoTech Energy,
University of Deusto, Avda. Universidades 24, 48007 – Bilbao, Spain
{ander.pijoan,oihane.esteban,cruz.borges,yoseba.penya}@deusto.es

Abstract. We present here an agent-based system tightly coupled to geographic information systems (GIS). Our objective is to simulate the growth of a city in order to foresee the evolution of the electrical demand in a given zone. The agents are deployed over a GIS-based Multi-Agent System platform where the geographical components have been abstracted from the agent system to the environment. The configuration model uses geographical information to improve the agents' connection and perception of the surrounding environment and based on their choices, we forecast urban evolution and derive the expected increment in electric consumption. We have validated our approach with real data and discuss here our conclusions.

Keywords: Agent-Based Simulation, Geographic Information System, Spatial Load Forecasting, Agent-Based Modelling

1 Introduction

Agent-based modelling (ABM) is experimenting a notable boost in new fields lately due to its versatility and ability to model and simulate human behaviour in very diverse disciplines, as seen in [15,6]. Paradoxically, though ABM is a well-known and intensively used tool in related areas, Spatial Load Forecasting (SLF) remains *terra incognita* for this paradigm.

SLF is a crucial task for the majority of stakeholders in the electric sector, since it is in charge of calculating the evolution of future energy demand in a certain zone. So far, the only attempt to bring together ABM and SLF is, to our notice, [2]. Still, ABM must be coupled tighter to Information Systems (GIS) in order to top forecasting's quality.

We advance the state of the art by describing our experience in integrating an ABM in a GIS along with Volunteer Geographic Information (VGI) in order to obtain an improved SLF system. The remainder of the paper is divided as follows. Section 2 gives a brief overview about the main concepts presented in the research. Section 3 describes both the architecture and logic schema of the application. Section 4 discusses the results obtained. And, finally, Section 5 draws the conclusions of the paper and the future work.

2 World-of-interest

2.1 Long Term Load Forecasting

One of the biggest challenges electrical distribution companies face is the growth in the demand for electrical power. The analysis of these phenomena is crucial since an improper estimation may lead to the saturation of electrical facilities and loss of power supply, along with the consequent economic loss and social distress. Under current economic conditions, this problematic boosts exponentially: distribution companies aim at getting the most out of the existing infrastructures, especially when their renovation can be really expensive. Thus, load forecasts are extremely important for energy suppliers, Transmission System Operators (TSOs), financial institutions, and other participants in electric energy generation, distribution, and retail.

In this venue, there is a special type of forecasting that deserves a closer look due to its economic importance: Spatial Load Forecasting (SLF). SLF applied to LTLF uses a model built on GIS to get together data related to electric distribution, land use and development indicators. In this way, area engineers are able to predict, years in advance, large load additions to the electric system, helping them determine whether the current infrastructure should be upgraded or extended. Failing to do so leads to the inability to cope with load peaks, appearance of brownouts, blackouts and, generally, low-quality supply. The key to this end is to be able to foresee changes in the consumption behaviour of the clients.

The concept of long-term load forecasting involves social, economic, policy and technical issues, to which we must add the limited information and the difficulty to operate with the scarce existing data [23]. Related to long-term load forecasting, horizontal demand growth is also closely linked to urban evolution. In fact, the main forecasting models derive from the fields of geography and sociology. Nowadays, these models are being merged with others stemming from artificial intelligence, integrating the best qualities of both areas: artificial intelligence provides the learning ability and the capacity to adjust existing data, while social and spatial models define the natural behaviour inherent to the problem at hand. The technical literature shows a wide range of methodologies and models for LTLF. Generally, they can be classified in two broad categories: parametric methods and artificial-intelligence-based methods. Parametric load forecasting methods can be classified into three further main approaches: time series, prediction methods, and regression methods [1]. In turn, artificial intelligence methods comprise neural networks [18], genetic algorithms [13] support vector machines [16], and fuzzy logic [7]. Model parameters are estimated using statistical techniques on historical data of the load and the factors that influence such consumption.

2.2 GIS as an environment for MAS based SLF

The exponential improvement in the performance of computer systems has motivated the development of tools that manipulate the geographical characteristics

of an object and model them on a map. In this context, Geographic Information Systems (GIS) offer an appropriate environment for the capture, storage and management of both alphanumeric and geographic information. One of the turning points of GIS is that they serve an important role as an integrating technology, paving the way that drives to the world of Multi-Agent System (MAS) and providing a much easier and tighter coupling.

In addition, within MAS technologies, the concept of environments has been recognized as an important and explicit element which helps model dynamic real world problems. [9] defines the structural parts of the environment that provide the system with a logical definition and abstraction. [21] gives a definition of environment in multi-agent systems, highlighting the exploitable design abstraction as a reference model that can serve as basis for environment engineering. Furthermore, there is a lengthy amount of work on agent-based simulations using GIS, whether it is a geographic phenomena or phenomena with an important geographic component, ranging from several aspects of urban modelling [14,5] to housing choice [11].

The MAS system presented hereby is able to simulate the variation in the load of the transformers and electrical substations located on a certain city. To this end, we have modelled the behaviour, evaluations and decisions a human takes when choosing a new place to live. Our configuration is based on the environmental approach proposed by *Russel and Norvig* [17,22] being:

Accessible The agents have access to the whole environment.

Non-deterministic A change in the state of the environment depends on the management of threads by the Operating System on which the configuration is deployed.

Dynamic The environment can change while the agent deliberated.

Discrete The number of percepts is limited and centralized.

In line with this model, the pseudo code can be described as follows:

Algorithm 1: Pseudocode for GIS-MAS Spatial Load Forecasting

```
procedure RUN-ENVIRONMENT(state, UPDATE-FN, agents, termination)
inputs: the initial state of the environment
while !termination(state) do
    for agent in agents do
        PERCEPT[agent] = Get-List-Greenfields(agent, state)
    end
    for agent in agents do
        ACTION1[agent] = Evaluate-Greenfields[PERCEPT(agent)]
        ACTION2[agent] = Assign-Greenfield[ACTION1(agent)]
    end
    state = UPDATE-FN(actions, agent, state)
end
```

Therefore, our model comprises two different types of agents:

Environment: The environment entities emulate the plots where a new building can be constructed. Every entity in this category has a list of properties representing the characteristics of the surrounding neighbourhood, 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,

these entities are also aware of the the electrical infrastructure that feeds their needs (in case new settlements do not require the installation of a new one).

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

Agent system: These agents emulate the 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 a particular agent i. Moreover, agents have an individual budget limit and a degree of greediness depending on which, they will query a different number of environment entities. 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 using a uniform random variable with the mean described in Table 2 and a 10% of standard deviation.

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

When the agents have been loaded into the platform, they select the number of environment entities that will be asked for information. The agent will then select the plot that maximizes the following function f:

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

where a is the preference vector of the agent, d is the distance vector of the infrastructure and I are the categories in Table 1. Next, the agent will try to buy this plot. In case some other agent has already bought it, the current agent will try to acquire the next best one until the plots reach the minimum desired quality set. Please note that it may be possible for an agent not to get a plot. Finally, the load generated by the current agent is added to the corresponding electrical infrastructure following the function l:

$$l(a,d) := E_t + I_a \cdot S_t \cdot A \cdot P_c,$$

where E is the previous load in that particular electrical infrastructure, I_a is the electrical intensity of agent a (i.e. how much power will the new settlement need), S_t is the simultaneity factor (see Section 3.1) 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, measured as:

$$P_c := \frac{|B_{300}| \sum_{c \in C_{300}} p_c}{|C_{300}| \sum_{b \in B_{300}} s_b},$$

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, p_c is the contracted power by client c, and s_b is the total surface of the building (measured as the constructed area times the floor count).

3 Infrastructure

The system modelled uses very different frameworks in order to take advantage of all the benefits each of them gives and make the platform fully functional and scalable.

3.1 Data

Current datasets cover Ciudad Real, a Spanish middle-sized city with about 32 thousand power consuming clients and a surface of 400 km^2. Electric infrastructure and clients' measurements were provided by the corresponding utility (Gas Natural Fenosa, a Spanish Distribution System Operator [DSO]) while buildings and landuse data was obtained by conflating the Spanish cadastre records with the VGI source OpenStreetMap [3]. Both datasets are stored in a PostgreSQL relational database bolstered with the PostGIS geographical extension for manipulating spatial data. Nevertheless, in order to extract more accurate conclusions, we had to do some previous pre-calculations.

On the one hand, each plot was assigned all its near basic services and properties. Local authorities define an area is accessible to citizens if it is within a walking distance of 300 meters, which would take 5 minutes by foot. A spatial query fetches all the facilities described in Table 1, calculates the straight-line distance from the given plot and normalizes it to $[0, 1]$.

One of the problems faced when working with developable land use, also known as greenfields, is that, though not yet urbanized, some of these areas have already been split into smaller parcels while others comprise a whole rustical zone. The clipped greenfields give some clues about the type of buildings they may contain. Without such information, it is hard to determine the type of construction and therefore how many citizens the greenfield will house. In order to overcome this problem we pre-calculated, using the spatial moving window smoothing [12],

the type of possible building each greenfield could contain according to all adjacent existing buildings within 300 meters. In addition, Spanish cadastre data contains extra information about the number of floors or levels of the existing buildings. Using the cadastrial reference (a unique identifier for all cadastre cartography), this information can be linked to its respective spatial geometry, therefore completing our GIS with third dimension data. The consequence of this estimation may be an excess or lack in the real number of citizens assigned to the greenfield, since the height and size of the real buildings may vary.

In addition, for a more precise distribution of new settlements, plots were also given a price. Although the Spanish cadastre registers the price for each plot, said information is private and is not provided in their open-data initiative. The most detailed prices found were extracted from recent appraisals performed by the appraiser Tasamadrid [20], which provides average prices per square meter grouped by postcode.

Finally, each plot is assigned a transformer substation, which the new settlements will connect to. The process is as follows: first a Voronoi diagram is calculated from the set of transformer substations that have more than one client attached (single-client transformers are owned individually, which means that they are not accessible by the DSO). Then, the plot connects to the transformer which area of influence intersects more with its own surface.

On the other hand, each transformer t was assigned a simultaneity factor S_t using electric measures of already existing infrastructures and comparing them with the power contracted by the clients. The real power used by electronic equipments is often less than the rated power, so it is rare in reality that all loads operate simultaneously. Since the electric grid and its elements need to be sized in order to manage demand peaks, the simultaneity factor is time independent and is calculated using the maximum power demand. It adjusts the theoretical total consumption of the clients to realistic conditions and ratio of usage which usually is around a 40%. However, the DSO's dataset did not include power measurements for the transformers. The lowest level of the electrical grid at where we had real measures was at substation outputs. Therefore, we had to calculate the simultaneity factor at this level, inheriting the simultaneity factor to all the transformers connected to it. The formula used is:

$$S_t := \frac{r_s}{\sum_{t \in T_s} \sum_{c \in C_t} p_c},$$

where r_s denotes the maximum measure registered at the substations output s, T_s denotes the set of transformers connected to that substation output, C_t denotes the set of clients connected to transformer t and finally p_c denotes the contracted power of client c.

By combining this data, when an agent is assigned an available plot, the system analyses the consumption of the neighbouring parcels and size of the buildings in order to predict how much power this new settlement will need. Said amount is then added to the total load of the transformer from which the plot feeds.

3.2 Implementation

Written in Python, SPADE is a free software multi-agent system platform based on the instant messaging XMPP technology [8]. The most noticeable features include support for virtual organizations, presence notifications, compliance with the FIPA standard, P2P communication between agents, remote invocation of services using the standard XML-RPC, inclusion of multiple knowledge-based engines, such as XSB-Prolog, SWI-Prolog, Flora-2, ECLiPse-Prolog and SPARQL.

Although the implementation of agents in SPADE is quite straightforward, we found some difficulties and drawbacks on the real experimentation. While SPADE provides many utilities for the construction of the infrastructure, given that our project does not need distributed agents, the heavy communication protocol that SPADE deploys has become more of a limitation than a facility. As the amount of agents starts to increase, operations like registration and intercommunication between agents become slower. This makes big simulations very heavy or directly unmanageable. Executions in a big server showed that the maximum amount of agents SPADE could create, while being fully functional, was around 600, including both agents and environment entities.

All the logic and data manipulation is done in a control program coded in the Python. Thus, through inheritance of SPADE's main classes, the agents are provided with tools to access the platform basic functions. On one hand, several types of agent can be registered on the Directory Facilitator, under the same classification. This allows other agents to retrieve the name of agents of a certain type. On the other hand, each type of agent defines a behaviour (execution flow) to be carried out, whether it is cyclic (a behaviour that repeats itself either while the agent is alive or until a certain condition is met), or one-shot (a behaviour that takes place only once). An agent can have multiple behaviours, where each behaviour defines which kind of messages the agent will receive along with the coded logic to be executed in every case.

The program receives the simulation zone and the amount of different agents to be created from the command line. Once all the information is gathered, it starts fetching data from PostGIS, creating the agents and registering them in SPADE platform. When the agents become alive, they start executing their pertinent behaviours, which involve, sending and receiving messages, as well as taking decisions based on their logic.

A more detailed explanation of the implementation can be consulted in [4].

4 Experimental Results

Despite the spatial data being only a snapshot of the city in 2013, all electric power clients are geolocated and have a registration date. From this, we can assume that the date of the building's creation is the same as the first client assigned to that particular building. Therefore, we get a complete historical map of the evolution of the city and can determine which areas were inhabited through years. Nevertheless, we cannot ensure when did the rural areas were zoned into

greenfields as the status of the plots change by local laws and is not recorded in public databases.

We have defined different metrics in order to test the results obtained with this model. The error can be split into two categories: spatial errors and effective errors.

Spatial Errors: In this category we have errors related to the spatial component of the forecast. Namely, we measure how many agents correctly select the year a plot that is going to be built (*hits*), how many agents incorrectly select the year a plot is going to be build (*semihits*) and how many agents have completely failed by selecting a greenfield that even today has not been built (*fails*). Namely, we have measured:

$$hits := \frac{1}{4}\sum_{y=2005}^{2008}\frac{\frac{a_y}{b_y}+1-\frac{k_y}{g_y}}{2}, \qquad fails := \frac{1}{4}\sum_{y=2005}^{2008}\frac{\frac{k_y}{g_y}+1-\frac{a_y+f_y}{b_y}}{2}$$

$$semihits := \frac{1}{3}\left(\frac{f_{2005}+f_{2006}+f_{2007}}{b_{2006}+b_{2007}+b_{2008}}+\frac{f_{2006}+f_{2007}}{b_{2007}+b_{2008}}+\frac{f_{2007}}{b_{2008}}\right),$$

where a_y denotes the number of agents that correctly select a plot that is built on year y, k_y denotes the number of agents that incorrectly set of a greenfield on year y, f_y denotes the number of agents that incorrectly set on a plot on year y but the plot is going to be built on the following years, b_y denotes the number of plots that have been built on year y and finally g_y denotes the number of greenfields on year y.

Moreover we have calculated the probability of obtaining the same result at random (*prob*). Namely, this procedure measures the probability that our model has not actually improved a random process. Using previous notation, this probability agrees with the probability of a_y matches on a binomial random variable with b_y repetitions and probability $\frac{n_y}{b_y+g_y}$ where n_y denotes the number of agents dispatched on year y. Namely, using the standard statistical notation for probability:

$$prob := \Pr_{\mathrm{B}\left(b_y, \frac{n_y}{b_y+g_y}\right)}[X = a_y].$$

Effective Errors: In this category we measure the load forecasting error. Traditionally, this error is calculated using the MAPE error [10]:

$$mape := \frac{1}{4|S|}\sum_{s\in S}\sum_{y=2005}^{2008}\frac{|r_y^s - p_y^s|}{r_y^s},$$

where S denotes the set of substations, $|\cdot|$ denotes the set cardinality operator, p_y^s denotes the model's forecast for the maximum load of substation s at year y and r_y^s denotes the real one.

Please note that this value will be very high as there are a lot of cases where the clients have not been connected to the nearest transformer due to technical issues impossible to model. In order to mitigate this problem, we could measure

the error at substation level but this would blur the results and hinder the possibility to identify zones where the model does not apply. Moreover, the calculation of this value is quite complex due to the number of database queries that need to be performed which, in turn, increases the execution time of every simulation. The results obtained confirm the previous statement since the variance of the measurement between simulations is high.

For each independent year which electrical growth we want to forecast, the validation process creates a historical map that describes the status of the buildings of the city. In addition, it creates several distributions of agents in order to contrast the process outcome with the real settlements:

Environment: The validation process identifies the buildings that were registered as such from a given year on and marks them as available greenfields, considering the date the building was created is the same as the oldest settlement registered on said building.

Agent System: All the scenarios will create the same amount of agents as new settlements that appeared on that year. The main difference will be the amount of agents of each type created in every case.

Greediness: We have validated the system considering agents with and without greediness. The best results are given by the experiments that do not consider agent's greediness because being aware of the whole environment avoids agents getting stuck on a local maxima.

Plots price: The unitary price of the plots is calculated using recent appraisals performed by the appraiser Tasamadrid, but there is no accurate way of knowing prices of previous years. For these validations the agents' affordable price has been increased, so they are able to choose the best available greenfield found without being limited by its price.

The experiments run intend to validate the forecasting ability of the system for one year ahead forecasts. This means that each result is evaluated independently, and the outcome is not considered for the following evaluation. The results of the experiments can be seen on Table 3.

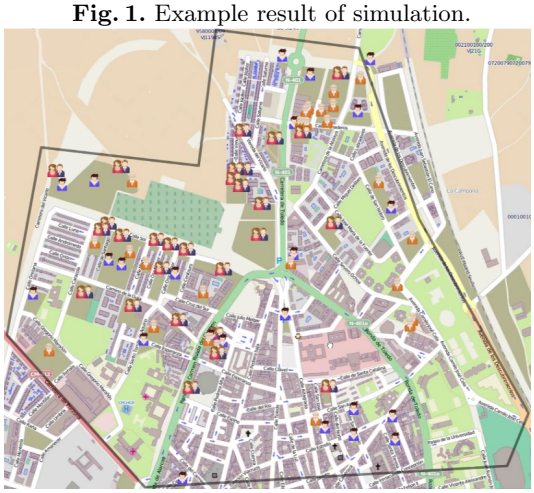
Table 3. Experimental results for the different agent type composition. Mean values for years 2005–2008. All measures are in %.

Model			Results			
Elderly	Families	Young	*hits*	*semihits*	*fails*	*prob*
100	0	0	51.95	17.47	48.05	5.72
0	100	0	54.20	17.08	45.80	6.29
0	0	100	53.64	19.03	46.36	6.73
33	33	33	48.71	16.89	51.29	5.56
66	33	0	48.06	17.78	51.94	6.27
66	0	33	49.68	19.11	50.32	6.74
33	66	0	46.70	18.58	53.30	7.27
0	66	33	49.90	18.33	50.10	6.74
0	33	66	48.63	17.43	51.37	5.89
33	0	66	46.55	17.91	53.45	6.33

These results show how different agent types distributions affect the accuracy of the prediction delivered by our model. As the typical housebuyers in Spain are families, it is expected that models with a high percentage of families agents perform better than the rest of distributions. The results confirm that hypothesis. The best agent mix consists on only agents of Family type while in the mixed cases, the cases with high percentage of Family agents perform at least as well as the other. Although *prob* column is consistently over 5 % please note that this is not a p-value; even more, note that this is not a statistical model but a forecasting model [19]. This column should be interpreted in the following terms: as we have presented 10 experiments and the probability of the model being a random process is, in the worst case, around 7 %, therefore, only the results of one of the experiments could be due to chance while the rest of them are due to the model correctly emulating human behaviour. For that reason, we can conclude that the model gets right the 70 % of the greenfields assigned ($hit+semihits$).

Qualitatively, we can see that the solutions follows the logic imposed by the vector of preferences in the settlement of the agents. As can be seen in Fig. 1, agents of type Elderly and Families prefer areas close to hospitals and supermarket, while Young agents prefer those close to leisure and sport centres.

Fig. 1. Example result of simulation.



5 Conclusions

Even though Spatial Load Forecasting is a sound approach, it has some limitations. It does not replace the experience and knowledge of network and area engineers. However, it allows to perform simulations that would otherwise be difficult to recreate. In our case, we found limitations on the chosen middleware, since it is more oriented towards small scaled and distributed problems. We believe that an ad-hoc implementation as well as the use of another middleware can be more of an advantage if the system requirements are well defined. The development

proposed needed a greater amount of computing power to make data calculations and to support a great number of agents than robust communication protocols.

However, splitting the area into smaller parts has facilitated the pertinent calculus as our type of problem allowed such division. This affects both the performance of the system and the granularity of the results. Even when determining prices, it is easier to calculate and gather a greater amount of data about certains parts of the city instead of the whole area.

On a different note, new open-data movements offer a whole new perspective for projects and developments. These project has benefited from both the opening of data from public administrations, such as Spanish cadastre, and Volunteer Geographic Information like OpenStreetMap. Although some of these datasets need a preprocessing stage, they give added value to the significance of the results.

The future work in this area will involve increasing the forecasting horizon to a five-year prediction and reassigning some of the clients to their corresponding transformer substation. Over the years, the resizing of the power grid and other technical issues have resulted in new settlements being connected to infrastructures to which they do not originally belong. This affects the quality of the results, due to the impossibility to model each particular case. Finally, we are looking forward to adding an evolutionary algorithm in order to train the model with the optimal parameters.

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