Agent Based Spatial Load Forecasting

(Extended Abstract)

Cruz E. Borges, Yoseba K. Penya and Ander Pijoan
Deusto Institute of Technology, DeustoTech Energy, University of Deusto, Bilbao, Spain
{cruz.borges,yoseba.penya,ander.pijoan}@deusto.es

ABSTRACT

Long-term load forecasting aims at predicting the evolution of the electric consumption in a certain area in order to resize the grid in accordance. There are two components to study: the increment in existing consumption and the appearance of new clients. We focus here on the latter. With this purpose, we present an ongoing work that applies agent-based modelling to this end. Representing each existing electric customer by an agent, candidate agents will decide their settlement based on their inquiries to present agents on their likes and actual urban constraints obtained from real sources (e.g. prohibition to build upon a lot marked as a park). We will test this system with a Monte-Carlo simulation and compare the obtained results with real data to validate our approach.

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

1. INTRODUCTION

Network planning is a crucial activity that utilities have to carry out in the long run in order to assure supply in the future. Usually, electric demand grows in two directions: vertically, meaning that already existing clients increment their consumption (think of the new consumers and gadgets that have appeared only in the last decade), and horizontally, meaning new customers checking in into the system (e.g. construction of a new building or a new industrial area). Specifically, we focus here on the horizontal long-term forecasting (known as *spatial forecasting* in the literature). Tackling this expansion involves high investments in infrastructures; in case the grid is not accordingly resized, it will not be able to cope with load peaks in the long-term, therefore leading to brownouts, blackouts and, generally, low-quality supply.

This task has not evolved much in the last 50 years: sparsely aided by computer calculations, the prediction is mainly based on key socio-economical indicators as the Gross Domestic Product (GDP), or the expected population growth. Moreover, the advent of the so-called *smartgrids* has further complicated the situation since utilities are now forced to plan the spreading of distributed energy resources and, soon, the influence of electric vehicles.

Surprisingly, agent-modelling has not been reported to be used for this purpose. It is a mature discipline that has been successfully applied to the study of many situations in which human actors participate [2] such as the simulation of price bubbles in markets [6], several aspects of urban modelling [3], [1], housing choice [5] or even culture's influence on trade processes [4]. In all cases, agents interact with other agents and the environment through a set of well-defined relationships (e.g. like/dislike) [1].

Needless to say, spatial load forecasting combines urban modelling and also economic key indicators prediction. Traditionally, data on these subjects has been released in a proprietary format or not in an electronic support at all. The explosion of Geographic Information Services (GIS) and the apparition of 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 will advance the state of the art in two ways. First, we will develop, for the first time, an agent-based spatial load forecasting system. Second, we will use standard open data GIS sources to allow agents acquire real information on the environment and act in consequence.

2. MODELLING SPATIAL FORECASTING

The objective of our system is to obtain an ensemble forecast the apparition of new electric clients and their typical demand in a certain area in the next 5 to 10 years. With this problem in mind, we have divided the target plot of land in lots according to the information extracted from the respective cadastre (which also helps us to define the types of the lots, including those susceptible to host new buildings or industrial areas). Then we have designed a multi-agent system in which agents represent a single electric supply and new incoming agents wanting to establish themselves in the area choose the exact lot according to possible construction constraints and their interactions with agents already established there. Consequently, there co-exist three different agent classes, as depicted in Fig. 1. **Fixed** agents (in blue) are associated to areas in which building is not allowed (from green zones and roads to shopping centres, hospitals or public transport facilities). Our model does not forecast the apparition of these massive infrastructures since their location is non-stochastic (i.e. depends on politics, laws, etc.). Nevertheless, we model them due to their influence in housing choice.

Settled agents represent buildings, individual households, shops or any kind of existing constructions. Every agent has a vector of variables encoding its preferences on the neighbourhood and an electricity consumption profile. Hence, **candidate** agents, desiring to find the most convenient location to settle down in the target area, will query settled and fixed agents for their view of the neighbourhood. As the preferences of settled agents and the candidate one can be different (e.g. a franchise looking for a new location in a single-family houses suburb), candidates will have to infer the type of the queried agents in order to weight their answers. Adding this information to the one retrieved from the environment (places allowed to build, close interesting facilities, etc.), candidates will re-construct their fitness function about the entire zone taking into consideration the vector of preferences and then will take a decision about the empty lot in which to establish themselves.

Now, running this model with a number of candidate agents will end up issuing a possible future scenario so we will integrate it within a Monte Carlo simulation of the spatial load growth in order to provide an ensemble forecast. Therefore, we will classify the output of every repetition so at the end of the process we will have a distribution of diverse *spatial load growth models* as well as their associated probabilities. Combining this result with the growth model of every type of load (obtained as aforementioned with other methods) we will issue our ensemble forecast of the spatial load growth of the city.

The overall process presents three main steps. First, **Data Acquisition**: retrieving the data from open GIS sources such as OpenStreetMap, National Cadastres and National Statistics Agencies, we will generate the initial state of the target canvas, including defining fixed agents and the initial population of settled agents and marking the available lots and their maximum load capacity. Second, **Query**: the set of candidates will consist on different types of agents (shops, a house, etc.) generated with respect to a type probability distribution. Note that their vector of coefficients will be randomly computed based on the probability distribution of their type. In this step, they will gather information on prospective lots (the amount of queries will be limited). Third, **Decision**: candidates will compete for the free locations, which will be allocated in a first-come-first-served basis (in a more advanced stage of the project we will design a mechanism to regulate this competition). To this end, candidates will pre-process the gathered data, then adjust an interpolating model to it and try to lock the lot with the best quality according to their preferences. If they do not manage it, they will try the next choice until they succeed or fail. Finally, established candidates will then transform into settled agents.

3. EXPERIMENTS

In order to validate our approach, we will compare the issued ensemble forecast with the real development of a city in Spain (Ciudad Real) in the following way. First we will obtain the spatial probabilistic distribution of the most likely scenario selected by the Monte Carlo simulation. Please note that this task can be carried out in parallel and, thus, does neither present scalability nor computational problems.

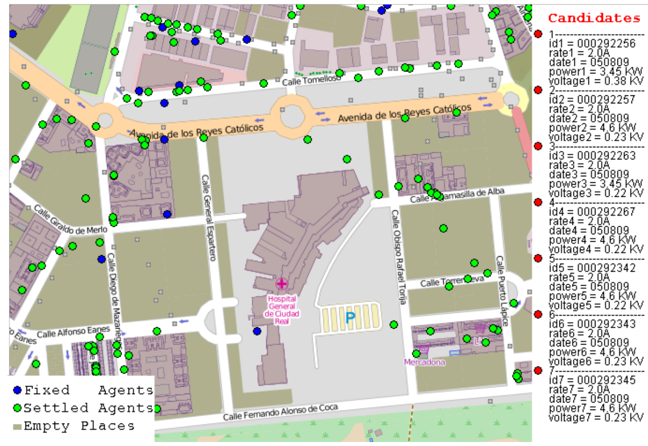

Figure 1: Snapshot of an experiment

Then we will calculate the Hamming and Manhattan distances between the real occupation and the expected value of the occupation of free lots in this most likely scenario.

Currently, we have finished the data acquisition and the query modules and are now working on the decision module and the integration in the Monte-Carlo simulation framework. Next tasks will involve providing intelligence to the candidate agent to enable it to perform the right queries and to take the optimal decision. Since they may exist different strategies, we will define several levels of intelligence (zero, local, evolutionary and *God*) to test multiple combinations of them. Similarly, in the decision phase, candidates must infer information from the data provided in the queries. More accurately, they have to guess the type of the inquired agent. In order to do so, we plan to apply a zero intelligence method or a learning method (Bayesian Networks).

4. REFERENCES

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

[2] I. Benenson. *Agent-Based Modeling: From Individual Residential Choice to Urban Residential Dynamics*, chapter 4, pages 67–95. Oxford University Press, London, 2004.

[3] A. Crooks, C. Castle, and M. Batty. Key challenges in agent-based modelling for geo-spatial simulation. *Computers, Environment and Urban Systems*, 32:417–30, 2008.

[4] G. J. Hofstede, C. M. Jonker, and T. Verwaart. Computational Modeling of Culture's Consequences. In 11^{th} *international conference on Multi-agent-based simulation*, 2010.

[5] R. Jordan, M. Birkin, and A. Evans. Agent-based simulation modelling of housing choice and urban regeneration policy. In 11^{th} *international conference on Multi-agent-based simulation*, pages 152–166, 2010.

[6] K. Steiglitz and D. Shapiro. Simulating the madness of crowds: price bubbles in an auction-mediated robot market. *Computational Economics*, 12:35–59, 1998.