A Hybrid Multi-Agent/Spatial Interaction Model System For Petrol Price Setting

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Biography

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GMAP Limited is a market planning consultancy which provides strategic location guidance to retail and service businesses.

Introduction

This paper focuses on using agent systems to model complex locally interacting dynamic systems. In particular, we have an interest in spatial price variations within competitive local markets, and a specific interest in the petrol prices market. We will present the development of an agent based model for petrol prices and consider the effects of different strategies for controlling the price of each petrol station. The model can be compared to an existing data set of real petrol prices collected over a two month period to determine which strategies are most effective. We shall also discuss the equilibrium behaviour of the optimal model and look at how the model predicts the spatial diffusion of price changes through the system.

Agents

Agent systems are a relatively new paradigm for developing software applications. Their vast potential in designing and building complex systems (Jennings, 2000) coupled with the increase in computing power over the last decade, has resulted in this technique becoming the focus of increased research. There is no universal definition of an intelligent agent (Franklin, 1996) with researchers continually debating whether definition should be by an agents application or environment (Goodwin 1993; Brenner 1998). With an ever-increasing list of agents appearing (Nwana, 1996), the most useful characterisation comes from Woolridge (1997):

"An agent is an encapsulated computer system that is situated in some environment and that is capable of flexible, autonomous action in that environment in order to meet its design objectives".

This approach is well suited to geographical applications where there is a discrete set of spatially distributed entities which interact with each other, and their environment.

Application

Petrol pricing exists within a complex network of subsystems, subsystem components, interactions and organisational relationships. In simplistic terms, changes in petrol prices at a local level are influenced by location of competitors and amount of custom. At a higher/national level, influences such as taxation and crude oil prices become significant. All these factors interact to affect the final price.

Agent architectures supply a methodology for building agent systems that specify how agents may be decomposed into component modules, and how these modules interact with their environment (Maes, 1994). One of the most common architectures are multi-agent systems (MAS). These systems are heterogeneous with no strong assumptions regarding the cooperation of the agents. Agents in a MAS environment can exist with no global control or globally consistent knowledge. In complex systems such as petrol pricing, this is advantageous because petrol stations are discrete entities with their own price setting strategies. Using this framework, it is easy for individual petrol stations to implement different price setting strategies, to model for example, the pricing policies of different multinationals or supermarket chains.

Development

The agent model was developed with an object-orientated language (Java). Individual petrol stations were created as objects and supplied with knowledge of their own price and that of their neighbours. Each petrol station is able to set their daily price based on various strategies, for example, limiting the amount by which they can undercut their neighbours. It is also possible to assign individual petrol stations different pricing strategies, for example, setting the ESSO stations to undercut all competitors within a 3km neighbourhood.

One of the strategies employed was the use of a spatial interaction model. Traditionally, spatial interaction models are used for what-if? scenarios (Birkin et al., 2002). For example, what will happen to the sales of supermarket X if supermarket Y locates nearby? Within this model, they are used to calculate volume of sales information which will be fed to each agent (station). This information will be used to calculate the amount of profit that is being made. The petrol station will then implement profit maximising strategies based on this information.

The interaction between the agent model and spatial interaction model can be summarised as:

1. The agent model is initialised with the real data (Day 0).
2. Additional data e.g. ward data is read into the SIM.
3. The fuel price and station location data is passed to the spatial interaction model.
4. The spatial interaction model calculates fuel sales for each station.
5. The fuel sales are passed to each station. Different garages can use this information in different ways depending on rule assignment.
6. Each agent calculates its new price and the simulation is returned to step 4 until equilibrium, or a set time limit is reached.

Diagrammatically, the interaction between the two models can be expressed as:

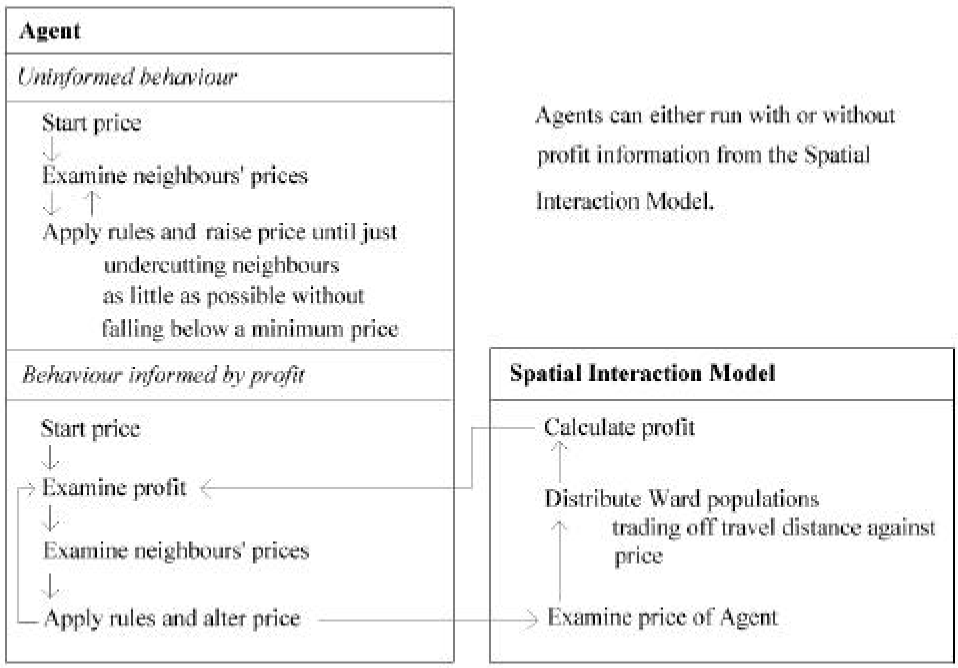

Figure 1: Conceptual representation of the interaction of the agent and spatial interaction model.

Results & Discussion

The petrol price model has been tested against known data for pump prices in the West Yorkshire area in the months of July and August 1999. The results using strategies based solely on the price of the neighbouring stations (no involvement of the spatial interaction model) showed that the agent model was representing some of the processes within the system. The best model performances came from simulations that hit equilibrium rapidly. In these cases, the agent model was not modifying the prices so the results were effectively the same as doing nothing (Figure 2). In reality, the primary motivation for a petrol station is the maximisation of profit which these strategies cannot capture. This information on sales (and hence profit) was incorporated by building and attaching a spatial interaction model to the agent model. This hybrid agent model has a sounder theoretical basis (it models real processes), but by solely assessing Figure 2 does not appear to improve on the performance of the agent model. However, this is misleading.

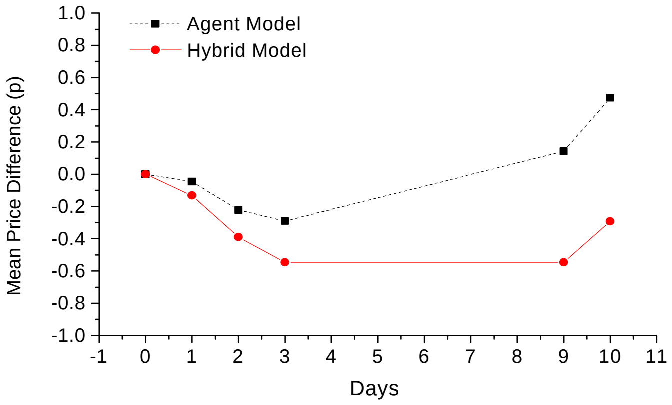

Figure 2: Graph showing the comparison of the trends of the mean price difference for the agent and hybrid model over time.

A better test of the performance of the two models is to assess whether they can reproduce the spatial variations in price observed in the real data. The agent and hybrid model were run with all the petrol stations being assigned the same initial price. The model was allowed to run to equilibrium. No price changes were observed with the agent model (Figure 3 (a)), since the rules used assumed that this was a stable situation. The hybrid model performs much better (Figure 3 (b)), and is beginning to reproduce price variations similar to that observed in the real data (Figure 3 (c)), for example between high priced rural areas and cheaper urban areas. The model still needs to produce a little more price differentiation within the urban areas. This might imply that the rules for rural and urban agents needs to be differentiated in future experiments.

Conclusions

The results of this work show that the creation of a hybrid agent model combining the flexibility of an agent model with the ability of a spatial interaction model to calculate sales information can provide a powerful way of modelling fixed markets. Further investigations will be presented involving idealised cases to study the equilibrium of the system and the spatial diffusion of price changes.

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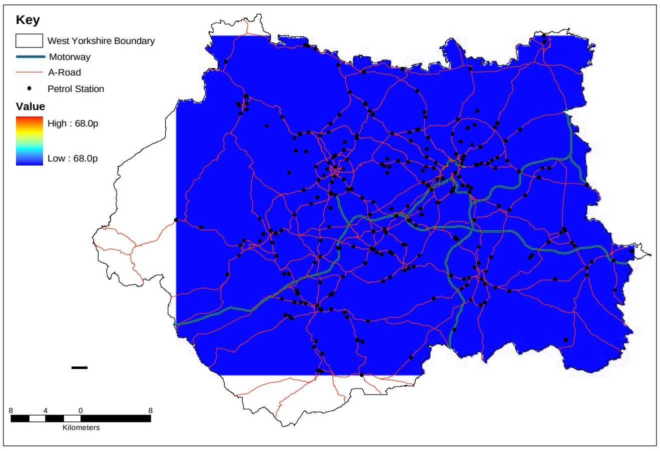
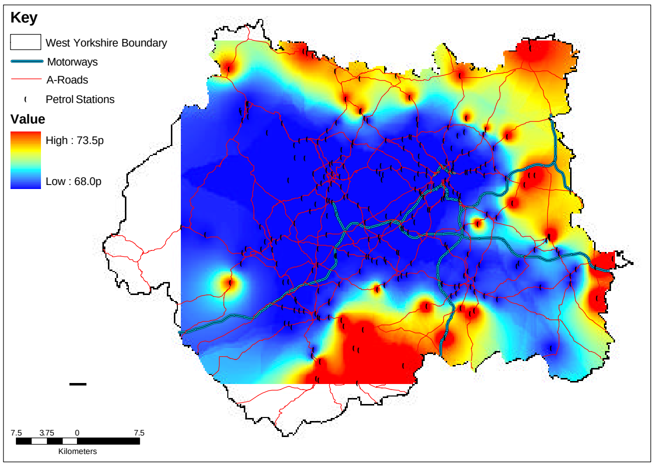
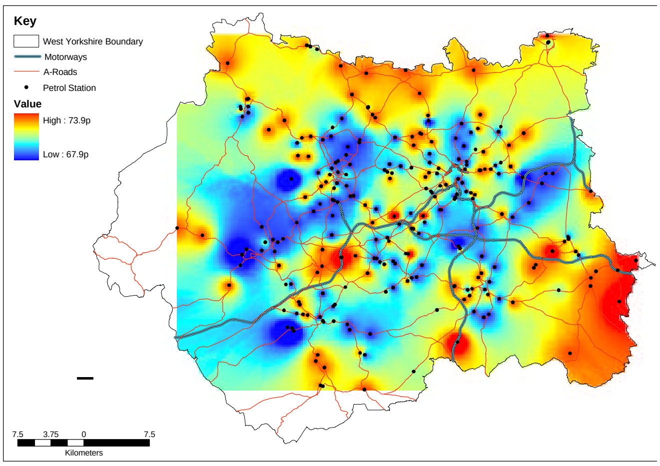


(c) Agent Model



(b) Hybrid-model



(c) Real Data (Day 1)

Figure 2: Interpolated price surface maps showing the final equilibrium state of the agent model (a), hybrid model (b) and the real data for the first day (c) as a comparison.