Optimizing the Location of Out-Care Centers in Urban Space Using Agent-Based Modeling

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ABSTRACT

Out-care centers are small health units with the aim to provide certain care functions in close proximity to patients. Planning for optimally locating such centers within an urban area is, however, not an easy task. This paper presents an agent-based model to support localization decision-making of such out-care centers within a specific urban setting. The model accounts for patient preferences when choosing a specific out-care center, for instance, travel time, waiting time at the center, walking distance in and around the center, and service level of the center. The model also uses historical patient history data to predict the number of patients that seek treatment within a specific area. To this end, the model implements a GIS link that links patient admittance data to GIS-based postal codes. Finally, the model can simulate the out-care center market dynamics within a region. It does so by modifying the initial arrangement of out-care centers by gradually relocating them in random directions with the aim of maximizing the market share, and therefore profits, of each individual center.

INTRODUCTION

In an effort to improve the efficiency of health-care delivery, many countries establish so called out-care centers that offer specific health services in close proximity to patients. The aim of localizing the provision of specific services is to reduce patient waiting times, patient comfort, and increase the productivity of health organizations.

While a system of out-care centers has proved successful in many instances and is, by now, a relatively well accepted part of the health care systems in many industrial countries, planning for the optimal location of such out-care centers is still a challenging task. Little knowledge exists about how to best locate a center and how many centers can be established in a given region before the local health market is saturated.

To support the decision-making process of how to best locate out-care centers within a specific region, this paper developed an agent-based decision support tool. The tool can simulate the number of treatments a given center would provide according to specific preferences of the patients. The tool can also simulate the logic of reallocating existing out-care centers in a specific region according to different preferences of patient to choose for a specific center and existing demographic data.
This paper introduces the basic functionality of this agent-based modeling tool and provides an illustrative example of the tool’s application within a specific area. To this end, we structured the paper as follows: The paper starts with introducing the general decision-making task of finding appropriate locations for out-care centers. It then continues with introducing agent-based modeling as a technique to support the given decision-making task. Afterward, the agent-based model that forms the basis of the decision support system is described, followed by a summary of how we calibrated and validated the model. We then illustrate the applicability of the model by analyzing several scenarios for out-care center location in a region of the Netherlands. The paper finally concludes with a theoretical discussion and suggestions for follow-up research activities.

LOCATION PLANNING FOR OUT-CARE CENTERS

Historically medical practitioners have been wanderers. Instead of patients traveling to them, the practitioners themselves went out to see the sick in their surroundings (Dominiczak, 2011). The first hospitals were designed to shelter the poor that otherwise could not afford respite space that supported their recovery, but very often, in fact, these were simply places for terminal care. The modern hospital as we know it only developed together with the evolution of modern health care technologies. These technologies required specific functions that demanded specialized spaces, such as laboratories, operating theaters, or medical screening rooms.

The integration of an increasing number of functions into single buildings streamlined the possibilities of providing modern health services, by elevating service related economies of scale. At the same time, however, this integration also increased the costs for maintenance of these buildings. The minimalist skyscraper became the most widely used form in hospital architecture. While having the most economical form, these new types of hospitals neglect basic human needs. They stripped patients away from their privacy (Schaefer, 2005), and neglect basic requirements that support the human healing process including, for example, sound sleep, positive distractions that reduce stress, the need for well-ventilated and light spaces and the need for privacy (Schaefer, 2005). Additionally, such centralized hospitals did not perform well in terms of patient safety. Hospital-acquired airborne or by direct contact transmitted infections are still a large problem in most existing hospitals (Ulrich & Zimring, 2004).

All these problems with existing centralized hospitals have created a new philosophy of how to best provide health services. Instead of establishing large all-purpose health care facilities, the proponents of this new philosophy suggest to establish smaller facilities that focus on a limited range of services and are located in proximity to the patients (Saltman et al., 2006). Such facilities have been commonly labeled as out-care centers and some proponents of this form of health service delivery have even gone so far to suggest single-use hospital facilities with a life-time of only three to six weeks that can be easily and environmentally-friendly disposed after their use (Boyde 2003). This suggestion is now often implemented in the form
of mobile health centers that are established at an ad-hoc basis to promote health service to citizens or to support specific functions required at special events.

Independent of the life-time of out-care centers, the question of where to best and meaningfully locate them moves to the center of attention while planning these facilities. As opposed to traditional hospitals that are usually located in the center of a city or at well accessible locations in the periphery of a city, out-care centers need to be located close to potential patients and be in general well accessible. Additionally, at least in the Dutch context, out-care centers operate in free market conditions and thus compete with each other for patients. With this requirement, establishing a new, economically feasible out-care center becomes a facility location problem (Farahani & Hekmatfar, 2009; Klose & Drexl 2005).

AGENT-BASED GEOGRAPHIC MODELING

Such facility location problems can be well supported using agent-based models and geographical information systems (GIS). Agent-based models are built using separate computer programs (the agents) that interact with each other and an environment. The interactions of agents are guided by rules that represent an abstraction of the behavior of a real world person or institution (Gilbert 2008). By modeling individual behavior and interaction, agent-based models allow to represent small scale behavior in a natural way. Researchers can then conduct experiments that allow for analyzing macro-level outcomes that are caused by these interactions between agents themselves and by the interactions between agents and their environment. These features of agent-based models are well-suited to support decision-making tasks to find locations for out-care centers. This is because they allow for modeling patients and their rational choices to choose a specific out-care center. Additionally, they also allow for modeling the role of out-care centers as agents that seek the best position in space to maximize their utility – the number of patients that seek treatment. Once developed, such an agent-based model can then be used to evaluate several scenarios of possible futures in which both the behavior of the micro-agents as well as the characteristics of the environment are considered variable.

Agent-based models additionally integrate well with GIS technologies that allow for a better understanding of the specific demographic characteristics of an area (Higgs & Gould, 2001; Koch 2012). The environment in which agents are acting can model a geographical area with specific characteristics that influence the behavior of agents (Gilbert, 2008: 15). Hence, linking agent-based models with GIS that represents these characteristics for a specific area allows for the development of area specific models that can account for the specifics of a certain geographical area, for example, in terms to health characteristics of the population, historical hospital admission data, or statistics about spatial accessibility.

This paper introduces an agent-based geographic model that builds upon these advantages of the two introduced technologies. Before presenting this agent-based model in detail, the next section first introduces the concept of agent-based modeling briefly and discusses why agent-based modeling is a good technology for the development of decision support systems to support the above described policy-level decisions.
AN AGENT-BASED MODEL TO OPTIMIZE THE LOCATION OF OUT-CARE CENTERS

The agent-based model is based upon a collection of conceptual components that are important during the decision-making process around the location of out-care centers. These components include a geographic landscape model to represent a specific study area. Additionally, the components include two different types of agents that represent a specific area within the landscape and a specific out-care center in the area respectively. These components are then linked by a time step based simulation algorithm that models the economic dynamics about geographic patient admissions in the analyzed area. This section describes each of these components in detail.

Urban landscape

The urban landscape of a specific arbitrary sized study area is modeled with spatial patches. Each of these patches acts as a spatial container for a number of parameters required by the simulation algorithm. The size of each patch is relative to the overall size of the study area. These parameters include the postal code of the area the patch is located in, the size of the postal code area, the number of patients that are admitted from this specific postal code area within a specific time unit, and the overall number of households within the postal code area. Additional, a specific variable indicates whether a patch hosts an out-care center or not. The agent-based model generates this landscape using the following types of input data. First, the model requires a GIS shape file that describes a region’s postal code areas in polygonal form and the number of households within the area. Second, the model requires a table that provides historical data of the number of patients from each postal code area that required a treatment for a health service under consideration in the mode. Using these input files, spatial patches can then be generated with the above described parameters. Figure 1 represents a visual example of a specific urban landscape model for a region.

Agents

The two agents that serve as components of the overall simulation model are the patches that form the landscape and an additional set of agents to represent out-care centers as dynamic entities. The behavior of the spatial patches during the simulation is that they generate a number of patients per time unit and send these patients to a preferred out-care center according to a parameterized preference. These preference parameters are based upon the spatial proximity of the patch to a specific center, characteristics of a center quantifying its service quality, its accessibility, and the average waiting time before a treatment is received.

The second set of agents represents out-care centers. Each of these centers is characterized by parameters describing the location of the center, as well as its respective service quality, accessibility, and average waiting time. Additionally, each out-care center agent has a variable to track the number of treatments it has provided during a specific simulation. The out-care center agents behavior is such that they search for an optimal spatial position within the urban landscape. This position maximizes the number of treatments they can offer. Assuming perfect market
conditions, out-care centers choose the best location for themselves independent of the location of other possible centers.

The next section describes how the behavior of these two types of agents is implemented and combined within the overall simulation algorithm.

Figure 1. Example of a landscape generated within the agent-based simulation model. The polygons delineate postal code areas. Houses represent out-care centers. Different shades denote the market shares of various out-care centers.

Simulation algorithm

Figure 2 provides a schematic overview about the implemented simulation algorithm. In the first step the different input data is provided and the model landscape is set-up as described above. After the set-up of the model landscape, users can initialize a number of existing out-care centers within the region under consideration. Based on this model landscape the simulation algorithm then calculates the preferred center for each of the patches based on a specific utility function that calculates a numerical indicator for the preference of patients to choose a specific center. This calculation is based on a numerical value representing the preference for patients from each patch to choose a specific center. This value is calculated as follows:

\[ P_{c_i} = w_{td} \times td + w_{t} \times t + w_{ac} \times ac \]

with

\[ P_{c_i} \quad \text{quantified preference indicator to choose center } c_i \]
Based on the calculation of the preference value for each center, each patch is then assigned the existing center with the minimum value. For this calculation we chose to operationalize accessibility as inverted parameter to provide a consistent interface for the development of scenarios. After the calculation of the preferred center per patch a simulation time step loop is started. During each time step within the loop the simulation algorithm then executes the following steps:

Generate admissions and update admission count for preferred center. For each spatial patch the number of patient admissions to the preferred center within the time step is generated. The number of generated admissions is based either upon the variable of each patch that represents the number of admissions from historical admission data or as an alternative proxy on the overall population of this patch. The simulation then uses this generated admission number to update the overall admissions for the patch’s preferred center.

Adjust locations of out-care centers according to the current market situation. After updating the admission count, the simulation then adjusts the location of each center according to the market condition within the area. To this end, each center calculates a potential market value for the patch it is located on currently and for its neighboring patches. This market value is calculated based on the number of patients that would be admitted to a center potentially located at the patch. Based on the calculation of the market value for the neighboring patches the simulation then moves the center under consideration to the patch with the highest market value.

Model update and move to next time step. At the end of each of the above time steps, the simulation algorithm updates the preferred center for each patch. To increase the run-time performance of the model, this is only done when a center has changed its location. After this recalculation the algorithms starts a new time step iterating through the above described procedure another time.

User interaction during the model run. While a simulation iterates in the above described way users have the possibility to dynamically influence the running simulation in a number of ways. First, users have the possibility to add additional out-care centers by clicking on a specific patch. Second, users can change the parameters of service quality and accessibility of the existing out-care centers. Finally, users can adjust the weight of the preference function.
CALIBRATION AND VALIDATION

We calibrated and validated the agent-based model in the empirical context of the Twente region in the east of the Netherlands. We chose this area because we had access to patient admission data for a local health service provider and because of the interesting demographic composition of this area that combines both urban and rural areas.

To initialize and set-up the landscape, we used a polygonal GIS shape file that represented the different postal code areas within the region and that contained data about the overall number of households within each of the areas. Additionally, we
used patient admission data from a local health service provides for an 18 month period to initialize the landscape. Finally, we established a baseline scenario for a first validation simulation by allocating the existing care centers of this health service provider within the landscape.

**Figure 3.** Outcomes of simulation runs for different scenarios. The left of the figure shows the initially planned base line position of out-care centers, the right shows the adjusted position of the centers after simulating an 18 months period of the local health-care market.

**NUMERICAL SIMULATIONS**

After calibration, we tested the model by using it to simulate four scenarios of possible out-care center locations within the Twente region. The chosen scenarios were based upon a number of suggested plans for establishing out-care centers of the
local health service provider. Hence, we evaluated the decision-support potential of the model against the realistic planning scenarios that existed at the health care provider. Figure 3 shows the outcomes of these simulation experiments; the rest of this section provides a preliminary analysis of these outcomes.

All scenarios suggested by the health care organization evolve around establishing a new out-care center in the region in the postal code area 7521 with a potential upgrade through additional centers in other locations. This situation is modeled by Scenario 1. Scenarios 2 and 3 then additionally add out-care centers in the postal code areas of 7543, 7535, and 7523 respectively. Table 1 summarizes the outcomes of simulating the above scenarios using the agent-based model.

A closer look at the simulation results reveals that the location of a new out-care center in the postal code area 7521 only would make economic sense if the existing center at location 7513 is abolished. The market dynamics simulation, during which out-care centers strategically change their positions in the given market space, reveals an even less positive picture for location 7521. Table 1 shows that for each scenario, the market share for center 7521 would significantly reduce after 18 months. Overall, it seems more feasible to establish out-care centers at the alternatives for 7521, evaluate with Scenarios 2-4. Of course, the results of this initial analysis need to be elaborated much more in future work. In the limited scope of a journal paper, however, such an elaboration is unfortunately not possible.

### Table 1. Summary of the simulation experiment outcomes

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<th>Change of location Treatments</th>
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### DISCUSSION AND CONCLUSION

This paper introduces an agent-based model to support decisions about locations of patient out-care centers. Such out-care centers are a response to existing centralized health service provision models in the way that they promise a safer and more client-oriented provision of services. However, to be economically feasible, out-care centers need to be strategically positioned within urban space to maximize their market share. The agent-based model introduced, can help with finding such economically appropriate locations.

The agent-based model allows doing so, by combining two types of agents: Out-care centers that move to economically-superior locations in space and patients that choose to visit the out-care center based on specific parameterized preferences. These agents operate within a space that uses geographic information about patient admissions within a certain area. Initial experiments using the model to support
decision-making tasks of a Dutch health provider show promising results. Next steps in this research will be a further improvement of the agent-based model, for example by including more accurate urban accessibility models or including realistic costs for moving out-care centers. Additional numerical experimentation with the model are also planned to understand general macro-level phenomena better, and, last but not least, we plan to explore how this model can be used to support creative decision-making within participatory workshops.

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