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Abstract

Purpose – Agent-based computer simulation gives new possibilities to model service supply chains which combine flow of people, geographical elements, demand patterns and service rates. The purpose of this paper is to demonstrate by using an example how agent-based modeling can be used for health service supply chain design.

Design/methodology/approach – Generic structure of agent-based service supply chain modeling is described. The presented example is healthcare supply chain with service distribution and service location problem. Main focus in presentation on model building, actual case data are not discussed.

Findings – In context of service supply chain, agent-based modeling has advantages compared to traditional discrete event approach. Agent-based simulation allows modeling of interactions of autonomous agents.

Practical implications – Reach of service for each geographical area may be used as a constraint for building service distribution network. Service supply chains consist of service providers and flow of customers with given geographical locations. Key performance indicators can be assessed in combination with service footprint.

Originality/value – Availability of geographical population data and agent-based simulation gives new possibility for service supply chain models.

Keywords Simulation, Agent-based modelling, Service supply chain

Paper type Technical paper

1. Introduction

Agent-based simulation has been utilized in various fields of research and the approach has gained increasing interest in operations management and supply chain management (Dyke Parunak *et al.*, 1998; Giannakis and Louis, 2011; Amini *et al.*, 2012). Most of the simulation studies are still using discrete events (DE) or system dynamic simulation. Traditionally flow of goods or people is handled by using numerical variables or objects containing property information. Agent-based simulation models bring some new possibilities to handle large amount of actors – agents – which may have complicated behavior and can interact with each other.

Agent-based simulation is applied when there are various participants in system who acts independently, interact with each other, react to system changes, and their total activity is nonlinear and not derived from summation of each individuals' behavior (Ge *et al.*, 2015). According to Vriend (2000) there are two types of agents learning; individual and population levels. In individual level, agents learn from its own experience, but in population level, learning occurs from other agents.

Modeling and development approaches developed for operations management are used in service supply chains (Sengupta *et al.*, 2006). Generally, service supply chains refers to planning and management of activities from support functions to end-users (Voudouris *et al.*, 2007). Material flow may be part of the service supply chain but not the main consideration as in supply chain management. Service supply chains have been studied in several fields to build frameworks (Baltacioglu *et al.*, 2007) and

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modeling system-wide effects such as demand amplification (Akkermans and Vos, 2003).

Process improvement and key performance indicators (KPI) for process evaluation share many similarities between traditional manufacturing operations and service operations such as customer service, maintenance and banking services. There are differences too: as services are intangible by nature and require interaction with people, not only physical material, and as evaluation of service quality is based on individual assessment of gap between expectations and reality, management of service has its own characteristics.

This paper illustrates possibilities of using agent-based simulation in service supply chains by showing a generic example of healthcare location problem. The model features the following aspects enabled by agent-based approach:

- use of geographical data for customer demand pattern generation;
- service model can be a queue with routing possibilities; and
- key performance evaluation against geographical footprint and service locations.

The structure of this paper is as follows. First, literature related to supply chain agent models is reviewed. Then the modeling approach is explained. The proposed approach uses customers, patients as interacting agents which have a location; service production part is then serving each customer as in traditional DE or queuing model. KPI can be used to evaluate the performance of planned scenarios. The modeling approach combines geographical information with agent-based analysis. Finally, generalization of the modeling approach is discussed in the conclusions section.

2. Literature

The overall concept of supply chain management is applicable to health services. Health service supply chains are comparable in some extent to industrial supply chains but have specific features (de Vries and Huijsman, 2011). Supply chain management has been used in system design perspective as well. Sinha and Kohnke (2009) applied the concept of supply chain linking the increasing need for healthcare services and availability of services.

2.1 Use of agent-based simulation in supply chains

Agent-based simulation has been used in various supply chain contexts during the past years. Hilletofth *et al.* (2009) presented agent-based decision support system for supply chains. Later Hilletofth and Lättilä (2012) presented an agent-based decision support system for supply chain context and illustrated decisions in two case study: one in manufacturing and other related to service. Hilletofth *et al.* (2010) developed agent-based decision support for maintenance service providers. Transportation-related supply chain simulations using geographical information have been presented by Henttu and Hilmola (2011).

Chu *et al.* (2015) applied agent-based simulation for multi-echelon inventory optimization problem modeled for a network consisting of plant, distributers and distribution centers. In this approach agent-based model was used with mathematical optimization. The focus of this model was to include more parameters in inventory systems due to utilizing inventories as buffers against demand violation and lead time fluctuations. The model consists of facility agent which monitor and replenish inventory, order agent which saves data such as demand, sender, receiver, and status; shipment agent which records data such as shipment quantity, shipping time, sender, receiver, and customer agent which creates orders based on related probability.

Mortazavi *et al.* (2015) considered the four echelon supply chain consist of distributer, retailer, manufacturer and supplier. Inventory quantity is assessed on weekly period and, then orders are placed. Retailers are allowed to perform the policy of partial demand satisfaction in modeling, and orders are sent to distributer each week. Manufacturing agent consists of two types of raw and finished products, and also it consists of producing operation which transfers the raw materials to finished products. Suppliers are also modeled as an agent and procurement time is considered for it. Mortazavi *et al.* (2015) applied learning method which is for instructing the agents to learn how to distinguish situations and select the related actions in order to maximize the numerical reward signals to reach an optimum strategy. Agents have to choose between using the knowledge and select the best action or discover various actions to assess the new opportunities for agent policy improvements.

Ge *et al.* (2015) modeled the farmers' behavior by agent-based simulation in agricultural supply chain optimization model. In this case, farmers are smart agents who can perform the experiments. They look over their neighborhood and collect the information in order to behave based on that data for next period. Ge *et al.* (2015) considered risk effort factor for farmers. If a delivery is misrepresented by farmers, a punishment will be charged to farmers. Penalty system leads to motivation toward increasing the efforts for improved delivery in a larger context. Agent interaction also is modeled by defining physical distance between farmers which based on it, farmers would exchange the information. If a farmer within specified distance has been tested by a system, then the neighborhood farmers would act more carefully in deliveries, on the other hand, if a farmer has not been checked for a time period, then the region farmers would reduce their efforts in accurate and valid deliveries (Ge *et al.*, 2015).

2.2 Healthcare simulations

Healthcare domain and delivery of service has been also an important application area for agent-based simulation. Taboada *et al.* (2011) performed a simulation modeling for emergency department (ED) of hospital. ED is one of the most critical hospital sections for both budget and service points of view. Due to variation in demands based on time, week days and years season, resource planning is complicated and demanding. For simulation process, author considered two different type of agent; active and passive. Active agents include all the individuals involved in ED sector such as doctors, patients, nurses, and administration staff, but passive agents represents services and other responsive systems such IT infrastructure and services needed for performing medical experiments and tests. Different areas such as waiting room, triage box, administration and treatment are considered and agents interact or even travel in these places. Second scenario was performed based on keeping patient arrival and number of staff static and changing the level of ED personnel experience to evaluate the throughput of system. From the simulation outcomes, it was concluded that increasing the experience in triage nurses or doctors should be planned (Taboada *et al.*, 2011).

Modeling with agent-based simulation method has been increasingly used since last decade in epidemics (Burke *et al.*, 2006; Huang *et al.*, 2004). Mao (2014) investigated on the triple diffusion of diseases. Based on Funk and Jansen (2013) Epidemics includes three parts; contagious diseases, data and information exist about the diseases, and how people react in preventive manner to diseases. Disease can be scattered by person to person contact, information spread by communicational links, and preventive actions can be circulated by social contagion such as learning by observation. This component synergy builds the epidemics dimensions. Contact between people form a network structure by which interactions and diffusion are possible. Modeling was performed through designing of three different layers. Diseases transfer through the direct contact between individuals (middle layer), disease control strategies such as isolation, case treatment and vaccinating program influence on extent of disease diffusion. Also, diseases circulation causes "word-of-mouth" discussion which spread information regarding diseases and preventive behavior. In order to provide a contact network, Mao (2014) considered the individuals as nodes which are connected through their relationship to one another on daily basis. Connections between individuals are performed three times per day and in four different kinds of location. Time periods include during day in workplaces, nights at home and leisure time at service places and house neighborhood. Individuals move to these four places during three time intervals to fulfill their daily life necessities, therefore, they are in contact with various groups of people and are in exposure to infectious individuals. These links builds contact network of population. Also, author stated that two types of population contacts are considered based on contact duration and closeness. Disease transmission happens when individuals are in contact with infectious people within the adequate time. The second type takes place occasionally at service places with consumers and clerks. Rate of transmission is lower due to less number of individuals contact and shorter time exposure with infected people.

Simulation has been used in analysis of healthcare supply chains. Gunal and Pidd (2006) performed a DE simulation of patient flow in Accident and emergency section in order to analyze the effects of factors which affect the healthcare performance indicators such as number of patients with lengths of stay (LOS) more than four hours. Holm and Dahl (2010) investigated on DE simulation of ED patient flow and analyze the effect of increasing the number of patients flow on department performance. Also, usage of extra resources in case of increased patients flow were identified by the simulation modeling. Bhattacharjee and Ray (2014) mention that DE simulation of patient flow is mostly applied in outpatient context and ED because of patients flow complexities and time-related feature of these environment.

Abo-Hamad and Arisha (2013) conducted the research on one of the well-known Dublin hospital which had overcrowding and long waiting time issues in ED. He considered following steps for simulation modeling; ED layout which includes hospital department and sections; ED staff containing individuals profession, number of employees and working hours; defining KPI; patient flow analysis which includes procedure of treatment from when patient enter to hospital; ED process mapping in which integrated defination modeling toolbox (IDEF) process for modeling the complicated systems is utilized; empirical data analysis in which author analyzed hospital database information in order to gain qualitative data such as patterns of patients arrival, patients grouping and routing data.

2.3 Facility location problems (FLP)

Use of geographical data in operations management is related to location problems. Application of FLP covers various areas, for example location of distribution center in supply chain, warehouse location for a commodity producer, sporting facility for a city planner and even database location in computer networks (Boloori and Farahani, 2012).

Facility location is an important feature of service planning process and it combines customer location, service location and service level. FLP problems can be distinguished based on two factors: time; and space. Space refers to area in which facilities are located and time indicates time of facility establishment.

More complicated approaches on FLP has been done, including: multi FLP (Daneshzand and Shoeleh, 2009); facility location-allocation problem – these two objectives are searched as optimized solution, location of facilities and allocating them to clients in order to respond to demands; discrete FLP (Boloori and Farahani, 2012).

Facility location-relocation problem has been studied for changing facility location due to external environment changes. Three factors should be taken into account regarding facility relocation; number, time and cost of relocation (Farahani *et al.*, 2009). Min and Melachrinoudis (1999) introduced the factors which influence on relocation decision significantly such as expenditure of land acquiring, bordering permission, moving equipment and staff, prompt distribution to clients and accessibility, reachability to suppliers, convenience in accessing to transportation networks, tax incentives, labor quality and labor relationship management.

Miller *et al.* (2007) stated three results which can be obtained by utilizing multi period facility location. First, proper time period regarding facility sites decisions, second defining the best locations, and third created opportunity for firm regarding analyzing the desirable/undesirable demand fluctuation in business market in multi period time planning while such an opportunity does not exist in single period FLP. Dynamic models provide a situation in which companies are able to work more on adjusting the parameters efficiently in each of time periods in comparison with single period which decision maker rarely are able to deal with uncertain parameters.

Also, Fuzzy approach has been utilized in FLP which can be categorized to two sections: choosing facility location, decision-making problem; location-allocation problem, optimization problem. ReVelle *et al.* (2008) focussed on two factors which should be determined before planning the details; first, pre-defined locations of customers and second, facilities with locations to be defined based on objective function.

Zhang *et al.* (2012) mentioned due to aging population, the role of methodologies and approaches for improving long-term homecare becomes more critical. Following this issue, in Belgium, Maya Duque *et al.* (2015) performed a research on homecare service planning. Homecare service procedure includes calling for service, pre-admission evaluating for setting patients' needs and required services, determining frequency of service (weekly number of referring, duration of service per visit, service period). After defining aforementioned parameters, the most suitable caregiver is assigned to patient (Maya Duque *et al.*, 2015).

Maya Duque *et al.* (2015) consider two objectives; fulfilling the patients and caregivers preferences at the most possible level, and minimizing the travel distance because the company pays the caregivers travel expenses.

Wu *et al.* (2007) performed a research on Taiwan healthcare management in order to determine the facility location between 17 medical areas. Due to existing aging population phenomena based on World Health Organization information in this country and subsequently, highly competitive service and health sector, selecting incorrect location leads to cost increment and vague future growth.

3. Case example on healthcare supply chain

In order to demonstrate potential of agent-based systems for decision-making process an example of health center location is presented. The question is to find alternatives for health center locations, where certain locations are fixed and certain locations are mobile serving periodically areas.

Location problems in service supply chains are related to several decisions:

(1) how many service locations are needed?
(2) which locations should be considered?
(3) what are the effects of location to service level and operational performance?
(4) what type of operating hours should be used at locations?

To resolve the challenge for management, simulation modeling can be utilized to examine regarding location of health centers and derived possible outcome on service level. By simulation, evaluating various scenarios for decision makers would be possible. As there are several conflicting objectives and system behavior is not completely known, a managerial cockpit type of simulation would present possibilities to evaluate alternatives. For more formulated problems, optimization approach could present solution but as problem definition is somewhat flexible, simulation by experimenting presents a suitable approach.

Considering the problem context and required elements for modeling, AnyLogic software has been used in this problem. First, geographical population data are used to generate customer agents – patients with certain demand probability and urgency. Second, each customer agent is connected to production facilities by using nearest matching. Then capacity utilization and service performance indicators can be calculated and evaluated. Different scenarios and alternative locations may be compared by rerunning the simulation (Figure 1).

3.1 Creating customer agents

Simulating the population density is performed with geographical information system (GIS) feature of AnyLogic software. A map of world is provided in this section of software, and points or regions can be explored by search tab. Information regarding map tiles, can be requested from different tile providers such as Mapquest or OSM. GIS feature of AnyLogic also retrieves necessary information such as routes, regions, cities, and there is a possibility to select a point or area for agents' location (Figure 2).

In order to illustrate, three potential locations which are suggested from related healthcare management are defined for healthcare center location, and healthcare center agent is located on each city point. The challenge for simulation is how to simulate population density which resembles to reality.

Information regarding population number by each municipality is collected from Official Finland Statistical website (Statistics Finland, 2015). Data referred to

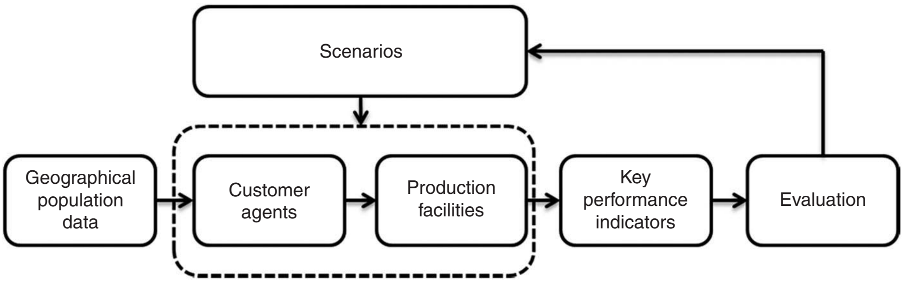


Figure 1.
Process steps for modeling service supply chain with geographical population data

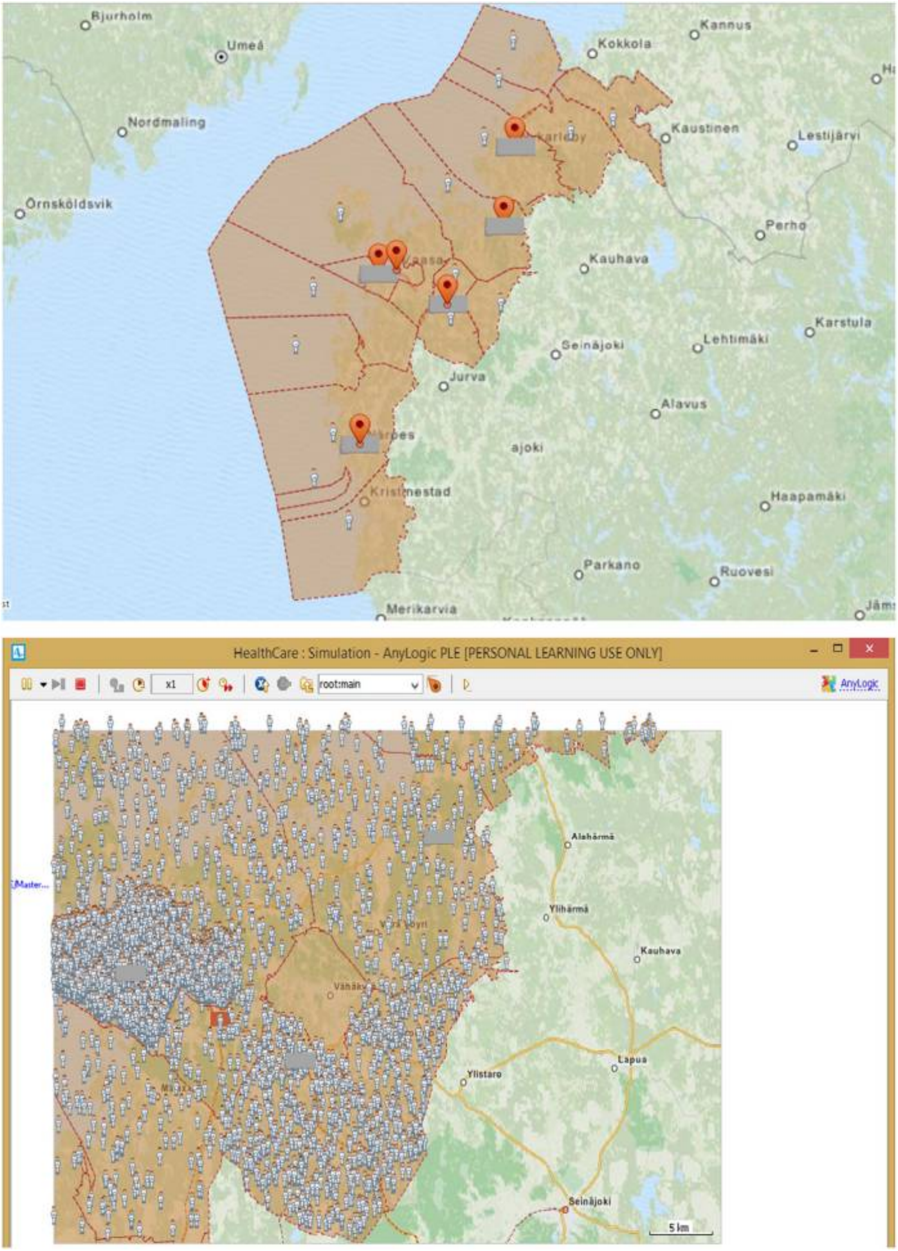
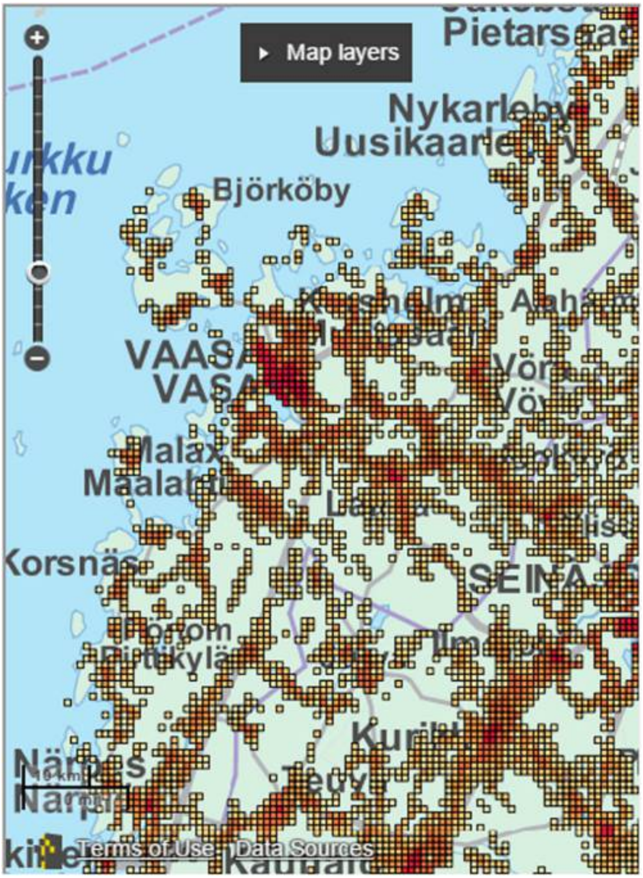


Figure 2.
GIS map with regions created agents on locations

population number is available as web service and downloadable for Microsoft Excel sheet in detailed 1 km × 1 km matrices provided by the Statistic Finland (Figure 3). This detailed population information is retrieved to the software with a Java function. Also, patients population are scattered in each 1 km × 1 km region by the software function.



Source: Statistics Finland

Figure 3.
Population grid data (1 km × 1 km) containing total population and age and gender distributions of each inhabited grid cells for Finland

In the next phase, patients should detect the nearest health center according to their own and health center geographical position. This process is performed by a Java Function which locates the nearest healthcare center agent.

In order to patients transport from the initial point toward the health center, routing information is required. In AnyLogic software, routing section has various options, for example, routing information can be requested from OSM server, loaded from PBF file or straight lines. Also routing method can be fastest or shortest and route types can be chosen for car, bike and by foot. In our modeling, routes are requested from OSM server, and routing method is fastest with routing type “car,” which refers to route planning along the main roads.

3.2 Modeling production facilities

Patient flow as significant factor which influence on healthcare services performance. Hall *et al.* (2006) describe the patient flow study as investigation on how patients move through the health system.

Bhattacharjee and Ray (2014) mention that patient flows in healthcare centers are similar to queuing structure which contains system structure (entry and exit points, paths between points, different single and multi-server nodes), patients and resources. According to them a major cause of uncertainty is arbitrariness in inter arrival time of planned and non-planned patients, not showing up of planned patients, volatility in service time in different phase of care, uncertainties regarding transition of patient health situation and movement between different health locations. Hulshof *et al.* (2012) explain that all type of patient flow including operative or clinical in any care process such as outpatient, inpatient, surgical, or emergency care, are considered as multi stage problem.

According to Jiang and Giachetti (2008) there is no necessity that each patient has to pass through all stages and each stage includes common tasks such as arriving, waiting, receiving service and leaving the block.

In our healthcare center location example, agents are blocks of simulation modeling and each one can contain different process or action. Three different agent types are created for simulation modeling; patient, healthcare center, and doctors:

(1) Each patient agent, based on classical method of SIR; susceptible, infectious, and recovered has different states in simulation time period. In other word, individuals initially are susceptible to disease which means they are in exposure of disease or have the potential of becoming sick.

(2) Based on a triangular probability distribution, susceptible people become sick and their state changes to infectious. In addition to shape of distribution, time dependent behavior such as seasonality due to people living in summer houses during the summer months or short time cycles – weekday patterns – may be introduced.

(3) For a time period which disease lasts to advance inside the body and emerge from latent condition, triangular probability distribution is considered and then transition to next state occurs.

(4) In the next phase, each patient based on their geographical coordinates, find the nearest health center and move toward it. This preference function may be adjusted to suite other possible situations such as giving freedom to agents to choose health centers based on queue length, randomly or other factors.

(5) After arriving to health center, transition between moving to healthcare center and recovering stats is triggered and patient enters the health center and process of healthcare service begins. Agent behavior may change during the process, for instance too long waiting time could result patent to leave queue without service.

(6) After receiving the health service in clinic, patient leaves the health center. Due to cyclic nature of this process, patients after recovery, are transferred into susceptible state again.

The whole loop of disease steps, is displayed in Figure 4. Each agent behavior may be modeled according to scenario analyzed.

3.3 Patient flow simulation

During the care procedure, patients move through different routes in health system. Different group of patients choose different routes which some of routes can be common and others different. Different nodes have possible various transitions to other states and even different patients classes have various probabilities of transitions between states.

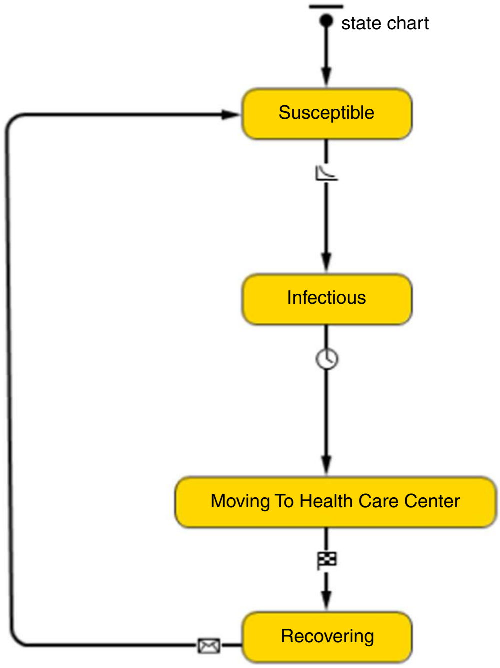


Figure 4.
Patient states and transition within agent

Defining the probabilities should be performed according to examining the previous data on patients' pathways (Cochran and Roche, 2009; Côté and Stein, 2007).

There are various process steps in health centers which each patient must pass through to receive the health service. The simple four stages process is considered for healthcare center agent which are mentioned as follows (Figure 5):

- Arrival: patients who have arrived to health centers, enter the care process in this phase.
- Service: patients who come into the healthcare, are transferred to this step in which they receive the treatment if there is available doctor, otherwise, they have to wait in queue until a doctor become accessible. Also, queue capacity is defined with maximum size and no patients are terminated from care process without seizing service. Service time is considered based on triangular probability distribution with hourly unit, and patients receive the service based on FIFO priority method.
- Resource pool: this block of simulation is associated with service block and it contains information regarding the resources for providing health service. Doctor

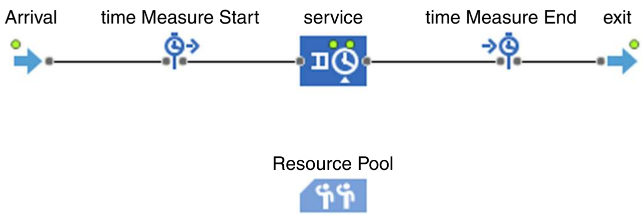


Figure 5.
Patient flow structure

agent is considered as resource unit and, a working schedule is arranged for doctors in which one doctor is assigned to night shifts starting from 00.00 to 8.00 a.m. and working breaks such as lunch time. For other time periods, two doctors are available. Also, working schedule is repeated for each day of week.

- Time measure start and end: these two blocks are added to patient flow in order to record each patient LOS.
- Exit: in this block, patient leave the health center and exit from care flow.

Each flow step may be parameterized to suite needs in of the process and scope of analysis.

3.4 KPI and evaluation

Simulation model can be run, once demand and service location parameters are given. In order to measure the output from simulation modeling, various performance indicators should be taken into account. KPI can be assigned to customers (patient agents) and service providing locations (health center agents, doctors, and nurses). Customer agent point of view can be analyzed as a range between minimum and maximum response times. Table I shows potential performance attributes which may be used comparing different scenarios. Average response time can be plotted on the map as well and service-level heat map approach can be used for visualization.

Service level which is critical aspect for health management is measured in the modeling by two major indexes; number of patient in queue and LOS. Number of patient in queue is collected from service block and can be demonstrated on a chart which changes along with modeling time (Figure 6).

LOS indicates a time period from the moment patients arrive to health center until they leave the clinic. LOS is displayed with a chart which vertical axis shows LOS in hours and horizontal axis time periods. LOS is also demonstrated with three graphs which include min, max and average LOS time period (Figure 7).

Internal operations are evaluated by analyzing capacity utilization. Each location can have different amount of doctors and nurses. Resource utilization for doctors is also measured in the modeling which shows degree of actual works to possible total working hours in percentage. Cost of operations is function of volume: higher capacity utilization should result lower operating costs. Capacity utilization is an important parameter for both service level and operating costs, and resource managers can identify if resources are over or under-utilized. In Figure 8, utilization percentage for all service locations per day is displayed.

Aspect	Performance attribute	Type
Customer	Waiting time	Time
	Distance to service provider	Response
	Access time to service provider	Response
	Queuing time	Response
Service provider	Number of patients in queue	Capacity utilization
	Length of stay	Response
	Flow: number of patients ratio	Capacity utilization
	Transport cost for customers	Customer
	Operational costs of service provider	Customer

Table I. Key performance indicators for scenario comparison

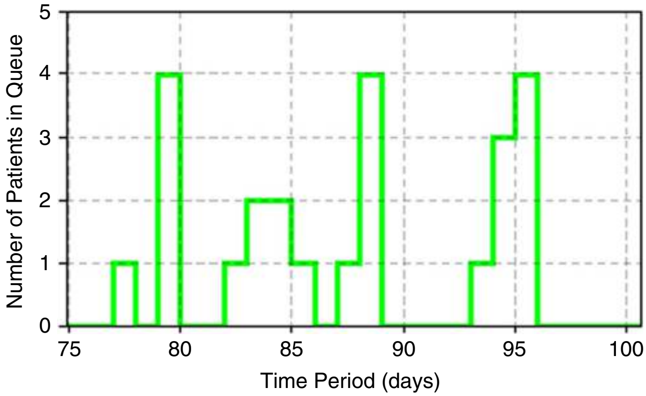


Figure 6.
Number of patients in queue

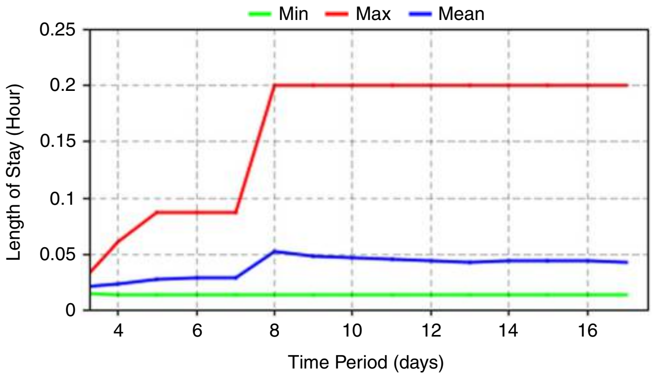


Figure 7.
Patients' length of stay as function of time

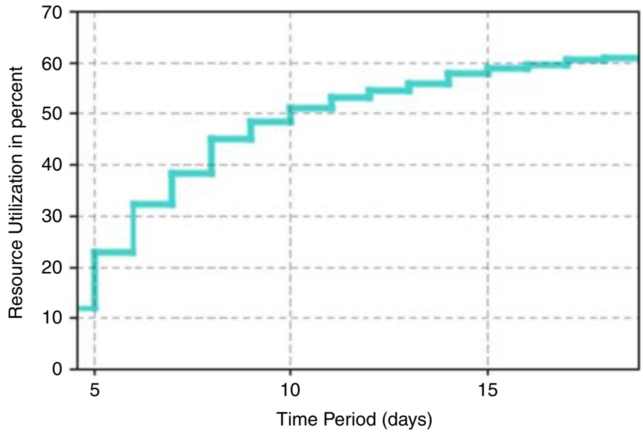


Figure 8.
Example of resource utilization graph

Additionally, another indicator which is applied in modeling is number of patients' ratio. Ratio between patient who enters a healthcare center and patient who departs, is displayed by a chart in which horizontal axis contains data and vertical axis present the number of patients in accumulative method (Figure 9).

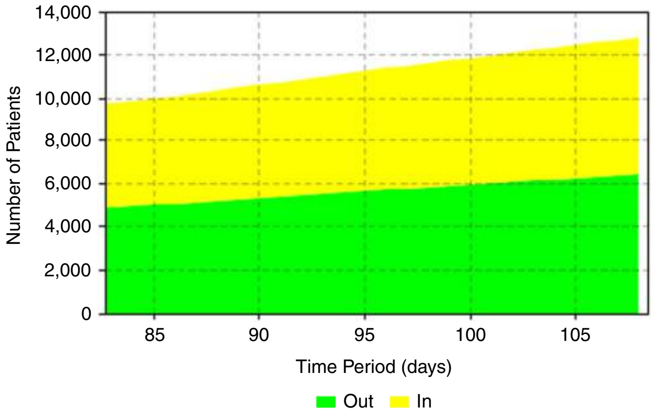


Figure 9.
Number of patients ratio yielded by different of inflow and outflow

4. Conclusions

This paper has demonstrated how agent-based simulation can be used in the field of healthcare service chain. The approach is suitable for other service supply chains which require analysis of customers as intelligent agents operating in certain geographical area. As presented in the literature review, similar approaches have been presented in other contexts (e.g Hilletofth *et al.*, 2010).

Agent-based modeling and contemporary simulation backages enable possibility to use GIS data to evaluate service supply chain performance. What-if analyses can easily conducted for decisions that need to combine location decision and service performance for each location. The presented service supply chain example has demonstrated a possible structure for model building. Three possible use types for agent-based decision support can be outlined:

(1) Expert scenario-building on simulator. Use of agent-based simulation with decision support can be combined with closer co-operating with domain experts. Scenario development is one possibility as suggested by Abo-Hamad and Arisha (2013).

(2) Vision building. Development of operations is another approach for service supply chains. Regarding simulation of patient flow, Bhattacharjee and Ray (2014) mentioned that patient flow modeling has significant benefit for hospitals service delivery by providing visions for enhancing process, capacity planning, resource assignment and planning, and appointment scheduling.

(3) Change management and commitment buiding by simulating. Result of simulation validation and verification also can be performed by three ways; face confirmation, comparison analysis and hypothesis testing. Interviews are performed with managers and nurses in order to approve the simulation results in face testing. In second method output of simulation model is compared with real health system results (Balci, 1997). This approach is important for model validation purposes but also for communication and commitment reasons.

Agent-based simulation models require still certain programming knowledge compared to DE simulation systems. Despite the learning curve, agent-based modeling has certain advantages. The focus of the approach is on customer-level analysis, not only on flow of materials or resource utilization. Each customer or serving agent has geographical location, which may affect the behavior. Agents may interact and communicate with each other. More advanced possibilies for complex agent behavior modeling are available for service supply chains and especially location-related decisions. Mash-up of public geographical population data and agent-based simulation enables new type of analyses.

The managerial implication of the proposed approach is that agent-based systems are suitable for complicated customer-oriented analyses when building service network strategies. Service location analysis with service levels and operational effiency related KPI may be combined in the same model. Demand patterns and time triggered events may be introduced to analyze special situations such as peak demand. In addition to service supply chains, similar apparoch may be used for last mile delivery planning. Also, defining priority for patients to choose between healthcare centers and seasonality population change of areas can be introduced to modeling. Further studies in this field could be beneficial. The problems may be different depending on population density and municipality structures. As new approaches and reforms are discussed, agent-based simulation could give new perspectives on balancing supply and demand as well as KPI behavior. Moreover, definfing contaigious diseases and interaction between agents combined with locationg healthcare centers can be considered as interesting future research.

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