An agent-based decision support model for assessment of stroke patient transport policies: The case of choosing hospital for diagnosis

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Abstract

The Southern Swedish hospital region is the home of nearly 2 million people, in which 5,684 individuals were diagnosed by stroke during 2016, according to statistics from the hospitals in the region. With this large number of stroke-diagnosed patients across the region, an effective stroke transport policy is inevitably important to provide fast treatment for these patients.

In this thesis, we developed an agent-based simulation model for evaluating the performance of transport logistics policies. We followed the Design Science Research methodology in order to design and develop the model. Using the model, we assessed two transport logistics policies for the Southern Swedish hospital region. We used a synthetic set of stroke patients, which we generated using Monte carlo simulation, for the processes of developing the model and assessing our two stroke transport logistics policies.

We argue that the assessment of transport logistics policies is important for the ability to improve the planning process, for example, when choosing hospital for diagnosis of patients showing stroke symptoms. The optimization of the stroke logistics process aims to ensure the quality and operational efficiency of the hospital sector as well as to increase the chance of survival of stroke patients.

Keywords: Agent-based model, discrete-event simulation, stroke logistics, transport logistics policies.
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**List of acronyms**

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<tr>
<th>Acronym</th>
<th>Definition</th>
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<tbody>
<tr>
<td>SUS</td>
<td>Skåne University Hospital</td>
</tr>
<tr>
<td>KPI</td>
<td>Key Performance Indicator</td>
</tr>
<tr>
<td>DES</td>
<td>Discrete Event Simulation</td>
</tr>
<tr>
<td>TIA</td>
<td>Transient Ischemic Attack</td>
</tr>
<tr>
<td>CT</td>
<td>Computed Tomography</td>
</tr>
<tr>
<td>MRI</td>
<td>Magnetic Resonance Imaging</td>
</tr>
<tr>
<td>tPA</td>
<td>Tissue Plasminogen Activator</td>
</tr>
<tr>
<td>MDP</td>
<td>Markov Decision Problem</td>
</tr>
</tbody>
</table>
1 Introduction

An optimal transport logistics policy with predictable behaviour is an extreme necessity in order to provide the immediate assistance for stroke patients. In 2013, stroke was considered as the second leading cause of death worldwide, corresponding to 11.8% of all deaths [25]. The absolute number of stroke diagnosed patients, or those who remained disabled after stroke, has increased in both males and females of all ages worldwide [26] [27]. According to the statistics of 2016 by the Swedish Board of Health and Welfare (Socialstyrelsen), stroke affects approximately 30,000 people every year in Sweden [28]. The same statistics show that only in the Southern Swedish hospital region (approximately corresponding to the counties of Skåne, Blekinge, Halland, and Kronoberg), this number is 5,684 (which represents ~ 0.28% of the population in the region). With this large number of stroke patients, high quality care with significant advancements is yet to shape, so that there can be more success factors and potential improvements in stroke treatment.

There are mainly two types of treatments for ischemic stroke, i.e., a stroke caused by a blood clot inside the brain: tPA (Tissue Plasminogen Activator) and endovascular procedure, which are commonly known as thrombolysis and thrombectomy, respectively. Thrombolysis works by dissolving the blood clot and in that way restoring the blood flow inside the brain. Thrombectomy is only used for large clots, where the surgeon manually removes the blood clot by using a stent retriever (i.e., a wired-caged device) [29]. Which treatment is to choose mainly depends on the size of the blood clot, although logistical issues also limit which treatment can be given to a particular patient. It is obvious that the management of patients with different types of stroke differs substantially from each other, and the ability to differentiate between different stroke types and to identify the stroke complications is therefore of integral importance in acute stroke care [31]. Therefore, an effective transport policy can yield many ideal outcomes in various ways, such as diverting ambulances through the shortest route, identifying the correct stroke type, and reducing the time to thrombectomy.
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However, in Sweden, thrombectomy is not yet widely adopted and only a few hospitals, such as Stockholm, Gothenburg, Linköping, and Lund offer interventional facilities for acute thrombectomy where patients are typically transferred by ambulance [30]. It should also be noted that different regions practice different policies for the transport of stroke patients to a thrombectomy centre. The policy that is currently used in the Southern Swedish hospital region is the so-called nearest hospital policy, in which the patient should be brought to the closest located hospital for diagnosis. If thrombectomy is required, the patient will then be transferred to the thrombectomy centre (located in Lund). Another possible policy, which we will evaluate as part of this thesis, is the so-called way to thrombectomy centre policy. In the way to thrombectomy centre policy, the patient is transported to the closest hospital in direction towards the nearest thrombectomy centre. If thrombectomy is required, then the patient will be transferred to the thrombectomy centre. In that way, the desire is to reduce the time until thrombectomy, which is important in particular for the patients that are located far from the thrombectomy centre.

To identify the ideal decision making policy, among all possible policies, it is important to be able to assess and study the impact of different policies. In stroke transport logistics, a set of activities (including decisions) needs to be carried out. A particular policy specifies how the decision should made, hence deciding which activities will be performed and how they will be performed. For instance, if a stroke occurs, an emergency call is made and an ambulance is sent to the patient. When the ambulance reaches the patient scene, a decision is made depending on the currently adopted policy concerning where to transport the patient, for example, to the nearest hospital or to the nearest hospital on the way to the thrombectomy centre. Each of the included activities requires a certain amount of time to complete, where a good logistic policy always strives to minimize the amount of time until treatment, hence aiming to save valuable time for the patients.

In order to assess the impact of different policies regarding stroke transport logistics without putting extra risk on achieving negative impacts on the health of the patients, we argue that a simulation model is required. A simulation model can be used to assess different policies in a controlled, simulated, environment in order to predict the outcome of various stroke transport decision-making policies before they are implemented in the real system. A simulation model also enables to take into account the dynamic population size and spatial attributes of patients. The analysis of the simulated outcome of the different policies can be used as guidance when deciding which policy to apply, for example, in a particular geographic region.
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Through the use of simulation, the wish is that both negative and positive effects of certain policies should be identified prior to implementation.

1.1 Background

1.1.1 Stroke

Stroke is a common disease among elderly people all around the world. Stroke is a medical condition caused by insufficient blood flow within a blood vessel inside the brain. This lack of blood flow causes severe damage to the brain cells, and if a patient does not receive immediate treatment, he or she has very little chance to survive. There are three main types of stroke: Ischemic, Hemorrhagic, and TIA (Transient Ischemic Attack).

Ischemic stroke refers to when the blood flow is poor (i.e., decreasing blood flow) and Hemorrhagic stroke refers to when there is a bleeding inside the brain. TIA is sometimes called a mini stroke, which happens due to the formation of a temporary blood clot in a vessel. In Ischemic stroke, the interruption of blood supply is caused by one or several large clots of blood (larger clots than for TIA strokes). Ischemic (including TIA) and Hemorrhage stroke account for 87% and 13% of all stroke cases in the world, respectively [43]. Stroke is typically diagnosed by various kinds of medical imaging such as CT scan and MRI, together with physical examinations. However, regardless of the type of stroke, all patients need to receive emergency support to begin immediate treatment.

1.1.2 Treatment of Stroke

Although stroke is a deadly disease, rapid action with proper diagnosis and treatment can minimize the level of risk of permanent disability and death. For Ischemic stroke attacks, which are the focus of our study, there are two main treatment procedures, i.e. thrombolysis (or tPA) and thrombectomy. In thrombolysis, drugs are used to dissolve the blood clot and restore the normal blood flow. In thrombectomy, the blood clot is manually removed by surgery.

1.1.3 Stroke Logistics in the Southern Sweden

Although thrombectomy is a very effective technique for Ischemic stroke cases where the clot is large, due to the lack of expertise and resource, not all hospitals in a region can provide this type of treatment. In the Southern Swedish hospital region (defined above), Lund SUS, situated in Skåne County, is the only clinic that provides emergency thrombectomy treatment for stroke patients (Figure 1).
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![Map of the southern hospital region in Sweden](image.png)

**Figure 1: Map of the southern hospital region in Sweden [44]**

It is very obvious that it takes longer time for those patients who live very far from the Lund SUS to arrive at the hospital than for those who live nearby. More so, time is a very crucial factor in stroke treatment. Therefore, an optimal transport policy is of paramount importance in stroke logistics in order to service the patients within least possible time.

### 1.1.4 Optimization of Stroke Logistics

In the beginning of this report, we mentioned two possible transport policies for the Southern Swedish hospital region. Having those into consideration, we built an artifact to assess the performance of the policies. An artifact is a purposeful product that is built to address heretofore unsolved problems, typically in an organizational context [40]. In our thesis, the artifact is a computer simulation model that allows us to observe the operational behaviour of ambulance logistics, e.g., by estimating the time spent to complete the stroke activities using different ambulance driving policies.

### 1.2 Goals and Research Question

For this thesis, our prime concern is to propose an agent-based simulation model, which is able to assess the impact of different policies related to the transport logistics of stroke patients. Our model allows to assess the performance of different policies; hence it aims to support decision-makers to identify the best stroke logistics policy in a particular region. In this way, we aim to contribute the improvement of the acute stroke care. The objectives of this research are to:

1. Create an agent-based simulation model, and
2. analyse two stroke transport logistics policies using the developed model. To accomplish the aforementioned goals, the following research question (RQ) is considered. 

**RQ: How can agent-based modeling be used in order to assess the impact of policies related to stroke transport logistics?**

### 1.3 Motivation

#### 1.3.1 Synthetic Stroke Population

Data limitations often restrict the scope of implementation of effective planning approaches for better treatment for the citizens. The Southern Swedish hospital region covers a total area of 27,335 km², and it is the home of approximately 2 million inhabitants. As reported by the Swedish National Board of Health and Welfare (Socialstyrelsen), 25.9% of the individuals who died during 2016 in North Middle Sweden (consisting of the three counties of Dalarna, Gävleborg, and Värmland) have sometimes been diagnosed by stroke (between the age of 20 and 85) [28][32]. In the same year, in the West Sweden (Västra Götland county) the rate is 7.7%. On the other hand, the rate in the Southern Sweden is 26.8%, which is higher than both the North Middle and West Sweden. With this large number of inhabitants and total number of stroke patients (5,684 in all age groups during 2016) in the Southern region, creating a synthetic population with an explicit representation of each stroke patient, and also initialising large number of individuals with the adequate attributes is a research challenge in the area of probability and statistics [33]. Moreover, to build an ideal policy for stroke care logistics, there is an obvious need to have an effective simulation approach with proper distribution and sampling types.

Although there are some research studies that address the issues of stroke and stroke patients in Sweden in general; however, most of the studies lack the in-depth study of the data aspects, and none of them concerns the synthetic population generation in Sweden. A study conducted by the Swedish National Board of Health and Welfare (Socialstyrelsen) [34] presents a quality and efficiency analysis of stroke care in Sweden. In their study, they emphasised on some particularly important areas of improvement based on two separate assessment criteria: performance of stroke care in county councils and stroke care in municipalities. However, the work does not show any effort of in-depth population study in any region of Sweden, nor does it include any information regarding the quality and performance of stroke in the Southern region. Lekander [35] studies the applicability of quality register data in
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health economic analysis of chronic conditions such as stroke. In particular, the author used data from the quality register and linked them with other data sources to test the applicability. Although the research includes several demographic attributes and statistical analysis to measure the applicability of the data, we have not identified any attempts of introducing the simulation approach to predict the possible number of outcomes of any variables. Adiga et al. [36] report on the methodologies for generating a synthetic population for the United States, yet the paper does not clearly mention the approach they have followed to generate the population. As it is stated in their paper, “the resulting model is a dynamic representation of human mobility and interaction over the course of a normative day”, whereas we intend to generate and simulate a stroke population with all the necessary spatial and demographic details.

According to the existing research, it is evident that simulation and population generation of stroke patients leaves many rooms for enhancements. Even more, we have not found that any of the current research trends have taken initiative to work with the stroke population in the Southern Sweden. Nonetheless, the evaluation of simulation modeling with population generation is becoming more optimistic over the past two decades, and more and more researchers are conducting exploratory research in this field [14].

1.3.2 Simulation Modeling and Assessment of Policies

In order to perform high performance stroke care, several factors need to be considered with high accuracy and precision. Examples of such factors are identifying the type of stroke, travelling time to the treatment centres, availability of the resources in the hospitals, etc. Therefore, we argue that an ideal and objective decision making policy can contribute to the improved stroke treatment and bring better opportunities for the patients to get the right treatment as fast as possible.

Through the evaluation of policies, a prominent strategy can be established to promote the rapid response to stroke events and reduce the time to treatment after the patient has shown symptoms of stroke. The core focus of our study is to suggest an artifact to evaluate policies that can eventually optimize the stroke transport logistics. In order to study the outcomes of different policies, we aim to suggest an agent-based model for stroke transport logistics simulation. We consider agent-based modeling in order to explicitly model the individuals and activities involved in the transport of stroke patients. In this way, it is possible to capture complex policies, where multiple individuals need to interact. Wallace et al. [20] emphasises on
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policy-relevant agent-based models stating: “it helps policy makers understand how to translate model results into more effective policies and increase their trust in the analysis”. Therefore, we become interested in developing a prototype of a model that can be used to evaluate and study policies related to stroke transport logistics.

However, the model we design focuses on the principle of DES (i.e. discrete event simulation). In the healthcare logistics process, actions of each event are performed in discrete points of time, and entities or components involved in the system are dependent on each other. Hence, changing the state of one entity affects the behaviour of other entities. Therefore, in the literature [24][37], it is highly recommended to build simulation models with a focus of discrete event technique to maximise the operational efficiency of the models. For example, Allen et al. [38] design an event-oriented decision making tool to make a schedule adjustment that impacts patient safety, patient satisfaction, hospital costs, as well as surgeon satisfaction. The authors test different rescheduling policies by changing two parameters: criterion amount and reschedule amount. In their research, no transport logistics events are addressed to observe the behaviour of the systems.

The predictive model of Getsios et al. [39] uses DES to estimate health and economic outcomes associated with smoking cessation interventions. Although their simulation approach allows to account for heterogeneity of patients and dynamic changes in disease progression, the main purpose of their model is to estimate population level health and economic impact of smoking cessation intervention.

However, the existing works in the domain of healthcare do not adequately build simulation models to assess the patient-relevant outcomes to improve the logistics. Moreover, the stroke relevant decision support tool for ambulances with detailed patient attributes is rarely dealt with in the available research efforts. This missing endeavour urges us to contribute more in this field so that our model results can be a valuable asset in hospital decision making as well as future clinical research activities.
2 Research Methodology

Literature study was the first and foremost method we used in order to gain relevant understanding about our area of research. In addition, we practiced the DSR (Design Science Research) approach in order to create our prototype of a stroke transport logistics simulation model. In order to evaluate and illustrate our prototype, we conducted an experiment where we compared two different stroke ambulance logistics policies within the Southern Swedish hospital region. In this section, we present the in-depth procedures that we followed to answer our research question.

2.1 Literature Review

The vital part of a research work is to carefully decide the proper research method(s). We reviewed a broad range of articles to acquire a conceptual understanding about the research idea that lead us to establish potential research methods. Moreover, the related research works helped us to understand the importance and consequence of an agent-based simulation model in the domain of healthcare. The current research gaps in the area and the scope of the research was realized through reading a wide selection of articles.

Crucial factors such as the diverse nature of stroke patients, their severity and urgency to provide appropriate treatment as well as management of different types of stroke were understood through studying various investigations presented in scientific papers. We mainly considered the following sources to retrieve material for our work.

- ACM digital library
- Google Scholar
- Springer
- European Stroke Journal
- Journal of Official Statistics
- Journal of Healthcare Engineering
- Journal of the Operational Research Society
- Winter Simulation conference
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- Journal of Artificial Societies and Social Simulation
- IEEE

We used search queries such as *stroke transport logistics, agent-based simulation model in healthcare, discrete-event simulation model in healthcare, ambulance diversion policies, and assessment of healthcare policy*, as well as various combinations of these search terms. To filter the most relevant papers from the databases, we used the boolean operators *AND* and *OR*. For a more precise selection of articles, we have chosen the range of publishing year from 2012 to 2018. However, to motivate our research problem we also investigated articles published earlier than 2012.

To ensure that we review quality research papers, as well as to gather more relevant research topics, we looked at the authors profile and explored papers with similar research interest. Before we decided to consider a paper, we read the abstract and conclusion several times in order to assure that the corresponding work suits our research needs. This practice of double checking the research objectives and findings of relevant papers was inspired by Brereton et al. [41] who warned readers by stating, “the standard of IT and software engineering abstracts is too poor to rely on when selecting primary studies”.

### 2.2 Design Science Research

#### 2.2.1 The Design Science Research Approach

The key reason to choose the DSR approach is that we consider *creation* and *evaluation* as the two most important processes involved in our research project. Through the creation of a new artifact, we create a simulation model that enables to analyse the performance of different stroke logistics policies. One of the main goals of DSR is to achieve new knowledge that can be used by professionals of the disciplines to architect solutions for their problem domains [47]. The outcome of our model is expected to serve the similar purpose, where it helps relevant stakeholders to design a higher quality stroke care as well as to choose the right hospitals for diagnosis. Moreover, according to the practical rules, which are sometimes referred as seven guidelines provided by Hevner et al. [40], a DSR must produce an “artifact created to address a problem”. The product of DSR should be a solution to “heretofore unsolved and important business problem” [40]. In particular, according to the guideline 6 (i.e., design as a search process) described by the author, the creation of the artifact should be a search process that emerges from existing theories.
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to design a solution to a defined problem [40] [45]. Therefore, in our research we choose DSR as a viable method where we build the model by accepting existing stroke data as input for the model as well as evaluating the model through assessing two stroke transport logistics policies.

As illustrated in Figure 2 [45], we make an initiation by asking the question: *what do we wish to accomplish through the creation of a new artifact?* In our research, the major concern is to assess the performance of any available ambulance transport policy for stroke patients. The performance of the policies has been measured over time.

The second phase is to develop the main solution to solve our problem, where we implement an algorithm and calculations to build a prototype. The first task of this step includes data collection. Then we generate a synthetic stroke population considering all the necessary patient attributes. We provide a detailed description of our data collection in the next section.

We implemented our simulation model in the Spyder environment of Python 3.6, using a Windows 10 computer. In demonstration we make a design & development-centered initiation to solve our problem using the artifact. We have taken into account our chosen policies as suitable context, and run different simulations for different policies. In the experimental evaluation phase we studied the outcome of the policies and observed their efficiency and effectiveness. The quantitative approach was considered to measure and assess the performance of the
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considered policies. We support our choice of adopting quantitative analysis by Cleven et al. [48], who remarked some existing approaches for artifact evaluation. In quantitative analysis, the evaluation characteristics of the evaluation objects are assessed and analysed on a numerical basis [48]. For instance, our model outputs the total service time (in minutes) of ambulances in both policies, regarding each stroke type (e.g., thrombolysis and thrombectomy). Then, we compare between the policies by calculating the average differences of service time, as well as the differences of standard deviations and medians.

2.2.2 Data Collection

In our study, we used the real statistical record of stroke patients for the year of 2016, which was provided by a representative of the Skåne University hospital. For additional statistical information we used other authentic sources such as Sweden’s official database of stroke register (Riksstroke) [42] and the Swedish National Board of Health and Welfare (Socialstyrelsen) [28].

The data that we collected had statistical information about stroke patients in the geographical area we planned to study in our thesis. This information included data about the counties, municipalities, population of each municipality, hospitals within each county, number of strokes in 2016 and for each of the municipalities, age groups, number of thrombectomy cases for each municipality and county, hour-based statistics for the number of stroke patients in Skåne county, and all available addresses in the studied area.

2.2.3 Selection of Tools and Technology

To be able to achieve our thesis goal we used a selection of available tools and technologies. Programming languages, web services, text editors and data sorting and analysis are all technologies that we used in our thesis work. In Table 1, we present all of the tools we used to conduct our work next to their purposes.
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Table 1: List of used tools and their purposes

<table>
<thead>
<tr>
<th>Tools</th>
<th>Purpose</th>
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</thead>
<tbody>
<tr>
<td>Python 3.6</td>
<td>Writing the code for population generation and our computational simulation model</td>
</tr>
<tr>
<td>Spyder</td>
<td>An IDE used to write and run the python code</td>
</tr>
<tr>
<td>Google Maps Geocoding API</td>
<td>Getting coordinates of patients and hospital addresses</td>
</tr>
<tr>
<td>Google Maps Distance Matrix API</td>
<td>Getting travelling durations between patient addresses and hospitals, as well as between hospitals</td>
</tr>
<tr>
<td>CSV Python library</td>
<td>Reading and writing Comma Separated Values (CSV) files</td>
</tr>
<tr>
<td>Openxlpy Python library</td>
<td>Reading and writing Excel files and generating charts</td>
</tr>
<tr>
<td>Excel 2016</td>
<td>Output analysis</td>
</tr>
<tr>
<td>Google Drive</td>
<td>Sharing necessary folders and files</td>
</tr>
<tr>
<td>Draw.io</td>
<td>Drawing charts and diagrams</td>
</tr>
</tbody>
</table>
3 Related Work

A large amount of research work has been done in the area of agent-based modeling for policy assessment. The majority of the research contributes in the domain of business and marketing, such as freight transport logistics, warehouse logistics, and crowdsourcing systems. A wide range of studies also focuses on building effective ambulance diversion policies for hospital emergency departments. However, the existing studies within the domain of healthcare have little concern on stroke patients and improvement of stroke transport logistics systems. For example, Taboada et al. [1] address the effects of patient derivation policies in emergency departments. Although an agent-based model is used to predict the policies, the patient population is not categorized by any specific diagnosis type such as stroke. Liu et al. [2] present a generalized agent-based model to simulate emergency departments in order to improve the patients’ treatment process.

However, we discovered an ample amount of literature discussing simulation modeling in transport logistics. In the following sections, we present a detailed overview of the relevant research contributions in the area of our study.

3.1 Synthetic Population Generation

Execution of agent-based simulation requires an initial dataset defining the necessary attributes of the targeted population. To deal with a large number of stroke patients and improve the stroke transport logistics, it is paramount to consider new data sources to support population synthesis at a more disaggregate level [3]. According to Namazi-Rad et al. [4], “the purpose of the reliable dynamic synthetic population is to create a valid representation of the population spatially distributed while addressing the daily population transitions”. The history of synthetic population generation dates back to 1993, where Rubin [5] is the first author who releases synthetic microdata that is constructed using multiple imputations. Rubin claims that the new dataset can be validly analysed through standard simulation models.

Wang et al. [6] conduct a population-based study where they investigate age and ethnic disparities in stroke incidence over time. The authors use stroke register data
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from the South London, but there is no computational simulation model implemented to generate the results. In order to calculate the age, ethnicity, and sex specific incidence rates, they consider 95% confidence interval, assuming a Poisson distribution. Moreover, they use the Cochran–Armitage test to analyse their trends over time.

A similar study [7], which is also a population-based epidemiological study on stroke incidents in the Southern Sweden, investigates temporal trends in stroke incidence and case-fatality in that region. Their study area comprises 8 municipalities in the Southern Sweden with the total number of 274,239 inhabitants, according to 2015 statistics. The 8 municipalities constitute the local catchment area of the Lund SUS. Like the previous study, the authors calculate age and sex standardized incidence rates using the direct method and with 95% confidence interval, assuming a Poisson distribution. However, the research work does not design any simulation model for their statistical analysis.

In our study, we generate a synthetic population for the Southern Swedish hospital region. The main goal of this stroke population generation is to use the population as input for the processes of developing and assessing stroke transport logistics policies. Some data are very crucial for achieving this goal, especially time and distance. Moeckel et al. [8] present a theoretical introduction about synthetic population and create two different applications to generate synthetic populations for two cities in occupied Palestine and Germany. While most synthetic population generation approaches concentrate on iterative proportional fitting, the authors combined this approach with Monte Carlo Microsimulation that enables to reproduce human behaviour at the individual level. The limitation in their research is the collection of individual microdata, which they are not allowed to retrieve from administrative registers because of data privacy concern in those countries. Therefore, their simulation models work with synthetic micro-level data that is retrieved from general accessible aggregate data. It is obvious that the main purpose of the work is similar to our work (i.e., creating a synthetic population), though the research objectives differ significantly. Their models are going to be applied in urban modeling concerning the public transport, whereas our synthetic population is planned to be applied in stroke transport logistics.

Knight et al. [9] create a synthetic population that represents the joint cardiovascular disease risk factors distribution among the adults in the New Zealand population.
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The authors develop a synthetic national population using realistic multivariable risk characteristics of cardiovascular disease. Their population construction is the initial step in developing a simulation model for analysing the possible impact of a set of national cardiovascular risk management strategies in New Zealand. Like our synthetic population generation approach, their study calculates values of demographic and non-demographic variables using the Monte-carlo method. Moreover, the authors validate the simulation output through comparison with the real dataset, in which they find the matching pattern without any remarkable difference.

3.2 Decision-making Policy in Hospital Transport Logistics

With the aging population in Europe, the healthcare systems need to ensure the highest level of satisfaction to their patients. An accurate and effective logistic system has direct impact on the quality of medical services. Dobrzańska et al. [10] present some modern forms of healthcare logistics systems, where they identify the consequences of using quality logistics services. Their findings suggest that development of logistics services in the medical activities can significantly improve the speed of response to queries and optimize the driving routes for patient transports. However, it is also noted from literature [11] that hospitals generally deal with numerous kinds of flows everyday; therefore, it is very hard to make any accurate prediction of any specific type of patient demand in hospitals. For this reason, in our simulation model, we calculate the times for all major possible activities involved in hospitals and ambulance services. For example, if a patient requires thrombectomy treatment and he or she is not already in the specialized hospital, then we calculate the total service time for the requested ambulance, and for door to puncture time for the patient.

Sung et al. [24] suggest modeling requirements for an emergency medical service system design evaluator, where they propose some common major events and related operational problems of an emergency service process (Figure 3).

![Figure 3: An example of an emergency service process provided by Sung et al. [24]](image-url)
Holodinsky et al. [12] study the impact of treatment times on transport decision-making for stroke patients where they compare two different treatment protocols (*drip and ship* versus *direct to endovascular thrombectomy*). In order to determine the impact of treatment time, they use conditional probability modeling. The study models pre-hospital transport concerning ischaemic stroke patients in order to improve treatment times in a particular geographic area of Ireland. Although the study argues that modeling patient transport for system-level planning has important implications for the future planning of acute stroke service, the authors do not describe any novel design approach to create such a model.

Reuter-Oppermann et al. [13] discuss individual planning problems for emergency medical service as well as providing solution approaches for each problem. They study planning problems of three countries: UK, Germany and the Netherlands. Based on the three aforementioned systems, a typical emergency medical service and its associate strategy are conferred. The study suggests that, in a typical system, the service provider is responsible for two main tasks: emergency calls and patient transports. Emergency calls are categorized into two types: life threatening and urgent calls. A response time target is set for each call and patient transport. For example, in the Netherlands, the life threatening calls must be reached within 15 minutes and urgent calls within 30 minutes. The authors also argue that the target that is decided by the regulator has significant impact on the optimal system design. In their study, a response time is considered as the main measurement metrics for emergency service providers.

### 3.3 Agent-based and DES Modeling

In our research, we are interested in explicitly modeling the individuals and the activities involved in the transport of stroke patients, which can be done using an agent-based model. Almagooshi [14] describes several simulation modeling tools including agent-based simulation and DES (Discrete Event Simulation). The author reviews a broad range of literature to identify a common layout of simulation models (see Figure 4).
Liu et al. [15] develop a systematic method to automatically calibrate an agent-based general medical department model with incomplete data. The authors search the best value of model parameters using simulation-based optimization. Moreover, they emphasise that an agent-based simulation model deals with different kind of independent parameters and dynamic individual behaviour of the system; therefore, reliable and complete real data from the target system is an initial need to design an effective simulation model. They also suggest to carefully select the system KPIs in order to compare the behaviour of two systems (i.e. simulator and actual emergency department) so that the KPIs address the two issues; the chosen KPIs should significantly reflect the target system’s macroscopic behaviour and it should be possible to retrieve from historical dataset. Welch et al. [16][17] list several commonly used metrics to measure an emergency medical department’s operations, for example, the patients’ length of stay, door-to-doctor time (also known as door-to-diagnostic), and ambulance diversion (amount of time needed to divert ambulances away from the emergency department).

Pira et al. [18] evaluate stakeholder policy acceptability in urban freight transport, where they integrate agent-based models with discrete choice models. Their combined models provide a ranking of policies that fulfill the heterogeneous desires and objectives of stakeholders. Kittipittayakorn et al. [19] follow a similar approach where they integrate DES and agent-based simulation. Their model is used to improve the patient waiting time in an orthopedic department of a hospital. The result of the study shows that using correct simulation model improves the total waiting time. The study suggests that the waiting time can be reduced from 1246 minutes to 847 minutes.
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3.4 Assessment of Policy through Simulation

In our research we evaluate our generated prototype by comparing two stroke transport logistics policies. We calculate the total time spent for each event involved in the logistics, and we consider time as the assessment metrics for each policy.

However, very few studies address the issue of policy assessment in the healthcare domain through simulation modeling. In the domain of public health practice, Wallace et al. [20] use various agent-based modeling approaches to assess the use of policies for tobacco regulation. Even though the core purpose of their work resembles our research objectives, the differences in population attributes and size between their and our study are significant. The authors present a standard framework to evaluate policy relevant models.

![Diagram of Evaluation framework for the policy-relevant agent-based models by Wallace et al. [20].](image)

Figure 5 illustrates the activities and associated outputs in the framework, in which the activities are categorized into two types: internal model development activities and external model development activities. Conceptual development, model implementation, model testing and validation, and policy testing are considered as internal model development activities, and the communication activity fits into the latter category. As a part of the communication activity, they share the initial
simulated results with relevant stakeholders to identify the data gaps and communication with empirical scientists.

Jagtenberg et al. [21] address the problem of dynamic ambulance dispatching in a large area of the Netherlands where they hypothesised that the closest-idle transport policy is most optimal. Moreover, in addition to the traditional closest-idle transport policy, they develop two alternative approaches (i.e., policies) based on a Markov Decision Problem (MDP) and a Heuristic technique. As their paper claims, the MDP models more than just the number of idle ambulances, which results in a better outcome by balancing the amount of detail in the system representation. The heuristic approach is proposed for ambulance dispatching, and can handle a geographical area with large numbers of ambulances. The authors validate their policies using discrete event simulation, and the assessment results show that significant improvements can be obtained by using the alternative policies. For example, the heuristic technique reduces the fraction of late arrivals by 18% compared to the traditional closest-idle transport policy. However, the drawback discussed is that the heuristic technique increases the average response time for ambulances.

Fazekas et al. [22] develop a framework for assessing healthcare planning approaches with no implicit mentioning about any approach they follow to build their simulation. The framework aims to suggest a tool for policy makers to analyse strengths and weaknesses of planning strategies in a given country. In their study, they consider Austria, Germany, Canada (Ontario), and New Zealand.

Kang et al. [23] investigate the effect of patient admission process policies on an emergency department. They study 6 different types of policies (4 basic types and 2 hybrid), and evaluate the patient effects by a DES model of patient flow. However, the paper does not deal with any transport or driving policy.
4 Model Description

In this chapter we present a theoretical overview of our developed simulation model as well as a description of the relevant approaches we have taken into consideration when building the model. This chapter also includes a section where we explain the statistical considerations we used when developing our simulation model.

It should be emphasized here that the main activity in our approach (shown as the central box in Figure 6) is to simulate a stroke population using a set of provided policies.

However, to execute the simulation, a few components are needed as input, including a (synthetic) population, a set of transport policies and some other types of input data, for example, the percentage of thrombectomy patients, and driving times between patient addresses and hospitals and between hospitals. As output, our model generates a set of records that includes the statistical data about the simulation.
4.1 Model architecture

The proposed model is composed of dependent components that define the structure and behaviour of it. As figure 6 illustrates, the structure of the simulation model consists of three main parts, i.e., input, simulation and output. The behavioural side of the model is basically depending on the simulation and the way it reacts towards the events that happen during the simulation.

Several inputs are needed in order to run our simulation model. Firstly, we need a population, which is the set of patients that will be used when assessing each of the considered policies. It should be noted that the population of stroke patients might be either real, in case there is historic data specifying in detail real stroke patients, or synthetic, in case there is only aggregate data available about stroke patients in the geographic area of study. The reason for using a synthetic population is to guarantee that a stroke patient population with characteristics corresponding to the real aggregate properties of stroke patients is available as input to the simulation model.

Secondly, the policies that will be assessed using our model have to be defined and provided. It should be noted that support for all of the considered policies needs to be explicitly built into the simulation model. Finally, it is necessary to include input data that specifies the thrombectomy patients’ percentage within the whole population, driving durations between addresses, ambulance response times, expected ambulance times at the scene, and thrombolysis time.

The second component, that is the agent-based simulation model, follows the DES structure for the activity flows during runtime. In Figure 7, we represent the overall flow for our simulation model, explicitly showing how events are managed using the DES approach.
Lastly, the output of the model will contain data that specifies all of the activities that were simulated expressed by their start and end times.

### 4.2 Agents

An agent is an object that is part of a program, and which is responsible for making decisions autonomously. An agent-based simulation model is a simulation model where at least one of the simulated entities or objects is modeled as an agent [46]. In our simulation model we have two types of entities that are modeled as agents. The ambulance and the hospital entities are modeled as agents, since both can make decisions autonomously and change the state of themselves or the state of other
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entities, leading to a change in the state of the whole environment or simulation. The ambulance agent decides which hospital the patient should be transported to, and that decision will affect the treatment starting time and the whole output of the simulation. The hospital agent decides whether the patient needs a thrombectomy and in that case it is responsible for ordering an ambulance for further transport to the thrombectomy centre.

4.3 Statistical considerations

Since the aim of building our simulation model is to improve the stroke transport logistics by assessing different transport policies, we consider statistical variables that explain and observe the effect of simulating those policies on a certain stroke population. Those variables are categorized into two groups: constant and experimental variables.

Constant variables are variables whose values do not change during the simulation, such as the population size, thrombectomy patients’ percentage, thrombolysis time, and the number of patients who needs transport from a diagnosis hospital to the thrombectomy centre. The purpose of using constant variables is to ensure that we are conducting a fair comparison between the outcomes of several policies.

The experimental variables are those variables whose values keep changing during the simulation and in that way support the analysis of the output of the model. The ambulance service time is an example of an experimental variable, whose value differs from a patient to another during the simulation of the policies. In order to perform a proper assessment of the policies, the values that will be assigned to each of the experimental variables will be the same for all simulated policies, in the same time different from patient to another. An exception for the ambulance travelling time is made, since the destination is chosen based on the simulated policy.

4.4 Implementation

The implementation of our simulation model starts by interpreting the input provided at the beginning of the simulation. In this initial step, the constant variables’ values are defined based on the input (i.e., population size, thrombectomy patients’ percentage, etc.). As for the experimental variables, their values are decided based
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on some constant variables’ values (i.e., the ambulance response time), as discussed later in this section.

The nature of our research is based on events that happen in a discrete manner of time within a certain environment (i.e. strokes within a population). For that, we used Discrete Event Simulation (DES) to build our simulation model. Moreover, DES is considered time efficient since it only simulates the points of time where things actually happen.

A DES model has a clock that represents the time of the simulation, as well as a list of events that will happen during the simulation and that is called the event list. Within a DES model, a certain event occurs causing an action or a set of actions and, possibly, adding a new event to the list. Each of the events will happen at a certain point of time during the simulation, where it represents either a starting-action and/or ending-action. At the end of each simulated activity, the simulation clock will be advanced to the time of the next event in the event list.

In Figure 8, we illustrate the set of events that happens for each patient in the population during the simulation.
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![Sequence of events during the simulation](image)

**Figure 8: Sequence of events during the simulation**

Each of the patients will have the same initial event, which is the stroke event. Each of the stroke events addresses the beginning of a new sequence of events for a particular patient. The first six events in the flowchart (stroke event – start thrombolysis treatment event) will happen for all the patients. The events in the blue box in the figure will only happen for the thrombectomy patients.

In order to prioritize the events based on their time of occurrence, we used an event list implemented as heap data structure. The heap’s initial size is decided using the population size entered as input at the beginning of the simulation. Every time a new event is created, it will be added to the event list, which is sorted based on the times of the events in the list. This enables the addition of new events as a consequence of another event’s actions. Whenever an activity has been completed, the corresponding event will be removed from the event list. The simulation run will automatically end when the event list is empty.
In order to give more insight about how the simulation works, we show in Figure 9 a typical sequence of events involving three patients. The simulation timeline represents the simulation clock. One of the strokes happened at 14:04 for (Patient 1) and it was added to the simulation event list at the beginning of the simulation. Please note that input to the simulation model is a set of stroke patients where the time of stroke is known for each patient; hence, we can add stroke events for each of the patients at the beginning of the simulation. When executing the stroke event for Patient 1, another event called “call ambulance event” will be added to the event list at the same time of the stroke event. At 14:21 of day 166 another activity (event) happened for Patient 1, that is, the ambulance arrival event.

In between those two events for Patient 1 (calling the ambulance and the ambulance arrival), another stoke event was added to the event list of the simulation for Patient 2 at 14:09. As the ambulance was on the way to Patient 2, the ambulance arrived to Patient 1 at 14:21 and it took 16 minutes to get the patient on the ambulance and ready to leave to the diagnosis hospital.

On the other hand, and during the time the paramedics were at the locations of Patient 1 and Patient 2 (each in a different location), it was the time for another stroke event to happen for (Patient 3) at 14:25 of the same day, creating a new event and adding it to the event list. This example applies for the rest of the population that is used to run the model.

Considering the computational part, the values of the experimental variables depend on the considered policies. For example, if the policy is to drive the patient to the nearest hospital for diagnosis, the ambulance service time will be affected by that
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policy decision and might be different than its value in the simulation of another policy.

The ambulance response times (referring to the time between calling the ambulance and its arrival at the location) and the time at the scene (representing the time spent at the patient’s location) are calculated based on the received data of the county where the patient lives. This is done by randomizing a number between the minimum and maximum times that are chosen based on the input provided at the beginning of the simulation.

For both of the response time and time at the scene values, we used a non-random seed to guarantee the generation of the same random numbers for the same patients within the simulation of each of the considered policies. The purpose of using seeds is to initialize the pseudo random number generators that are used so that they give the same series of random number for each of the considered policies. Unifying those attributes’ values within several policies’ simulations makes it easier to compare policies.

Travelling times between addresses were calculated using the Google distance matrix API, and the generated travel times were used in order to calculate the total ambulance service times.

The hospital related variables (i.e. Door-To-Needle time) are assigned based on the data input given at the beginning of the simulation. However, the Door-To-Puncture time it is only assigned for patients who are diagnosed to need a thrombectomy.

Finally, an output will be generated including records that represent all of the statistical data we need to assess the simulated policies. Ambulance total service time, total treatment time and total time until treatment are considered as the most important variables and are used as measurements for assessing the considered policies.
5 Synthetic population

A synthetic population is a set of stroke patients generated using available aggregate statistics of stroke patients. The census dataset we consider in our study represent a large number of stroke patients in each municipality with a set of age ranges and times of the strokes.

However, the original dataset of the target population is an aggregate representation of values that were recorded based on the real events over a certain period of time. Therefore, it is essential to consider new data sources to support population synthesis at more disaggregated level [3], which improves the potential richness of demographic attributes as well as helping us to predict the consequences under different scenarios. To achieve that, we used Monte Carlo simulation to generate a disaggregated data set as described below.

The synthetic population that we generate to be used as input to our simulation model contains a set of patients. Each of the patients has a set of attributes that describe the characteristics of that patient, including the time of the stroke, the address (street name, postal area number, building number) and the age of the patient.

5.1 Monte carlo simulation

We used Monte carlo simulation to generate a stroke population for a specific period of time. As input to the Monte carlo simulation, we used aggregate statistics with the necessary spatial attributes, as well as age, time etc. of the stroke patients in a particular geographic region. We use statistical sampling, since the input dataset for this simulation and all the values are represented using aggregate statistics.

The collected data was analysed and rearranged in order to be used as an input for our Monte carlo population generation simulation. This data is listed as items in the first column of Table 2, followed by the considered attributes of each of them in the second column.
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<table>
<thead>
<tr>
<th>Items</th>
<th>Attributes</th>
</tr>
</thead>
<tbody>
<tr>
<td>Counties</td>
<td>Age group, number of strokes, and number of municipalities.</td>
</tr>
<tr>
<td>Municipalities</td>
<td>Age group, number of strokes, and addresses.</td>
</tr>
<tr>
<td>Age groups</td>
<td>Population and number of strokes for each of the groups.</td>
</tr>
<tr>
<td>Addresses (location)</td>
<td>County, city, street name, postal code and building numbers.</td>
</tr>
<tr>
<td>Times of strokes</td>
<td>Number of strokes per hour for the considered year.</td>
</tr>
</tbody>
</table>

5.2 Simulation implementation

Our population generation approach, which is based on the principles of Monte Carlo simulation, starts by deciding the size of the stroke population and it ends with a generated population of stroke patients, which can be used as input to our simulation model.

The flowchart in Figure 10 visualizes the algorithm of our population generation simulation. The blue box represents the process that needs to be repeated each day of the simulation, and the grey box shows the process that runs for each of the patients for a specific day. After calculating the population size, a counter is added to make sure that the simulation runs for a specific number of days.
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The size of the population in the simulation is calculated using a 95% confidence level in order to have a statistically significant population. The resulting population size was used to specify the number of patients per day, by calculating the mean for the number of patients per day. A rounded value of the mean was considered to represent the number of patients per day, and the remaining number of patients of the whole population was added to randomly chosen days for the time period of the simulation.

For each day, a number of patients is generated, and for each of the patients, the time of stroke, age group, address and county are generated. As mentioned above, the main goal of the population generation simulation (using Monte carlo simulation) is to provide input data for our agent-based simulation model.

As the flowchart in Figure 10 shows, the process in our synthetic population generation simulation is sequential, and some of the patients’ attributes are related and dependent on other attributes. Determining the municipality, for example, is
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dependent on which county was sampled for a patient, and only addresses within the chosen municipality can be generated.

We validated the output from the population generation simulation model by running it for 365 days for the input data described below (in Chapter 6), to be able to compare the results (on aggregate level) to the real data collected for year 2016.
6 Case Study

6.1 Population Generation
We ran our population generation model in order to generate a population based on the statistical calculations described in Chapter 5. The output of this process was a population of 5902 stroke patients. Each patient of the population had its own attributes including stroke time, age and address. For our case study, we used the generated population as input for the next step, which is the simulation of the policies.

6.2 Simulation of Patients
This step included the actual calculations that yielded the statistical data we used for the analysis and understanding of each of the considered policies. In our case, we used the generated population of 5902 stroke patients and the simulation was run twice, once for each of our two policies. In addition, and to be more consistent with the comparison between policies, we let the same subset of patient be thrombectomy in both of our simulation runs In particular, we randomly selected 10% of the patients to be thrombectomy patients. Additional data was provided at the beginning of the simulation, describing the expected ambulance response times and the times spent at the patient scene (layover time). That data represented the minimum and maximum times possible for these ambulance’s attributes. In our study, each of the times (ambulance response and layover times) had a 15.0 minutes as the minimum time for all counties, where 20.0, 20.4, 23.0 and 25.0 minutes were the maximum values for Blekinge, Skåne, Halland and Kronoberg, respectively.

6.3 Considered Policies
We consider two specific policies, which we used in order to evaluate and illustrate our simulation model. In addition, the results of our case study provide insight into the performance of the two policies.
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We refer to the two policies as the nearest hospital policy and the way to thrombectomy centre policy. In the nearest hospital policy, which is illustrated in Figure 11, the patient is transported to the hospital closest to the location of the stroke incident (i.e., patient’s address). In the way to thrombectomy centre policy (see Figure 12), the policy is to transfer the patient to the nearest hospital on the way to a thrombectomy centre (i.e. Lund SUS in our study). However, if the nearest hospital is located within 10 minutes driving time from the patient’s location, the ambulance will transport the patient to the nearest hospital regardless whether this hospital is located on the way towards the thrombectomy centre.

Figure 11: Nearest hospital policy
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6.4 Computational Results

6.4.1 Analysis of Outcomes

The simulation of the population had two separate outcomes as we ran it once for each of the two considered policies (i.e., the nearest hospital policy and the way to thrombectomy centre policy). We analysed each of the outcomes and compared the the values of the first ambulance service time, the second ambulance service time and the total service time until.

In our analysis, we considered two main categories of patients in our comparison between the two policies’ outcomes, i.e., patients who needed thrombectomy (thrombectomy patients) and patients who did not need thrombectomy (thrombolysis patients). It should be noted that thrombectomy patients also receive thrombolysis, before thrombectomy is initiated.

Figure 12 shows the output of both policies considering the ambulance’s duration of time needed to serve and transport thrombolysis patients to the hospital for diagnosis. Patients who needed only thrombolysis represent 90% of the stroke population.
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Figure 13: Histogram showing the time needed by the ambulance to serve thrombolysis patients and drive them to the diagnosis hospital.

The results show that following the nearest hospital policy is more beneficial for thrombolysis patients than the way to thrombectomy centre policy. In the nearest hospital policy, 4280 patients (i.e., 80.6%) of the thrombolysis patients had a total ambulance service time between 40-70 minutes, whereas in the way to thrombectomy centre policy only 3470 patients (65.3%) were served within the same period of time. Generally, the results presented in Figure 13 indicate longer ambulance service durations for the patients using the way to thrombectomy centre policy with an average of 67.2 minutes in comparison with 59.0 minutes for the nearest hospital policy.

Furthermore, the simulation results show that the way to thrombectomy centre policy has a higher standard deviation than the nearest hospital policy, i.e., 16.8 minutes for the nearest hospital policy and 25.9 minutes for the way to thrombectomy centre policy. This reflects the fact that following the way to thrombectomy centre policy the ambulance needs more time than following the nearest hospital policy to transport thrombolysis patients to a hospital for diagnosis.
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The line chart represented in Figure 14 illustrates the service time in minutes for transporting thrombectomy patients to their first hospital, i.e., the hospital where diagnosis was made.

The thrombectomy patients, forming 10% of the population in our case study, had similar pattern of time as the thrombolysis patients for the first ambulance service time. This is demonstrated by the fact that more patients arrived to the hospital within 40-70 minutes in the nearest hospital policy output than in the way to thrombectomy centre policy. However, the longer time the ambulance needed to get to the diagnosis hospital, the more time is saved for those patients.
Figure 15: The consumed time by the ambulance that drove thrombectomy patients from the diagnosis hospitals to the Lund SUS (the thrombectomy centre in our case study).

Figure 15 shows the times that were needed to transport the thrombectomy patients that were transported from their diagnosis hospital, other than Lund SUS, to the Lund SUS for thrombectomy. The chart includes both policies’ results. The results were divided into 9 separate time slots from 55 minutes as the minimum to 190 minutes as the maximum, each covering 15 minute periods of time. For most of the thrombectomy patients, the results show that using the way to thrombectomy centre policy is better for these patients compared to the nearest hospital policy.

By analysing the output of the way to thrombectomy centre policy, we found that 41.3% of thrombectomy patients who needed a second transport were served within 55 to 70 minutes compared to only 25.4% for the nearest hospital policy. As for the rest of the thrombectomy patients we calculated the standard deviation interval for each of the outputs, and that yielded [100.4 - 106.6] and [88.5 - 93.5] minutes for the nearest hospital policy and way to thrombectomy centre policy, respectively. The longer the interval, the more time was needed to serve those patients.
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Our results considering the total service time for thrombectomy patients, from the stroke was reported until the beginning of thrombectomy in the Lund SUS, is represented in the cumulative line chart in Figure 16. In this figure, the patients are clustered according to service time intervals, each of which represents 10 minutes, starting with 95 minutes and ending with a maximum of 325 minutes. Generally, and for all counties together, we can observe that the time pattern for both outputs are similar to each other, although there are slight differences between them considering the statistical calculations. The average, for example, differs with 3.0 minutes. On the other hand, the median value indicates a larger difference between the time of stroke and the beginning of thrombectomy, represented by 193.5 and 188.8 minutes for nearest hospital policy and way to thrombectomy centre policy, respectively.

6.4.2 Model Validation

Validation of our model had to be done for the synthetic population simulation and the output of the simulation model. The synthetic population generated was validated using the statistical values calculated at the end of the population generation simulation.

The number of patients for each of the age groups of the generated population was accumulated and compared to its corresponding value from the 2016 census data. Figure 17 shows a chart representing the number of patients per age group for both populations (simulated synthetic and 2016 census).
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Figure 17: Comparison between the number of strokes for each age group for the synthetic population and the 2016 census data.

Figure 17 shows that the highest number of stroke patients was for the age group 75-79. The patients who had strokes from this age group represented 16.40% of the total stroke population. On the other hand, strokes from the same age group represented 16.47% in the 2016 census data.

Figure 18: Comparison between the number of strokes for different hours of the day for the synthetic population and the 2016 population.
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Figure 18 shows a comparison between the number of strokes by the time of the day of the stroke incidents (by hour) in the county of Skåne. We observed very small differences in this aspect between the 2016 census data and the synthetic population. The comparison for the time aspect was made only for Skåne county due to the statistics we had access to, where aggregate data about the time for strokes were available only for the county of Skåne. The data collected from 2016 about the time of strokes in Skåne County was also used as an input to simulate the times of strokes for patients in the rest of the counties in the studied region. By looking at the curves in Figure 18, it is obvious that our population generation model generates a time curve that is similar to the 2016 census data.

![Strokes per county (compared to 2016)](image)

**Figure 19: Number of strokes per county**

According to the census dataset, Skåne County is the highest populated area in the investigated region and it was inhabited by 1,324,565 persons for the time of the study. Rationally, that increases the probability to have the highest percentage of the stroke population from that county. This is demonstrated in Figure 19, where 3,973 stroke patients out of 5,684 were registered in Skåne in the 2016 census data, compared to 3,919 out of 5,902 in our synthetic population, which is not a very big difference. From the figure, it can be noticed that for the other counties, the number of stroke patients are almost the same in both the 2016 census data and the simulated data.
In Figure 20, we demonstrate the number of stroke patients for each of the municipalities in the four considered counties for both the 2016 census data and for our synthetic population. As can be observed from the figure, there is no large gaps between the two populations, although for Malmö the number of simulated stroke patients are slightly higher than the in 2016 census data. This is explained by the synthetic population size and that Malmö has more inhabitants than all the other cities.
7 Discussion

Through the creation of our new artifact, i.e., an agent-based simulation model for analysis of stroke transport logistics policies, we were able to evaluate two different stroke transport logistics policies by performing a case study. The simulated impact of the considered policies contributes in order to deciding the best of stroke transport logistics policies, in particular for the Southern Swedish hospital region.

In our experimental evaluation step, we evaluated our synthetic population generation approach by comparing our generated synthetic population with the original dataset on an aggregate level. We observed similar patterns of all attributes of the generated synthetic population as we had in our 2016 census data.

We used our synthetic population of stroke patients to build our agent-based model and we categorized the outputs for two types of stroke treatments: thrombolysis and thrombectomy patients. Thrombolysis patients represent 90% of the total number of stroke patients, and the rest of them are in need of thrombectomy treatment. We notice that more thrombolysis patients (80.6%) are served in less amount of time (between 40 and 70 minutes) when the decision making of the ambulance is based on the nearest hospital policy. On the other hand, for the way to thrombectomy centre policy, only 65.3% of the thrombolysis patients are served within the same amount of time. This is justifiable, because in the nearest hospital policy, patients are carried to the closest hospital for diagnosis. Therefore, the ambulance’s total service time is faster than in the way to thrombectomy centre policy. Even more, thrombolysis treatment is more available than thrombectomy, where thrombectomy patients require more time to reach the treatment centre, particularly if they live far away from the thrombectomy centre. However, this indicates that for thrombectomy patients, the way to thrombectomy centre policy is more optimal. The simulation output supports our argument where it shows that 41.3% patients are transferred to the thrombectomy centre by the second ambulance between 55 and 70 minutes. For the other policy it only covers 25.4% of the thrombectomy patients within the same amount of time. It is important to note that a second ambulance is required when a patient needs thrombectomy treatment as the patient must be transferred to the
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thrombectomy centre. However, it is also noticed that the total time to thrombectomy is very similar for both of the policies.

The core objective of our model is to calculate the time spent for each activity involved in the stroke ambulance logistics process. The existing literature suggests building DES and agent-based models to assess the performance of policies in various fields of sciences; however, little is discovered in the hospital domain with primary focus on stroke patients. More so, the population attributes and geographical area we are considering in our thesis is rarely dealt with in existing research. Our contribution fills this gap through the creation of a new artifact, which takes vital initiative to optimize the stroke logistics, and which we apply in the Southern Swedish Hospital region.

Although the statistical analysis of the simulation output indicates that our agent-based model is valid and reliable, there are certainly some data limitations that hinder us to obtain more accurate and rigorous outputs. For instance, in the census data, the value of door to needle time is not available for sufficient number of hospitals. This issue was solved by interviewing a leading neurologist at the Skåne university hospital; according to his recommendation we considered 40 minutes average time for the door to needle time at all of the considered hospitals.

The main challenge during the development phase of our model was reading Swedish characters in the programming platform. Many street names and municipality names include Swedish language specific characters, i.e., å, ä and ö. To solve this problem we converted all such characters into corresponding English alphabets, for example, å as aa, ö as oe, and ä as ae.
8 Conclusions and Future Work

In this thesis we have built an agent-based simulation model to assess the performance of two stroke transport logistics policies in the Southern Swedish hospital region. Due to lack of input data, we generated a synthetic stroke population using a Monte carlo simulation approach. The generated synthetic population contains all of the necessary attributes such as stroke time, age, city, etc. We used this population as an input for our simulation model. We run one simulation for each of two ambulance driving policies and analysed the output, e.g., which policy can provide service for most number of patients in less amount of time.

We found that using the nearest hospital policy, the ambulance can transfer patients within shorter amount of time to the diagnosis hospital than in the way to thrombectomy centre policy. On the other hand, using the way to thrombectomy centre policy, the thrombectomy patients are expected to arrive at the thrombectomy centre in shorter amount of time than for nearest hospital policy. We have also observed that the number of patients transported to the hospital significantly differs from one policy to another. However, the main purpose of our research is to build an agent-based model for assessment of stroke transport logistics policies, where we illustrate and evaluate the model by studying two different policies. Therefore, at this stage, determining the most optimal or best policy is beyond the scope of our work.

8.1 Future Work

Many different experiments and enhancements could have been done if time was plentiful. However, we have many ideas that can improve the model in general. One important and crucial point we could not implement in our model is to consider the possible waiting times at diagnosis hospitals and thrombectomy centres. Adding this to our model will definitely yield a different and more exciting result to study and analyse, which might be also used for analysing and understanding the situation of the resources that are available in the studied region.
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Another interesting inclusion would be to consider the use of mobile stroke units, known as CT scan ambulances. Having this added to our developed model it would show even more impressive results, especially, when it comes to saving lives of patients.

Lastly, collecting more data that is related to the durations of the treatments, as well as considering helicopters as a transport alternative would also have an impact on the model’s outcome.
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9 References


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