An Agent-based Model for Simulating Travel Patterns of Stroke Patients

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Abstract—**For patients suffering from a stroke, the time until the start of the treatment is a crucial factor with respect to the recovery from this condition. In rural regions, transporting the patient to an adequate hospital typically delays the diagnosis and treatment of a stroke, worsening its prognosis. To reduce the time to treatment, different policies can be applied. This includes, for instance, the use of Mobile Stroke Units (MSUs), which are specialized ambulances that can provide adequate care closer to where the stroke occurred. To simulate and assess different stroke logistics policies, such as the use of MSUs, a major challenge is the realistic modeling of the patients. In this article, we present an approach for generating an artificial population of stroke patients to simulate when and where strokes occur. We apply the model to the region of Skåne, where we investigated the relevance of travel behavior on the spatial distribution of stroke patients.**

Keywords-Agent-based Social Simulation; Synthetic Population; Population Generation; Mobile Stroke Unit.

I. INTRODUCTION

Every year, more than 1 million people in the European Union suffer from a stroke and the one-month case-fatality is up to 35% [1]. The occurrence of strokes is associated with the age of the individual and most of those suffering from a stroke are 70 years of age or older. Hence, as the number of people that are older than 70 years will increase, the number of strokes is also expected to increase [2][3].

There are two types of acute strokes, acute ischemic strokes (AIS), where a clot or narrowed blood vessel blocks the flow of blood to the brain, and hemorrhagic strokes, caused by a burst blood vessel [4]. Both types of strokes require immediate treatment and delays negatively affect the patients' outcomes. Yet, the treatment of these two kinds of strokes differs greatly. To dissolve the blood clot and to restore the blood flow, an AIS needs to be treated with thrombolytic medication as quickly as possible. In case of hemorrhagic strokes, however, there is a contraindication for thrombolysis as it might kill the patient. Instead, the effect of blood thinners must be counteracted to control and stop the bleeding. Hence, making the right diagnosis is a vital first step for the efficient treatment of strokes.

Imaging of the brain, e.g., through CT or MRI scans, and specific laboratory tests are required to adequately diagnose the cause of a stroke. However, especially in urban areas, the access to such scanners and laboratories is limited and the patient needs to be transported to a suitable hospital, causing valuable time to pass. A stroke logistics policy that can be applied to address this challenge is the deployment of Mobile Stroke Units (MSUs), which are specialized ambulances with all equipment required to diagnose stroke patients. Through this, the time between the onset of symptoms and the beginning of treatment of the stroke can be shortened, which significantly can improve the prognosis of the patients. The feasibility of this concept and its capability to prevent brain damage of stroke patients was demonstrated by Walter et al. [5].

To investigate the suitability and effects of stroke logistics policies for a specific region, computer simulation can be used. This allows for investigating different policies under realistic conditions without jeopardizing the health of the patients as they can be analyzed and compared in an artificial system. The use of simulation in healthcare is well established. Barnes et al. [6], for instance, provide a comprehensive overview of how simulation can be applied in healthcare operations management and underline the successful application of simulation for evaluating policy alternatives. An increasing application of simulation in healthcare has also been identified by Almagooshi [7], e.g., for the analysis of patient flows, emergency departments, and treatment of, e.g., stroke.

A major challenge when simulating stroke logistics is the modeling of the patients' whereabouts. For instance, in terms of MSUs, where the number of vehicles is limited, the locations of the MSUs should be determined such that the time to treatment can be reduced for all inhabitants of the region. To this end, Amouzad Mahdiraji et al. [8] studied the average time to treatment for different distributions of MSUs and showed that a small number of MSUs can indeed significantly reduce the time to treatment for most inhabitants in the region. For their study, the authors used demographic data on the inhabitants' place of residence for determining where the demand for emergency care occurs. However, this does not consider that individuals travel and might not be at home when having a stroke, for instance, due to leisure activities, shopping, or work. Yet, the spatial distribution of strokes potentially affects the suitability of different stroke logistics policies and, thus, might need to be considered when assessing their suitability.

In this article, we present an agent-based model for generating a synthetic population of stroke patients and to simulate their travel behavior. This allows for testing different policies without jeopardizing the health of the patients. We apply this model to the region of Skåne in southern Sweden to investigate how travel behavior is expected to affect the spatial distribution of stroke patients. Moreover, the generated synthetic population of stroke patients can be used to assess different stroke logistics

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policies, e.g., to compare different placements of MSUs and to assess how this affects the time to treatment.

The rest of the article is structured as follows. Section II presents related work on the use of agent-based modeling and simulation in healthcare, on policy making for treatment of acute strokes, and on methods for population generation. In Section III, the model for generating a population of stroke patients with travel behavior is presented. Section IV presents and discusses the results of the case study in Skåne, Sweden, and in Section V, conclusions are drawn, and future work is presented.

II. BACKGROUND

Diagnosis and treatment processes in healthcare often include multiple consecutive steps and involve different specialists and caregivers. Planning and optimizing such complex processes are challenging and requires the comparison of potential configurations under different circumstances. Evaluating these processes in the real-world prior to their implementation might not only be costly and time consuming but also pose a danger to the patients' well-being. To overcome this, simulation can be used. By building a virtual model of the real-world, an artificial system can be created to investigate different scenarios and to observe the effects different measures and decisions might have on the process of care provision.

A. *Agent-based modeling and simulation in healthcare*

There exist different simulation paradigms, i.e., approaches for modeling and simulating phenomena or systems. In healthcare, as well as in other domains where humans are the object of investigation, individual-based simulation paradigms are often applied. An example is agent-based simulation (ABS), a form of microsimulation, which consists of the simulation of states and behavior of individuals over time [9]. Here, each individual is represented by an agent, an autonomous entity that, for example, imitates human-like behavior and reasoning. This includes the subjective perception of the environment but also the individual decision making based on the personal traits and characteristics of each individual, which leads to individual actions and behavior.

In logistics and production, for instance, the use of simulation is well established [10]. But also in healthcare, for instance in terms of the ongoing Covid-19 pandemic, the use of simulation is feasible [11]. Cabrera et al. [12] use simulation for designing a decision support system that can provide management support for emergency departments. This is achieved by analyzing the optimal staff configuration to minimize patients' waiting time and maximize patient throughput. A more extensive simulation model of hospital processes has been proposed by Djanatliev & German [13]. It combines individual-based simulation with system dynamics for analyzing different innovative workflows prior to their implementation, e.g., prostate cancer screening and effects of MSUs on onset-to-treatment times.

Simulations of stroke treatment were presented by, for instance, Monks et al. [14] and Chemweno et al. [15]. Monks et al. investigate clinical benefits of reducing delays in thrombolysis (alteplase) of AIS patients. They propose a discrete-event simulation model of stroke patients arriving at a large district hospital, where measures can be adopted to reduce in-hospital delays (e.g., prealert of paramedics) and where certain limitations of alteplase treatment (i.e., extension of treatment deadline from 3 to 4.5 hours and patient age over 80 years) can be relaxed. To assess and compare the benefits of policies for reducing waiting times, the authors model two treatment paths, the traditional treatment and one that takes measures into account for reducing in-hospital delays. The results show that an extension of the time window in combination with reduced delays can lead to 5-times increased thrombolysis rates. Chemweno et al. present a discrete-event simulation of the diagnostic path of patients in a stroke unit to investigate the effect of different test capacities. This is to overcome shortcomings of traditional queuing theory models, which cannot predict waiting times due to the complexity of treatment pathways and interrelationships between required resources. This allows for the assessment of policy changes in capacity profiles and test resources. The study outlines the effects different policies might have on waiting times, e.g., adding extra timeslots, shifting from MR to CT scans, and implementing joint timeslots.

B. *Policies for Treatment of Acute Strokes*

For the treatment of acute ischemic strokes, intravenous thrombolysis to dissolve the blood clot is the only approved reperfusion treatment [16]. However, according to Fassbender et al. [17], only less than 5% of the stroke patients receive this therapy. One potential explanation is that the critical time window of 3 hours is exceeded due to the transport to the hospital. To reduce the time to treatment, the use of Mobile Stroke Units (MSUs) was proposed, i.e., specialized vehicles that are equipped with devices required for adequately diagnosing and treating stroke patients. Walter et al. [5] compared the use of MSUs to hospital treatment and found that the time from alarm to therapy could be reduced from 76 to 35 minutes. Calderon et al. [18] analyzed the worldwide status of MSUs and compared different services outlining the success of the approach. The economic viability of MSU treatment was analyzed by Kim et al. [19], underlining its cost-effectiveness due to earlier provision of therapy.

The success of MSUs and their effect on treatment times also depends on where they are located. Rhudy et al. [20] visually analyzed data of MSU dispatches and the occurrence of strokes to optimize service provision. For Sydney, Australia, Phan et al. [21] searched for optimal locations for MSUs by investigating travel times from suburbs to each potential MSU hub. For a similar purpose, Amouzad Mahdiraji et al. [8] developed an agent-based model that allows for analyzing the benefits of different MSU configurations. In their study, Amouzad Mahdiraji et al. investigated the average time to treatment for different distributions of MSUs and showed that a small number of MSUs can significantly reduce the time to treatment for most inhabitants in the region. Moreover, agent-based

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simulation can also be used to assess other stroke logistics policies, e.g., whether patients should be brought to the closest hospital or to a specialized thrombectomy center [22]. To assess this, Al Fatah et al. developed a simulation model of logistical operations of stroke patients, i.e., whether patients should be transported to the closest hospital or towards a stroke center. The results showed that those patients that require special treatment indeed benefit from being transported in the direction of a stroke center whereas those who do not require specialist treatment benefit from being transported to the closest hospital.

None of the presented approaches takes travel behavior into consideration when investigating and optimizing locations and service designs of MSUs. Instead, individuals are assumed to stay at their home location, which can be derived from census data or randomly selected using Monte Carlo approaches [22].

C. *Population Generation*

To generate realistic results when applying agent-based simulation, individuals and their behavior must be modeled in a realistic way. Especially when modeling a larger population of individuals, it is important that the relevant features of the artificial population, e.g., age distribution or employment status, correspond to those of the original population. However, due to privacy reasons, data on each individual's properties is usually not available. The challenge associated with synthetic population generation is that aggregated data, e.g., census data, and disaggregated personal data need to be combined to model each individual, such that the characteristics of the modeled population correspond to the used input data [23][24]. In transportation, for instance, population generation is used to model individual demand for mobility services [25][26].

III. An Agent-based Model for Generating a Population of Stroke Patients with Travel Behavior

To allow for a more dynamic and realistic assessment of stroke logistics policies, we developed an agent-based model that takes travel behavior of individuals into account. To this end, we generate a synthetic population of potential stroke patients, combining socio-demographic census data, data on real strokes cases from a healthcare provider, and travel data from a transport service provider. This allows for the simulation of the dynamical spatial and the temporal component of stroke occurrence and treatment.

For the study, we selected Skåne, a region in southern Sweden. Skåne consists of approximately 1.4 million inhabitants, that live in 33 municipalities with a total area of nearly 11 000 km^2. In Skåne, there are 9 hospitals with emergency departments that can treat acute strokes. In 2015, there were 3 973 stroke incidents recorded in Skåne out of which 3 830 patients also live in Skåne. Moreover, 12 patients that have their place of residence in Skåne were treated in the neighboring counties Kronoberg, Blekinge, or Halland and most of the patients are 45 years of age and older. Based on data from the regional healthcare provider, *Södra Sjukvårdsregionen* (Southern Health Care Region; SHR), we derived the daily distribution of strokes per hour (see Figure 1). Most strokes are reported during the afternoon with most of the incidents occurring around 4 p.m.

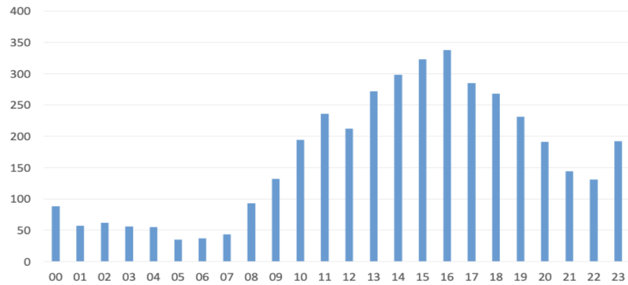

Figure 1. Total number of strokes per hour extracted from data of the regional healthcare provider.

To model travel behavior, we used data from a regional travel survey (*Resvaneundersökning för Skåne; RVU*) that was conducted in Skåne in 2013 [27]. As part of this study, travelers were asked about their traveling habits and the resulting dataset contains information on approximately 56 000 distinct trips. This includes, for instance, the origin, destination, duration, and purpose of the trip but also socio-demographic data on the travellers, e.g., age, gender, and place of residence.

Finally, for generating a realistic population, we used a census dataset from *Statistiska centralbyrån* (Statistics Sweden; SCB), the Swedish government agency for statistics. The SCB dataset includes, for instance, information of the density and age of the population of Skåne. Yet, this data only provides information on the permanent residence of individuals and not on their actual location. To allocate the anonymized trips of the RVU dataset to actual individuals from the SCB dataset, we randomly match the datasets based on the individuals' age group and home municipality.

For modeling the inter-arrival time of stroke incidents, we used a non-homogeneous Poisson process (NHPP) [28]. In contrast to ordinary Poisson processes, that are used to model events that occur with a fixed average rate of arrivals (λ), the rate of arrivals can vary over time in an NHPP where $\lambda(t)$ is the rate function for time segment t for all $t \in [0, t_0]$ and $\lambda_u(t)$ is the maximum number of actions in a time series with $0 \leq \lambda(t) \leq \lambda_u(t)$. By this means, we can explicitly model the accumulation of stroke events during the afternoon. In our NHPP, we divide each day into 24 time segments, each equipped with a specific probability that a stroke occurs during this hour in relation to the number of strokes occurring per day.

Based on the generated number of daily stroke incidents, we define two probability mass functions to distribute strokes across age groups and municipalities. These two distributions are then used to generate stroke incidents. Each generated stroke event consists of the patient's age group, municipality, day of the year, and time of the day. This dataset is then matched with the population dataset, to

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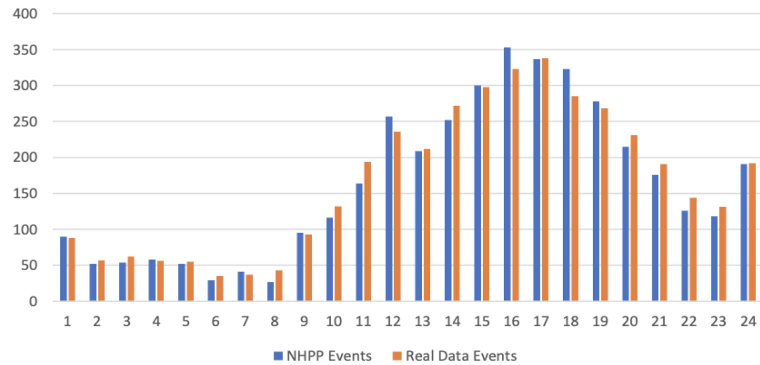
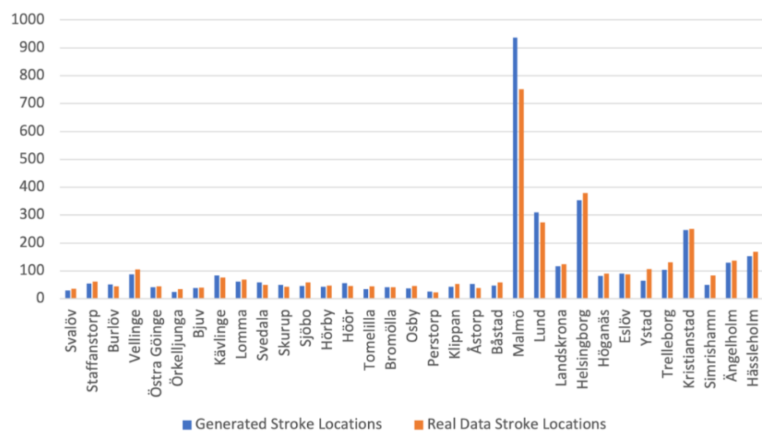
predetermine the stroke patients as well as the point in time when the stroke will occur.

When executing the model, the travel behavior, i.e., each trip of an individual, and the resulting locations of each individual of the population is simulated over time. The generated NHPP events define when the individual stroke incidents occur, and, at the generated time of each stroke incident, the individual's current location can be determined based on the simulated trips.

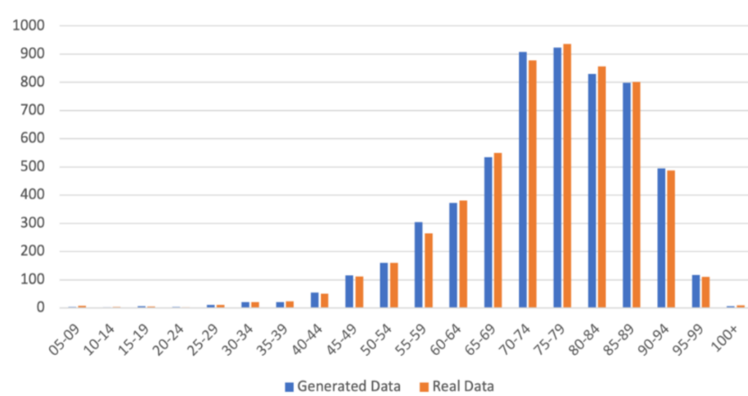
In recent years, ODD (Overview, Design concepts, and Details) protocols have been used to describe the structure and the dynamics of agent-based models in a standardized document [29]. They provide more detailed insights into the model and the underlying assumptions, which can be relevant for the interpretation of the results as well as for replicating experiments. The ODD of the model presented in this article can be found in [30].



(a) hour of the day (RSE: 0.026, RRSE: 0.160)



(b) municipalities in Skåne (RSE: 0.067, RRSE: 0.259)



(c) age group (RSE: 0.002, RRSE: 0.046)

Figure 2. Distribution of stroke incidents: (a) per hours of the day (b) per municipality in Skåne (c) per age group. For each distribution, the Relative Squared Error (RSE) and Root Relative Squared Error (RRSE) are given as measures of the quality of the generated data.

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IV. Results of the Scenario Study in Skåne

We implemented the agent-based model of stroke patient travel behavior in the *Repast Simphony* simulation framework [31]. In the simulation, each time unit (tick) corresponds to 1 minute in reality. Hence, each day is simulated as 1440 ticks. For each tick, it is determined whether an individual will go on a trip and move to another location. When the predetermined stroke events occur, it is checked whether the individual is on a trip, to determine where the stroke occurred.

The probability distributions that we extracted from the dataset are shown in Figure 2. The charts show the real data (orange) in comparison to the NHPP events we calculated (blue). There are only minor deviations from the original data for the stroke incidents per hour, per municipality, and per age group. To quantify how well the artificial data replicates the original data, the Relative Squared Error (RSE) and Root Relative Squared Error (RRSE) are given as measures. No significant deviation of the generated data from the real data can be observed considering the hour of the day (RRSE: 0.160) and the age group (RSSE: 0.046). Only for the municipalities in Skåne, a difference can be observed for Malmö (RRSE: 0.259). This might be due to a bias, which results from Malmö's role as center of the region and as the city has notably more inhabitants compared to all other cities and municipalities in Skåne.,

Instead of simulating all inhabitants of Skåne, we only simulated the trip activities of those individuals that were predetermined to suffer from a stroke. This is to reduce the computational complexity of the simulation. To reduce the effect of stochastic variations in the results, we replicated the simulation five times and calculated the average values from these runs.

On average, 3 912 strokes occur in our simulation. The results indicate that 3 839 (98.1%) strokes occur at home whereas 73 (1.9%) strokes happen while the individual is on a trip and at another location. To check the plausibility of these results and to validate the study, we compare them to existing data. In the RVU travel data, only 15% of the recorded trips are performed by individuals that are 65 years of age or older, the main risk group for suffering from a stroke. Out of these trips, only 35% are taken in the afternoon, which is the time of the day where the occurrence of a stroke is most likely.

Moreover, we analyzed the dataset of stroke incidents from SHR. Out of 3 842 stroke incidents of patients that live in Skåne, which were recorded within SHR, 3 830 actually got their treatment in Skåne. 3 106 (80.84%) of the patients that got a treatment in Skåne also got it within their municipality or at the hospital that is responsible for their municipality. Out of the remaining 736 patients (19.16%) that did receive their treatment at another hospital, 497 patients live in municipalities where the responsible hospital does not provide emergency services around the clock. Of the remaining 239 patients, 80 were treated at Skåne University Hospital, which also provides highly specialized treatments for severe cases, 57 received treatment at private facilities, whose exact location is unknown, and 59 were treated at a hospital in a neighboring municipality, which might be due to the patients living closer to the hospital in the neighboring municipality. In total, only 46 patients (1.2%) receive their treatment obviously outside their home municipality, where it can be assumed that they were traveling. This corresponds to the results of our simulation.

V. Conclusions

In this article, we address the challenge of generating a realistic population of stroke patients, which takes travel behavior into account. Such an artificial population of stroke patients is required in agent-based simulations and allows for the assessment of different stroke logistics policies, such as the optimal placement of MSUs across a region. We used aggregated and individual-based data from different sources, from which we derived probability distributions that were then used to generate an artificial population of agents.

To demonstrate the feasibility of the presented approach, we used data from the region of Skåne in southern Sweden. In the presented study, we simulated the travel behavior of stroke patients to investigate where strokes occur. Through this, a better understanding of the spatial distribution of stroke occurrence is achieved. This is relevant, for instance, for the optimal distribution of MSUs, such that the time to treatment is reduced for stroke patients.

Our results show that the generated artificial population corresponds to the real data in terms of the time of the day at which strokes occur, the distribution of strokes across the municipalities, and the age group of the patients. In total, approximately 1.9% of the strokes occur while the individual is on a trip and not in their municipality of residence. This observation corresponds to data on strokes that was provided by the healthcare provider. Hereby, were able to show by means of simulation that traveling only has a minor impact on where strokes occur and, thus, for policy making in stroke logistics.

The generated artificial population of stroke patients is based on socio-demographic, healthcare, and travel data of the investigated region, to ensure the realistic representation of the real-world population. Yet, the presented model can also be applied to other regions, assuming that the required input data is accessible. This facilitates the conducting of agent-based simulation studies for investigating the effects different stroke logistics policies might have. It also increases the credibility of the simulation results such that conclusions can be drawn regarding the real world.

As part of future work, we plan to incorporate the results from the population generation into simulations for assessing and comparing different policies for stroke logistics. Moreover, we intend to investigate and include seasonality effects into the model, i.e., tourists that come to the region and changed travel behavior during weekends.

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