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ScienceDirect

Procedia Computer Science 198 (2022) 132–139

Procedia Computer Science

www.elsevier.com/locate/procedia

The 11th International Conference on Current and Future Trends of Information and Communication Technologies in Healthcare (ICTH 2021)
November 1-4, 2021, Leuven, Belgium

A Micro-Level Simulation Model for Analyzing the Use of MSUs in Southern Sweden

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Abstract

A mobile stroke unit (MSU) is a special type of ambulance, where stroke patients can be diagnosed and provided intravenous treatment, hence allowing to cut down the time to treatment for stroke patients. We present a discrete event simulation (DES) model to study the potential benefits of using MSUs in the southern health care region of Sweden (SHR). We included the activities and actions used in the SHR for stroke patient transportation as events in the DES model, and we generated a synthetic set of stroke patients as input for the simulation model. In a scenario study, we compared two scenarios, including three MSUs each, with the current situation, having only regular ambulances. We also performed a sensitivity analysis to further evaluate the presented DES model. For both MSU scenarios, our simulation results indicate that the average time to treatment is expected to decrease for the whole region and for each municipality of SHR. For example, the average time to treatment in the SHR is reduced from 1.31h in the baseline scenario to 1.20h and 1.23h for the two MSU scenarios. In addition, the share of stroke patients who are expected to receive treatment within one hour is increased by a factor of about 3 for both MSU scenarios.

Keywords: Ischemic stroke; stroke transport; MSU; DES; time to treatment; stroke logistics

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1877-0509
10.1016/j.procs.2021.12.220

1. Introduction

Stroke is a leading cause of death and disability around the world [1]. A stroke occurs when a blood clot or bleeding in the brain reduces the blood flow to the brain. An ischemic stroke, which is the most common stroke type, happens when one or more clots reduce the blood flow inside the brain, and patients should receive thrombolysis and sometimes thrombectomy, depending on the size of the clot. The type of stroke can be determined by a computed tomography (CT) scan on the brain of the patient.

Treatment should be instigated as early as possible. In particular, a 60-minute period known as the "golden hour" has been introduced in ischemic stroke treatment [2] to emphasize the importance of early treatment. However, due to logistical challenges, it is often difficult to provide rapid treatment for stroke patients. Since CT scanners are in general only available at hospitals, it is not possible to start diagnosis and treatment until after the patient has been transported to the nearest acute hospital.

A mobile stroke unit (MSU) is a special stroke ambulance that has become an alternative for prehospital diagnosis and treatment of stroke patients [2]. An MSU is equipped with a CT scanner, enabling ambulance personnel to diagnose the stroke patients and provide intravenous stroke treatment already inside the ambulance. Thus, the use of MSUs, as the MSU operations in Berlin, Cleveland, and Melbourne suggest, has the potential to cut down the time to treatment for many stroke patients [2-4].

To improve the stroke transport logistics, different policies, including the use of MSUs, can be implemented. However, before implementing a policy, its performance needs to be assessed. Due to the difficulties of evaluating decision policies using real patients, the use of simulation is preferable. Simulation can be used to assess policies before being implemented in the real system while taking into account various attributes of the stroke population, such as population size, stroke time, and patient locations. Simulation also enables to analyze policies without risking the health of the patients who are already in a vulnerable condition. The simulation output can be used by decision-makers when deciding which policy to apply in a particular region.

Agent-based simulation and discrete event simulation (DES) have been used for the analysis of emergency medical service (EMS) transport in stroke. For example, Bogle et al. [5] present a DES model to evaluate the effects of altering important specifications of an EMS routing algorithm for patients with large vessel occlusion stroke in two different counties in the USA. Al Fatah et al. [6] use agent-based simulation to assess two stroke transport policies regarding where to transport suspected stroke patients for diagnosis, i.e., *nearest hospital* policy and *nearest hospital towards the stroke center* policy, in the southern healthcare region of Sweden (SHR). However, the mentioned studies only consider regular ambulances, and to the best of our knowledge, no previous studies use simulation to evaluate MSU related transport policies.

In a previous study [7], we propose a macro-level average time to treatment estimation model in order to analyze the potential benefits of placing MSUs in the SHR. The previously proposed model is not able to study the individual patients and the individual emergency vehicles (EVs) as it generates an average expected time to treatment for a whole population. In addition, the macro-level modeling paradigm is unable to take into account the effects of simultaneous stroke incidents, e.g., if an MSU is needed at two places at the same time. In the current paper, we present a DES model for evaluating prehospital stroke transport policies related to the use of MSUs. This type of modeling allows to simulate the activities of individual entities over time; hence, allowing more realistic modeling. In addition, it enables to add stochasticity, including location and time of stroke incidents, to the model. Thus, the proposed model is able to simulate the main actions and decisions involved in the logistical operations of stroke patients, and it takes as input a population of stroke patients. In a case study, set in the SHR, we use our simulation model to compare a baseline scenario containing only regular ambulances with two MSU scenarios, each containing three MSUs.

The rest of this paper is organized as follows. Section 2 introduces our DES model for MSU-related stroke logistics policies assessment. Section 3 presents the scenario study, followed by the results and discussion. Finally, Section 4 concludes the paper.

2. Discrete event simulation model

In this section, we describe our simulation model for the evaluation of MSU-related stroke logistics policies. The model makes use of a zone-based approach, and it simulates the actions applied for each individual patient. The geographical region considered by the model is divided into a non-overlapping set of subregions, where it is assumed that all of the patients in each subregion are located in its centroid, and all transports to and from a specific subregion are made to and from its centroid.

The simulation model consists of three main components: input, simulation model, and output. The *input* is required in order to run the simulation model and to regulate everything that is not static. As input, the model takes a synthetic stroke population, data about hospitals and EVs, and transport data, including the driving times between EV stations and patient locations, and between patient locations and hospitals. The *simulation model* includes all of the logic, and it generates a log of all activities that have occurred as *output*, including the start and end time for each of the simulated activities. The total service time of EVs and the time to treatment for each patient are examples of output variables.

Our model is implemented based on the principle of the DES framework, which is a paradigm used to model the operation of a system as a series of events that occur over time, where an event is an instantaneous occurrence that may change the state of the system. In our model, each action is modeled using two events, i.e., a start event and an end event, enabling to model that the simulated actions do not occur instantaneously. Fig. 1 represents the overall flow of our simulation model. The model has a clock representing the simulated time and a queue of future events that are scheduled for processing. The size of the queue is not static as the events are dynamically added and removed at run-time. During the simulation, new events are continuously created and sorted into the queue based on their time of occurrence; the next event is always the first event in the queue. The occurrence of a certain event causes an action or a set of actions, and often, adding a new event to the queue. Each of the events will occur 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 event, the corresponding event will be removed from the event queue, and the simulation clock will advance to the time of the next event in the queue. Once event queue is empty, or the simulation end time has been reached, the simulation terminates.

For each individual in a set of stroke patients, the model simulates the main actions and decision-making that occur from the time of receiving a call concerning a suspected stroke incident until the thrombolysis is initiated. See Fig. 2 for the chain of actions that are expected to take place for each stroke patient in our DES model. The actions and decisions included in the model are based on the current stroke logistics process for an ischemic stroke patient requiring thrombolysis adopted in the SHR. The chain of activities for a particular patient is initiated by a stroke incident, which triggers a call to the emergency center. The subsequent actions will be created for each patient during the simulation according to the care chain presented in Fig. 2. For patients transported by a regular ambulance, the time to treatment is the expected time from when a stroke happens until the patient receives thrombolysis in the acute

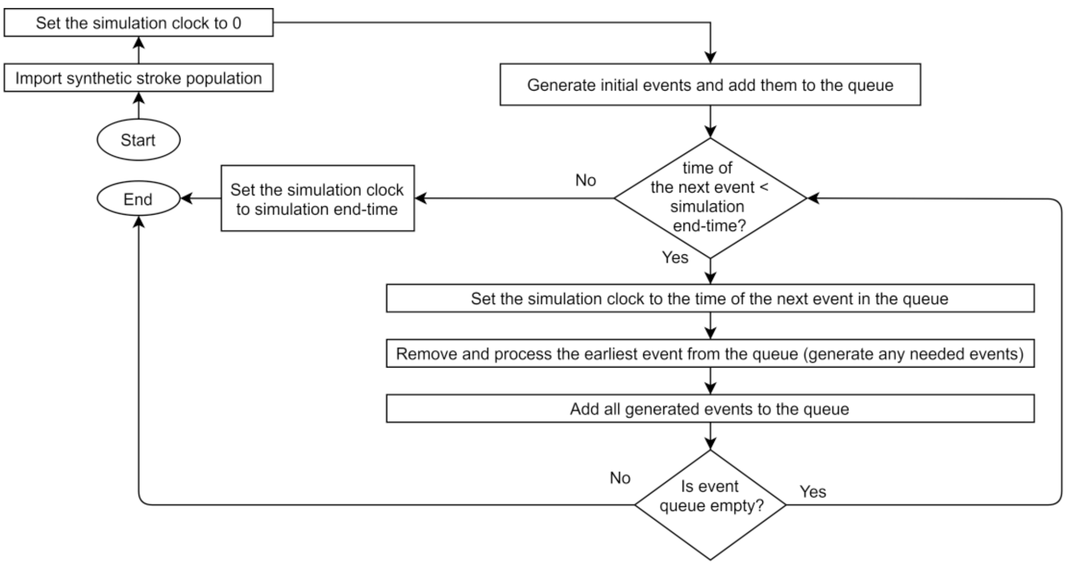

Fig. 1. Flowchart of the DES algorithm used in our simulation model.

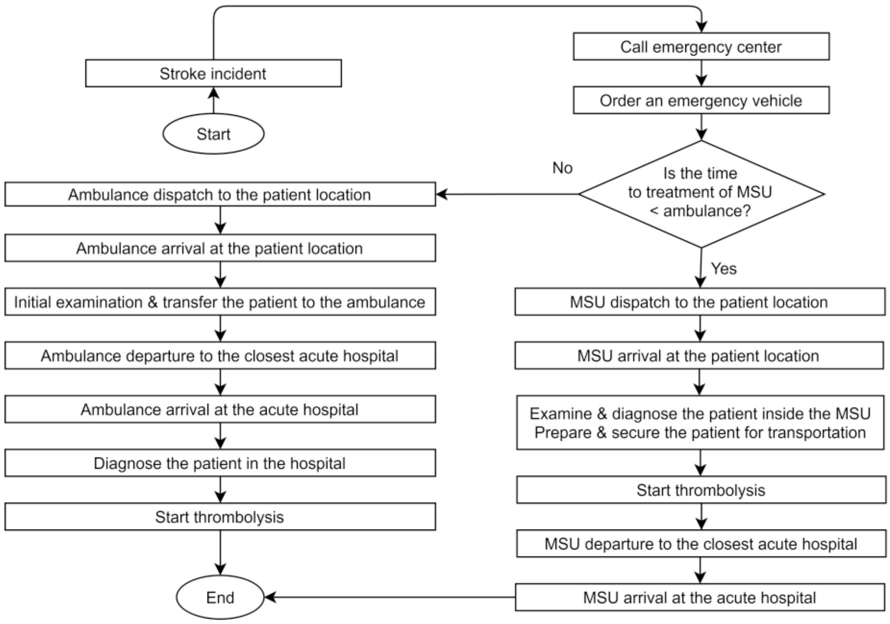

Fig. 2. Flowchart demonstrating the sequence of actions that happen for each stroke patient during the simulation. Please note that the term *ambulance* is used instead of *regular ambulance* in the flowchart.

hospital. For the MSU cases, the time to treatment is the expected time from when a stroke happens until the patient receives thrombolysis inside the MSU. When an EV arrives at the acute hospital and drops off the patient, it becomes available for the next patient. Please note that we assumed that all the modeled patients are suspected stroke patients, and that they need to be transported to an acute hospital.

Once a stroke incident occurs, the model compares the expected travel times of different available EVs between the EV sites and the patient location and then dispatches the EV, either a regular ambulance or an MSU, to the scene, depending on which vehicle is expected to provide the fastest time to treatment. When there is no available regular ambulance or MSU sufficiently close for a stroke case, the model estimates which busy EV can provide the fastest time to treatment and then waits until the chosen busy EV becomes available. In such a situation, there would be waiting time, which is defined for each stroke event as the time difference between when the chosen EV becomes available and the post-response time for the current stroke event.

3. Scenario study

In a scenario study, we applied our DES model to study the potential effects of using MSUs in Sweden's Southern Swedish Health care Region (SHR), where about 3900 individuals suffer a stroke each year [8]. The SHR includes 4 counties and 49 municipalities, and it contains 13 acute hospitals equipped with CT scanner and 39 ambulance sites (see Fig. 3 (a)).

We used two types of data, i.e., demographic data for 2018 from Statistics Sweden [9] and stroke data from Sweden's Southern Regional Health Care Committee [10]. The demographic data includes the number of residents for 21 age-groups, i.e., $\{[0,4),[4,8),...,[95,99),[100,\infty)\}$, for each of the set of disjoint subregions of SHR. The stroke data set consists of the number of stroke cases for each municipality of SHR and each age-group, as well as the aggregated times of strokes for 2016.

In our scenario study, we considered three different scenarios: a baseline scenario and 2 MSU scenarios with different characteristics. The baseline scenario corresponds to the current situation in the SHR, where only regular ambulances are used. The two MSU scenarios are denoted as MSU1 and MSU2, and each of them contains 3 MSUs in addition to the regular ambulances. It should be noted that we considered the same MSU scenarios and locations as

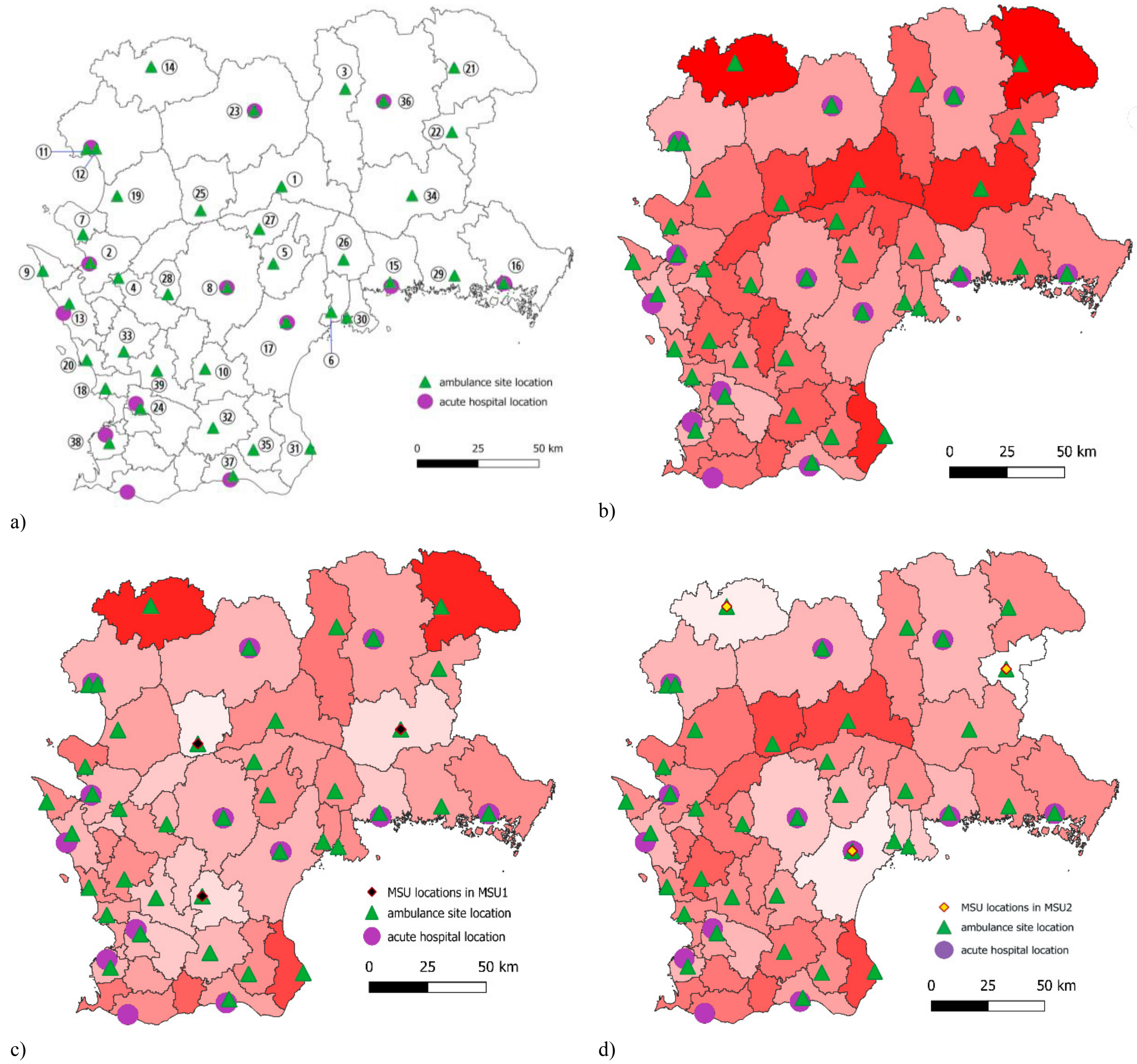

Fig. 3. Overview of SHR (a), and the average time to treatment for each of the municipalities of SHR considering the baseline scenario (b), MSU1 (c), and MSU2 (d).

we did in the companion paper by Amouzad Mahdiraji et al. [7], allowing us to compare and assess the performance of the two models. In MSU1, MSUs are placed near the large municipalities, and in MSU2, MSUs are placed near the sparsely populated areas. Fig. 3 (c) and (d) show the MSU locations in the MSU1 and MSU2 scenarios.

We also carried out a sensitivity analysis to further assess the proposed DES model, where we 1) increased the number of available MSUs in each MSU location from one to 10 in the MSU1 and MSU2 scenarios and 2) tripled the number of stroke patients in the SHR. For each scenario, we run the simulation model 10 times with 10 different sets of synthetic stroke patients, taking the averages of the outputs for each of the scenarios.

We generated the driving times using the Openrouteservice toolbox in QGIS, which provides an interface towards open street map (openstreetmap.org). We assumed that a regular ambulance drives 5% faster than a passenger car, and an MSU drives at the same speed as a passenger car. We used Google maps and official documentation provided by the health care authorities in the region to acquire the locations of acute hospitals and ambulance sites. The rest of the assumptions, including the modeled activities, were the same as in the study by Amouzad Mahdiraji et al. [7].

3.1. Synthetic stroke population

Due to privacy reasons, there was no access to any individual level patient data for the considered region; we, therefore, used real aggregated stroke data [10] and demographic data [9] in the synthetic population generation model. These data sets, which we used as input to the synthetic stroke generation model, contain the number of inhabitants in each sub-region, as well as the statistical distributions of the time, location, and age of the stroke patients. The model is stochastic, and it generates a new set of patients with varying size, locations, and stroke times, each time it is run.

Our model assumes that the number of stroke incidents for each of the hours of the day is Poisson distributed, and the time between two stroke events is exponentially distributed. The population generation simulation starts by deciding the size of the stroke population and the number of simulation days. To deal with the issue that the expected number of stroke incidents varies over the hours of the day, we first extended each day, in such a way that it consists of a number of time periods of equal length, all having the same number of expected stroke incidents per period. Then, in the extended day, we determined the time of each of the expected stroke incidents. After that, we compressed the extended day again to the initial day length. For each of the generated stroke incidents, we then sampled each patient location and age according to the aggregated statistics.

In our scenario study, we used our synthetic population generation model to create 10 different sets of stroke patients for the SHR, each corresponding to one year. On average, the generated stroke populations contained 3946 patients.

3.2. Results

In Table 1, we present the simulation results of our DES model for each scenario regarding the average time to treatment and the share of the stroke patients who are expected to get treatment within 60, 75, and 90 minutes. The simulation results in Table 1 indicate that after placing MSUs in the SHR, the average time to treatment is expected to decrease for both MSU scenarios compared to the baseline scenario. Furthermore, MSU1 provides faster treatment on average compared to MSU2, which is probably due to that the MSUs in MSU1 are located in more populated

Table 1. Comparison of the DES model and the macro-level model [7] concerning the average time (in hours) to treatment for the whole SHR and the share of the stroke population in the SHR whose time to treatment is expected to be initiated within 60, 75, and 90 minutes for each scenario. The numbers within the curly brackets show the ambulance site IDs. The simulation runs that belong to the sensitivity analysis are marked with an asterisk (*) in the *Model* column.

Scenario	MSU sites	Model	Numb. of MSUs in each site	Stroke population	Average time to treatment	Expected time to treatment		
						< 1.0 h	< 1.25 h	< 1.5 h
Baseline	-	Macro model [7]	-	All inhabitants	1.33	3.96%	47.80%	80.90%
		DES	-	3946	1.31	3.85%	46.26%	80.19%
		DES*	-	11453	1.33	3.82%	45.50%	77.98%
MSU1	{11, 27, 36}	Macro model [7]	1	All inhabitants	1.18	13.3%	70.40%	94.0%
		DES	1	3946	1.20	11.48%	66.16%	91.91%
		DES*	10	3946	1.18	13.06%	69.86%	93.80%
		DES*	1	11453	1.25	8.82%	55.64%	86.95%
		DES*	10	11453	1.18	13.25%	68.87%	93.54%
MSU2	{15, 18, 24}	Macro model [7]	1	All inhabitants	1.22	11.70%	58.50%	89.50%
		DES	1	3946	1.23	10.74%	56.08%	88.03%
		DES*	10	3946	1.22	11.66%	57.33%	88.93%
		DES*	1	11453	1.27	8.93%	48.22%	84.22%
		DES*	10	11453	1.23	11.74%	51.95%	87.02%

regions, having a higher number of stroke incidents than the other regions. In addition, the share of patients who are expected to receive treatment within an hour significantly increased for both MSU scenarios compared to the baseline.

In Fig. 3 (b) to (d), we show, for each of the three scenarios, how each MSU in each of the two MSU scenarios is expected to influence the average time to treatment for each municipality in the SHR. The green triangles, purple circles, and black and yellow diamonds illustrate the locations of ambulance stations, hospitals, and MSU locations in MSU1 and MSU2, respectively. It should be emphasized that the lighter the color is in the maps, the shorter the average time to treatment is for the corresponding municipality. It can be further seen that where the considered MSUs are placed, the average time to treatment is reduced in the corresponding municipality as well as in the nearby municipalities.

In Table 1, we also compare the generated results of our DES model with the corresponding results for the macro-level model proposed by Amouzad Mahdiraji et al. [7]. In the current paper, we move forward from a deterministic set-up by proposing a model built on the DES paradigm, which allows to incorporate uncertainty into the simulation set-up. In addition, it allows for a more realistic scenario where the individual patients are simulated over time, and where stroke incidents may occur simultaneously. The proposed DES model considers the availability of ambulances and MSUs, e.g., when there are two simultaneous stroke incidents in a region, the MSU is assigned to one of the stroke incidents; however, for the other stroke incident, the closest regular ambulance will be dispatched instead. In our scenario study, we used the same MSU scenarios as suggested by Amouzad Mahdiraji et al. [7]; however, we applied a synthetic stroke population as input to the DES model.

According to Table 1, the time to treatment is almost equal for the two compared models, i.e., the macro-level and the DES model; however, the DES model shows a slightly longer time to treatment for all scenarios. The reason for the slight differences in the results for the two models probably is that the DES model is able to take into account a limited availability of EVs and the possibility of simultaneous stroke incidents. The more coincident cases there are in the synthetic stroke population, the longer the time to treatment would be.

3.3. Sensitivity analysis

To further validate our DES model, we conducted a sensitivity analysis, which is presented in Table 1 and in Table 2. In the first part of our sensitivity analysis, we placed 10 MSUs in each site, and in the second part of our sensitivity analysis, we enlarged the synthetic stroke population of SHR three times, i.e., to 11453. Finally, we combined the two parts for the MSU1 and MSU2 scenarios, i.e., we both increased the number of MSUs and the number of patients. When there are 10 MSUs in each site, the average time to treatment decreases for both MSU scenarios compared to the situation where one MSU is placed in each station. When the stroke population is tripled, the average time to treatment increases, and it can be observed that the results for the DES model when having 10 MSUs in each site are equal to the macro-level model results. The reason is that when we increase the number of MSUs to 10, we assure that there is always an MSU available for each stroke case, which is also the case in the macro-level model, which is not able to limit the number of MSUs. If we reduce the number of MSUs to one in each of the ambulance sites, the average time to treatment is longer for the DES model since simultaneous stroke cases sometimes occur in a region, meaning that a regular ambulance has to be dispatched to a patient instead of an MSU. By calculating the difference between the results when having 1 and 10 MSUs in each site, we estimated that the number of patients that could not get an

Table 2. Comparison of the number of MSU dispatches and the share of the total MSU dispatches of each MSU scenario using the DES model in our sensitivity analysis. The numbers within curly brackets show the ambulance site IDs. See Fig. 3 (a) for more information.

Scenario	MSU1				MSU2			
MSU sites	{11, 27, 36}				{15, 18, 24}			
Number of MSUs in each site	1	10	1	10	1	10	1	10
Stroke population	3946	3946	11453	11453	3946	3946	11453	11453
Number of MSU dispatches	1651	1948	3385	6185	1017	1141	2217	3299
MSU dispatching ratio (%)	41.84	49.37	29.56	54.00	25.77	28.91	19.36	28.80

MSU, even though they needed one, was 297 and 124 in MSU1 and MSU2, respectively (see also Table 2). This difference explains why the results of the standard experiment of DES in Table 1 are slightly worse, and most likely more realistic, than for the macro-level model. In addition, when the stroke population is tripled, with the same set-up, the share of MSU dispatches decreases for both MSU scenarios.

In Table 2, we present the number of MSU dispatches and the MSU dispatching ratio, which is defined as the ratio of the total number of MSU dispatches to the total number of EV dispatches for each MSU scenario for the DES model. The simulation results indicate that MSU1 has more MSU dispatches and a higher MSU dispatching ratio than MSU2; hence, the MSUs in MSU1 are expected to help a higher number of stroke patients. Also, by placing 10 MSUs in each EV station, the number of MSU dispatches increases for both MSU scenarios, and again, in this situation, the number is higher for MSU1. In addition, for the standard experiment, the average dispatching distance is 45.38 km and 40.54 km for the MSUs in MSU1 and MSU2, respectively. The probable reason that the average dispatching distance is shorter for MSU2 is that the MSUs in MSU2 are located farther from the densely populated areas; therefore, for most stroke cases, it is more beneficial to dispatch a regular ambulance rather than an MSU.

4. Conclusions

We have presented a discrete event simulation (DES) model to evaluate MSU-related policies. The model simulates the main actions and decisions involved in stroke transport logistics. From the simulation outputs, we compared the time to treatment, the number of MSU dispatches, and the average dispatching distance of MSUs for the considered scenarios. The simulation results showed that the use of MSUs is expected to lead to a reduced time to treatment in the considered case study, i.e., in southern Sweden, and to help more stroke patients get rapid treatment. Also, with the use of MSUs, the share of patients who are expected to receive treatment within an hour was approximately tripled. Another result was that when MSUs are located in or near the highly populated regions, the number of MSU dispatches is expected to considerably increase, and inhabitants who live quite far from an MSU station are expected to benefit from the MSUs. Finally, by comparing the results of this study with the results of a deterministic model [7], supported by our sensitivity analysis, we conclude that the DES model is able to provide more realistic results than the results that can be obtained using the macro-level modeling approach.

Acknowledgments

This work is partially financed by Sweden's Southern Regional Health Care Committee and The Kamprad Family Foundation for Entrepreneurship, Research & Charity.

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