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A flexible hybrid simulation model for hospital capacity management through multimodal transfers of COVID-19 patients

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ABSTRACT

The global pandemic provoked by the SARS-CoV-2 virus in recent years has presented new challenges to health care systems. One major issue is the risk of overloading hospital capacities during regional surges, especially in intensive care units. Strategic patient transfers between regions with different loads can mitigate this risk. To coordinate such nationwide strategic patient transfers in Germany, the clover-leaf system was initiated. The transfer decision consists of allocating patients to destination hospitals as well as scheduling patients on transport vehicles which includes the possibility of combining different modes of transport, for instance ground-based with an ambulance and air-based with a helicopter, during one transfer. As potentially conflicting objective dimensions the impact of the transfers on the transferred patients and the impact on loads in intensive care units have to be considered. To support the decision makers a hybrid simulation model combining agent-based and discrete-event modeling is developed by an interdisciplinary team of medical and operations research experts. The main contribution of the simulation model is the modeling of multimodal patient transfers which to the best of our knowledge has not been considered in the existing literature. Next to the simulation model, several transfer strategies in the form of decision rules are proposed. These transfer strategies are used to benchmark transfer plans created by the decision makers in a test scenario based on nationwide data of the German health care system. Using simulation allowed to evaluate the transfer plans in different objective dimensions and informed the decision-making process.

1. Introduction

1.1. Motivation

The COVID-19 pandemic led to a sudden increase in the number of patients that needed treatment in an intensive care unit. Even though Germany had the highest intensive care capacity per capita in Europe, there was a risk of reaching regional capacity limits [1]. One way to reduce the risk of overcrowding is to transfer patients from regions with a high intensive care unit utilization into regions with a lower utilization. Usually, patient transfers between hospitals are organized decentrally by local coordination

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centers and handled by the emergency medical services. In case of regional surges of COVID-19 patients however, local transfers are not sufficient anymore and patients need to be transferred over longer distances to different parts of the country and across federal states. Each of the sixteen federal states in Germany is responsible for their respective emergency medical services and prior to the COVID-19 no system for coordinated nation-wide patient transfers existed.

In order to coordinate nation-wide transfers of patients centrally, the so called clover-leaf concept was initiated in Germany [2,3]. The idea of the clover-leaf concept is to aggregate the federal states into five clover-leaves (see Fig. 1). For each clover-leaf, one Single Point of Contact (SPOC) was defined. If load balancing in the intensive care units within one clover-leaf was not possible anymore, the five SPOC jointly decided how many patients should be transferred into which clover-leaf. Each SPOC then coordinates the detailed allocation of destination hospitals and transport vehicles within their respective clover-leaf.

Fig. 1. Clover leaf concept applied to Germany.

When deciding where the patients should be transferred to, two possibly conflicting objectives have to be considered. From the perspective of the transferred patient, a short transfer duration imposes less risk of a health deterioration. From the perspective of intensive care unit capacities, a transfer into a region with low current and expected utilization is preferred. It is likely, that the region with the lowest utilization will not be the closest to the origin region of the patient.

As modes of transport, the following two alternatives were mainly considered when initiating the clover-leaf system, making it a multimodal transport problem: ground-based transport with an ICA or air-based transport with an ICH. If both the sending and receiving hospital have a landing place for helicopters on site, transport by ICH will be faster and therefore preferable for the patient. If one or both hospitals do not have a landing place on site, an intermediary transport with an ICA to or from a landing place outside the hospital becomes necessary. Each handover of a patient between ICA and ICH firstly needs time, thus increasing the transfer duration. Additionally, each handover is associated with a risk for the patient due to the necessary change of equipment. Based mainly in the disaster nature of the situation and also the fact, that nation-wide transfers were not expected on a daily basis, the cost difference between transport by ICA and ICH was not considered in the decision.

To aid in the decision making, predictions on the further development of the pandemic situation were generated by Refisch et al. [4], Grodd et al. [5] and used by the German Federal Ministry of Health and the SPOC to monitor the situation.

The transfer problem in a pandemic setting exhibits several characteristics that led to the choice of developing a simulation model. The problem is a multiobjective problem and especially at the beginning of a pandemic it is unclear whether priorities and therefore the objectives of the problem might change. Simulation enables the evaluation of a give solution regarding arbitrary objectives if all necessary statistics are collected in the simulation. Additionally, several modes of transport with different characteristics were in discussion at the beginning of the research project. Simulation lends itself well to being adapted and allows comparing what-if scenarios which can aid in such decision-making. Lastly, simulation is well suited to model the dynamic interactions of transport vehicles in the case of transfers with handovers. Especially when considering stochastic process times, simulation appears as a suitable modeling choice for the problem under study.

The work's contribution consists of a hybrid simulation model based on the clover-leaf concept. Hybrid simulation models combine different modeling methods and have successfully been applied to healthcare settings in a pandemic environment [6]. This virtual planning system was developed interdisciplinary by medical practitioners and modelers from the operational research field. The model encompasses the entire process required for patient transport including the particularities associated to each patient implemented in a Geographical Information System (GIS) environment. It also includes a multimodal transport approach which is not presented in the emergency medical service field (see Section 1.2). To the best of our knowledge, this is the first attempt for including this type of decision in a model related to emergency systems.

This simulation model permits evaluating solutions, ideas, and techniques related to the patient transport in an emergency context and is a first step towards a virtual decision support system for nationwide patient transfers. Additionally, it is transferable to multimodal transport problems outside the application of a pandemic.

The paper is structured as follows: Section 1.2 presents a literature review on simulation models related to emergency medical systems and the presence and use of multimodal transport in several applications. In Section 3, we introduce the clover-leaf concept and the transport process involved. Subsequently, we describe our simulation model and the respective validation methods. In Section 4, we present the results obtained when applying the designed simulation model to our case study and the transfer strategies for the two main decisions studied in this case. Finally, in Sections 5 and 6 discussions and conclusions are drawn and further research paths are suggested.

1.2. Related literature

This research aims to support in the capacity management of intensive care units by transferring patients in a pandemic context. On a wider scope, this research is concerned with managing scarce medical resources for which ethical considerations should be taken into account [7,8]. Supporting the management of intensive care units through methods from operations research has been studied since before the COVID-19 pandemic [9]. Transferring patients has been identified as one of the ways to balance the loads in hospitals, especially in a pandemic context [10–13]. Existing studies however have focused mainly on the decision on when and how many patients should be transferred and less on how patients are transferred between hospitals.

To the best of our knowledge, there is no literature on using simulation to study multimodal patient transfers in a pandemic context. There are however two research areas that are connected to our research, namely simulation of emergency medical services and simulation of multimodal transport networks.

Simulation is a commonly used tool to study logistic aspects of emergency medical services. The literature review on simulation applied to emergency medical services of Aboueljinane et al. [14] show, that first studies using simulation have been conducted as early as 1969. Similar to our research, the behavior of ambulances is modeled, but usually on a local and not a nation-wide scale. The relevant aspects of the studies for our work are mainly the chosen simulation modeling approach and the modeling of the road network.

Concerning the simulation modeling approach, Discrete Event Simulation (DES) is the most common. van den Berg and van Essen [15] use a DES model to compare different static optimization models for ambulance location planning. The ambulances move in straight lines and the driving times are derived from a model developed by the Dutch National Institute of Public Health and the Environment. Ridler et al. [16] developed a DES simulation and optimization tool in order to evaluate models for strategic decisions such as station locations as well as decisions on the tactical and operational level, such as the ambulance deployment and redeployment problem. Within the simulation, the road network from OpenStreetMap [17] is used. Most emergency medical service studies focus on emergency rescue operations. Oftentimes, the emergency medical services are also responsible for scheduled patient transports. Kergosien et al. [18] integrate both emergency rescue and inter-hospital transfers in their DES simulation model. The ambulances move in straight lines and the travel times are based on historical travel time data. The interplay between emergency rescue and patient transports is also studied by Lavoie et al. [19]. They develop a DES model using the Google Maps API for travel distances. The simulation is then used to investigate effects of re-dispatching rules and different ambulance fleet mixes of three types of ambulances.

An alternative approach to DES is Agent Based Simulation (ABS). Aringhieri et al. [20] argue, that ABS lends itself well to modeling emergency medical service operations due to its ability to explicitly model the behavior and state-changes of the ambulances. The driving speeds in their simulation model are based on historical data and the ambulances follow straight lines in the simulation. The simulation model is used to examine the effects of different average driving speeds, changes in ambulance capacity and GPS-enabled dispatching of ambulances outside their home station. A second study using ABS was conducted by Jánošíková et al. [21]. In their work, simulation was used to validate the solutions of a location optimization model for ambulance stations. In the simulation, the road network data from OpenStreetMap [17] was used.

Combining DES and ABS in so-called hybrid simulation models is a growing trend [22]. Hybrid modeling allows to combine the advantages of different simulation approaches. Olave-Rojas and Nickel [23] employed hybrid modeling to investigate the effects of different staffing levels in coordination centers on emergency medical service operations. In the simulation, OpenStreetMap [17] data was used to model the road network.

While the modeling of ambulance behavior, especially for scheduled patient transports is relevant for our research, the modeling of multimodal transports is missing in emergency medical service simulations. Looking at multimodal transports outside of healthcare, a recent literature review found three studies using simulation [24]. Zhang [25] uses a simulation model of intermodal transports between road, rail and waterway to evaluate a capacitated schedule based flow assignment problem. Hrušovský et al. [26] developed a hybrid simulation model combining DES and ABS. The simulation was used in an integrated simulation–optimization approach to find transportation plans in a multimodal transport network consisting of trucks, trains and vessels. Layeb et al. [27] employed simulation in a simulation-based optimization model for solving scheduling problems in a multimodal transportation system, again consisting of road-based, railway-based and water-based transportation. These approaches differ from our research firstly due to focusing on ground-based, water-based and rail-based vehicles instead of ground-based and air-based. Secondly and more important, the focus is only on choosing the modes of transport for fixed transport destinations. In our problem, the transport destinations are not fixed and have to be considered jointly with the transport modes.

The works described in this section include – but not entirely – all the variables and the interrelations presented in the patient transport not only between resources such as ambulances, helicopters and hospitals but also between crucial variables such as medical diagnoses, travel time, the need of syringe pumps, among others. In this context, this work proposes a hybrid simulation model including a DES approach for modeling the patient pathway through the transport process and an ABS approach for modeling the behavior of the ground- and air-based transport resources.

2. Problem description

To motivate the methodological choices, the problem introduced in Section 1 is described in more detail in the following.

2.1. Setting and decisions

The setting under study exhibits the following key characteristics which influence the methodological choices. The clover-leaf system is only activated, when intra-clover-leaf transfers in one of the clover-leaves are not possible anymore due to the high load of intensive care units within that clover-leaf. If one of the clover-leaves identifies a risk of getting overloaded, it firstly defines a set of patients which are suitable to be transferred to other clover-leaves. The SPOC of all clover-leaves then convene and jointly decide which patient is transferred when to which hospital using which transport vehicle. To allow sufficient time for the operational organization of the transfers, a lag of two days between taking the transfer decisions and conducting the transfers is expected. The decision therefore consists of the following problems:

- Allocation of patients to hospitals
- Scheduling of patients on transport vehicles

The decisions are based on the current and predicted capacities of the hospitals [4,5]. As transport vehicles, ICH and ICA are mainly considered. As additional possibilities, trains, buses and airplanes were also discussed. These vehicles could potentially transport more than one patient at a time, but the primary focus of this paper is on the ICH and ICA. Once the patients are transferred, the clover-leaf system is only activated again if a clover-leaf is at risk of getting overloaded.

2.2. Objectives

The following three objectives are considered in the decision:

1. Minimize the transfer duration for the patients: Transferring patients has been linked to adverse effects on their health for a range of diseases [28]. If a transfer cannot be avoided it should therefore be kept as short as possible in order to reduce the risk for the patient.
2. Minimize changes of transport vehicles: Next to the transport duration, changing transport vehicles also poses a risk for the patients. This is due to the necessary change of equipment, such as ventilators. A change of transport vehicle occurs when a patient is transferred from an ICA to an ICH. This is necessary if the sending or receiving hospital does not have a landing place for helicopters on site.
3. Minimize the maximum utilization of intensive care capacities: The goal of transferring patients is load balancing between different regions. Transferring patients into a region should therefore not lead to over-utilizing the capacity of the receiving region.

Especially the first and last objective can be conflicting, if the closest regions to the sending region are close to their capacity limit. The cost of the transfers is explicitly not considered due to the criticality of the situation. Additionally, inter-clover-leaf transports are not expected to happen on a regular basis. This makes the cost of the transfers negligible in comparison to the risk of not being able to treat patients in intensive care units due to an overload.

2.3. Constraints

For each of the two decisions, different types of compatibilities need to be considered:

Patient-hospital compatibility needs to be ensured in the *allocation of patients to hospitals*. In Germany, each hospital is categorized into one of three tiered care levels. To ensure that a patient receives the same level of care after a transfer, the destination hospital of patient needs to have the same or a higher care level than the source hospital.

Patient-transport vehicle compatibility needs to be ensured for the *scheduling of patients on transport vehicles*. Firstly, the transport vehicle needs to contain the necessary equipment such as a sufficient number of syringe pumps in order to provide the necessary care for the patient during the transport. Secondly, the maximum patient width, height and weight for which a transport vehicle is designed need to be compatible with the patient that is to be transported. Thirdly, patients with COVID-19 often need to be supplied with oxygen and necessitate a certain oxygen flow rate. The total oxygen capacity of a transport vehicle needs to be sufficiently large to supply the patient for the transport duration.

Shift and flight time compatibility needs to be ensured in the *scheduling of patients on transport vehicles*. A transport vehicle cannot start a transport before its shift starts and the transport should be concluded before the shift ends. ICH additionally can be limited regarding their flight times, as not all ICH are equipped for flying before sunrise or after sunset.

Hospital-transport vehicle compatibility needs to be ensured in the combination of the *allocation of patients to hospitals* and *scheduling of patients on transport vehicles*. If a hospital for instance does not have a helipad, it is not possible to pick-up or drop-off a patient at that hospital using an ICH.

3. Methods

In the following, firstly the outline of the methodology is presented, before the methodological contribution in the form of a simulation model is presented, including a description of the concept model in Section 3.2 and the implementation as an executable simulation model in Section 3.3. Subsequently, the transfer strategies used in the computational experiments are introduced in Section 3.4.

3.1. Outline of the methodology

Fig. 2 presents the outline of the methodology. The *setting* under study and the *objectives* informing the transfer decision are detailed in Section 2 and consider the effects of the transfer decision on the load in intensive care units and on the health of the transferred patients. The *transfer decision* determines, when which patient is transferred to which hospital with which mode of transport. The resulting *transfer process* can then be evaluated by how well it achieved the objectives.

The main aim of this paper is the development of a *simulation model* with which different approaches to taking the transfer decision can be compared. Next to simulating decisions taken by the decision makers – the SPOC –, several *transfer strategies* in the form of decision rules are developed in this paper and compared to the decisions taken by the SPOC. From a methodological point of view, the transfer decision appears suitable to be modeled by an optimization model. The development of such a model lies outside the scope of this paper, but presents a promising avenue for further research, which is discussed further in Section 5.

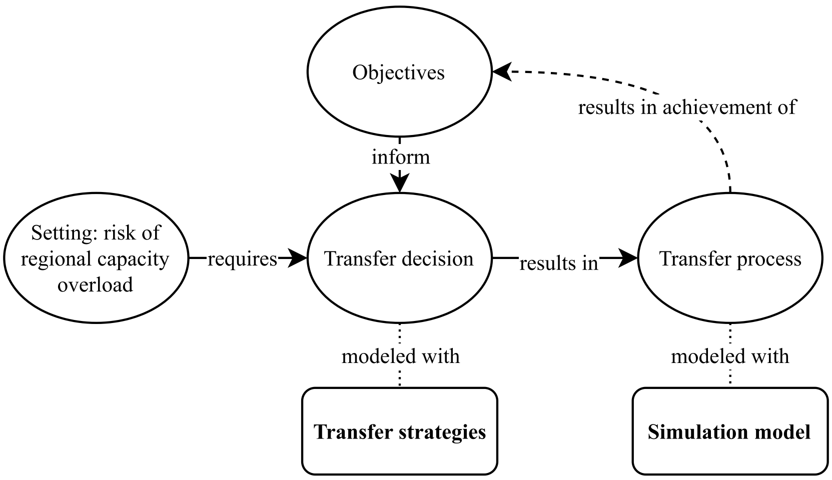


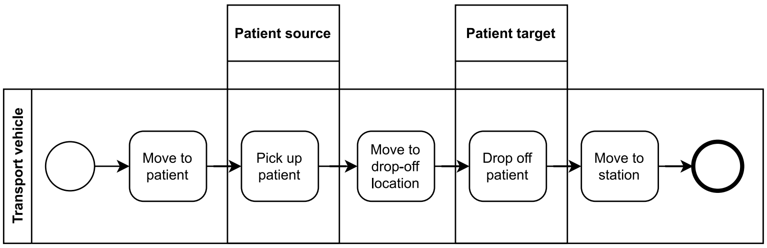
Fig. 2. Methodology outline.

3.2. Concept model

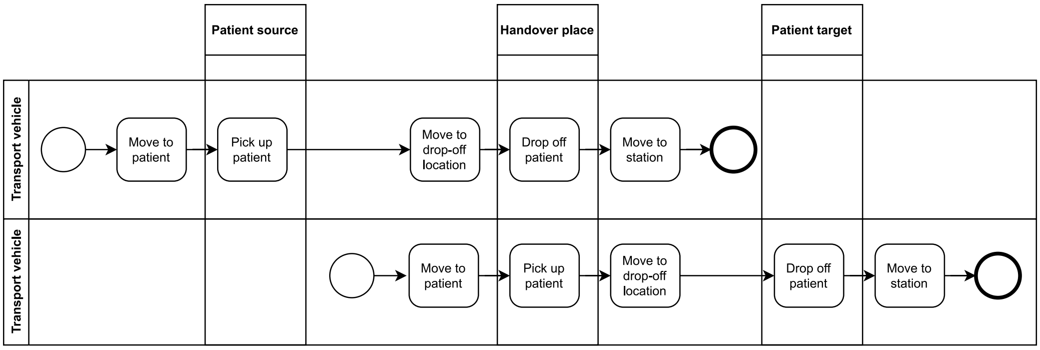
Before the implemented simulation model is described in Section 3.3, the conceptual model is presented in the following.

3.2.1. Process overview

The two basic process variants that we want to model are depicted in Fig. 3. In the simplest case (Fig. 3(a)), the patient is picked up at a hospital – the patient source – by a transport vehicle. The patient is then transported to a second hospital – the patient target –, after which the transport vehicle returns to its station. The second variant (Fig. 3(b)) includes handing the patient over from one transport vehicle to a second one during the transfer. While not explicitly depicted, one transfer could also include multiple handovers between transport vehicles. One such instance occurs, when neither hospital has a heliport, but part of the transfer is still conducted by an ICH. In that case, the patient is picked up by an ICA, then handed over to an ICH and then handed over a second time again to an ICA. One patient transfer can therefore consist of multiple transports.



(a) process between hospitals



(b) process between hospitals with a handover place

Fig. 3. process schemes for patient transport.

3.2.2. Modeling approach

The transfer process can be modeled from two perspectives: The first perspective is the patient perspective. Patients enter and leave the model and go through a series a process steps. This perspective lends itself well to be modeled by discrete-event modeling using process flow charts. This allows to capture the patient pathway in the model which enables to evaluate the transfer process regarding its effects on patient's health, one of the main objectives stated by the decision makers. The second perspective is the transport vehicle perspective. Transport vehicles are a constant part of the model and can repeatedly perform transports of patients. This perspective lends itself well to be modeled agent-based using state-charts. State-charts allow for a detailed control of the behavior of the transport vehicles in the model. This is especially important in the case of transfers including a hand-over where two transport vehicles need to be synchronized. Combining both discrete-event and agent-based modeling in one simulation model is called hybrid modeling and allows to combine the advantages of both approaches [22].

3.2.3. Modeled entities

Before the process flow chart and state-chart of the conceptual model are introduced, the entities contained in the model including their characteristics are presented. Fig. 4 depicts the overview of the entities including their characteristics.

Hospitals are part of the model with the following characteristics: The *Location* contains the coordinates of a hospital for visualization and travel time computation. Each hospital either has a *helipad* or it does not, determining whether an ICH can land directly at the hospital or whether an intermediary transport by ICA is necessary. The current as well as predicted capacities in the intensive care unit of a hospital are included in the model. This enables to implement decision rules based on capacities in the model. Lastly, the care level of a hospital is part of the model to ensure patient-hospital compatibility as described in Section 2.3.

Handover places are modeled with their locations to be able to model accurate transport times.

Transport vehicles are an integral part of the model. They include their station location for driving time modeling. The equipment is specified to ensure patient-transport vehicle compatibility as described in Section 2.3. Similarly, shift information is used to ensure shift compatibility. The capacity of a vehicle indicates how many patients it can transport. The type of vehicle is a necessary information for driving time calculations as well as to ensure the hospital-transport vehicle compatibility.

Patients contain their source hospital in the model as well as their characteristics such as width, height, weight, oxygen need and amount of needed syringe pumps.

Transport orders are modeled to facilitate the extendability of the model. The modeling view is that transport vehicles are assigned transport orders. Transport orders are defined by an origin location and a destination location, which can be either hospitals or handover places. Additionally, the scheduled pick-up time of the transport order is specified, which determines when the transport vehicle should be at the origin location. Finally, a transport order can contain one or multiple patients. This concept enables the flexibility of modeling an arbitrary number of handovers for a patient. It additionally enables an easy integration of transport vehicles with a capacity for more than one patient. This enables the modeling of batch transfers where patients from potentially different hospitals are transported to one handover place. From this handover place multiple patients can be transported to a second handover place using for instance a train and then be transported to their destination hospitals separately.

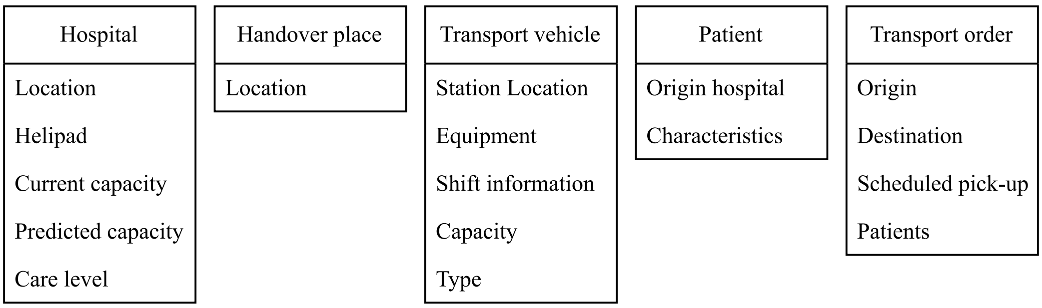


Fig. 4. Modeled entities and their parameters.

3.2.4. Agent-based modeling of transport vehicles

The state chart used to model the behavior of the transport vehicles is depicted in Fig. 5. Transport vehicles are initially *available at their idling location*. At the scheduled starting time of a transport order, the transfer vehicle starts *preparing*, for instance conducting pre-flight checks in case of an ICH. The transport vehicle then starts *moving to the pick-up location* of the transport order. If patients are at the pick-up location, the transport vehicle starts *picking up patients*. If the pick-up location is a handover place, it might happen that the preceding transport vehicle is delayed in which case transport vehicle will be *waiting for preceding transport vehicle(s)*. As soon as all patients of the transport order are picked up, the transport vehicle starts *moving to the drop-off location*. If the drop-off location is the transfer destination of the patients, the transport vehicle starts *dropping off the patient(s)*. If the drop-off location is a handover place and the succeeding vehicle is not yet at the handover place, the transport vehicle will be *waiting for succeeding transport vehicle(s)*. After having dropped off all patients of the transport order, the transport vehicle starts *moving to idling location*. Since the transferred patients are carrying a virus, *disinfecting* the transport vehicle is necessary before it is available again at the idling location.

3.2.5. Discrete-event modeling of the patient pathway

To facilitate observing the patient pathways in the simulation it is modeled using discrete-event modeling. The process-flow chart of the patient pathway is depicted in Fig. 6. The modeled patient pathway starts with the patient *getting picked up* at the origin hospital. The patient is then *being transported* either directly to the destination hospital or to a handover place. Once at the destination hospital, the patient is *being dropped off* and the modeled part of the patient pathway ends. If the transport ends at a handover place, the patient is *being handed over* to the succeeding transport vehicle after which the patient again is *being transported* either to the destination hospital or to another handover place.

The concept of transport orders connects the patient perspective and the transport vehicle perspective in the modeling logic. Transport vehicles, which can potentially transport multiple patients at once, transport one transport order at a time. One transport order contains one or multiple patients. One patient can therefore sequentially be part of different transport orders during its transfer.

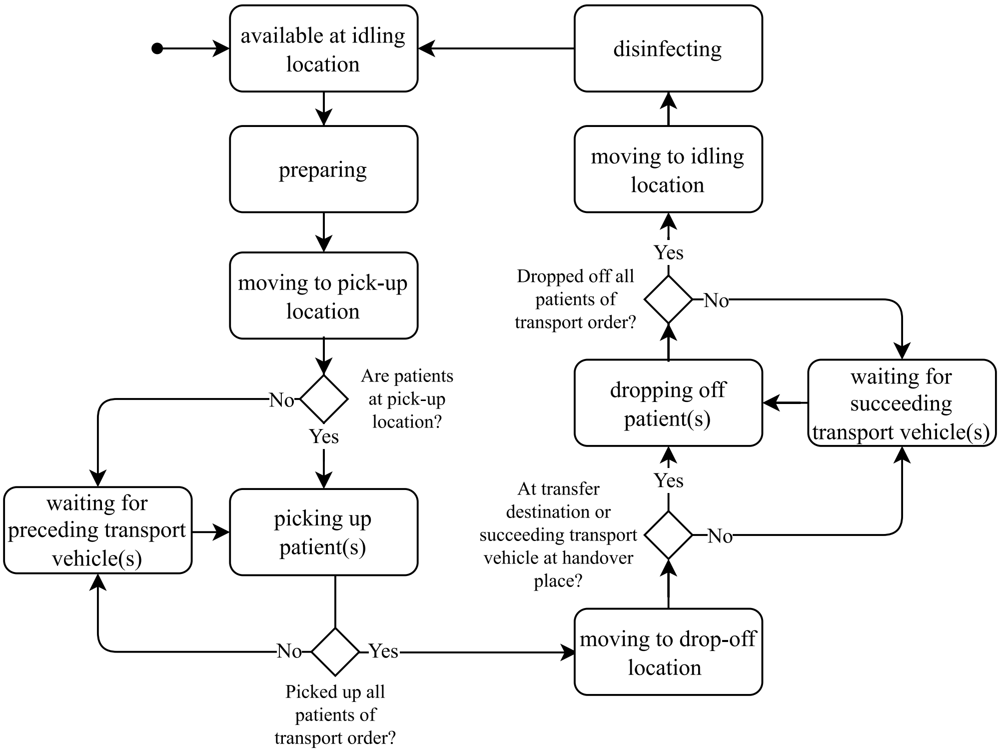


Fig. 5. State-chart of transport vehicles.

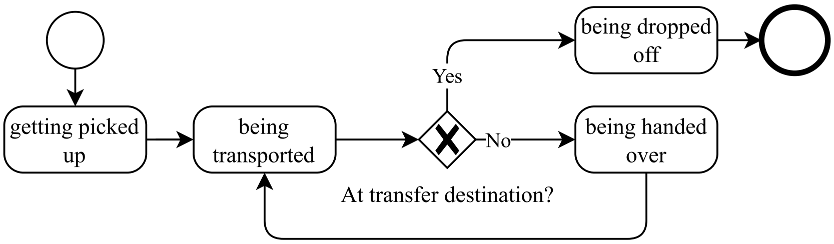


Fig. 6. Process flow chart of the patient pathway.

3.3. Simulation model

The implementation of the presented concept model as an executable simulation model is described in the following. The model was implemented using AnyLogic, a simulation software which allows for combining agent-based, discrete-event and system dynamics modeling within one simulation model. AnyLogic is based on the Java programming language and follows an object-oriented approach where each modeled entity is implemented as an agent type. An agent can contain state charts, following an agent-based modeling approach, but it can also contain process flow-charts following a discrete-event modeling approach, or it can contain simply its parameters. Each entity described in Section 3.2.3 is implemented as one agent type in the simulation model. The *transport vehicle* contains state-charts described in Section 3.3.1, *hospitals* and *handover places* contain process flow charts described in Section 3.3.2 and the agent types *patient* and *transport order* simply contain their parameters.

3.3.1. Implementation of agent-based transport vehicle modeling

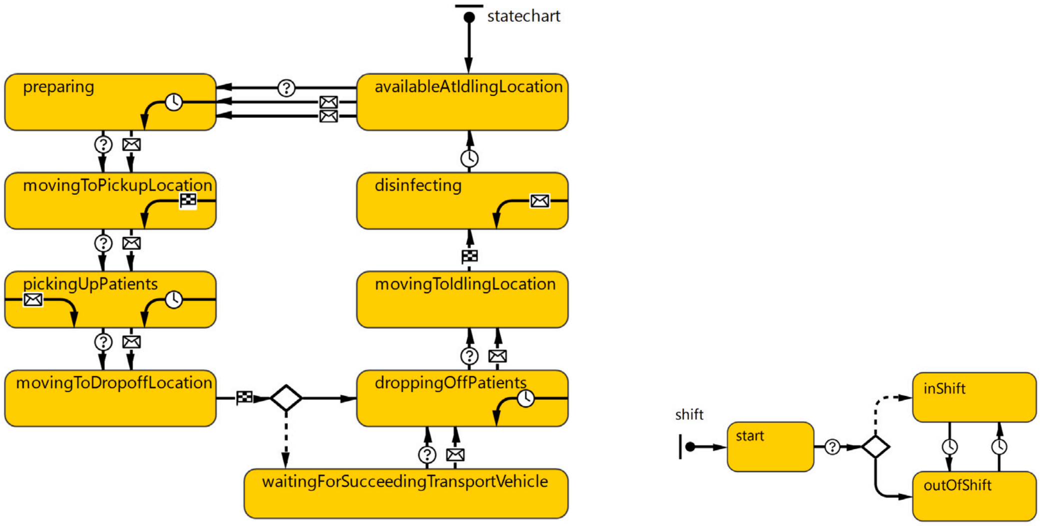
The implementation of the agent-based modeling of transport vehicle behavior is depicted in Fig. 7(a). The states are equivalent to the states described in Section 3.2.4 with the following simplifications.

The concept model is designed to be able to model transport vehicles with a capacity of one or more patients. The application for which the executable simulation model was developed considers only ICH and ICA with a capacity of one patient. This means that from the perspective of a transport vehicle there is always only one preceding or succeeding vehicle at a handover place. This allows for a simplified coordination of patient handovers making the decisions *picked up all patients of transport order?* and *dropped off all patients of transport order?* depicted in Fig. 5 obsolete.

In case of a handover of a patient between two transport vehicles the process time for the handover is controlled by the transport vehicle arriving with the patient. This enabled to include potential waiting times into the state *pickingUpPatients* for the transport vehicle leaving with the patient which allowed for a further simplification of the implemented state chart.

To extend the model to consider transport vehicles with a capacity of more than one patient, a decision would need to be included after the state *droppingOffPatients* with one path leading to *movingToIdlingLocation* and a second path leading to *waitingForSucceedingTransportVehicle*.

In order to consider the shift times of the transport vehicles a second state-chart was implemented for the transport vehicle agents and is depicted in Fig. 7(b). Modeling shift times using a state-chart supported in validating the simulation model as it enables the visual control of consistent behavior between the two state-charts during runtime. The shift times need to be considered to ensure that the transport vehicles start their transports only when they are within their shifts. It is additionally possible that the handover of patients to the destination hospital is conducted during the shift, but the remaining shift time is not sufficient to move back to the idling location. In practice, the crew of the transport vehicle stays overnight and starts moving back to the idling location at the following day. In the simulation the transport vehicle will stay in the state *droppingOfPatients* until the shift starts on the following day in this case.



(a) State-chart for transport vehicle behavior modeling.

(b) State-chart for transport vehicle shift modeling.

Fig. 7. Agent-based modeling of transport vehicles.

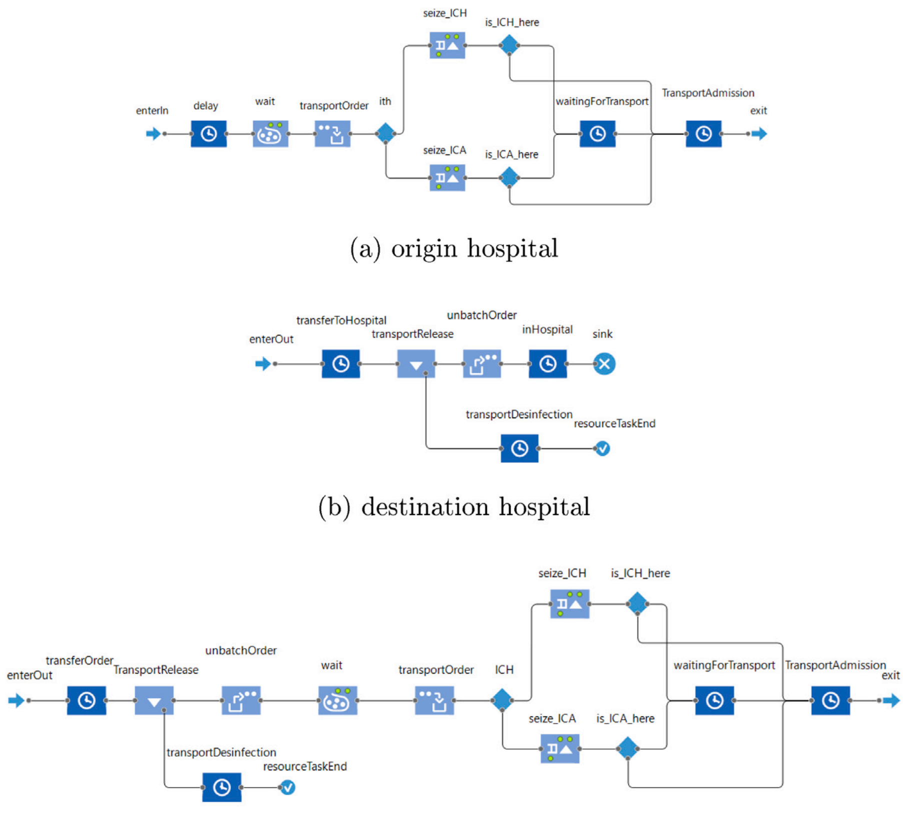
3.3.2. *Implementation of discrete-event patient pathway modeling*

The discrete event modeling of the patient pathway is separated into three modular process flow charts. The process starts in the origin hospital agent of the patient depicted in Fig. 8(a). The patient is connected to a transport order which in turn is connected to a transport vehicle. As soon as the transport vehicle arrives at the origin hospital the transport order containing the patient is loaded into the transport vehicle and exits the process flow chart in the origin hospital agent.

If the transfer does not necessitate a handover, the transport order then enters the process flow chart in the destination hospital agent depicted in Fig. 8(b). At the destination hospital the transport order containing the patient is dropped off, and the transport vehicle is released. The modeled part of the patient pathway then ends in the destination hospital.

If the transfer necessitates a handover, the transport order enters the flow chart in the corresponding handover place agent depicted in Fig. 8(c). The patient is disconnected from the transport order of the transport to the handover place and connected to the transport order leaving the handover place. This transport order is then connected to the transport vehicle conducting the subsequent transport and the transport order leaves the process flow chart in the handover place agent. If a further handover is necessary it will enter the process flow chart in the next handover place agent, otherwise it will enter the process flow chart in the destination hospital.

The modularization of the process flow chart allows for modeling transfers with an arbitrary number of handovers. Connecting patients to transport orders allows for transports with an arbitrary number of patients without having to change the process flow chart itself.



(a) origin hospital

(b) destination hospital

(c) handover place

Fig. 8. Discrete event simulation modeling for hospitals and handover places.

3.3.3. Spatial environment using a geographic information system

Within the simulation model, the agents move in a Geographic Information System (GIS) environment as depicted in Fig. 9. Using a GIS-environment supports in validating the simulation model by animating the behavior of the transport vehicles. It additionally aids in communicating the simulation model to practitioners.

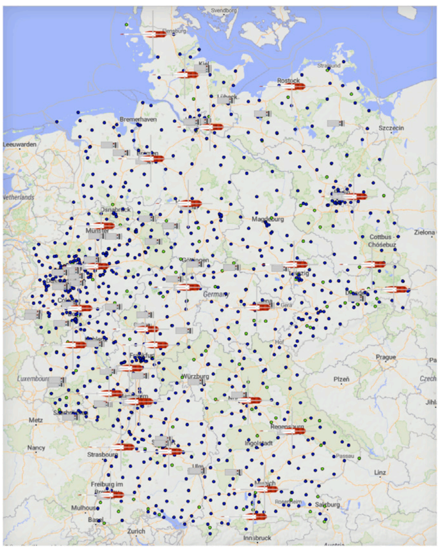


Fig. 9. GIS environment of the simulation model with ICH (red), ICA (gray), hospitals (blue) and handover places (green).

3.3.4. Verification and validation

There exist several approaches for simulation verification and validation according to [29,30]. In this work we implemented (i) Face validation, represented by practitioners and professionals of the Institute for Rescue and Emergency Medicine from the University Hospital Schleswig-Holstein, Germany; (ii) Visual validation, by means of the process visualization presented which includes patient and vehicle animation, as depicted in Fig. 9; and (iii) Trace validation, represented by the comparison of the data obtained from the simulation model and the values from the experts.

3.4. Transfer strategies

The problem described in Section 2 could potentially be modeled as an optimization model. This approach however presents several challenges. The decision consists of an allocation problem and a scheduling problem which are interconnected. As isolated scheduling problems are notoriously hard to solve, finding exact solutions using an off the shelf solver in a reasonable time for real-world instances is unlikely. This would necessitate implementing a metaheuristic or developing a problem-specific heuristic solution approach. Additionally, the presence of multiple, potentially conflicting objectives necessitate the employment of a multicriteria optimization approach. Lastly, the stochasticity in process times, such as handover times, need to be handled. While a deterministic modeling approach could already produce a useful decision support, this further enhances the effort necessary to model and solve an optimization model.

For these reasons, we propose several simple transfer strategies in the form of decision rules. The transfer strategies have been published in the German language, but this paper constitutes the first publication in the English language [31]. The aim of the transfer strategies is to provide decision makers with benchmark decisions focusing on the different objectives. A transfer strategy consists of rules to answer the following two questions:

- To which hospital should a given patient be transferred?
- How should the patient be transferred to the destination hospital?

The strategies aim at reaching the following, partly conflicting, objectives explained in Section 2.2:

1. Minimize the transfer duration for the patients.
2. Minimize changes of transport vehicles.
3. Minimize the maximum utilization of intensive care capacities.

Especially the first and last objective can be conflicting, if the closest regions to the sending region are close to their capacity limit. Therefore, different strategies were developed.

3.4.1. Hospital selection

The rules for choosing the hospital can be divided into rules focusing on minimizing the transport duration for the transferred patients and rules focusing on maintaining a high hospital capacity:

- Closest hospital with any current capacity (H1)
- Closest hospital with any current and predicted capacity (H2)
- Hospital with the highest current capacity (H3)
- Hospital with the highest current capacity within the region with the highest current capacity (H4)
- Hospital with the highest predicted capacity (H5)
- Hospital with the highest predicted capacity within the region with the highest predicted capacity (H6)

Rules *H1* and *H2* aim at minimizing the transport durations for the patients. For the predicted capacity, the predictions of Refisch et al. [4] were used. The same predictions were also used by the German Federal Ministry of Health and the SPOC for their assessment of the pandemic situation. To evaluate the benefit of basing the transfer decisions on the predictions, we differentiated between using the capacity at the time of decision and the predicted capacity. The lead time of the predictions are discussed in Section 4.1.1.

Rules *H3, H4, H5* and *H6* aim at minimizing the maximum utilization of intensive care capacities. The same reasoning as for rules *H1* and *H2* led to differentiating between current and predicted capacity. For rules *H3* and *H5* the decision was based on the capacity at hospital level. However, if there is one hospital with a high capacity in an otherwise highly utilized region, these rules can lead to undesired results by transferring patients into regions with low capacity. To avoid this situation, rules *H4* and *H6* were developed. With these rules, the hospital selection is taken step-wise: Firstly, the clover-leaf with the highest capacity is selected. Secondly, the federal state with the highest capacity within that clover-leaf is selected, thirdly the care-cluster with the highest capacity within that federal state is selected and lastly the hospital with the highest capacity within that care-cluster is selected.

From a medical perspective, it should be ensured, that the destination hospital has at least the same level of care as the sending hospital. Therefore, the capacities are calculated separately for each level of care. The hospital selection rules are then applied only based on the capacity in the same level of care as the sending hospital. If there is no capacity at the same level of care, the rules are applied to the capacity in the next-higher level of care until either a hospital is found, or it can be concluded that there is no capacity on the same or a higher level of care. In that case the patient would not be transferred in the simulation.

3.4.2. Transport mode selection

Within the scope of the research project, two modes of transport were compared: Ground-based transport with ICA and air-based transport with ICH. Usually, cost plays a major role in the decision between ground-based and air-based transport [32]. In the case of strategic patient referrals in a pandemic situation however, cost was not identified as a relevant factor for the decision. This leaves the transport time and the necessary changes of vehicles as the relevant factors for the decision. If both the sending and the destination hospital have a landing place for ICH on site, there is no change of vehicle necessary and the transport duration for the patient is shorter when using an ICH. If this is not the case, the patient first has to be transported to a landing place by an ICA and then transferred to an ICH or vice versa (depending on whether the sending or destination hospital has no landing place). If both hospitals do not have a landing place, the patient has to change vehicles twice. This increases the transport duration and additionally, each transfer of vehicle is associated with a risk for the patient.

To evaluate the effects of different strategies, the following rules for choosing a transport mode were defined:

- Transport with ICA (TM1)
- Transport with ICH and intermediate transports by ICA where necessary (TM2)
- Distance-based decision for ICA or ICH (TM3)

With rule *TM1* the patients are transferred only by ICA. The choice of the specific ICA is based on minimizing the total driving distance from the station of the ICA to the sending hospital and back from the destination hospital to the station. The distance between sending and destination hospital is the same for all ICA and therefore not relevant for choosing a specific ICA. Additionally, it was ensured, that the ICA can reach the destination hospital within their shift time and that it fulfills the patients needs, e.g. it carries the necessary amount of oxygen in case of ventilation. If there is enough shift time left, the ICA will drive back to its station immediately. Otherwise, it will stay at the destination hospital overnight and drive back to its station on the following day.

With rule *TM2* the patients are transferred with ICH. If one or both hospitals do not have a landing place, an intermediate transport to or from a handover place by an ICA is added.

The objective of the rule *TM3* is the following: Choose transfer by ICA or ICH in such a way, that the transfer duration for the patient is minimized. In order to estimate, if a transfer by ICA or ICH is faster, the driving distance between the starting and the landing place of the ICH was used. If one handover between ICA and ICH would be necessary, transfer by ICH was only chosen, if this distance exceeds 50 km. If two handovers would be necessary, the distance has to exceed 100 km. Otherwise, the patient is transferred with ICA. The detailed explanation and calculation of the distance limits can be found in Appendix A.

The input for applying the decision rules is a sorted list of the patients which need to be transferred. The rules of a strategy are then applied sequentially to each patient while considering the constraints stated in Section 2.3. Firstly, the destination hospital is selected and secondly, the transport vehicles are determined. The transfer strategies are a simple heuristic approach to modeling the decision and do not necessarily lead to optimal decisions.

4. Computational experiments

Within the research project, the simulation was used to benchmark patient transfer plans of decision makers – the SPOC of each clover-leaf – against the transfer strategies presented in Section 3.4. The benchmarking took place within an exercise in which the process from the occurrence of demand for patient transfers to the allocation of those patients to destination hospitals and transport modes was executed with a set of artificial patients. In the following, the experimental setup is explained and the results of the experiments are shown.

4.1. Experiment setup

To investigate the effects of the different transfer strategies, simulation experiments were conducted. A simulation experiment is defined by the choice of *resource parameters*, *process parameters* and *patient parameters*, which are described in the following. To obtain reliable simulation results, for each experiment 100 independent runs were simulated. The assumption was made that patients will stay in the intensive care unit for eleven days after having reached their destination hospital. Given that only patients with a sufficiently stable condition are selected for transfers this was deemed an upper bound for the remaining length of stay of patients in the intensive care unit of the destination hospital and was used to generate a pessimistic evaluation of the effects of the transfers on the capacities in the destination hospitals.

4.1.1. Resource parameters

The resource parameters define the available transport resources, the hospitals with their capacities and the handover places. The data regarding the transport resources, was provided by the different clover-leaves, since no central database of intensive care transport resources exists in Germany. In total, 90 ICA and 31 ICH were considered. For each transport resource the following characteristics are available: maximum patient width, height and weight; amount of oxygen; amount of syringe pumps. These characteristics are used to check, which patient can be transported by which transport resource.

Data regarding the hospitals was available through a national database. In total 1112 hospitals were included in the simulation. Each hospital is classified into one of three tiered care levels and one of four tiered emergency care levels. These care levels are used to ensure, that patients are not transferred into a hospital with a lower (emergency) care level. The predicted capacities used for strategies *H2*, *H5* and *H6* are for the seventh day after the date of the decision. This is based on the conclusion of Grodd et al. [5], that their predictions are robust in the range of five to ten days into the future. 964 handover places are available in total. These include all hospitals with a heliport, all home bases of ICH and an additional 60 landing places outside of hospitals.

From a technical point of view, the hospital capacities could be generated artificially in order to create decision scenarios with specific characteristics. This would make it necessary to define desired characteristics and to develop a method to generate realistic data. Another possibility is to use historical data. Due to the availability of historical data and to provide the decision makers with familiar data during the benchmarking, this approach was chosen. This necessitates choosing a suitable historical date, from which the data is to be used. To determine such a date, the following requirements were defined: Rising number of hospitalized patients for at least 14 days, between 50 and 150 free ICU beds in each clover-leaf and prediction of a further rise in patient numbers for at least the coming seven days. These requirements aim at finding historical dates, at which the capacity was low enough, that a local surge of patients within a clover-leaf could have led to a capacity overload. At the same time a certain capacity should still be available in the clover-leaves in order to leave sufficient degrees of freedom for the decision to be able to evaluate the effects of the different decision strategies. To smooth out the effects of delays in data reporting, a three-day moving average for the number of occupied beds was used. As a suitable date for the transfer decision, the 04.12.2021 was chosen (s. Fig. 10).

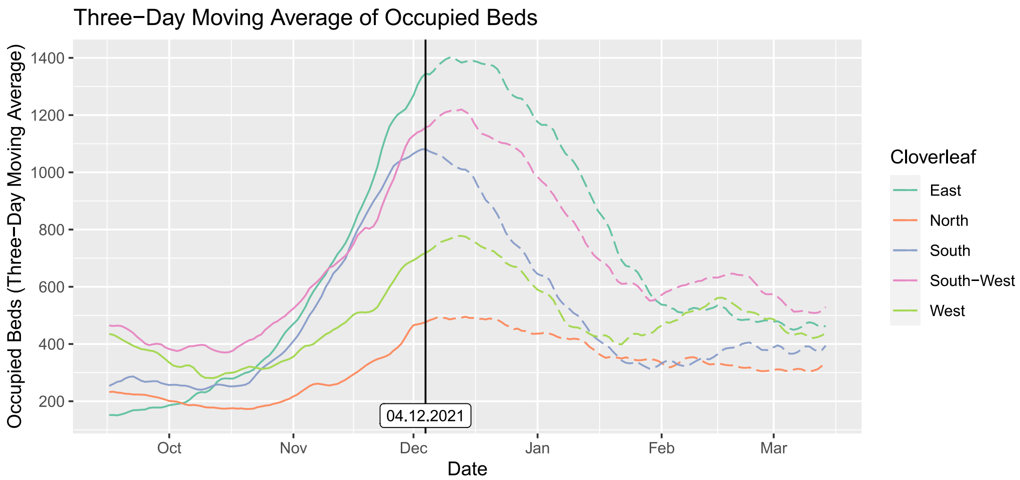


Fig. 10. Three-Day moving average of occupied beds in the clover-leaves. 04.12.2021 was chosen as a suitable date for the simulation experiments.

4.1.2. Process parameters

Regarding the process times, the *preparation time* of the transport resources between alarm at the base and beginning to drive/fly to the patient pick-up place, the *driving/flight times* and the *handover times* are needed. The *preparation times* and the *handover times* were based on the data of 320 historic (short-term) patient transfers. To model the time intervals in the simulation, the empirical cumulative distribution functions were calculated and used in the simulation model.

The *driving times* between all ICA bases, hospitals and handover places were precomputed using openrouteservice.org by HeiGIT [33]. These driving times are based on regular road cars. Based on the available historic patient transfer data and validation with the medical experts, the driving times were scaled down by a factor of 0.7 to account for the lower driving speeds of ICA in comparison to road cars. The *flight times* are calculated during the simulation using the Euclidean distance and a flight speed of 220 km/h, based in Jagtenberg et al. [34]. Using deterministic travel times follows existing simulation models of emergency medical services identified in the literature review in Section 1.2.

4.1.3. Patient parameters

The set of patients, that are to be transferred, was defined by medical doctors within the research project. The set included 50 patients including their relevant characteristics such as width, height, weight, oxygen need, syringe pumps and the Horovitz-Index, with which the patients can be sorted by the severity of their condition. For each experiment, one clover-leaf is selected as the source clover-leaf. The patients are then assigned randomly to source-hospitals within that clover-leaf. Each strategy was simulated once for each clover-leaf as the source clover-leaf.

4.2. Results

4.2.1. Transfer strategies

Before benchmarking the transfer plans of the SPOC, the transfer strategies were compared. From a patients' perspective, the most relevant indicators are the necessary changes of vehicles and the transport duration. The average results for those indicators over all simulation runs are shown in Fig. 11, including the 95% confidence intervals for the means. Looking at the transport modes we can see, that transporting only by ICA (TM1) leads to the longest transport durations and the least changes of vehicles.

Comparing using an ICH for every patient (TM2) and deciding the transport mode based on distance (TM3) it becomes apparent, that the distance-based strategy dominates the pure ICH-strategy for every hospital selection strategy both in transport duration and changes of vehicles. Considering the hospital strategy, as expected choosing the closest hospital with any current or current and forecasted capacity (H1, H2) leads to shorter transport durations and fewer changes of vehicles compared to strategies focusing on maintaining a high capacity in the hospitals (H3- H6). To conclude, the strategies show the expected behavior in the simulation. For the numeric results, the reader is referred to Table B.1 in the Appendix.

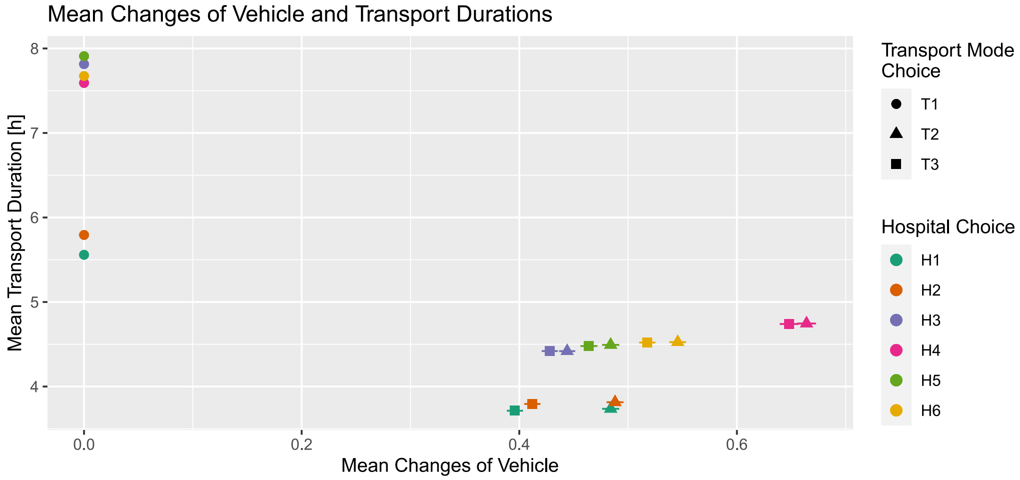


Fig. 11. Mean of changes of vehicles and transport durations for the different transfer strategies. Bars indicate the 95%-confidence intervals.

From a hospital perspective, the relevant indicator is the impact of the transfer strategies on the intensive care capacities. The minimum intensive care capacity of each care cluster, that received at least one patient, in each scenario and each independent simulation run was observed over the length of stay of the transferred patients. Fig. 12 shows the sample mean of those observations including the 95%-confidence interval. The outlined bars represent capacities without the simulated transfers and the solid bars the capacities considering the simulated transfers. For the strategies focusing on a short transport duration (H1 and H2) no statistically significant difference was found between basing the decision on current or on predicted capacities. Somewhat surprisingly, the strategies focusing on single hospital capacities (H3 and H5) led to the lowest resulting capacities. This can result from the fact, that focusing only on the hospital level capacities can lead to patient transfers into regions with a low capacity outside the destination hospital. This situation is avoided in the strategies with a step-wise approach (H4 and H6), leading to significantly higher minimum capacities. For the numeric results, the reader is referred to Table B.3 in the Appendix.

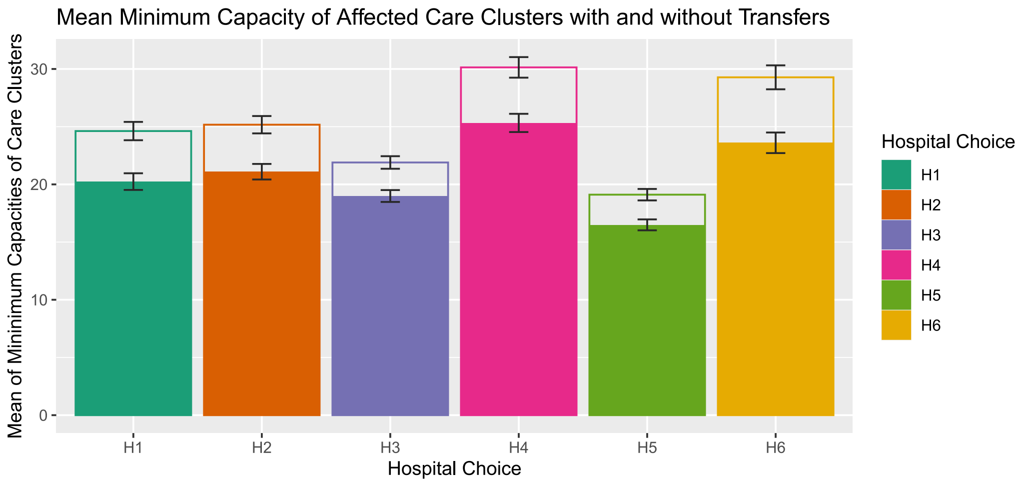


Fig. 12. Mean of minimum capacity of care clusters receiving at least one patient with transfers (solid bars) and without transfers (outlined bars), including 95% confidence intervals of the means.

4.2.2. Benchmarking of decision makers

The transport plans of the SPOC were created in two sequential rounds. One clover-leaf was selected to be the source of the patients. In a first round, the SPOC determined together which clover-leaf will take in how many patients. Subsequently, each receiving clover-leaf created the detailed plan, which patient will be transferred when to which hospital and with which mode of transport. The source clover-leaf then were assigned an additional 20 patients with another clover-leaf as the source in order to have a detailed transport plan from every clover-leaf. Those plans were run through the simulation and compared to selected transfer strategies for the same patients. The results were then presented to the SPOC to inform a discussion and refinement of their decision process.

To reduce the complexity of the comparison, four transfer strategies were selected for the benchmarking: The transport mode was either only ICA (TM1) or distance-based (TM3), since TM3 dominated TM2. For the hospital selection, one strategy focusing on short transport durations (H2) and one focusing on hospital capacity (H6) were selected.

The simulation results are shown in Fig. 13 and the numeric results can be found in Table B.2 in the Appendix. It appears that the decision makers chose a trade-off between the proposed transfer strategies, leading to average changes of vehicles as well as average transport durations in between the proposed transfer strategies.

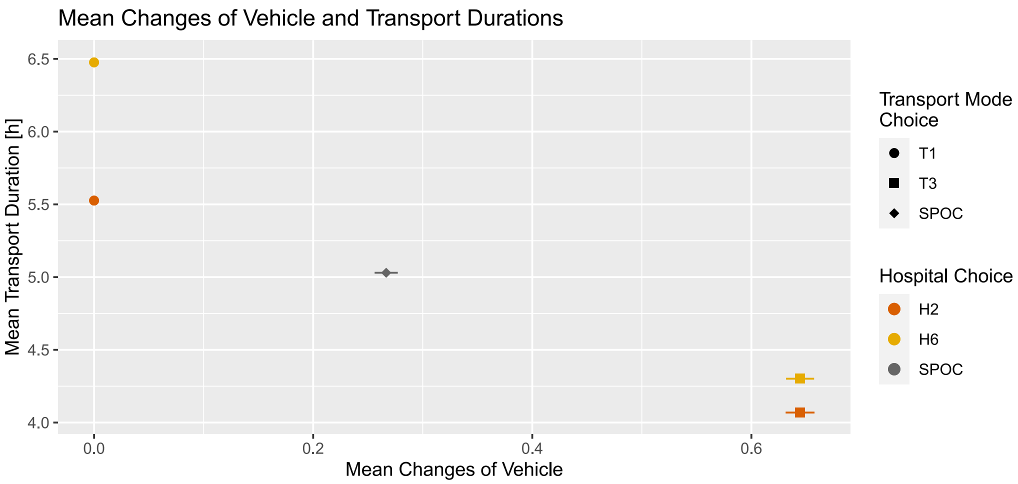


Fig. 13. Benchmarking of transfer plans created by decision makers against transfer strategies. Means including 95%-confidence intervals (horizontal lines) are depicted.

Considering the hospital utilizations in Fig. 14, the transfer plans of the decision makers lead to a lower minimum resulting capacity than a strategy explicitly considering the forecasted capacities (H6). One interpretation is, that more emphasis is put on the patient perspective. It is also possible, that the decision makers possess knowledge about backup capacity in the destination hospitals, which is not included in the available data, but could be activated in practice. However, the results are a clear indication, that explicitly considering the forecasted hospital capacities can support in avoiding the overload of regions that receive the transferred patients. The numeric results can be found in Table B.4 in the Appendix.

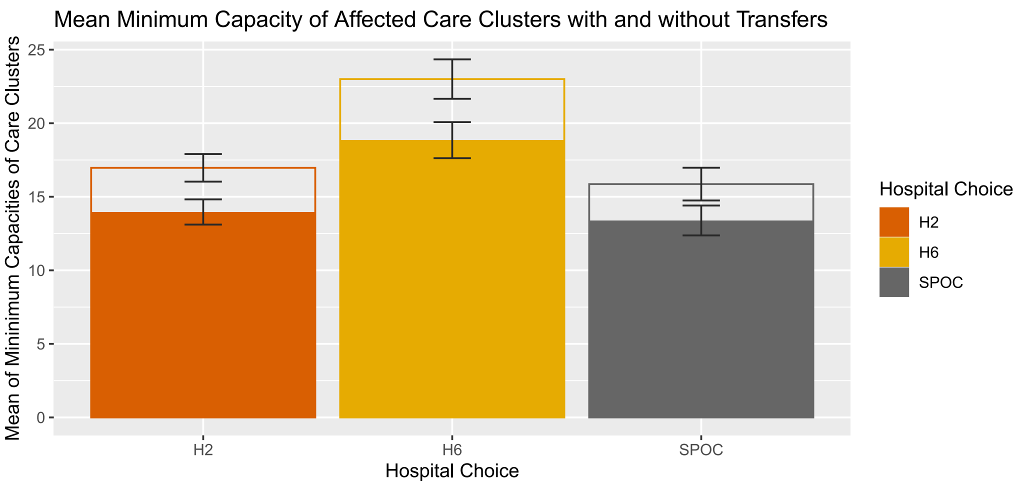


Fig. 14. Mean of minimum capacity of care clusters receiving at least one patient with transfers (solid bars) and without transfers (outlined bars), including 95% confidence intervals of the means.

5. Discussion

The aim of the research project was to develop a simulation model to evaluate nation-wide transfer strategies for strategic COVID-19 patient transfers.

A hybrid modeling approach combining discrete-event and agent based modeling was chosen. This enabled the combination of modeling the patient pathway as well as the behavior of the transport vehicles, combining the strengths of both modeling approaches.

The modular and flexible modeling of the discrete-event part of the simulation allows for scalability in terms of transfer destinations and handover-places between transport vehicles. Additionally, it enables the future inclusion of additional transport vehicle types, such as trains, buses or airplanes. Trains have already been used in France for the transport of COVID-19 patients [35]. Transports with more than two changes of vehicles can be simulated with the chosen approach as well. Scaling down the model to use it e.g. for simulating patient transports after mass casualty incidents is also enabled by the modular and flexible modeling.

Since the simulated system was not yet in use when the simulation project started, it was not possible to perform the validation of the model based on historical data, which tends to provide very robust results. By using animation, trace validation as well as extensive face validation with practitioners, the simulation model is still deemed valid. Additionally, the implemented transfer strategies showed the expected results in the simulation, adding further arguments to the validity of the model. Limitations of the simulation are firstly the use of deterministic instead of stochastic travel times. Additionally, the most granular utilization data was available on a regional and not on a hospital level. The utilization of the hospitals was calculated based on regional data, therefore not accounting for variation on the proportional utilization of hospitals within a region.

Simulation was used to support strategic decision-making by providing quantitative evaluations of possible decision strategies. Within the healthcare domain, the use of quantitative, analytic methods such as simulation for strategic logistic planning decisions is not wide-spread [25].

The decision problem of strategic patient transfers can be seen as a multi-objective decision problem. The goals of short transfers for the current patients and maintaining high hospital capacity for future patients in as many regions as possible can be conflicting. Simulation lends itself well to tackle multi-objective problems by allowing for a differentiated analysis of simulation results. This makes the effects of different strategies and trade-offs between the goals transparent.

Cost was not considered as an objective dimension by the decision makers due to the pandemic nature of the situation. The overall cost for patient transfers consists of the fixed costs for acquiring and maintaining a certain level of resources including the transport vehicles as well as the personnel. Next to the fixed costs for the resources, variable costs occur for each transfer. The decisions considered in this paper, namely allocating patients to hospitals and scheduling patients on transport vehicles, influence only the variable costs for conducting the transfers. As strategic transfers in a pandemic situation do not occur on a regular basis the overall potential for the reduction of variable costs was deemed irrelevant compared to the goals of maintaining care capacity and reducing the risk for the transferred patients. Considering the application of the presented methodology to more routine healthcare operations, cost would likely play a larger role due to the increased number of transfers and therefore increased total variable costs. Next to the effect of transfer decisions on the variable cost it could also be of interest to investigate how to determine the level of available resources considering the objectives of cost, care capacity and impact on transferred patients.

The development of the simulation model was the trigger for a nationwide gathering of transport vehicle capacity data, that did – due to the federal system in Germany – not exist prior to the research project. Additionally, a digitalization and evaluation of paper-based transfer protocols was conducted. The use of simulation therefore led to a collection and harmonization of data, that can also enable the use of additional quantitative methods in the future.

Within the clover-leaf system each SPOC is responsible for one clover-leaf. This leads to a focus of each decision maker on only a part of the system. The simulation model enabled the decision makers to take a holistic view of the system. The comparison of the transfer plans of the decision makers with the implemented transfer strategies also facilitated a discussion between the decision makers about what factors are taken into consideration within the different clover-leaves.

The development of transfer strategies enabled the benchmarking of the decisions taken by decision makers. They present a rather simplistic approach and do not necessarily lead to optimal solutions in any of the objectives. Their advantages lie in their ease of implementation and that they are easily communicated. The problem could also be modeled as an optimization model and the results of the optimization model could then be compared to the transfer strategies and the decision makers using the simulation. Given the conflicting objectives, a multicriteria optimization approach appears suitable. A sensitivity analysis should be part of developing an optimization model. This paper benchmarked the decision makers transfer plan in a specific scenario which is why the transfer strategies were compared only for that scenario. A sensitivity analysis enables understanding the influence of parameters on the model outcome when developing an optimization model for the future use in unknown scenarios.

Looking at the results of the simulation experiments it can be seen, that the decision makers created transfer plans that lead to compromise solutions in terms of transport duration and changes of vehicles compared to the ‘pure’ strategies. One interpretation is, that the decision makers implicitly considered the conflicting objectives, even though no explicit decision rules could be formulated by them. Another interpretation is, that the transfer strategies fulfilled their purpose of leading to ‘extreme’ solutions and of spanning the solution space.

In the presented case-study, all patients originate in one clover-leaf which limits the generalizability to situations in which more than one clover leaf need to transfer patients. The simulation model as well as the presented transfer strategies are based on a defined set of patients which need to be transferred, a set of potential destination hospitals and a set of available transport vehicles. These sets are independent of whether the patients originate in one or multiple clover leaves and of how many clover leaves are capable of taking on patients. Modeling a situation in which more than one clover leaf reaches its capacity limit and triggers the transfer of patients at the same time is therefore possible with the presented approach.

The simulation model was applied to a case-study of the German health care system. As especially the clover-leaf system is specific to the German system, the findings are not necessarily transferable to other health care systems. The simulation model itself however is designed independent of the clover-leaf system and the German health care system. By choosing a level of abstraction in the modeling where patients are transferred by one or multiple transport vehicles between origin and destination hospitals including possible handover places the simulation model aims to be applicable to different health care systems where the investigation of multimodal patient transfers is of interest.

In the context of patient transfers, several decisions are taken which should take ethical considerations into account. The decision that it is necessary to transfer patients needs to weigh the potential harm to future patients due to a lack of resources for treatment against the possible risk for transferred patients. Next, it needs to be decided which patients should be transferred. This should be based on objective, medical criteria which set a threshold on expected potential harm to patients due to the transfer. The allocation of patients to hospitals and the scheduling of patients on transport vehicles jointly determine the transfer duration and the number of transport vehicle changes during the transfer which constitute the main risk drivers for patients during a transfer. In this paper patients were prioritized using the Horovitz-Index. The Horovitz-Index objectively describes the current state of lung function which was the main concern for patients with COVID-19. The aim of using the Horovitz-Index is to balance the risks for the transferred patients and to ensure that patients with worse conditions are transferred with less risk. In other settings, adapted parameters such as blood pressure, catecholamine requirement, cardiac function, etc. must be used for prioritization. Looking at the application in more routine healthcare operations and the possible consideration of costs in the decision, any potential financial savings need to be weighed against the potential harm to patients. By being able to analyze the effects of different approaches, simulation can support in these ethical considerations by providing quantitative estimations of the effects of decisions.

6. Conclusion and outlook

Rising numbers of intensive care patients during the COVID-19 pandemic posed the threat of regional overloads of intensive care capacity in hospitals. To reduce the risk of regional overcrowding, the so called clover-leaf system was initiated in Germany. The purpose of the clover-leaf system is to coordinate strategic, nation-wide transfers of COVID-19 patients for load balancing in the intensive care units. The scope of the presented research project is the question of where and how to transfer the patients. The question of where refers to the destination hospital for a given patient and the question of how refers to the transport vehicles that are used for the transfer.

To support in answering those questions, a virtual planning system in the form of a flexible, hybrid simulation model for multimodal patient transfers was developed. The model combines discrete-event and agent based modeling and is scalable as well as adaptable to different setting such as multimodal patient transports after mass casualty incidents. Developing the model in an interdisciplinary team consisting of medical experts as well as experts from operations research ensured the applicability of the model.

Within our research, the model was used to benchmark transfer plans of the decision makers against different transfer strategies. To that end, three strategies for transport mode selection and six strategies for the destination hospital selection were developed and implemented into the simulation model. The comparison of the simulation results of the decision makers transfer plans and the transfer strategies was used to inform a discussion between the decision makers and refine their decision process.

The decision makers are each responsible for one geographic part of Germany. Simulating the whole country enabled the decision makers to take a holistic view on the system and provided a quantitative evaluation of planning approaches on a strategic level. As is often the case in healthcare setting, the planning problem has multiple, partly conflicting objectives. Simulation is well suited to handle multiple objectives, by allowing the analysis of the effects of different strategies on different objectives. The results of the simulation indicated that the decision makers implicitly considered the different objectives, as their transfer plans resulted in compromise solutions compared to the transfer strategies. An additional benefit of developing the simulation was that it triggered a central data gathering and data harmonization, e.g. of the capacities of intensive care transport vehicles. The collected data can enable the use of further analytic methods in the future. A direction for future research is the development of a decision support system, that is able to generate transfer plans for a given set of patients taking the different objectives into account. The transfer strategies, that were developed so far did not have the aim of resulting in 'good' transfer plans, but to serve as a benchmark in regard to different objectives. Methodologically such a decision support system could contain an optimization model. The simulation can then be used either to analyze the results of the simulation model in different scenarios. Another possibility is to take a combined simulation–optimization approach. Regarding possible objectives of an optimization model, ethical considerations can be taken into account for instance by using fairness concepts present in the emergency medical service literature [36,37]. In the present case study the focus lies on the central tendency of transfer durations and necessary changes of vehicles. Considering measures of variability in the effects on the transferred patients can provide a broader basis for a decision support.

Next to the formulation of an optimization model, developing improved heuristic decision rules can also be investigated. The current sequential nature of the transfer strategies does not consider the effect of the sequence of the patients or the interconnectedness of hospital choice and transport vehicle choice. A second direction for future research is the application of the simulation model to similar contexts with multi-modal transfers of multiple patients. Examples of similar settings are transfers after mass casualty incidents or the distribution and transfers of patients coming into a country either from military conflicts or large scale natural disasters in other countries. Especially when investigating more routine health care operations, a cost analysis can also be of interest. As it is possible to quantify the resource usage for transfers with the existing simulation model, such a cost analysis could be conducted given the relevant cost information.

To further improve the simulation model, additional stochasticity can be included. This mainly concerns the modeling of the driving and flight times of the transport vehicles as well as the length of stay of patients in the destination hospital. Especially when investigating more routine transfer scenarios, new patients for transfers could also be generated dynamically.

Funding sources

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Appendix A. Distance-based transport mode selection

The aim of the distance-based transport mode selection is to choose the mode, which leads to a shorter transfer for the patient. How that decision is taken is illustrated by the following example: We assume that the receiving hospital has a landing place, but the sending one does not. We then imagine two ICA, ICA A and ICA B. Both start at the sending hospital at the same time. ICA A will drive directly to the receiving hospital. ICA B will drive to a handover place, where the patient is transferred to an ICH, which then flies to the receiving hospital. We assume, that the handover place is on the route of ICA A. While ICA B stops at the handover place and the patient is handed over to the ICH, ICA A drives on. After the handover is done, the ICH will start flying to the receiving hospital. Since the speed of the ICH is greater than the speed of ICA A it will overtake the ICA at some point. The question therefore is: Will the ICH overtake the ICA before it reaches the receiving hospital?

This depends on the distance between the handover place and the receiving hospital. If we generalize it to the cases, where the sending hospital has a landing place but the receiving one does not or if both hospitals do not have a landing place, it depends on the distance between the starting and the landing place of the ICH. To calculate this distance, we need to define the following parameters and variables:

- v_g: ICA-Speed (ground-based)
- v_a: ICH-Speed (air-based)
- d_h: Handover duration between ICA and ICH
- r: Ratio between euclidean and road distance
- D_g: Driving distance on the road (ground-based)
- D_a: Flight distance (air-based)
- t_g: transport time of ICA (ground-based)
- t_a: transport time of ICH including necessary handover times (air-based)

At the point, where the ICH overtakes the ICA, the transport times and the (euclidean) transport distance of both modes of transport are equal, giving us: $t_g = t_a$ and $D_g * r = D_a$. We can therefore calculate the break-even distance as follows:

$$
\begin{aligned}
&t_g = \frac{D_g}{v_g} \\
&t_a = \frac{D_a}{v_a} + d_h = \frac{D_g * r}{v_a} + d_h \\
&t_g = t_a \Leftrightarrow \frac{D_g}{v_g} = \frac{D_g * r}{v_a} + d_h \\
&\Leftrightarrow D_g * v_a = D_g * r * v_g + d_h * v_g * v_a \\
&\Leftrightarrow D_g * (v_a - r * v_g) = d_h * v_g * v_a \\
&\Leftrightarrow D_g = \frac{d_h * v_g * v_a}{v_a - r * v_g} * \frac{\frac{1}{v_g * v_a}}{\frac{1}{v_g * v_a}} \\
&\Leftrightarrow D_g = \frac{d_h}{1/v_g - r/v_a}
\end{aligned}
$$

The break-even distance D_g, after which the ICH overtakes the ICA therefore can be calculated with Eq. (A.1):

$$
D_g = \frac{d_h}{1/v_g - r/v_a} \tag{A.1}
$$

To calculate the break-even distance, we assume the following parameter values:

- $v_g = 75$ km/h
- $v_a = 220$ km/h
- $d_h = 0.5$ h for each handover

- $r = 0.7$

The average speed for ICA is based on historical data and estimates from practitioners. The average speed for ICH was taken from Jagtenberg et al. [34]. The duration for the handover between ICA und ICH was based on estimates from practitioners and the ratio between euclidean flight distance and road distance was based on a sample of distances from OpenStreetMap [17]. Given these parameter values and depending on the necessary number of handovers, transport by ICH is chosen, if the driving distance between the starting and landing place of the ICH exceeds 49.25 km (one handover) or 98.5 km (two handovers) respectively. In accordance with the project partners, the distances were rounded to 50 km and 100 km respectively.

Appendix B. Numeric results

See Tables B.1–B.4.

Table B.1
Average transport durations and average vehicle changes of the heuristic strategies including 95% confidence intervals.

	Transport mode choice	Hospital choice	Transport duration	Vehicle changes
1	T1	H1	5.56 (±0.02)	0 (±0)
2	T1	H2	5.79 (±0.02)	0 (±0)
3	T1	H3	7.81 (±0.02)	0 (±0)
4	T1	H4	7.59 (±0.02)	0 (±0)
5	T1	H5	7.91 (±0.03)	0 (±0)
6	T1	H6	7.67 (±0.03)	0 (±0)
7	T2	H1	3.74 (±0.02)	0.48 (±0.01)
8	T2	H2	3.81 (±0.02)	0.49 (±0.01)
9	T2	H3	4.42 (±0.02)	0.44 (±0.01)
10	T2	H4	4.75 (±0.02)	0.66 (±0.01)
11	T2	H5	4.49 (±0.02)	0.48 (±0.01)
12	T2	H6	4.53 (±0.02)	0.55 (±0.01)
13	T3	H1	3.71 (±0.02)	0.4 (±0.01)
14	T3	H2	3.79 (±0.02)	0.41 (±0.01)
15	T3	H3	4.42 (±0.02)	0.43 (±0.01)
16	T3	H4	4.74 (±0.02)	0.65 (±0.01)
17	T3	H5	4.48 (±0.02)	0.46 (±0.01)
18	T3	H6	4.52 (±0.02)	0.52 (±0.01)

Table B.2
Average transport durations and average vehicle changes of the SPOC and selected strategies including 95% confidence intervals.

	Transport mode choice	Hospital choice	Transport duration	Vehicle changes
1	SPOC	SPOC	5.03 (±0.02)	0.27 (±0.01)
2	T1	H2	5.53 (±0.03)	0 (±0)
3	T1	H6	6.48 (±0.03)	0 (±0)
4	T3	H2	4.07 (±0.02)	0.64 (±0.01)
5	T3	H6	4.3 (±0.02)	0.64 (±0.01)

Table B.3
Average minimum care capacity of care clusters with and without transfers including 95% confidence intervals.

	Hospital choice	Capacity with transfers	Capacity without transfers
1	H1	20.24 (±0.72)	24.62 (±0.79)
2	H2	21.1 (±0.67)	25.17 (±0.75)
3	H3	18.99 (±0.51)	21.9 (±0.54)
4	H4	25.32 (±0.79)	30.14 (±0.89)
5	H5	16.49 (±0.47)	19.11 (±0.5)
6	H6	23.6 (±0.89)	29.28 (±1.04)

Table B.4
Average minimum care capacity of care clusters with and without transfers including 95% confidence intervals.

	Hospital choice	Capacity with transfers	Capacity without transfers
1	H2	13.97 (±0.86)	16.97 (±0.94)
2	H6	18.85 (±1.23)	23 (±1.34)
3	SPOC	13.39 (±1.02)	15.86 (±1.11)

Data availability

The authors do not have permission to share data.

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