Master Thesis

Industrial Engineering and Management

The optimal allocation of casualties to hospitals in case of a mass-casualty incidence

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January 4, 2021

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Management summary

During a mass casualties incident (MCI), treatment capabilities are overwhelmed by casualties. An MCI is characterized by either the sheer number of injured casualties needing treatment simultaneously or a small number of casualties who require advanced care or a combination of both. Furthermore, an MCI creates a sudden spike in demand for emergency response resources. Having a limited number of (air and land) ambulances causes longer waiting times for casualties, which eventually leads to a lower survival rate. Examples of MCIs are the Enschede's fireworks explosion in 2000 or Beirut's explosion in 2020.

During an MCI, a dispatcher is responsible for coordinating ambulances. Furthermore, in cooperation with the associated ambulance staff who are available on-site, the dispatcher is responsible for distributing casualties to the surrounding hospitals without overwhelming the hospitals.

During an MCI, each casualty is categorized into a triage level. In this research, we have distinguished two types of triage levels, T1 and T2. T1 casualties need to receive treatment in a hospital within two hours after the MCI happens. T2 casualties need to receive treatment in a hospital within four hours.

Hospitals are classified into different levels. The classification of hospitals is based upon their abilities to treat trauma casualties. Level 1 hospitals can treat each casualty. Level 2 hospitals have the abilities of a Level 1 hospital, but some facilities are not available. Level 3 hospitals can treat isolated injuries such as hip fractures or burns. T1 casualties preferably receive treatment in a Level 1 or 2 hospital. T2 casualties can receive treatment at any hospital. Besides, the Netherlands is equipped with a major incident hospital. This hospital might open for an MCI. The major incident hospital is located at Utrecht.

An example of Acute Zorg Euregio (AZE) preparing their region for an MCI is organizing Emergo Train System (ETS) exercises. Those exercises focus on simulating the allocation process of casualties to hospitals during an MCI. Two ETS exercises were organized in the autumn of 2019.

AZE wants to know if a model can objectively allocate casualties to hospitals optimally using data from the ETS exercises of autumn 2019. In this research, we have answered and formulated this desire into the following research question.

"What mathematical model can be developed to improve the assignment of casualties to hospitals with limited resources in case of an MCI?"

We chose Integer Linear programming (ILP) to solve this assignment problem. The ILP model presents all the possible decisions of a dispatcher during the ETS exercises of autumn 2019. Furthermore, the performance of the ETS exercises of autumn 2019 was compared to the ILP model. Before the comparison was made, some changes were applied to the model to enable a fair comparison.

The ILP model (days 1 and 2) does not overwrite the treatment capacities of the hospitals, while in both ETS exercises, this happens a few times. Furthermore, no casualties arrive late at the hospitals in the ILP model, while in the ETS exercises one T1 casualty arrives late at the hospital.

The ILP model improves the T1 and T2 makespan of the ETS exercises. On day 1, The T1 makespan in the ETS exercise is 140 minutes and in the model, it is 109 minutes. The ILP model decreases the T1 makespan by 31 minutes. On day 1, the T2 makespan in the ETS exercise is 210 minutes and in the ILP model, this is 181 minutes. So, the ILP model decreases the T2 makespan by 29 minutes. On day 2, approximately the same decrease on the T1 and T2 makespan is found.

On the contrary, the average T1 and T2 throughput times are worse in the ILP model than in the ETS exercises. On day 1, the average T1 throughput time for the model is 63.7 minutes and for the ETS exercise of 54.2 minutes. The ILP model increases the average T1 throughput time by 9.5 minutes. On day 1, the average T2 throughput time for the model is 65.6 minutes and in the ETS exercise this is 54.4 minutes. The ILP model increases the average T2 throughput time by 11.2 minutes. On day 2, approximately the same increase on the average T1 and T2 throughput time is found.

In conclusion, a trade-off exists between the average throughput time and makespan. We have shown this by looking into the ranges of ambulances completing their trip. The finish time among the ambulances doing trip 1 variates less in the ILP model than the ETS exercise. On day 1, the first ambulance of the ILP model finishes trip 1 within 151 minutes and the last finishing ambulance within 181 minutes, which is a difference of 30 minutes. In the ETS exercise (day 1), the ambulance finishes trip 1 first within 127 minutes and the last ambulance after 181 minutes, which is a difference of 81 minutes. The same observation is done for day 2. In literature is found that the makespan is an important KPI and therefore, this KPI is minimized in the ILP model. Future research is needed to conclude which KPI is more critical and improves the survival rate of the casualties.

Besides, eight scenarios are conducted, by adapting the base ILP model, to determine which scenario(s) improved the assignment of casualties to hospitals most during an MCI. A scenario where six T1 casualties are allocated to a Level 3 hospital and a scenario in which only T1 casualties are allowed to hospitalize at hospital Enschede are the best performing scenarios. All the scenarios in which the major incident hospital is included results in worse performance. Therefore, we do not recommend using the major incident hospital when the MCI is located in the region of AZE.

For future research, we suggest developing a (meta) heuristics in which stochastic elements are included. Stochastic elements to include are for instance, the possibility of hospitalizing T1 casualties to a Level 3 hospital, uncertain travel times and the varying duration of dropping off and stabilizing casualties. Another way of implementing more complexity in a future model is to include the T1 and T2 survival probabilities. By implementing those survival probabilities, it might be possible to answer which KPI, the makespan or average throughput time, is more important. Another possibility for future work is to develop Integer Linear Program algorithms such as column generation to find the optimal global solution to this allocation problem.

For AZE, we suggest using the model developed in this thesis to compare future ETS exercises on their performances. Moreover, developing a decision-making tool in real-time to be used during an ETS exercise and possibly during an actual MCI might help the dispatchers make better decisions. A first step is made by developing a new Excel sheet for logging the performance of future ETS exercises. Finally, the following suggestions can improve the execution of ETS exercises:

- Check if all the variables of the ETS exercise are up-to-date. Making the ETS exercises more realistic creates higher engagement of the participants. Components that need to be checked on reality are the ambulances, travel times, and treatment capacities of the hospitals.
- Improve the documentation of the ETS exercises. Firstly, write down how the variables of the ETS exercises are derived. Secondly, describe the different components and the assumptions of the ETS exercise. Finally, whenever variables are changed, update them in the documentation. In this way, the ETS designer can look back and remembers how the ETS exercise is conducted.

Acknowledgment

This thesis is written to complete the master of Industrial Engineering and Management at the University of Twente. My era as a student ends strangely due to the circumstances we are living in today. Unfortunately, this affected me during my thesis. Only, after one month of working at Acute Zorg Euregio, the rest of the thesis I had to do from home. Working at home had its ups and downs, but I am proud of the end result. The following people I would like to thank for the support during my thesis.

Firstly, I would like to thank my supervisors of the University of Twente. Derya, my first supervisor, thank you for guiding me. In one blink, you knew what was going and could give me valuable feedback. Patricia, I was delighted to have you as my second supervisor. The provided feedback of both of you helped me to bring my thesis to a higher level. Secondly, I want to thank Nancy for her support, my supervisor of Acute Zorg Euregio. I want to thank her for making this assignment possible. Our weekly phone meetings were always joyful. Without those meetings, it would not have been possible to finish this thesis. Furthermore, by having those meetings, I got the behind-the-scenes of what I typically would have experienced at Acute Zorg Euregio. Finally, I would like to thank my family, boyfriend and friends for their support.

I am looking forward to starting a new chapter in my life. During my studies, I have grown a lot personally and obtained many skills. To continually challenge myself and trying out new things is something I take with me for the rest of my life.

Context

Chapter 1: Introduction

This chapter is divided into five sections. Firstly, this chapter gives a brief introduction to the healthcare institution Acute Zorg Euregio (Section 1.1). Secondly, the definition of a mass-casualty incident is given. Also, the different components of a mass-casualty incident are addressed (Section 1.2). Thirdly, problem analysis is done to identify the core problem (Section 1.3). Based on the problem analysis, the objectives and research questions are defined (Section 1.4). Lastly, the research approach and the structure throughout this thesis are presented (Section 1.5).

1.1. Acute Zorg Euregio

In the Netherlands, health care institutions are obligated to guarantee a constant healthcare level, including during emergencies and disasters (Acute Zorg Euregio, n.d.). Eleven emergency care networks monitor the level of emergency healthcare. These institutions take care of the regional coordination and organization of emergency care. AZE is the designated emergency care network for the Dutch regions Twente and Oost-Achterhoek. AZE is also working together with the German regions, Landkreis Grafschaft Bentheim, Kreis Borken and Kreis Steinfurt (see Figure 1). Regionally, this institution supports the coordination and the collaboration between their chain partners such as hospitals, general practitioners and regional ambulance services. Nationally, AZE is in collaboration and contact with other emergency care networks. These networks translate national advice into operational direction and execution on regional levels. Furthermore, AZE shares its knowledge and research throughout its region by providing education, training and theme-based meetings aiming at optimizing emergency care and quality of care (Acute Zorg Euregio, n.d.).

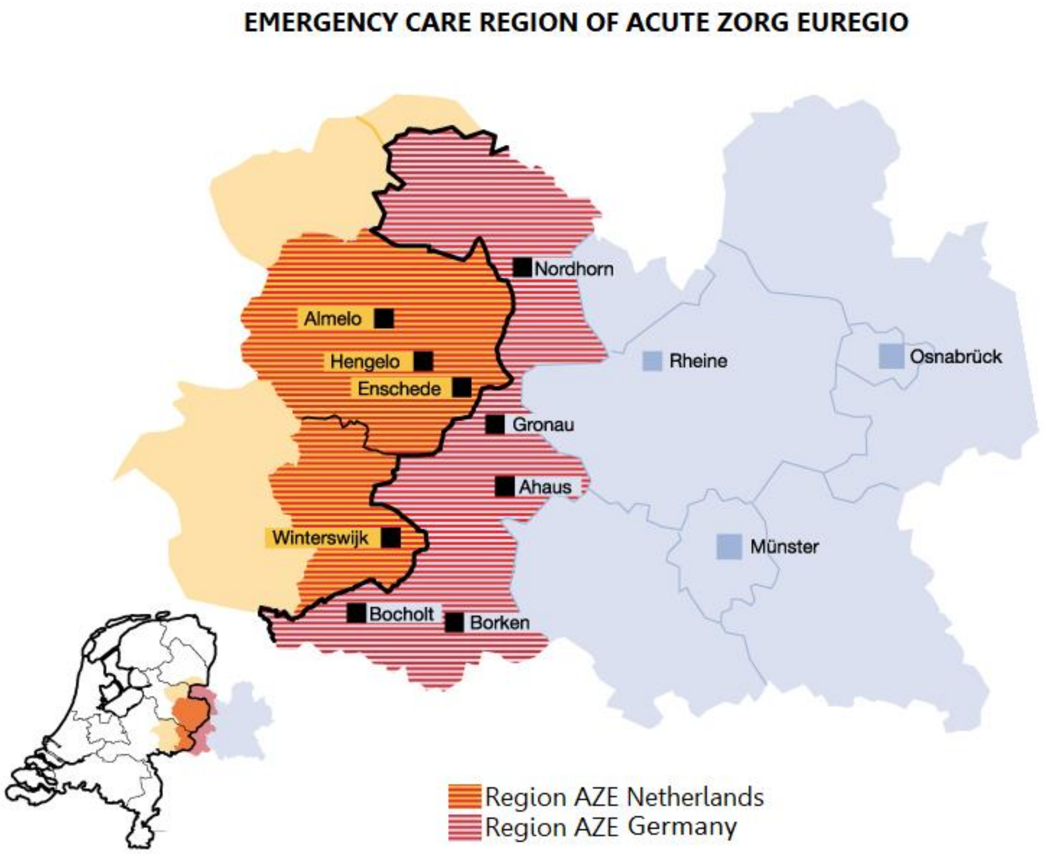

Figure 1 Emergency care region of AZE (Source: Acute Zorg Euregio, n.d.).

1.2. Mass-casualty incidents

This section provides information about the different aspects of a mass-casualty incident (MCI). Firstly, the definition and complexity of an MCI are explained (Section 1.2.1). Secondly, a way to prepare for an MCI is described (Section 1.2.2). Lastly, the decisions made by a dispatcher during an MCI are addressed (Section 1.2.3).

1.2.1. The complexity of a mass-casualty incident

Mass-casualty incidents (MCIs) are defined as incidents where the number of casualties overwhelms the local emergency response and hospital treatment capabilities. In this research, we use the terms patient and victim as synonyms for the term casualty. Examples of MCIs are Beirut's explosion in 2020, the terrorist attack in New-Zealand in 2019 and the firework explosion in Enschede in 2000.

AZE aims to prepare its chain partners in such a way that each casualty receives the best emergency care. For an MCI, there are several reasons why this is difficult to achieve. Firstly, the number of victims overwhelms local treatment capabilities. The victims are either a sheer number of injured casualties, all needing treatment simultaneously or a small number of victims who require advanced care (Repoussis et al., 2016, p. 531). Secondly, local resources are finite. Therefore an MCI might create a sudden spike in demand for emergency response resources (Mills et al., 2013). Having a limited number of (air and land) ambulances causes a slower response time, which eventually leads to a lower survival rate.

All-together this makes it complex to give the best treatment to each casualty. Therefore, the Netherlands has developed several policy frameworks to provide the best treatment for each casualty during an MCI (Damen & Moors, 2016). Disaster-preparedness activities are used to practice policy frameworks to obtain specific skills. An example of AZE organizing a disaster-preparedness activity is doing an Emergo Train System exercise. In the next subsection, the Emergo Train System exercise is briefly introduced.

1.2.2. Emergo Train system

Emergo Train System (ETS) is a “simulation system that is widely used for education and training in emergency and disaster management” (Emergo Train System, n.d.). The system consists of several magnet boards representing different components of an MCI such as the incident location, hospital location or the resources available in the exercises (see Figure 2). On those boards, different kinds of magnets are attached presenting resources or casualties. A casualty is presented by using a human-shaped magnet, which is called “Guba” in ETS (see Figure 3) (Hornwal et al., 2016). On this magnet, information about the Guba such as gender and type of injuries is provided. The resource magnets present different emergency services such as medical, fire, or police services. In this research, only medical services are included. For instance, a medical service is an (emergency) dispatcher. A dispatcher decides for each casualty where he/she is hospitalized during an MCI. ETS can simulate a scenario in which the dispatcher has to decide on such kinds of challenges. More information about the decisions made by a dispatcher is given in the next subsection. Whenever an ETS exercise is finished, an evaluation is done. It is analyzed on different kinds of Key Performance Indicators (KPIs). The chosen KPIs depends on the learning objectives and the scenario of the ETS exercise. More information about ETS and KPIs is given in Chapter 2.

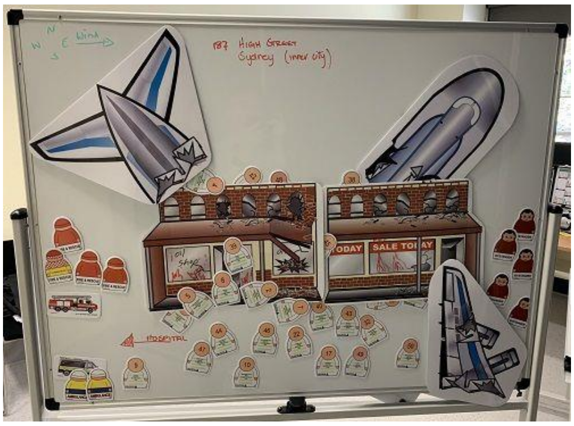

Figure 2 Example of an ETS whiteboard (Source: Hong Kong Jockey Club Disaster Preparedness and Response Institute, 2019).

Figure 3 Human-shaped magnet (Source: Emergo Train System, n.d).

1.2.3. *The role of the dispatcher*

The dispatcher is responsible for managing the operations of ambulances in the immediate aftermath of a disaster. A disaster is massively complicated due to the dynamics and uncertainty with the planning conditions (Talarico et al., 2015). The process of emergency care starts as soon as the dispatcher receives an emergency call. By asking questions to the caller, the number of victims and the type of injuries is estimated. Whenever the estimated number of casualties is more than ten, the dispatcher uses the policy framework GGB-model (Grootschalige Geneeskundige Bijstand model; Large-scale medical assistant model). This framework gives guidance on how many emergency response resources such as (air and land) ambulances and medical (aid) teams are alarmed (Cools et al., 2015). During the MCI, information is transferred between the ambulances and the dispatcher by using a communication system called C2000 (Ministerie van Justitie en Veiligheid, 2020). The information is used to estimate the number of casualties accurately. With this given information, the dispatcher decides to increase or decrease the number of ambulances.

During an MCI, several components make a dispatcher operate in a hectic and abnormal situation. Calls are coming in demanding help, while the dispatcher has to coordinate the ambulances to and from the scene. In consideration with the associated ambulance it is decided where a casualty is hospitalized. If the number of ambulances is limited, the dispatcher decides which ambulance should return to the MCI. Either way, AZE aims to prepare the dispatcher in a way that each casualty receives the treatment as fast and best as possible (Acute Zorg Euregio, n.d.).

1.3. Problem analysis

As is described in Section 1.2.3, during a large-scale MCI, a dispatcher makes many decisions under a hectic and short timespan. A dispatcher makes the best decision for each casualty with the available information at the time. It is perhaps challenging for a dispatcher to estimate the impact that a particular decision or strategy has on the subsequent assignment of casualties. Moreover, the decisions about the allocation of casualties to hospitals are based upon the dispatcher's experience and the associated emergency healthcare team of an ambulance. An interactive support system would help a dispatcher make the best assignment for all the casualties assignments to hospitals. This system could automatically decide where a casualty should be hospitalized given the estimated number of casualties, type of injury, available resources, hospitals' treatment capacity, etc. The support system should be deployable for a dispatcher to check whether the best decision is made for each casualty during an MCI or an ETS exercise. Whenever the situation changes due to the uncertainties of an MCI, the interactive support system should be able to adapt. Unfortunately, such type of interactive support is not available at the moment. To develop such an interactive support system, first the optimal allocation of casualties and ambulances after an MCI or ETS exercise should be found. At the moment, this is not available. An MCI or ETS exercise evaluation is currently based on experience and performance indicators such as throughput time and makespan. By knowing the optimal allocation after an MCI or ETS exercise, the evaluation of MCIs and ETS exercises can be improved.

1.4. Motivation and research questions

The core problem we address during this research is the process of finding the optimal solution for assigning casualties to hospitals in case of an MCI. In this research, a mathematical model is developed to find the optimal allocation of casualties and ambulances to aid the dispatcher. The model is deployable for analyzing the performance of certain KPIs after an MCI or an ETS exercise. The model takes the number of casualties, transportation times, the available number of ambulances and the treatment capacity of each hospital as inputs. In return, it provides dispatchers and AZE more insight into how dispatchers should make decisions. Moreover, it motivates to continuously improve the preparation for an MCI. This leads to shortening the treatment response time and increasing the survival rate of casualties. Furthermore, this mathematical model contributes to research in the field of disaster planning. The model produces realistic decisions, which are verified by comparing the model results with two (existing) ETS exercises. Finally, this model is the first step in making an interactive support system, which can be used by dispatchers during an MCI. The main research question is formulated as follows:

"What mathematical model can be developed to improve the assignment of casualties to hospitals with limited resources in case of an MCI?"

The main research question consists of multiple aspects that should be solved separately. By dividing the main research question into multiple sub-questions, the main question can be answered at the end of this research. The following sub-questions are answered by each chapter:

Context (Chapter 2)

Sub-question 1 – 'What kind of activities are performed to deliver the best treatment for each casualty in the pre-hospital phase?'

1. *Which aspects are taken into consideration for the assignment of casualties to hospitals?*
2. *How are the ETS exercises of autumn 2019 performed and what are the results?*

Literature Review (Chapter 3)

Sub-question 2 - 'Which existing approach is most applicable to the assignment of casualties to hospitals and how to measure the effectiveness of such approaches?'

1. *Which key performance indicators (KPIs) fit best to assess the performance of the model?*

2. *Which approaches are available in the literature for optimizing the distribution of casualties in case of an MCI and to what extent are they useful for this research?*
3. *What has been done in the preliminary research conducted by AZE and applies to this research?*

Mathematical formulation (Chapter 4)

Sub-question 3 – 'How to develop an optimization approach that models the decisions made by the dispatcher in the ETS exercises of autumn 2019? '

1. *Which research framework can be set for modeling the decisions of a dispatcher?*
2. *Which data and input variables are used for the model to make it realistic?*
3. *What are the objectives, parameters and constraints of the models?*

Experimental design (Chapter 5)

Sub-question 4 – '*What kind of scenarios are conducted on the optimization approach* and how is the performance of the optimization model assessed? '

1. *What kind of scenarios are conducted on the optimization approach?*
2. *Which KPIs fit best to compare the different scenarios?*

Results (Chapter 6)

Sub-question 5 'What are the results of the model?'

1. *What are the results of the model when using the data from the ETS exercise and are they comparable with the ETS exercises of autumn 2019?*
2. *What are the results of the various scenarios?*
3. *How does the model perform in comparison to the past ETS exercises?*

Conclusion and recommendations (Chapter 7)

Sub-question 6 'In which way can the mathematical model improve the assignment of casualties to hospitals with limited resources? '

1.5. Research approach

This thesis is structured by providing answers to each sub-question. Each sub-question is answered within one of the chapters. After answering all sub-questions, the main research question is answered. Chapter 2 answers the first sub-research question. This chapter addresses the factors that are determining where a casualty is hospitalized. Moreover, information on how the ETS exercises performed in the autumn of 2019 is given. It regards how these ETS exercises are prepared, executed and evaluated. Chapter 3 answers sub-question 2 by conducting a literature review. Before describing the related research streams through a literature review, we give the reader basic knowledge about mathematical modeling, simulation studies and heuristics, which are different types of techniques in the field of Operations Research. Chapter 4 answers sub-question 3 by developing a mathematical model, which mimics the dispatcher's decisions in the ETS exercises. Chapter 5 includes the experimental design of this research. In Chapter 6, the execution and the comparison of the results of the model and the ETS exercises are presented. Chapter 7 answers the main research question. Moreover, the conclusions and discussion of this research are presented.

Chapter 2: Context

This chapter answers research question 1: "What kind of activities are performed to deliver the best treatment for each casualty? ". This chapter is divided into six sections. Section 2.1 describes the factors that influence the hospitalization of a casualty in the case of an MCI. Section 2.2 addresses the difference in hospital capabilities and levels in the Netherlands. Section 2.3 explains what triage is and the different categories of triage. Section 2.4 presents how ETS exercises are conducted. Section 2.5 explains how the ETS exercises of autumn of 2019 were conducted. Finally, Section 2.6 closes this chapter by answering research question 1.

2.1. Factors determining where a casualty is hospitalized

As stated in Subsection 1.2.3., the dispatcher's responsibility is to assign the casualties of an MCI to the surrounding hospitals. The goal for each casualty is to receive treatment at the right time and location. Furthermore, it is also aimed to prevent overcrowding at the hospitals that are closest to the incident scene. Whenever the number of casualties is too large for the surrounding hospitals, casualties get allocated to hospitals even further away to avoid overwhelming the surrounding hospitals' treatment capacities. The information given to the dispatchers is used to determine which GGB code (Large-scale medical assistance code, Grootschalige Geneeskundige Bijstand code) is issued. The different codes can be found in Appendix A. The GGB code is scaled down or up during the MCI. The issued GGB code gives the dispatcher guidance on how many ambulances to alert. Based on the following factors, the dispatcher decides where a casualty is hospitalized (ROCAH RAV Haaglanden, 2019):

- Triage level
- Type of injury
- Age
- Hospital level

Furthermore, the dispatcher makes use of the actual treatment capacity of the hospitals. In the ETS exercises the age of the Guba is included. Children are prioritized over adults. However, they were not many child Gubas involved in the ETS exercises of autumn 2019. Therefore, the age factor is neglected in this research. In the next sections, the differences in hospital levels (Section 2.2) and triage levels (Section 2.3) are explained.

2.2. Hospitals levels

Hospitals are classified into different levels (de Vos, 2016; Moors, n.d.; Noord Nederland Acute Zorgnetwerk, 2020). The classification of hospitals is based upon their abilities to treat trauma patients. Level 3 hospitals can treat isolated injuries such as hip fractures or burns. Level 2 hospitals can treat stable patients with vital injuries. In comparison to level 1 hospitals, some facilities are not available in Level 2 hospitals. Level 1 hospitals can treat heavily injured casualties with neurotrauma (a trauma that impacts the brain and spinal cord), polytrauma (simultaneous injuries to serval organs or body systems).

2.3. Triage categories and hospitalization

The term triage is defined as "the process of sorting patients and categorizing them based on clinical acuity" (Vassallo et al., 2016). Triage is classified into four categories: T1, T2, T3 and T4. In the ETS exercises of autumn 2019, only Gubas with triage category T1 and T2 are within scope. The main reason for not including T3 and T4 Gubas in this research is given at the end of this section. For the completeness of this research, we explain each category in this section.

The MIMMS triage sieve flowchart is used by a paramedic for assigning a casualty to one of the categories (in het Veld et al., 2016) (see Appendix B). After establishing the triage category, a casualty gets a particular color bracelet corresponding to their triage category. Table 1 describes the color for each category of triage. Triage category T1 is given to the most heavily injured casualties, including casualties with neurotrauma and/or polytrauma. Each triage category has a certain timespan in which a casualty needs treatment (Vassallo et al., 2016; Wilson et al., 2013). Casualties with triage category T1 need treatment preferably within two hours. Most critical casualties need to receive more specialized treatment in a higher-level hospital (de Vos, 2016). Therefore, a T1 casualty needs treatment preferably at a Level 1 or 2 hospitals. Casualties with triage category T2 are considered the second-highest triage category. A T2 casualty must receive treatment preferably within 2-4 hours. T2 casualties need treatments in a hospital as well. The difference with a T1 casualty is that a T2 casualty can receive treatment regardless of the hospital level. Casualties with triage category T1 or T2 are transported to a Casualty Clearing Area at the MCI, where they wait for transportation by (air and land) ambulances to a hospital. Casualties with triage category T3 are less hurt than T1 and T2 casualties. Therefore, T3 casualties receive treatment at the incident location itself. They must receive treatment within four hours. T4 casualties have unfortunately passed away. T3 and T4 casualties do not require any decisions of a dispatcher. Therefore, T3 and T4 casualties are not included in this research.

Table 1 The preferable assignment of casualties to hospitals

Category	Treatment within	Triage color	Hospital	Injuries
T1	Immediately, but within 2 hours	Red	L1, L2	Neurotrauma / polytrauma
T2	-4 hours	Yellow	L1, L2, L3	Vital injuries
T3	> 4 hours	Green	Field hospital	Isolated injuries
T4	-	-	-	Passed away

2.4. ETS

As stated in Subsection 1.2.2, ETS is a disaster-preparedness activity for simulating an MCI. The required resources and preparations of an ETS exercise are addressed (Subsection 2.4.1). Secondly, how ETS exercises are executed is introduced (Subsection 2.4.2). Thirdly, an explanation is given how the ETS exercises are analyzed on their performance (Subsection 2.4.3).

2.4.1. Preparation

Before performing an ETS exercise, some preparation is done by the ETS designers. The designers decide which scenario is simulated and which simplifications are made in comparison to reality. Furthermore, the learning objective of an ETS exercise is devised by ETS designers. Based on the learning objective, a decision is made on the number of included hospitals, ambulances, and Guba types. Also, the transportation time is determined by the ETS designers. Lastly, based on the learning objective suitable participants are invited to take part in the ETS exercise (Hornwal et al., 2016).

2.4.2. Execution

After designing, preparing and organizing, the ETS exercise is executed. Various whiteboards full of Gubas and ambulances are placed in a room (see Figure 4). The red warning tape in the figure depicts a symbol for the part of the disaster, which has not been accessed yet and means that a Guba placed inside the red warning tape does not participate in the exercise yet. After some time, these Gubas are coming in the exercises. After that, the Guba gets assigned to an ambulance. In an ETS exercise, there are two groups of participants. The first group is sitting behind the tables. Those participants are the dispatchers in the ETS exercise. The dispatchers have several documents available with information about transportation times, treatment capabilities and capacity of hospitals. The dispatcher uses those documents for deciding where a Guba is hospitalized. The second group is standing in front of the whiteboards (see Figure 4). They are responsible for logging the results. Furthermore, they make sure no constraints are violated in the ETS exercise. Lastly, one participant is a runner. The runner is responsible for moving the Gubas from the whiteboard to the dispatchers and back to the whiteboard (Hornwal et al., 2016).

Figure 4 Execution of the ETS exercises (Source: Draijer, 2017).

2.4.3. Evaluation

An ETS exercise is finished when all the Gubas have reached a hospital. According to previously defined Key Performance Indicators (KPIs), an evaluation takes place after the exercise is finished. By doing an evaluation, the participants can reflect on themselves and get insights on what went well and what needs improvement (Hornwal et al., 2016).

2.5. ETS exercises autumn 2019

As previously mentioned in Chapter 1.2.2 AZE conducted two ETS exercises in the autumn of 2019. This section describes how those ETS exercises were prepared (Subsection 2.5.1). Also, the KPIs chosen for evaluating those ETS exercises are described in Subsection 2.5.1. The execution of the ETS exercises of autumn 2019 is not explained because they were executed in the same way as discussed in Subsection 2.4.2. The evaluation of the ETS exercises of autumn 2019 is addressed in Subsection 2.5.2. Both exercises used the same scenario, but the participants differed. The participants of the ETS exercises were all dispatchers.

2.5.1. Preparation

The learning objective of the ETS exercises of autumn 2019 was to understand how the dispatchers allocate the Gubas of an MCI to the hospitals. Moreover, the exercises were performed to test whether the triage category was connected to the right hospital level.

The ETS exercises were finished when the last Guba arrived at a hospital. The ETS designer of autumn 2019 devised an MCI scenario on a liberty festival at Goor (see the red dot in Figure 5). According to this scenario, the stage of the festival collapsed and caused a fire. The scenario included 90 Gubas in which 26 were classified as T1 type and 64 were type T2. The triage category of the Gubas was known by the participants and could not change during the exercises. Each Guba was assigned to one of the 27 hospitals (see hospital signs in Figure 5). Information about the hospital's treatment capabilities and the capacity per hour was given to the participants. A total of 47 ambulances were included in the ETS exercises. Those ambulances were originating from regions Ijsseland (23 land ambulances), Twente (17 land ambulances), Noordoost Gelderland (19 land ambulances) and Germany (10 land ambulances). No air ambulances were used in those ETS exercises.

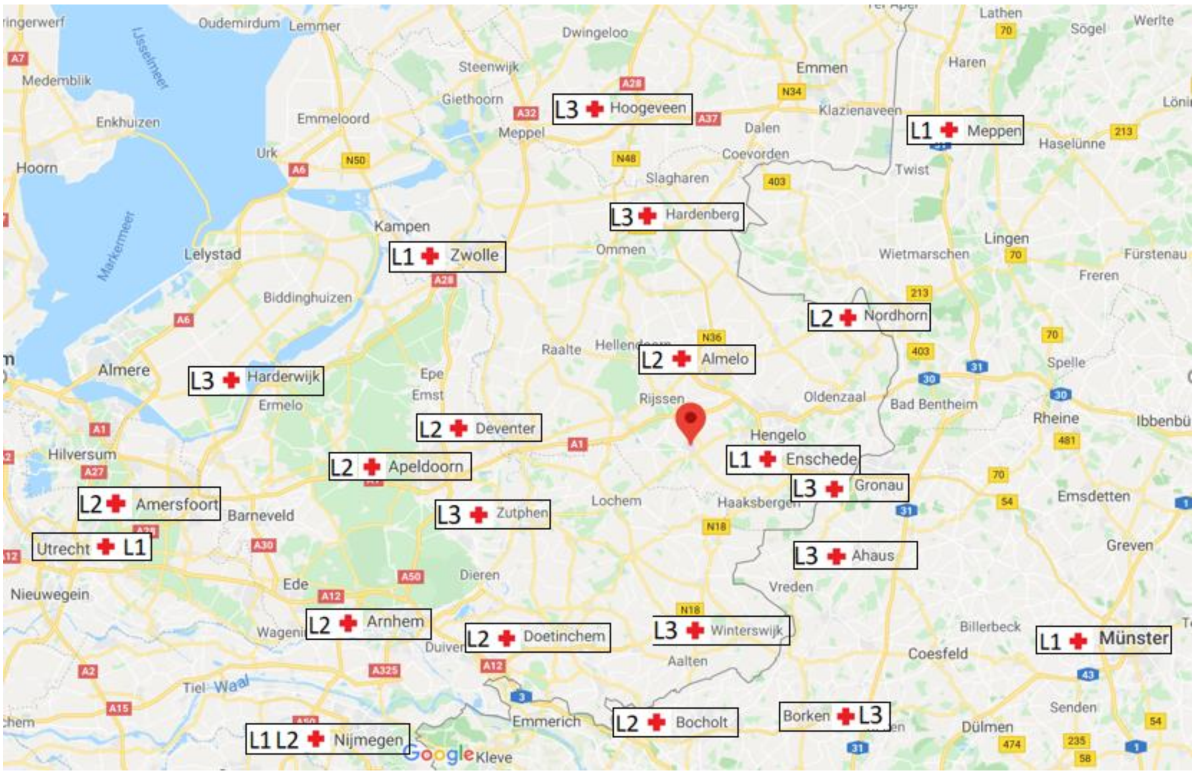

Figure 5 Hospital levels

For the ETS exercises, some simplification and assumptions were made. For the ETS exercises of autumn 2019, the following assumptions and simplifications were made:

1. A casualty receives treatment in the hour of the arrival at the hospital.
2. Each ambulance carries only one casualty at a time.
3. The travel time matrix is symmetric.
4. Each ambulance finishes its last trip at a hospital.
5. All ambulances are available at the beginning of the disaster.
6. The triage category of a casualty cannot change throughout the MCI.
7. A T2 casualty can occupy a T1 bed at the emergency department of a hospital.
8. The age discrepancy of the Gubas is neglected.
9. German ambulances arrive one hour after the MCI has happed.
10. All ambulances are using sirens and warning lights.

One of the ETS exercises' assumptions was that on each trip of an ambulance, at most one Guba was transported to a hospital. The term “trip” was defined as traveling from the ambulance start location to the MCI and then from the MCI to the hospital. Each ambulance can perform multiple trips in a row. There were three variants of trips possible (see Figure 6). Each variant is discussed in the next paragraphs.

The first variant of a trip was when an ambulance travels from its initial location to the MCI to pick up a casualty and deliver the Guba to a hospital (see red dotted lines in Figure 6). In this figure, between position t0 and t1 the ambulance team drives from its initial location, Raalte, to the MCI located at Goor. This takes 28 minutes. Stabilizing the Guba for transportation is done in between time positions t1 and t2 and takes 15 minutes. The ambulance in this setting leaves the MCI location at t2 (t=43 min) and transports the Guba to a hospital. In this example, the participants decide to transport the Guba to the hospital Almelo. The ambulance arrives at the hospital at t3 (t = 60 min). The ambulance team drops off the Guba, which takes 10 minutes. At time t4 (t = 70 min) the first trip is completed. The preparation time and the drop-off time of a Guba are determined by using data of the AZE's trauma registration (see Appendix C).

The second variant of a trip was similar to the first variant, except that idle and off-load time was included in this trip variation (see black dotted lines Figure 6). The ambulance had an idle time when no Guba was available for the stabilization step. This was caused by the time a Guba comes into the ETS exercise. In the ETS exercises, this was called the release time of a Guba. Before the release time of a Guba no decision was made on this Guba. The participants did not know in advance when a Guba comes into play. In this example at t2 (t=40 min), the Guba is released and is stabilized for transportation. At time t3 (t=55 min), the ambulance team starts transporting the casualty to the hospital located at Almelo. As soon as the ambulance arrives on t4 (t4 = 72 min) at the hospital. In between t4 and t5 (t5 = 77 min) the ambulance must wait a few minutes before the casualty is dropped off at the hospital. At time t6 (t6= 87 min), the trip is completed.

The third variant of a trip happened after an ambulance completes one of the described trips before (See red or black line Figure 6). The participants decided to start a new trip. Instead of driving from its initial location, the ambulance drives from the hospital to the MCI and back to a hospital. In this example, both ambulances start their second trip at hospital Almelo. The second trip looks like one of the two variants discussed before.

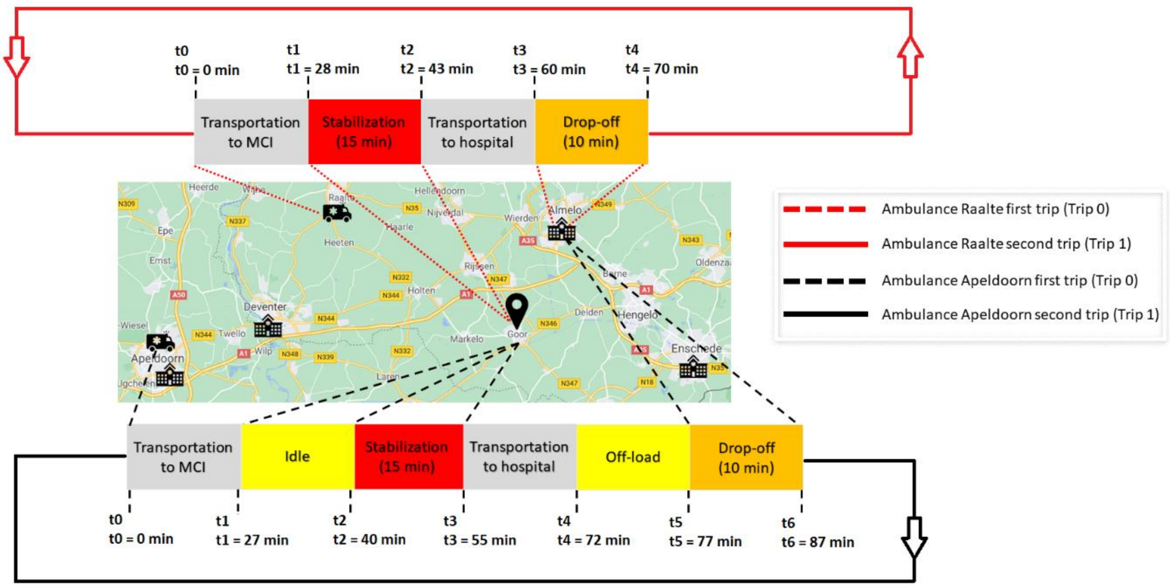

Figure 6 Modification and components of a trip

Another assumption is that each ambulance was using sirens and warning lights in the ETS exercises of autumn 2019. In reality, the ambulance crew decides if the ambulance is using warning lights and sirens. Lights and sirens help the ambulance to travel faster through traffic while transporting the patient. Altogether, this makes intuitive sense because a better outcome is achieved when the patient receives definitive care sooner (Murray & Kue, 2017). The difference between (not) using lights and sirens is influenceable by multiple factors. Some factors found in the literature are the number of stoplights encountered, traffic intensity, and distances traveled (O'Brien et al., 1999). So, the impact of using lights and sirens depends on the situation itself, how much the use of sirens and lights positively impacts the survival rate of patients.

Since the travel time of ambulances depends on multiple factors, the ETS designers made an approximation for determining those travel times. They used Google Maps' for determining the ambulances travel times. Using Google Maps is an accurate method for estimating trip-base transportation times (Wallace et al., 2014). For an ambulance that uses warning lights and sirens, the transportation times of Google Maps travel times are multiplied with a factor of 0.7 (See Appendix C). This factor is compared to the regional trauma registration of AZE and is approximately the same. Looking into the determined transportation times of the ETS exercises in autumn 2019, some inconsistency can be observed. Appendix D shows that the factor of this exercise ranges between 0.60 and 0.86. Unfortunately, this is untraceable whether the transportation times of Google Maps have been changed over time or the ETS designer referred to a different transportation time. To correctly compare, the transportation times used in the ETS exercises of autumn 2019 are used in the mathematical formulation. However, those travel times might not represent the real travel times of the ambulances using sirens and warning lights correctly.

2.5.2. Evaluation

As previously mentioned in Section 1.3 the evaluation is based on the experience of the ETS instructor and some KPIs. The following KPIs are used for analyzing the performance of the ETS exercises of autumn 2019:

1. The total number of T1 Gubas hospitalized at each hospital.
2. The total number of T2 Gubas hospitalized at each hospital.
3. The makespan.
4. Average throughput time of the Gubas.
5. The latest departure from the disaster scene among the T1 Gubas.
6. The latest departure from the disaster scene among the T2 Gubas.
7. The number of ambulances deployed on each trip.

Most of the chosen KPI are self-explanatory. Except for KPIs 3, 4 and 7, those need explanation. The term makespan (3) is defined as the completion time of the lastest job to leave the system (Pinedo, 2008, p. 18). Applicable to this problem, this definition is translated to the difference between the latest arrival of the Gubas at a hospital after dropping off and the starting time of the ETS exercise. In the ETS exercise, the throughput time (4) is defined as the difference between the arrival time at the hospital and the starting time of triage.

As mentioned in Subsection 2.4.1, an ambulance can make multiple trips from the MCI site to the hospital and back. It depends on the dispatcher whether an ambulance is deployed for a second or third trip. KPI (7) analyses how many ambulances are deployed for one, two, or three trips, respectively. Appendix E summarizes the performance of both ETS exercises. For developing the model in this research, the KPIs used in the ETS exercises are considered together with findings from the literature for deciding which KPIs are used for testing the performance of the model.

2.6. Conclusion

Casualties with triage category T1 or T2 receive treatment in a hospital. T1 casualties must receive treatment in an L1 or L2 hospital and need treatment within two hours. A T2 casualties can receive treatment regardless of the hospital level but needs treatment within two and four hours. T3 and T4 casualties do not require the decisions of dispatchers. Therefore, they are out of scope.

The Emergo Train System (ETS) is a disaster-preparedness activity for simulating an MCI. Such type of exercise is a way to prepare dispatchers for those types of incidents. The disaster scene is simulated by using magnet boards. Two ETS exercises were held in the autumn of 2019. The same scenario was used in both of the ETS exercises. However, dispatchers differed. The scenario and all the input variables such as treatment capacity and capabilities of hospitals, transportation times, and Guba types included in the exercises were determined by the ETS designers.

Furthermore, the designers determined the learning objectives. During the exercise, the participants assigned each Guba to a hospital, dependent on the triage level. The triage level of a Guba was known by the participants and could not change during the ETS exercises. All measurements of the exercises (KPIs) were written down in Excel sheets. Later on, the KPIs were calculated for the evaluation part of the ETS exercises. It is essential to know the outcome and performance of the ETS exercises because data is also used in the developed model and performance indicators are compared.

Chapter 3: Literature review

This chapter discusses literature related to this research topic and answers research question 2: 'Which existing approach is most applicable to the assignment of casualties to hospitals and how to measure the effectiveness of such approaches?'. This chapter is divided into three sections. Section 3.1 describes some background information about different modeling and solution techniques. Also, the advantages of each technique are discussed. Section 3.2 addresses in-depth the related work of the literature review per stream. Section 3.3 closes this chapter by answering research question 2.

3.1. Methods

The topic of this research is solvable by using a different kinds of methods. One method is optimization modeling. The topic of this research is formulated as an optimization problem. An optimization problem is solved by using an optimization model. Optimization modeling is a collection of variables and the relationships needed to describe essential features of a given problem (Rader, 2013, p. 1). There are different kinds of methods available to solve optimization problems. All the different kinds of methods aim at minimizing or maximizing the objective value. Optimization models are divided into two categories (see Figure 7). The first category is mathematical programming and is discussed in Subsection 3.1.1. The second category is optimization algorithms and is explained in Subsection 3.1.2. Another method applicable to this topic of research is simulation models and is addressed in Subsection 3.1.3.

3.1.1. Mathematical programs

A mathematical program is a mathematical structure where decision variables represent problem choices. The decision variables are used to define certain restrictions and requirements of the optimization problem. The decision variables are used to minimize or maximize the objective function (Grond, 2016; Rader, 2013). There are three common variations within the mathematical program (see Figure 7). The first one is a linear program (LP). In this program, all the decisions variable are continuous and each constraint is either a linear inequality or a linear equation. The second is the integer linear program (ILP). The main difference to an LP is that an ILP is required to have only integer variables. The last common variation of the mathematical program is a so-called mixed-integer linear program (MILP). At least one variable is an integer and at least one variable is discrete. A mathematical program seeks to find the global optimum. This solution is the best feasible function value of the program. A disadvantage of this method is that it may require simplification in constraints, solution space or linearization of the problem (Grond, 2016). Such models often use a lot of computation time (Rader, 2013).

3.1.2. Optimization algorithms

Optimization algorithms are divided into exact and not exact algorithms, as depicted in Figure 7. An exact method can find the optimal solution to an optimization problem but has the same disadvantage as a mathematical program. An exact method requires a lot of computation time. The group of not exact optimization algorithms is divided into (not) guaranteed methods.

The group of heuristics is divided into two main types: simple and metaheuristics. Simple heuristics are also called constructive heuristics. Those types of heuristics aim to construct their final solution by building a partially incomplete solution as it iterates. A metaheuristic constructs its final solution by starting from some initial complete feasible solution and iteratively modifies the current solution to get a new one until a better solution is obtained (Rader, 2013). Heuristics seek reasonable solutions. However, the main disadvantage of a heuristic is that it cannot guarantee feasibility, optimality or even an estimation on how close the solution is to the global optimum. They typically handle large problems more efficiently than mathematical programs (Grond, 2016).

3.1.3. Simulation models

A simulation model is defined as a method that imitates the operation of a real-world system as it evolves. A simulation model usually takes a set of assumptions about the system's operation, expressed as mathematical relations between the object of interest in the system. In comparison to mathematical programs, simulation models are easier to apply. Also, simplifying assumptions are less needed in simulation models. Simulation models are not an optimization method, which is the disadvantage of simulation models (Winston & Goldenberg, 2004). However, the heuristics are possibly implementable into the simulation models (Grond, 2016).

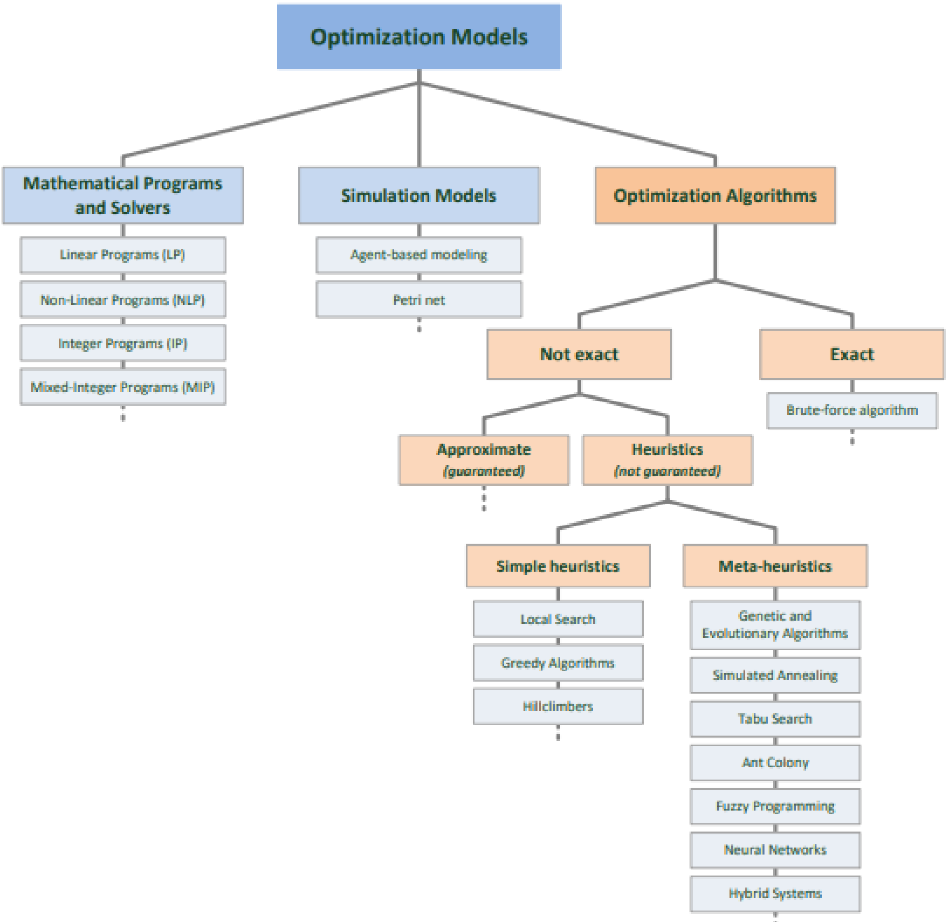

Figure 7 Examples and classifications of optimization models and algorithms (Source: Grond, 2016).

Much research is conducted to relieve resource allocation in MCIs (Caunhye et al., 2012; Manopiniwes & Irohara, 2014). In contrast, less attention is given to the transportation of casualties and in particular, in conjunction with triage (Repoussis et al., 2016; Sung & Lee, 2016). No generally accepted evidence-based guidelines exist to advise dispatchers on fundamental questions such as which hospitals to include in a specific MCI response and how many casualties to transport to each. Ambulance dispatching has been performed mostly based on the reliability and validity of the dispatcher's cognitive abilities (Repoussis et al., 2016, p. 532). Altogether, this topic of research is relatively novel and could prove an interesting field for research.

Sacco et al. (2005) show one of the first attempts to analytically model resource-constrained patient prioritization. The paper proposes an ILP to optimally determine the patient transportation priority. Follow-up studies of Sacco et al. (2005) define a stream about prioritization as an ambulance scheduling problem, which is often formulated as an ILP or IP model. The outcome of such types of studies is to provide tactical insight for resource allocation by characterizing the structure of optimal policies for the stochastic scheduling problem (Sacco et al., 2005).

3.2. Related work

The rest of this section is structured by distinguishing three different types of literature streams. The first stream is about the vehicle routing problem (see Subsection 3.2.1). Before moving to more specific vehicle routing problems, the general ideas about this problem are explained. The papers of the first stream apply to a lot of different optimization problems. The second stream is about scheduling or routing the ambulances of an MCI (see Subsection 3.2.2). Those types of studies assume that information needed to solve the mathematical program is available at the MCI scenes. The outcome of such a type of model is a "real-time" prioritization solution in the form of an ambulance schedule (Sung & Lee, 2016). The third stream includes the use of simulation models to tactically develop insights on the resource allocation during an MCI (see Subsection 3.2.3). Furthermore, in this stream, we include general rules and principles applied to patient prioritization in MCIs.

3.2.1. Vehicle routing problems (VRP)

One of the best-known routing problems is at the same time the simplest one, namely the traveling salesman problem (TSP). This problem is formulated as: "seeks a minimum cost route visiting each location exactly once" (Rader, 2013, p. 103). The basic VRP is an extension of the TSP and seeks to find a set of m vehicle routes such that (a) each route begins and ends at the depot, (b) every customer is included in exactly one route, (c) the total demand of each route does not exceed the maximum vehicle capacity and the total cost associated with each route is minimized (Rader, 2013). An example of what a VRP looks like is given in Figure 8.

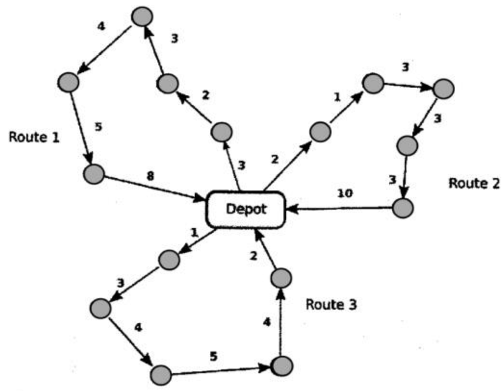

Figure 8 Example of single depot VRP for three routes (Source: Tunga, 2017).

On the basic VRP many different variations of the basic VRP model are developed. A common variation of the VRP is discussed first before moving to the VRP variation found in the literature. After addressing the common VRP variations, more specific and relatable VRP variants are addressed (see Table 2).

A common variation of the VRP is the VRP with time windows (VRPTW). Over the last 20 years, VRPTW has been an area in which many papers have been published on exact, heuristics and metaheuristics methods (El-Sherbeny, 2010, p. 123). In the VRPTW each vehicle has to visit a customer within a specific time frame. The vehicle may arrive before the time window opens but the customer cannot service it until the time windows open. It is not allowed to arrive after the time window has closed (El-Sherbeny, 2010). The second common variation of VRP is the VRP with release and due dates.

Table 2 Research stream on VRP

Applied by	Method	Objective function
Mirabi et al. (2016)	Mathematical model	Minimize transportation costs
Zhen et al. (2020)	Mathematical model	Minimize transportation costs

Mirabi et al. (2016) focus their research on the multi-depot VRP with time windows (MVRPTW). This is almost the same as the VRPTW variation. However, there are some differences. In Mirabi et al. (2016) there are multiple options from which the vehicle can leave the depot. Furthermore in this formulation, a vehicle is not allowed to have a flexible beginning and ending depot.

Both modifications are not possible in the VRPTW formulation. The mathematical formulation of Mirabi et al. (2016) aim at minimizing the transportation cost. The transportation cost consists of the traveled distance and a penalty cost for not serving the customers on time. In comparison to this research, the beginning and location in our model can differ too. As mentioned in Chapter 2.5, in the ETS exercises, the beginning and end location of each vehicle's first trip might differ. The "depot" is the same whenever the same hospital is chosen on the second trip. However, this should be flexible as well. Another comparable component with our research is that each Guba needs treatment within a certain time-window. However, in our case, they are only two types of time windows instead of having a separate time-window for every customer. The treatment time intervals of each triage category are addressed in Chapter 2.3. As a solving method, the paper chooses a novel Genetic Algorithm clustering method. This method is compared to the fuzzy C mean and K-means algorithm. In the fuzzy C mean algorithm, each point is allocated to the clusters by a degree of joining. Meaning a single point is possibly a member of two or several clusters simultaneously (Mirabi et al., 2016). A K-means algorithm splits a data set into a fixed number of k clusters. Each point is assigned to one of the clusters (Söder, 2008).

Zhen et al. (2020) formulate a MILP for a multi-depot multi-trip VRPTW. Also, the capacity constraint of a vehicle is taken into account. This paper aims to optimize the assignment of trips and customers to vehicles and the sequence of vehicles visiting customers. The paper chooses a hybrid particles swarm optimization algorithm (HPSO) and a hybrid genetic algorithm (HGA) as a solving method.

Both papers have differences that are important to highlight. First of all, Zhen et al. (2020) assume each trip to start and end at the same depot. In our model, we want to allow each vehicle to have a different start and end location and a vehicle can make multiple trips. When applying this assumption of Zhen et al. (2020) much flexibility is lost in the assignment of casualties to hospitals. In this way, the mathematical formulation would not present all the possible decisions of a dispatcher. In Mirabi et al. (2016) this flexibility is given. However, in Mirabi et al. (2016) the vehicle is not allowed to make multiple trips. Finally, both papers formularize that a vehicle can visit multiple customers on one trip. In our model, we would not allow visiting multiple casualties on the trip since an ambulance can only transport one casualty at a time.

3.2.2. Ambulance scheduling and routing problem

During the literature review, we have found four papers on the ambulance scheduling problem in the context of an MCI. Table 3 summarizes those papers. In this section, we highlight the interesting findings of each paper and compare them to our research.

Table 3 Research stream on the ambulance scheduling and routing problem

Applied by	Method	Objective function
Talarico et al. (2015)	Mathematical model	Minimize the weighted sum of the latest service completion time among each casualty group
	Optimization model (heuristics)	Minimize the weighted sum of the latest service completion time among each casualty group
Repoussis et al. (2016)	Mathematical model	Minimize the completion time of the latest treatment in the hospital among all the patients
	Optimization model (heuristics)	Minimizing the (weighted) total flow time for each patient and the completion time of the latest treatment in the hospital among all the patients
Wilson et al. (2013)	Optimization model (heuristics)	Minimizing fatalities, suffering and makespan
Sung and Lee (2016)	Mathematical model (column generation)	Maximize the number of excepted survivals for each group of patients
Draijer (2017)	Mathematical model	Minimize the latest arrival time of each group of patients

Talarico et al. (2015, p. 120) propose two mathematical formulations to obtain route plans that minimize the latest treatment completion time in the hospital among the casualties. They distinguish two types of groups. The first group consists of slightly injured people who are treated in the field. The second group consists of seriously injured people who are brought to a hospital. The completion time of each patient group is minimized. The mathematical model is using weights to prioritize seriously injured people over slightly injured people.

Repoussis et al. (2016, p. 531) propose a response model of the aftermath of an MCI that is used to provide operational guidance for regional emergency planning as well as to evaluate strategic preparedness plans. Repoussis et al. (2016) model the sequences of events during an MCI of each casualty, beginning with the waiting time for an available ambulance and the time when a casualty completes the hospital service time. They distinguish two types of casualties, namely critically injured patients and non-critical patients. As depicted in Table 3, the MILP formulation of Repoussis et al. (2016) minimizes the latest treatment completion time among the patients in the hospital.

Sung and Lee (2016) propose a MILP model applicable in the immediate aftermath of an MCI. The MILP model determines the order in which victims are transported to their destination hospital. Sung and Lee (2016) distinguish two types of triage categories, namely an immediate and a delayed group of patients. This paper assumes that the patients in each triage category follow a survival probability profile given by a known function of time. This model's objective function is to maximize the number of expected survivors from an MCI by using the probability profiles of both triage categories.

Talarico et al. (2015), Repoussis et al. (2016) and Sung and Lee (2016) have different arguments for proposing their applied method, which is deployed for solving their problem. Talarico et al. (2015, p. 126) mention that the ambulance scheduling problem must be solved within seconds to respond properly to the emergency requests and to replan the routing if updated information becomes available. Therefore, Talarico et al. (2015) propose another approach by using a (meta)heuristics. Their main argument is that (meta) heuristics are usually faster than an exact approach and can have near-optimal quality solutions. The model formulation by Repoussis et al. (2016) is based upon the ideas of flexible job shop scheduling problems (FJSP) with unrelated parallel machines. FJSP is extensively studied in literature and is well known to be hard to optimize using the exact MIP solution. Therefore, Repoussis et al. (2016) propose a hybrid multi-start local search framework for solving their problem formulation. Lastly, Sung and Lee (2016) base their model formulation upon a parallel machine scheduling problem. Such types of problems are well-known to be NP-hard (Chen & Powell, 1999; van den Akker et al., 1999). Moreover, the survival probability function, which is used as the objective function in the model, is non-linear. A non-linear function is even harder to solve in the mathematical modeling method. To overcome these difficulties, Sung and Lee (2016, p. 626) re-formulate the model to a set-partitioning problem. This set-partitioning problem is then solved by using a column generation approach.

Talarico et al. (2015) conclude that a larger number of hospitals help in serving seriously injured patients by reducing the trip duration to transport them to a hospital with free capacity. In Talarico et al. (2015) the casualties are spread over a large area caused by a hurricane, while in this research, the casualties of the MCI are located at one location. In Talarico et al. (2015, p. 132) the capacity of hospitals seems to have a minor effect on the obtained solution. In conclusion, our research is different in some ways from Talarico et al. (2015). In Talarico et al. (2015) the casualties are spread over a large area, while in this research, the casualties are located on one site. The conclusions made by Talarico et al. (2015) are relevant but the scenario is significantly different in comparison to our research.

Repoussis et al. (2016) answer the question regarding the role of additional distant hospitals. They found out that adding remotely located facilities increases the traveled distance but reduces the makespan. Moreover, Repoussis et al. (2016) suspect that when longer transportation times are introduced, the allocation of patients to hospitals is more balanced and the capacity of the hospital system considered as a whole is more effectively utilized. Lastly, they conclude when the number of ambulances increases, the response times improve. However, this effect quickly fades out. The bottleneck is moved from the ambulances to the hospitals. Repoussis et al. (2016) the MCI occur in Manhattan in New York. This is one of the most urban areas in the world. In comparison to the region of AZE this is significantly different. The region of AZE is in comparison to Manhattan not an urban environment. The travel time for the ambulances to reach a hospital is way longer than in Repoussis et al. (2016) due to the difference in location of the scenario. For instance, the hospital closest to the MCI in our scenario has a travel time of 17 minutes, while in Repoussis et al. (2016) the longest travel time to the hospital from the MCI is 18 minutes. This stresses that the scenarios are significantly different from each other.

Wilson et al. (2013) propose a constructive heuristic and a Variable Neighborhood Descent metaheuristic. The heuristics make decisions relating to the extrication, treatment and transporting of casualties. The heuristic aims to minimize the fatalities, suffering and makespan. The performances of the metaheuristic are measured on: the expected number of fatalities, how quickly casualties are delivered to the hospital and how appropriate the hospital allocation choice is. For the expected number of fatalities, Wilson et al. (2013) implemented a Markov chain representing the stochastic process of the health of a trapped casualty. The paper of Wilson et al. (2013) is related to the research. However, there are two main differences. Firstly, in Wilson et al. (2013) the MCI takes place in London, which is just like Manhattan, one of the most urban areas in the world. In comparison to the MCI of this research, it not an urban environment. Secondly, the MCI in Wilson et al. (2013) is multi-sited. In this thesis, the MCI is single sited.

Sung and Lee (2016) show that the number of survivors is maximized when the delayed group of casualties receives treatment first. After that, the immediate group of casualties receives treatment. In comparison to this research, the delayed group of casualties can in our research be compared to the group of T2 casualties and the immediate group of casualties to the group of T1 casualties. Sung and Lee (2016) dispatchers believe more urgent patients deserve higher priority, which intuitively makes more sense. Sung and Lee (2016, p. 632) believe this discrepancy between the dispatchers' belief and the model outcome is attributed to the two key components. Firstly, the chosen objective function in the model may not include some of the dispatchers' KPIs. Secondly, the way the survival probabilities are modeled results in favoring the second highest casualties group over the highest group of casualties. In the ETS exercises, the triage level cannot change throughout the exercise and due to this a casualty cannot die. The simplifications made in the ETS exercises are the basis for the model such that it can be compared to the ETS exercises. In conclusion, the chosen objective function in Sung and Lee (2016) does not apply to this research. However, this paper gives valuable insights into the available methods for solving this type of problem.

Draijer (2017) is developed in cooperation with AZE. Draijer (2017) proposes a MILP model. The model assigns each casualty to an ambulance and makes sure that the patient gets transported to the right hospital. This model minimizes the latest arrival time at the hospital of each casualty group. Heavily injured casualties are prioritized over less injured cases. Evaluating the results of this model with the ETS exercises shows promising results. However, this MILP model is built under rather strict assumptions. Especially, the data from the ETS exercise was lacking for analyzing the MILP model correctly with the ETS exercises. Besides, not all limitations on resources are investigated. Those promising results need to be validated by improving and expanding the mathematical model. Draijer (2017) is most relatable to this research. In their research, they aim to improve the allocation of casualties to hospitals in MCI. This goal is the same as we strive to optimize in this research. Also, the incident has taken place in the same region as in this research.

3.2.3. Simulations models

During this literature review, two simulation studies are found that are relatable to the context of an MCI. Table 4 summarizes those papers. In this section, the interesting findings of each paper are highlighted and compared to this research.

Table 4 Related work of the stream simulation models

Applied by	Method	Objective function
Hawe et al. (2015)	Simulation model	Minimizing the final hospital arrival time of a critically injured casualty
Wilson et al. (2016)	Simulation model	Minimizing the fatalities and suffering among all the casualties

Hawe et al. (2015) use an agent-based simulation to model the decisions regarding how the resources of emergency services should be divided over a multi-site MCI. Hawe et al. (2015) conclude the higher proportion of critically injured casualties at an incident site, the higher proportion of resources should be allocated to that site. Since we only have one incident site, such type of simulation studies is not particularly interesting to investigate further. The scenario of Hawe et al. (2015) occur in London, which is an urban environment. A city like London significantly differs from this research scenario, which is a more rural scenario.

Wilson et al. (2016) continue the research of Wilson et al. (2013). They improved their model by changing their static model into a dynamic one. Static simulation represents a disaster incident at a particular point in time, while a dynamic simulation can evolve. In this research, the simulation study minimizes fatalities and the suffering of casualties. A higher priority is given in the objective function to minimizing fatalities than suffering. Wilson et al. (2016, p. 346) show that the extension of the model from its initial static design to the dynamic case has resulted in significant improvements in terms of both expected fatalities and the suffering of casualties. Before making a dynamic model like this one, there should be a static model. Currently, AZE does not have a static model for the MCIs.

3.3. Conclusion

Different approaches exist in the literature to improve the response time, the allocation of casualties to hospitals and resource allocation in the immediate aftermath of an MCI. These approaches found in the literature are divided into three different streams: ambulance scheduling problems, simulation models and VRPs. The papers on the ambulance scheduling problem and the VRP stream are most applicable to this research. All the papers found on those streams first formulate a mathematical program. Most of those papers argue that the running time of such types of programs might be a problem. After having set up the mathematical program, most of the papers propose a heuristic. The heuristic is built upon the constraints of the mathematical program. Some of the papers are incorporating stochastic elements to make the results even more realistic. We neither consider stochasticity nor propose a heuristic or simulation model at this point. We first want to formulate a mathematical program before adding any complexity. The mathematical program should present all the possible decisions of a dispatcher and should be compared with the ETS exercises of autumn 2019. In those ETS exercises, they use deterministic variables, which is another argument for choosing deterministic variables over stochastic variables.

Chapter 4: Mathematical formulation

This chapter answers research question 3: “How to develop an optimization approach that models the decisions made by the dispatcher in the ETS exercises of autumn 2019?“. In Chapter 3, we conclude that a mathematical programming approach fits best to this problem type. An optimization approach is chosen to solve the underlying problem. This chapter aims to formulate the model. This chapter is divided into three sections. Section 4.1 describes the model assumptions and definitions, which are used in the ILP model. Section 4.2 proposes the ILP model. Moreover, all the different ILP model components such as the sets, decisions variable, parameters, objective function and constraints are explained. Section 4.3 finishes this chapter by answering research question 3.

4.1. Model assumptions and definitions

The scenario of the ETS exercises of autumn 2019 forms the basis for this ILP model. A detailed explanation of this scenario is described in Chapter 2.5. The assumption and simplification made in those ETS exercises are implemented in the ILP model. Before presenting the model assumptions, the following terms are defined.

- Throughput time: By throughput time we understand the difference in time between a casualty coming into play in the ETS exercise (release time) and the arrival time of this casualty at the hospital.
- Makespan: The difference between the latest arrival of the Gubas at a hospital after dropping off and the starting time of the ETS exercise.
- Trip completion: An ambulance can finish its trip after dropping off the casually at the hospital. After the drop-off, a new trip of an ambulance can start.

In literature, throughput time is defined as the average elapsed time taken for input to move through the process and become output (Slack et al., 2016). By interpreting the throughput time definition of the ETS exercises of autumn (see Chapter 2.5.2), it seems wrong not to take each Guba drop-off time into account to calculate the average throughput time of casualties. However, as the drop-off time is constant in the ETS exercises and takes 10 minutes for all trips, it could be neglected for calculating the throughput time. The results are, in any case, not affected by the drop-off time. In a real MCI, each casualty is unloaded first by the ambulance aids before it arrives at the hospital. For the sake of completeness, the drop-off time is therefore taken into account but does not change the conclusions. The definitions of makespan and trip completion are originating from Chapter 2.5 and are used in this ILP formulation.

Besides the simplifications of the ETS exercises in autumn 2019 (see Chapter 2.5.1) , some additional assumptions are defined. Each of the simplifications is justified either by literature or AZE. The following additional assumptions, next to the ones we defined already in are formulated for the ILP model:

1. A T2 casualty can occupy a T1 bed at the emergency department of a hospital.
2. An ambulance is allowed to make a maximum of two trips.

We assume in (8) that a T2 casualty can occupy a T1 bed in a hospital. Whenever T1 capacity is left, it can be filled with T2 casualties. The other way around is not possible because T1 casualties require more intensive treatment. In the ETS exercise of autumn 2019, we do not observe any T2 casualties that occupy a T1 bed in a hospital. Therefore, we take this as a model assumption. AZE experts support this assumption (8). Assumption (9) defines the maximum number of trips that are allowed by an ambulance. Repoussis et al. (2016) use assumption (9) in their model as well. Moreover, in the ETS exercises of autumn 2019, an ambulance made at most two trips. So for simplicity, we assume a maximum of two trips.

4.2. ILP model formulation

This section aims to propose a new formulation of the casualty allocation problem. The outcome is a static schedule for a fleet of ambulances, which give aid to a set of casualties and transport them to a set of hospitals. The model determines the order in which casualties are transported. Furthermore, the model determines where each casualty gets hospitalized. The formulation in this section is deployable for analyzing the performance of an ETS exercise or an MCI. So far, we have used the term "casualty" to indicate a person who needs assistance at the MCI. In the ILP model, the term patient is used to indicate. These terms can be used interchangeably and are considered synonyms. This problem is formally described by using the notation that is described in the following section. First, we explain the (sub)sets and decision variables before presenting the mathematical formulation. The objective function and constraints are explained afterward.

4.2.1. Sets

P set of patients	$\{0,1,\dots,\mathrm{P}\}$, $\mathrm{P} = \mathrm{P}^{\mathrm{T1}} \cup \mathrm{P}^{\mathrm{T2}}$
P^{T1} subset of T1 patients	$\subseteq \mathrm{P}$
P^{T2} subset of T2 patients	$\subseteq \mathrm{P}$
H set of hospitals	$\{0,1,\dots,\mathrm{H}\}$
$\mathrm{H}^{\mathrm{MAJ}}$ subset major incident hospital	$\subseteq \mathrm{H}^{\mathrm{L1}}$
$\mathrm{H}^{\mathrm{UMC}}$ subset UMC hospital	$\subseteq \mathrm{H}^{\mathrm{L1}}$
H^{L1} subset of Level 1 hospitals	$\subseteq \mathrm{H}$
H^{L2} subset of Level 2 hospitals	$\subseteq \mathrm{H}$
$\mathrm{H}^{\mathrm{L1L2}}$ subset of Level 1 and 2 hospitals	$\mathrm{H}^{\mathrm{L1L2}} = \mathrm{H}^{\mathrm{L1}} \cup \mathrm{H}^{\mathrm{L2}}$
V set of vehicles	$\{0,1,\dots,\mathrm{V}\}$
K set of trips	$\{0,1,\dots,\mathrm{K}\}$
I set of time − intervals	$\{0,1,\dots,\mathrm{I}\}$

The set of patients P, consist of two subsets: urgent patients P^{T1} and less urgent patients P^{T2}. T1 patients require care within two hours and T2 patients require care within four hours. The set of hospitals consist of three types of hospitals. The difference in triage levels and hospital levels is given in Chapter 2. In the mathematical formulation, a separate subset is available for the major incident hospital ($\mathrm{H}^{\mathrm{MAJ}}$) and Universitair Medisch Centrum Utrecht $\left(\mathrm{H}^{\mathrm{UMC}}\right)$. Both hospitals are located in Utrecht and have Level 1 treatment capabilities. The ambulances' set is given by using notation V. The term ambulance is interchangeable with the term vehicle. In the set hospital H, $\mathrm{h} = 0$ is defined as the initial location of vehicle v at the start $\mathrm{t} = 0$ of the MCI. The number of trips is noted with the letter K. The set of time intervals is noted with I.

4.2.2. Parameters

C_h = Total treatment capacity of hospital h given per hour

$C_{h^{T1}}$ = T1 treatment capacity of hospital h given per hour

V_v = Initial travel time of vehicle v to reach the MCI for the first time in minutes

V_h = Travel time from the MCI to hospital h/ from hospital h to MCI in minutes

R_p = The release time of a patient in minutes

M = A large number (47 in this case)

S = The stabilization time of a patient, which takes 15 minutes

D = The drop off time of a patient, which takes 10 minutes

Time_i = The upper or lower bound of a time interval i $\{0,60,120,..,I\}$

Most of the parameters and decision variables are self-explanatory. Variable R_p needs additional explanation. The term R_p is defined as the release time of each patient (see Chapter 2.5). This includes the time a patient comes into the ETS exercises. If the patient is not released, no decisions can be made on this patient.

4.2.3. Decision variables

$$Y_{hpvk} = \begin{cases} 1 \text{ If Vehicle v on trip k originates from hospital h to "load" patient p from the MCI} \\ 0 \text{ Otherwise} \end{cases}$$

$$Z_{hpvk} = \begin{cases} 1 \text{ If Vehicle v on trip k transports to hospital h to drop off patient p} \\ 0 \text{ Otherwise} \end{cases}$$

A_{vk} = The arrival time at the hospital of vehicle v on trip k in minutes

F0 = The latest arrival at the hospital among al the vehicles of trip 0 in minutes

F1 = The latest arrival at the hospital among al the vehicles of trip 1 in minutes

T_p = The penalty time of patient p is not arriving in its interval in minutes

$$N_{ihp} = \begin{cases} 1 \text{ If patient p arrives at hospital h in time} - \text{interval i} \\ 0 \text{ Otherwise} \end{cases}$$

$$\theta = \begin{cases} 1 \text{ if the major incident hospital is open} \\ 0 \text{ Otherwise} \end{cases}$$

4.2.4. Model formulation

The ILP model consists of 23 constraints. To maintain an overview, we explain the constraints by categorizing them into five groups. The first group of constraints (2-9) is about how vehicles are making their trips. The second group of constraints (10-12) formulates when the major incident hospital opens or closes. The third group of constraints (13-15) calculates the trip completion time of each vehicle. The fourth group of constraints (16-19) ensures that the hospitals' treatment capacity is not violated. The fifth group of constraints (20-23) determines the components of the objective function and includes the sign constraints (24-25).

$$\min\ F0 + F1 + \sum_{p \in P} T_p \tag{1}$$

s.t.

$$\sum_{h \in H} \sum_{v \in V} \sum_{k \in K} Y_{hpvk} = 1 \qquad \forall\, p \in P \quad (2)$$

$$\sum_{h \in H^{L1L2}} \sum_{v \in V} \sum_{k \in K} Z_{hpvk} = 1 \qquad \forall\, p \in P^{T1} (3)$$

$$\sum_{h>0\, \in H} \sum_{v \in V} \sum_{k \in K} Z_{hpvk} = 1 \qquad \forall\, p \in P^{T2}\ (4)$$

$$\sum_{p \in P} Y_{0pv0} = 1 \qquad \forall\, v \in V\ (5)$$

$$\sum_{h \in H} \sum_{p \in P} Y_{hpvk} \leq 1 \qquad \forall\, v \in V, k \in K\ (6)$$

$$\sum_{h \in H} \sum_{p \in P} Z_{hpvk} \leq 1 \qquad \forall\, v \in V, k \in K\ (7)$$

$$\sum_{p \in P} Z_{hpvk} \geq \sum_{p \in P} Y_{hpvk+1} \qquad \forall\, h \in H, v \in V, k \in (K-1)\ (8)$$

$$\sum_{h \in H} Y_{hpvk} - \sum_{h \in H} Z_{hpvk} = 0 \qquad \forall\, p \in P, v \in V, k \in K\ (9)$$

The objective function (1) is minimized by taking three components into account. The first component is the latest trip completion among all the vehicles of trip 0. This latest trip completion is determined in constraint (22). In this way, vehicles making only one trip are not allocated to a hospital further away than necessary. The second component is the latest completion time among all the vehicles of trip 1. This latest completion time is determined by constraint (23). This constraint does the same as a constraint (22), but constraint (23) applies to all the vehicles making a second trip. The last component of the objective function (1) is the penalty for delayed patients. T1 patients have stricter time requirements than T2 patients. In this way, we aim to influence the model by giving priority to T1 patients over T2 patients when assigning them to an ambulance.

Constraints (2) ensures that each patient is handled only once. Constraints (3) and (4) assign the patients to the right hospital level and is based on their triage level. Constraint (3) forces T1 patients to get allocated to L1 or L2 hospitals. Constraint (4) ensures that each T2 patient is assigned to an L1, L2 or L3 hospital. According to the constraint (5), each vehicle is deployed for trip 0. The initial location of the vehicle is noted with $h = 0$. Constraints (6) and (7) enforce each vehicle v to transport a maximum of one patient per trip k. Constraint (8) ensures that no trip $k + 1$ can exist for a vehicle if there was no trip k. Besides, if trip $k + 1$ starts, the end location of trip k of the vehicle v is the start position for trip $k + 1$. Finally, constraint (9) verifies that each patient is carried and transported on the same trip with the same vehicle.

$$M(1-\theta) \geq \sum_{p \in P} \sum_{v \in V} \sum_{k \in K} Z_{hpvk} \qquad \forall\, H^{UMC}\ (10)$$

$$5 - \sum_{p \in P} \sum_{v \in V} \sum_{k \in K} Z_{hpvk} \leq M(1-\theta) \qquad \forall H^{MAJ} \; (11)$$

$$M\theta \geq \sum_{p \in P} \sum_{v \in V} \sum_{k \in K} Z_{hpvk} \qquad \forall H^{MAJ} \; (12)$$

According to constraint (10), the UMC emergency department closes whenever the decision is made to open the major incident hospital. The staff of the UMC emergency department moves then to the major incident hospital. Constraint (11) regards the opening of the major incident hospital. The major incident hospital opens when five or more patients are allocated to this hospital. Constraint (12) enforces patients to receive treatment at the major incident hospital when it is open, if it is closed, no patients can be hospitalized there.

$$A_{vk} \geq \sum_{h \in H} \sum_{p \in P} R_p Y_{hpvk} + \sum_{h \in H} \sum_{p \in P} V_h Z_{hpvk} + \sum_{h \in H} \sum_{p \in P} (S+D) Z_{hpvk} \qquad \forall\, v \in V, k \in K \; (13)$$

$$A_{v0} \geq \sum_{h \in H} \sum_{p \in P} V_v Y_{hpv0} + \sum_{h \in H} \sum_{p \in P} V_h Z_{hpv0} + \sum_{h \in H} \sum_{p \in P} (S+D) Z_{hpv0} \qquad \forall\, v \in V \; (14)$$

$$A_{vk} \geq A_{vk-1} + \sum_{H \in H} \sum_{p \in P} V_h Y_{hpvk} + \sum_{h \in H} \sum_{p \in P} V_h Z_{hpvk} + \sum_{h \in H} \sum_{p \in P} (S+D) Z_{hpvk} \qquad \forall\, v \in V, k > 0 \in K \; (15)$$

Constraint (13) makes sure that no patient is transported until the patient is released. Constraints (14) and (15) guarantee that no patient is transported if the assigned ambulance has not arrived yet at the MCI location. Constraints (13-15) determine the trip completion time of trip k of vehicle v. By formulating it this way, the ILP model has the freedom to incorporate waiting times for an ambulance.

$$\sum_{i \in I} \sum_{h \in H} N_{ihp} = 1 \qquad \forall p \in P \; (16)$$

$$Z_{hpvk} = 1 \; >> \sum_{i \in I, i < I-1} N_{ihp}\, \mathrm{time}_i \leq A_{vk} \leq \sum_{i \in I,\; i < I-1} N_{ihp}\, (\mathrm{time}_{i+1} - 1) \qquad \forall\, h \in H, p \in P, v \in V, k \in K \; (17)$$

$$\sum_{p \in P} N_{ihp} \leq C_h \qquad \forall\, i \in I, h \in H \; (18)$$

$$\sum_{p \in P^{T1}} N_{ihp} \leq C_h{}^{t1} \qquad \forall\, i \in I, h \in H \; (19)$$

Constraint (16) forces each patient to be classified into one of the defined time-intervals. Constraint (17) is an indicator constraint. The Gurobi solver supports indicator constraints. Those types of constraints are a new way of controlling whether a constraint takes effect based on the value of a binary variable (AIMMS, 2020; AIMMS B.V., 2018). Traditionally, such relationships are expressed by the so-called big-M formulation. Big-M methods introduce unwanted side effects and numerical instabilities into a mathematical program. Indicator constraints take those unwanted side effects away. Constraint (17) determines in which time-interval vehicle v completes its trip k. Z_{hpvk} is the binary decisions variable. If Z_{hpvk} equals one, A_{vk} is classified into one of the time-intervals. By classifying each patient into one time-interval, each patient is connected to the right hospital and the hour of the hospital arrival. Constraints (18) and (19) ensure that the given hospital treatment capacity per hour is not violated for T1 and the total number of patients.

$$\sum_{i \epsilon I-1} \sum_{h \epsilon H} N_{ihp} * Time_{i+1} - R_p \leq 120 + T_p \qquad \forall\, p \in P^{T1} \quad (20)$$

$$\sum_{i \epsilon I-1} \sum_{h \epsilon H} N_{ihp} * Time_{i+1} - R_p \leq 240 + T_p \qquad \forall\, p \in P^{T2} \quad (21)$$

$$F0 \geq A_{v0} \qquad \forall\, v \in V \quad (22)$$

$$F1 \geq A_{v1} \qquad \forall\, v \in V \quad (23)$$

$$F1, F0, A_{vk}, T_p \geq 0 \text{ integer} \qquad (24)$$

$$Y_{hpvk}, Z_{hpvk}, N_{ihp}, O \in \{0, 1\} \qquad (25)$$

The left part of constraints (20) and (21) approximately calculate the throughput time of each casualty. Those constraints subtract the patient's release time from the upper bound when they arrive at a hospital. A better way is to know the exact arrival time of a patient at the hospital. Unfortunately, this is not possible because of the way constraint (15) is formulated. For each trip k of a vehicle v the allocated patient changes. When the set of patients is added to the decision variable A_{vk} , the completion time of trip $k-1$ cannot be determined correctly. Other ways of connecting the patient's set to vehicles and trips were explored. However, they were unsuccessful without getting non-linear constraints. The right part of constraints (20) and (21) originates from the treatment time. If the difference is bigger than the given treatment time, each minute that goes over is penalized by the objective function. Constraint (22) uses the largest completion time among all the vehicles of trip 0. Constraint (23) does the same for trip 1. Constrain (24) and (25) are the sign restrictions of the ILP model.

4.3. Conclusion

The ILP model presents all the possible decisions in the ETS exercises. The data from the ETS exercises of autumn 2019 forms the basis for the ILP model. We use the ETS exercises' input variables such as travel times, the number of available ambulances, and the number of casualties. Some assumptions are made before proposing the ILP model. All the model assumptions are justified: either by literature or AZE experts. As an objective function, the latest arrival time among the vehicles of trip 0 and trip 1 are taken into account and minimized. Furthermore, in the objective function T1 casualties are priozited over T2 casualties.

Chapter 5: Experimental design

This chapter answers research question 4: "*What kind of scenarios are conducted on the optimization approach and how is the performance of the optimization model assessed*? ". This chapter is divided into four sections. Section 5.1 presents the key performance indicators for analyzing the results. In Section 5.2 gives an approach for comparing the ILP model with the ETS exercises of 2019. Section 5.3 explains different scenarios that are conducted on the ILP model. Section 5.4 finally answers research question 4.

5.1. Scenarios

For designing scenarios, the same input parameters are used from the ETS exercises of autumn 2019. In this section, various scenarios are proposed. The scenarios are conducted on the ILP model. The goal of conducting these scenarios is to describe the impact of making certain decisions having certain circumstances. Examples that may have an impact are the increase of hospital treatment capacities, by closing all the German or forcing all the casualties to go to the major incident hospital.

All the scenarios in this section are made in consideration with the AZE experts. For some of the scenarios, the constraints are changed in comparison to the ILP formulation of Chapter 4.2. In Appendix F it is stated for those scenarios how and which constraint(s)changed. The scenarios are divided into four categories. In data analyses of the results, the scenarios are compared to find similarities and differences amongst each other. The first category is about the impact of allocating T1 casualties to a Level 3 hospital. The second category is about the major incident hospital located at Utrecht. The third category is about the resources provided by Germany. The fourth category is presenting different scenarios about the hospital in Enschede.

Category 1: Base scenarios

T1 casualties are preferably allocated to a Levels 1 or 2 hospital. Sometimes, this is not possible in an MCI and the decision to allocate a T1 casualty to a Level 3 hospital is made. Determining this impact is interesting to show if this decision has any impact. The following scenarios are designed to determine this impact:

0. T1 Gubas should go to Level 1 or 2 hospitals.
1. Six T1 Gubas are allocated to Level 3 hospitals.

Scenario 0 presents the base model, which is addressed in Chapter 4.2. Scenario 1 is comparable to what we have seen in the ETS exercises of autumn 2019. In total, six T1 Gubas get allocated to a Level 3 hospital on day 1 and seven on day 2. For Scenario 1 six T1 casualties are allocated to Level 3 hospitals.

Category 2: Major incident hospital

As mentioned in Chapter 2.5, in the AZE region, different opinions exist on hospitalizing casualties at the major incident hospital of Utrecht. The major incident hospital is usually closed but can open in case of an MCI. Some experts argue that the distribution of casualties would be better when all or most casualties are hospitalized at the major incident hospital. Regular emergency care can continue by applying this category. Also, an MCI is stressful for dispatchers. Allocating all the casualties to the major incident hospital might remove some of the stress. The final argument for taking the major incident hospital into account is that there are more resources available at the major incident hospital in comparison to regional Level 1 hospitals. On the other hand, other experts argue that the surrounding hospitals of the AZE region have sufficient treatment capacity and capabilities to provide each casualty with the best and right treatment on time. Furthermore, they argue that the transportation time to the major incident hospital is too long. It would take (with siren) at least an hour to reach the major incident hospital from the region of AZE. The aim of conducting different scenarios of this category is to understand the impact of hospitalizing casualties at the major incidents hospital. The following scenarios are designed:

2. All T1 Gubas go to the major incident hospital.
3. All T2 Gubas go to the major incident hospital.
4. All Gubas go to the major incident hospital.

Scenario (2-4) presents the possible strategies for hospitalizing the casualties at the major incident hospital.

Category 3 Assistance of resources and hospitals from Germany

As previously mentioned, the region of AZE is located in a border area with Germany (Chapter 1.1). The experts of AZE are especially interested in the impact of using the assistance of Germany in the case of an MCI. It is important to know the impact, to understand the importance of international cooperation. The following scenarios are proposed to investigate the impact:

5. Casualties of the MCI are not allowed to be allocated to the German hospitals.
6. German ambulances can only go to German hospitals.

Scenario 5 does not allow to hospitalize casualties from the MCI in the Netherlands at the German hospitals. Scenario 6 enforces allocating each Guba that is picked up by a German ambulance to go to a German hospital. In this way, we can determine whether the flexibility of sending German ambulances to a Dutch hospital has an impact.

Category 4: Other variations

In this category, we aim at determining the impact of closing the hospital located at Enschede. The hospital of Enschede is a Level 1 hospital and has the largest treatment capacity in the region of AZE. The following scenario is designed to determine the impact:

7. T2 casualties are not hospitalized at hospital Enschede (as a result, T1 treatment capacity per hour is increased by two for hospital Enschede).
8. Hospital Enschede is closed.

According to Scenario 7, no T2 casualties are allowed to be hospitalized in hospital Enschede. When no T2 casualties are hospitalized at hospital Enschede, there is some treatment capacity left for T1 casualties. In consideration with the AZE experts, we increase the treatment capacity of T1 casualties by two. Scenario 8 does not allow any of the casualties to be hospitalized at the hospital in Enschede. We are just curious what the consequences are of closing the largest hospital in the region of AZE.

5.2. Key Performance Indicators (KPIs)

During the literature review, several KPIs were identified. Furthermore, several additional KPIs were used in the ETS exercises of autumn 2019 to determine the performance of the exercises. All those KPIs are used as inspiration for defining the KPIs of this research. In this research, the following KPIs are taken into account:

- Makespan of T1 and T2 casualties.
- The average throughput time of T1 and T2 casualties.
- The utilization rate of the hospitals per hour.
- Number of T1 and T2 casualties arrive on time/late at the hospital.

In Chapter 4.1 we defined the definitions makespan and throughput time. The KPI makespan is by Talarico et al. (2015), Repoussis et al. (2016) and Draijer (2017). Talarico et al. (2015) and Repoussis et al. (2016) define makespan slightly different than we do. Those papers include the hospital treatment times of a casualty. The hospital's treatment time however is out of scope for our research and we therefore do not include it in our definition of makespan. Draijer (2017) uses the same definition of makespan as we do. Furthermore, the makespan and the average throughput time are used to analyze the performance of the ETS exercises of autumn 2019. This is the main argument for having the throughput time as KPI. The duration of the throughput time can be influenced by the model. The makespan also depends on the release time of the Gubas in the ETS exercises. The KPIs makespan and throughput time are determined separately for T1 and T2 casualties. The idea of distinguishing two groups of casualties is based upon two arguments. The first one is found in Chapter 2.3, in which each casualty gets a certain triage category (Vasallo et al., 2016). According to this triage category, the most heavily injured casualties (T1 casualties) require faster and more specialized treatment than less injured casualties (T2 casualties). The second argument originates from papers such as Talarico et al. (2015) and Draijer (2017). Those studies divide casualties into groups in which each group has a certain weight to indicate the importance of a group. In the ETS exercises of autumn 2019 the makespan of T1 and T2 casualties is considered as separate KPIs. Without distinguishing triage categories, we cannot check if T1 casualties are prioritized over T2 casualties. Moreover, by distinguishing the two groups, we can check if the dispatchers of the ETS exercises of autumn 2019 use this priority rule in reality. We do not check the overall makespan since it is just a maximum of T1 makespan and T2 makespan. Also, the average throughput time is not considered as KPI since this is just the average of the average throughput times of T1 and T2 casualties. The utilization rate of each hospital is another important KPI. As mentioned in Chapter 2.1, the dispatcher's responsibility is to distribute the casualties of an MCI to the surrounding hospitals. This argument is also substantiated by Repoussis et al. (2016), who state that a hospital should not be overwhelmed by an MCI. Despite the importance of this KPI no papers are found in the literature about using the utilization rate of a hospital. Also, in the ETS exercises of 2019 the utilization rate is not considered as a KPI. The last KPI is defined as the number of casualties arriving on time and late at the hospital. Hawe et al. (2015) use the same triage categories and incorporate the time interval in which each triage category requires medical treatment in a hospital. Sung and Lee (2016) are maximizing the expected number of survivals and are using the survival probability function for a pessimistic, moderate and optimistic scenario for each casualty group. Both papers indicate the importance of having a KPI determining the number of casualties arriving on time and late at the hospital. The makespan determines the number of on-time/late casualties. If T1 casualties reach the hospital within two hours, we assume the casualties receive treatment on time. If the casualty arrives after two hours at a hospital, we assume the casualty arrives late. Also, here the triage categories are distinguished

5.3. Comparison approach

The ILP model was formulated in Chapter 4. This model presents the decision-making process of a dispatcher during the ETS exercises. To justify whether the model is realistically presenting the decisions of a dispatcher, we use the ETS exercises of 2019 to compare with the results of the model. During the data analysis of the ETS exercises, some discrepancies were revealed. For comparing the ILP model, the model is adapted to the situation of those executed ETS exercises. The differences and implementation of the discrepancies are addressed in this section.

The first discrepancy is about the documented release time of the Gubas. Recall that no decisions can be made on the allocation of a Guba until is released. Figure 9 shows for each Guba the documented release time and the time a Guba is prepared/stabilized for transport. Both exercises show that Gubas are stabilized before their given release time. An explanation is that a different release time was used during the execution of the ETS exercises in autumn 2019 and it was not updated in the documentation. This explanation is most logical because ETS day 1 and ETS day 2 look quite similar to each other in terms of release times. Another possible explanation is that the release time of the Gubas was sometimes forgotten to be noted down. Either way, for the comparison, the document release time of the Gubas is adapted to the start stabilization time for each ETS exercise.

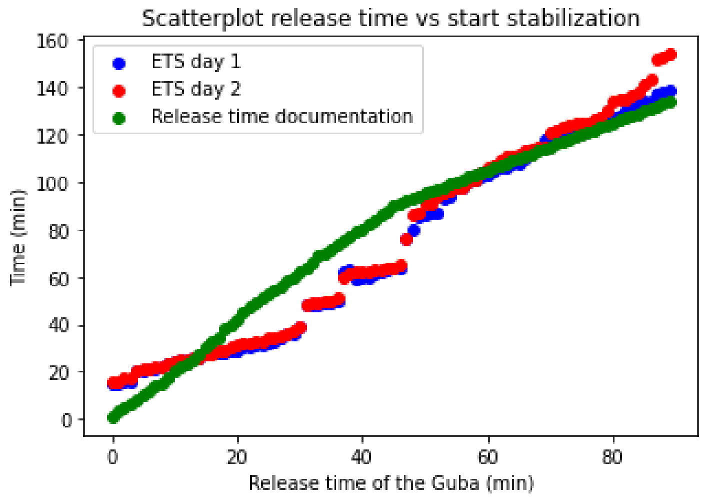

Figure 9 Scatterplot release time versus start transportation time

The ETS designers have found another discrepancy. Two Gubas were scheduled at the same time in the same ambulance. A coincidence or not, this happened in both of the exercises. In both exercises, those Gubas were left out of the performance analysis. To correctly compare, we remove these two Gubas, who were scheduled on that ambulance, from the sum of Gubas, making the total number of Gubas 88 instead of 90.

Chapter 2.3 states that a T1 casualty preferably receives treatment at a Level 1 or 2 hospital. In the case of an MCI, a dispatcher may decide to allocate a T1 to a Level 3 hospital to increase the survival rate of the casualty. Both ETS exercises were allocating T1 casualties to Level 3 hospitals. In the ETS exercise of day 1, six T1 Gubas were allocated to a Level 3 hospital. In the ETS exercise of day 2 seven T1 Gubas were allocated to a Level 3 hospital. Such considerations are not implementable in the ILP model without adding stochastic elements. Therefore, we define a separate subset of Gubas in the ILP model. This subset consists of T1 Gubas that were allocated in the ETS exercise day 1 or 2 to a Level 3 hospital. A separate constraint is made that ensures that the Gubas of this subset is allocated to a Level 3 hospital in the ILP model.

Another discrepancy was found by analyzing the results of the ETS exercises. The hourly hospital capacities were sometimes violated. For instance, hospital Zutphen's T1 treatment capacity was violated in both ETS exercises by one T1 patient at the second hour. Moreover, the T1 treatment capacity of hospital Enschede was violated in ETS exercise day 1. For comparison, we do not manipulate the treatment capacities of the hospitals. The difference is minor and has most likely no impact on the performance.

5.4. Conclusion

The KPIs used to determine the model's performance are the makespan, average throughput time, the utilization rate of each hospital and the number of casualties late/on time. KPIs makespan, average throughput time and the number of casualties late/on time are determined separately for T1 and T2 casualties. ETS exercises of 2019 are used to justify whether the model presents the same kind of decisions as a dispatcher does in the MCI. During the data analysis of those ETS exercises, some discrepancies were revealed. For comparing the ILP model with the ETS exercises of autumn 2019, the model is modified to execute those ETS exercises.

Chapter 6: Results

This chapter answers research question 5: "What are the results of the model?". Section 6.1 describes the computation method for solving the scenarios and the experiments. Section 6.2 compares the performance of the ETS exercises (days 1 and 2) with the model (days 1 and 2). Section 6.3 shows the performance of each scenario. Lastly, Section 6.4 answers research question 5.

6.1. Computation method

The ILP model is implemented in Python. All the scenarios and experiments are conducted on a PC equipped with Intel Core i7–9750 clocked at 2.69 Gigahertz, 16 GigaByte RAM memory, and is running on Windows 10 64-bit edition. All the formulations are solved by using Gurobi 9.1. The maximum allowable computation time for running an experiment is 24 hours. Whenever the optimum value is not found, the gap is mentioned.

6.2. Results comparing ILP models to the ETS exercises

Alternative objectives are developed for the ILP model. Those objectives are executed to find the best objective for the model. By changing the objectives, the outcomes of the model changes. The performance of each objective is assessed by measuring the KPIs. Those KPIs are defined and described in Chapter 5.2. Each objective is compared to the ETS exercises of autumn 2019. The following three objectives are implemented as an alternative model.

Model 1 presents the base model, which is presented in Chapter 4.2. Model 1, minimizes the makespan among trip 0 and trip 1 and penalizing for not arriving at the hospital within the given treatment time (two hours for T1 and four hours T2). The objective of Model 1 is formulated as follow:

$$\min\ F0 + F1 + \sum_{p \epsilon P} T_p$$

Model 2 minimizes the makespan among trip 1 and penalizing casualties for not arriving at the hospital within the given treatment time (two hours for T1 and four hours T2). The objective of Model 2 is formulated as follow:

$$\min\ F1 + \sum_{p \epsilon P} T_p$$

Model 3 minimizes the makespan among trip 1 and penalizing casualties for not arriving at the hospital within the given treatment time for T1 of 100 minutes and T2 of 230 minutes. The objective of Model 3 is formulated as follows

$$\min\ F1 + \sum_{p \epsilon P} T_p$$

To compare the alternative ILP models with the ETS exercises of autumn 2019 some changes are implemented. Those changes are explained in Chapter 5.3.

The results of each alternative model (Day1) are depicted in Table 5. The first thing that stands out is the makespan of the T2 casualties. Comparing the ETS exercise (day 1) with the ILP models, the T2 makespan is decreased from 210 minutes to 181 minutes, which is an improvement of 29 minutes.

Model 2 is performing worse on the T1 makespan In comparison to the ETS exercise. The T1 makespan in the ETS exercise is 140 minutes and Model 2, 179 minutes. This is a decline of 39 minutes. The T1 makespan of the ETS exercise is reduced by Model 1, from 140 minutes to 109 minutes, which is 31 minutes shorter. Moreover, Model 3 improves the T1 makespan. Comparing the ETS exercise with

Model 3, the T1 makespan in reduced from 140 minutes to 119 minutes, which is an improvement of 21 minutes.

All models perform worse than the ETS exercises on the average T1 and T2 throughput time. The average T1 throughput time of Model 1, Model 2 and Model 3 is respectively 63.7, 62.4 and 57.2 minutes. Model 3 has the best average T1 throughput time among all the models. The T1 throughput is increased from 54.2 minutes (ETS exercise) to 57.2 minutes (Model 3), which is a difference of 3 minutes. However, when looking at the average T2 throughput, Model 3 performs worse than the other models. In the ETS exercise, the average T2 throughput time is 54.4 minutes, while in Model 3 this is 70.3 minutes. The best average T2 throughput time among the models is Model 1 with 65.6 minutes.

Table 5 Summary of performances Model and ETS exercise day 1

	T1 casualties		**T2 casualties**	
	Average throughput time (minutes)	**Makespan (minutes)**	**Average throughput time (minutes)**	**Makespan (minutes)**
ETS day 1	54.2	140	54.4	210
Model 1	63.7	109	65.6	181
Model 2	62.4	179	64.4	181
Model 3	57.2	119	70.3	181

Table 6 summarizes the performances of the KPIs for each alternative model (day 2) and ETS exercise (day 2). Once again, all Models outperform the T2 makespan compared to the ETS exercise. Comparing the ETS exercise with the models, the T2 makespan is decreased from 203 to 195 minutes.

The T1 makespan is reduced in some of the alternative models. Comparing the ETS exercise with Model one, the T1 makespan is improved by Model 1 from 121 to 110 minutes. This is a decrease of 11 minutes. Again Model 2 is performing worse on the T1 makespan than the ETS exercise. The T1 makespan of Model 2 is 179 minutes. Therefore, Model 2 is not considered further for executing the scenarios.

Also, on day 2 the average T1 and T2 throughput times perform worse in the alternative model than in the ETS exercise. Model (1-3) has an average T1 throughput time of 67.3, 70.9 and 61.3 minutes. Model 3 performs best on the average T1 throughput time among all the models with 61.3 minutes. However, the impact of improving the average T1 throughput time is nullified by worsening the throughput time of T2 casualties. Model 3 has an average T2 throughput time of 72.6 minutes. Model 1 performs best on the average T2 throughput time with 69.9 minutes. Comparing the ETS exercise with the model, the T2 throughput time is increased from 55.7 to 69.9 minutes.

Table 6 Summary of performances of each alternative objective for day 2

	T1 casualties		T2 casualties	
	Average throughput time (minutes)	**Makespan (minutes)**	**Average throughput time (minutes)**	**Makespan (minutes)**
ETS day 2	55.1	121	55.7	203
Model 1	67.3	110	69.9	195
Model 2	70.9	179	74.8	195
Model 3	61.3	116	72.6	195

Figure 10 and Figure 11 depict the number of casualties who arrive late at the hospital for the models day 1 and day 2. In Model 2, two casualties arrive late. Model 1 and 3 no T1 casualties are late. All T2 casualties arrive on time at the hospital.

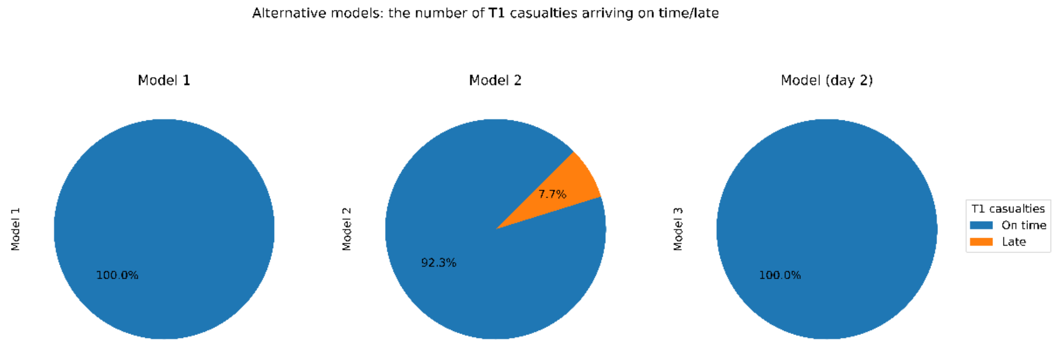

Figure 10 The number of on-time and late T1 casualties for day 1

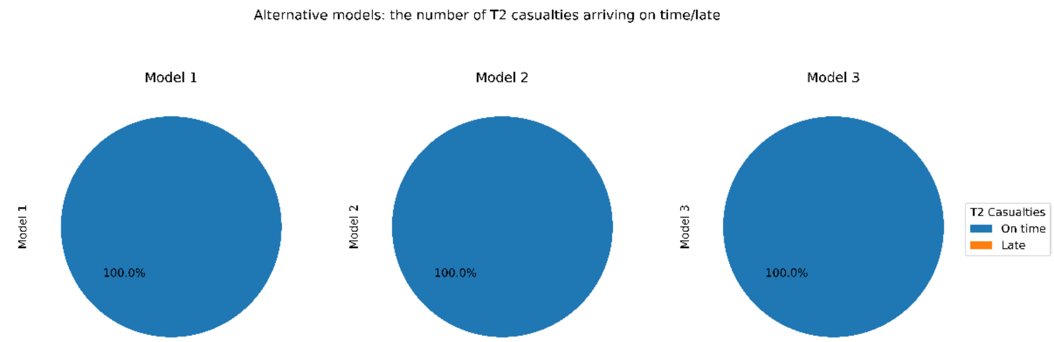

Figure 11 The number of on-time and late T2 casualties for day 1

In conclusion, Model 1 performs the best in terms of the general KPIs without overfitting the parameters. This model provides the best makespan among the three models. Furthermore, no casualties arrive late at a hospital. The rest of this section focuses on comparing Model 1, which is the base model, with the ETS exercises of autumn 2019. From now on, when we are talking about the Model (day 1 or 2) or ILP model, the objective of Model 1 is implemented.

By doing an in-depth analysis, we check if the model is making realistic and logical decisions. An important component to take into account is the distribution of casualties to the surrounding hospitals. Most important is that the maximum treatment capacity is not exceeded. Figure 12 depicts the performances of the Model (day 1) and the ETS exercise (day 1) results in terms of the T1 utilization rate of the hospitals per hour. Figure 13 does the same comparison in terms of the total utilization rate. Appendix G depicts the number of (T1 and total) casualties hospitalized per hospital per hour. Recall Chapter 5.2 explains why the total utilization rates are considered and not the T2 utilization rates.

The T1 utilization rate of the hospital presents a distorted picture of the ETS exercise (day 1) (see Figure 12). Hospitals Zutphen and Enschede receive more T1 casualties per hour than their respective capacities documented in the ETS exercises. All the T1 casualties arrive at the hospital within two hours in Model (day 1). In the ETS exercise, all the T1 casualties arrive at the hospital within two hours, except for one casualty, which arrives at the hospital Münster in the third hour (see Appendix G). Most hospitals used in the ETS exercise are used in the Model as well. Hospitals Stadlohn and Utrecht are not used in the ETS exercises, while in the model those hospitals receive casualties. On the contrary, hospital Münster is used in the ETS exercise, while in the model no casualties are allocated to hospital Münster.

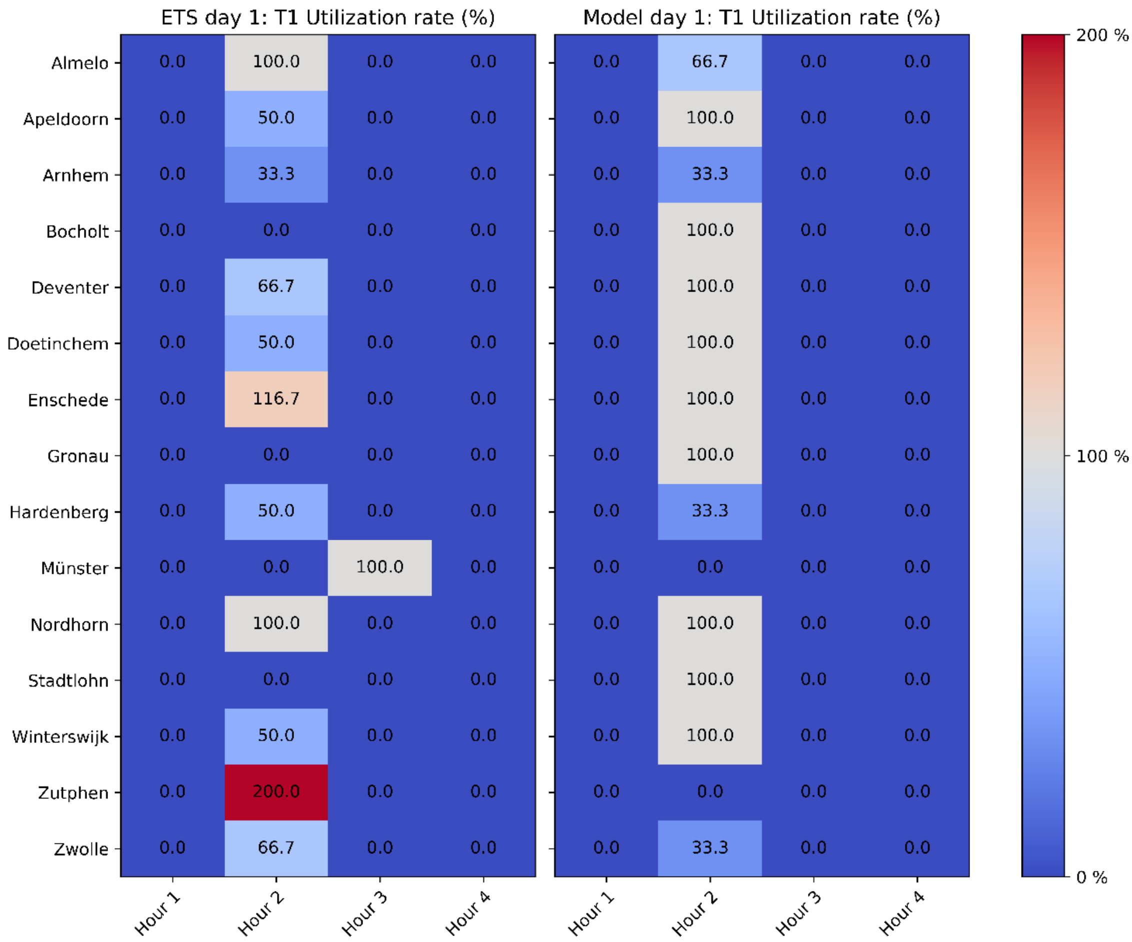

Figure 12 Day 1 T1 utilization rates of each hospital per hour

Figure 13 depicts the total utilization rates of each hospital per hour. The total treatment capacity of the hospital is not exceeded in the ETS exercises day 1 and in the Model (day 1). Both have arrivals of casualties at the hospital in the fourth hour of the MCI. The maximum treatment capacity of some hospitals is reached in the model (e.g., hospital Almelo), whereas in the ETS exercise the maximum treatment capacity of the hospitals is never reached.

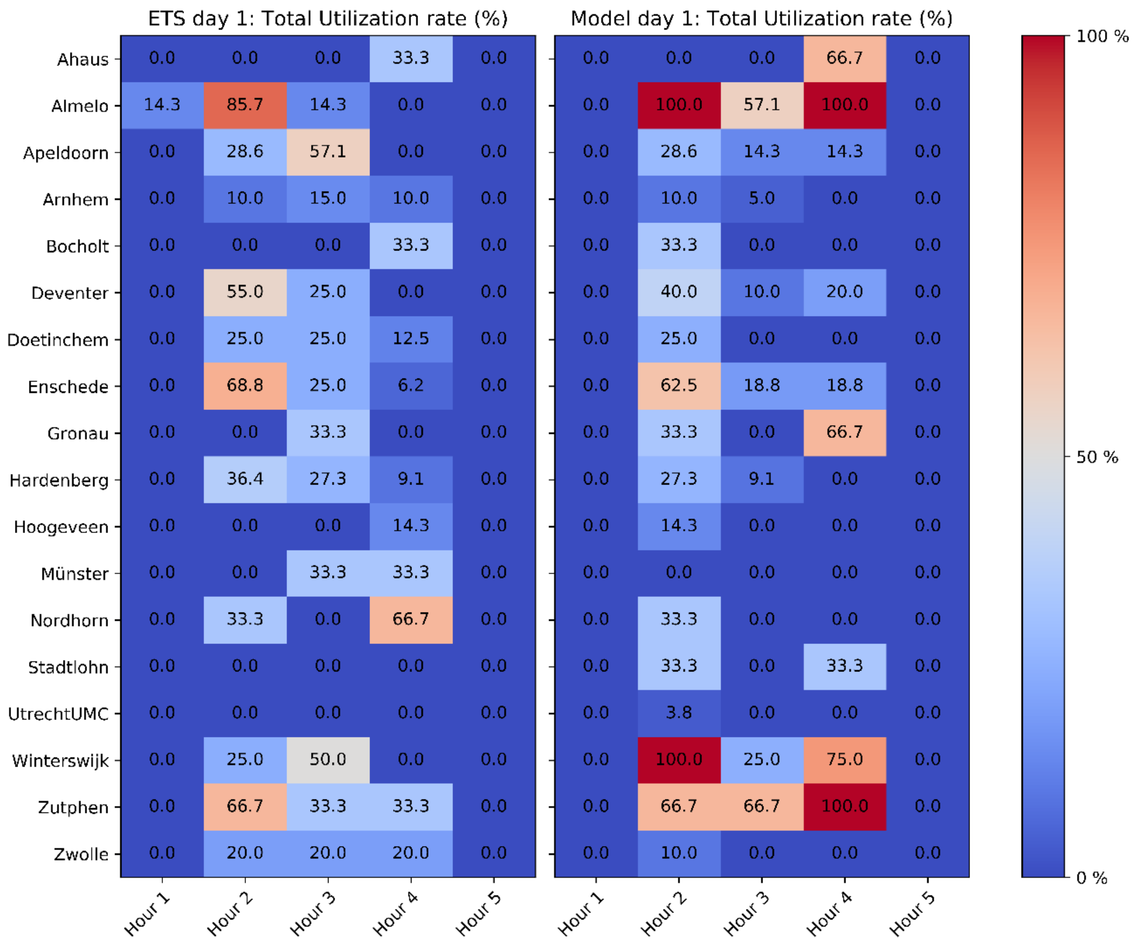

Figure 13 The total utilization rate of each hospital per hour

Figure 14 shows the trip completion time of each ambulance trip for the ETS exercise (day 1) and the proposed Model (day 1). The definition of trip completion is given in Chapter 4.1. In the ETS exercise, the ambulance completing trip 1 first is ambulance 05-104 after 127 minutes and the last ambulance is DLD-07 after 210 minutes. A difference of 83 minutes is found. In the ILP model, the first ambulance completing trip 1 is 06-151 within 151 minutes and the last ambulance is 06-157 within 181 minutes, which is a difference of 30 minutes. So, the range of the ILP model is much smaller than in the ETS exercise. The same observation is done in the ILP model and ETS exercise of day 2 (see Appendix G). Furthermore, in the ETS exercise, the sequence in which each ambulance arrives for the first time at the MCI seems to influence the trip completion time. For example, the German ambulances, abbreviated with DLD, take the longest to arrive at the MCI for the first time. The ambulances from Germany have in comparison to ambulances with abbreviations 06, 04 and 05 that are originating from the Netherlands longer trips.

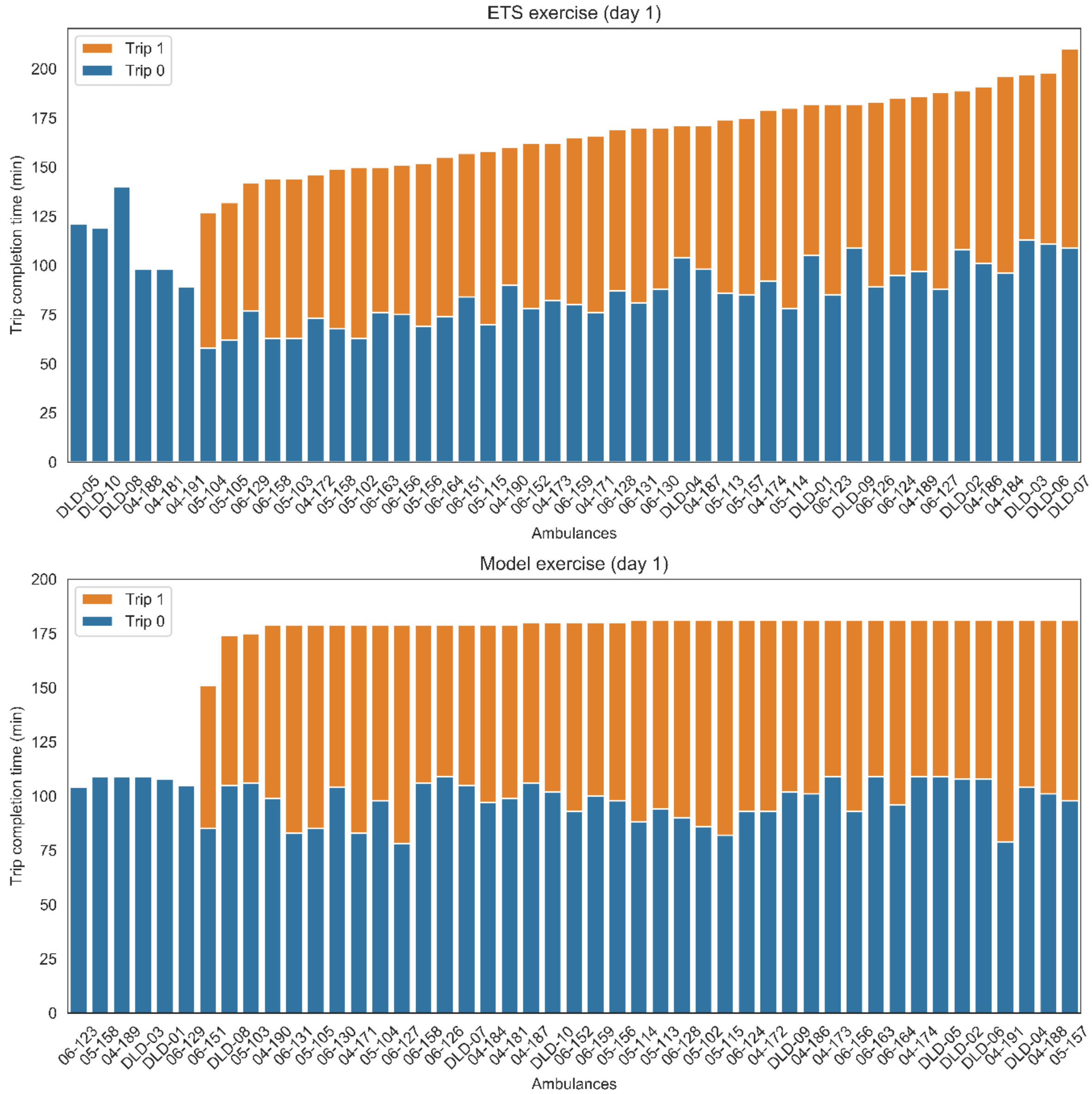

Figure 14 The difference between the Model (day 1) and the ETS exercise (day 1), the ambulance trip completion of each trip (a) ambulances sorted by total trip completion time (linear increasing) and (b) ambulances again sorted by total completion time (constant)

Figure 15 depicts the trip composition of the casualties transported by all the ambulances for the ETS exercise (day 1) and Model (day 1). The composition is the same for the ETS exercise and the model. On the total number of ambulances, including 47 ambulances, 55.3 % are transporting a T1 casualty and 44.7 % are transporting a T2 casualty on trip 0. The ambulances on trip 1 are only transporting T2 casualties. Meaning all T1 casualties are transported to the hospital by ambulances on trip 0. For the Model (day 2) and ETS exercise (day 2), the trip composition is the same as depicted in Figure 15.

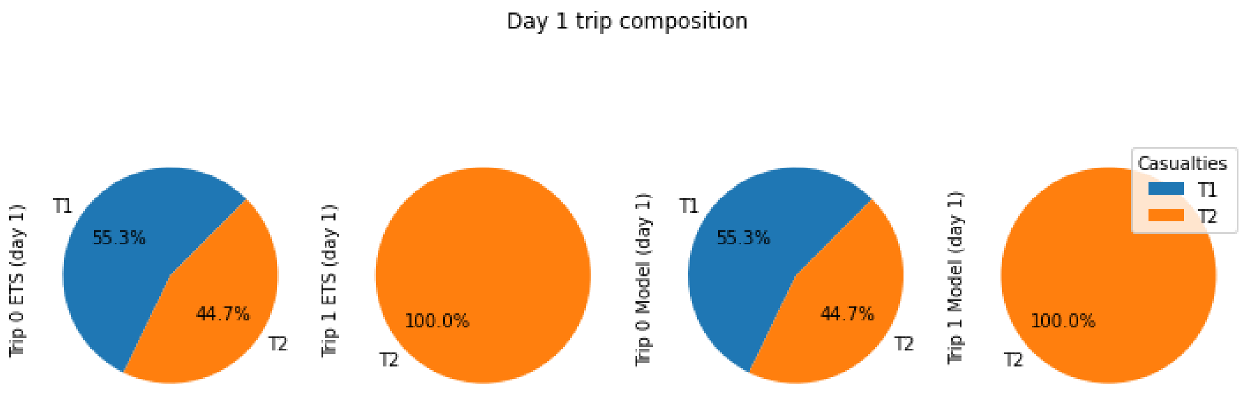

Figure 15 Trip composition

Figure 16 depicts the number of casualties arriving on time/late at the hospital for the ETS exercise (Day 1) and Model (day 1). In the ETS exercise, 3.7 % of the T1 casualties arrive late, which is one T1 casualty. No T1 casualties arrive late in the model. So, the model improves the performance of the ETS exercise by one T1 casualty. In the Model as well as the ETS exercise, all T2 casualties arrive on time at the hospital. For Model (day 2) and ETS exercise (day 2), the number of casualties arriving on time and late is the same as depicted in Figure 16.

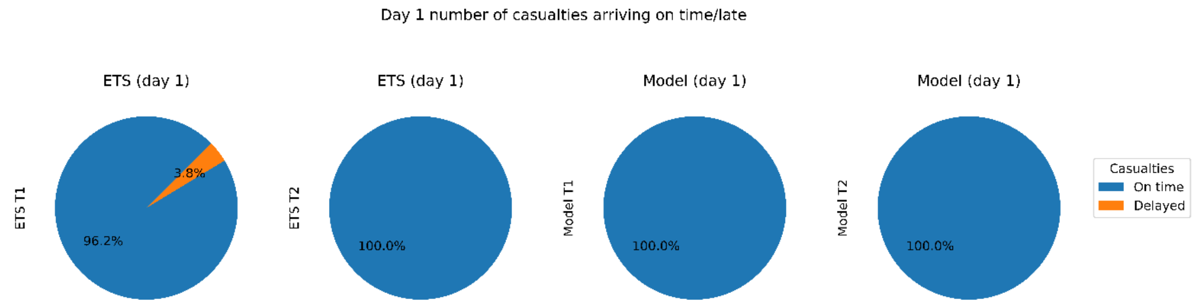

Figure 16 Number of on-time and late casualties

We have carried out similar analyses to Model (day 2) and the ETS exercises (day 2). The in-depth comparison can be found in Appendix G. We summarize the results of Appendix G here. When comparing the performance of Model (day 2) with the ETS exercise (day 2), the following is observed:

- In the ETS exercise of day 2, the T1 treatment capacity is exceeded for hospital Zutphen in the second hour of the MCI. The total treatment capacity is not exceeded. In the model, no treatment capacity is exceeded.
- The range of the ILP model is much smaller than in the ETS exercise. In the ETS exercise, the ambulance completing trip 1 first is ambulance 05-103 after 118 minutes and the last ambulance is 04-187 after 203 minutes, which is a difference of 85 minutes. In the ILP model, the first ambulance that finishes trip 1 is 04-187 within 162 minutes and the last finishing ambulance is 05-114 within 195 minutes, which is a difference of 33 minutes. So, the variation of the ILP model is much smaller than in the ETS exercise.

6.3. Scenario results

Chapter 5.1 introduces various scenarios that are of interest. Here, each scenario is summarized before moving to the results of those scenarios. Scenario 0, is the base model and is described in Chapter 4.2.4. In Scenario 1, six T1 casualties are hospitalized at a Level 3 hospital. In Scenario 2, the T1 casualties are allocated to the major incident hospitals and the T2 casualties are allocated to any hospital. In Scenario 3, T2 casualties are allocated to the major incident hospital and T1 casualties are allocated to a Level 1 or 2 hospital. In Scenario 4, all the casualties are allocated to the major incident hospital. In Scenario 5, German hospitals are not allowed to hospitalize casualties of the MCI. In Scenario 6, German ambulances are allocated to German hospitals only. In Scenario 7, no T2 casualties are allowed to get hospitalized at the hospital Enschede and therefore, the T1 treatment capacity of Enschede is raised by two casualties. In this way, two additional T1 casualties are allowed to receive treatment at the hospital Enschede. In Scenario 8, hospital Enschede is closed for all casualties.

Table 7 shows the performance of the scenarios for T1 casualties. Scenario 7 performs the best on the average T1 throughput times with 55.7 minutes. However, Scenarios 0, 1, 5, 6 and 8 are quite close, respectively 58.3, 57.9, 57.1, 59.0 and 58.6 minutes. Scenarios (2-4) are performing worse in terms of average T1 throughput time than the other scenarios. Scenarios 2, 3 and 4 have an average T1 throughput time of respectively 89.2, 62.3. and 79.7 minutes. Scenario 2, in which all T1 casualties are allocated to the major incident hospital, has the highest T1 throughput time among all the scenarios.

Scenarios 5, 7 and 8 perform the best on the T1 makespan with 122 minutes. Scenarios 0,1 have a T1 makespan of 128 minutes compared to Scenarios 5, 7 and 8. This is an increase of 6 minutes. Scenario 3 and 6 have a T1 makespan of respectively 139 and 133 minutes. The highest T1 makespan is obtained in Scenario 2 with 179 minutes. In this scenario, all the T1 casualties are allocated to the major incident hospital.

The number of delayed T1 casualties is the lowest in Scenario 1 by having two T1 casualties arriving late at the hospital. Scenario 7 has three T1 casualties arriving late at the hospital. In Scenarios 0, 6 and 8 the number of delayed T1 casualties is five and in Scenario 5 this is four. So, this difference in comparison to Scenario 1 and 7 is not that big. Most T1 casualties arriving late at the hospital are reached in Scenarios 2 and 4 by having thirteen T1 casualties arriving late.

Table 7 The performance of the scenarios on T1 casualties

#	T1 casualties		
	Average throughput time (minutes)	**Makespan (minutes)**	**Delayed (# of casualties)**
0	58.3	128	5
1	57.9	128	2
2	89.2	179	13
3	62.3	139	7
4	79.7	155	13
5	57.1	122	4
6	59.0	133	5
7	55.7	122	3
8	58.6	122	5

Table 8 shows the performance of the scenarios for T2 casualties. Scenario 1 has the best average T2 throughput time with 63.5 minutes. However, the average T2 throughput time is approximately the same for Scenarios 0, 5 and 7, respectively, 68.5, 63.9 and 64.9 minutes. In Scenario 4 the average T2 throughput times is 123.5 minutes, this is almost twice as high as in Scenario 1.

The T2 makespan is the lowest in Scenario 1, with 185 minutes. Furthermore, Scenarios 0, 5 and 7 have a low T2 makespan too, respectively 189, 187 and 187 minutes. Scenarios 2 and 6 perform worse on the T2 makespan with, respectively, 215 and 203 minutes. Scenarios 3 and 4 have the worse T2 makespan with 284 minutes.

In Scenarios (0-2) and (5-8) zero T2 casualties arrive late at the hospital. In Scenario 3 twelve T2 casualties arrive late at the hospital. In Scenario 4, T2 casualties arrive late at the hospital, namely 35 T2 casualties.

Table 8 shows the performance of the scenarios for the objective value and the optimality gap. The objective values of Scenarios (2-4) are relatively high compared to the other scenarios. Especially, Scenario 4 has the highest objective value with 509 minutes. In Scenarios 0, 1, 5, 7, and 8 the objective values are close to each other, ranging from 318 to 324 minutes. Scenarios 1, 5 and 7 have an objective value of 318, 320 and 320 minutes. Those scenarios have a lower objective value than in the base model (Scenario 0) with 322 minutes. The following arguments explain those objective values:

- Scenario 1, 6 T1 casualties are allocated to a Level 3 hospital. In the base model (Scenario 0), such type allocation is not possible. Therefore, Scenario 1 has a lower objective value than Scenario 0.
- Scenario 5, no German hospitals are used, has a smaller problem size than Scenario 0. This is an uncommon behavior of an ILP model since a smaller problem size usually does not result in a better objective value. Therefore, we gave Scenario 0 an initial solution, which was the solution of Scenario 5. The initial solution in Scenario 0 resulted in having the same objective value as in Scenario 5. So, the main argument for having a lower objective value in Scenario 5 is the optimality gap. The optimality gap in Scenario 5 is 14.7%, while in Scenario 0 this is 20.2%.
- Scenario 7, more T1 capacity is available at hospital Enschede, which is the main argument why Scenario 7 is performing better than Scenario 0.

Overall the optimality gap, the difference between the LP-relaxation and the feasible solution, is high as it ranges between 11 % to 27 %. The lowest gap is obtained in Scenario 4 in which all the casualties are allocated to the major incident hospital.

Table 8 The performance of the scenarios on T2 casualties, objective value and the optimality gap

#	T2 casualties			Model	
	Average throughput time (minutes)	**Makespan (minutes)**	**Delayed (# of casualties)**	**Objective value**	**Gap (%)**
0	68.5	189	0	322	20.2
1	63.5	185	0	318	21.4
2	75.2	215	0	415	27.0
3	107.2	284	12	450	26.4
4	123.5	284	35	509	11.0
5	63.9	187	0	320	14.7
6	72.4	203	0	337	12.5
7	64.9	187	0	320	18.4
8	76.9	191	0	324	20.7

Appendix H addresses the utilization rate and the number of casualties hospitalized in each hospital per hour and for each scenario. We can summarize this appendix as follows:

- Scenario 0: The closest hospitals such as Almelo, Deventer, Enschede, Gronau, Winterswijk and Zutphen reach their maximum T1 treatment capacity in the second hour of the MCI. The total treatment capacity is reached multiple times in hospitals Almelo and Gronau.
- Scenario 1: The T1 treatment capacity is reached in hospitals Almelo, Bocholt, Deventer, Enschede and Nordhorn. The total treatment capacity is only reached in hospital Almelo.
- Scenario 2: shows that all T1 casualties are hospitalized at the major incident hospital. The maximum T1 treatment capacity is not reached for the major incident hospital. The total treatment capacity is reached at hospitals at Almelo and Gronau.
- In Scenario 3: the T1 maximum treatment capacities are reached in the second hour of the MCI at hospitals Almelo, Apeldoorn, Bocholt, Deventer and Nordhorn. The maximum total treatment capacities are not reached in any of the hospitals due to all T2 casualties are hospitalized at the major incident hospital.
- Scenario 4: All the casualties are hospitalized at the major incident hospital. The treatment capacities of the T1 casualties and total is not reached in any of the hospitals. Most casualties arrive at the hospital in the fifth hour after the MCI happened. In the other scenario, this did not happen.
- Scenario 5: Hospitals Almelo, Apeldoorn, Deventer, Doetinchem and Enschede reach their maximum T1 treatment capacity. Moreover, the total treatment capacity of hospital Almelo and Zutphen is reached. All casualties arrive within four hours of the MCI.
- Scenario 6: The total treatment capacity of hospitals Almelo, Ahaus, Gronau, Winterswijk and Stadtlohn is reached. The German hospitals are reaching their maximum treatment capacity quickly since they cannot handle lots of casualties per hour.
- Scenario 7: shows that the extra T1 treatment capacity of hospital Enschede is used in the second hour of the MCI. Furthermore, the same hospitals are reaching their maximum treatment capacity as in Scenario 1.
- Scenario 8: Hospital Enschede is not used and results in more hospitals reaching their maximum treatment capacity per hour.

The trip compositions are analyzed (see Figure 17). In Scenario 0 all the T1 casualties are scheduled on trip 0. On the total number of ambulances, including 47 ambulances, 55.3 % are transporting a T1 casualty on trip 0 and 44.7 % are transporting a T2 casualty. The ambulances making a trip 1 transport T2 casualties. Scenarios 1 and (3-8) have the same trip composition. Therefore, those trip compositions are not depicted and do not need more explanation.

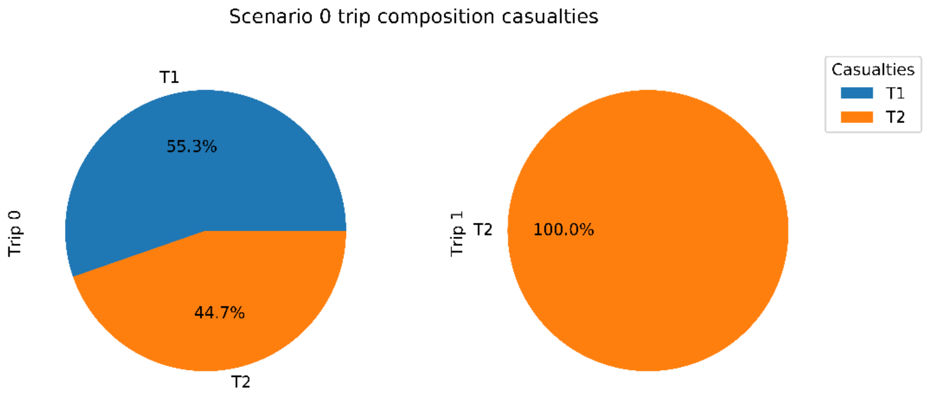

Figure 17 Trip composition scenario 0

Scenario 2 has a different trip composition in comparison to Scenarios (0-1) and (3-8) (see Figure 18). In Scenario 2, 16.3 % of the ambulances are transporting T1 casualties on trip 1. In comparison to the other scenarios, all the T1 casualties are scheduled on trip 0. By scheduling a few T1 casualties on trip 1, more ambulances transport T2 casualties on trip 0. The ambulances on trip 0 transport 40.4 % T1 casualties and 59.6 % T2 casualties.

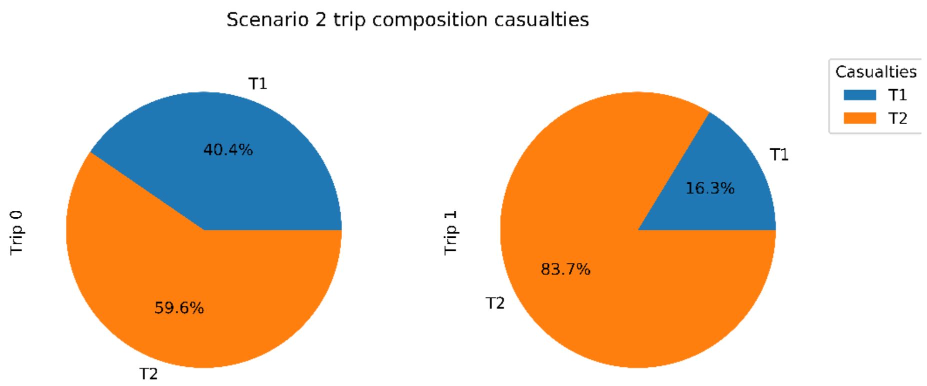

Figure 18 Trip composition scenario 2

6.4. Conclusion

The ILP program presents all the possible decisions that were possible for the ETS exercises of autumn 2019. Moreover, the performance of the ILP model is comparable to those ETS exercises.

The ILP model has a T1 makespan of 109 minutes on day 1 and 110 minutes on day 2. The ETS exercise of autumn 2019 has a T1 makespan of 140 minutes on day 1 and 121 minutes on day 2. The ILP model improves the T1 makespan of the ETS exercise by 31 minutes on day 1 and 11 minutes on day 2.

The T2 makespan of the ILP model is 181 minutes on day 1 and 195 minutes on day 2. For the ETS exercises, the T2 makespan on day 1 is 210 minutes and on day 2 203 minutes. The ILP model improves the T2 makespan by 29 minutes for day 1 and 8 minutes for day 2.

In the ILP model, no casualties arrive late at the hospital, while in both ETS exercises, one T1 casualty arrives late at the hospital. Furthermore, no treatment capacity is violated by the models, while in the ETS exercises, this happens a few times. The trip composition of the models is the same as in the ETS exercises.

On the contrary, the ILP model is performing worse on the average T1 and T2 throughput time. On day 1, the average T1 throughput time for the model is 63.7 minutes and for the ETS exercise, this is 54.2 minutes, which is 9.5 minutes longer. The average T2 throughput time of day 1 is in the ILP model 65.6 minutes and in the ETS exercise 54.4 minutes, which is 11.2 minutes longer. We observe the same on day 2. On day 2, the average T1 throughput time for the model is 67.3 minutes and for the ETS exercise, this is 55.1 minutes. The average T2 throughput time of day 2 is in the ILP model 69.9 minutes and in the ETS exercise 55.7 minutes.

In conclusion, a trade-off is going on between the average throughput time and the makespan. This is supported by looking at the ranges in which the ambulances are finishing trip 1. In the ETS exercise (day 1), the ambulance completing trip 1 first is ambulance after 127 minutes and the last ambulance is after 210 minutes. A range of 83 minutes is found. In the ILP model (day 1), the first ambulance completing trip 1 is within 151 minutes and the last ambulance is within 181 minutes, which is a range of 30 minutes. On day 2, the same observation is done. In the ETS exercise (day 2), the ambulance completing trip 1 first is within 118 minutes and the last ambulance is within 203 minutes, which is a difference of 85 minutes. In the ILP model (day 2), the first ambulance that finishes trip 1 is within 162 minutes and the last finishing ambulance is within 195 minutes, which means a difference of 33 minutes. So, the range of the ILP model is much smaller than in the ETS exercise.

Several scenarios are performed on the ILP model. The best objective value is reached when six T1 casualties are allocated to a Level 3 hospital. In the scenario in which the T1 treatment capacity of hospital Enschede is increased by two, the second-best objective value is obtained. Both scenarios well on the number of casualties arriving late at the hospital.

In all the scenarios where the major incident hospital is forced to support, the same observation is obtained. Hospitalizing casualties at the major incident hospital is not the best strategy to improve the survival rate of casualties because the major incident hospital is relatively far away. The treatment capacity of the (surrounding) hospitals of AZE is sufficient to handle an MCI with many casualties.

The impact of allocating German ambulances to German hospitals has a minor impact on the objective value, T1 makespan and throughput time. The T2 makespan and the average T2 throughput time are higher but do not result in many casualties arriving late at the hospital.

The impact of closing hospital Enschede has a minor impact on the KPIs. Measuring no impact by closing hospital Enschede, which is the largest and highest hospital level in the region of AZE, indicates that the number of ambulances is the bottleneck of an MCI. Also, not allowing casualties to get hospitalized at German hospitals has almost no impact on the performance. This indicates once again that the number of ambulances is the bottleneck.

Chapter 7: Conclusion

This chapter is divided into three sections. Chapter 7.1 answers the main research questions. Chapter 7.2 describes the discussion of this research. Chapter 7.3 gives suggestions for future research and future ETS exercises.

7.1. Conclusion

In this section, the main research question is answered. The main research question is formulated as follows:

"What mathematical model can be developed to improve the assignment of casualties to hospitals with limited resources in case of an MCI?"

We have developed an ILP model that assigns casualties to hospitals that applies to different MCI scenarios with limited resources. We have shown that the ILP model improves various KPIs compared to the ETS exercises of autumn 2019. The treatment capacity of the hospital is not overwritten by the ILP model, while in the ETS exercises, this happens a few times. Moreover, in the ILP model, no casualties arrive late at the hospital. In both ETS exercises, one T1 casualty arrives late at the hospital.

The ILP model improves the T1 and T2 makespan of the ETS exercises. On day 1, The T1 makespan in the ETS exercise is 140 minutes and in the model, 109 minutes. The ILP model decreases the T1 makespan by 31 minutes. On day 1, the T2 makespan in the ETS exercise is 210 minutes and in the ILP model, this is 181 minutes. So, the ILP model decreases the T2 makespan by 29 minutes. On day 2, approximately the same decrease on the T1 and T2 makespan is found.

On the contrary, the average T1 and T2 throughput times are worse in the ILP model than in the ETS exercises. On day 1, the average T1 throughput time for the model is 63.7 minutes and for the ETS exercise of 54.2 minutes. The ILP model increases the average T1 throughput time by 9.5 minutes. On day 1, the average T2 throughput time for the model is 65.6 minutes and in the ETS exercise this is 54.4 minutes. The ILP model increases the average T2 throughput time by 11.2 minutes. On day 2, approximately the same increase on the average T1 and T2 throughput time is found.

In conclusion, a trade-off exists between the average throughput time and makespan. We have shown this by looking into the ranges of ambulances completing their trip. The finish time among the ambulances doing trip 1 variates less in the ILP model than the ETS exercise. On day 1, the first ambulance of the ILP model finishes trip 1 within 151 minutes and the last finishing ambulance within 181 minutes, which is a difference of 30 minutes. In the ETS exercise (day 1), the ambulance finishes trip 1 first within 127 minutes and the last ambulance after 181 minutes, which is a difference of 81 minutes. The same observation is done for day 2. In literature is found that the makespan is an important KPI and therefore, this KPI is minimized in the ILP model. Future research is needed to conclude which KPI is more critical and improves the survival rate of the casualties.

By adapting the base ILP model, several scenarios are conducted to conclude which scenarios improve the assignment of casualties to hospitals during an MCI. A scenario in which six T1 casualties are allocated to a Level 3 hospital and a scenario in which only T1 casualties are allowed to hospitalize at hospital Enschede is the best overall performing scenario. All the scenarios in which the major incident hospital is included results in having a worse performance. Therefore, we cannot recommend using the major incident hospital when the MCI is located in the region of AZE.

7.2. Discussion

The discussion section is divided into three subsections. Subsection 7.2.1. explains the theoretical contribution of this research. Subsection 7.2.2. describes the practical contribution of this research. Subsection 7.2.3. addresses the limitations of this research.

7.2.1. Theoretical contribution

During the literature review, we have noticed that the topic of MCIs has recently gained more attention due to the increase of terrorist attacks and the possible increase in natural disasters. While existing studies have studied MCIs in urban environments or environments where the casualties are spread over a large area, those studies did not address MCIs in a more rural place or MCIs on a single site location. Besides, in this research, the chosen MCI scenario is taking place in a cross-border area. As far as we know, only limited research is done on that topic. This thesis is the first start for further research to fill this gap. The restrictive assumptions and simplifications of the MILP model of Draijer (2017) are addressed and relaxed in this research. Lastly, the proposed ILP model in this thesis is generalizable and deployable for different kinds of MCIs. The number of casualties, ambulances, and hospitals' treatment capabilities can be changed and applicable for testing different locations and strategies.

7.2.2. Pratical Contribution

Comparing the ETS exercises executed before 2019, the ETS exercises of autumn 2019 are significantly improved. We have improved the ETS exercises even more by developing a model, which is deployable for analyzing future ETS exercises more objectively. Also, a better estimation of doing different scenarios is possible by using this model. The model variables and parameters are easily adaptable to a new scenario without doing a complete new ETS exercise. We suggest AZE to use this model for comparing future ETS exercises.

7.2.3. Limitations

An exact method, the branch and bound method, is used to find the optimal allocating of casualties to hospitals in case of an MCI. This method is an appropriate method for solving these types of problems. Due to the large problem size of this research, it does not solve to optimality in 24 hours. Heuristics or ILP algorithms such as column generation can be developed to make the model solvable within a reasonable time limit. Regardless, since the current feasible solution is in most KPIs better than the ETS exercises, it is appropriate to stop the solver and deliver the best solution. Furthermore, in the ETS exercises, the treatment capacities of the hospitals are sometimes violated. This could never happen in the ILP model, which is a big advantage since an ILP model always respects the constraints.

As previously mentioned, several scenarios are conducted on the model. Scenarios in which hospital Enschede or all the German hospitals are closed had almost no impact on the KPIs. This indicates that the number of ambulances is the bottleneck.

The collected data of the ETS exercises of autumn 2019 forms the input parameters of the ILP model. The more detailed this data collection was done, the more likely the ILP model presents a realistic MCI. During this research, it was sometimes questionable whether the data is reliable. Some changes were made to compare the ETS exercise with the model. Those changes include miscalculations in the ETS exercises and implementing discrepancies to the ILP model. Even though the ILP model might not fully present a realistic MCI due to those discrepancies in the data, it represents the executed ETS exercises of 2019 in a realistic way. For the ILP model, only one additional assumption is needed to describe the ETS exercises of autumn 2019.

7.3. Future work

Subsection 7.3.1. gives suggestions for future research. Subsection 7.3.2. recommends future ETS exercises.

7.3.1. Research

In future work, it is possible to include more complexity since we have shown that the model is capable of making realistic and correct decisions. As previously mentioned in Subsection 7.2.3., developing a (meta)heuristic is possible for further work. In this heuristic, stochastic elements such as the possibility of hospitalizing T1 casualties to a Level 3 hospital can be included. Moreover, Instead of using the T1 and T2 treatment time intervals, a survival probability function can be implemented to make the heuristic more realistic. By implementing those survival probabilities, it might be possible to answer which KPI, the makespan or average throughput time, is more important. Also, the time to stabilize and drop-off a casualty at a hospital has some time variation, which can be implemented in heuristics. Currently, the stabilizing and dropping off time are static parameters in the ILP model. The variation of those activities is derivable by doing data analysis on the trauma registration of AZE. Finally, making the travel times stochastic is another possibility to implement in a heuristic.

Finally, figuring out why dispatchers in the ETS exercise avoid reaching the maximum treatment capacity of hospitals. We hypothesize that the dispatchers prefer to be on the safe side and hence conservatively plan when it comes to the capacity constraints. A pass rate, which decides if a casualty is allowed to get hospitalized at a particular hospital or not, is advised when it is necessary to minimize the number of times the maximum hospital treatment capacity is reached.

7.3.2. Acute Zorg Euregio

Additional suggestions are provided to improve the execution of ETS exercises. We have the following suggestions:

- Check if all the variables of the ETS exercise are up-to-date. Making the ETS exercises more realistic creates higher engagement among the participants. Components that need to be checked on reality are the ambulances, travel times, and treatment capacities of the hospitals.
- Improve the documentation of the ETS exercises. Firstly, write down how the variables of the ETS exercises are derived. Secondly, describe the different components and the assumptions of the ETS exercise. Finally, whenever variables are changed, update them in the documentation. In this way, the ETS designer can look back and remembers how the ETS exercise is conducted.
- Discuss how the results should be logged in the ETS exercises. We developed a new excel sheet for logging the results of the ETS exercise. Appendix I is the implementation of this excel sheet explained. Also, feedback from the AZE experts on the given suggestions of this thesis is given.

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Appendix A: GGB chore chart

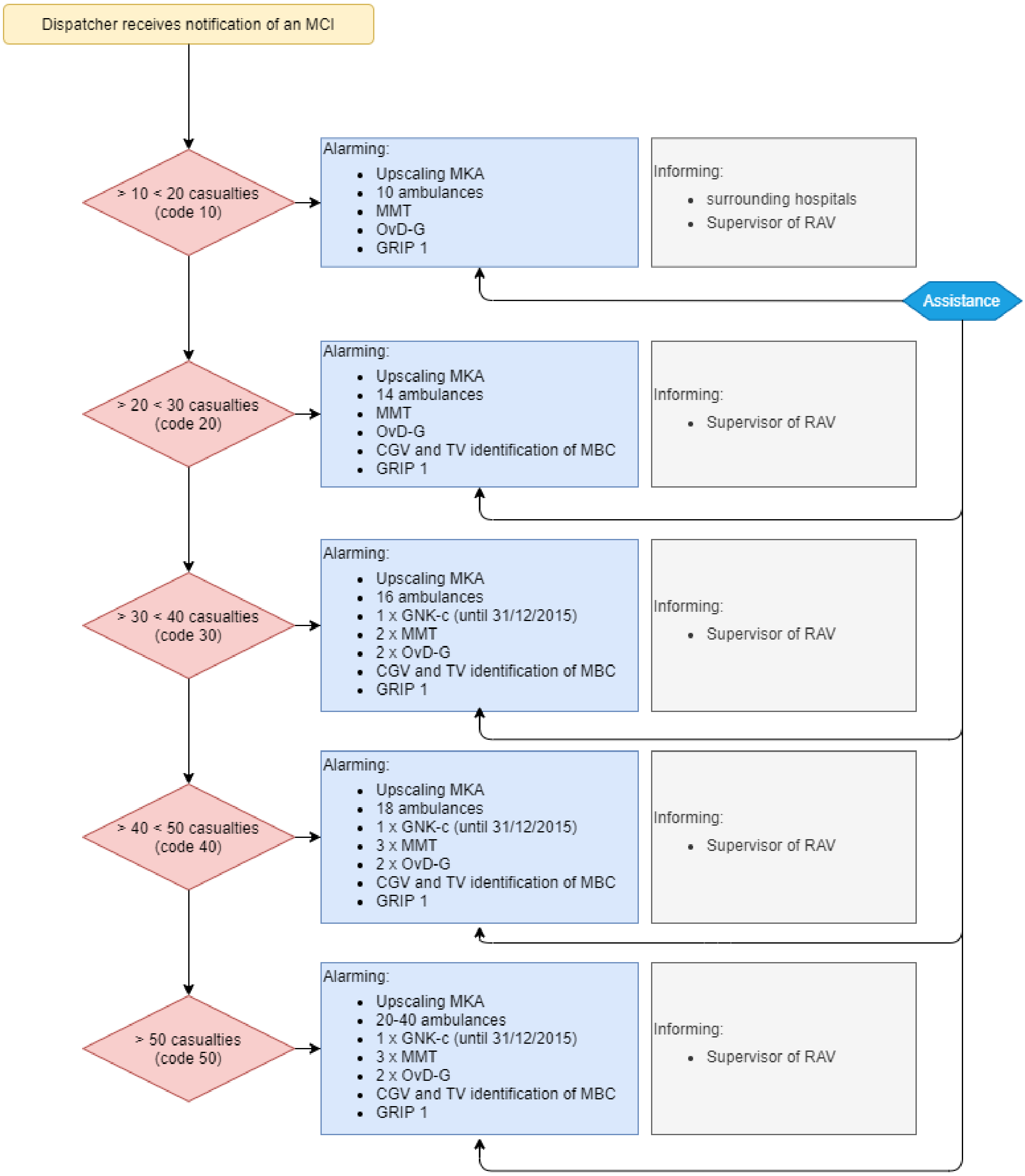

Figure 19 Tasks map of a dispatcher during an MCI (Source: Cools, 2015).

Appendix B: MIMMS Sieve flowchart

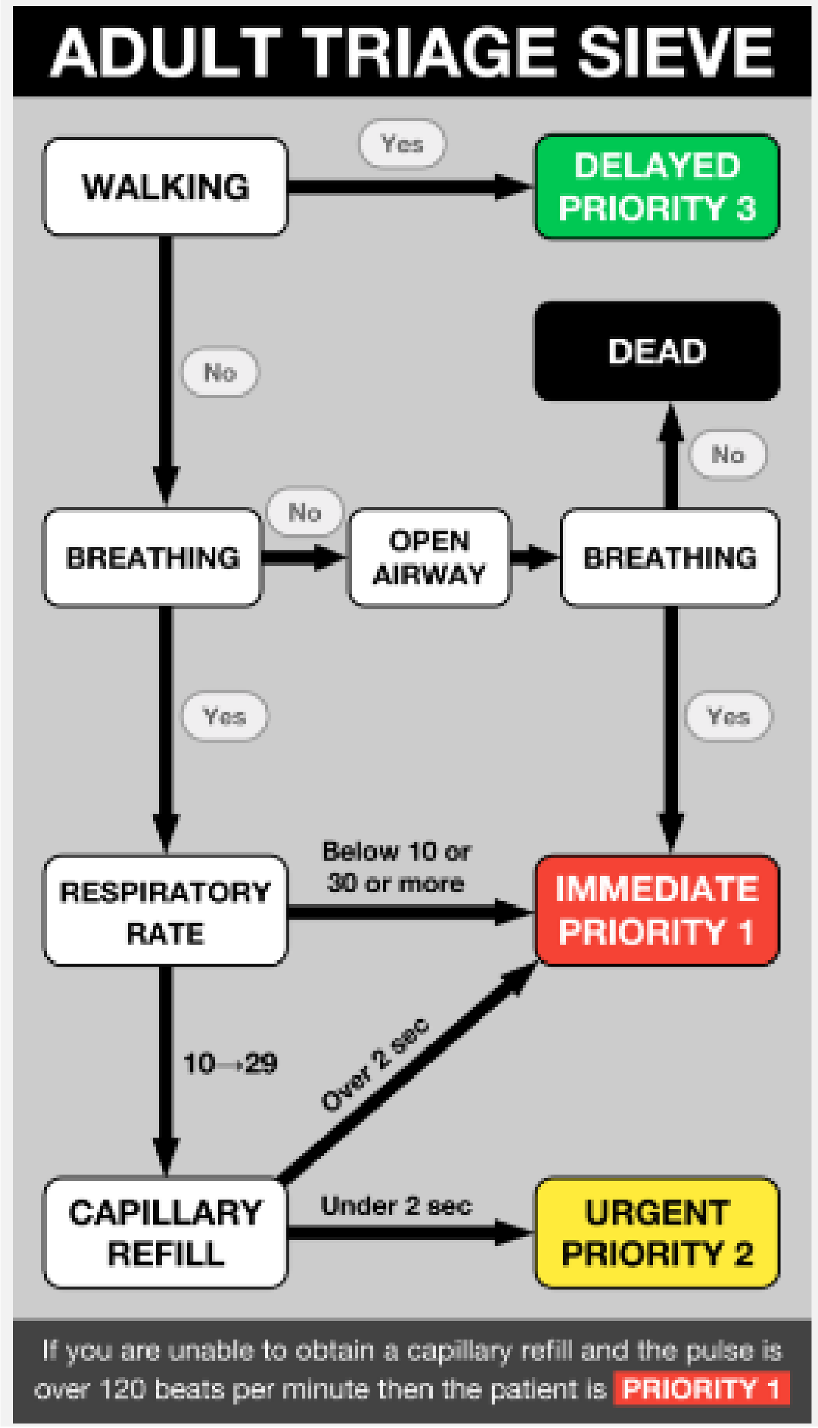

Figure 20 Adult triage sieve (Source: Sillet, 2018).

Appendix C: Interview ETS designer 15-08-2020

[Confidential]

Appendix D: Transportation times

[Confidential]

Appendix E: Summary results of the ETS exercise in autumn 2019

[Confidential]

Appendix F: Scenarios constraints

Scenario 0 is the base model, which is described in Chapter 4.2. For conducting the Scenarios (1-4) and 6, additional or changing the constraints is needed to conduct the scenario. Those changes in comparison to the base model are addressed in this appendix.

Scenario 1

In Scenario 1, six T1 casualties are allocated to a Level 3 hospital. To make this possible, we have defined an additional subset and constraint to make this happen:

P^{T1L3} subset of T1 patients who get allocated to a level 3 hospital $\subseteq P$

$$\sum_{h=1}^{H}\sum_{v\in V}\sum_{k\in K} Z_{hpvk} = 1 \qquad \forall\, p \in P^{T1L3}$$

Scenario 2

In the base model (Scenario 0) each T1 casualty is allocated to a Level 1 or Level 2 hospital. In Scenario 2, each T1 casualty is assigned to the major incident hospital. To make this possible, we have to change constraint (3) of the base model. In Scenario 2, constraint (3) looks as follows:

$$\sum_{v\in V}\sum_{k\in K} Z_{H^{MAJ}pvk} = 1 \qquad \forall\, p \in P^{T1}$$

Scenario 3

In the base model (Scenario 0) each T2 casualties is allocated to a hospital. The level of the hospital does not matter. In Scenario 3, each T2 casualty is assigned to the major incident hospital. To make this possible, we have to change constraint (4) of the base model. In Scenario 3, constraint (4) looks as follows:

$$\sum_{v\in V}\sum_{k\in K} Z_{H^{MAJ}pvk} = 1 \qquad \forall\, p \in P^{T2}$$

Scenario 4

In the base model (Scenario 0) each T1 casualty is allocated to a Level 1 or Level 2 hospital. Furthermore, each T2 casualties is allocated to a hospital. In Scenario 4, each casualty is assigned to the major incident hospital. To make this possible, we have to change the constraints (3-4) of the base model. In Scenario 4, constraint (3-4) are merged into the following constraint:

$$\sum_{v\in V}\sum_{k\in K} Z_{H^{MAJ}pvk} = 1 \qquad \forall\, p \in P$$

Scenario 6

Scenario 6, forces German ambulances to travel to German hospitals in the MCI. An additional subset and constraint are needed to make this possible. The following subset and constraint are added:

V^{GER} subset of German vehicles $\subseteq V$

$$\sum_{h\in H}\sum_{p\in P} Y_{hpvk} - \sum_{h\in H}\sum_{p\in P} Z_{hpvk} = 0 \qquad \forall\, v \in V^{GER}, k \in K$$

Appendix G: Comparison of the ETS exercise and the ILP model

[Confidential]

Appendix H: Results scenarios

[Confidential]

Appendix I: Excel sheet

[Confidential]