Electric ambulances

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Preface

This master thesis is part of the Master Project Business Analytics, the last course towards graduating the master Business Analytics at the Vrije Universiteit Amsterdam. It contains the results of my research conducted at UMCG Ambulancezorg, a company that provides ambulance care in the dutch province Drenthe.

I would like to thank René Bekker, my supervisor from the Vrije Universtiteit. The meetings with René helped me to correctly formulate the mathematical optimization model and structure the report. Furthermore, I would like to thank my supervisor Jaap Hatenboer at UMCG Ambulancezorg for providing me all kinds of material related to electric vehicles. Although not officially involveded with this project, I also would like to thank Harriëtte Holt at UMCG Ambulancezorg. Finally, I would like to thank Elenna Dugundji for being my second reader.

Hessel Jonker
Zwolle, November 2017

Abstract

Electric vehicles have some limitations, such as restricted driving range and the long time required for battery charging. The goal of this research is to determine the impact of electric ambulances on the availability of ambulances and on the performance of the ambulance network of UMCG Ambulancezorg for different battery sizes and charging speeds.

We also investigate if another policy than 'return to post after serving a call' could erase the negative impact of electric ambulances on the availability and performance. Therefore, we develop two optimizations models. The goal of the optimization models is to maximize the difference between the battery level and the expected energy consumption of the ambulance with the smallest difference. The first model decides if an ambulance should drive to another post, swap the ambulance vehicle and drive back to post with the other vehicle, instead of driving back to post immediately after serving a patient. The second model possibly relocates ambulances to another post. A simulation model is developed to determine the impact of elecetric ambulances and the optimization models.

Simulation results show that electric ambulances have no impact on the availability of ambulances nor on the performance of the ambulance network when ambulances are equipped with a relatively large battery (80+ kWh) in combination with a low charging speed (10 kW/s), or when ambulance are charged at the post or at the hospital with a relatively high charging speed (20+ kW/s) in combination with a small battery (60 kWh). On the other hand, ambulances equipped with a small battery (≤60 kWh) and which are charged with a low charging speed (≤5 kW/s), negatively impact the availability of ambulances and the performance significantly. The performance decreases with 0.6 percentage point, the response time increases with 5 seconds and the overall kilometers driven per week increases with 140 kilometers. The first optimization model is able to erase the negative impact on the performance and the response time while it increases the weekly driven kilometers with 730. The second model results in even more kilometers driven per week than model 1 but is not able to erase the negative impact.

Because the simulation model is based on some assumptions, we do not recommend to replace all ambulances by electric ambulances at ones. Instead, we recommend to start with one electric ambulance at post Roden to gain experience. Roden is located close to the university medical center Groningen (UMCG) which is the only hospital in the north of the Netherlands to provide all advanced care. Therefore, the ambulance of Roden never needs to travel big distances. If the experience is positive, we recommend to expand electric ambu-

lances to the posts Assen, Annen, Eelde, Borger and Dieverbrug because these posts are situated near Groningen. We recommend to replace the ambulances at the posts Meppel, Hoogeveen, Beilen, Coevorden, Emmen, Klazinaveen and Emmen Noord as last because these posts are located relatief far away from Groningen.

Contents

1. Introduction

Motivation

UMCG Ambulancezorg provides ambulance care in Drenthe, a province of the Netherlands. In 2015 roughly 30.000 urgent calls were served by 20 ambulances with an internal combustion engine (ICE). It is estimated that these vehicles produce an estimate of 1.200.000 kg of CO2. Electric vehicles (EV) are a possible solution for UMCG Ambulancezorg to reduce the emission of CO2 caused by ambulances with an ICE. However, electric vehicles "have some limitations owing to current battery technology, such as restricted electric driving range and the long times required for battery charging" [15]. These limitations possibly make ambulances less available to provide ambulance care. Although there are currently no electric ambulances available on the market, UMCG Ambulancezorg wants to know what the charging speed and battery capacity should be of an electric ambulance (EA) such that an EA has no significant negative impact on the availability of ambulances and on the performance of the ambulance network. In the current situation ambulances return to their post after serving a patient. Another policy could involve swapping ambulance vehicles. Instead of driving directly to their post, the ambulance drives to another post, exchange the current ambulance vehicle for the ambulance vehicle at the other post and then drives back to its post. It is yet unclear if another policy could decrease or even erase the negative impact of EA's on the availability of ambulances and the performance of the ambulance network.

Research question

The project is focussed on the impact of electric ambulances on the availability of ambulances and the performance of the ambulance system. Availability refers to how often an ambulance is not dispatched due to energy shortage whereas the ambulance is the first choise to sent to a patient if it had enough energy. Performance relates to performance indicators like the average response time (time between start call and arrival of the ambulance at the patient) or the fraction of calls of which the response time is less than X minutes. This leads to the following research questions:

- What is the impact of electric ambulances on the availability for different battery sizes and charging speeds?
- What is the impact of electric ambulances on the performance for different battery sizes and charging speeds?

Other policies could possibly erase the negative impact of EA's on the availabilty and performance. This leads to the following research questions:

- Does another policy than 'return to post after serving a call' improves the availability of EA's?
- Does another policy affects the performance?
- Does another policy leads to more ambulance movements and distance traveled?

The bigger objective of this research is to give insight in which ambulances could possibly be replaced by an EA in the current situation and what the charging speed and battery capacity of the EA should be. A simulation model is developed and used to answer the research questions and evaluate policies.

Outline

The structure of this thesis is as follows. Chapter 2 discusses briefly ambulance care, electric vehicles and ambulances planning. Result of data analysis are presented in chapter 3. The simulation model is described in chapter 4 and chapter 5 describes the optimization models as alternative to the policy 'return to post after serving a call'. Chapter 6 contains the results of the simulations and chapter 7 presents the conclusion and recommendations. The outcome of various statistical tests are presented in the appendix.

2. Background information

This chapter gives a short overview of ambulance care, electric vehicles and ambulance planning.

Ambulance care

According to the sector organisation Ambulancezorg Nederland [12] ambulance care "is the mobile care provided professionally to a patient with a condition or injury, . . . and, if necessary, the responsible transport of a patient or the referral of a patient to another care provider. The main objective of ambulance care is to prevent or limit damage to health based on the patient's care requirements." [13].

The ambulance process starts with a call to the dispatch centre. An operator of the dispatch centre answers the call and starts asking questions to determine the location of the patient, the type of ambulance care required and the priority of the call. If the call requires ambulance care an operator assigns an ambulance to the call and alarms the crew of the assigned ambulance. After being alarmed the ambulance crew starts driving to the call location. Once the ambulance arrives at the scene, the nurse starts examining and treating the patient and is thereby supported by the driver. If the patient needs medical treatment at a hospital, the crew prepares the patient and transports the patient to the hospital. At the hospital the patient is handed over to a doctor or nurse of the emergency department. If the patient needs no medical treatment at a hospital, the nurse refers the patient to another care provider or gives care advise and the ambulance leaves without transporting the patient. After the patient has been treated at the scene or has been transported to a hospital, the crew contacts the dispatch centre which assigns them to a new call or sends them to their post.

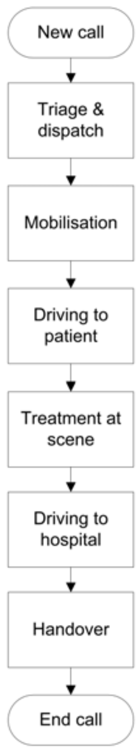


Figure 2.1: ambulance process

Ambulance care consist of a couple of components that interact over time and that form a complex whole, the ambulance system. Table 2.1 shows the various components of the ambulance system. The dispatch centre determines the care needs of the patient and coordinates the ambulances and thereby it is the link between the patient and the ambulance.

Table 2.1: components of a ambulance system

Component	Description
patient	person who receives ambulance care
crew	ambulance nurse and driver
ambulance	vehicle used to transport patient and crew
dispatch centre	link between patient and ambulance
road network	collection of roads used to travel
hospital	care facility where patient receives further treatment
post	location where a shift waits to be dispatched

Electric vehicle

Energy consumption

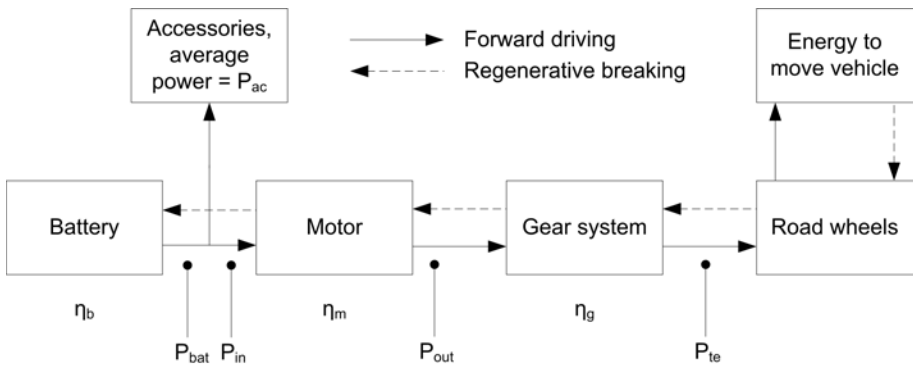


Figure 2.2: Energy flow of a battery powered electric vehicle. Derived from figure 7.13 of [9]

Each vehicle moves because a motor converts an energy source into motion and delivers it to the wheels through a drive shaft and gear system. This process is visualized in figure 2.2 for a battery powered electric vehicle where the battery supplies an amount of P_{bat} electric power of which P_{in} is used by the electric motor. The electric motor produces P_{out} mechanical power and the drive shaft and gear system delivers P_{te} mechanical power at the wheels. Equation 2.1 describes the relationship between P_{bat} and P_{te} [9]. Note that P_{bat} is always larger than P_{out} and P_{te} because the efficiency of an electric motor, η_m, and the efficiency of a gearbox, η_g, is never 100%. When the motor is used to slown down the vehicle, it converts motion into electricity and this is known as regenerative braking.

The power supplied at the wheels per second (Ws) consists of accelerating, air, gradient and rolling resistance. Hence, the power supplied at the wheels can be estimated using equation 2.2. Table 2.2 denotes all variables used by equation 2.2 to calculate P_{te}. Variables such as A, C_D, M are constants but varies per vehicle while variables like ρ, θ and g are location dependent. The rolling resistance coefficient depends on the type of road and vehicle tire. This equation is used by [18] to estimate the theoretical energy consumption of a

Table 2.2: definition variables equation 2.2

variable	description	variable	description
A	projected area of the EV [m^2]	M	mass [kg]
θ	roadway grade [degree]	v	velocity [m/s]
τ	rolling resistance coefficient	α	acceleration [m/s^2]
C_D	air resistance coefficient	ρ	air density [kg/m^3]
g	G-force [m/s^2]		

converted Nissan D21 pick-up. [18] compare the estimation with the actual energy consumption and conclude that the equation "can successfully estimate EVs instantaneous power and trip energy consumption". The same equation is used by [6] to compare the theoretical and empirical energy consumption of a Mitsubishi i-MiEV. [6] also conclude that "the estimated value is almost same with the observation value".

$$P_{bat} = P_{in} + P_{ac} \qquad P_{in} = \frac{P_{out}}{\eta_m} \qquad P_{out} = \frac{P_{te}}{\eta_g} \tag{2.1}$$

$$P_{te} = R_{accelerating} + R_{air} + R_{gradient} + R_{rolling} \tag{2.2}$$

$$= M \cdot v \cdot \alpha + \frac{\rho}{2} \cdot C_D \cdot A \cdot v^3 + M \cdot g \cdot \sin(\theta) \cdot v + \tau \cdot M \cdot g \cdot v \tag{2.3}$$

Charging

A vehicle with an ICE can be refuelled within a couple of minutes while charging an EV takes much more time. For instance, charging a BMW i3 with a 33 kWh lithium ion (li-ion) battery for 80% takes at least 30 minutes, whereas the range is roughly a fourth of a conventional vehicle [4]. Besides the battery capacity, the charging time depends on the infrastructure used. Charging a Nissan Leaf with a 30 kWh battery for 80% takes roughly 30 minutes at a fastcharging station which can be found most often near highways nowadays. At home, the Leaf can be fully charged using a special charging station or the normal power network within 5.5 and 12 hours, respectively [14].

Figure 2.3 shows characteristic curves of a li-ion battery where the green, red and blue curves represent the battery voltage, current and state-of-charge (SOC), respectively. A fully charged battery has an SOC of 100%. The slope of the blue and red lines are linear in the constant current (CC) region, roughly until 110 minutes, and non-linear afterwards in the constant voltage (CV) region. The current is equal to the charging speed (A) divided by battery capacity (Ah). By increasing the current, the slope of the blue line gets steeper while the CC region ends earlier. Usually, the charging time of a li-ion battery is linear in the range from 20% to 80/90% SOC [11]. Charging the upper 20% SOC can take as much time as charging the lower 80% SOC when using fast charging as shown in figure 2.4 for a BMW i3. After 50 minutes fast charging with 50 kW per second the yellow line reaches 80% SOC after 30 minutes and 100% SOC 20 minutes later. Observe that the orange, grey and yellow line of figure 2.4 have roughly the same shape as the green, red and blue curves of figure 2.3.

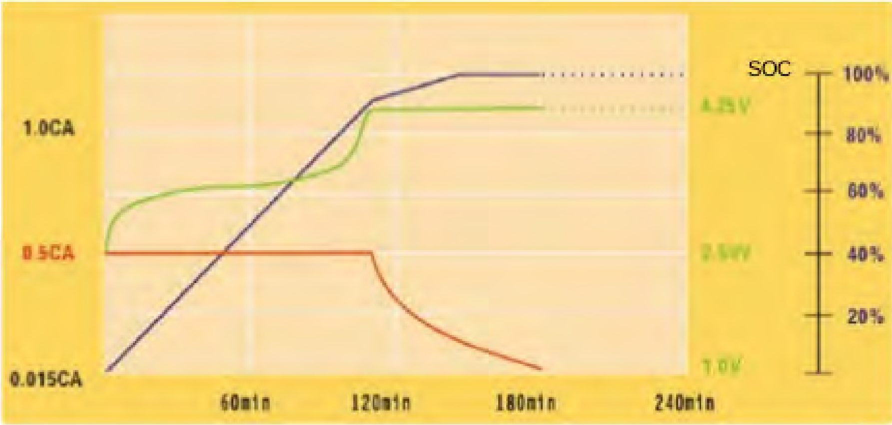


Figure 2.3: charging profile for an EV Li-ion battery [11]

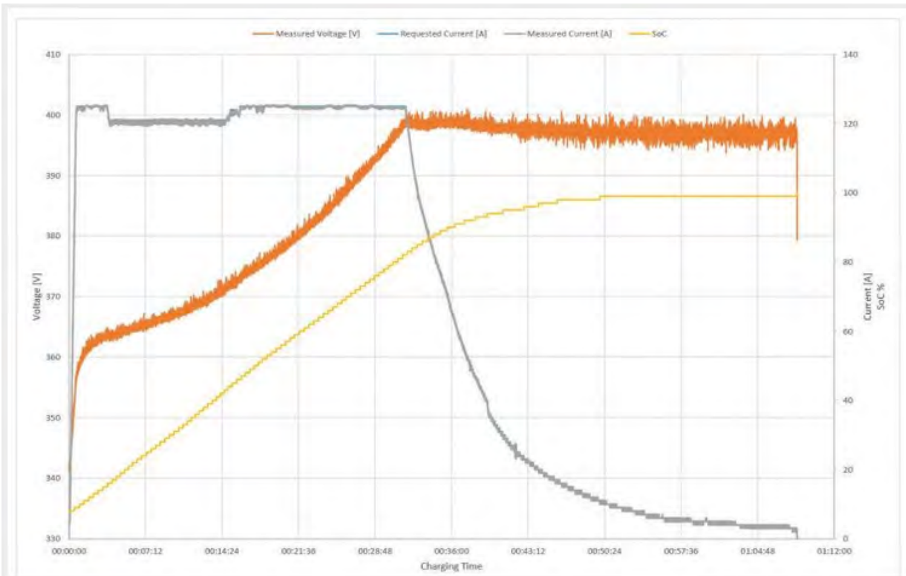


Figure 2.4: charging profile 33 kWh BMW i3 fast charging – 8-80% in 30 minutes [7]

Ambulance planning

In this chapter we describe two common models used for ambulance planning based on [5], [1] and [10]. These models are defined on graphs.

Location set covering model

The aim of the location set covering model (LSCP) is to minimize the number of ambulance post needed to cover all demand points. The set of demand points is denoted by $\boldsymbol{V}$ and the set of potential ambulance posts is denoted by $\boldsymbol{W}$. A demand point $i \in V$ is said to be covered by post $j \in W$ if $t_{ij} \leq r$ where t_{ij} is the shortest travel time from vertex i to vertex j and r the distance threshold for a demand point to be considered as being covered. The set of posts covering demand node i is denoted as $W_i = \{j \in W : t_{ij} \leq r\}$.

$$\begin{array}{lrcll} \min & \sum_{j \in W} x_j & & & \\ \text{s.t.} & \sum\limits_{j \in W_i} x_j & \geq & 1 & i \in V \\ & x_j & \in & \{0,1\} & j \in W \end{array} \tag{2.4}$$

Here, x_j is 1 if located at vertex j and 0 otherwise.

Maximal covering location problem

The aim of the maximal covering location problem (MCLP) is to maximize coverage for a fixed number of p ambulances. The sets W, V and W_i are equaly defined as for the LSCM. The first constraint ensures that each demand point i is covered at least once while the second constraint ensures that p ambulances are used to cover all demand points.

$$\begin{array}{lrcll} \max & \sum_{i \in V} d_i y_i & & & \\ \text{s.t.} & \sum\limits_{j \in w_i} x_j & \geq & y_i & i \in V \\ & \sum\limits_{j \in W} x_j & = & p & \\ & x_j & \in & \{0,1\} & j \in W \\ & y_i & \in & \{0,1\} & i \in V \end{array} \tag{2.5}$$

Here, x_j is 1 if an ambulance is located at vertex j, y_i is 1 if vertex i is covered by at least one ambulance, d_i denotes the demand of vertex i and p denotes the number of ambulances.

3. Data analysis

It is common to model the arrival of patients as a non-homogeneous Poisson process and non-driving process times like *at scene* as a random variable. This chapter shows that it is plausible to model the arrival of patients as a non-homogeneous Poisson process and that the spatial distribution of calls is equal per hour, day and month. Furthermore, statistical distributions are fitted using historic data for non-driving process steps. Finally, process times involving driving are compared to driving times based on a route planner.

Number of calls per day and hour

Characteristic for ambulance care is the random appearance of patients in space and time and the varying duration of the different process times per patient. This means, the location and time of the next patient and the duration of the process times are unknown. It is common to model the arrival of patients as a non-homogeneous Poisson process [1][16]. A Poisson process is described by [8] as follows: Let $N(t)$, for every $t \in [0,\infty]$, be a random variable that counts the number of events in $[0,t]$. Then we call $N(t)$ a counting process. We also define $N(s,t) = N(t) - N(s)$, the number of arrivals in $(s,t]$, for $0 \leq s < t$. The counting process $N(t)$ on $[0,\infty)$ is called a (homogenous) Poisson process with rate λ if:

- $N(s,t)$ has a Poisson distribution with expectation $\lambda(t-s)$ for all $0 \leq s < t$;
- $N(s,t)$ and $N(s',t')$ are stochastically independent for all $0 \leq s < t \leq s' < t'$.

When λ depends on t, the Poisson process is called a non-homogeneous Poisson process and $N(t,s)$ has a Poisson distribution with expectation $\int_s^t \lambda(\mu) d\mu$. Figure 3.2 shows that the number of urgent calls per hour depends on the weekday and hour of the day. Besides the first six hours of the Sunday, the number of urgents calls per hour is roughly the same for each day of the week. Therefore, if we model the arrival of patients as Poisson process, we should model it as a non-homogeneous Poisson process. Although it is difficult to formally show that all $N(s,t)$ are stochastically independent, we can argue why it is a reasonable assumption. First, the time and location of a patient is independent of the time and location of the previous patient. Second, the number of calls differ per day. The graphs of figure 3.1 show the number of calls per day of the year 2016 for the whole day and the hours 7, 13 and 19. Clearly, the number of calls differ per day and it looks like there is no correlation between hours. Therefore, the stochastically independency seems to hold for the arrival of patients.

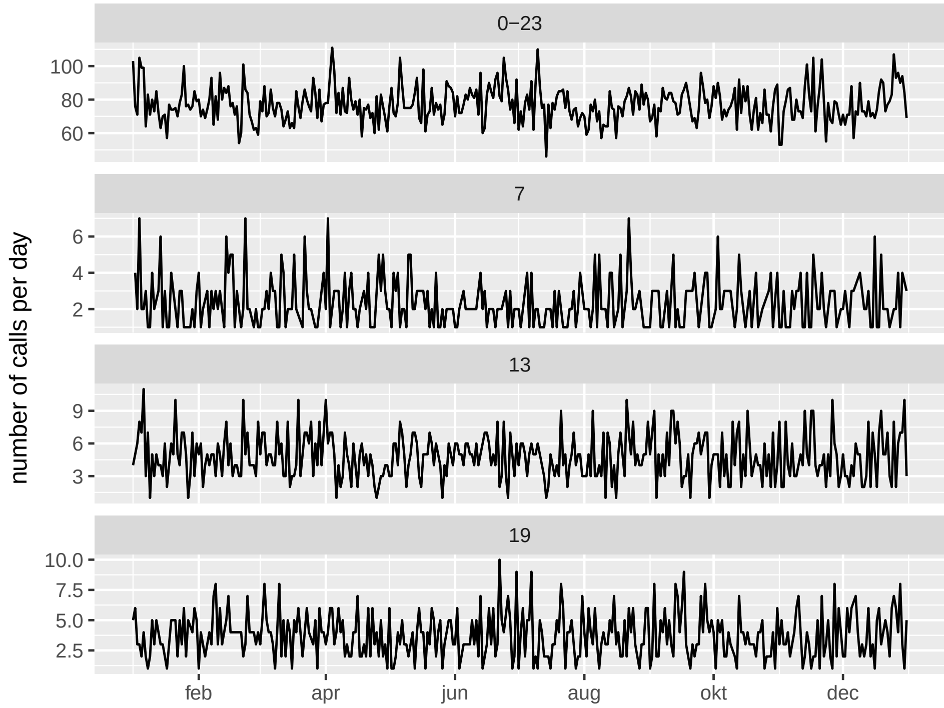


Figure 3.1: number of calls per day

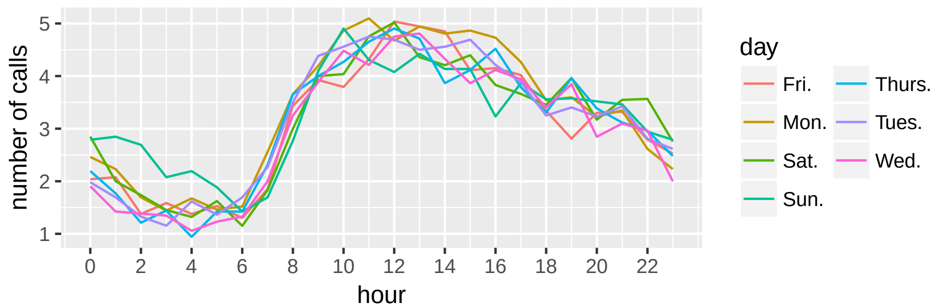


Figure 3.2: average number of calls per weekday and hour 2016

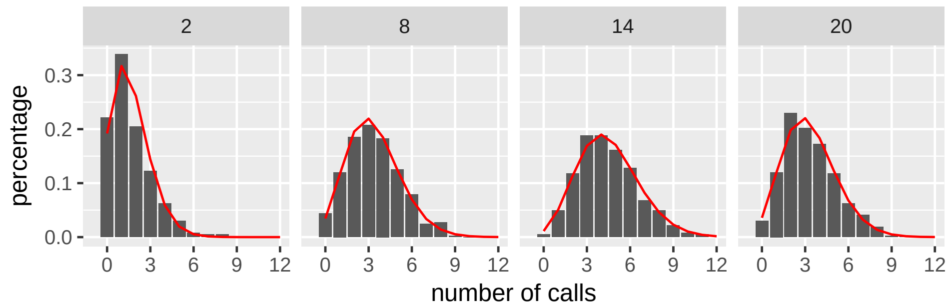


Figure 3.3: distribution of the number of calls per hour

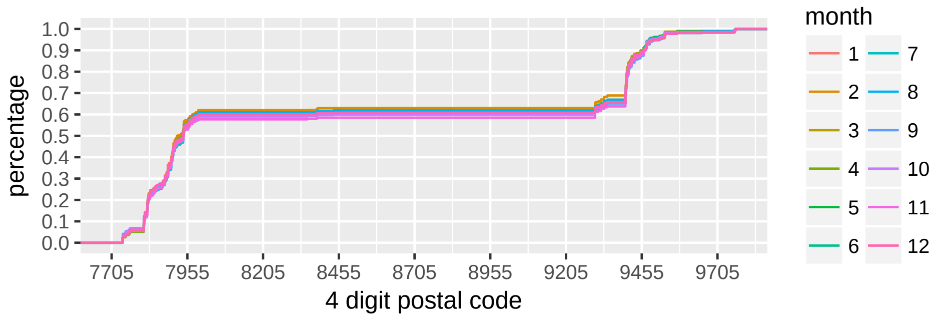


Figure 3.4: 2016 historic distribution of urgent calls over the postal codes per month

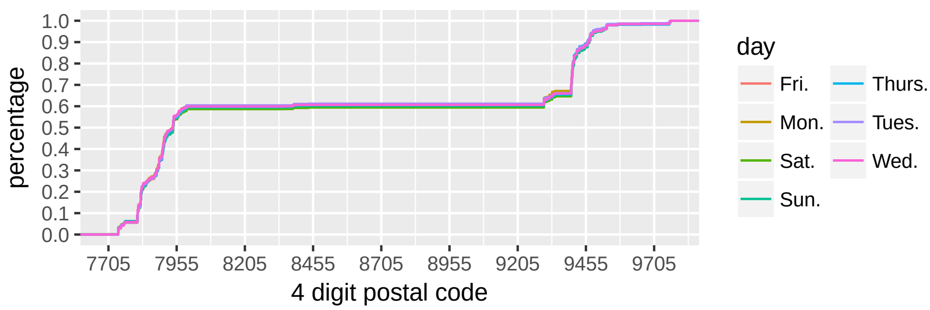


Figure 3.5: 2016 historic distribution of urgent calls over the postal codes per day

Figure 3.3 shows the emperical distribution of the number of calls per day and hour with the red line the Poisson distribution with $\lambda = mean$. A chisquare-test is used to test if the emperical distribution can be desribed by a Poisson distribution. Section A of the appendix describes the chisquare-test and the results. Only the hours 2 and 23 have a p-value smaller than 0.05 which indicates that the emperical distribution can be desribed by a Poisson distribution. Therefore, the Poisson distribution requirement of the definition seems to hold for the arrival of patients. Because both requirement of the Poisson process definition seem to hold for the arrival of patients, modeling the number of calls per day and hour as a non-homogeneous Poisson process is a reasonable choice.

Distribution of calls

Figure 3.4, 3.5 and 3.6 shows how urgent calls are distributed over the different postal codes per month, weekday and time blocks of 4 hours. Based on these figures it looks like calls are spread over the postal codes with a certain chance which is equal per month, weekday and hour. Figure 3.7 shows the spatial distribution of calls over the region which is divided in squares of 2.5 kilometers. The color of the squares indicate the chance that a call occurs in that square. The red dots are the location of the ambulance posts.

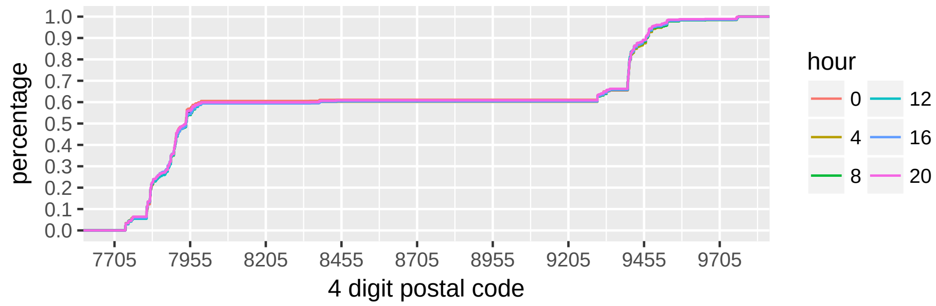
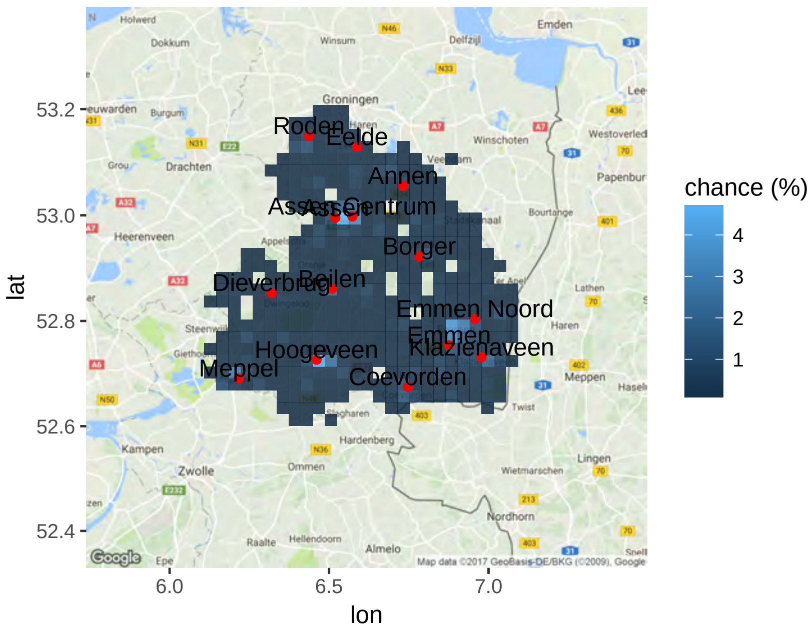


Figure 3.6: 2016 historic distribution of urgent calls over the postal codes per hour

Figure 3.7: Spatial distribution of calls



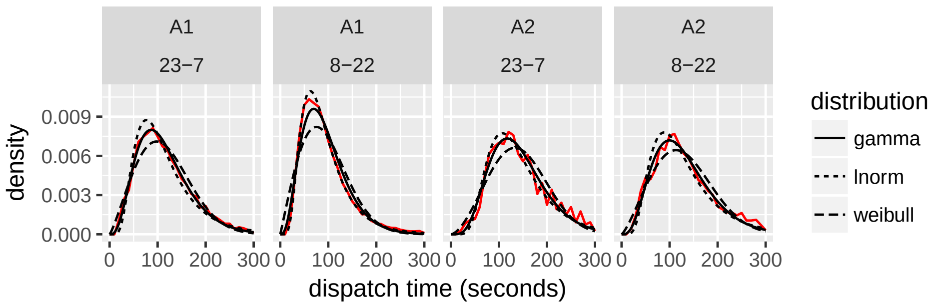


Figure 3.8: distribution dispatch time

Process times

The process times *dispatch time*, *mobilization time*, *at scene time* and *handover time* are positive, continuous and asymmetric. Therefore, the gamma, the log-normal and the weibull distribution are fitted on the historic data using the R package fitdistrplus. Fitdistrplus uses the maximum likelihood estimation (MLE) method for parameter estimation. The Kolmogorov-Smirnov test is used to test if the distributions have a good fit with the emperical process times. Section A contains the results of the Kolmogorov-Smirnov test with the parameter values. Figure 3.8, 3.9, 3.10 and 3.11 show the fitted distributions (black line) and the historic data (red line) of the dispatch time, mobilization time, at scene time and handover time, respectively. These figures show that the process times can differ per time period and priority. The dispatch times differ at night from day time for urgent calls (A1), probably because of a different triage method during these two periods at the dispatch centre. Furthermore, because the ambulance crew is sleeping at night, the mobilization times are longer than during the day and evening. The time at scene is much longer when the patient is not transported. For urgent calls, the handover time is only a little bit longer. The final distribution and parameters used in the simulation model can be found in section B of the appendix.

Driving time

The duration of process steps which involves driving such as *Driving to patient* probably depends on the start and destination location of the ambulance and time of departure. Figure 3.12 shows a scatter plot of the historic driving times and the theoretical driving times of the process step *Driving to patient* when driving with lights and sirens. Open Source Routing Machine (OSRM) 5.8.0 is used to calculate the theoretical driving times. An advantage of OSRM is that it gives the location and the time of point in the route which can be used to detemine the location of ambulances in the simulation. Because ambulances exceed the speed limit when driving with lights and sirens, the speed limit used by OSRM is increased by 20%. Points of which the emperical and theoretical driving times are equal lie on the red line. Clearly, the theoretical and historic driving times sometimes differ more than 50 seconds.

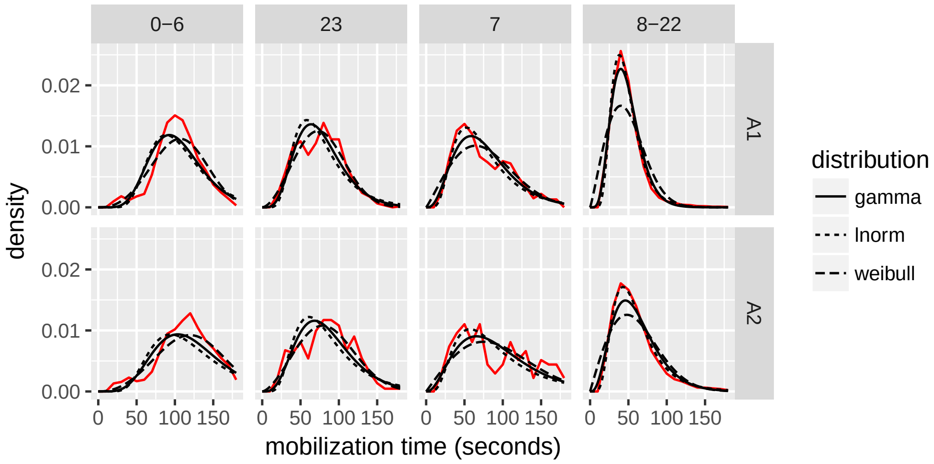


Figure 3.9: distribution mobilization time

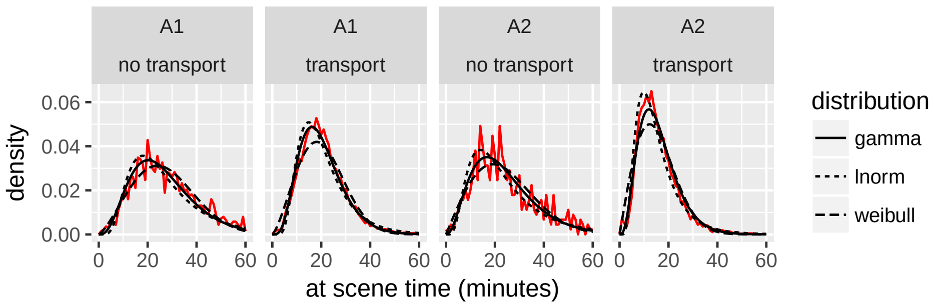


Figure 3.10: distribution at scene time

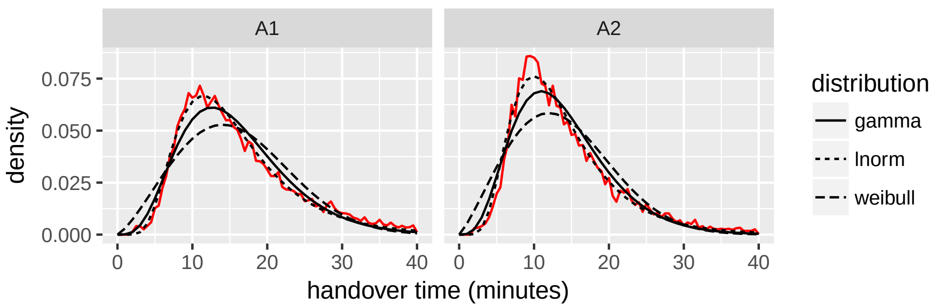


Figure 3.11: distribution handover time

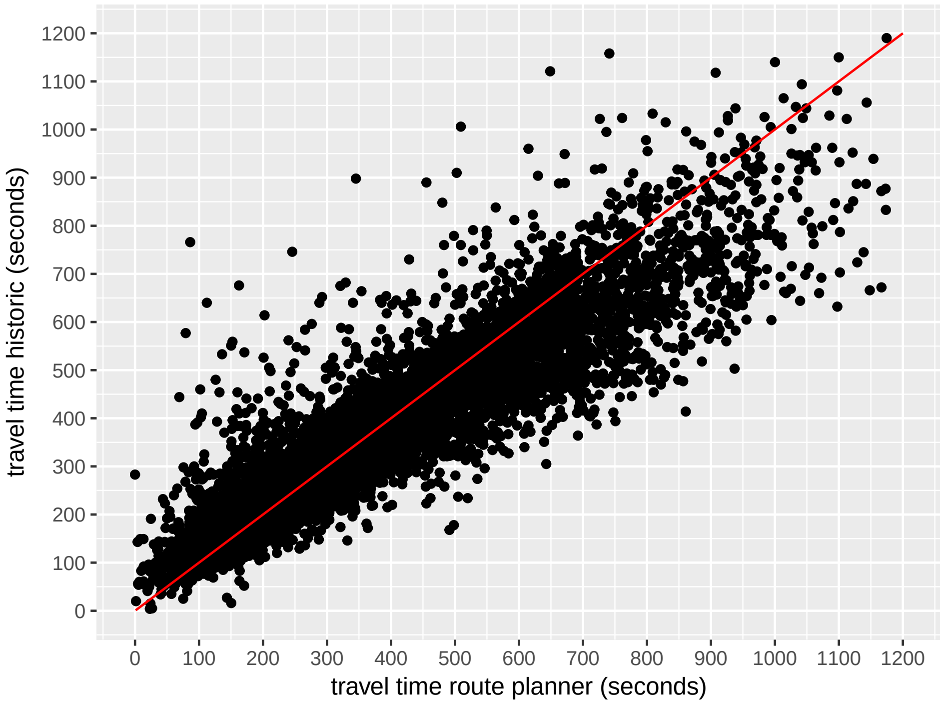


Figure 3.12: scatter plot historic travel time and travel time route planner

4. Simulation model

A generic simulation model is described by [16] and three core components are distinghuised: (i) call generation, (ii) dispatch of ambulances, and (iii) ambulance journey. This section describes four processes: the call generator process which generates calls, the dispatch centre process who assigns an ambulances to calls, the ambulance process which serves calls and the scheduler process which ensures that ambulance shifts start and end. We describe how the energy consumption is modelled within the simulation. Finally, we validate the simulation model. First, the simulation model is discussed.

Process-oriented approach

The simulation models the ambulance system and can be classified as a discrete-event dynamic system (DEDS). This means that the state of the model evoles over time through jumps at discrete points in time. The state of the ambulance system is described by $\{X, S_1, L_1, B_1, \ldots, S_n, L_n, B_n\}$ with X the number of calls in the queue waiting to be assigned to an ambulance and S_i, L_i and B_i the state, the location and the battery level of ambulance shift i. Table 4.1 describes all possible states of an ambulance shift. The state of the ambulance system changes when a new call enters the system, when a call is assigned to an ambulance or when an ambulance changes from state. The simulation model is programmed in Java and uses the JavaSim package to implement the process-oriented approach. In contrast to the event-oriented approach, calls and queues are objects in the program that can be manipulated. The queue is a passive object that contain various calls (or empty), and the calls themselves contain information such as their arrival time and location of the patient. The call generator, the dispatch centre, the ambulance and the scheduler, however, are active objects (processes), which can interact with each other and the passive objects. Because of their dynamic nature, DEDS, require a time-keeping mechanism to advance the simulation time from one event or process to another as the simulation evolves over time. The mechanism recording the current simulation time is called the simulation clock. To keep track of events, there exists an event list that keeps track of the current and pending events ordered by their time of occurrence. With the process-oriented approach the event list contains processes. Essential to the process-oriented approach are the functions HOLD, PASSIVATE and ACTIVATE. The first function can only be used by and on an active process because HOLD interupts the execution of the currently active process temporarily. The process is then put further up in the event list. The second and third function can be used to passivate or activate processes. The

Table 4.1: All possible states of an ambulance shift

Status	Description
At post	Ambulance shift waits at post to be assigned to a call
Mobilizing	Ambulance crew makes its way to the ambulance and prepares itself for departure
Driving to patient	Ambulance drives to the location of the call
At scene	Ambulance is at the location of the call and the ambulance crew treats the patient
Driving to hospital	Ambulance transports the patient from the call location to the hospital
At hospital	Ambulance is at the location of the hospital and the ambulance crew transfers the patient to the hospital staf
Driving to post	Ambulance drives to the location of the post
End shift	Ambulance drives to post but is unavailable for new calls
Passive	Ambulance is at post but is unavailable for new calls

passivated process is then removed from the event list while an activated process is placed on the event list at the current time or at a specified time. In JavaSim each process is a thread. When HOLD is used the thread of the current active process is interrupted and the thread of the first process in the event list resumes where it was interrupted previously.

Main

The main class of the simulation is described by algorithm 1. The main function of this class is to initialize the simulation by creating all the passive and active objects and start the simulation by activating the call generator process.

Algorithm 1 Main

```
Initialize: create queue, call generator, dispatch centre, scheduler and ambulances
ACTIVATE call generator
HOLD(duration of simulation)
STOP
```

Call generator

The call generator is described by algorithm 2. The function of this object is to create call objects, place them in the queue and activate the dispatch centre. A call object consists of the following variables:

- arrival time call
- call location
- priority driving to call
- boolean if patient needs to be transported
- hospital to which the patient needs to be transported to

- priority driving to hospital

From the data analyses we know that the number of calls varies per weekday and hour but that the distribution of calls over the province is the same per month, weekday and hour. Therfore, we only need to generate arrival times for the whole province and then determine the location instead of generating arrival times for each subregion of the province. The arrival times are generated by a nonhomogeneous Poisson process with rates depending on the weekday and hour of the simulation time. The rates are equal to the average number of calls per day and hour of figure 3.2. The nonhomogeneous Poisson process is generated from a homogeneous Poisson process using thinning. The call location is generated in two steps and is similar to [16] which divides the spatial area into rectangles and uses an empirical discrete distribution for distributing calls on cells. First, a 4 digit postal code is generated from the empirical distribution of the urgent calls over the 4 digit postal codes. Second, an address is randomly drawn from the 4 digit postal code and the location of the address is used as call location. The call priority is non-urgent unless a sample from the standard uniform distribution is smaller than the corresponding percentage from figure B.1 which depends on the hour and day of the week. The same procedure is applied to determine if a call needs transport using figure B.2 which depends on the hour and day of the week and the priority of the call. The call destination is sampled from the empirical distribution of destinations which depends on the location and priority of the call.

The Apache Commons Math 3.6.1 library is used to generate random variables for the Poisson process and the other call attributes.

Algorithm 2 Call generator

t: time simulation clock in seconds
$MaxTime$: simulation duration
$period$: hour of the week with $24 \times 7 = 168$ possible values
$\lambda(period)$: rate of nonhomogeneous Poisson process at time $period$
$\lambda = \max\{\lambda(1), \ldots, \lambda(168)\}$
while $t \leq MaxTime$ **do**
  $period = (t \mod (7 \cdot 24 \cdot 3600)) \operatorname{div} 3600;$
  $nextInterArrivalTime = Exp(\lambda^{-1}).sample()$
  HOLD($nextInterArrivalTime$)
  $p = U(0,1).sample()$
  if $p \leq \frac{\lambda(period)}{\lambda}$ **then**
    $call.location = getLocation()$
    $call.priority = getPriority(period)$
    $call.transport = getTransport(period, call.priorityToCall)$
    if call.transport = TRUE **then**
      $call.destination = getDestination(call.location, call.priority)$
      $call.priorityToDestination = call.priority$
    end if
    $callQueue.add(call)$
    ACTIVATE dispatch centre
  end if
end while

Ambulance

The ambulance process follows the process of figure 4.1 and is described by algorithm 5 in section B of the appendix. Each status of table 4.1 is represented as a rectangle in the flowchart while the diamond-shaped rectangles represent a choise. The status *End of shift* means that the period when an ambulance crew works, the shift, is over. Therfore, the ambulance drives back to the post such that the crew can go home and the ambulance becomes unavailable and the status changes to *passive*. This flow chart shows that an ambulance which is mobilizing or driving to patient can be cancelled. This means that the dispatch centre assigns the another ambulance to patient because of a shorter driving time to the patient. At the start of the simulation an ambulance process has status *at post* when it is available to respond to calls and otherwise *Passive*. The function of this process is to serve calls and is activated by the dispatch centre when it is assigned to a call or by the scheduler process when a shift starts or ends.

OSRM is used to calculate the duration of process steps which involves driving such as *Driving to patient*. Besides the total driving time, OSRM returns information about the route such as the location and time of intermediate points on the route. Figure 4.2 shows a route with intermediate points. These intermediate points are used to determine the position of a driving ambulance.

For the non-driving process steps *Mobilizing*, *At scene* and *At hospital* the duration of the process step are modelled as indepent random variables. The Apache Commons Math 3.6.1 library is used to generate these random variables and are based on the data analyses of chapter 3. The distribution and parameters used can be found in section B of the appendix .

Every ambulance process contains a passive vehicle object. The function of this object is to keep track of the battery level when a vehicle ends driving or when it starts or ends charging. Equation (2.2) is used to calculate the energy consumption of a route driven by an vehilce. We assume that the acceleration is 0 during the whole route and the velocity is equal to the distances between two points divided by the driving time between two points. The values of the other parameters can be found in section B of the appendix and are based on a VW Transporter, which is the common vehicle type for ambulance. Charging a li-ion battery is linear up to 80% of the SOC and charging the upper 20% SOC can take as much time as charging the lower 80% SOC. Therefore, the charging speed for the upper 20% SOC of the battery is reduced by a facter 4. The vehicle object can be exchanged between two shift processes which will be used by the optimization models.

Dispatch centre

The dispatch centre is described by algorithm 3. It is activated by the call generator when a call is generated, by a ambulance process when the ambulance becomes available at scene or at hospital after serving a call or by an ambulance process which becomes available after being passive. The dispatch centre process first reroutes ambulances and then assigns calls to ambulances.
Rerouting consists of two steps. First, the driving time of the available ambulance to all assigned calls of which the assigned ambulance has status 'Mo-

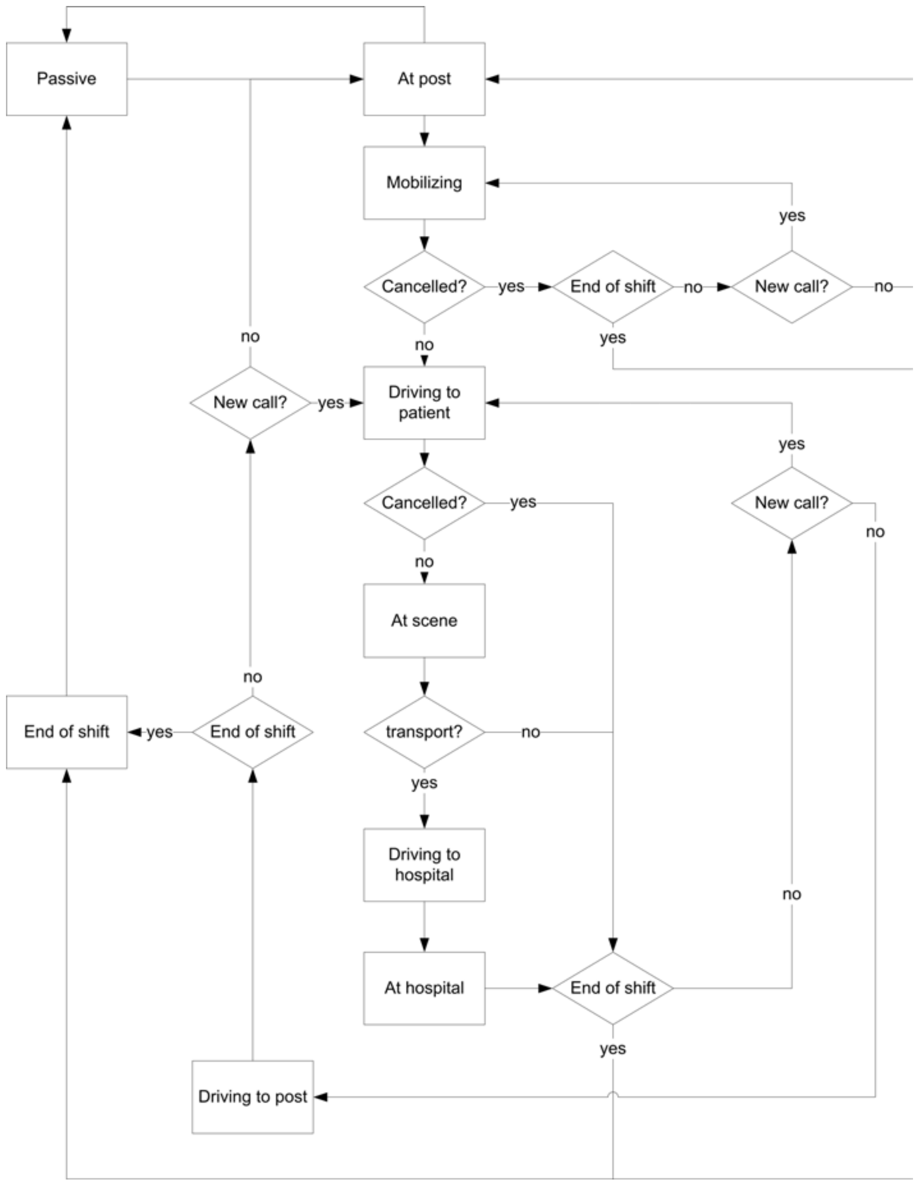


Figure 4.1: flow chart of the ambulance process

bilizing' or 'Driving to patient', is calculated. Second, these driving times are compared to the remaining driving times of the assigned ambulances. If the driving time of the available ambulance is smaller than the remaining driving time of an assigned ambulance then the available ambulance is assigned to the call of the assigned ambulance and the two steps are repeated with the assigned ambulance as the available ambulance. If the driving time is greater than the remaining driving time of each assigned ambulance then the available ambulance returns to post.
After rerouting the dispatch centre assigns all unassigned calls to the closest

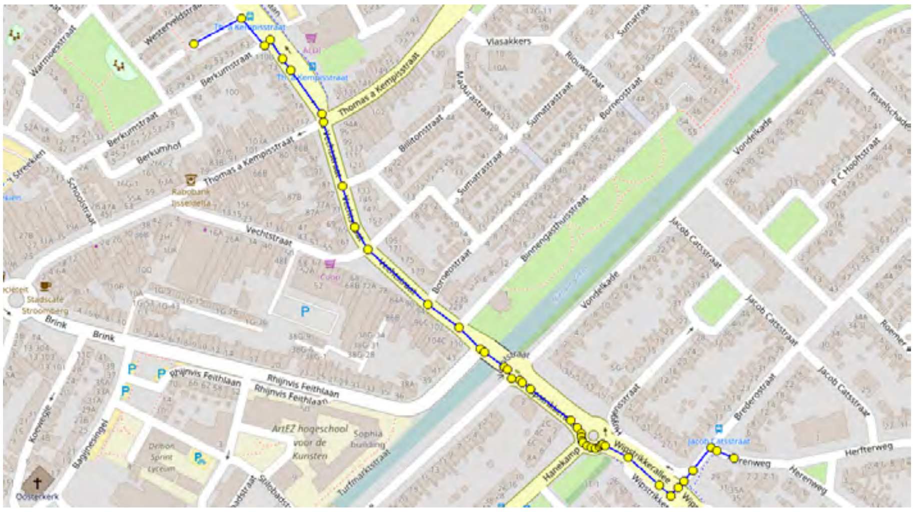


Figure 4.2: route with intermediate locations

ambulance with status 'At post' or 'Driving to post'.

Algorithm 3 Dispatch centre

while $t \leq MaxTime \vee callQueue \neq \emptyset$ **do**
  if an ambulance becomes available after serving a call **then**
    reroute ambulances and activate free and rerouted ambulances
  end if
  if $callQueue \neq \emptyset$ **then**
    assign calls to ambulances and activate ambulances
  end if
  PASSIVATE
end while

Scheduler process

The scheduler process is decribed by algorithm 4. The function of this process is to make ambulances available or unavailable when the shifts should start or end and the process is activated once by the main process. The start and end times of the different ambulances are described in table B.1 in the appendix

Model validation

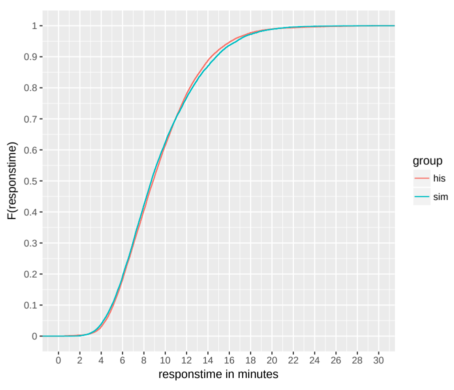
Figure 4.3a shows the empirical cumulative distribution function of the response time for the historic and simulated data. The response time of the simulation are similar to the ones of the historic data. Figure 4.3b shows the number of calls served per post per year for the historic and simulated data. Clearly, the number of historic and simulated calls per post is almost similar for all posts. Because the ambulance of Eelde starts in Assen, the ambulance crew possibly

Algorithm 4 Scheduler process

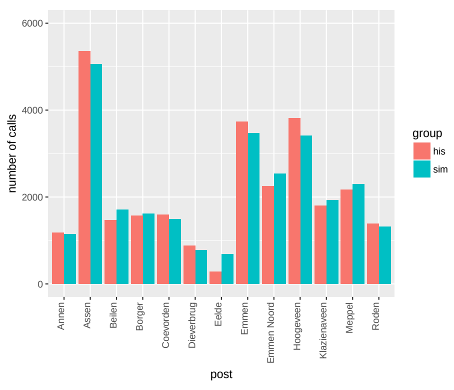
while $t \leq MaxTime \lor callQueue \neq \emptyset$ **do**
  $a = \{b \in$ all ambulances$|b.status \in \{$'Driving to post', 'At post'$\}\}$
  for all a **do**
    if time end of shift $\leq$ current time **then**
      change status to 'End of Shift' and activate process a
    end if
  end for
  $a = \{b \in$ all ambulances$|b.status \in \{$'Passive'$\}\}$
  for all a **do**
    if time start of shift $\leq$ current time **then**
      activate process a
    end if
  end for
  ACTIVATEAT(getNextStartOrEndTimeShifts())
  PASSIVATE
end while

Figure 4.3: Comparision of the historic data and the simulation data

(a) Ecdf of the response time



(b) number of calls per post



forgets to change the post in the digital registration system which could explain the difference between the simulation and the historic outcome. The difference between the simulation and the historic outcome for the posts Emmen, Emmen Noord and Hoogeveen could possibly be caused by a relocation of the post Emmen in October 2016. Based on these two figures the simulation produces realistic outcomes, although it slightly under estimates the percentage of urgent calls with a response time less or equal to 15 minutes.

5. Optimization models

In the current situation an ambulance returns to post after serving a call. The dispatch centre could also decide to relocate ambulance vehicles. For example, send ambulance A, when it becomes available at a hospital, to ambulance B at post B, switch the ambulance vehicle of ambulance A with the vehicle of ambulance B and return to post A, such that the battery level fits the expected energy demand of the post better. This section describes two models which try to improve the availability of electric ambulances by swapping or relocating ambulances. Both models are Integer Linear Programming (ILP) models and are inspired by the Maximal Covering Location Problem and the Location Set Covering Model.

Model 1

The difference between the battery capacity and the expected energy demand of the ambulance with the minimum difference between the battery capacity and the expected energy demand can be maximized, by swapping ambulances. Swapping consists of 2 steps. During the first step, ambulance A, with status *At post* or *Driving to post*, drives to the post of ambulance B, with status *At post* or *Passive*. At the second step the crew of ambulance A drives to their post with the ambulance vehicle of ambulance B while ambulance B remains at post with the ambulance vehicle of ambulance A. The problem is to decide which ambulances should be swapped?

In order to model this problem we first define the set S which contains all ambulance with status *At Post*, *Driving to post* or *Passive* where each ambulance is expressed as a number and therfore $S = \{1, \ldots, |S|\}$. Moreover, we define the following sets:

- $S_p = \{x \in S | \text{state of ambulance } x = Passive\}$
- $S_d = \{x \in S | \text{state of ambulance } x = \textit{Driving to post}\}$
- $S_a = \{x \in S | \text{state of ambulance } x = \textit{At post}\}$
- $S_{ap} = S_a \cup S_p$
- $S_{ad} = S_a \cup S_d$

Second, we define the binary decision variable x_{slv} which is equal to 1 if ambulance s moves from the current location to the post of ambulance l, swaps the current vehicle s for vehicle v and drives back to the post of ambulance s with vehicle v, and 0 otherwise.

Finally, we define the constant EL_{slv} as the current battery level of the vehicle of ambulance s minus the energy consumption for swapping and minus the expected energy demand. EL_{slv} consists of B_s, $E1_{sl}$, $E2_{ls}$ and E_l. Here, B_s is the battery level of the vehicle of ambulance s before the first step of swapping, $E1_{sl}$ is the energy consumption to move from the current location of ambulance s to the post of shift l, $E2_{ls}$ is the energy consumption to move from the post of ambulance l to the post of ambulance s and E_s is the expected energy demand at the post of ambulance s.

The constant E_s is calculated as follows. First, the region where UMCG ambulancezorg provides ambulance care is divided in squares and each square is assigned to the post with the smallest driving time from the post to the centre of the square (figure 5.1). Second, the expected energy demand per square is calculated by multiplying the expected number of calls per square per hour with the energy needed to drive from post to square and from square to the university medical center Groningen (UMCG). Each call potential needs complex care and the UMCG is the only hospital in the north of the Netherlands which can provide this care. Therefore, each ambulance shoud be able to reach the UMCG. The expected number of calls per square per hour depends on the hour of day and day of the week. Finally, E_s is calculated by summing the expected energy demand of all squares which are assigned to post s. Note that, E_s and E_x can be equal because ambulance s and x can have the same post. The calculation of the energy consumption is the same method as used by the simulation model.

In order to prevent swaps resulting in a minimal improvement, the energy consumption is multiplied with q and a fine F is substracted from the battery. EL_{slv} is defined as follows:

$$EL_{slv} = \begin{cases} B_s - q \times (E1_{sl} + E2_{ll}) - E_l - F & \text{if } s \neq l, v = l \\ B_s - q \times (E1_{ss} + E2_{sl}) - E_l - F & \text{if } s = l, v \neq l \\ B_s - E1_{ss} - E2_{ss} - E_s & \text{if } s = l, v = l \end{cases}$$

The objective of this model is to maximize c, the difference between the battery capacity and the expected energy demand of the ambulance with the smallest difference between the battery capacity and the expected energy demand. This is known as a max-min problem. Because an ambulance should only be swapped when it increases c, the number of swaps, m, is subtracted from c. By multiplying c with 1000, the model maximizes c first and m secondly, because c is an integer and m is always smaller than 100. The problem is then formulated as follows:

$$
\begin{array}{llcll}
\max & 1000 \times c - m & & & \\
\text{s.t.} & \sum_{v \in S} \sum_{l \in S} x_{slv} & = & 1 & s \in S \\
& \sum_{l \in S_{ap}} x_{sll} + \sum_{l \in S_{ad}, s \neq l} x_{ssl} + x_{sss} & = & 1 & s \in S_a \\
& \sum_{l \in S_{ap}} x_{sll} + x_{sss} & = & 1 & s \in S_d \\
& \sum_{l \in S_{ad}} x_{ssl} + x_{sss} & = & 1 & s \in S_p \\
& x_{svv} & = & x_{vvs} & s \in S_{ad}, v \in S_{ap} \\
& \sum_{s \in S} \sum_{v \in S} x_{slv} \cdot EL_{slv} & \geq & c & l \in S_{ad} \\
& \sum_{s \in S_{ad}} \sum_{l \in S_{ap}, s \neq l} x_{sll} & = & m & \\
& x_{slv} & \in & \{0,1\} & s, v, l \in S
\end{array}
\tag{5.1}
$$

Here, the first constraint ensures that each ambulance is choosen only once while the second, third and fourth constraint ensures that only a feasible action is chosen. The fifth constraint ensures that two ambulances are at the same location when the vehicles are swapped. The second last constraint ensures that c is smaller or equal to the energy left after relocating ambulance S while the last constraint sets m equal to the number of swaps. Because this model, and the model in the next section, take a snapshot of the state of the ambulance system, the model can be used at each moment. In the simulation model the optimization model is executed periodically or when a ambulance drives back to post after it has served a patient.

Model 2

The previous model only allowed swaps and no relocation of ambulance to other post. This model is an adjustment of the previous model and allows relocations but restricts vehicle swaps to ambulance who are passive. In order to model this problem we first define the sets S, S_p, S_d, S_a, S_{ap} and S_{ad} as in the previous section.

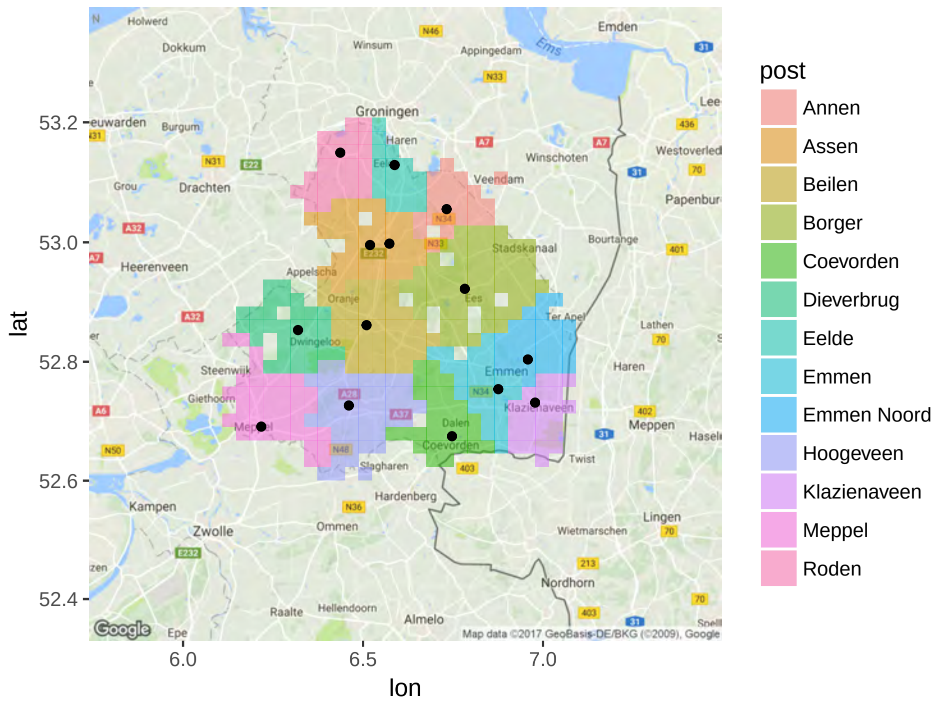
Second, we define the binary decision variable x_{slvk} which is equal to 1 if ambulance s moves from the current location to location l, swaps the current vehicle s for vehicle v and drives to post k with vehicle v, and 0 otherwise.

Finally, we define the constant EL_{slvk} which is defined equivalent to EL_{slv} from the previous model:

$$
EL_{slvk} = \begin{cases} B_s - q \times (E1_{sl} - E2_{ll}) - E_l - F & \text{if } l \neq s, v = l, k = s \\ B_s - q \times (E1_{ss} - E2_{sv}) - E_v - F & \text{if } l = s, v \neq l, k = s \\ B_s - q \times (E1_{sl} - E2_{ll}) - E_l - F & \text{if } l \neq s, v = s, k = l \\ B_s - E1_{ss} - E2_{ss} - E_s & \text{if } l = s, v = s, k = s \end{cases}
$$

Here, B_s, $E1_{xx}$, $E2_{xx}$ and E_s are defined as in the previous section.

Figure 5.1: region devided in squares



The problem is then formulated as follows:

$$
\begin{array}{llcll}
\max & 1000 \times c - m & & & \\
\text{s.t.} & \displaystyle\sum_{v \in S} \sum_{l \in S} \sum_{k \in S} x_{slvk} & = & 1 & s \in S \\
& \displaystyle\sum_{s \in S} \sum_{l \in S} \sum_{v \in S} x_{slvk} & = & 1 & k \in S \\
& \displaystyle\sum_{l \in S_p} x_{slls} + \sum_{l \in S_{ad}, s \neq l} x_{slsl} + x_{ssss} & = & 1 & s \in S_{ad} \\
& \displaystyle\sum_{l \in S_{ad}} x_{ssls} + x_{ssss} & = & 1 & s \in S_p \\
& x_{svvs} & = & x_{vvsv} & s \in S_{ad}, v \in S_p \\
& \displaystyle\sum_{s \in S} \sum_{l \in S} \sum_{v \in S} x_{slvk} \cdot EL_{slvk} & \geq & c & k \in S_{ad} \\
& \displaystyle\sum_{s \in S_{ad}} \sum_{l \in S_{ad}, s \neq l} x_{slsl} + \sum_{s \in S_{ad}} \sum_{l \in S_p} x_{slls} & = & m & \\
& x_{slvk} & \in & \{0,1\} & s,v,l,k \in S
\end{array}
\tag{5.2}
$$

Here, the first constraint ensures that each ambulance is choosen only ones while the second constraint ensures that only one ambulance is located at location k. The third and fourth constraint ensures that only a feasible action is chosen. The fifth constraint ensures that two ambulance are at the same location when the vehicles are swapped. The second last constraint ensures that c is smaller or equal to the energy left after relocating ambulance s while the last constraint sets m equal to the number of swaps.

6. Results

This chapter describes how we use simulation to answer the research question and it presents the research results.

Scenario's

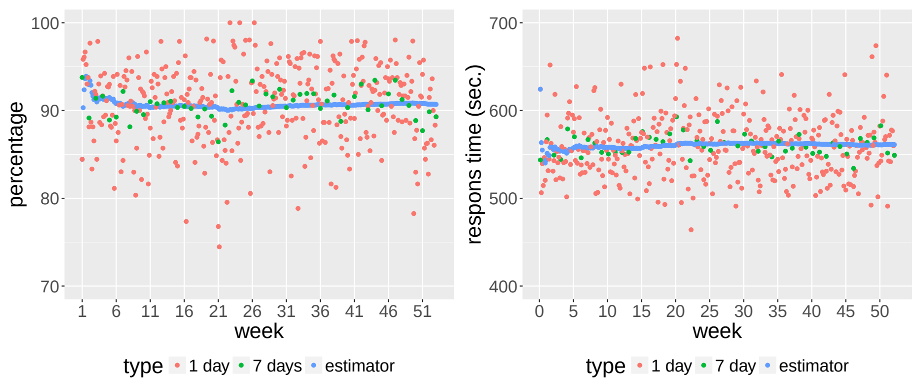
In order to answer the research question we devoleped a simulation model which follows the ambulance process of figure 2.1. Recall that this model consists of three main parts: the call generator, the dispatch centre and the ambulance process. In short, the process starts when the call generator generates a patient at specific time and location whereafter the dispacth centre decides which ambulance to assign to the call and the ambulance starts serving the patient. The energy consumption depends on the speed limits of roads and is based on the route planner OSRM. Ambulances are charged when the ambulance is at post or at hospital. Table B.1 denotes all the different ambulance objects within the simulation.

With the simulation model we try to determine if electric ambulances decrease the availabity of ambulances and the performance of the ambulance network. The availability is measured as *the number of times an ambulance has a battery level less than X kWh after serving a patient*. When the patient is not transported the battery level of the ambulance when arriving at scene is used and else the battery level when arriving at hospital is used. The performance of the ambulance network is measured as the performance and the response time. The performance is defined as *the number of urgent calls with a response time less than or equal to 15 minutes* whereas the response time refers to *the average response time of all urgent calls*. Besides the availability and the performance, the distance travelled is measured to quantify the cost of the optimization models.

To estimate the impact of electric ambulances the batch means method is used. Therefore, 52×7 days are simulated and the statistics are based on $N = 52$ batches. We choose 52 batches because the call demand shows a weekly cycle whereas the choise of 52×7 days is twofold. First, because the estimate of the response time and the performance over time of the figures 6.1a and 6.1b is stable after 52×7 days. Second, because the simulation time of the second optimization model takes almost two hours while dubbeling the simulated days only results in slightly smaller 95% confidence interval. In the next two sections several graphs show the sample mean and the 95% confidence interval (CI) of the sample mean for different measurments. The sample mean is defined as $\hat{l} = \frac{1}{N}\sum_{i=1}^{N} Y_i$ with Y_i the estimate of batch i. The green and red dots in figures

Figure 6.1: Simulation results per day (red dot) and per 7 days (green dots) and an estimator over time (blue dots)

(a) Performance (b) response time



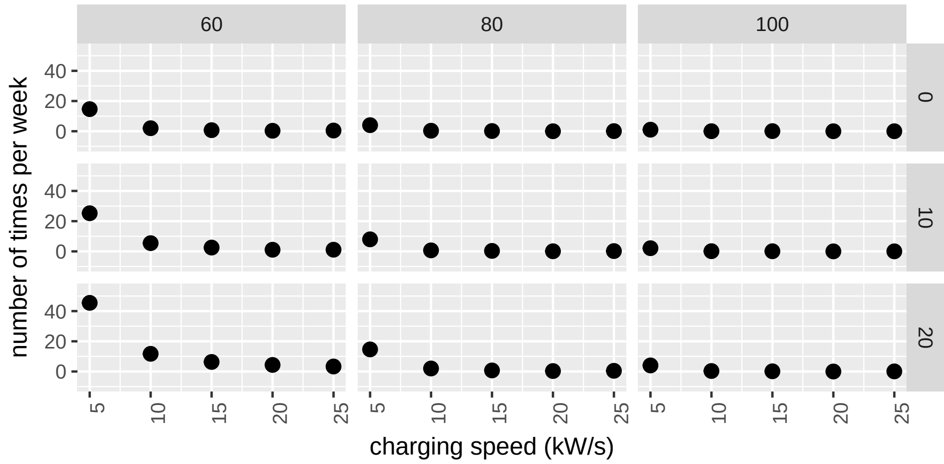
6.1a and 6.1b are examples of the performance and response time estimates per week (batch) and day, respectively. The 95% CI is based on $\hat{l} \pm z_{0.975} \frac{S}{\sqrt{N}}$ with $S^2 = \frac{1}{N-1} \sum_{i=1}^{N} (Y_i - \hat{l})^2$ the sample variance and $z_{0.975}$ the 0.975-quantile of the standard normal distribution. To test if the outcome of two simulation runs are different, a paired t-test is used with $N-1$ degrees of freedom.

Impact electric ambulances

The impact of electric ambulances on the availability of ambulance depends on the charging speed and the battery size. Figure 6.2 shows the sample mean, the 95% CI disappear underneath the points, of the availability for different battery sizes (60, 80 and 100) and different battery levels (0, 10 and 20). When all ambulances are equipped with a large battery (80 or 100) or when ambulances are relatively fast charged (20 or 25), the battery level of an ambulance after serving a call is at least 20 kWh. But when ambulances have a battery with capacity 60 kWh and are charged at 5 kW/s, this results, on average, 17 times per week in a negative battery level after serving a call. And 41 times per week it results in a battery level lower than 20 kWh.

But what is the impact of ambulances who are unavailable due to energy shortage? To answer this question the restricted modus of the simulation is used and it differs on two points from the unrestricted modus. First, the dispatch centre assigns only ambulances with enough energy to drive to the patient and to transport the patient or to drive back to post, depening on if the patient needs transport. Secondly, ambulances remain at hospital charging until the battery contains enough energy to drive back to post. These two differences influence the outcome of the simulation as shown in figures 6.3, 6.4 and 6.5. Each figure shows the performance, response time and kilometers driven for different charging speeds (5, 10, 15, 20 and 25), battery sizes (60, 70, 80, 90, 100 and 110) and simulation modus (not restricted and restricted). The upper graphs of these figures only shows the results of scenarios with battery size 80

Figure 6.2: Availability for battery level 0, 10 and 20 kWh, battery size 60, 80 and 100 kWh and different charging speeds.



kWh. The choise of a 80 kWh battery is arbitrary, we could have chosen any battery size because the unrestricted modus only records the enegy level but the enegy level has no influence on the simulation outcome. For all battery sizes and charging speeds the outcome of the restricted simulations are similar to the unrestricted simulations except for the restricted simulation with battery size 60 kWh and charging speed 5 kW/h. Section C containts the results of the paired t-test which tests if the performance, response time and kilometers of the unrestricted simulation differs from the restricted simulation. These results show that ambulances with battery size 60 and 70 kWh and charging speed 5 kW/s decrease the performance and increase the response time and the kilometers driven, significantly. Other combinations of battery size and charging speed have no significant impact, although some null hypothesis of the performance are rejected. This is possibly a coincidence because simulations with the same battery capacity but a lower charging speed are not rejected.

Impact other policy

In the previous section we saw that electric ambulances with large batteries or high charging speed have no negative impact on the availability, performance and response time. We also saw that an ambulance with a small battery of 60 kWh and a charging speed of 5 kw/s decreases the availability, performance and response time. Could this negative impact of electric ambulances be erased by using another policy than 'return to post after serving a call'? Figure 6.6 shows the availability for different parameter values of $\boldsymbol{F}$ and $\boldsymbol{q}$ of the two optimization models with battery size 60 kWh and charging speed 5 kW/s. Recall that the optimization models subtract a fine $\boldsymbol{F}$ from the battery and multiply the energy consumption for swapping or relocation with $\boldsymbol{q}$ to reduce swapping and relocation actions with little improvement. For both models,

Figure 6.3: Impact electric ambulances on the performance

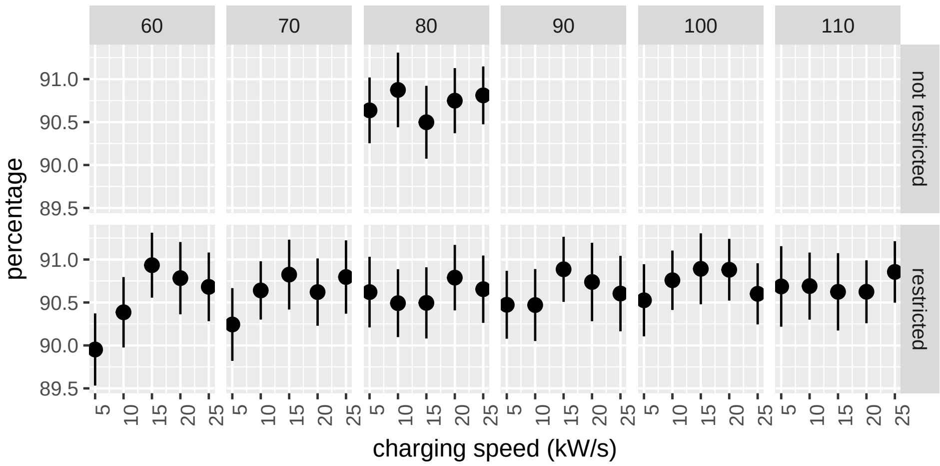


Figure 6.4: Impact electric ambulances on the average response time

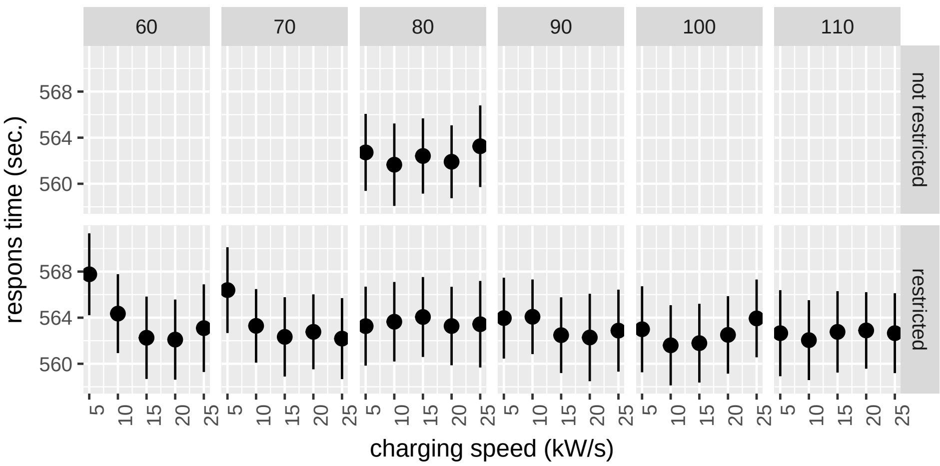


Figure 6.5: Impact electric ambulances on the distance travelled

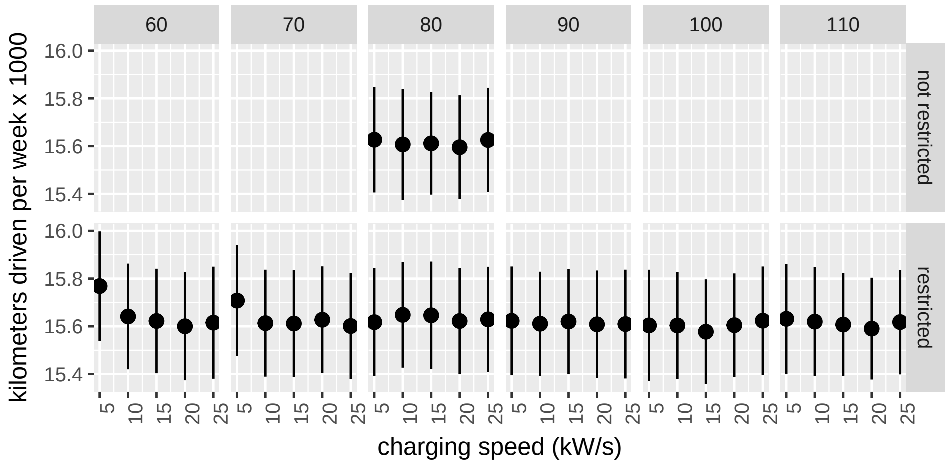


Figure 6.6: Availability for battery level 0, 10 and 20 kWh, battery size 60 kWh and different charging speeds.

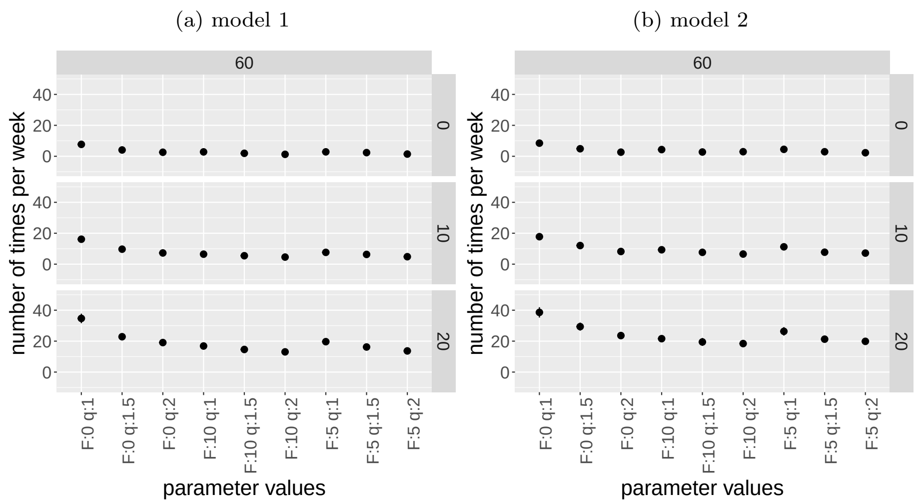
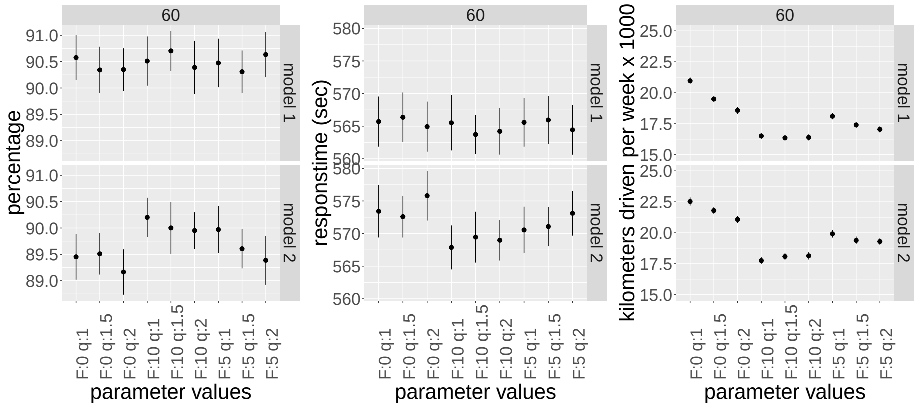


Figure 6.7: Simulation results optimization models

(a) Performance (b) response time (c) Kilometers



almost all parameter combinations reduce the number of times per week an ambulance has a negative battery level from 17 to zero. Also, the number of times per week an ambulance has a battery level less than 20 kWh after serving a call is reduced from 41 to 20 and at best even to 15. But does the optimization models impact the performance and the response time? And at what cost? The figures 6.7a, 6.7b and 6.7c show the sample mean and the **95%** CI of the performance, the response time and the kilometers driven of both models for different parameter values. What stands out is that the performance and the response time of model 1 is roughly the same for all parameter values while this is not the case for model 2. Both models show the same behavior for the kilometers driven although model 1 drives less kilometers than model 2 for each parameter combination. Section C containts the results of the paired t-test which tests if the performance, response time and kilometers of the unrestricted simulation differs from the simulation with optimization model. These results show that the second model decrease the performance and increase the response time and the kilometers driven significantly for all parameter combinations. Furthermore, for some parameter values the first model results in significantly more kilometers driven but no significantly different performance and response time. This means, model 1 prevents that ambulances get an empty battery which results in no deterioration of the performance and the response time while increasing the kilometers driven per week with 730.

7. Conclusion

Simulation results show that electric ambulances have no impact on the availability of ambulance nor on the performance of the ambulance network when ambulance are equipped with a battery of 80 kWh or more, or when ambulance are charged 20 kW/s or more at the post or at the hospital. On the other hand, ambulances equipped with a 60 kWh battery and who are charged 5 kW/s at the post or at the hospital, negatively impact the availability of ambulances. This results in a significantly decrease of the performance with 0.6 percentage point and a increase of 5 seconds on the response time and 140 extra kilometers on the overall kilometers driven per week. When the first optimization model is used, the negative impact on the performance and response time is erased but at a price off 730 extra kilometers driven per week. Where the first model is able to reverse the negative impact of electric ambulances, the second model is not able to erase the deterioration of the performance and the response time while it drives at least 1700 kilometers more than model 1.

Despite the positive simulation results, it is not recommended to replace all ambulances at the same time by electric ambulances with a battery of 100 kWh because of four reasons. First, in the simulation model ambulances only serve urgent calls. In reality ambulances also transport patients between hospitals and between hospitals and the home of the patient. Although, this is compensated by exluding two ambulances who are available during the day from the simulation model. Second, the energy consumption is estimated based on a theoretical formula where we ignore the energy needed for accelaration. This can possibly have a big influence on the results because ambulances accelarate aggressively. Third, the call generator only generates calls which require a single ambulance. In reality, sometimes large incidents occur requiring multiple ambulances. This temporarily results in fewer ambulances available for serving the normal ambulance demand and therby the remaining availbale ambulances need to respond to more calls and drive more kilometers. A consequence could be that one of the remaining ambulances becomes unavailable due to energy shortage which puts even more presure on the remaining ambulances. This could result in a domino effect of ambulance becoming unavailable due to energy shortage. Fourth, the simulation model assumes that ambulances can be charged at the hospitals. Charging 10 kW/s or more requires additional infrastructure which is perhaps not cost efficient. Therefore, we recommend to start with one electric ambulance at the post Roden to gain experience. The choise of Roden is twofold. First, figure 7.1 shows that of the ambulances who are 24 hours per day available, Roden drives at most 300 kilometers per day. With a average energy consumption of 0.5 kWh/km, the ambulance should have enough time between consecutive calls to recharge the battery. Second, Roden

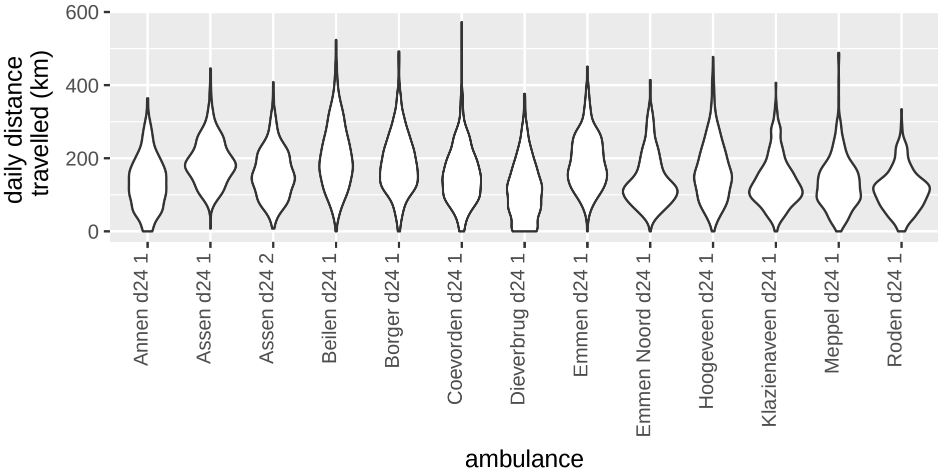


Figure 7.1: Density plot daily distance travelled per ambulance

is located close to Assen and Groningen and therefore, it never needs to drive large distances to the hospital. If the results for Roden are positive, we reocommend to expand electric ambulances to the post Assen because of a high demand with small travel distance and to the posts Annen, Eelde, Borger and Dieverbrug because of the low demand with relatively large travel distance to the patient. These posts are also located relatively close to Groningen, such that a trip to the UMCG does not drain the whole battery. The ambulance of the posts Meppel, Hoogeveen, Beilen, Coevorden, Emmen, Klazinaveen and Emmen Noord should be replaced as last because of a high demand or because of a large travel distance to the patient and to the hospital in combination with the a large travel distance to Groningen. Furthermore, if electric ambulances do become common practise but the battery size and charging speed issue still applies, we advise to consider optimizing the ambulance availability in real time with a method like the optimization model 1 of this research project.

Appendices

A. Data analyses

Poisson test

The chi-squared test procedure is used to test if the number of calls per hour is Poisson distributed and is described below. If $np \leq 5$ for the most left bin, than the bin is combined with neighbor bins until $np > 5$. The same procedure is applied to the most right bin.

1. H_0 : the number of calls per hour i is $Poisson(\lambda_i)$ distributed with $\lambda_i = \text{mean(number of calls per hour } i)$
   H_1 : the number of calls per hour i is not $Poisson(\lambda_i)$ distributed with $\lambda_i = \text{mean(number of calls per hour } i)$
2. The test statistic $T = X^2 = \sum_{j=0}^{k=16-1} \frac{(N_{ij}-np_{ij})^2}{np_{ij}}$ is χ^2_{k-2} distributed
   N_{ij}: number of days with j calls within hour i
   k: number of bins
   p_{ij}: probability of j calls within hour i
3. Calculate critical region $K = \{\geq x\}$ with $P_{H_0}(T \geq x) = 0.05$
4. Reject the null hypothesis when $T \in K$, else accept the null hypothesis

hour	statistic	df	p	indexmin	indexmax
0	2.4983428	5	0.776744622	1	7
1	9.2679972	5	0.098840388	1	7
2	14.9031593	4	0.004906344	1	6
3	1.5223062	4	0.822682990	1	6
4	0.5066922	4	0.972846235	1	6
5	5.4820540	4	0.241311453	1	6
6	3.4969413	4	0.478343575	1	6
7	0.9478355	5	0.966662520	1	7
8	3.8215117	7	0.800091037	1	9
9	3.2503721	8	0.917677071	1	10
10	6.9861607	8	0.538126565	2	11
11	6.3265687	8	0.610702060	2	11
12	7.0899801	8	0.526956391	2	11
13	6.8431122	8	0.553650588	2	11
14	2.8293094	8	0.944608212	2	11
15	3.7260265	8	0.880957855	2	11
16	9.5323312	8	0.299394845	1	10
17	5.7817639	8	0.671662428	1	10
18	4.2774773	7	0.747320114	1	9
19	2.8117924	7	0.901849995	1	9

20	4.2412288	7	0.751611112	1	9
21	7.6874127	7	0.360962670	1	9
22	4.9743395	6	0.547108471	1	8
23	14.5693634	6	0.023883966	1	8

Parameter values data analysis process time

Dispatch time

houres	priority	distribution	p value	parameter 1	parameter 2
23-7	A1	gamma	0.3741	shape = 4.1588	rate = 0.0365
23-7	A1	lognormal	0.0001	μ = 4.6098	σ = 0.5203
23-7	A1	weibull	0.0000	shape = 2.1967	rate = 128.9498
23-7	A2	gamma	0.5459	shape = 5.7886	rate = 0.0409
23-7	A2	lognormal	0.1428	μ = 4.8635	σ = 0.4386
23-7	A2	weibull	0.0064	shape = 2.6374	rate = 159.5096
8-22	A1	gamma	0.0000	shape = 4.0059	rate = 0.0429
8-22	A1	lognormal	0.1169	μ = 4.4045	σ = 0.5103
8-22	A1	weibull	0.0000	shape = 2.0266	rate = 105.5504
8-22	A2	gamma	0.0711	shape = 4.3791	rate = 0.0339
8-22	A2	lognormal	0.0000	μ = 4.7423	σ = 0.5080
8-22	A2	weibull	0.0000	shape = 2.2807	rate = 146.1662

Mobilisation time

houres	priority	distribution	p value	parameter 1	parameter 2
0-6	A1	gamma	0.0000	shape = 10.4175	rate = 0.1000
0-6	A1	lognormal	0.0000	μ = 4.5931	σ = 0.3511
0-6	A1	weibull	0.0071	shape = 3.9973	rate = 114.1639
0-6	A2	gamma	0.0000	shape = 8.1542	rate = 0.0721
0-6	A2	lognormal	0.0000	μ = 4.6655	σ = 0.3915
0-6	A2	weibull	0.2789	shape = 3.7806	rate = 125.0542
23	A1	gamma	0.0035	shape = 6.0015	rate = 0.0788
23	A1	lognormal	0.0000	μ = 4.2478	σ = 0.4338
23	A1	weibull	0.1529	shape = 2.8228	rate = 85.6995
23	A2	gamma	0.0639	shape = 5.3233	rate = 0.0635
23	A2	lognormal	0.0039	μ = 4.3313	σ = 0.4692
23	A2	weibull	0.6868	shape = 2.7444	rate = 94.2646
7	A1	gamma	0.0799	shape = 4.4717	rate = 0.0597
7	A1	lognormal	0.0241	μ = 4.1997	σ = 0.4912
7	A1	weibull	0.0026	shape = 2.2629	rate = 84.8749
7	A2	gamma	0.3562	shape = 3.6590	rate = 0.0416
7	A2	lognormal	0.1323	μ = 4.3334	σ = 0.5546
7	A2	weibull	0.1810	shape = 2.1163	rate = 99.7097
8-22	A1	gamma	0.0003	shape = 6.0572	rate = 0.1258
8-22	A1	lognormal	0.1507	μ = 3.7968	σ = 0.3950
8-22	A1	weibull	0.0000	shape = 2.3215	rate = 54.0259
8-22	A2	gamma	0.0000	shape = 4.7024	rate = 0.0801
8-22	A2	lognormal	0.4472	μ = 3.9526	σ = 0.4579
8-22	A2	weibull	0.0000	shape = 2.1707	rate = 67.0579

At scene time

transport	priority	distribution	p value	parameter 1	parameter 2
no transport	A1	gamma	0.2957	shape = 4.0738	rate = 0.1517
no transport	A1	lognormal	0.0034	μ = 3.1750	σ = 0.5366
no transport	A1	weibull	0.2324	shape = 2.3179	rate = 30.4691
transport	A1	gamma	0.2583	shape = 4.8507	rate = 0.2369
transport	A1	lognormal	0.0180	μ = 2.9221	σ = 0.4722
transport	A1	weibull	0.0486	shape = 2.4417	rate = 23.2815
no transport	A2	gamma	0.9597	shape = 3.3337	rate = 0.1391
no transport	A2	lognormal	0.1005	μ = 3.0190	σ = 0.6137
no transport	A2	weibull	0.3100	shape = 2.0155	rate = 27.0786
transport	A2	gamma	0.1433	shape = 3.6102	rate = 0.2342
transport	A2	lognormal	0.0576	μ = 2.5923	σ = 0.5201
transport	A2	weibull	0.0013	shape = 2.0480	rate = 17.9258

Handover time

priority	distribution	p value	parameter 1	parameter 2
A1	gamma	0.0000	shape = 4.8169	rate = 0.3027
A1	lognormal	0.1832	μ = 2.6600	σ = 0.4705
A1	weibull	0.0000	shape = 2.2726	rate = 18.0305
A2	gamma	0.0000	shape = 4.7614	rate = 0.3393
A2	lognormal	0.3440	μ = 2.5326	σ = 0.4706
A2	weibull	0.0000	shape = 2.2153	rate = 15.8996

B. Simulation model

Ambulances used in the simualtion

Table B.1: availability of ambulances

Shift	Days	Start	Duration
Annen 1	Mon/Sun	08:00	24 hours
Assen 1	Mon/Sun	08:00	24 hours
Assen 2	Mon/Sun	08:00	24 hours
Assen Centrum 1	Mon/Sun	08:00	9 hours
Beilen 1	Mon/Sun	08:00	24 hours
Borger 1	Mon/Sun	08:00	24 hours
Coevorden 1	Mon/Sun	08:00	24 hours
Dieverbrug 1	Mon/Sun	08:00	24 hours
Eelde 1	Mon/Fri	08:00	9 hours
Emmen 1	Mon/Sun	08:00	24 hours
Emmen 2	Mon/Fri	08:00	9 hours
Emmen Noord 1	Mon/Sun	08:00	24 hours
Hoogeveen 1	Mon/Sun	08:00	24 hours
Hoogeveen 2	Mon/Sun	08:00	9 hours
Klazienaveen 1	Mon/Sun	08:00	24 hours
Meppel 1	Mon/Sun	08:00	24 hours
Meppel 2	Mon/Fri	08:00	9 hours
Roden 1	Mon/Sun	08:00	24 hours

Parameter values call generator

Call priority

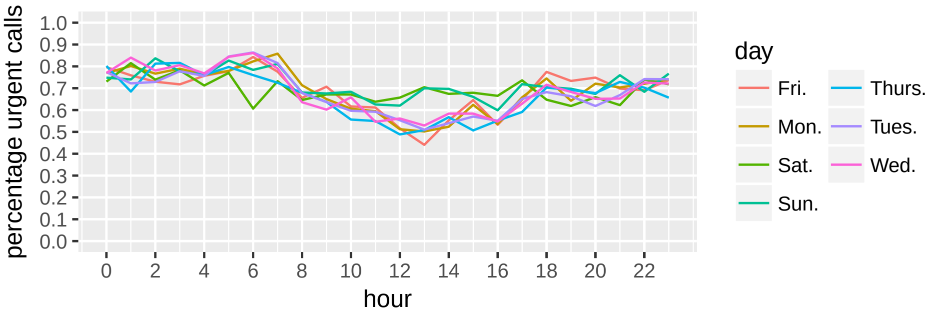


Figure B.1: percentage urgent calls per day and hour based for 2016

Transport

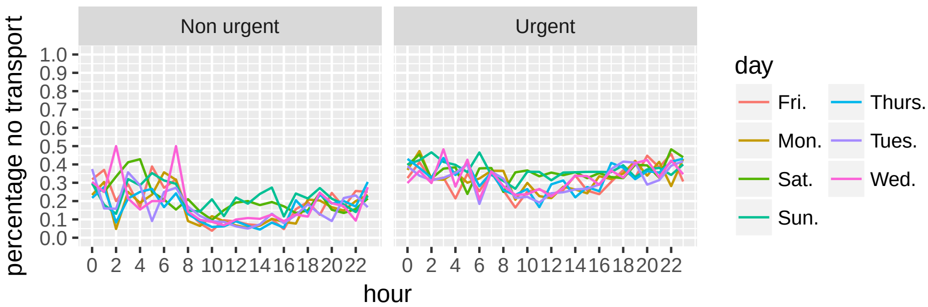


Figure B.2: percentage calls with no transport per day, hour and priority

Pseudocode shift process

Algorithm 5 Ambulance process

```
while t ≤ MaxTime OR callQueue ≠ ∅ do
  if status is 'At post' then
    PASSIVATE
  else if status is 'Mobilizing' then
    HOLD(mobilization time)
    if cancelled during mobilization AND new call assigned then
      setStatus('Mobilizing')
    else if cancelled during mobilization AND end of shift then
      setStatus('End shift')
    else if cancelled during mobilization then
      setStatus('At post')
    else { not cancelled }
      setStatus('Driving to patient')
    end if
  else if status is 'Driving to patient' then
    HOLD(driving time to patient)
    if cancelled during driving AND new call assigned then
      setStatus('Driving to patient')
    else if cancelled during driving AND end of shift then
      setStatus('End shift')
    else if cancelled during driving then
      setStatus('At post')
    else { not cancelled }
      setStatus('At scene')
    end if
  else if status is 'At scene' then
    HOLD(time at scene)
    if patient needs transport then
      setStatus('Driving to hospital')
    else if end of shift then
      setStatus('End shift')
    else { ambulance becomes available }
      ACTIVATE dispatch centre
      PASSIVATE
    end if
  end if
```

```
    if status is 'Driving to hospital' then
      HOLD(driving time to hospital)
      setStatus('At hospital')
    else if status is 'At hospital' then
      HOLD(time at hospital)
      if end of shift then
        setStatus('End shift')
      else { ambulance becomes available }
        ACTIVATE dispatch centre
        PASSIVATE
      end if
    else if status is 'Driving to post' then
      HOLD(driving time to post)
      if assigned to call during driving to post then
        setStatus('Driving to patient')
      else if end of shift during driving to post then
        setStatus('end shift')
      else { ambulance arrives at post }
        setStatus('At post')
      end if
    else if status is 'End shift' then
      HOLD(driving time to post)
      setStatus('Passive')
    else if status is 'Passive' then
      PASSIVATE
      ACTIVATE dispatch centre {ambulance becomes available }
      PASSIVATE
    end if
  end while
```

Ambulance vehicle characteristics

Parameter	description	Value	Unit	source
ρ	airdensity	1.24	kg/m^3	
C_D	drag coefficient	0.36	-	[2]
A_f	frontal area of the vehicle	3.61	m^2	[3]
v	velocity	-	m/s	
a	acceleration	0	m/s^2	
g	gForce	9.8		
f_{rl}	rolling resistance constant	0.015	-	[17]
m	mass	3200	kg	[3]
$theta$	roadway grade	0	degree	

Distribution and parameters

Dispatch

houres	priority	distribution	parameter 1	parameter 2
23-7	A1	gamma	shape = 4.1588	rate = 0.0365
23-7	A2	gamma	shape = 5.7886	rate = 0.0409
8-22	A1	lognormal	$\mu = 4.4045$	$\sigma = 0.5103$
8-22	A2	gamma	shape = 4.3791	rate = 0.0339

Mobilisation

houres	priority	distribution	parameter 1	parameter 2
23-7	A1	weibull	shape = 3.9973	rate = 114.1639
23-7	A2	weibull	shape = 3.7806	rate = 125.0542
8-22	A1	lognormal	$\mu = 3.7968$	$\sigma = 0.3950$
8-22	A2	lognormal	$\mu = 3.9526$	$\sigma = 0.4579$

At scene

transport	priority	distribution	parameter 1	parameter 2
transport	A1	gamma	shape = 4.8507	rate = 0.2369
transport	A2	gamma	shape = 3.6102	rate = 0.2342
no transport	A1	gamma	shape = 4.0738	rate = 0.1517
no transport	A2	gamma	shape = 3.3337	rate = 0.1391

Handover

priority	distribution	parameter 1	parameter 2
A1	lognormal	$\mu = 2.6600$	$\sigma = 0.4705$
A2	lognormal	$\mu = 2.5326$	$\sigma = 0.4706$

C. Results

Simulation model

The t-test procedure is used to test if the outcome of two simulations are similar and is described below.

1 H_0 : the outcome of the two simulations are similar
  H_1 : the outcome of the two simulations are not similar
2 The test statistic $T = \sqrt{n}\frac{\overline{Z}-0}{S}$ has a t-distibution with $v = n-1$ degrees of freedom
  $Z_i = X_i - Y_i$: difference between the outcome of simulation X and Y of week i
  $\overline{Z} = \frac{1}{n}\sum_{i=1}^{n} Z_i$: mean difference between simulation X and Y
  $S^2 = \frac{\sum_{i=1}^{n}(Z_i - \overline{Z})^2}{n-1}$: sample variance of the difference between simulation X and Y
3 Calculate critical region $K = \{\geq x\}$ with $P_{H_0}(T \geq x) = 0.05$
4 Reject the null hypothesis when $T \in K$, else accept the null hypothesis

Performance

bat	speed	pvalue	df	statistic	meandifference	rejected
60	5	0.0006	51	3.68	0.6841	H0 rejected
70	5	0.0236	51	2.33	0.3928	H0 rejected
80	5	0.9308	51	0.09	0.0158	H0 not rejected
90	5	0.3484	51	0.95	0.1635	H0 not rejected
100	5	0.5876	51	0.55	0.1110	H0 not rejected
110	5	0.7852	51	-0.27	-0.0502	H0 not rejected
60	10	0.0021	51	3.23	0.4881	H0 rejected
70	10	0.2186	51	1.25	0.2337	H0 not rejected
80	10	0.0295	51	2.24	0.3820	H0 rejected
90	10	0.0473	51	2.03	0.4039	H0 rejected
100	10	0.4590	51	0.75	0.1154	H0 not rejected
110	10	0.2783	51	1.10	0.1834	H0 not rejected
60	15	0.0263	51	-2.29	-0.4360	H0 rejected
70	15	0.0286	51	-2.25	-0.3266	H0 rejected
80	15	0.9895	51	0.01	0.0027	H0 not rejected
90	15	0.0446	51	-2.06	-0.3882	H0 rejected
100	15	0.0313	51	-2.21	-0.3938	H0 rejected
110	15	0.5054	51	-0.67	-0.1259	H0 not rejected
60	20	0.8558	51	-0.18	-0.0341	H0 not rejected
70	20	0.5261	51	0.64	0.1283	H0 not rejected
80	20	0.8081	51	-0.24	-0.0399	H0 not rejected
90	20	0.9604	51	0.05	0.0107	H0 not rejected

100	20	0.4594	51	-0.75	-0.1318	H0 not rejected
110	20	0.5006	51	0.68	0.1246	H0 not rejected
60	25	0.4729	51	0.72	0.1292	H0 not rejected
70	25	0.9327	51	0.08	0.0146	H0 not rejected
80	25	0.3380	51	0.97	0.1562	H0 not rejected
90	25	0.3100	51	1.03	0.2071	H0 not rejected
100	25	0.1744	51	1.38	0.2101	H0 not rejected
110	25	0.7968	51	-0.26	-0.0447	H0 not rejected

response time

bat	speed	pvalue	df	statistic	meandifference	rejected
60	5	0.0000	51	-4.48	-5.0437	H0 rejected
70	5	0.0058	51	-2.88	-3.6701	H0 rejected
80	5	0.6370	51	-0.47	-0.5454	H0 not rejected
90	5	0.2924	51	-1.06	-1.2423	H0 not rejected
100	5	0.8146	51	-0.24	-0.2734	H0 not rejected
110	5	0.9466	51	0.07	0.0671	H0 not rejected
60	10	0.0236	51	-2.33	-2.6985	H0 rejected
70	10	0.1910	51	-1.33	-1.6351	H0 not rejected
80	10	0.0652	51	-1.88	-1.9929	H0 not rejected
90	10	0.0513	51	-2.00	-2.4242	H0 not rejected
100	10	0.9661	51	0.04	0.0525	H0 not rejected
110	10	0.7379	51	-0.34	-0.3972	H0 not rejected
60	15	0.8864	51	0.14	0.1539	H0 not rejected
70	15	0.9341	51	0.08	0.0777	H0 not rejected
80	15	0.1335	51	-1.52	-1.6478	H0 not rejected
90	15	0.9432	51	-0.07	-0.0709	H0 not rejected
100	15	0.5418	51	0.61	0.6221	H0 not rejected
110	15	0.7112	51	-0.37	-0.3568	H0 not rejected
60	20	0.8569	51	-0.18	-0.1883	H0 not rejected
70	20	0.4214	51	-0.81	-0.8609	H0 not rejected
80	20	0.1028	51	-1.66	-1.3639	H0 not rejected
90	20	0.7501	51	-0.32	-0.3716	H0 not rejected
100	20	0.5292	51	-0.63	-0.5975	H0 not rejected
110	20	0.3369	51	-0.97	-0.9833	H0 not rejected
60	25	0.8876	51	0.14	0.1669	H0 not rejected
70	25	0.2970	51	1.05	1.0740	H0 not rejected
80	25	0.8586	51	-0.18	-0.1752	H0 not rejected
90	25	0.7025	51	0.38	0.3798	H0 not rejected
100	25	0.6144	51	-0.51	-0.6788	H0 not rejected
110	25	0.5974	51	0.53	0.6021	H0 not rejected

Kilometers

bat	speed	pvalue	df	statistic	meandifference	rejected
60	5	0.0000	51	-5.73	-141.8300	H0 rejected
70	5	0.0089	51	-2.72	-80.9129	H0 rejected
80	5	0.7207	51	0.36	9.2830	H0 not rejected
90	5	0.8871	51	0.14	3.8294	H0 not rejected

100	5	0.3354	51	0.97	22.7151	H0 not rejected
110	5	0.8504	51	-0.19	-4.5881	H0 not rejected
60	10	0.1868	51	-1.34	-34.1963	H0 not rejected
70	10	0.7966	51	-0.26	-6.1957	H0 not rejected
80	10	0.0743	51	-1.82	-40.9814	H0 not rejected
90	10	0.8710	51	-0.16	-3.8179	H0 not rejected
100	10	0.9007	51	0.13	3.4615	H0 not rejected
110	10	0.6037	51	-0.52	-12.5923	H0 not rejected
60	15	0.7042	51	-0.38	-10.7898	H0 not rejected
70	15	0.9944	51	-0.01	-0.1730	H0 not rejected
80	15	0.1527	51	-1.45	-34.6251	H0 not rejected
90	15	0.7348	51	-0.34	-8.5408	H0 not rejected
100	15	0.1368	51	1.51	34.1647	H0 not rejected
110	15	0.8359	51	0.21	4.1723	H0 not rejected
60	20	0.8488	51	-0.19	-4.9165	H0 not rejected
70	20	0.1892	51	-1.33	-32.2231	H0 not rejected
80	20	0.2569	51	-1.15	-26.9056	H0 not rejected
90	20	0.5790	51	-0.56	-13.1147	H0 not rejected
100	20	0.6974	51	-0.39	-9.5225	H0 not rejected
110	20	0.8400	51	0.20	4.8211	H0 not rejected
60	25	0.6785	51	0.42	10.3485	H0 not rejected
70	25	0.2256	51	1.23	24.4339	H0 not rejected
80	25	0.8746	51	-0.16	-3.3914	H0 not rejected
90	25	0.4849	51	0.70	16.2311	H0 not rejected
100	25	0.9332	51	0.08	2.0624	H0 not rejected
110	25	0.7017	51	0.39	7.9043	H0 not rejected

Optimization models

Performance

bat	speed	q	f	ilp	pvalue	df	statistic	meandifference	rejected
60	5	1.0	0	ilp1	0.7676	51	0.30	0.0597	H0 not rejected
60	5	1.5	0	ilp1	0.1547	51	1.44	0.2941	H0 not rejected
60	5	2.0	0	ilp1	0.1480	51	1.47	0.2870	H0 not rejected
60	5	1.0	5	ilp1	0.3257	51	0.99	0.1617	H0 not rejected
60	5	1.5	5	ilp1	0.0977	51	1.69	0.3283	H0 not rejected
60	5	2.0	5	ilp1	0.9901	51	0.01	0.0024	H0 not rejected
60	5	1.0	10	ilp1	0.4611	51	0.74	0.1251	H0 not rejected
60	5	1.5	10	ilp1	0.7230	51	-0.36	-0.0676	H0 not rejected
60	5	2.0	10	ilp1	0.2154	51	1.25	0.2466	H0 not rejected
60	5	1.0	0	ilp2	0.0000	51	5.14	1.1836	H0 rejected
60	5	1.5	0	ilp2	0.0000	51	5.64	1.1266	H0 rejected
60	5	2.0	0	ilp2	0.0000	51	7.03	1.4714	H0 rejected
60	5	1.0	5	ilp2	0.0031	51	3.10	0.6665	H0 rejected
60	5	1.5	5	ilp2	0.0000	51	6.15	1.0302	H0 rejected
60	5	2.0	5	ilp2	0.0000	51	5.67	1.2491	H0 rejected
60	5	1.0	10	ilp2	0.0140	51	2.55	0.4350	H0 rejected
60	5	1.5	10	ilp2	0.0064	51	2.85	0.6349	H0 rejected

60	5	2.0	10	ilp2	0.0001	51	4.41	0.6849	H0 rejected

response time

bat	speed	q	f	ilp	pvalue	df	statistic	meandifference	rejected
60	5	1.0	0	ilp1	0.0099	51	-2.68	-2.9832	H0 rejected
60	5	1.5	0	ilp1	0.0012	51	-3.44	-3.6449	H0 rejected
60	5	2.0	0	ilp1	0.0891	51	-1.73	-2.2092	H0 not rejected
60	5	1.0	5	ilp1	0.0081	51	-2.75	-2.8588	H0 rejected
60	5	1.5	5	ilp1	0.0097	51	-2.69	-3.2277	H0 rejected
60	5	2.0	5	ilp1	0.1270	51	-1.55	-1.7078	H0 not rejected
60	5	1.0	10	ilp1	0.0148	51	-2.52	-2.7894	H0 rejected
60	5	1.5	10	ilp1	0.3054	51	-1.04	-0.9993	H0 not rejected
60	5	2.0	10	ilp1	0.1480	51	-1.47	-1.4861	H0 not rejected
60	5	1.0	0	ilp2	0.0000	51	-6.52	-10.7018	H0 rejected
60	5	1.5	0	ilp2	0.0000	51	-7.64	-9.8709	H0 rejected
60	5	2.0	0	ilp2	0.0000	51	-8.85	-13.0878	H0 rejected
60	5	1.0	5	ilp2	0.0000	51	-6.02	-7.8380	H0 rejected
60	5	1.5	5	ilp2	0.0000	51	-7.09	-8.3577	H0 rejected
60	5	2.0	5	ilp2	0.0000	51	-8.17	-10.3950	H0 rejected
60	5	1.0	10	ilp2	0.0000	51	-4.77	-5.1535	H0 rejected
60	5	1.5	10	ilp2	0.0000	51	-4.70	-6.7345	H0 rejected
60	5	2.0	10	ilp2	0.0000	51	-4.63	-6.2598	H0 rejected

Kilometers

bat	speed	q	f	ilp	pvalue	df	statistic	meandifference	rejected
60	5	1.0	0	ilp1	0	51	-68.30	-5341.3862	H0 rejected
60	5	1.5	0	ilp1	0	51	-67.07	-3867.8879	H0 rejected
60	5	2.0	0	ilp1	0	51	-48.90	-2951.4320	H0 rejected
60	5	1.0	5	ilp1	0	51	-39.60	-2479.6632	H0 rejected
60	5	1.5	5	ilp1	0	51	-34.35	-1775.4612	H0 rejected
60	5	2.0	5	ilp1	0	51	-31.99	-1420.9939	H0 rejected
60	5	1.0	10	ilp1	0	51	-20.60	-883.8077	H0 rejected
60	5	1.5	10	ilp1	0	51	-23.58	-731.9010	H0 rejected
60	5	2.0	10	ilp1	0	51	-20.09	-767.2292	H0 rejected
60	5	1.0	0	ilp2	0	51	-65.03	-6899.6241	H0 rejected
60	5	1.5	0	ilp2	0	51	-61.55	-6169.1414	H0 rejected
60	5	2.0	0	ilp2	0	51	-69.97	-5448.2412	H0 rejected
60	5	1.0	5	ilp2	0	51	-52.21	-4284.2968	H0 rejected
60	5	1.5	5	ilp2	0	51	-43.81	-3758.3277	H0 rejected
60	5	2.0	5	ilp2	0	51	-48.62	-3668.9865	H0 rejected
60	5	1.0	10	ilp2	0	51	-28.70	-2124.3605	H0 rejected
60	5	1.5	10	ilp2	0	51	-35.37	-2455.5933	H0 rejected
60	5	2.0	10	ilp2	0	51	-31.45	-2509.5959	H0 rejected

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