Ingeborg Ulevåg

Resilience Analysis of Health Care Facilities in Emergency

Master's thesis in Reliability, Availability, Maintenance and Safety (RAMS)
Supervisor: Yiliu Liu (NTNU)
June 2021

Master's thesis

NTNU
Norwegian University of Science and Technology
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Preface

This master's thesis is the final requirement for completion of the master's degree in Mechanical Engineering with specialization in Reliability, Availability, Maintainability and Safety (RAMS) at Norwegian University and Science and Technology (NTNU). The thesis has been written during the spring semester 2021, under the guidance of supervisor Yiliu Liu of NTNU.

The report is motivated by the situations that arose when medical resources became a scarce commodity following the outbreak of COVID-19. There is a large global focus related to medical resources and the health service's handling of the pandemic.

The reader is assumed to have knowledge of basic probability calculus and methods related to its use. It is also beneficial for the reader to have knowledge of the COVID-19 pandemic and the impact it has had on society.

Trondheim, 2021-06-10

Ingeborg Ulevåg

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Acknowledgment

First of all, I would like to acknowledge Yiliu Liu for his guidance and patience through the development of this master's thesis. His commitment, guidance and patience has been an inspiration in producing this thesis. He has given me feedback that has led me in new directions and given me valuable insight into a field I had little knowledge of. For that I am most grateful.

I am also very grateful for the knowledge the RAMS group at NTNU has given me during the specialization period of my master's degree. It has been truly inspiring. Finally, I would like to thank friends and family for supporting me in my choices and encouraging me to keep going. Especially my mother and father have supported and helped me when I have needed it most during my studies at NTNU, which is something I really appreciate.

I.U.

Executive Summary

The COVID-19 pandemic has highlighted the need for a well-functioning and robust health care system. The hospitals have been at the center of dealing with the pandemic where, among other things, resources have been in short supply. Resilience is a term that can improve the understanding of hospitals' resistance to stress and adverse events, such as a pandemic.

The master's thesis aims to develop an understanding of how hospitals have handled the COVID-19 pandemic and utilized their resources to limit lost resilience. By using the Bayesian network and calculating lost resilience based on the hospitals' availability during a given time interval, one has the opportunity to form a picture of the resilience that a given hospital has.

The results can be used to assess whether the hospital's handling has been sufficient, and one can use the developed method to make reasoned proposals to decision makers. The results indicate that by determining given target values for the parameter availability, one can get the percentage of the various resources needed to achieve the particular value. There is uncertainty associated with the data base, and updates are needed to increase the credibility of the results. The method itself works and can provide support for further development of the hospitals' and other systems' resource management.

Sammendrag

COVID-19-pandemien har understreket behovet for et velfungerende og robust helsevesen. Sykehusene har vært i sentrum for å takle pandemien der blant annet ressurser har vært en mangelvare. Resiliens er et begrep som kan forbedre forståelsen av sykehusenes motstand mot stress og uønskede hendelser, for eksempel i en pandemi.

Masteroppgaven sikter mot å utvikle en forståelse for hvordan sykehusene har håndtert COVID-19-pandemien og utnyttet sine ressurser for å begrense tapt resiliens. Ved å benytte seg av Bayesiansk nettverk og kalkulere tapt resiliens ut fra sykehusenes tilgjengelighet i løpet av et gitt tidsintervall, har man mulighet til å danne seg et bilde av resiliensen som et gitt sykehus har.

Resultatene kan benyttes til å vurdere om sykehusets håndtering har vært tilstrekkelig, og man kan benytte seg av den utviklede metoden til å komme med begrunnede forslag til beslutningstakere. Resultatene tilsier at ved å fastsette gitte målverdier for parameteren tilgjengelighet, kan man få den prosentvise andelen av de ulike ressursene som trengs for å oppnå den bestemte verdien. Det er usikkerhet knyttet til datagrunnlaget, og oppdateringer er nødvendig for å øke troverdigheten til resultatene. Metoden i seg selv fungerer og kan gi støtte til videre utvikling av sykehusenes og andre systemers ressurshåndtering.

Contents

Chapter 1

Introduction

A well-developed society is often characterized by a well-functioning health care system and other critical societal functions. How dependent society is on these functions is seldom made clear before emergencies and major adverse events occur. In order to develop suitable services to cope with unforeseen and serious incidents, one has to identify characteristics of the facilities and services. This will create the basis for development of a well-prepared system. There are many facilities that are included in such a system, including the health service with hospitals and other institutions. The health care system is complex and their functions need to be organized and coordinated to make it well-functioning. In order to make improvements in how the system functions, we need to understand the current situation.

1.1 Background

The health sector is often not mentioned or noticed to a great extent before undesirable events occur. It is only when you feel the strain of the system that you begin to recognize the importance of the health sector. The COVID-19 pandemic is a clear example of how the focus of the civilized world is drawn towards the pressure on the health sector. The COVID-19 pandemic has consisted of several surges of patients being admitted to hospitals. Patients all over the world have needed the same treatment, which have led to a shortage of equipment. Ventilators and protective equipment have been limiting factors in the treatment of patients. It has also been made clear how critical sufficient numbers of healthcare professionals are for dealing with an event of this extent. How hospitals use their resources to cope with a global and demanding challenge can give us a picture of the availability and resilience of the system.

Problem Formulation

Modern health care has never faced a similar global problem as the COVID-19 pandemic. With the sudden need for ventilators, protective equipment, intensive care units and health care personnel, it became clear how vulnerable the health care system is. It is important to have a clear overview of how the hospitals are able to adapt to unexpected events. Resilience is a concept that addresses this ability, and it will therefore be useful to see how the health sector benefits from methods analyzing resilience. By using methods to examine resilience in connection with the health sector, one can assess how the system is able to counteract the loss of resilience. This is also useful in connection with further development of the health sector.

Since resilience is a broad concept applied to a wide variety of disciplines, there are many different methods that can be used to analyze the property. By simulating relevant scenarios and using the results for further analysis, one can assess the resilience of the system in the specified time interval, or make suggestions for future handling of a similar situation. For this, a suitable method is needed to calculate resilience with the available data and results from the simulation.

1.2 Objectives

The aim of this master's thesis is to assess and evaluate the resilience of a hospital, so that one can identify critical factors for maintaining the availability. This can also be used as a basis for decisions to secure the capacity of the health sector. In order to realize the aim, several sub-goals must be examined:

1. To define resilience and identify which other terms can be used to understand the meaning of resilience in the health care system.
2. To identify different areas affected by resilience in the health sector.
3. To determine the type of method that can be used to calculate the resilience of the given situation.
4. To simulate realistic scenarios to express the hospital's availability based on given data.
5. To calculate resilience based on the appropriate method and results from the simulation.
6. To discuss the results and the basis for further recommendations of the method.

1.3 Approach

The thesis begins by presenting relevant definitions and concepts to build an understanding of resilience and the connection to the health sector. The terms are used to identify and present relevant particulars that are used to define variables in the subsequent analysis. The method used for the simulation in the following analysis have been found using literature review done in the preparation for the master's thesis. The methods used in the analysis have been found using search engines such as Scopus and Google Scholar. Then the analysis is performed using the software Netica for simulation, and Excel for the calculation. The results and model in its entirety are discussed in detail to be validated. Finally, some suggestions for further research are presented.

1.4 Limitations

There are some limitations to this master's thesis. They are as follows:

- There are several limitations associated with the data base used in the master's thesis. The pandemic is ongoing, and the focus of the hospital network is on direct handling rather than quality assurance of data.
- The software used to simulate the system has several limitations related to the size and extensiveness of the network. Based on the resources and time available, the software used is assumed to be good enough for this purpose. With more time and a more secure data base, it would be more beneficial to utilize the software's features more extensively.
- The COVID-19 pandemic has led to restrictions on NTNU's facilities. Productivity has been affected by this. This may have influenced the quality of the report, as it was partly written from home, but I assume that the consequence of this is fairly minor.
- There is a lot of uncertainty associated with dealing with pandemics and measures that affect this, so the particulars and relationships between the variables mentioned in the report are assessed on the basis of my own assumptions.

1.5 Outline

The chapters for the thesis are structured as following:

- Chapter 2: Definitions
  The chapter presents a definition of resilience, and other relevant terms that can be used

to understand resilience in the health sector. The chapter also presents concepts used in calculating and understanding the resilience of a system.

- Chapter 3: Hospitals and Resilience
  This chapter introduces which part of the health sector is to be used for further analysis as the study object. A broader segment of the health sector is also presented to understand the connections between the various parts. The chapter also goes through various particulars where resilience is prominent. The particulars are divided into sections where they are most relevant.

- Chapter 4: Dynamic Bayesian Network
  The chapter presents theory and the basis for the methods Bayesian network and dynamic Bayesian network. It is also presented how the method can be used for the purpose of the master's thesis to calculate resilience to hospitals which later is to be assessed.

- Chapter 5: Approaches for Resilience Calculation
  The chapter goes through various approaches that can be used to calculate resilience in systems. The approaches are evaluated against available resources.

- Chapter 6: Case Study: Resilience Assessment of Hospitals
  The chapter presents a simulation of the development of the pandemic. Different variables used and the network are described. Finally, the results of the calculation of resilience for the simulation is presented.

- Chapter 7: Discussion
  The chapter contains a discussion of the interpretation of the results. The methods used to arrive at the results are assessed and limitations and uncertainty are presented. The usefulness of the method for use in other scenarios is also discussed.

- Chapter 8: Conclusion and Recommendation for Further Work
  The last chapter reviews the findings from the report and concludes from this. Recommendations for further work are also presented on the basis of this.

Chapter 2

Definitions

To understand and evaluate complex systems, it is necessary to have an overview of what meaning is relevant to descriptive concepts. Relevant terms and definitions must be introduced. This is especially important as concepts can be interpreted in many different ways related to the context in which they are used. An example of such a concept is resilience. Furthermore, the chapter presents several concepts that are used in the understanding of resilience.

2.1 Resilience

Resilience has no common definition. Different theories and models have introduced different versions of resilience definitions. In order to discuss and understand matters related to resilience, a clear definition has to be specified. According to Wiig et al. (2020), different concepts of resilience are represented in different fields of study. Nemeth et al. (2008) presents a general definition regarding resilience which can be descriptive in relation to health care. This definition will be used for this report. It is as follows:

☞ **Resilience**: "The intrinsic ability of a system to adjust its functioning prior to, during, or following changes and disturbances so that it can sustain required operations, even after a major mishap or in the presence of continuous stress" (Nemeth et al., 2008).

Wiig et al. (2020) presents another definition which is directly targeting resilience in health care. Resilience is defined as "the capacity to adapt to challenges and changes at different system levels, to maintain high quality care". The definition is developed to cover different areas. These areas are:

- To not only focus on the risk and safety related to the situation, but also include the quality of the system.

- To include different capacities on different system levels in order to adapt to the situation.
- To pay attention to challenges and disruptions related to the care being provided.
- To be attentive to key elements, such as coordination and collaboration.

These concepts and areas are relevant to discuss in order to understand resilience in hospitals.

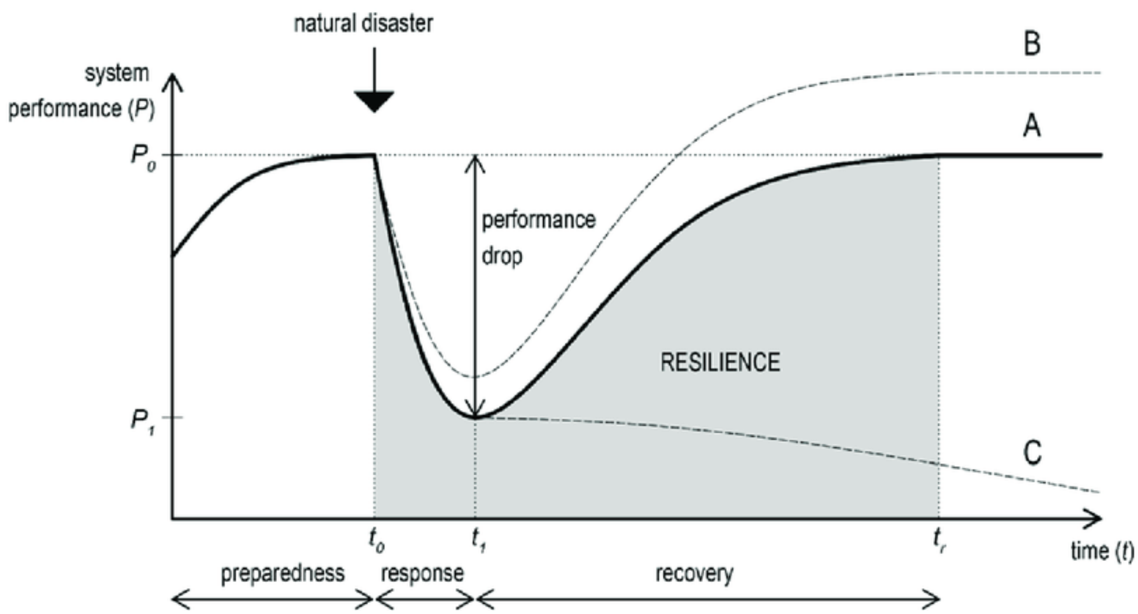


Figure 2.1: Function representing resilience of a system encountering a natural disaster (Koren et al., 2017).

Based on figure 2.1, the definition proposed by Nemeth et al. (2008) clearly describes the area called resilience. A natural disaster happens, or changes/disturbances as mentioned in the description, and resilience works to improve the performance. Since the definition also mentions "prior to" disturbances, I would perhaps also include the preparedness as a part of resilience. This is because it serves the purpose of improving the performance. The preparedness has a strong affiliation to the way a system is able to perform during the response and recovery phase. The A, B and C curves represent different scenarios. Good handling of the situation may lead to an even better performance than before the event. This is represented by curve B. The people involved may be able to exploit their resources more effectively, learning from their experience. The performance drop is also lower for this scenario. If they do not have enough resources or are unable to respond sufficiently, it may lead to a system collapse. This is represented by curve C. Curve A represents a scenario where the performance returns to the original level prior to the event.

2.2 Capacity

Another term used to understand resilience within facilities is capacity. According to Cambridge Dictionary (nda), the term is defined as

☞ **Capacity**: "The total amount that can be contained or produced" (Cambridge Dictionary, nda).

If one associates this definition with systems that are exposed to unexpected events, capacity can describe the amount of resistance the system is able to handle. Wildavsky (1988) uses the term capacity in his description of resilience. This closely relates the two terms. Resilience is being described as the system's ability to handle unwanted events, which can directly be connected to capacity. The term ability can easily be switched with capacity. This gives the description of resilience to be the system's capacity to handle unwanted events.

Capacity can be described as a property of the system, where resilience describes the dynamics. Resilience will vary depending on capacity, and at a lower capacity, the performance of the system decreases. Using figure 2.1 as a base, the preparedness may be the existing routines and storage in a health care facility. These need to be able to handle different situations with different requirements. The response time will decide how much the performance of the system will drop and how the resources of the institutions are utilized to improve performance. The evaluation needs to be continuous as unexpected events may interfere during the recovery phase. New disturbances may occur as well, and the preparedness may already have been reduced prior to the incident. Capacity is presented as the area underneath the lines which describes the system's performance at different times. With reduced performance, the additional capacity is also limited. The system's performance and capacity are thus closely linked to each other and in a way describe the same issue.

Vugrin et al. (2011) expresses the capacity of a system based on three aspects. These three aspects are fundamental in the framework that Vugrin et al. (2011) uses to express system capacity. The aspects are absorptive capacity, adaptive capacity and restorative capacity. The capacities are affected by the resilience of the system. Absorptive capacity is defined as "the degree to which a system can automatically absorb the impacts of system perturbations and minimize consequences with little effort" (Vugrin et al., 2011). Adaptive capacity addresses the ability of a system to reorganize to restore performance, and restorative capacity is described as the ability of the system to dynamically recover and repair (Vugrin et al., 2011). These factors are closely linked to the resilience and ability of the system to maintain and restore performance in terms of system capacity. The factors are also used in several different methods to calculate resilience.

A method developed by Francis and Bekera (2014) uses the mentioned factors, and the method is explained in section 5.1.2.

2.3 Availability and sufficiency

Availability is a term that is related to whether a system is able to perform under given conditions. Cai et al. (2018) defines availability as

☞ **Availability**: The state where a system is able to perform a required function under given conditions at a given time interval, given resources are available (Cai et al., 2018).

Related to the definition above, the availability of a hospital can be linked to individual components that make up the system. Hospitals consist of many resources, such as health personnel and equipment. If the availability of resources is limited, the hospital will not be able to treat the number of patients they have the maximum capacity for. The capacity of the system can therefore be interpreted based on the availability of the components at given times.

Availability in hospitals can also be linked to another concept, sufficiency. In order to achieve sufficiency, the hospitals need to be sufficient. Sufficient is defined by Cambridge Dictionary (ndc) as “enough for a particular purpose” (Cambridge Dictionary, ndc). In order for hospitals to maintain availability, resources must be both available and in a sufficient amount to be able to achieve their function. Sufficient will thus help to express whether the availability is acceptable for the hospital. These terms will be used to explain the performance of the system and will be assessed on that basis.

2.4 Other relevant definitions

As mentioned in section 2.1, resilience is a term relevant in different scientific disciplines. The different disciplines have different representations of resilience. Different terms and definitions are used to give support and understand the overall subject. Following is a presentation of some terms related to resilience based on the different disciplines.

2.4.1 Technical terms

Studying resilience with engineering and technical background, four properties are often presented. Those are defined by Bruneau et al. (2003) as different dimensions for resilience. The properties are robustness, redundancy, resourcefulness and rapidity.

☞ **Robustness**: The ability of systems to withstand a given level of stress or demand without suffering degradation or loss of function (Bruneau et al., 2003).

A robust system will, based on this definition, not be heavily affected by disturbances, and will be able to perform its function. A robust health care system will, for that reason, be able to treat patients at an approved level with disturbances. The health care system will deliver high quality care, even with ongoing disturbances, such as a pandemic.

☞ **Redundancy**: The ability for a system or it's elements to be able to perform each other's functions, their substitutability (Bruneau et al., 2003).

According to the article *Resilience of the Canterbury Hospital System to the 2011 Christchurch Earthquake* by Jacques et al. (2014), there may be a lack of redundancy in health care. The system is based on specialized practitioners, limiting the possibility to achieve redundancy. If there is a high demand in one part of the system, other parts may not be able to fulfill their functions.

☞ **Resourcefulness**: "The capacity to identify problems, establish priorities, and mobilize resources when conditions exist that threaten to disrupt some system" (Bruneau et al., 2003).

In other words, resourcefulness includes how the system is able to adapt to disturbances and organize available resources to be used where they are mostly needed. The resources may be used for other functions than what they are meant to, and consequently this property is connected with redundancy. The resources in health care are mainly equipment and personnel, and both elements need to be able to adapt.

☞ **Rapidity**: "The capacity to meet priorities and achieve goals in a timely manner in order to contain losses and avoid future disruption" (Bruneau et al., 2003).

It is the system's ability to act fast when disturbances occur and reduce the disruption. This term is relevant for systems that are under pressure due to limited time. In health care, there is often a matter of time before the state of the patients are affected, which means that quick response is of the essence.

2.4.2 Organizational terms

Properties related to organizational aspects are also relevant in understanding resilience. The organizational dimension covers how different facilities interacts to manage their functions in relation to loss of performance. The dimension is based on the capacity of organizations in maintaining their critical functions. The terms mentioned in section 2.4.1 as technical properties may also be used to describe resilience for organizations. Another dimension that affects both technical and organizational dimensions is the social dimension. It includes how society adjusts to loss of performance for critical facilities. This will affect all members of society, and hence the health care system. Following is a representation of properties that are associated with the organizational dimension.

☞ **Flexibility**: "The ability to change or be changed easily according to the situation" (Cambridge Dictionary, ndb).

Flexibility is related to how a system is able to adapt to the circumstances and changes, and how it performs under different situations. This is especially relevant when the system is affected by disturbances. In relation to the health care system, flexibility is important in order to adapt, when disturbances occur. In the face of unknown situations and difficulties, the health care system and its organizational structure needs to act flexible to reduce the drop of performance.

As mentioned in section 2.1 regarding the definition of resilience in health care, coordination is a key element in resilience. Coordination is an organizational term where different facilities and instances are involved to cover different functions. This makes it possible to exploit the organization's resources where they are most needed.

Berg and Aase (2019) presents several characteristics related to the organizational aspect of resilience in health care. The article presents studies and how different levels within health care maintain resilience. Anticipation is a characteristic which is presented and discussed at different levels. The term is described as "an act of looking forward and relates to the future, which enables individuals to enact proactively and prevent adverse events from happening" (Berg and Aase, 2019). Different levels have different anticipations which influence their responses. Results from the article states that on the individual level, practitioners anticipate what they are facing, such as threats. A higher level includes teams, use the term anticipation in relation to collaboration with other specialists and team members. The level containing management has anticipation of requirements and the system itself (Berg and Aase, 2019). Another concept mentioned in the article is sensemaking.

☞ **Sensemaking**: "The perception of something that is experienced with regard to the current situation" (Berg and Aase, 2019).

Individuals who practice sensemaking are able to make sense of unexpected events, while members of teams use their resources to develop a common understanding of the situation. This will lead to the necessary changes and measures being implemented (Berg and Aase, 2019). Other concepts are trade-offs and adaptions. Trade-offs include making compromises and assess different options before choosing the most fit option. Adaptions are changes and adjustments in order to handle complex situations (Berg and Aase, 2019).

Chapter 3

Hospitals and Resilience

Health care is a term that includes all institutions and activities, both private and public, with the purpose to rehabilitate and give patients care during illness (Nylenna and Braut, 2019). In Norway, the structure in the health sector can be organized within the specialist health service and the primary health service. Figure 3.1 gives a representation of the different parts in the Norwegian health sector (Regjeringen, 2014):

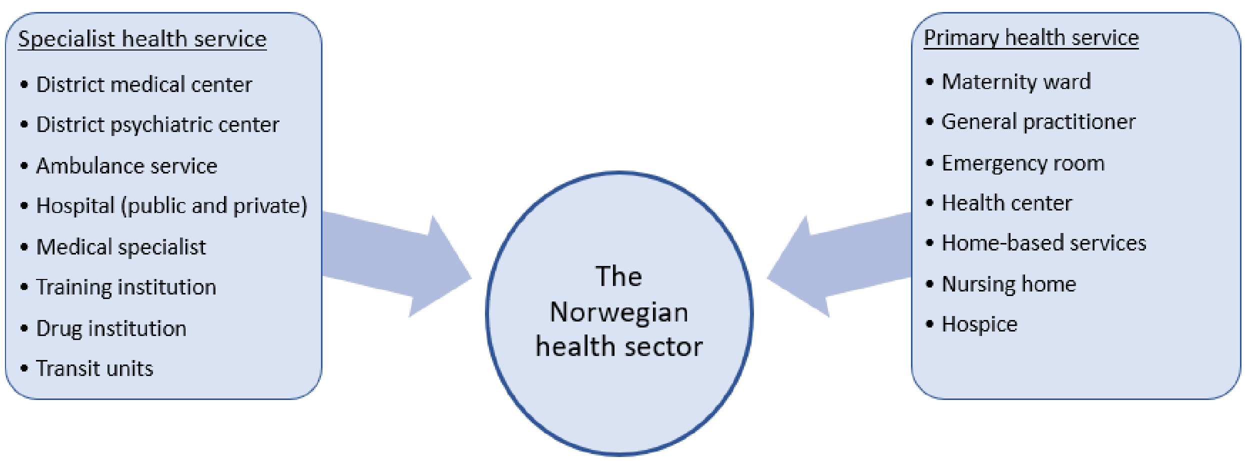


Figure 3.1: Overview of the different parts in the Norwegian health sector (Regjeringen, 2014).

Trondheim municipality has as a well-functioning society, were all services mentioned above are available (Trondheim Kommune, 2020). All the services have a function to treat patients, and therefore has an impact on the health care system as a whole. The health care system can consequently be described as a rather large and intertwined system. It will therefore not be possible to go in depth of all sectors and facilities mentioned. It will be of more value to examine smaller units based on the resources available for the analysis. The most relevant subsystem, which will be considered as the study object, is the hospitals. The hospital is affiliated with Trondheim municipality and is in an emergency situation for this analysis.

3.1 Hospitals

Hospitals are institutions that offer specialized treatment to those who need it. The hospitals are also responsible for covering education and research in relevant areas (Regjeringen, nd). Hospitals consist of several departments. Examples of such departments are Emergency Room (ER), Intensive Care Unit (ICU), outpatient clinic, laboratories and bed posts (Iversen and Braut, 2021). The size of the hospital is often decisive for which departments are present at the institution. Hospital employees are nurses, doctors, bioengineers, radiographers, physiotherapists, psychologists and employees who take care of work tasks outside the health service. These include economists and engineers (Iversen and Braut, 2021).

The hospital in Trondheim is called St. Olavs Hospital. It is a university hospital that has several divisions in Trøndelag county. The main division is located on Øya in Trondheim. In addition to the administrative part of the hospital, the hospital consists of various clinics. An excerpt of these follows under and is obtained from St. Olavs hospital (2020):

- Surgical clinic
- Clinic for emergency medicine
- Clinic for physical medicine and rehabilitation
- Clinic for cardiac medicine
- Clinic for lung and occupational medicine
- The cancer clinic
- The neurology clinic
- Laboratory medical clinic

Hospitals have strict guidelines related to the COVID-19 pandemic that employees must follow. Although some departments are more affected than others, due to more extensive routine changes, all departments related to the hospital will notice a change in work practice. Departments that are considered to be most affected are the ICUs, department of infectious diseases and the laboratories. At the ICUs and department of infectious diseases, the staff are in direct contact with the patients during treatment. The ICUs treat patients with the most severe disease courses. The department of infectious diseases, on the other hand, treats patients with milder courses of the disease, but who have a need for oxygen and monitoring. The laboratories are also strongly affected as they take care of the analyzes of the infection tests from a larger geographical area. The amount of tests is greater than in normal operation for this department.

Another factor that is crucial in dealing with the COVID-19 pandemic is the availability of medical equipment. Protective equipment, ventilators and equipment for testing infection have been critical as there has been a need across larger parts of the world. Equipment for testing for COVID-19 infection, is also a limiting factor. At the beginning of the pandemic, there was a desire from the authorities to flatten the infection curve, so that the health service would not be overburdened. This would also open up the possibility of acquiring the necessary equipment, as the demand was very high for specific items such as face masks, visors and ventilators. After a decrease in the number of infected, which is described as the first surge, the health service has been given the opportunity and time to build up the stock of equipment. On the other hand, the amount of hospitals and personnel has not been possible to influence to the same degree, so there is still a strong desire to keep the infection curve flat.

3.1.1 Resilience, capacity and availability in hospitals

As mentioned in section 2.2, capacity has a close connection to resilience. The capacity can further be linked directly to hospitals and the health sector. Different capacities may include the maximum number of patients, the maximum number of workers or the amount of equipment a facility can hold. Hospitals are equipped to take in a limited number of patients. During normal operation there is no need to have resources for a large number of patients. COVID-19 has given many institutions this issue, where a large number of people need special equipment at the same time. Both economy, and politics are also factors that impact the capacity of the institutions.

Capacity is not only limited to the physical aspects. Also mental capacity is an aspect that needs to be considered. The human resource is often limited to experience, anticipation and its ability to adapt (Berg and Aase, 2019). All these characteristics are confined by the mental capacity which controls how the person reacts to different situations. These are again relevant for hospital workers, as their work tasks require high mental capacity.

As mentioned in section 2.3, the capacity of a system can be interpreted based on the availability of the components at given times. For example, a lower availability for health care personnel than during normal operation may affect the number of patients who can be treated. This lowers the capacity at the given time, which in turn affects the system's resilience. At lower total availability, the system is less resilient and has a lower capacity to handle unwanted events.

3.2 Particulars in hospitals

Hospitals have different areas, so-called particulars, which affect how the system handles unexpected situations. These particulars need to be pointed out in order to understand hospitals in the context of an assessment of resilience. These can be based on different levels that affect individuals, the organization and society as a whole.

3.2.1 Individual particulars

Particulars based on how individuals behave and relate to the environment are necessary when the hospitals are the study object. The system, which the hospitals are a part of, is fundamentally made up by individuals. It is the individuals who make decisions and perform actions. The organization can facilitate how the employees should behave, but all in all, it is the individual's choice that determine the outcome. For that reason, is it important to understand which individual particulars that are relevant, in relation to the study object.

Personal traits

The personal traits and characteristics affect how health care workers perceive their surroundings. Several studies have examined how different characteristics affect resilience in health care. Eley et al. (2013) examines how the personality using temperament and character measures affect the individual's ability to respond to challenges. Traits such as harm avoidance, persistence and cooperativeness are given scores. The scores were based on different characteristics. The results indicated that high self-directedness and low harm avoidance were strongly correlated to resilience. Low scores on harm-avoidance correspond, according to the study, to having self-confidence and accepting uncertainty and risk. So you are not worried about future problems that are yet to occur. High self-directedness corresponds to being credible and dutiful (Eley et al., 2013). Overall, this expresses resilient behavior, which means that one is able to counteract unexpected resistance and do what is expected. This study is an example of personal traits being correlated to resilience.

The characteristics that correlated with resilience were again strongly linked to cooperativeness. The result confirms that resilience is affected by the system of which it is a part, and cannot be assessed on the basis of certain features. It is a dynamic property and must be considered accordingly. Cooperativeness can be linked to redundancy and resourcefulness, as it is based on the utilization of the resources available and the cooperation between the resources. Similarly, the characteristics that have little correlation with the resilience common features, belong to individual characteristics. Characteristics such as novelty seeking, reward dependence and self transcendence had little influence and correlation on resilience according to the study of Eley et al. (2013). These can be interpreted as characteristics of individuals who do not want to contribute to redundancy and resilience in the system, with focus on individual development. This is consistent with the interpretation of resilience as an intrinsic ability of a system to adapt to irregularities.

Health care workers are commonly known to have certain traits. Caring and friendly are qualities that describe the staff. The specific characteristics will affect how they handle patients. If employees are caring and express a lot of attention to the patients by spending a lot of time with them, it will affect the number of patients they tend to. This can affect the resilience of the health system where possibly fewer people receive the care they need. In order to maintain the necessary level of care, more employees will then be needed. This can make the health system more vulnerable if they are facing a performance drop where health care workers become a critical resource.

Qualifications

The qualifications of health care personnel affect their way of understanding situations. If employees have a wide range of knowledge and qualifications, they are able to perform a wider range of tasks. This will contribute to redundancy in relation to the fact that more people will be able to do the necessary tasks. Consequently, the health system will be able to offer high quality care. If an unexpected event happens and the performance drop, the system will be better equipped to handle the situation with redundant workers. Similarly, employees' qualifications are related to the system's robustness. The system becomes more resistant to unexpected events, and more experience also increases the anticipation and sensemaking among the employees. The employees will be able to anticipate consequences and what is required in different situations, which in turn expands their set of qualifications.

3.2.2 Organizational particulars

The organizational level is responsible for coordination, resource management and development of procedures and routines. This provides the basis for how situations can be handled.

Organization of the system

How the system is organized is an important factor in how unexpected events that reduce system performance is handled. The number of available practitioners, the number of ICUs and how they are organized, and the number of ventilators are factors that are able to affect how the COVID-19 pandemic is being handled. These are factors that also affect the capacity of the health care facility. Many institutions have had difficulties in organizing its resources. Also, the organization's level of preparedness is important to take into account. Routines make everyday work tasks standardized, which helps to maintain the level of care. Procedures assist in the daily work, but also provide the basis if irregularities occur. Emergency preparedness procedures are examples that determine how an organization should handle situations, but they also facilitate adaptations.

In short, organizations demonstrate flexibility and redundancy in organizing available resources. The rapidity of this organization often determines the fall in performance if unexpected events occur. These are concepts that are mentioned as descriptive factors for resilience in chapter 2, and show the relevance of the concepts in practice in combination with a dynamic system corresponding to a hospital.

3.2.3 Social particulars

As seen during the COVID-19 pandemic, society has been imposed measures of varying severity. These have been implemented to reduce the pressure on the health care system, often presented as surges of patients. Initially, it was pointed out that the purpose of the measures was to flatten the curve related to the number of infected persons, which would lead to fewer admissions to the hospitals. These measures can be regarded as factors that indirectly affect the need for resources and the capacity of the health care system.

How strictly the population follows the guidelines can, as previously mentioned, be important for the health care system. Guidelines introduced by the Norwegian government in dealing with the pandemic, requiring the use of masks and social distancing. Whether the population has followed these guidelines or not, can be challenging to establish. It is not possible to know with certainty what proportion of the population chooses to follow the guidelines, but it is reasonable to assume that a large part of the population has followed them. Based on this, one can also link the social particulars with the individual particulars, since societies are made up of individuals who have different characteristics. The mentioned characteristics from section 3.2.1 that represent resilience are thus relevant to social particulars as well.

Chapter 4

Dynamic Bayesian Network

To assess a dynamic system, a method that can handle complex relationships of factors is needed. One method that is capable of this is the Bayesian network. A further development of the Bayesian network is the dynamic Bayesian network. This takes into account the dynamics of a system over a period of time, which is very useful if one is to study a complex system with many factors over a limited period. A hospital in emergency that is also affected by social factors, is such a system.

Particulars are, as mentioned in chapter 3, areas that affect how systems handle unexpected events. This corresponds to factors that change over a given period, making hospitals a dynamic system. This is especially true during emergencies, where new factors are becoming relevant. In reliability engineering, Bayesian network and dynamic Bayesian network are considered suitable methods for analyzing such systems.

4.1 Bayesian Network

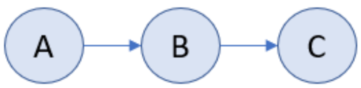
Bayesian network is a graphical method that uses probabilistic techniques. The techniques are based on Bayes' theorem and the method is used for assessments and argumentation with uncertainty and lack of data. Using Bayes' theorem, one can predict the probability of unknown variables based on known variables, and update the probability of known variables based on evidence. This is called forward and backward analysis, respectively. This feature makes the Bayesian network a flexible and robust reasoning method that is relevant in many different areas (Khakzad et al., 2016).

4.1.1 Basic concepts

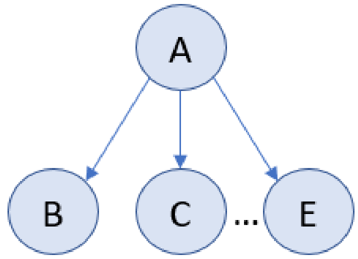
The system consists of factors, in the form of nodes, and directed arcs that bind the nodes together. A node describes the state of the factor and the arc shows the direct influence one node has on another. Each node is associated with a Conditional Probability Table (CPT). A CPT presents the distribution of probabilities between variables and their connection to the previous node (Rausand, 2013). One limitation of the method is that one cannot analyze cycles. This is because causal relations have a quantitative side. If a node has two parent nodes, the individual conditional probabilities do not say anything about how the parents influence each other. It is thus necessary to specify conditional probabilities that include both parent nodes together. This can for example be expressed as $P(C \mid A, B)$. Feedback cycles are challenging to model quantitatively (Jensen et al., 1996). This is solved by using only directed arcs and avoiding connecting nodes together in cycles.

A node that is preceding another node is called the parent of the following node. The subsequent node is called the child. If a node has no parent, it is a root node. Root nodes' probability tables are unconditional and called prior probabilities. They are necessary in order to get a complete overview and strengthening the reasoning about certainty (Jensen et al., 1996). Child nodes will have conditional probabilities. To calculate such probabilities, joint probability distribution is used. Joint probability distributions are further described in the section 4.1.2 on the mathematical basis for the Bayesian network. The variables represented by the nodes can be expressed as yes/no, true/false, or different ratings such as low/medium/high (Hosseini and Ivanov, 2020).

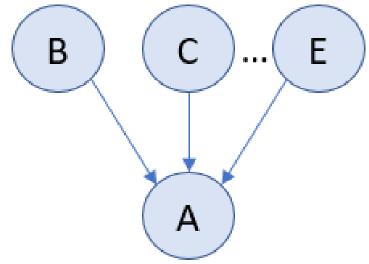
The nodes can be connected to each other in different ways. These provide the basis for three fundamental causal networks. The connections are called serial connections, diverging connections and converging connections. Serial connections deal with connections where nodes are consecutive in a single path. Figure 4.1 (a) shows three nodes with a direct connection from one end to the other. Node A influences B, and B influences C. Figure 4.1 (b) describes diverging connections that a parent node A influences several child nodes. Converging nodes are when a child node has multiple parent nodes. This is shown in figure 4.1 (c). If there is no knowledge of node A except on the basis of knowledge of the parent nodes B to E, then the parent nodes are considered independent (Jensen et al., 1996).
Figure 4.1 can also be used to explain a term called d-separation. Jensen et al. (1996) defines it as "two variables A and B in a causal network are d-separated if for all paths between A and B there is an intermediate variable V such that either the connection is serial or diverging and the state V is known, or the connection is converging and neither V nor any of Vs descendants have received evidence" (Jensen et al., 1996). If node B in figure 4.1 (a) is known, node A and C are d-separated. This is because the communication between the two nodes A and C is blocked.



(a) Serial connection



(b) Diverging connection



(c) Converging connection

Figure 4.1: Different connections of nodes in fundamental causal networks (Jensen et al., 1996).

Similarly, nodes B to E are d-separated in figure 4.1 (b) if node A is known (Jensen et al., 1996). In short, d-separation prevents influence and evidence from being transmitted between nodes. On the other hand, evidence affecting the certainty of node A in figure 4.1 (c) will make the parent nodes B to E dependent. This is called conditional dependence (Jensen et al., 1996).

Jensen et al. (1996) presents an overview of what a Bayesian network consists of. It is as follows:

- A set of variables that contains directed arcs between the variables.
- The associated variables in the set have a finite set of mutually exclusive states.
- A directed acyclic graph is developed based on the variables and arcs.
- Each variable with parents has an associated conditional probability table.

4.1.2 Mathematical basis

The basic concept on which Bayesian network is based on is conditional probability. Conditional probability means that an event depends on the outcome of a previous event. One can then say that the event is given by a previous event, and the notion is $P(A \mid B) = x$. An underlying formula for probability calculus is $P(A \mid B)P(B) = P(A,B) \Rightarrow P(A \mid B)P(B) = P(B \mid A)P(A)$ (Jensen et al., 1996). From this formula yields Bayes' theorem:

$$P(B \mid A) = \frac{P(A \mid B)P(B)}{P(A)} \tag{4.1}$$

To handle the probabilities associated with a larger set of variables, joint probability distribution is used. The distribution is calculated by taking the product of all the conditional probabilities in the Bayesian network.

$$P(U) = \prod_i P(A_i \mid pa(A_i)) \tag{4.2}$$

where $pa(A_i)$ are the parent nodes of the corresponding variable A_i (Jensen et al., 1996).

Example

Assume that the CPT for variable A given variable B is as represented in table 4.1.

Table 4.1: CPT for variable A given B, $P(A \mid B)$. Note that the sum of the columns is equal to 1.

	b_1	b_2	b_3
a_1	0.4	0.2	0.5
a_2	0.6	0.8	0.5

If the probability of variable B is given as $P(B) = (0.2, 0.3, 0.5)$, the fundamental rule can be applied to find the joint probability table. The fundamental rule is given by $P(a_i \mid b_j) \cdot P(b_j) = P(a_i, b_j)$. In other words, each cell in the CPT is multiplied by the corresponding b_j value.

For example, if you want to calculate $P(a_1, b_1)$, you use the value given for the current combination between the variables in the CPT, $P(a_1 \mid b_1)$, and the corresponding known value, $P(b_1)$. The calculation becomes $P(a_1, b_1) = P(a_1 \mid b_1) \cdot P(b_1) = 0.4 \cdot 0.2 = 0.08$. The joint probabilities for the remaining combinations of the variables are displayed in table 4.2. The calculations use the corresponding values from the CPT in table 4.1 and the known value for variable B.

Table 4.2: The joint probability table for variable A and B, $P(a_1, b_1)$. Note that the sum pf all the entries should be equal to 1.

	$b_1 = 0.2$	$b_2 = 0.3$	$b_3 = 0.5$
a_1	$0.4 \cdot 0.2 = 0.08$	$0.2 \cdot 0.3 = 0.06$	$0.5 \cdot 0.5 = 0.25$
a_2	$0.6 \cdot 0.2 = 0.12$	$0.8 \cdot 0.3 = 0.24$	$0.5 \cdot 0.5 = 0.25$

The joint probability table can be used to find the probability of the variable A. This is done by adding the values of each row together. For example, the probability of variable A becomes equal to $P(A) = (0.39, 0.61)$.

4.1.3 Creating a Bayesian network

In order to develop and build a Bayesian network, there are various factors that need to be identified in advance. Hypothesis variables are the events on which the network is to map and model. It is often impossible or expensive to observe. Furthermore, information variables must be identified. These gather information through observations. Finally, the variables are linked using causal structure. Using the causal structure between the information variables and the hypothesis variables, information from the information values makes it possible to draw conclusions related to the certainty of the variables (Jensen et al., 1996).

4.1.4 Bayesian network and resilience assessment

Bayesian networks can be used to model the causality of different factors. Factors related to resilience are often characteristics related to the disruptive event, such as intensity, and various strategies that counteract the disruptive event to limit the impact and loss of performance (Hosseini and Ivanov, 2020). By modeling the disruptive event and factors that represent the resilience of the system, the Bayesian network can express the development of the system.

Since resilience is a deterministic variable that is assumed to be a long term measure, it is not beneficial to calculate resilience directly using the Bayesian network method. Availability is a factor that is linked to the quality of a system, and can be linked to resilience. By using the Bayesian network, it is possible to express the availability of a system based on the development of the disruptive event and the system, and later use the results to calculate the resilience of the system. The method for calculating resilience based on availability found with the Bayesian network is considered in chapter 5.

There are several benefits to using the Bayesian network as a method. Ayello et al. (2014) mentions that Bayesian networks provide an opportunity to assess several different factors and combinations of those that can lead to an outcome. This makes the method flexible and gives one the opportunity to get an overview of a specific situation. Another advantage of using Bayesian networks is, according to Ayello et al. (2014), that it is a graphical model. This makes the method easy to understand and provides the opportunity to visualize complex chains in a clear way. As the method is based on Bayes' theorem, it is possible to use reversibility. This is an advantage as it provides an opportunity to transfer information between variables based on what is known. There are no forms of input and output, only known and unknown probabilities. If two variables are linked together, the knowledge about the individual probabilities will be improved regardless of which variable is preceding the other (Ayello et al., 2014).

By using the Bayesian network, one can according to Ayello et al. (2014) make informed decisions, as the method uses a rigorous mathematical method. This method makes it possible to assess complex systems where variables are linked independently of the previous variables. Another advantage is that Bayesian network provides an opportunity to easily update probabilities without affecting the strength between their relationships. If you acquire new information and knowledge, you only need to update the evidence related to the relevant variable. It does not affect the structure of the network. On the other hand, Bayesian networks have certain limitations. According to Ayello et al. (2014), in order to handle the order of the Bayesian inference numerically, one must use a directed acyclic graph. In order to maintain the strength between the relationships to the causes and the consequences, one cannot use feedback loops (Ayello et al., 2014).

4.2 Dynamic Bayesian Networks

Dynamic Bayesian networks are a further development of Bayesian networks, where one connects temporal dependencies between the variables. The method makes it possible to model flexible structures through a probabilistic framework. Time dependencies are often relevant when you want to model dynamic systems. This is not taken into account when using the general Bayesian network method. The study object for the forthcoming analysis is a dynamic system where conditions can change during the modeling. Dynamic Bayesian network is then considered necessary to get as accurate an analysis as possible.

4.2.1 Description

Dynamic Bayesian network has two approaches, one that is interval based and one that is instant based. The interval-based approach calculates probabilities within each individual time interval (Khakzad et al., 2016). The specified interval is divided into $n+1$ sub-intervals belonging to a state for a random variable of interest (Boudali and Dugan, 2005). A dynamic Bayesian network based on the interval-based approach is easy to construct, but an undesirable outcome is that large CPTs are created if you want to increase the accuracy with smaller intervals (Khakzad et al., 2016).

Instant-based dynamic Bayesian networks also divide the timeline into a specific number of time intervals. What distinguishes this approach from the interval-based approach, is that the instant-based approach generates equal Bayesian networks for each interval and connects them using arcs between the time slices. Figure 4.2 is an illustration of how to create identical networks for each time slice, and how the variables are linked between corresponding variables in the previous time interval. The node is thus not only conditionally dependent on its parent node from the same time interval, but also on itself from the previous time slice. By being dependent on itself from the previous time interval, the node is also conditional depending on the parent node from the previous time slice (Khakzad et al., 2016). To be able to model and predict the state of a time slice, only information from one time slice behind is needed, for example $t-1$ if the current time is t. For that reason, only two time slices are used in the modeling (Neapolitan et al., 2004).

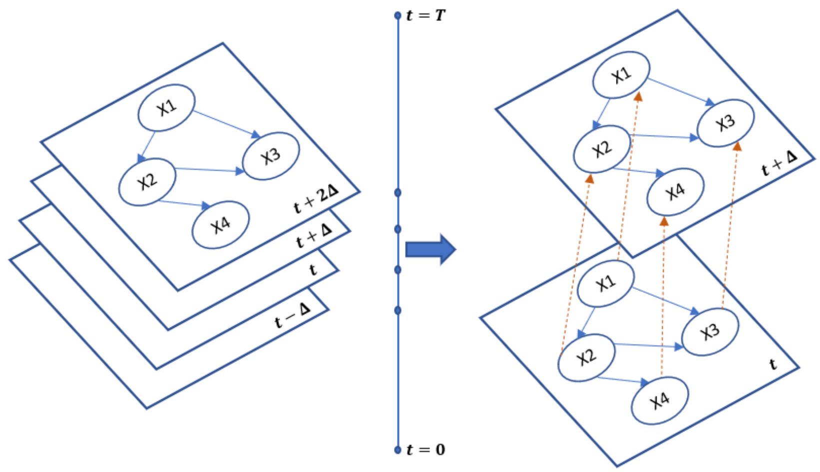


Figure 4.2: Illustration of how Bayesian networks transmit between time intervals in dynamic systems (Khakzad, 2015).

Chapter 5

Approaches for Resilience Calculation

To assess the resilience of a system, a method specifically developed to take resilience into account is needed. There are many different methods that aim to assess resilience, and it is therefore necessary to consider which method is best suited for each individual purpose.

Hospitals are, as previously described, a dynamic system where various factors influence the response to unexpected events. It is necessary to find a method that results in a measure of resilience in order to be able to make decisions based on this. Since Bayesian networks and dynamic Bayesian networks are used to simulate the pandemic, a resilience calculation method is needed that links the result of the simulation to resilience in the given time interval.

5.1 Review of approaches

Several different methods have been developed to arrive at a measure of resilience. The methods can be either qualitative or quantitative. Hosseini et al. (2016) introduces and reviews several different methods in his article, and this article is used as a starting point for the presentation of methods mentioned in this chapter.

5.1.1 Qualitative approaches

The qualitative methods are often based on either conceptual frameworks or semi-quantitative indices, according to Hosseini et al. (2016). The frameworks consist of several steps, where the first steps are about identifying the system by understanding what is to be evaluated and what affects the system. The next steps are about developing models to identify countermeasures as resistance, before implementing them and evaluating the result (Hosseini et al., 2016). The various frameworks presented in Hosseini's article are often specifically aimed at different domains and sectors. They should therefore be assessed against the relevant setting and situation in order to have the best benefit from the method. Kahan et al. (2009) has developed a conceptual framework that is more general and covers a wide range of sectors. The method uses 8 guiding principles for resilience, which are as follows:

1. **Threat and hazard assessment**: The purpose of this section is to reduce and limit the potential for possible damage to the system through various efforts. These can be expectation, identification, and avoidance.

2. **Robustness**: The point deals with the concept of robustness, as described in section 2.4.1, where the system must be able to withstand stress in order to maintain main functions. The system must also be able to degrade gradually when it is not possible to resist stress.

3. **Consequence mitigation**: The principle "incorporates the capabilities and capacities of critical systems and their key functions to control and reduce cascading adverse effects of a damage event and then recover quickly and resume normal activity" (Kahan et al., 2009). The purpose of the point is to prevent the system from being overwhelmed.

4. **Adaptability**: The principle addresses the property of being able to adapt to the situation so that the system can maintain equilibrium when something unexpected happens.

5. **Risk-informed planning**: Factors for threat, vulnerability and consequence must be identified through a risk assessment. Successful implementation of the findings from this assessment will also contribute to a better development of the system to be able to cope with unknown events.

6. **Risk-informed investment**: The principle is that the system must be able to allocate resources where needed, and the assessments must be based on an informed understanding of the risk.

7. **Harmonization of purposes**: The 6 principles mentioned above must be able to harmonize in order to effectively fulfill its purpose. Resources must be available, and plans must be flexible and adaptable for the system to be able to cope with unforeseen events.

8. **Comprehensive of scope**: This point deals with the fact that in order to be able to use the principles, one must recognize and understand that resilience covers the entire system.

The principles are general and can be applied to many different systems within different sectors. This makes the method flexible. Hosseini et al. (2016) also presents several frameworks based on various factors and characteristics used in developing and assessing the resilience of systems.

As mentioned, semi-quantitative indices are also used as a method for assessing resilience in systems. Then you have a selection of questions that will assess different characteristics related to resilience for systems on a set scale. The index is developed by combining assessments based on expert opinions (Hosseini et al., 2016). The characteristics may represent terms mentioned in chapter 2 or particulars mentioned in section 3.2. The most important thing is that the indicators should be relevant to the system and represent important concepts that describe the resilience.

5.1.2 Quantitative approaches

Quantitative assessment approaches can be used to assess the performance of a system regardless of the structure. This also provides the opportunity to be able to compare the results between different systems. The methods can be categorized as deterministic or probabilistic, and dynamic or static (Hosseini et al., 2016).

Deterministic approaches

Bruneau et al. (2003) has, as mentioned in section 2.4.1, defined four dimensions for resilience; robustness, redundancy, resourcefulness, and rapidity. Bruneau et al. (2003) also proposes a concept to measure lost resilience, based on the terms robustness and rapidity. The concept is later known as the resilience triangle, and it has been the starting point for several quantitative methods for calculating resilience. Figure 5.1 is an illustration of this concept. Bruneau et al. (2003) introduces a metric based on the resilience triangle. The metric is deterministic and static, and is primarily designed to measure the loss of resilience in a society after an earthquake. A measure of quality over a time interval between t_0 and t_1 is used to illustrate lost resilience, RL. The quality, $Q(t)$, represents different types of performance measures. The metric is presented in equation 5.1. Figure 5.1 visualizes RL as the shaded area. Smaller RL value indicates higher resilience, as less resilience has been lost when an unexpected event occurs. The method is considered applicable to many different sectors and systems, as quality is a general concept. Applicability is an important advantage of the method. A significant assumption on which the proposed metric is based is that the quality before the unexpected event is 100%, which is considered unlikely. Another assumption is that the quality drops immediately after the system experiences a disruptive event, which is not always the case for more dynamic systems. (Hosseini et al., 2016).

$$RL = \int_{t_0}^{t_1} [1 - Q(t)]\, dt \tag{5.1}$$

Zobel (2011) has also used the same starting point as Bruneau et al. (2003), namely the resilience triangle paradigm. Zobel (2011) proposes a metric where one wants to calculate the percentage of the total possible loss over a given interval. Equation 5.2 shows the metric. The parameters are $T \in [0, T^*]$, which describes the time it takes for the system to fully recover, T^*, which is the

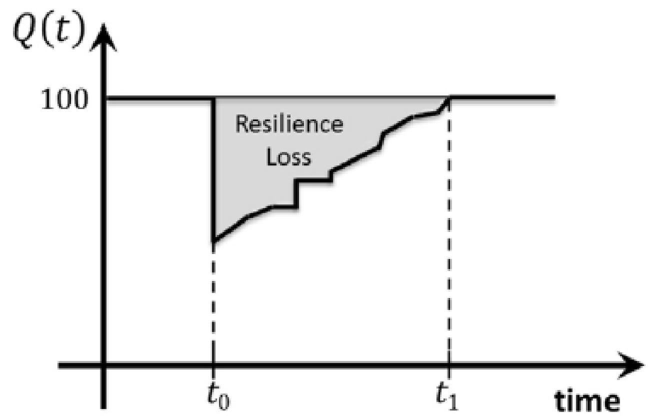


Figure 5.1: Resilience lost based on reduced quality within a time interval. The figure is retrieved from Hosseini et al. (2016), and is based on the report of Bruneau et al. (2003).

length of the time interval, and $X \in [0,1]$, which describes the percentage of lost functionality after an unexpected event.

$$R(X,T) = \frac{T^* - \frac{XT}{2}}{T^*} = 1 - \frac{XT}{2T^*} \tag{5.2}$$

Henry and Ramirez-Marquez (2012) describes resilience as a ratio between recovery at time t to loss at an earlier time. This is expressed as equation 5.3. The method expresses the performance of the system in the form of a function, $F(t)$, that goes through three different phases, stable original state, disrupted state, and stable recovered state. Figure 5.2 shows the different states the system goes through and when different events or measures are implemented. Equation 5.4 shows how the resilience $Я_F$ is evaluated, where t_r is the time the system and e_j is the disruptive event.

$$R(t) = \frac{Recovery(t)}{Loss(t_d)} \tag{5.3}$$

$$Я_F(t_r \mid e_j) = \frac{F(t_r \mid e_j) - F(t_d \mid e_j)}{F(t_0) - F(t_d \mid e_j)} \tag{5.4}$$

Another method is proposed by Francis and Bekera (2014). They propose a dynamic resilience metric ρ_i for event i, which takes into account the speed of the recovery S_p, the performance at its original state F_0, the performance at a new steady state after the recovery phase F_r, and the performance immediately after the disruption F_d. Equation 5.5 expresses this resilience calculation. The metric is based on adaptive capacity, absorptive capacity and restorative capacity, which are further explained in section 2.2.

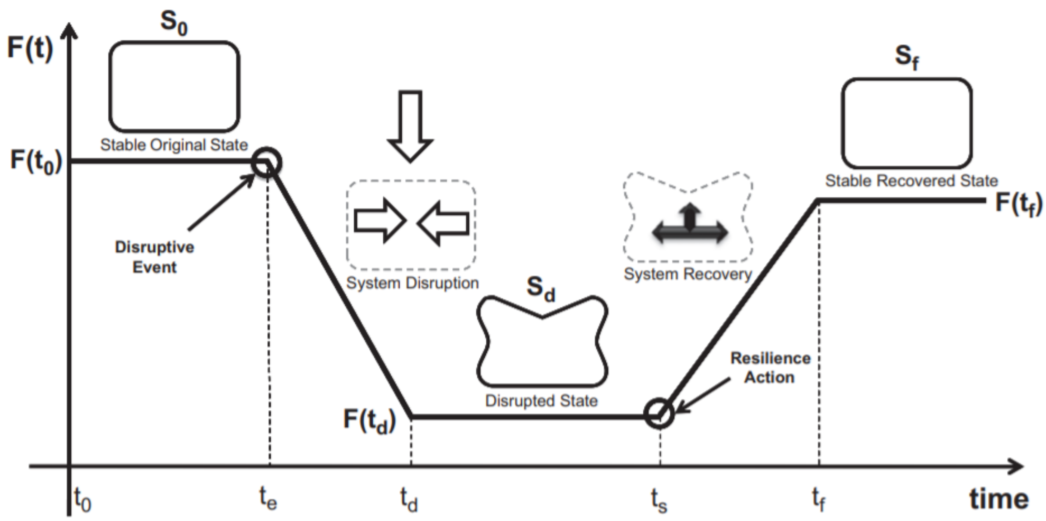


Figure 5.2: The performance of a system through different phases. Retrieved from Henry and Ramirez-Marquez (2012).

$$\rho_i = S_p \frac{F_r}{F_0} \frac{F_d}{F_0} \tag{5.5}$$

Probabilistic approaches

Similar to several of the deterministic methods mentioned in the section above, have Chang and Shinozuka (2004) proposed a probabilistic approach based on the system's performance before and after a disruption. The method measures the elements loss of performance and length of recovery, where equation 5.6 represents the measure. The variable A corresponds to the preset performance standard in a given scenario i, while r^* and t^* are given performance standards, respectively robustness and rapidity. Both r^* and t^* are maximum values for total acceptable loss and absolute duration. r_0 is the initial loss, and t_1 is the time of full recovery (Chang and Shinozuka, 2004). The method was developed to assess and measure the resilience associated with infrastructure and earthquakes, but it is applicable to other systems and disruptions (Hosseini et al., 2016).

$$R = Pr(A \mid i) = Pr(r_0 < r^* \; and \; t_1 < t^*) \tag{5.6}$$

Youn et al. (2011) has developed a probabilistic method to find an expression of resilience. The method is based on mitigation and contingency strategies, and resilience is described as a combination of reliability and restoration. Equation 5.7 describes the relationship. Reliability measures the ability the system has to maintain capacity and performance when a disruption occurs. Restoration measures the ability to restore capacity and the performance of a system. This is done by detecting, predicting and mitigating the effects of disruptions (Youn et al., 2011). The method differs from the previously mentioned methods in that it addresses reliability. Reliability is to be regarded as a preventive measure. The method is also not time dependent, which makes it more suitable for engineered systems where failure testing can be performed (Hosseini et al., 2016).

$$\Psi(\text{resilience}) = R(\text{reliability}) + \rho(\text{restoration}) \tag{5.7}$$

Ayyub (2014) has also developed an approach that assesses the resilience, R_e , of a system based on the performance of the system. The model is expressed in equation 5.8. The variables included are T_i, which corresponds to the time at which a disruption occurs, T_f which represents the time at which the system fails, T_r is the time at which the system is restored, F represents the failure profile, and R is the recovery profile. The different times are also used in the values that describe the duration, $\Delta T_f = T_f - T_i$ and $\Delta T_r = T_r - T_f$. Both the failure profile and the recovery profile are found using equations based on system performance. Equation 5.9 and 5.10 express these equations, respectively. The f and r used in equation 5.9 and equation 5.10 describe different causes of failures and different results of recovery strategies (Ayyub, 2014). The metric is considered very comprehensive and addresses both mitigation strategies and contingency strategies (Hosseini et al., 2016).

$$R_e = \frac{T_i + F\Delta T_f + R\Delta T_r}{T_i + \Delta T_f + \Delta T_r} \tag{5.8}$$

$$F = \frac{\int_{t_i}^{t_f} f dt}{\int_{t_i}^{t_f} Q dt} \tag{5.9}$$

$$R = \frac{\int_{t_f}^{t_r} r dt}{\int_{t_f}^{t_r} Q dt} \tag{5.10}$$

5.2 Evaluation of approaches

The approaches presented in the sections above all aim to assess resilience, which is one of the purposes of the thesis. It is therefore possible to use qualitative and quantitative methods. On the other hand, the data and principles considered must be available for a method to be usable. There is limited data available related to the COVID-19 pandemic, as the pandemic is ongoing and it has not been possible to analyze the effect of the management of the pandemic in a larger perspective. Based on the data and resources available, the range of methods is limited to include only quantitative approaches.

Between the deterministic and probabilistic approaches, also the data and resources available are what set the limit. Probabilistic methods are usually more comprehensive and require more time and understanding of the system. Based on the fact that the pandemic clearly affects the performance of the health care system and the hospital, this highlights the functionality of the mentioned deterministic approaches. Bruneau's approach is applicable to the current situation where the impact of the pandemic on hospital resilience is to be assessed. The variables in the method are quality over a certain range. Quality is a form of performance that can be linked to availability, as it says something about the system's ability to achieve its function as a hospital. Quality also includes several other factors, such as efficiency, but based on the available data, it is assumed that there is sufficient with availability as a measure.

Bruneau's approach is based on several assumptions. For example, the method assumes that the quality is at 100% before the disruption occurs. The resilience triangle also has some issues in that it can be challenging for decision makers to understand the result and use it for decisions. Although RL is stated as a percentage, it is challenging to make decisions based on the simple value. The method also assumes that the disruptive event has an immediate impact on the system. This may be the case for some systems, although another approach is to gradually degrade performance over time. It is also assumed that the recovery efforts begin immediately after the disruptive event (Hosseini et al., 2016).

Chapter 6

Case Study: Resilience Assessment of Hospitals during the COVID-19 Pandemic

By using a resilience assessment method consisting of Bayesian network and a resilience calculation method based on the parameter availability, one can form a picture of the development of hospital's resilience during the COVID-19 pandemic. This will be the basis for assessment and evaluation of whether the method works, given a specific time interval and realistic values for the variables. The variables used in the Bayesian network are factors that affect the hospital and hospital availability. An example from 1 December 2020 is used to present the network used in the simulation, even though the simulation consists of several similar networks based on the structure, during the given time interval.

6.1 Netica

The software used to create the Bayesian network for this master's thesis is Netica. Netica is a program for working with belief network, i.e. Bayesian network, and influence diagrams. You get the opportunity to draw the network, and connect the variables by creating relationships between them using probabilities and equations. The program is developed by Norsys Software Corp (Norsys Software Corp., 2021). The limited version will be used in the master's thesis.

6.2 Bayesian network

6.2.1 Variables

In order to examine the resilience of hospitals, there are various factors that must be considered and looked at in context. These are represented as nodes in the Bayesian network, where the node hospital availability is the hypothesis variable for the analysis. The reason that resilience is not the final variable in the network is that resilience is assumed to be a long term measure. Bayesian network represents instantaneous measures for the system to be analyzed, which does not correspond to the variable resilience. Availability says something about whether the system is available or not at some point. It is possible to link the variable hospital availability directly to resilience by using Bruneau's approach, which is elaborated in section 5.1.2 and 5.2.

The conditional probabilities are determined based on assumptions. The assumptions are based on actual events throughout the course of the pandemic in 2020. The variables have been derive from the particulars mentioned in section 3.2. Among other things, the particulars personal traits and qualifications are mentioned in section 3.2.1. This is represented in the form of the variable hospital personnel, since it is challenging to quantify qualitative characteristics. The variables ICU beds and ventilators represent the organizational particulars, as they are part of how the system is organized. Overall, the individual particulars and organizational particulars constitute the hospital's capacity. Social particulars are covered in the form of mask use and social distance, and these represent the social aspect associated with the spread of infection.

Infection intensity

Infection intensity is a variable that represents the intensity and infection pressure of the COVID-19 virus. The variable is a necessity for the subsequent factors related to society and the factors directly related to the hospital. This helps to provide a clear picture of the development of the spread of the infection. The factors that belong to society are social distancing, mask use and the number of patients. The factors that are directly linked to the hospital are hospital personnel, ventilators and ICU beds.

The node infection intensity is based on the Reproduction number (R number) over different periods of time during the pandemic. The R number is an expression that describes "the average number of new cases generated by one infected individual in a fully susceptible population" (Kristiansen et al., 2020). The model calculations of the infection rate R used by Norwegian Institute of Public Health (NIPH) place great emphasis on the development of the number of patients admitted to hospitals with a COVID-19 diagnosis in Norway (Folkehelseinstituttet, 2021b,c).

The R number is presented weekly in reports from NIPH during the pandemic. These are given in approximate monthly intervals with an average value and a confidence interval of 95%. Table 6.1 shows the overview of various R number from the start of the pandemic in March 2020 to February 2021 on a national level. There are shortcomings in the overviews of more local data, so the national overview is estimated to be the most accurate and credible. Based on the R numbers, infection intensity is presented as a sixth degree function with a value for each day between 5 March 2020 and 31 December 2020. Figure 6.1 shows the sixth degree function as a dashed trendline for the R number at different times based on table 6.1. The values for infection intensity each day are shown the table in section A.1 in the appendix A. The total average based on the average values over the various time intervals in the table 6.1, is 1.06. This is approximately equal to 1. The approximated value is fixed and used as a distinction between high and low values related to the R number. The distinction corresponds to 50% high values and 50% low values. Two thresholds are also set for extremely high and extremely low values, of 1.5 and 0.5, respectively. For example, with R numbers above 1.5, there will be a 100% probability of high intensity values.

Table 6.1: Average R number between the beginning of the outbreak in 2020 and 1 February 2021 (Folkehelseinstituttet, 2021d)

Reproduction number	**Average (95% CI)**	
R0 (from the beginning of the outbreak - March 15)	3.2	(2.5 – 3.9)
R1 (from March 15 - April 20)	0.5	(0.4 – 0.6)
R2 (from April 20 - May 11)	0.7	(0.3 – 1.0)
R3 (from May 11 - June 30)	0.7	(0.2 – 1.1)
R4 (from July 1 - July 31)	1.0	(0.4 – 1.6)
R5 (from August 1 - August 31)	1.0	(0.8 – 1.4)
R6 (from September 1 - September 30)	0.9	(0.8 – 1.1)
R7 (from October 1 - October 25)	1.3	(1.1 – 1.5)
R8 (from October 26 - November 4)	1.3	(1.1 – 1.6)
R9 (from November 5 - November 30)	0.8	(0.7 – 0.9)
R10 (from December 1 - January 4)	1.08	(1.03 – 1.13)
R11 (from January 4 - January 21)	0.6	(0.5 – 0.7)
R12 (from January 22 - January 31)	0.8	(0.6 – 1.2)
R13 (from February 1)	1.0	(0.7 – 1.3)

To find the different probabilities of high infection intensity, the formula in equation 6.1 is used. Low infection intensity is $1 - P(\text{High infection intensity})$. This method is used to find probabilities for each day in the periods in which it is relevant to analyze. The variable called "infection intensity" in equation 6.1 is the value for the current day from the column "Approximated infection intensity" in the table in section A.1 in appendix A.

$$P(\text{High infection intensity}) = \frac{\text{Infection intensity} - 0.5}{1.5 - 0.5} \cdot 100\% \tag{6.1}$$

An example used for further calculations in explaining variables is infection intensity on 1 December 2020. Table 6.2 shows the result from the calculations based on equation 6.1. The R-number based on the sixth degree equation is estimated to be approximately 0.892. The values in the table 6.2 are transmitted to the network for the current day in the Netica software.

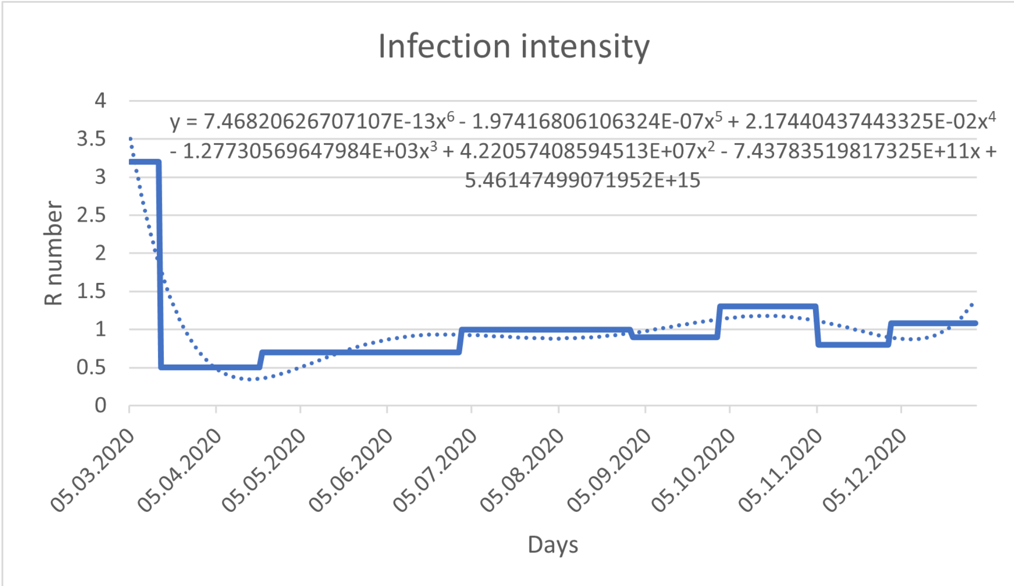


Figure 6.1: R number with corresponding sixth degree trendline from the beginning of the pandemic 5 March 2020 to 31 December 2020.

Table 6.2: Probability table for the variable infection intensity at 1 December 2020.

High	Low
$\frac{0.892-0.5}{1.5-0.5} \cdot 100\% = 39.2\%$	$100\% - 39.2\% = 60.8\%$

ICU beds

An ICU is described as a unit that requires high staffing and advanced, expensive equipment. Patients placed in these wards have impaired vital organ functions (Lauvsnes and Konstante, 2015). ICU beds are part of a specific measure of how many patients there is room for in a ward. Other goals are equipment needed to treat patients and personnel with the expertise to treat them. These are factors that represent the hospital's capacity related to the intensive care unit. The node ICU beds have probabilities related to how likely there are available bedposts. The total number of ICU beds is a variable that can be varied and changed over time periods, but it takes time. Knutsen and Murray (2021) states that no increase in beds in the ICU has been documented during the pandemic, but this report assumes a slight increase in availability at high infection intensity. The reason for this increase, which is expected to take place in October, is that there is more knowledge related to treatment and situation from this time onwards. This will be represented in the Bayesian networks from October 2020 in the simulation.

To assess the proportion of ICU beds available, a rough overview is needed of how many beds there are in total. In total in "Helse Midt-Norge", of which the hospital St. Olavs is a part, there are a total of 49 ICU beds during regular operation, and 110 ICU beds with an increased demand (Helse Midt-Norge, 2020b). With increased demand, it is assumed that they use creative solutions that are used in emergency situations. Of these ICU beds, it is assumed that there are 19 ICU beds during normal operation, and 40 ICU beds during increased demand at St. Olavs hospital. This is in accordance with a statement from St. Olav's hospital (Snøfugl, 2020).

Another necessity in order to be able to assess the amount of ICU beds available, an overview of the number of admitted patients in a given period is needed. The table in section A.2 in appendix A contains the necessary data to assess this in the column "Admitted to a hospital affiliated with the municipality". Figure 6.2 compares the number of registered infected people in Trondheim and admitted patients for infection with COVID-19 at hospitals associated with the municipality.

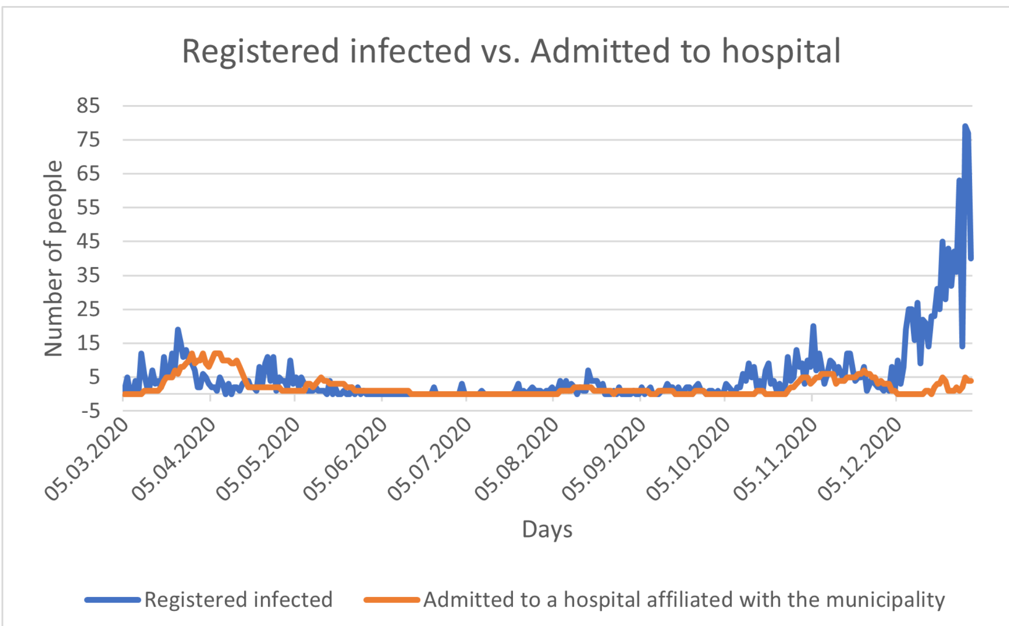


Figure 6.2: Graph comparing the registered infected and the patients admitted to hospital over the time period between 5 March 2020 to 31 December 2020.

Based on the total number of ICU beds mentioned above and the overview of used ICU beds in figure 6.2, it is possible to assess the probabilities of available ICU beds considering different infection intensities. They are thus conditional probabilities. Based on the tables in section A.1 and A.2 in appendix A, it is visible that the number of admitted patients usually does not exceed 25% of the total ICU beds at increased demand. The columns "Approximated infection intensity" and "Admitted to a hospital affiliated with the municipality" are used for this comparison. It is assumed that the number of hospitalized patients is in the intensive care unit and therefore uses ICU beds. Based on this, the CPT of the node is considered to be similar to table 6.3

between March and September 2020, and similar to 6.4 between October and December 2020. The table differs from table 4.1 from the example in that the rows are summed to 1, and not the columns. This is due to the fact that it is more clear to present the parent variable as a single column. It follows that you use the equation $P(b \mid a)$, or $P(\text{ICU beds} \mid \text{R number})$, if you follow the same notation as in the example in section 4.1.2. It is necessary to be consistent.

Table 6.3: CPT for the variable ICU beds between March 2020 and September 2020.

R number	**Available**	**Unavailable**
High	20%	80%
Low	85%	15%

Table 6.4: CPT for the variable ICU beds between October 2020 and December 2020.

R number	**Available**	**Unavailable**
High	25%	75%
Low	85%	15%

Using the values from the variable infection intensity as a known variable, and table 6.3 or 6.4, one can find the joint probabilities of the two variables. The calculation of the joint probabilities is done in the same way as the example in section 4.1.2. The calculation is done for each time slice in the simulation as the values from the variable infection intensity vary between different time intervals. You must also use the corresponding table for ICU beds that are in the same time interval as the parent node. For example, the joint probability table for the time 1 December 2020 can be calculated by using a table 6.2 as a known variable. By multiplying the cells in the table 6.4, which is in the correct time interval, by the corresponding values from the table 6.2, you end up with the following joint probability table (table 6.5) for ICU beds and infection intensity. The procedure is similar to the example in section 4.1.2, except that you solve for $P(b, a) = P(b \mid a) \cdot P(a)$, where variable a corresponds to infection intensity and variable b corresponds to ICU beds.

Table 6.5: Joint probability table for the variables ICU beds and infection intensity at 1 December 2020.

Infection intensity	**Available**	**Unavailable**
High (= 39.2%)	(39.2% · 25% =) 9.8%	(39.2% · 75% =) 29.4%
Low (= 60.8%)	(60.8% · 85% =) 51.68%	(60.8% · 15% =) 9.12%

The probabilities of the individual variable ICU beds can be identified using the joint probability table 6.5. Equation 6.2 shows the probability distribution for the variable ICU beds. ICU beds$_1$

is the probability for available beds, while ICU beds$_2$ represent the probability for unavailable beds given the probability of the infection intensity. The result is similar to node represented in the network from Netica in figure 6.3.

$$\begin{aligned} P(\text{ICU beds}) &= (\text{ICU beds}_1, \text{ICU beds}_2) \\ &= (9.8\% + 51.68\%,\ 29.4\% + 9.12\%) \\ &= (61.5\%,\ 38.5\%) \end{aligned} \tag{6.2}$$

Ventilators

A ventilator is a medical device that breathes for the patient (Opdahl, 2020). Ventilators are considered a limited resource required for the treatment of severely affected COVID-19 patients. It is a resource that is possible to produce more of, so the variable can change over time. Similar to the variable ICU beds, ventilators also have probabilities related to how likely there are available ventilators. Skjesol and Bråten (2020) says that there are 45 ventilators available at St. Olavs. In addition, the hospital has several anesthesia machines that do the same benefit if more machines are needed. Helse Midt-Norge (2020a) also reports that 49 more ventilators will be delivered to Helse Midt-Norge after some time. Based on assumptions that the ventilators will be evenly distributed, St. Olavs will have 60 ventilators available when the ventilators are delivered.

Based on the total number ventilators at different time periods, one can make different probabilities for the two levels of intensities of the infection. The conditional probabilities are based on data from the table in section A.2 in appendix A, which is visualized in figure 6.2, in combination with an assumption that the equipment is also used for treatment other than COVID-19 treatment. The CPT of the node is considered to be similar to table 6.6 in the beginning of the pandemic, similar to table 6.7 when the hospital has received the first delivery of ventilators in April 2020, and corresponding table 6.8 from May 2020 and until December 2020. Engen and Røsvik (2020) points out that there is no need for more ventilators than what has all been delivered. To carry out the analysis, it is not necessary to have an accurate overview of how many ventilators or ICU beds there are in total. It is enough with an estimate, as it gives an indication of how serious the situation may be.

Table 6.6: CPT for the variable ventilators in March 2020.

R number	**Available**	**Unavailable**
High	25%	75%
Low	95%	5%

Similar to the section with ICU beds, it is possible to find the joint probabilities between the parent node infection intensity and the ventilators node. The calculation is done for each time

Table 6.7: CPT for the variable ventilators in April 2020.

R number	**Available**	**Unavailable**
High	40%	60%
Low	95%	5%

Table 6.8: CPT for the variable ventilators between May 2020 and December 2020.

R number	**Available**	**Unavailable**
High	50%	50%
Low	95%	5%

in the simulation, as the values vary between different time periods. It is important to use values from the table which corresponds to the same time interval as the parent node. An example is if you want to find the joint probability table for the node ventilators on 1 December 2020, then you use table 6.2 as known values, and table 6.8, which is in the correct time interval. Using the joint probability table, one can also find the probability distribution for the variable ventilators. Table 6.9 shows the joint probability table between the variables infection intensity and ventilators at 1 December 2020, and equation 6.3 shows the probability distribution of the node ventilators at similar time. Ventilators_1 is the probability for available ventilators, while Ventilators_2 represent the probability for unavailable ventilators given the probability of the infection intensity. The values corresponds to the ventilators node in the Bayesian network in figure 6.3.

Table 6.9: Joint probability table for the variables ventilators and infection intensity at 1 December 2020.

Infection intensity	**Available**	**Unavailable**
High (= 39.2%)	$(39.2\% \cdot 50\% =)$ 19.6%	$(39.2\% \cdot 50\% =)$ 19.6%
Low (= 60.8%)	$(60.8\% \cdot 95\% =)$ 57.76%	$(60.8\% \cdot 5\% =)$ 3.04%

$$\begin{aligned} P(\text{Ventilators}) &= (\text{Ventilators}_1, \text{Ventilators}_2) \\ &= (19.6\% + 57.76\%,\ 19.6\% + 3.04\%) \\ &= (77.4\%,\ 22.6\%) \end{aligned} \tag{6.3}$$

Hospital personnel

Hospital personnel are defined as staff with qualifications and qualities to be able to handle equipment and patients who require special treatment, also known as intensive care nurses. This is a limited resource where it takes a long time to acquire the necessary competence. An average nurse does not have the necessary qualifications needed to handle the very sick patients or the equipment that comes with them. As a rule, intensive workers from Denmark and Sweden are imported to maintain ordinary operations (Sundby, 2021). Quarantine restrictions make it challenging to conduct proper treatment when an important proportion of the employees do not stay in Norway for the majority of time. There is also insufficient recruitment and training of new intensive care nurses, as the personnel with competence is used to treat patients (NTB Nyheter, 2021).

There is a lack of information related to the total number of intensive care nurses. The infection intensity affects the number of available personnel, as a high intensity leads to more infected and quarantined persons. It should be mentioned that nurses are often in contact with many different people. This makes them particularly vulnerable, even though they are generally good at infection control. Available staff means that there are many at work and the staff have the opportunity to handle patients optimally. Unavailable personnel means that the personnel do not have the necessary qualifications or the system is understaffed. Based on this, the node hospital personnel's CPT can look similar to table 6.10. It is also worth noting that foreign health workers have been avoided to the extent possible to avoid quarantine issues among employees. But throughout 2020, health professionals were mostly subject to some form of quarantine. Different hospitals have different approaches, but the hospital relevant to this analysis has avoided health workers from abroad as best it can (Skår and Grov, 2020). Conditional probabilities are therefore assumed to be stable throughout the course of the pandemic in 2020, on which the simulation is based.

Table 6.10: CPT for the variable hospital personnel in 2020.

R number	**Available**	**Unavailable**
High	35%	65%
Low	95%	5%

Using the same procedure as for the variable ICU beds and ventilators, it is possible to find the joint probabilities between the parent node, infection intensity, and the hospital personnel node. The calculations need to be done for each time slice in the simulation, as the infection intensity values vary between different time slices. For example, the joint probability table between infection intensity, which is a known variable, and hospital personnel for 1 December 2020, will look like table 6.11. Equation 6.4 finds the probability distribution of the node hospital personnel at 1 December 2020 based on the joint probabilities. Hospital personnel$_1$ is the probability for available hospital personnel, while hospital personnel$_2$ represent the probability for unavailable hospital personnel given the probability of the infection intensity.

Table 6.11: Joint probability table for the variables hospital personnel and infection intensity at 1 December 2020.

Infection intensity	**Available**	**Unavailable**
High (= 39.2%)	(39.2% · 35% =) 13.72%	(39.2% · 65% =) 25.48%
Low (= 60.8%)	(60.8% · 95% =) 57.76%	(60.8% · 5% =) 3.04%

$$
\begin{aligned}
P(\text{Hospital personnel}) &= (\text{Hospital personnel}_1, \text{Hospital personnel}_2) \\
&= (13.72\% + 57.76\%,\ 25.48\% + 3.04\%) \\
&= (71.5\%,\ 28.5\%)
\end{aligned}
\tag{6.4}
$$

Hospital capacity

Hospital capacity is a variable that is affected by factors that represent the hospital during the course of the pandemic. The definition of capacity is, as mentioned in section 2.2, the total amount a system can handle. Both hospital personnel, ventilators and ICU beds are critical factors that affect the hospital's ability to handle a situation, and the factors have a maximum and upper limit. Combined, the three factors will constitute a total capacity for the hospital as a whole.

Unlike the variables the node hospital capacity is based on, namely hospital personnel, ICU beds and ventilators, the values for the node hospital capacity's conditional probabilities are not based on direct data. The reason for this is that it is challenging to find data that argues for the distribution and the impact the factors have on capacity. Based on this, an equal weighting is used for the three factors, where 100% available and 100% unavailable are the different extremes of the scale. Table 6.12 is the CPT for the node, and presents the distribution of conditional probabilities between the parent nodes hospital staff, ventilators and ICU beds. It is worth noting that realistically speaking, hospital personnel, ventilators and ICU beds do not have as great an impact on capacity. Several articles point out the importance of hospital personnel as it is a resource that is very challenging to replace and which is crucial for the function of the other variables. It is thus a significant simplification to assume and assign the variables equal weighting, but it is possible to change and update the probability when new and credible evidence emerges.

Using the same procedure as for the previous variables, one can use the probability distribution of the parent nodes, respectively the result from equation 6.4, equation 6.3, and equation 6.2,

Table 6.12: CPT for the variable hospital capacity in 2020.

Hospital personnel	**Ventilators**	**ICU beds**	**Available**	**Unavailable**
Available	Available	Available	100%	0%
Available	Available	Unavailable	67%	33%
Available	Unavailable	Available	67%	33%
Available	Unavailable	Unavailable	33%	67%
Unavailable	Available	Available	67%	33%
Unavailable	Available	Unavailable	33%	67%
Unavailable	Unavailable	Available	33%	67%
Unavailable	Unavailable	Unavailable	0%	100%

and table 6.12 to find the joint probabilities for 1 December 2020. The joint probabilities are only relevant for 1 December 2020, as the probability distributions for the parent nodes only apply to that time slice. The joint probability table between hospital personnel, ventilators, ICU beds, and hospital capacity for 1 December 2020 is presented in table 6.13. Equation 6.5 shows how to arrive at the probability distribution of the variable hospital capacity. Hospital capacity$_1$ is the probability for available hospital capacity, while hospital capacity$_2$ represent the probability for unavailable hospital capacity given the probabilities of the parent nodes hospital personnel, ventilators, and ICU beds. There are some differences between the result from the calculation in Netica compared with the calculation in the example in the table 6.13 and equation 6.5, due to rounding differences for previous values in the report. Netica gives the most accurate results, and it is these values that are used in calculations for subsequent variables.

$$
\begin{aligned}
P(\text{Hospital capacity}) &= (\text{Hospital capacity}_1, \text{Hospital capacity}_2) \\
&= (34.03\% + 14.28\% + 6.66\% + 2.05\% + 9.09\% + 2.80\% + 1.31\% + 0\%, \\
&\quad 0\% + 7.03\% + 3.28\% + 4.17\% + 4.48\% + 5.69\% + 2.65\% + 2.48\%) \\
&= (70.22\%, 29.78\%) \\
&\approx (70.1\%, 29.9\%)
\end{aligned} \tag{6.5}
$$

Social distancing

Social distancing is a concept that means keeping physical distance between people. Requirements for social distancing are aimed at reducing the spread of infection by reducing contact rates (Greenstone and Nigam, 2020). The node social distancing deals with the distance function associated with the spread of infection. The analysis addresses three different levels of distance. These are lockdown, distance and none. The level of lockdown is defined as an injunc-

Table 6.13: Joint probability table for the variables hospital capacity, hospital personnel, ventilators and ICU beds at 1 December 2020.

Hospital personnel	Ventilators	ICU beds	**Available**	**Unavailable**
Available (= 71.5%)	**Available** (= 77.4%)	**Available** (= 61.5%)	(71.5% · 77.4% · 61.5% · 100% =) 34.03%	(71.5% · 77.4% · 61.5% · 0% =) 0%
Available (= 71.5%)	**Available** (= 77.4%)	**Unavailable** (= 38.5%)	(71.5% · 77.4% · 38.5% · 67% =) 14.28%	(71.5% · 77.4% · 38.5% · 33% =) 7.03%
Available (= 71.5%)	**Unavailable** (= 22.6%)	**Available** (= 61.5%)	(71.5% · 22.6% · 61.5% · 67% =) 6.66%	(71.5% · 22.6% · 61.5% · 33% =) 3.28%
Available (= 71.5%)	**Unavailable** (= 22.6%)	**Unavailable** (= 38.5%)	(71.5% · 22.6% · 38.5% · 33% =) 2.05%	(71.5% · 22.6% · 38.5% · 67% =) 4.17%
Unavailable (= 28.5%)	**Available** (= 77.4%)	**Available** (= 61.5%)	(28.5% · 77.4% · 61.5% · 67% =) 9.09%	(28.5% · 77.4% · 61.5% · 33% =) 4.48%
Unavailable (= 28.5%)	**Available** (= 77.4%)	**Unavailable** (= 38.5%)	(28.5% · 77.4% · 38.5% · 33% =) 2.80%	(28.5% · 77.4% · 38.5% · 67% =) 5.69%
Unavailable (= 28.5%)	**Unavailable** (= 22.6%)	**Available** (= 61.5%)	(28.5% · 22.6% · 61.5% · 33% =) 1.31%	(28.5% · 22.6% · 61.5% · 67% =) 2.65%
Unavailable (= 28.5%)	**Unavailable** (= 22.6%)	**Unavailable** (= 38.5%)	(28.5% · 22.6% · 38.5% · 0% =) 0%	(28.5% · 22.6% · 38.5% · 100% =) 2.48%

tion against meeting others outside the household, where only the most necessary of shops are open. There are restrictions on how many people that can stay in the shops at a time. During the pandemic, Norway has chosen a handling without a curfew, so this solution is assumed to be unlikely. The population is advised to keep their distance at all times when moving in public. At the distance level, it is a general recommendation to keep a distance of 1 to 2 meters between each other at all times. Stores are open, but there are still restrictions on how many people can stay in the store at a time and how many close contacts it is allowed to have during a week. It is allowed to have smaller gatherings of people. The level none has no restrictions and you can move as you wish.

The probabilities are developed on the basis of how society has reacted to increased and decreasing infection intensity. For example, it is assumed that there is a higher probability of a lockdown at high infection intensity, as this is more frequently discussed when this is the case. There was also a greater probability of a lockdown at the beginning of the pandemic, as there was great uncertainty. On the other hand, the measures that have been implemented have been more similar to the description of the distance level. Norway's approach is to implement measures that can be intrusive to avoid having to go up to the lockdown level. There is generally a low probability of the none level, as large parts of society have been aware that it takes little before the infection intensity increases again. The conditional probabilities are developed based on these observations. The CPT for the variable social distancing is therefore assumed to be stable throughout the course of the pandemic in 2020, and is shown in table 6.14.

Table 6.14: CPT for the variable social distancing in 2020.

R number	**Lockdown**	**Distance**	**None**
High	13%	85%	2%
Low	5%	90%	5%

Using the same procedure as for the previous variables, it is possible to find the joint probabilities between the parent node, infection intensity, and the social distance node. The calculations need to be done for each time slice in the simulation, as the infection intensity values vary between different time slices. For example, the joint probability table between infection intensity, which is a known variable, and social distancing for 1 December 2020, will look like table 6.15. Equation 6.6 shows how to arrive at the probability distribution of the variable social distancing at 1 December based on the joint probabilities. Social distancing$_1$ is the probability of lockdown, social distancing$_2$ is the probability of the distance level, while social distancing$_3$ is that there is no measures related to distance. All the probabilities are given the probability of the infection intensity.

Table 6.15: Joint probability table for the variables social distancing and infection intensity at 1 December 2020.

Infection intensity	**Lockdown**	**Distance**	**None**
High (= 39.2%)	(39.2% · 13% =) 5.10%	(39.2% · 85% =) 33.32%	(39.2% · 2% =) 0.78%
Low (= 60.8%)	(60.8% · 5% =) 3.04%	(60.8% · 90% =) 54.72%	(60.8% · 5% =) 3.04%

$$\begin{aligned} P(\text{Social distancing}) &= (\text{Social distancing}_1, \text{Social distancing}_2, \text{Social distancing}_3) \\ &= (5.10\% + 3.04\%,\ 33.32\% + 54.72\%,\ 0.78\% + 3.04\%) \\ &= (8.14\%,\ 88.04\%,\ 3.82\%) \end{aligned} \tag{6.6}$$

Mask use

Another tool used to control the spread of infection is the use of face masks. COVID-19 is a virus that is transmitted in close contact through droplets from the respiratory tract (Folkehelseinstituttet, 2021a). Face masks should prevent the spread of the mentioned drops. The node mask use can be modeled as the percentage of the population who wear face masks in public. In Norway, face masks are not mandatory in every public situation. There are also local differences. There are requirements for face masks where it is difficult to keep distance, there is increased infection intensity, and in other predefined situations.

The use of masks is represented as used and unused in the CPT. There are some limitations associated with the choice of conditional probabilities for the use of masks. Norway spent a long time before there was a recommendation for the use of face masks. There are also major differences in the use of face masks related to geography, as the infection intensity is usually highest in the cities. I assume that 100% corresponds to the entire population using face masks. By taking into account Norway as a whole over the course of the pandemic in 2020, the CPT will look like table 6.16.

Table 6.16: CPT for the variable mask use in 2020.

R number	**Used**	**Unused**
High	55%	45%
Low	30%	70%

The variables that represent measures to limit the spread of infection, such as social distancing and mask use, technically affect the infection intensity as well. Increased distancing and mask use further reduces transmission of infection, which reduces infection intensity. This is neglected in the analysis as it is not possible to model cycles. The reason why is explained in section 4.1.1 and section 4.1.4.

Using the same procedure as for the previous variables, it is possible to find the joint probabilities between the parent node, infection intensity, and the mask use node. The calculations need to be done for each time slice in the simulation, as the infection intensity values vary between different time slices. For example, the joint probability table between infection intensity, which is a known variable, and mask use for 1 December 2020, will look like table 6.17. Equation 6.7 shows how to arrive at the probability distribution of the variable mask use at 1 December based on the joint probabilities. Mask use$_1$ is the probability for masks being used, while mask use$_2$ represent the probability for masks not being used given the probability of the infection intensity.

Table 6.17: Joint probability table for the variables mask use and infection intensity at 1 December 2020.

Infection intensity	**Used**	**Unused**
High (= 39.2%)	(39.2% · 55% =) 21.56%	(39.2% · 45% =) 17.64%
Low (= 60.8%)	(60.8% · 30% =) 18.24%	(60.8% · 70% =) 42.56%

$$\begin{aligned}
P(\text{Mask use}) &= (\text{Mask use}_1, \text{Mask use}_2) \\
&= (21.56\% + 18.24\%,\ 17.64\% + 42.56\%) \\
&= (39.8\%,\ 60.2\%)
\end{aligned} \tag{6.7}$$

Number of patients

As social distancing and the use of masks are measures to limit the spread of infection, this has a direct impact on the number of infected and hospitalized patients. The node number of patients is represented by high and low, which says something about whether there is a high number of admitted patients or not. Based on the data from the table in section A.2 in appendix A, a limit of 10 patients is set as the difference between high and low number of patients. As the situation is presented throughout 2020, the number of patients is mostly in the low area. This gives the following CPT for the node number of patients presented in table 6.18. The probabilities are also set to be stable over the course of the analysis.

Table 6.18: CPT for the variable number of patients in 2020.

Social distance	**Mask use**	**High**	**Low**
Lockdown	Used	10%	90%
Lockdown	Unused	15%	85%
Distance	Used	15%	85%
Distance	Unused	25%	75%
None	Used	80%	20%
None	Unused	95%	5%

Using the same procedure as for the previous variables, one can use the probability distribution of the parent nodes, respectively the result from equation 6.6 and equation 6.7, and table 6.18 to find the joint probabilities for 1 December 2020. The joint probabilities are only relevant for 1 December 2020, as the probability distributions for the parent nodes only apply to that time slice. The joint probability table between social distance, mask use and the number of patients for 1 December 2020 is presented in table 6.19. Equation 6.8 shows how to arrive at the probability distribution of the variable number of patients. $\text{Number of patients}_1$ is the probability for a high level of patients, while $\text{number of patients}_2$ represent the probability for a low level of patients given the probabilities of the social distancing and mask use.

Table 6.19: Joint probability table for the variables number of patients, social distancing and mask use at 1 December 2020.

Social distance	Mask use	**High**	**Low**
Lockdown (= 8.14%)	**Used** (= 39.8%)	(8.14% · 39.8% · 10% =) 0.32%	(8.14% · 39.8% · 90% =) 2.92%
Lockdown (= 8.14%)	**Unused** (= 60.2%)	(8.14% · 60.2% · 15% =) 0.74%	(8.14% · 60.2% · 85% =) 4.17%
Distance (= 88.04%)	**Used** (= 39.8%)	(88.04% · 39.8% · 15% =) 5.26%	(88.04% · 39.8% · 85% =) 29.78%
Distance (= 88.04%)	**Unused** (= 60.2%)	(88.04% · 60.2% · 25% =) 13.25%	(88.04% · 60.2% · 75% =) 39.75%
None (= 3.82%)	**Used** (= 39.8%)	(3.82% · 39.8% · 80% =) 1.22%	(3.82% · 39.8% · 20% =) 0.30%
None (= 3.82%)	**Unused** (= 60.2%)	(3.82% · 60.2% · 95% =) 2.18%	(3.82% · 60.2% · 5% =) 0.11%

$$\begin{aligned} P(\text{Number of patients}) &= (\text{Number of patients}_1, \text{Number of patients}_2) \\ &= (0.32\% + 0.74\% + 5.26\% + 13.25\% + 1.22\% + 2.18\%, \\ &\quad 2.92\% + 4.17\% + 29.78\% + 39.75\% + 0.30\% + 0.11\%) \\ &= (22.97\%, 77.03\%) \end{aligned} \tag{6.8}$$

Hospital availability

In section 2.3, availability is defined as the state of a system when it is able to perform a given function under given conditions. Hospital availability therefore describes the opportunity one has to be able to utilize the resources associated with the hospital should a need arise. Whether the resources are sufficient or not is also expressed in the form of the term availability, as it describes the quality of the system given the definition in section 2.3. Therefore, high availability will express a high degree of sufficient resources, which low availability does not express. The node is based on the total capacity represented in the variable hospital capacity, in addition to the number of patients admitted due to the COVID-19 virus, represented as the variable number of patients. Overall, they describe the total access to the hospital. Based on pure intuition, it is assumed that the conditional probabilities between the previous variables and hospital availability are as presented in the table 6.20. The probabilities are based on assumed availability in different situations. The hospital in the analysis has not experienced all the different scenarios during the course of the pandemic, but the probabilities can be updated if new evidence is discovered later.

Table 6.20: CPT for the variable hospital availability in 2020.

Number of patients	**Hospital capacity**	**High**	**Low**
High	Available	60%	40%
High	Unavailable	5%	95%
Low	Available	95%	5%
Low	Unavailable	15%	85%

Using the same procedure as for the previous variables, one can use the probability distribution of the parent nodes, respectively the result from equation 6.5 and equation 6.8, and table 6.20 to find the joint probabilities for 1 December 2020. The joint probabilities are only relevant for 1 December 2020, as the probability distributions for the parent nodes only apply to that time slice. The joint probability table between hospital capacity, number of patients and the hospital availability for 1 December 2020 is presented in table 6.21. Equation 6.9 shows how to arrive at the probability distribution of the variable hospital availability. Hospital availability$_1$ is the probability for high availability, while hospital availability$_2$ represent the probability for low availability given the probabilities of the hospital capacity and number of patients. As this is the value the network is designed to find, the value for high availability will be retrieved from each simulation and collected in the "Availability" column of the table in section A.2 in appendix A.

Table 6.21: Joint probability table for the variables hospital availability, number of patients and hospital capacity at 1 December 2020.

Number of patients	Hospital capacity	**High**	**Low**
High (= 23.0%)	**Available** (= 70.1%)	(23.0% · 70.1% · 60% =) 9.67%	(23.0% · 70.1% · 40% =) 6.45%
High (= 23.0%)	**Unavailable** (= 29.9%)	(23.0% · 29.9% · 5% =) 0.34%	(23.0% · 29.9% · 95% =) 6.53%
Low (= 77.0%)	**Available** (= 70.1%)	(77.0% · 70.1% · 95% =) 51.28%	(77.0% · 70.1% · 5% =) 2.70%
Low (= 77.0%)	**Unavailable** (= 29.9%)	(77.0% · 29.9% · 15% =) 3.45%	(77.0% · 29.9% · 85% =) 19.57%

$$\begin{aligned} P(\text{Hospital availability}) &= (\text{Hospital availability}_1, \text{Hospital availability}_2) \\ &= (9.67\% + 0.34\% + 51.28\% + 3.45\%, \\ &\quad 6.45\% + 6.53\% + 2.70\% + 19.57\%) \\ &= (64.7\%, 35.3\%) \\ &\approx (64.6\%, 35.4\%) \end{aligned} \tag{6.9}$$

6.2.2 Network

Figure 6.3 shows the Bayesian network for 1 December 2020 from the software Netica. The network has different node sets with different colors to distinguish the areas to which they belong. The blue nodes represent the variables associated with the hospital, while the orange nodes represent the variables associated with society. The node infection intensity is common to both the hospital and community nodes, as it illustrates the development of the pandemic. The green node, hospital availability, is the hypothesis variable.

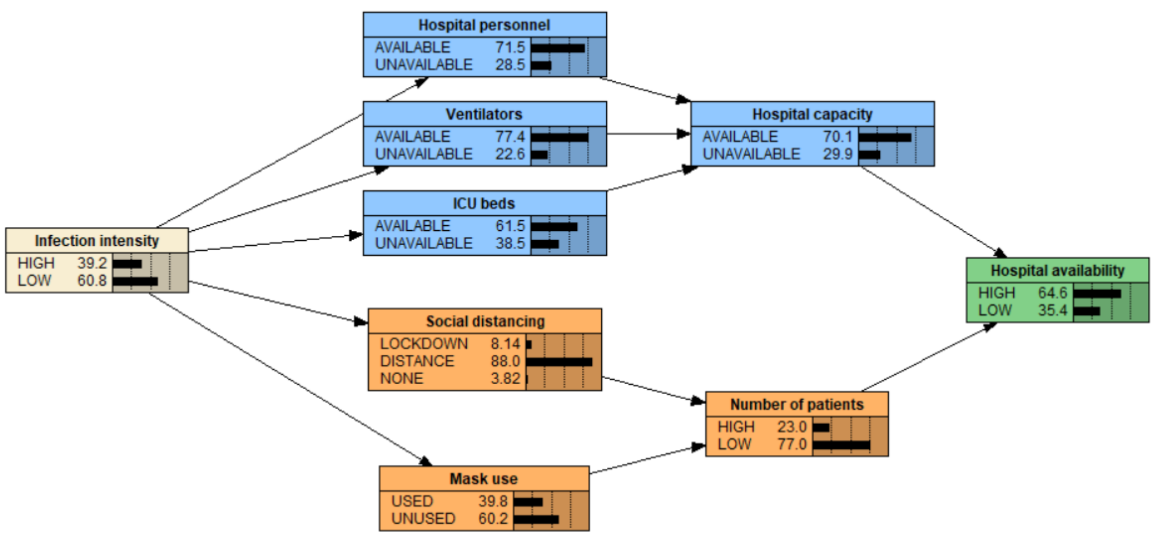


Figure 6.3: Example of Bayesian network for 1 December 2020. Displays the nodes presented in section 6.2.1 divided into different categories using colors.

As mentioned in the section 6.2.1, the results from the various equations in the section reflect the values of the network. The values describe the probability values for each variable, and are found using conditional probabilities, joint probabilities, and Bayes' theorem. The values for infection intensity are specific to each time slice. The values are presented in the table in section A.1 in appendix A in the column "Approximated infection intensity". They are found using equation A.1. The values are updated for each time slice in the current time interval to be simulated.

Furthermore, the subsequent nodes after the node infection intensity are conditioned by the value of the infection intensity. The procedure for finding the values is shown in equation 6.2, equation 6.3 and equation 6.4 for the nodes related to hospitals, and equation 6.6 and equation 6.7 for the nodes related to society. The conditional probabilities of the nodes ventilators and ICU beds are also adjusted after the update made for the probabilities in April and May 2020, and October 2020, respectively. Calculations for the values of the nodes hospital capacity, number of patients and hospital availability are shown in equation 6.5, equation 6.8 and equation 6.9, respectively. There may be some discrepancies in the values as the previous values appear somewhat rounded in Netica. If one uses the rounded values to manually calculate joint probabilities and hence probability distributions, there will be some discrepancies. The values for the nodes hospital capacity, number of patients and hospital availability are more accurate in Netica than in manual calculations, as Netica takes the decimals into account.

6.3 Dynamic Bayesian network

To perform a dynamic simulation of the Bayesian network, a simulation of the network is performed in Netica for each time slice in the interval, where nodes are updated with current values. The network has an identical structure as a figure 6.3 for each time slice in the simulation. For example, the values for the node infection intensity for each time slice are updated, and the nodes ventilators and ICU beds are adjusted two and one time(s), respectively, during the interval. The value associated with high availability in the hospital availability node is manually collected in a spreadsheet in Excel.

For the analysis, one simulation of the total time interval has been carried out. Values for infection intensity, ventilators and ICU beds are changed during the given interval. The values for high hospital availability can be found in the column "Availability" in section A.2 from appendix A. The values from the column "Availability" from appendix A are plotted in the graph in the figure 6.4.

The simulation used in the master's thesis does not directly use the connection between nodes and their predecessor in the network. The software Netica has a function that connects nodes with their predecessors to create a dynamic network, similar to the system described in section 4.2.1. The software assumes that they are a dynamic model, which can lead to values and results that do not necessarily coincide with actual values. As Netica is considered a flexible program-

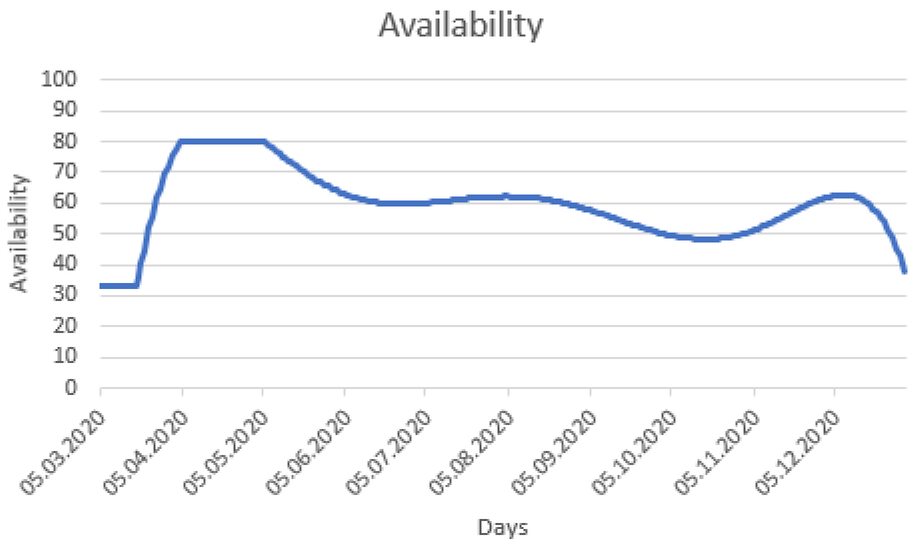


Figure 6.4: Graph presenting the availability at different times in the interval 5 March 2020 to 31 December 2020.

ming tool where you can easily update values, a manual update of values for each time slice is used in this master's thesis. This is to get as realistic a simulation as possible. The principle presented in section 4.2.1 applies, but the updates are done manually rather than retrieved from an automatic and presumed update of the system.

In order to visualize the effect of changing the conditional probabilities of variables, a simulation was also carried out with corresponding variables with different updates of the variables. The variables after the node infection intensity were kept constant, which clarifies the effect of the changes made on the variables ICU beds and ventilators in the simulation presented in the sections above. In other words, one can model two scenarios with the same starting point, where the factors in one scenario are updated while the other is kept stable. Scenario 1 describes the situation where the nodes ICU beds and ventilators update conditional probabilities at the times mentioned in section 6.2.1, and the node infection intensity is updated for each time slice in the interval. Scenario 2 only updates infection intensity values for each time slice in the interval. No other variables are updated. The names scenario 1 and scenario 2 are used in the explanation of the different curves in the graph in figure 6.5. The values for scenario 1 can be found in the table in section A.2 in appendix A, and the values for scenario 2 can be found in the table in section A.3 in appendix A.

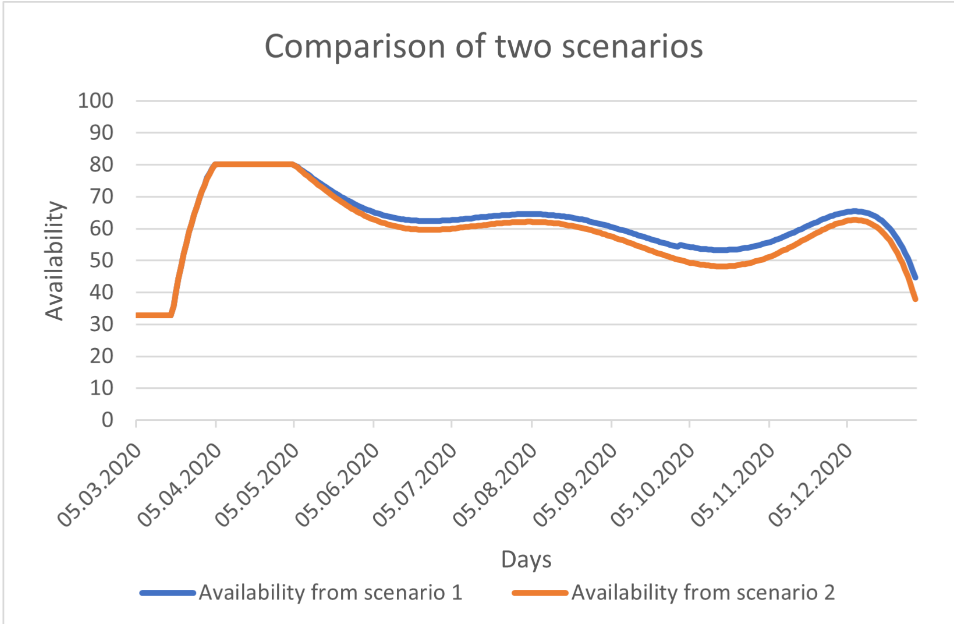


Figure 6.5: Graph presenting the availability at different times in the interval 5 March 2020 to 31 December 2020, representing two scenarios. The scenarios are with and without changes of the variables following the node infection intensity.

6.4 Resilience calculation

Based on equation 5.1 it is possible to produce a value that represents lost resilience. The results from the networks connected to the dynamic Bayesian network are hospital availability for the system at each time slice. This value can, as mentioned in section 5.2, be used as an expression of the quality of the system. The table in section A.2 in appendix A uses equation 5.1 to calculate lost resilience for each time slice. By adding the values together, one finds the total lost resilience for the system. The last row in the mentioned table contains this value. For the performed simulation, the variables infection intensity, ventilators and ICU beds are updated. Lost resilience is calculated for the scenario in the column "Resilience lost" in section A.2 in appendix A. The total lost resilience is calculated to be 11409.3. Figure 6.6 shows the total lost resilience as the light blue shaded area. The area corresponds to the mentioned value 11409.3 and is corresponding to the area called “Resilience lost” in figure 5.1.

It is unlikely that the availability of the hospital corresponded to 100% before the pandemic was a fact. Hosseini et al. (2016) mentions that 100% quality before a disruption is an unrealistic assumption. This, on the other hand, is an assumption in Bruneau’s approach to quantifying resilience. Assuming that the availability was 90% in the period before data related to the development of the pandemic was made available in the form of reports from NIPH, the graph representing availability will look similar to figure 6.7. The light blue shaded area corresponds

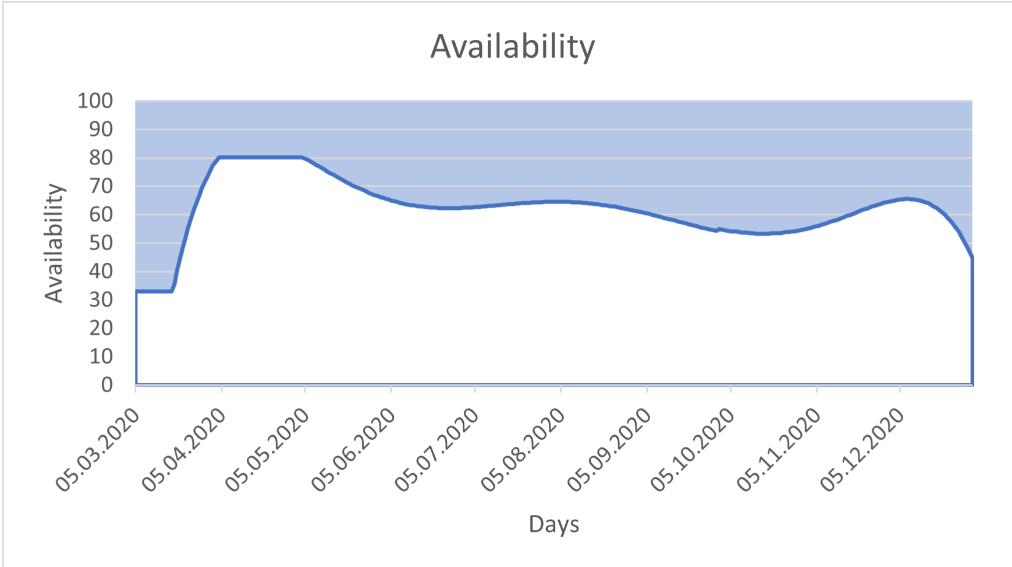


Figure 6.6: Graph presenting the lost resilience based on the factor availability at different times in the interval 5 March 2020 to 31 December 2020.

to lost resilience. As the assumption that the hospital does not normally have 100% availability, there will constantly be resilience lost. Figure 6.8 shows similar values as figure 6.7, but the shaded area corresponds to the resilience of the hospital, similar to figure 2.1.

Even if the assumption is that the system's availability is 90% under normal circumstances, this will apply to the system even after the disruption is considered above. If one only compares by changing measures while the incident is still ongoing, the assumption of 100% before the disruption occurs does not matter. In general, the total lost resilience after the disruption occurs will be less, as the system does not lose from the maximum achievable value, but the system's normal value. But as mentioned, this will apply to the system at all times, and a desire and purpose will be to implement measures so that the system is at 100% before disruptions occur.

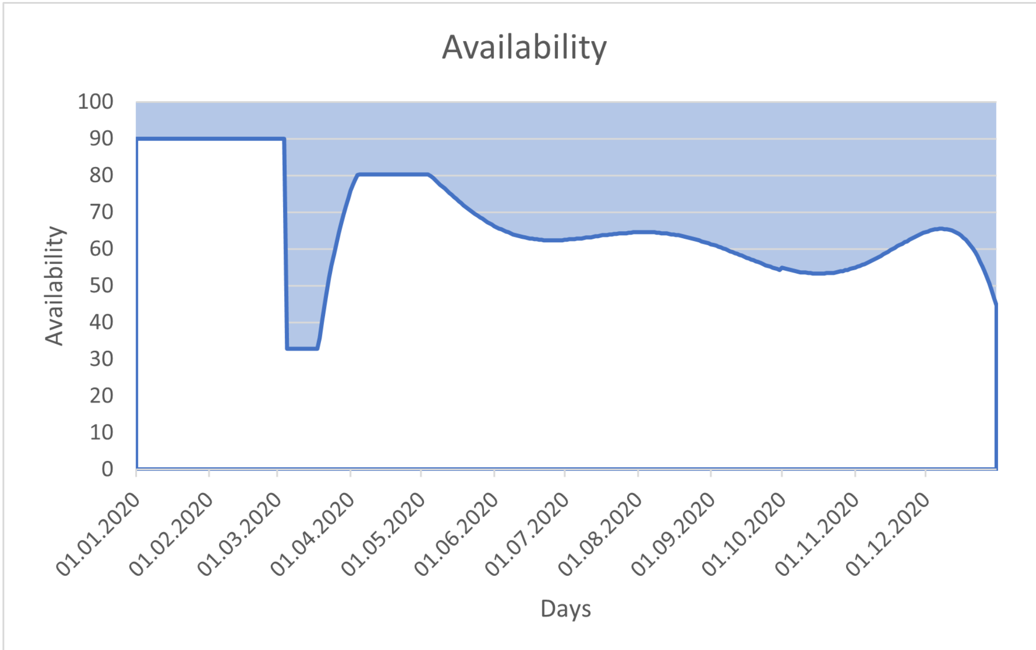


Figure 6.7: Graph presenting the lost resilience based on the factor availability at different times in the interval 1 January 2020 to 31 December 2020.

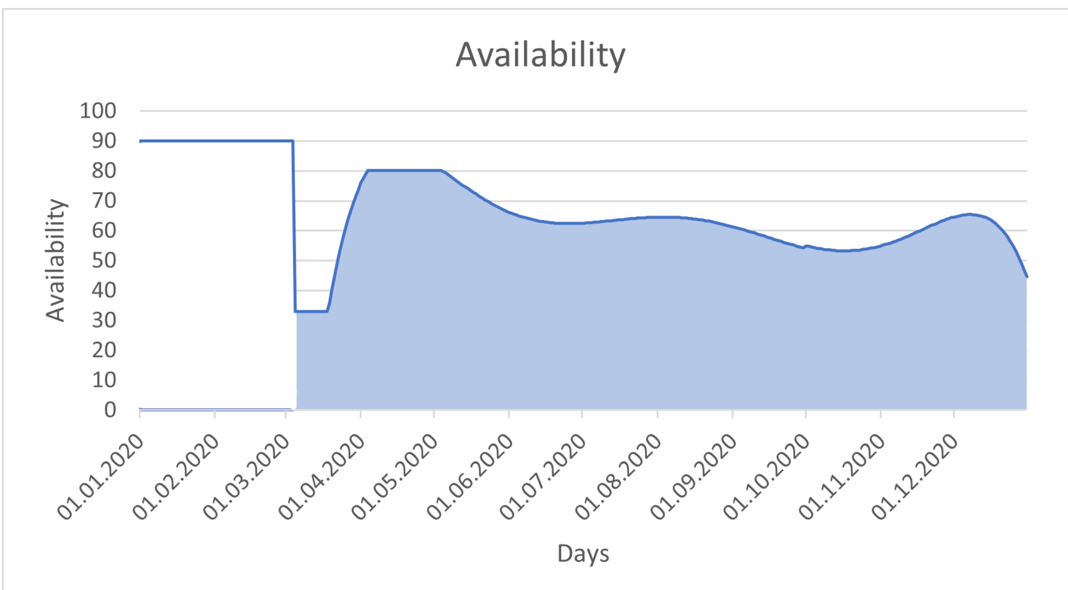


Figure 6.8: Graph presenting the resilience based on the factor availability in the interval 5 March 2020 to 31 December 2020. Based on figure 2.1.

6.5 Alternative simulation

The variables infection intensity, social distancing and mask use can be set to represent given alternative scenarios. By determining the values of the variables, which in reality are uncontrollable factors, one can, based on a given target value for hospital availability, see what is required of the partially controllable factors related to the hospital's capacity. Figure 6.9 represents such a simulation. The variables infection intensity are set to have a 100% probability of high value, social distancing has a 100% probability of the level distance, and mask use has a 100% probability of using masks. By setting the target value for hospital availability to be 89%, the values for the remaining nodes are automatically set to achieve this final value. This is due to the properties of the Bayesian network method which allows reversibility related to Bayes' theorem, as mentioned in section 4.1.4.

As mentioned, Netica automatically updates the unspecified values when updating the target value. In the case presented in figure 6.9, a hospital capacity of 71.3% available resources is needed to achieve a hospital availability at 89%, which is further distributed over the variables hospital personnel, ventilators and ICU beds. Assessments that can be made on the basis of this are discussed further in section 7.2 in chapter 7.

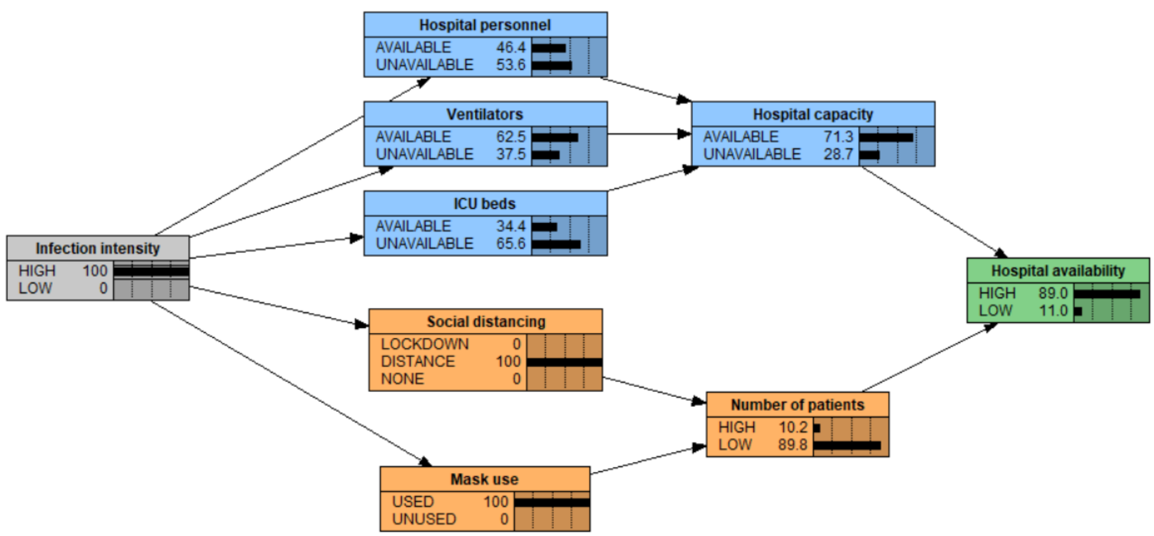


Figure 6.9: Alternative Bayesian network where variables such as infection intensity, social distancing, and mask use are fixed. The node hospital availability is given a fixed target value.

6.6 Other results

The result of availability from the scenario where infection intensity, ICU beds and ventilators are updated, can be used to make comparisons. Figure 6.10 compares the hospital's availability with the number of patients admitted to hospital due to COVID-19 infection, which is collected from the column "Admitted to a hospital affiliated with the municipality" in the table in section

A.2 in appendix A. The y-axis of the graph represents both the number of admissions for the blue curve "Admitted to hospital" and the percentage availability for the orange curve "Availability". Since the curves should only show trends, these different units do not affect the result of the graph. However, the difference of the units is worth noting.

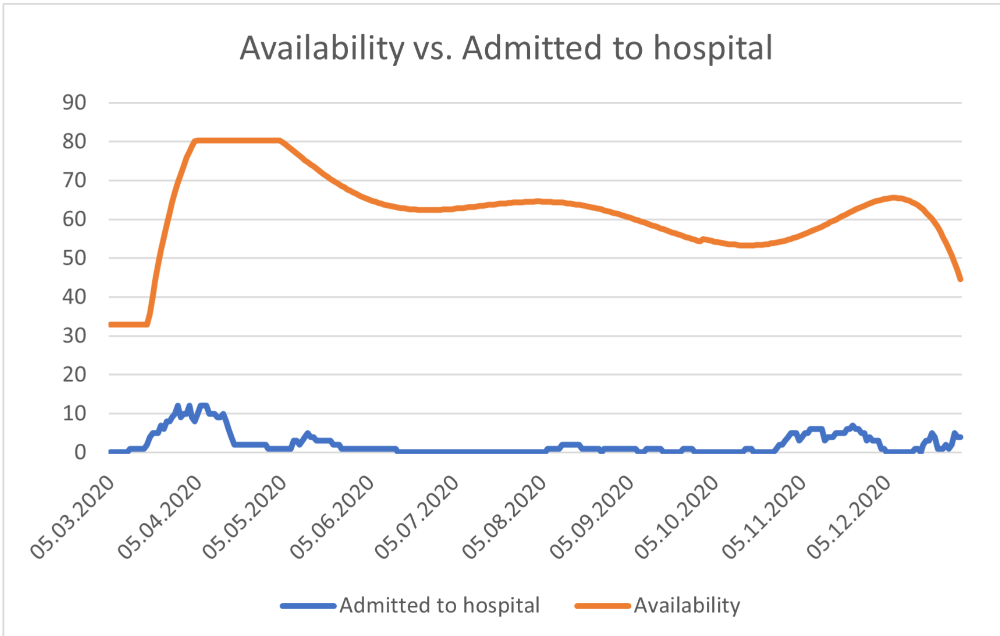


Figure 6.10: Graph presenting hospital availability and the number of patients admitted to hospital due to COVID-19 infection in the interval 5 March 2020 to 31 December 2020.

Chapter 7

Discussion

The results from the model and the simulation can be used to make recommendations for handling future situations. In order for this to be possible, one must be able to understand what information and conclusions can be drawn from the case already studied. In this way, one can be able to see the usefulness of the method and evaluate the functionality in the given situation.

7.1 Interpretations

In chapter 2, resilience is presented as a system's property to counteract loss of performance if a disturbance should occur. Figure 2.1 is a clear example that represents the response and recovery of performance within a given time interval. The figure has system performance as its axis to represent the system's influence and response. It is challenging to specify what system performance entails, as it is very individual which factors are relevant in different systems. Availability is a factor that can represent the performance and quality of the system at any given time. For this reason, it is possible to compare figure 2.1 with figure 6.8 based on the result of the analysis.

The shaded area in both graphs in figure 2.1 and figure 6.8 corresponds to the resilience. For the graph in figure 6.8, the area corresponds to the recovery phase during the time interval, since the drop in performance is so steep. This is based on the assumed immediate fall in quality which is an assumption from Bruneau's method from section 5.1.2, and the result of the available data. The curve, on the other hand, does not show a steady and gradual rise towards the system performance or availability that was the case before the pandemic. Graph 6.8 shows a continuous rise and fall in availability over the specified time period. This may be because the severity and impact have varied over the time interval. As mentioned in the beginning in section 1.1, the pandemic has consisted of several surges of patients being admitted to the hospital. The surges are also visualized along the orange curve in the figure 6.2. Based on the limited resources and data available, the parameter availability shows a good correlation that expresses resilience for the system.

Bruneau's method, which is used to quantify resilience based on the hospital's availability over a period in section 6.4, results in only a simple numerical value. The value represents the area that says something about lost resilience, but it can be challenging to draw conclusions based on the value. This is especially true if there is no basis for comparison. It is also challenging to be able to draw conclusions from the result on how the development of the pandemic has been during the year, and which factors affect resilience at different times. On the other hand, it is possible to interpret the results related to lost resilience from the graphs that show the availability of the system during the interval. If one uses the direct connection explained in the paragraphs above between resilience and the parameter availability, one can see that there is a clear connection between the variation of infection intensity of resilience to the system. Based on this, it is possible to interpret how the development of the pandemic affects the resilience of the hospital, and which availabilities are considered sufficient for the hospital's functions.

As there is a connection between infection intensity and resilience, based on the parameter availability, one is able to point out when the hospital's resilience is pressured. This is a conclusion that is known to the general public, as the health authorities decide which measures are to be implemented on the basis of the R number, i.e. the intensity of infection. The method used in the analysis confirms this. The results from the analysis, among other things presented in the graph in figure 6.8, also show that as measures are implemented with increased infection intensity, i.e. with declining availability, availability increases shortly afterwards. This also helps reduce the lost resilience.

There are not many variables that change conditional probabilities during the simulation of the dynamic Bayesian network in the case study. The node infection intensity is conditionally linked to all the subsequent nodes, and it can be said with certainty that the impact of changes on the node is significant. The probabilities of the node are also the values that change the most during the simulation. The values representing the probability distribution of the subsequent nodes would most likely not have had the same variation if the values for the variable infection intensity had been more stable. This clarifies the power of influence the variable has on the subsequent variables. The variables ventilators and ICU beds have relatively small changes during the time interval for the analysis. The values change two and one time(s), respectively, during the time interval. This makes the conditional probabilities for the variables close to constant. Minimal changes are seen in connection with these changes, which clarifies that the variable infection intensity has the greatest influence.

To compare actual results from the pandemic with the simulation, one can look at the number of hospital admissions due to COVID-19 and the results from the availability simulation. Figure 6.10 has combined the development of the two curves so that one can assess the trends against each other. It would be natural that when availability decreases, the number of admitted patients increases. This is because an increasing number of admitted patients at a hospital require more resources, which reduces the availability of the hospital. This is not necessarily the case in the figure 6.10, where at the beginning of the pandemic until approximately May 2020, there was both increasing availability and an increasing number of admissions. The reason for this may be uncertainty related to data, which is further explained in section 7.1.2.

Furthermore, the number of admissions, according to figure 6.10, remains relatively low and stable until November 2020. Around November 2020, there is an increase in the number of admissions, and previously there has been a steady decline in availability. The decline occurs somewhat before the increase in the number of patients admitted to hospitals, which may be due to the backlog between being infected with COVID-19 and admitted to hospitals due to the virus. It is assumed that it will take some time before the infected become ill enough to be admitted. This is also reflected in an increase in availability around the end of November, before the availability is falling again during December 2020. There is also a decrease in the number of admissions between the end of November 2020 and beginning of December 2020. Based on the available data where there is a relatively credible data base, the model agrees with actual events. This is useful because it shows that the curve the model results in fits with actual events. This assessment is based only on one factor, which is the number of admitted patients. The availability is affected by the number of hospitalized patients, but other factors also have an impact. This means that the curve is not completely fitted. The analysis is limited to what data is available.

As there is a limited interval the analysis is based on, and the pandemic is still real after the end of the interval, the hospital's availability will most likely increase to the value before the outbreak. The graphs that illustrate the results from the analysis therefore show a smaller overview of the situation as one does not see the final and total increase as one expects. The pandemic is ongoing, and it is not possible to form a complete picture of the hospital's resilience until the course of the pandemic is over. On the other hand, the availability could give the decision makers an indication of how the hospital responds to the variation of different infection intensities and available resources. This is useful for the hospital's further handling of the situation, as it will be clear to see how the system reacts to various changes.

7.1.1 Limitations

One weakness the analysis points out is that the system does not appear to be able to increase the availability to the value before the disruption occurred during the interval. Neither the measures implemented by the hospital nor society are able to raise the availability of the system to a particularly great extent. This is visible in the graph in the figure 6.8 that the availability varies with a downward trend towards the end of the interval. The hospital has also not been close to the value from before the pandemic started earlier in the analysis either. It is worth mentioning that the value from the beginning of the pandemic for the hospital's availability is estimated to be 90% based on intuition. At the beginning of the analysis around April and May 2020, when the probability of low infection intensity was 100%, the availability was calculated to be around 80%. Even with increased knowledge and more resources available later in the time interval, the system is not close to the same availability of 80%. The societal challenges associated with strong social measures may place a limit, which means that the availability of hospitals is considered acceptable and sufficient at the given moments.

Another limitation of the method is the fact that the model cannot model cycles. It is known that social measures are implemented based on the R number and the intensity of the infection. This is not modeled to avoid cycles, which means that you get an incomplete picture of the situation. On the other hand, the values associated with infection intensity are updated manually, which allows a form of indirect influence from the other variables. This manipulates the outcome and makes the results more accurate given the limitations of the method.

7.1.2 Uncertainty

Uncertainty is also a factor that affects the outcome of the method. At the beginning of the pandemic, there was great uncertainty associated with the development of the pandemic. This is because modern society has not experienced similar events before. The world has become more and more accessible through travel, which is not positive in terms of the spread of infection. Many countries were in need of the same type of equipment for treatment and testing. This contributed to increased uncertainty about the situation. For this reason, much of the available data that was initially published is based on assumptions. This increases the uncertainty associated with what the real values are, even if the assumptions are based on thorough reasoning.

This uncertainty is especially visible at the beginning of the pandemic. For example, it is seen in the value of the infection intensity at the beginning of the time interval for the analysis in figure 6.1. There is also a deep decline at the beginning of the pandemic in the graph in the figure 6.8, where there was a high number of hospitalizations and lack of equipment. The number of admissions is visible in figure 6.2. Shortly afterwards, there is a sharp increase in hospital availability, before the graph displays smoother transitions. Most likely, there is a more gradual transition in April 2020, which points to the uncertainty in that situation. The drop at the beginning in the graph in figure 6.8 can also be described as the response of the hospital was not optimal in relation to limiting the drop in performance. Preparedness is an important part of the work to reduce falls in performance, thus limiting lost resilience.

Another uncertainty associated with the method is the values used as conditional probabilities between the variables. These are based on pure intuition and assumptions, which gives a subjective direction to the outcome. This can affect the outcome of availability, as it is the starting point for the mathematical assessment of the network. The background to the assumed values is, as mentioned, a lack of data basis and understanding of the situation, which will be available after the situation is over. On the other hand, the results of the analysis will give an indication of the development and how the various factors affect the system as a whole. The method makes it possible to change values along the way if updates are made or if new information is made available.

7.2 Managerial implications

As mentioned, the method can be used as a basis for recommendations for further handling of the situation. The pandemic is constantly evolving, and in order to be able to adapt to changes and developments, the method used for the analysis must be flexible. Bayesian network facilitates making changes to values if evidence and data are made available at a later occasion. This is, as mentioned in section 4.1.4, an advantage when using the Bayesian network to simulate various events. This is also, as mentioned in section 7.1.2, a great advantage as there is great uncertainty associated with the pandemic. As new evidence emerges and one becomes aware of the situation, the method allows to make these changes. This property means that the method can be used for situations that are not necessarily similar to the situation used in the analysis. By simple changes of values, variables and ratios between variables, one is able to simulate the availability and resilience of the system.

A conclusion that can be drawn from the analysis is that with increased infection intensity, the hospital's availability decreases and resilience is lost. This can be used by decision makers to implement measures to counteract the loss of resilience. Increased infection intensity is thus a clear sign of implementing measures that counteract the drop in availability and increase the resilience of the system. This is, as mentioned in section 7.1, something that is already used in the implementation of social measures. That said, it is a conclusion that the decision makers can rely on when implementing measures.

In order to be able to assess the effect of changes in variables, one has to compare the outcomes with and without changes. Figure 6.5 visualizes these differences. It can be seen that even small changes in conditional probabilities, which are the changes that are made in this analysis, have a difference in the total availability of the system. There is also the biggest difference at the times when there is the lowest availability. This may indicate that the measures related to the hospital's capacity have a greater effect when the availability becomes low and decreases, but does not contribute to raising the availability further. By increasing the capacity of the hospital, i.e. by changing the variables ICU beds and ventilators to more favorable conditional probabilities for the hospital, it shows that it has an effect that increases the availability and reduces lost resilience. This supports the claim that measures which increase the hospital's capacity and social measures have a positive effect related to reducing lost resilience.

In favor of increasing the availability, and henceforth the resilience and quality of the system, it is necessary to implement stronger measures. There is a large distance between the value for availability before the onset of the pandemic compared to the values from the simulation. This is a sign that the management of various areas, such as hospitals or society in general, must implement measures if it is desirable to raise the resilience of the hospital. As mentioned in section 7.1.1, it can be challenging to implement stronger social measures. This is because powerful measures can be very costly. On the other hand, one must weigh the desire to reduce lost resilience and reduce infection intensity, against societal challenges associated with stricter measures. Figure 6.5 confirms that by increasing the capacity of the hospital at certain times, the lost resilience is reduced. By further increasing the capacity of the hospitals, the availability of the hospitals will be increased. But this does not solve the societal problem where one wants fewer people to get sick and die. Increased availability and lost resilience have as their main purpose to limit catastrophic outcomes of treatment of patients. One has to implement measures that affect this as close to the root of the problem as possible. This is an important point that must be taken into account when developing new measures.

Another application for the method is to use the simulation method described in section 6.5. By setting a fixed target value for hospital availability, which then represents a sufficient level of resilience to the hospital, one can rely on the amount of resources required to achieve this. This exploits the phenomenon called conditional dependence between parent nodes in the Bayesian network, explained in section 4.1.1. Related to this, the hospital's resources can be influenced and strengthened, if it is possible to form a picture of what one can prepare for in different scenarios of the development of infection in society. Based on the total number of resources, one can calculate how much of the resources that must be available for the treatment to be sufficient. For example, 46.4% available health personnel are needed to achieve a specified level of hospital availability at 89% probability for a high value, based on the simulation in figure 6.9. This is a useful application that decision makers can assess based on real scenarios and prepare for in advance. By updating values in the model so that the conditional probabilities are as similar as possible to the real-world scenario, the method will be able to produce realistic values for the system in question.

Chapter 8

Conclusions and Recommendations for Further Work

8.1 Summary and Conclusions

In this thesis, resilience has been discussed in relation to hospital and the hospital's handling of the COVID-19 pandemic. A method was developed with the aim of analyzing the hospital's resilience in demanding situations, and assessing which factors influenced the result. Several calculation methods for resilience were evaluated against each other and against the application. An extensive simulation to present the use of the method was also carried out, and assessments are based on the correlation between the result of the simulation and real values.

The objectives of the report have, among other things, been to define resilience and identify which terms can be used to understand resilience in the health care system. This was carried out in chapter 2, and the concepts were also linked to the health sector in chapter 3. Furthermore, the objective was to identify different areas affected by resilience in the health sector. This is presented as particulars in chapter 3. There are many areas that are directly and indirectly affected, which means that not all areas have been identified. It is therefore possible to expand the overview if new areas are discovered. Subsequently, various methods that can be used to calculate resilience are presented and assessed in chapter 5, before simulations are carried out using the Bayesian network in chapter 6. Chapter 6 also calculates resilience based on results from the simulation and the appropriate method from chapter 5. It was Bruneau's approach that was considered the most suitable method for calculating hospital resilience given the prerequisites for the analysis. Finally, the results are discussed against real values and based on the usefulness for future assessments.

The results from the simulation refer to both limitations and uncertainty related to the data basis and the method. This can be strengthened through increased knowledge of the system and a more secure data base. On the other hand, the results from the method appear to coincide with actual values and events. This strengthens the credibility of the method. The method is also suitable for calculating the percentage of resources needed to be able to achieve a predetermined target value for resilience. This is useful for decision makers and will clarify where resources are needed and what appear to be weaknesses in the system. As mentioned in the chapter 1, the purpose of the master's thesis is to calculate the resilience of hospitals and make assessments based on this. The result indicates that the method developed in this master's thesis is able to do so. With increased security of data and updated values, the method will be more applicable.

8.2 Recommendations for Further Work

In this thesis, only the COVID-19 pandemic has been used as a scenario, which provides many opportunities for further work. To improve the developed model and method, one can implement the function in Netica that allows dynamic modeling. This will make the simulation less time consuming as the values do not need to be updated manually. On the other hand, they can affect the accuracy of the simulation, but these are trade-offs that can be considered in retrospect. In addition, strengthening the data base and making necessary updates regarding nodes and variables will be a sensible way to go to improve the method. Furthermore, implementing the method and utilizing the results to actually manage the resilience of the hospitals will also be the ultimate goal. By aiming to improve resilience, there is a need for continuous development and updating of the method so that it is adapted to undesirable events that may occur in the future and prepare the system.

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Acronyms

CPT Conditional Probability Table.

ER Emergency Room.

ICU Intensive Care Unit.

NIPH Norwegian Institute of Public Health.

R number Reproduction number.

Appendix A

Data and Calculations from Excel

In order to have an overview of relevant data at different time periods, Excel was used. Different columns represent different types of information and calculations necessary to obtain an overview of the situation. Below is a quick overview of the contents of the different spreadsheets with various columns and what the columns were used for.

A.1 R number, infection intensity and probability calculation

- **Number:** Shows ascending numbers from 1 to a total of 302 used to calculate approximate infection intensity. The numbers represent days, where 1 corresponds to 5 March 2020, and 302 represents 31 December 2020.
- **Date:** Overview of the date the values on the row apply to. Used as an axis in the graph in figure 6.1.
- **R number:** Current R number for the date. Reflects the values in table 6.1.
- **Approximated infection intensity:** Based on the R number in the graph in figure 6.1, one finds a sixth degree trendline that gives a more fluid transition between the various R values. The equation that represents the trendline is reproduced in equation A.1. For each row the equation is calculated, where x corresponds to the value from the column "Number".

$$\begin{aligned} Y &= 7.46820627539664E-13\cdot x^6 - 7.31138574995537E-10\cdot x^5 \\ &+ 2.79034811863409E-07\cdot x^4 - 0.0000523369214702335\cdot x^3 \\ &+ 0.00496906113230366\cdot x^2 - 0.21495818178056\cdot x + 3.71158098520186 \end{aligned} \tag{A.1}$$

- **Probability for high infection intensity:** To calculate the probability of high infection intensity, two thresholds for extremely high and extremely low values are used as a starting point. These are at 1.5 and 0.5, respectively. If the approximate infection intensity is outside these limits, it is assumed that there is 100% certainty in either high or low value. The following Excel commands are used for the calculation

  $$IF(x > 1.5; 100; IF(x < 0.5; 0; (x - 0.5) / (1.5 - 0.5)^{*} 100)).$$

  x is replaced by the column "Approximated infection intensity". The calculation is done for each row.

- **Probability for low infection intensity:** The probability of low infection intensity is calculated using the expression $100 - x$, where x corresponds to the value from the column "Probability for high infection intensity" for the current date. The calculation is done for each row.

Number	Date	R number	Approximated infection intensity	Probability for high infection intensity	Probability for low infection intensity
1	05.03.2020	3,2	3,50	100,00	0,0
2	06.03.2020	3,2	3,30	100,00	0,0
3	07.03.2020	3,2	3,11	100,00	0,0
4	08.03.2020	3,2	2,93	100,00	0,0
5	09.03.2020	3,2	2,75	100,00	0,0
6	10.03.2020	3,2	2,59	100,00	0,0
7	11.03.2020	3,2	2,43	100,00	0,0
8	12.03.2020	3,2	2,28	100,00	0,0
9	13.03.2020	3,2	2,14	100,00	0,0
10	14.03.2020	3,2	2,01	100,00	0,0
11	15.03.2020	3,2	1,88	100,00	0,0
12	16.03.2020	0,5	1,76	100,00	0,0
13	17.03.2020	0,5	1,65	100,00	0,0
14	18.03.2020	0,5	1,54	100,00	0,0
15	19.03.2020	0,5	1,44	94,22	5,8
16	20.03.2020	0,5	1,35	84,75	15,3
17	21.03.2020	0,5	1,26	75,85	24,1
18	22.03.2020	0,5	1,18	67,50	32,5
19	23.03.2020	0,5	1,10	59,68	40,3
20	24.03.2020	0,5	1,02	52,37	47,6
21	25.03.2020	0,5	0,96	45,55	54,5
22	26.03.2020	0,5	0,89	39,19	60,8
23	27.03.2020	0,5	0,83	33,29	66,7
24	28.03.2020	0,5	0,78	27,82	72,2
25	29.03.2020	0,5	0,73	22,76	77,2
26	30.03.2020	0,5	0,68	18,09	81,9
27	31.03.2020	0,5	0,64	13,81	86,2
28	01.04.2020	0,5	0,60	9,89	90,1
29	02.04.2020	0,5	0,56	6,31	93,7
30	03.04.2020	0,5	0,53	3,07	96,9
31	04.04.2020	0,5	0,50	0,14	99,9
32	05.04.2020	0,5	0,48	0,00	100,0
33	06.04.2020	0,5	0,45	0,00	100,0
34	07.04.2020	0,5	0,43	0,00	100,0
35	08.04.2020	0,5	0,41	0,00	100,0
36	09.04.2020	0,5	0,40	0,00	100,0
37	10.04.2020	0,5	0,38	0,00	100,0
38	11.04.2020	0,5	0,37	0,00	100,0
39	12.04.2020	0,5	0,36	0,00	100,0
40	13.04.2020	0,5	0,36	0,00	100,0
41	14.04.2020	0,5	0,35	0,00	100,0
42	15.04.2020	0,5	0,35	0,00	100,0
43	16.04.2020	0,5	0,35	0,00	100,0
44	17.04.2020	0,5	0,35	0,00	100,0
45	18.04.2020	0,5	0,35	0,00	100,0
46	19.04.2020	0,5	0,35	0,00	100,0
47	20.04.2020	0,5	0,35	0,00	100,0
48	21.04.2020	0,7	0,36	0,00	100,0
49	22.04.2020	0,7	0,36	0,00	100,0
50	23.04.2020	0,7	0,37	0,00	100,0

51	24.04.2020	0,7	0,38	0,00	100,0
52	25.04.2020	0,7	0,39	0,00	100,0
53	26.04.2020	0,7	0,40	0,00	100,0
54	27.04.2020	0,7	0,41	0,00	100,0
55	28.04.2020	0,7	0,42	0,00	100,0
56	29.04.2020	0,7	0,43	0,00	100,0
57	30.04.2020	0,7	0,44	0,00	100,0
58	01.05.2020	0,7	0,45	0,00	100,0
59	02.05.2020	0,7	0,47	0,00	100,0
60	03.05.2020	0,7	0,48	0,00	100,0
61	04.05.2020	0,7	0,49	0,00	100,0
62	05.05.2020	0,7	0,51	0,76	99,2
63	06.05.2020	0,7	0,52	2,14	97,9
64	07.05.2020	0,7	0,54	3,54	96,5
65	08.05.2020	0,7	0,55	4,95	95,1
66	09.05.2020	0,7	0,56	6,36	93,6
67	10.05.2020	0,7	0,58	7,78	92,2
68	11.05.2020	0,7	0,59	9,19	90,8
69	12.05.2020	0,7	0,61	10,60	89,4
70	13.05.2020	0,7	0,62	12,00	88,0
71	14.05.2020	0,7	0,63	13,39	86,6
72	15.05.2020	0,7	0,65	14,76	85,2
73	16.05.2020	0,7	0,66	16,12	83,9
74	17.05.2020	0,7	0,67	17,46	82,5
75	18.05.2020	0,7	0,69	18,78	81,2
76	19.05.2020	0,7	0,70	20,07	79,9
77	20.05.2020	0,7	0,71	21,34	78,7
78	21.05.2020	0,7	0,73	22,58	77,4
79	22.05.2020	0,7	0,74	23,79	76,2
80	23.05.2020	0,7	0,75	24,97	75,0
81	24.05.2020	0,7	0,76	26,11	73,9
82	25.05.2020	0,7	0,77	27,23	72,8
83	26.05.2020	0,7	0,78	28,30	71,7
84	27.05.2020	0,7	0,79	29,35	70,7
85	28.05.2020	0,7	0,80	30,35	69,6
86	29.05.2020	0,7	0,81	31,32	68,7
87	30.05.2020	0,7	0,82	32,26	67,7
88	31.05.2020	0,7	0,83	33,15	66,9
89	01.06.2020	0,7	0,84	34,00	66,0
90	02.06.2020	0,7	0,85	34,82	65,2
91	03.06.2020	0,7	0,86	35,60	64,4
92	04.06.2020	0,7	0,86	36,33	63,7
93	05.06.2020	0,7	0,87	37,03	63,0
94	06.06.2020	0,7	0,88	37,69	62,3
95	07.06.2020	0,7	0,88	38,31	61,7
96	08.06.2020	0,7	0,89	38,89	61,1
97	09.06.2020	0,7	0,89	39,43	60,6
98	10.06.2020	0,7	0,90	39,94	60,1
99	11.06.2020	0,7	0,90	40,41	59,6
100	12.06.2020	0,7	0,91	40,84	59,2
101	13.06.2020	0,7	0,91	41,23	58,8
102	14.06.2020	0,7	0,92	41,59	58,4
103	15.06.2020	0,7	0,92	41,91	58,1

104	16.06.2020	0,7	0,92	42,21	57,8
105	17.06.2020	0,7	0,92	42,46	57,5
106	18.06.2020	0,7	0,93	42,69	57,3
107	19.06.2020	0,7	0,93	42,88	57,1
108	20.06.2020	0,7	0,93	43,04	57,0
109	21.06.2020	0,7	0,93	43,18	56,8
110	22.06.2020	0,7	0,93	43,28	56,7
111	23.06.2020	0,7	0,93	43,36	56,6
112	24.06.2020	0,7	0,93	43,42	56,6
113	25.06.2020	0,7	0,93	43,44	56,6
114	26.06.2020	0,7	0,93	43,45	56,6
115	27.06.2020	0,7	0,93	43,43	56,6
116	28.06.2020	0,7	0,93	43,39	56,6
117	29.06.2020	0,7	0,93	43,33	56,7
118	30.06.2020	0,7	0,93	43,25	56,7
119	01.07.2020	1	0,93	43,16	56,8
120	02.07.2020	1	0,93	43,05	57,0
121	03.07.2020	1	0,93	42,92	57,1
122	04.07.2020	1	0,93	42,78	57,2
123	05.07.2020	1	0,93	42,63	57,4
124	06.07.2020	1	0,92	42,46	57,5
125	07.07.2020	1	0,92	42,29	57,7
126	08.07.2020	1	0,92	42,11	57,9
127	09.07.2020	1	0,92	41,92	58,1
128	10.07.2020	1	0,92	41,72	58,3
129	11.07.2020	1	0,92	41,52	58,5
130	12.07.2020	1	0,91	41,32	58,7
131	13.07.2020	1	0,91	41,11	58,9
132	14.07.2020	1	0,91	40,90	59,1
133	15.07.2020	1	0,91	40,69	59,3
134	16.07.2020	1	0,90	40,49	59,5
135	17.07.2020	1	0,90	40,28	59,7
136	18.07.2020	1	0,90	40,08	59,9
137	19.07.2020	1	0,90	39,89	60,1
138	20.07.2020	1	0,90	39,70	60,3
139	21.07.2020	1	0,90	39,51	60,5
140	22.07.2020	1	0,89	39,34	60,7
141	23.07.2020	1	0,89	39,17	60,8
142	24.07.2020	1	0,89	39,01	61,0
143	25.07.2020	1	0,89	38,86	61,1
144	26.07.2020	1	0,89	38,73	61,3
145	27.07.2020	1	0,89	38,60	61,4
146	28.07.2020	1	0,88	38,49	61,5
147	29.07.2020	1	0,88	38,39	61,6
148	30.07.2020	1	0,88	38,31	61,7
149	31.07.2020	1	0,88	38,24	61,8
150	01.08.2020	1	0,88	38,19	61,8
151	02.08.2020	1	0,88	38,16	61,8
152	03.08.2020	1	0,88	38,14	61,9
153	04.08.2020	1	0,88	38,14	61,9
154	05.08.2020	1	0,88	38,15	61,8
155	06.08.2020	1	0,88	38,19	61,8
156	07.08.2020	1	0,88	38,24	61,8

157	08.08.2020	1	0,88	38,32	61,7
158	09.08.2020	1	0,88	38,41	61,6
159	10.08.2020	1	0,89	38,53	61,5
160	11.08.2020	1	0,89	38,66	61,3
161	12.08.2020	1	0,89	38,81	61,2
162	13.08.2020	1	0,89	38,99	61,0
163	14.08.2020	1	0,89	39,18	60,8
164	15.08.2020	1	0,89	39,40	60,6
165	16.08.2020	1	0,90	39,63	60,4
166	17.08.2020	1	0,90	39,89	60,1
167	18.08.2020	1	0,90	40,16	59,8
168	19.08.2020	1	0,90	40,46	59,5
169	20.08.2020	1	0,91	40,78	59,2
170	21.08.2020	1	0,91	41,11	58,9
171	22.08.2020	1	0,91	41,47	58,5
172	23.08.2020	1	0,92	41,84	58,2
173	24.08.2020	1	0,92	42,24	57,8
174	25.08.2020	1	0,93	42,65	57,4
175	26.08.2020	1	0,93	43,08	56,9
176	27.08.2020	1	0,94	43,53	56,5
177	28.08.2020	1	0,94	43,99	56,0
178	29.08.2020	1	0,94	44,47	55,5
179	30.08.2020	1	0,95	44,97	55,0
180	31.08.2020	0,9	0,95	45,48	54,5
181	01.09.2020	0,9	0,96	46,00	54,0
182	02.09.2020	0,9	0,97	46,54	53,5
183	03.09.2020	0,9	0,97	47,09	52,9
184	04.09.2020	0,9	0,98	47,66	52,3
185	05.09.2020	0,9	0,98	48,23	51,8
186	06.09.2020	0,9	0,99	48,81	51,2
187	07.09.2020	0,9	0,99	49,41	50,6
188	08.09.2020	0,9	1,00	50,01	50,0
189	09.09.2020	0,9	1,01	50,62	49,4
190	10.09.2020	0,9	1,01	51,23	48,8
191	11.09.2020	0,9	1,02	51,85	48,1
192	12.09.2020	0,9	1,02	52,48	47,5
193	13.09.2020	0,9	1,03	53,11	46,9
194	14.09.2020	0,9	1,04	53,74	46,3
195	15.09.2020	0,9	1,04	54,37	45,6
196	16.09.2020	0,9	1,05	55,00	45,0
197	17.09.2020	0,9	1,06	55,62	44,4
198	18.09.2020	0,9	1,06	56,25	43,7
199	19.09.2020	0,9	1,07	56,87	43,1
200	20.09.2020	0,9	1,07	57,49	42,5
201	21.09.2020	0,9	1,08	58,10	41,9
202	22.09.2020	0,9	1,09	58,70	41,3
203	23.09.2020	0,9	1,09	59,30	40,7
204	24.09.2020	0,9	1,10	59,88	40,1
205	25.09.2020	0,9	1,10	60,45	39,5
206	26.09.2020	0,9	1,11	61,01	39,0
207	27.09.2020	0,9	1,12	61,56	38,4
208	28.09.2020	0,9	1,12	62,09	37,9
209	29.09.2020	0,9	1,13	62,60	37,4

210	30.09.2020	0,9	1,13	63,10	36,9
211	01.10.2020	1,3	1,14	63,57	36,4
212	02.10.2020	1,3	1,14	64,03	36,0
213	03.10.2020	1,3	1,14	64,46	35,5
214	04.10.2020	1,3	1,15	64,88	35,1
215	05.10.2020	1,3	1,15	65,26	34,7
216	06.10.2020	1,3	1,16	65,63	34,4
217	07.10.2020	1,3	1,16	65,97	34,0
218	08.10.2020	1,3	1,16	66,28	33,7
219	09.10.2020	1,3	1,17	66,56	33,4
220	10.10.2020	1,3	1,17	66,81	33,2
221	11.10.2020	1,3	1,17	67,04	33,0
222	12.10.2020	1,3	1,17	67,23	32,8
223	13.10.2020	1,3	1,17	67,39	32,6
224	14.10.2020	1,3	1,18	67,51	32,5
225	15.10.2020	1,3	1,18	67,61	32,4
226	16.10.2020	1,3	1,18	67,66	32,3
227	17.10.2020	1,3	1,18	67,69	32,3
228	18.10.2020	1,3	1,18	67,68	32,3
229	19.10.2020	1,3	1,18	67,63	32,4
230	20.10.2020	1,3	1,18	67,54	32,5
231	21.10.2020	1,3	1,17	67,42	32,6
232	22.10.2020	1,3	1,17	67,26	32,7
233	23.10.2020	1,3	1,17	67,06	32,9
234	24.10.2020	1,3	1,17	66,82	33,2
235	25.10.2020	1,3	1,17	66,55	33,5
236	26.10.2020	1,3	1,16	66,23	33,8
237	27.10.2020	1,3	1,16	65,88	34,1
238	28.10.2020	1,3	1,15	65,49	34,5
239	29.10.2020	1,3	1,15	65,06	34,9
240	30.10.2020	1,3	1,15	64,60	35,4
241	31.10.2020	1,3	1,14	64,09	35,9
242	01.11.2020	1,3	1,14	63,55	36,4
243	02.11.2020	1,3	1,13	62,98	37,0
244	03.11.2020	1,3	1,12	62,37	37,6
245	04.11.2020	1,3	1,12	61,73	38,3
246	05.11.2020	0,8	1,11	61,05	38,9
247	06.11.2020	0,8	1,10	60,34	39,7
248	07.11.2020	0,8	1,10	59,60	40,4
249	08.11.2020	0,8	1,09	58,84	41,2
250	09.11.2020	0,8	1,08	58,04	42,0
251	10.11.2020	0,8	1,07	57,22	42,8
252	11.11.2020	0,8	1,06	56,38	43,6
253	12.11.2020	0,8	1,06	55,52	44,5
254	13.11.2020	0,8	1,05	54,63	45,4
255	14.11.2020	0,8	1,04	53,73	46,3
256	15.11.2020	0,8	1,03	52,82	47,2
257	16.11.2020	0,8	1,02	51,89	48,1
258	17.11.2020	0,8	1,01	50,96	49,0
259	18.11.2020	0,8	1,00	50,02	50,0
260	19.11.2020	0,8	0,99	49,08	50,9
261	20.11.2020	0,8	0,98	48,14	51,9
262	21.11.2020	0,8	0,97	47,21	52,8

263	22.11.2020	0,8	0,96	46,29	53,7
264	23.11.2020	0,8	0,95	45,38	54,6
265	24.11.2020	0,8	0,94	44,49	55,5
266	25.11.2020	0,8	0,94	43,62	56,4
267	26.11.2020	0,8	0,93	42,78	57,2
268	27.11.2020	0,8	0,92	41,98	58,0
269	28.11.2020	0,8	0,91	41,21	58,8
270	29.11.2020	0,8	0,90	40,49	59,5
271	30.11.2020	0,8	0,90	39,81	60,2
272	01.12.2020	1,08	0,89	39,20	60,8
273	02.12.2020	1,08	0,89	38,64	61,4
274	03.12.2020	1,08	0,88	38,15	61,8
275	04.12.2020	1,08	0,88	37,75	62,3
276	05.12.2020	1,08	0,87	37,42	62,6
277	06.12.2020	1,08	0,87	37,18	62,8
278	07.12.2020	1,08	0,87	37,05	63,0
279	08.12.2020	1,08	0,87	37,02	63,0
280	09.12.2020	1,08	0,87	37,10	62,9
281	10.12.2020	1,08	0,87	37,31	62,7
282	11.12.2020	1,08	0,88	37,65	62,3
283	12.12.2020	1,08	0,88	38,14	61,9
284	13.12.2020	1,08	0,89	38,78	61,2
285	14.12.2020	1,08	0,90	39,58	60,4
286	15.12.2020	1,08	0,91	40,55	59,5
287	16.12.2020	1,08	0,92	41,71	58,3
288	17.12.2020	1,08	0,93	43,06	56,9
289	18.12.2020	1,08	0,95	44,61	55,4
290	19.12.2020	1,08	0,96	46,39	53,6
291	20.12.2020	1,08	0,98	48,39	51,6
292	21.12.2020	1,08	1,01	50,64	49,4
293	22.12.2020	1,08	1,03	53,15	46,9
294	23.12.2020	1,08	1,06	55,92	44,1
295	24.12.2020	1,08	1,09	58,98	41,0
296	25.12.2020	1,08	1,12	62,33	37,7
297	26.12.2020	1,08	1,16	66,00	34,0
298	27.12.2020	1,08	1,20	69,99	30,0
299	28.12.2020	1,08	1,24	74,33	25,7
300	29.12.2020	1,08	1,29	79,02	21,0
301	30.12.2020	1,08	1,34	84,09	15,9
302	31.12.2020	1,08	1,40	89,56	10,4

A.2 Resilience calculation and collected data

- **Date for calculation:** The column is identical to the “Date” column, and it is used as the axis in the graph in the figure 6.4.

- **Availability:** The column contains values for availability as a result of the calculation in Netica. The value is entered directly into the table for each date with the current values for infection intensity and updated values for ventilators and ICU beds. The values are plotted in the graph in figure 6.4.

- **Resilience lost:** The column is based on equation 5.1, $100-Q(t)$. The value $Q(t)$ is replaced with the corresponding value in the “Availability” column. The values are finally summed to illustrate the total lost resilience.

- **Registered infected:** Overview of registered infected in Trondheim municipality in the relevant period. Retrieved from VG (2021).

- **Accumulated registered infected:** Overview of accumulated registered infected in Trondheim municipality in the relevant time period. Based on values from the “Registered infected” column.

- **Admitted to a hospital affiliated with the municipality:** Overview of the number of hospitalized in Trondheim municipality at different times in the relevant time interval. Retrieved from VG (2021).

Date (for calculation)	Availability	Resilience lost	Registered infected	Accumulated registered infected	Admitted to a hospital affiliated with the municipality
05.03.2020	32.9	67.1	1	1	0
06.03.2020	32.9	67.1	5	6	0
07.03.2020	32.9	67.1	0	6	0
08.03.2020	32.9	67.1	0	6	0
09.03.2020	32.9	67.1	4	10	0
10.03.2020	32.9	67.1	0	10	0
11.03.2020	32.9	67.1	12	22	0
12.03.2020	32.9	67.1	6	28	1
13.03.2020	32.9	67.1	2	30	1
14.03.2020	32.9	67.1	2	32	1
15.03.2020	32.9	67.1	7	39	1
16.03.2020	32.9	67.1	3	42	1
17.03.2020	32.9	67.1	4	46	1
18.03.2020	32.9	67.1	2	48	2
19.03.2020	35.7	64.3	11	59	4
20.03.2020	40.2	59.8	5	64	5
21.03.2020	44.3	55.7	6	70	5
22.03.2020	48.3	51.7	12	82	5
23.03.2020	52	48	8	90	7
24.03.2020	55.4	44.6	19	109	6
25.03.2020	58.7	41.3	15	124	8
26.03.2020	61.6	38.4	11	135	8
27.03.2020	64.4	35.6	13	148	9
28.03.2020	67	33	10	158	10
29.03.2020	69.4	30.6	9	167	12
30.03.2020	71.6	28.4	7	174	9
31.03.2020	73.6	26.4	2	176	10
01.04.2020	75.9	24.1	2	178	10
02.04.2020	77.4	22.6	6	184	12
03.04.2020	78.8	21.2	5	189	9
04.04.2020	80.1	19.9	3	192	8
05.04.2020	80.2	19.8	2	194	10
06.04.2020	80.2	19.8	2	196	12
07.04.2020	80.2	19.8	1	197	12
08.04.2020	80.2	19.8	5	202	12
09.04.2020	80.2	19.8	3	205	10
10.04.2020	80.2	19.8	0	205	10
11.04.2020	80.2	19.8	3	208	10
12.04.2020	80.2	19.8	0	208	9
13.04.2020	80.2	19.8	2	210	9
14.04.2020	80.2	19.8	2	212	10
15.04.2020	80.2	19.8	1	213	8
16.04.2020	80.2	19.8	3	216	6
17.04.2020	80.2	19.8	4	220	4
18.04.2020	80.2	19.8	4	224	2
19.04.2020	80.2	19.8	2	226	2
20.04.2020	80.2	19.8	2	228	2
21.04.2020	80.2	19.8	1	229	2
22.04.2020	80.2	19.8	8	237	2
23.04.2020	80.2	19.8	3	240	2

24.04.2020	80.2	19.8	9	249	2
25.04.2020	80.2	19.8	11	260	2
26.04.2020	80.2	19.8	4	264	2
27.04.2020	80.2	19.8	11	275	2
28.04.2020	80.2	19.8	1	276	2
29.04.2020	80.2	19.8	5	281	2
30.04.2020	80.2	19.8	4	285	1
01.05.2020	80.2	19.8	4	289	1
02.05.2020	80.2	19.8	2	291	1
03.05.2020	80.2	19.8	10	301	1
04.05.2020	80.2	19.8	3	304	1
05.05.2020	79.8	20.2	5	309	1
06.05.2020	79.3	20.7	2	311	1
07.05.2020	78.7	21.3	5	316	1
08.05.2020	78.1	21.9	3	319	1
09.05.2020	77.5	22.5	1	320	3
10.05.2020	77	23	1	321	3
11.05.2020	76.4	23.6	1	322	2
12.05.2020	75.8	24.2	2	324	3
13.05.2020	75.2	24.8	1	325	4
14.05.2020	74.7	25.3	1	326	5
15.05.2020	74.1	25.9	1	327	4
16.05.2020	73.6	26.4	0	327	4
17.05.2020	73	27	4	331	3
18.05.2020	72.5	27.5	0	331	3
19.05.2020	71.9	28.1	2	333	3
20.05.2020	71.4	28.6	0	333	3
21.05.2020	70.9	29.1	0	333	3
22.05.2020	70.4	29.6	1	334	3
23.05.2020	69.9	30.1	0	334	2
24.05.2020	69.5	30.5	0	334	2
25.05.2020	69	31	2	336	2
26.05.2020	68.6	31.4	0	336	1
27.05.2020	68.2	31.8	2	338	1
28.05.2020	67.7	32.3	0	338	1
29.05.2020	67.3	32.7	1	339	1
30.05.2020	66.9	33.1	0	339	1
31.05.2020	66.6	33.4	0	339	1
01.06.2020	66.2	33.8	0	339	1
02.06.2020	65.9	34.1	0	339	1
03.06.2020	65.6	34.4	0	339	1
04.06.2020	65.3	34.7	0	339	1
05.06.2020	65	35	0	339	1
06.06.2020	64.7	35.3	0	339	1
07.06.2020	64.5	35.5	0	339	1
08.06.2020	64.2	35.8	0	339	1
09.06.2020	64	36	0	339	1
10.06.2020	63.8	36.2	0	339	1
11.06.2020	63.6	36.4	0	339	1
12.06.2020	63.4	36.6	0	339	1
13.06.2020	63.3	36.7	0	339	1
14.06.2020	63.1	36.9	0	339	1
15.06.2020	63	37	0	339	0

16.06.2020	62.9	37.1	0	339	0
17.06.2020	62.8	37.2	0	339	0
18.06.2020	62.7	37.3	0	339	0
19.06.2020	62.6	37.4	0	339	0
20.06.2020	62.5	37.5	0	339	0
21.06.2020	62.5	37.5	0	339	0
22.06.2020	62.4	37.6	0	339	0
23.06.2020	62.4	37.6	2	341	0
24.06.2020	62.4	37.6	0	341	0
25.06.2020	62.4	37.6	0	341	0
26.06.2020	62.4	37.6	0	341	0
27.06.2020	62.4	37.6	0	341	0
28.06.2020	62.4	37.6	0	341	0
29.06.2020	62.4	37.6	0	341	0
30.06.2020	62.4	37.6	0	341	0
01.07.2020	62.5	37.5	0	341	0
02.07.2020	62.5	37.5	0	341	0
03.07.2020	62.6	37.4	3	344	0
04.07.2020	62.6	37.4	0	344	0
05.07.2020	62.7	37.3	0	344	0
06.07.2020	62.8	37.2	0	344	0
07.07.2020	62.8	37.2	0	344	0
08.07.2020	62.9	37.1	0	344	0
09.07.2020	63	37	0	344	0
10.07.2020	63.1	36.9	1	345	0
11.07.2020	63.2	36.8	0	345	0
12.07.2020	63.2	36.8	0	345	0
13.07.2020	63.3	36.7	0	345	0
14.07.2020	63.4	36.6	0	345	0
15.07.2020	63.5	36.5	0	345	0
16.07.2020	63.6	36.4	0	345	0
17.07.2020	63.7	36.3	0	345	0
18.07.2020	63.7	36.3	0	345	0
19.07.2020	63.8	36.2	0	345	0
20.07.2020	63.9	36.1	0	345	0
21.07.2020	64	36	0	345	0
22.07.2020	64.1	35.9	1	346	0
23.07.2020	64.1	35.9	3	349	0
24.07.2020	64.2	35.8	0	349	0
25.07.2020	64.2	35.8	1	350	0
26.07.2020	64.3	35.7	0	350	0
27.07.2020	64.3	35.7	1	351	0
28.07.2020	64.4	35.6	2	353	0
29.07.2020	64.4	35.6	1	354	0
30.07.2020	64.5	35.5	1	355	0
31.07.2020	64.5	35.5	1	356	0
01.08.2020	64.5	35.5	0	356	0
02.08.2020	64.5	35.5	1	357	0
03.08.2020	64.6	35.4	1	358	0
04.08.2020	64.6	35.4	2	360	0
05.08.2020	64.5	35.5	1	361	0
06.08.2020	64.5	35.5	1	362	0
07.08.2020	64.5	35.5	4	366	1

08.08.2020	64.5	35.5	1	367	1
09.08.2020	64.4	35.6	4	371	1
10.08.2020	64.4	35.6	1	372	1
11.08.2020	64.3	35.7	3	375	1
12.08.2020	64.3	35.7	2	377	2
13.08.2020	64.2	35.8	0	377	2
14.08.2020	64.1	35.9	2	379	2
15.08.2020	64	36	1	380	2
16.08.2020	63.9	36.1	1	381	2
17.08.2020	63.8	36.2	7	388	2
18.08.2020	63.7	36.3	4	392	2
19.08.2020	63.6	36.4	4	396	1
20.08.2020	63.4	36.6	4	400	1
21.08.2020	63.3	36.7	2	402	1
22.08.2020	63.2	36.8	3	405	1
23.08.2020	63	37	0	405	1
24.08.2020	62.9	37.1	0	405	1
25.08.2020	62.7	37.3	0	405	1
26.08.2020	62.5	37.5	1	406	0
27.08.2020	62.3	37.7	0	406	1
28.08.2020	62.1	37.9	2	408	1
29.08.2020	61.9	38.1	0	408	1
30.08.2020	61.7	38.3	0	408	1
31.08.2020	61.5	38.5	0	408	1
01.09.2020	61.3	38.7	0	408	1
02.09.2020	61.1	38.9	1	409	1
03.09.2020	60.9	39.1	0	409	1
04.09.2020	60.6	39.4	0	409	1
05.09.2020	60.4	39.6	2	411	1
06.09.2020	60.2	39.8	0	411	1
07.09.2020	59.9	40.1	1	412	1
08.09.2020	59.7	40.3	2	414	0
09.09.2020	59.4	40.6	0	414	0
10.09.2020	59.2	40.8	0	414	0
11.09.2020	58.9	41.1	0	414	1
12.09.2020	58.7	41.3	1	415	1
13.09.2020	58.4	41.6	1	416	1
14.09.2020	58.2	41.8	3	419	1
15.09.2020	57.9	42.1	2	421	1
16.09.2020	57.6	42.4	2	423	1
17.09.2020	57.4	42.6	0	423	0
18.09.2020	57.1	42.9	2	425	0
19.09.2020	56.9	43.1	0	425	0
20.09.2020	56.6	43.4	1	426	0
21.09.2020	56.4	43.6	2	428	0
22.09.2020	56.1	43.9	2	430	0
23.09.2020	55.9	44.1	0	430	0
24.09.2020	55.6	44.4	2	432	1
25.09.2020	55.4	44.6	3	435	1
26.09.2020	55.2	44.8	1	436	1
27.09.2020	54.9	45.1	1	437	1
28.09.2020	54.7	45.3	0	437	0
29.09.2020	54.5	45.5	1	438	0

30.09.2020	54.3	45.7	1	439	0
01.10.2020	54.9	45.1	0	439	0
02.10.2020	54.8	45.2	1	440	0
03.10.2020	54.6	45.4	0	440	0
04.10.2020	54.4	45.6	0	440	0
05.10.2020	54.2	45.8	3	443	0
06.10.2020	54.1	45.9	2	445	0
07.10.2020	54	46	1	446	0
08.10.2020	53.8	46.2	0	446	0
09.10.2020	53.7	46.3	2	448	0
10.10.2020	53.6	46.4	2	450	0
11.10.2020	53.6	46.4	6	456	0
12.10.2020	53.5	46.5	4	460	0
13.10.2020	53.4	46.6	9	469	0
14.10.2020	53.3	46.7	5	474	0
15.10.2020	53.3	46.7	8	482	0
16.10.2020	53.3	46.7	2	484	1
17.10.2020	53.3	46.7	4	488	1
18.10.2020	53.3	46.7	1	489	1
19.10.2020	53.3	46.7	7	496	0
20.10.2020	53.4	46.6	9	505	0
21.10.2020	53.4	46.6	3	508	0
22.10.2020	53.4	46.6	4	512	0
23.10.2020	53.5	46.5	1	513	0
24.10.2020	53.6	46.4	3	516	0
25.10.2020	53.8	46.2	0	516	0
26.10.2020	53.9	46.1	3	519	0
27.10.2020	54	46	11	530	1
28.10.2020	54.2	45.8	4	534	2
29.10.2020	54.3	45.7	5	539	2
30.10.2020	54.5	45.5	13	552	3
31.10.2020	54.7	45.3	8	560	4
01.11.2020	54.9	45.1	9	569	5
02.11.2020	55.2	44.8	3	572	5
03.11.2020	55.4	44.6	10	582	5
04.11.2020	55.7	44.3	8	590	3
05.11.2020	55.9	44.1	20	610	4
06.11.2020	56.2	43.8	7	617	5
07.11.2020	56.5	43.5	12	629	5
08.11.2020	56.8	43.2	8	637	6
09.11.2020	57.1	42.9	3	640	6
10.11.2020	57.5	42.5	6	646	6
11.11.2020	57.8	42.2	10	656	6
12.11.2020	58.1	41.9	9	665	6
13.11.2020	58.5	41.5	6	671	3
14.11.2020	58.8	41.2	8	679	4
15.11.2020	59.2	40.8	6	685	4
16.11.2020	59.6	40.4	4	689	4
17.11.2020	59.9	40.1	12	701	5
18.11.2020	60.3	39.7	12	713	5
19.11.2020	60.7	39.3	7	720	5
20.11.2020	61.1	38.9	4	724	5
21.11.2020	61.4	38.6	5	729	6

22.11.2020	61.8	38.2	5	734	6
23.11.2020	62.1	37.9	8	742	7
24.11.2020	62.5	37.5	1	743	6
25.11.2020	62.9	37.1	3	746	6
26.11.2020	63.2	36.8	5	751	5
27.11.2020	63.5	36.5	3	754	5
28.11.2020	63.8	36.2	2	756	3
29.11.2020	64.1	35.9	2	758	4
30.11.2020	64.4	35.6	1	759	3
01.12.2020	64.6	35.4	3	762	3
02.12.2020	64.8	35.2	1	763	3
03.12.2020	65	35	8	771	1
04.12.2020	65.2	34.8	1	772	1
05.12.2020	65.3	34.7	10	782	0
06.12.2020	65.4	34.6	3	785	0
07.12.2020	65.5	34.5	8	793	0
08.12.2020	65.5	34.5	19	812	0
09.12.2020	65.4	34.6	25	837	0
10.12.2020	65.4	34.6	25	862	0
11.12.2020	65.2	34.8	16	878	0
12.12.2020	65	35	27	905	0
13.12.2020	64.8	35.2	9	914	0
14.12.2020	64.4	35.6	22	936	0
15.12.2020	64.1	35.9	21	957	1
16.12.2020	63.6	36.4	14	971	1
17.12.2020	63	37	23	994	0
18.12.2020	62.5	37.5	23	1017	2
19.12.2020	61.7	38.3	31	1048	3
20.12.2020	60.9	39.1	25	1073	3
21.12.2020	60.1	39.9	45	1118	5
22.12.2020	59.1	40.9	28	1146	4
23.12.2020	58	42	43	1189	1
24.12.2020	56.7	43.3	32	1221	1
25.12.2020	55.4	44.6	42	1263	1
26.12.2020	54	46	36	1299	2
27.12.2020	52.4	47.6	63	1362	1
28.12.2020	50.7	49.3	14	1376	2
29.12.2020	48.8	51.2	79	1455	5
30.12.2020	46.8	53.2	77	1532	4
31.12.2020	44.6	55.4	40	1572	4
Total lost resilience		11409.3			

A.3 Resilience calculation with only infection intensity updated

- **Date:** Overview of the date the values on the row apply to.
- **Availability (only infection intensity updated):** The column contains values for availability as a result of the calculation in Netica were only the variable infection intensity is updated. The value is entered directly into the table for each date with the current values for infection intensity. The values are plotted in the graph in figure 6.5.
- **Resilience lost (only infection intensity updated):** The column is based on equation 5.1, $100 - Q(t)$. The value $Q(t)$ is replaced with the corresponding value in the "Availability" column. The values are finally summed to illustrate the total lost resilience when only the variable infection intensity is updated.

Date	Availability (only infection intensity updated)	Resilience lost (only infection intensity updated)
05.03.2020	32.9	67.1
06.03.2020	32.9	67.1
07.03.2020	32.9	67.1
08.03.2020	32.9	67.1
09.03.2020	32.9	67.1
10.03.2020	32.9	67.1
11.03.2020	32.9	67.1
12.03.2020	32.9	67.1
13.03.2020	32.9	67.1
14.03.2020	32.9	67.1
15.03.2020	32.9	67.1
16.03.2020	32.9	67.1
17.03.2020	32.9	67.1
18.03.2020	32.9	67.1
19.03.2020	35.7	64.3
20.03.2020	40.2	59.8
21.03.2020	44.3	55.7
22.03.2020	48.3	51.7
23.03.2020	52	48
24.03.2020	55.4	44.6
25.03.2020	58.7	41.3
26.03.2020	61.6	38.4
27.03.2020	64.4	35.6
28.03.2020	67	33
29.03.2020	69.4	30.6
30.03.2020	71.6	28.4
31.03.2020	73.6	26.4
01.04.2020	75.5	24.5
02.04.2020	77.2	22.8
03.04.2020	78.7	21.3
04.04.2020	80.1	19.9
05.04.2020	80.2	19.8
06.04.2020	80.2	19.8
07.04.2020	80.2	19.8
08.04.2020	80.2	19.8
09.04.2020	80.2	19.8
10.04.2020	80.2	19.8
11.04.2020	80.2	19.8
12.04.2020	80.2	19.8
13.04.2020	80.2	19.8
14.04.2020	80.2	19.8
15.04.2020	80.2	19.8
16.04.2020	80.2	19.8
17.04.2020	80.2	19.8
18.04.2020	80.2	19.8
19.04.2020	80.2	19.8
20.04.2020	80.2	19.8
21.04.2020	80.2	19.8

22.04.2020	80.2	19.8
23.04.2020	80.2	19.8
24.04.2020	80.2	19.8
25.04.2020	80.2	19.8
26.04.2020	80.2	19.8
27.04.2020	80.2	19.8
28.04.2020	80.2	19.8
29.04.2020	80.2	19.8
30.04.2020	80.2	19.8
01.05.2020	80.2	19.8
02.05.2020	80.2	19.8
03.05.2020	80.2	19.8
04.05.2020	80.2	19.8
05.05.2020	79.8	20.2
06.05.2020	79.2	20.8
07.05.2020	78.5	21.5
08.05.2020	77.8	22.2
09.05.2020	77.1	22.9
10.05.2020	76.5	23.5
11.05.2020	75.8	24.2
12.05.2020	75.1	24.9
13.05.2020	74.5	25.5
14.05.2020	73.8	26.2
15.05.2020	73.2	26.8
16.05.2020	72.6	27.4
17.05.2020	71.9	28.1
18.05.2020	71.3	28.7
19.05.2020	70.7	29.3
20.05.2020	70.1	29.9
21.05.2020	69.5	30.5
22.05.2020	68.9	31.1
23.05.2020	68.4	31.6
24.05.2020	67.8	32.2
25.05.2020	67.3	32.7
26.05.2020	66.8	33.2
27.05.2020	66.3	33.7
28.05.2020	65.8	34.2
29.05.2020	65.4	34.6
30.05.2020	64.9	35.1
31.05.2020	64.5	35.5
01.06.2020	64.1	35.9
02.06.2020	63.7	36.3
03.06.2020	63.3	36.7
04.06.2020	63	37
05.06.2020	62.7	37.3
06.06.2020	62.4	37.6
07.06.2020	62.1	37.9
08.06.2020	61.8	38.2
09.06.2020	61.6	38.4
10.06.2020	61.3	38.7

11.06.2020	61.1	38.9
12.06.2020	60.9	39.1
13.06.2020	60.7	39.3
14.06.2020	60.5	39.5
15.06.2020	60.4	39.6
16.06.2020	60.2	39.8
17.06.2020	60.1	39.9
18.06.2020	60	40
19.06.2020	59.9	40.1
20.06.2020	59.9	40.1
21.06.2020	59.8	40.2
22.06.2020	59.7	40.3
23.06.2020	59.7	40.3
24.06.2020	59.7	40.3
25.06.2020	59.7	40.3
26.06.2020	59.7	40.3
27.06.2020	59.7	40.3
28.06.2020	59.7	40.3
29.06.2020	59.7	40.3
30.06.2020	59.7	40.3
01.07.2020	59.8	40.2
02.07.2020	59.9	40.1
03.07.2020	59.9	40.1
04.07.2020	59.9	40.1
05.07.2020	60	40
06.07.2020	60.1	39.9
07.07.2020	60.2	39.8
08.07.2020	60.3	39.7
09.07.2020	60.4	39.6
10.07.2020	60.5	39.5
11.07.2020	60.6	39.4
12.07.2020	60.7	39.3
13.07.2020	60.8	39.2
14.07.2020	60.8	39.2
15.07.2020	60.9	39.1
16.07.2020	61	39
17.07.2020	61.1	38.9
18.07.2020	61.2	38.8
19.07.2020	61.3	38.7
20.07.2020	61.4	38.6
21.07.2020	61.5	38.5
22.07.2020	61.6	38.4
23.07.2020	61.6	38.4
24.07.2020	61.7	38.3
25.07.2020	61.8	38.2
26.07.2020	61.9	38.1
27.07.2020	61.9	38.1
28.07.2020	62	38
29.07.2020	62	38
30.07.2020	62.1	37.9

31.07.2020	62.1	37.9
01.08.2020	62.1	37.9
02.08.2020	62.1	37.9
03.08.2020	62.2	37.8
04.08.2020	62.2	37.8
05.08.2020	62.1	37.9
06.08.2020	62.1	37.9
07.08.2020	62.1	37.9
08.08.2020	62.1	37.9
09.08.2020	62	38
10.08.2020	62	38
11.08.2020	61.9	38.1
12.08.2020	61.8	38.2
13.08.2020	61.7	38.3
14.08.2020	61.6	38.4
15.08.2020	61.6	38.4
16.08.2020	61.5	38.5
17.08.2020	61.3	38.7
18.08.2020	61.2	38.8
19.08.2020	61	39
20.08.2020	60.9	39.1
21.08.2020	60.8	39.2
22.08.2020	60.6	39.4
23.08.2020	60.4	39.6
24.08.2020	60.2	39.8
25.08.2020	60	40
26.08.2020	59.8	40.2
27.08.2020	59.6	40.4
28.08.2020	59.4	40.6
29.08.2020	59.1	40.9
30.08.2020	58.9	41.1
31.08.2020	58.7	41.3
01.09.2020	58.4	41.6
02.09.2020	58.2	41.8
03.09.2020	57.9	42.1
04.09.2020	57.6	42.4
05.09.2020	57.4	42.6
06.09.2020	57.1	42.9
07.09.2020	56.8	43.2
08.09.2020	56.5	43.5
09.09.2020	56.3	43.7
10.09.2020	56	44
11.09.2020	55.7	44.3
12.09.2020	55.4	44.6
13.09.2020	55.1	44.9
14.09.2020	54.8	45.2
15.09.2020	54.5	45.5
16.09.2020	54.2	45.8
17.09.2020	53.9	46.1
18.09.2020	53.6	46.4

19.09.2020	53.3	46.7
20.09.2020	53	47
21.09.2020	52.7	47.3
22.09.2020	52.4	47.6
23.09.2020	52.2	47.8
24.09.2020	51.9	48.1
25.09.2020	51.6	48.4
26.09.2020	51.4	48.6
27.09.2020	51.1	48.9
28.09.2020	50.8	49.2
29.09.2020	50.6	49.4
30.09.2020	50.4	49.6
01.10.2020	50.1	49.9
02.10.2020	49.9	50.1
03.10.2020	49.7	50.3
04.10.2020	49.5	50.5
05.10.2020	49.3	50.7
06.10.2020	49.2	50.8
07.10.2020	49	51
08.10.2020	48.9	51.1
09.10.2020	48.7	51.3
10.10.2020	48.6	51.4
11.10.2020	48.5	51.5
12.10.2020	48.5	51.5
13.10.2020	48.3	51.7
14.10.2020	48.3	51.7
15.10.2020	48.2	51.8
16.10.2020	48.2	51.8
17.10.2020	48.2	51.8
18.10.2020	48.2	51.8
19.10.2020	48.2	51.8
20.10.2020	48.3	51.7
21.10.2020	48.3	51.7
22.10.2020	48.4	51.6
23.10.2020	48.5	51.5
24.10.2020	48.6	51.4
25.10.2020	48.8	51.2
26.10.2020	48.9	51.1
27.10.2020	49	51
28.10.2020	49.2	50.8
29.10.2020	49.4	50.6
30.10.2020	49.7	50.3
31.10.2020	49.9	50.1
01.11.2020	50.1	49.9
02.11.2020	50.4	49.6
03.11.2020	50.7	49.3
04.11.2020	51	49
05.11.2020	51.3	48.7
06.11.2020	51.7	48.3
07.11.2020	52	48

08.11.2020	52.4	47.6
09.11.2020	52.8	47.2
10.11.2020	53.2	46.8
11.11.2020	53.5	46.5
12.11.2020	54	46
13.11.2020	54.4	45.6
14.11.2020	54.8	45.2
15.11.2020	55.2	44.8
16.11.2020	55.7	44.3
17.11.2020	56.1	43.9
18.11.2020	56.5	43.5
19.11.2020	57	43
20.11.2020	57.4	42.6
21.11.2020	57.9	42.1
22.11.2020	58.3	41.7
23.11.2020	58.7	41.3
24.11.2020	59.1	40.9
25.11.2020	59.6	40.4
26.11.2020	59.9	40.1
27.11.2020	60.3	39.7
28.11.2020	60.7	39.3
29.11.2020	61	39
30.11.2020	61.4	38.6
01.12.2020	61.6	38.4
02.12.2020	61.9	38.1
03.12.2020	62.1	37.9
04.12.2020	62.4	37.6
05.12.2020	62.5	37.5
06.12.2020	62.6	37.4
07.12.2020	62.7	37.3
08.12.2020	62.7	37.3
09.12.2020	62.6	37.4
10.12.2020	62.5	37.5
11.12.2020	62.4	37.6
12.12.2020	62.2	37.8
13.12.2020	61.8	38.2
14.12.2020	61.5	38.5
15.12.2020	61	39
16.12.2020	60.5	39.5
17.12.2020	59.8	40.2
18.12.2020	59.1	40.9
19.12.2020	58.2	41.8
20.12.2020	57.3	42.7
21.12.2020	56.3	43.7
22.12.2020	55.1	44.9
23.12.2020	53.8	46.2
24.12.2020	52.3	47.7
25.12.2020	50.7	49.3
26.12.2020	49	51
27.12.2020	47.1	52.9

28.12.2020	45.1	54.9
29.12.2020	42.9	57.1
30.12.2020	40.5	59.5
31.12.2020	37.9	62.1
Total lost resilience (only infection intensity updated)		12164.9

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