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Crowding at the Emergency Department of the Scheper Hospital Emmen

A system-wide imbalance analysis with staffing optimization and capacity planning to stay in the flow

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M.Sc. Thesis

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“And sure enough even waiting will end...
if you can just wait long enough”

-William Faulkner-

Preface

In front of you lays my thesis with the title 'Crowding at the Emergency Department of the Scheper Hospital Emmen; a system-wide imbalance analysis of the lead times, staffing optimization and capacity planning to stay in the flow'. For me, it is the last component to graduate for the master program Health Sciences of the University of Twente. This research was performed in a familiar setting for me, the Scheper Hospital Emmen, were I work at the Intensive Care Unit (ICU) since 2007. It was a great pleasure to perform my research at such a crucial part of the hospital like the ED. Along these lines, I would like to thank all the nurses and physicians of the ED by providing me full cooperation and enthusiasm that was needed to execute this research. I especially would like to thank Luuk Tomson, manager of the ED and my internal supervisor. Thank you for believing in me and giving me the opportunity to do this study. I would also like to thank René Siebring and Hans Steenhuis for their effort of extracting the valuable data that was necessary for my research. Also a special thanks to Marian Pinkster, senior manager of Treant Zorggroep, for all of her help and support. I also express my gratitude to my colleagues of the ICU. Thank you for dealing with a 'crippled colleague' throughout my study.

I would also like to thank my supervisors dr. C.J.M. Doggen, Associate Professor and Chair of the Department Health Technology and Services Research, MIRA institute for Biomedical Technology and Technical Medicine, and dr. P.C. Schuur, Associate Professor of the Faculty of Behavioral Management and Social Sciences and the Department of Industrial Engineering and Business Information Systems, from the University of Twente. Dear Carine and Peter, thanks you for your guidance throughout the entire process of writing this thesis. From beginning to end, your advices and support were very helpful to me.

Finally, I would like to thank my parents and girlfriend for their patience and love, by giving me the time and space to work on this thesis. Thank you for believing in me and stimulate me to improve myself. Your encouraging and loving words served me well.

I hope all who read this thesis will find it interesting and worth reading.

Sincerely,
Maurice Darwinkel
Emmen, August 26, 2017

Management samenvatting

Introductie

Spoedeisende hulp (SEH) afdelingen wereldwijd hebben te maken met problemen op het gebied van personeelsplanning en beddencapaciteit door het hoge patiënten aanbod. Hierdoor kan de patiënten doorstroom stagneren of zelfs stil vallen wat tot gevolg heeft dat de SEH (tijdelijk) sluit. Een onwenselijk situatie die ook in Nederland voorkomt. In het laatste kwartaal van 2015 werd ruim 600 keer een (tijdelijke) stop voor ambulances afgekondigd in de regio Amsterdam omdat de SEH-afdelingen niet langer verantwoorde zorg konden garanderen. Deze “verstopping” van de SEH wordt in de internationale literatuur aangeduid als “crowding” en is veelvuldig gedocumenteerd. Sinds de Amerikaanse publicatie Hospital-based Emergency Care: At the Breaking Point in 2006, zijn er meer dan duizend artikelen over “crowding” verschenen. We weten dat patiënten slechter af zijn als zij verblijven op een SEH die “crowded” zijn: zij krijgen minder effectieve zorg en hebben meer kans op overlijden of complicaties. Daarnaast levert een “verstopte” SEH een verhoogde werkdruk op en neemt de tevredenheid van het personeel af. Aangezien het de verwachting is dat de vraag naar spoedeisende hulp alleen maar gaat toenemen de komende jaren, willen we hier wat aan doen. We kunnen het begrip “crowding” operationaliseren naar een onbalans in de zorgvraag en het zorgaanbod.

Daarom dat we onderzoek hebben gedaan naar de doorstroom van patiënten van de SEH in het Scheper Ziekenhuis Emmen dat onderdeel is van Treant Zorggroep. In Nederlands zijn tot op heden weinig “crowding” onderzoeken gedaan. Doel van ons onderzoek is om vast te stellen of en wanneer deze verstopping zich voordoet. Tevens willen we op zoek gaan naar mogelijk oplossingen hiervoor. We beperken ons hierbij tot het doelmatig en efficiënt inzetten van de verpleegkundigen en artsen op de SEH. Om zo tot een optimaal mogelijk resultaat te komen binnen de huidige beschikbaarheid van het personeel op de SEH. Tevens kijken we naar de capaciteit van de SEH en onderzoeken we hoeveel (extra) bedden we nodig hebben voor een optimaal resultaat zodat de onbalans tussen vraag en aanbod niet meer aanwezig is.

Methoden

We hebben data-analyses uitgevoerd voor de periode van 1 februari 2017 tot en met 30 april 2017. Gegevens werden verkregen van het elektronisch patiënten dossier van de SEH, genaamd NEXUS. Tevens werd observationeel onderzoek verricht gedurende maart van 2017.

We starten met een literatuur onderzoek naar wat we al weten over “crowding”. Tevens gaan we op zoek naar methoden om deze onbalans tussen zorgvraag en zorgaanbod te meten. Er blijken drie belangrijke meetinstrumenten van “crowding” te zijn. We kiezen voor de methode van de bezettingsgraad in verband met de retrospectieve data-analyse die we gaan uitvoeren. Tevens zijn de overige meetinstrumenten ontwikkeld in de Verenigde Staten en (nog) niet gevalideerd voor de situatie in Nederland. We kiezen voor twee drempelwaarden namelijk >1.0 (of 100%) en >0.85 (of 85%). Als de drempelwaarde boven de 1.0 komt dan is de zorgvraag duidelijk meer dan het zorgaanbod en hebben we een onbalans aangetoond. Echter operationeel onderzoek heeft ons aangetoond dat als de bezettingsgraad boven de 0.85 komt, dit ten koste gaat van het zorgproces en deze stagneert. Daarom dat we ook voor deze drempelwaarde kiezen.

De huidige SEH wordt in kaart brengen. We kijken naar de patiënten karakteristieken, hoe ze binnen komen op de SEH, aan welke specialisme ze worden toegewezen, met welke triage code en hoe ze de SEH verlaten. We maken een conceptueel model van onze SEH met een instroom-, doorstroom- en uitstroom fase. We stellen prestatie indicatoren op om de verschillende fasen in de spoedzorg te meten. Voor de instroom fase berekenen we de wachttijd en de tijd voordat de arts de patiënt fysiek heeft gezien. De doorstroom fase wordt berekend door de verblijfsduur op de SEH te meten. De uitstroom fase kan berekend worden door de tijd te meten vanaf wanneer de behandeling op de SEH stopt en de patiënt daadwerkelijk de SEH verlaat. Tevens gaan we controle grafieken opstellen waar we kunnen testen of sommige medisch specialismen de behandeltijd overschrijden zonder dat we dit statistisch kunnen toewijzen aan toeval. Om een eerlijk beeld te krijgen splitsen we de patiënten per triage code op zodat we de specialismen binnen dezelfde urgentie code kunnen analyseren en vergelijken.

Om verbetering en optimalisatie van de inzet van verpleegkundigen en artsen te verkrijgen moeten we de SEH omvormen in een wiskundig model. Hoewel simulatie meer voor komt, kiezen we voor reden van simpliciteit en omdat we willen weten waar verbetering te vinden is, voor het wachtrijmodel. Voor zover wij weten is dit een noviteit binnen de Nederlandse SEH afdelingen. Het wachtrijmodel is echter al wel succesvol getest voor spreekuren op de polikliniek van de anesthesie van het Leids Universitair Medisch Centrum. Wachtrijsystemen worden wiskundig met behulp van technieken uit de kansrekening geanalyseerd met het doel de meest effectieve maatregelen te vinden tegen een te lange wachttijd, of het gedrag van deze systemen te kunnen voorspellen en controleren. Wachtrijen leiden vaak tot veel irritatie. De wachtrijtheorie is daarom ook wel bekend als de wiskunde van de ergernis. Hoewel er verschillende aankomsten zijn en patiënten op verschillende manieren de SEH kunnen verlaten, kiezen we ervoor om dit niet te doen. We berekenen een gemiddelde aankomst per tijdsperiode (wat samen valt met de verschillende diensten van de verpleegkundigen en artsen). Daarnaast wordt geen onderscheid gemaakt in het vertrek van de patiënt. De zorgverleners worden apart opgesplitst in artsen en verpleegkundigen. De huidige situatie wordt eerst berekend met de huidige bezetting van de verpleegkundigen en artsen. Vervolgens gaan we alternatieve oplossingen aandragen en deze testen met hetzelfde model. We kijken hierbij vooral naar de benuttingsgraad.

Uiteindelijk kijken we, onafhankelijk van de resultaten van het wiskundig wachtrijmodel, naar de capaciteit van de SEH. Hoeveel (extra) bedden hebben we nodig zodat de onbalans niet gebeurd. Hierbij houden we wederom de drempelwaarde van >1.0 en >0.85 aan. We kijken wanneer de bovenste grens van het 95% BI deze drempelwaarde niet meer passeert.

Resultaten

De literatuur verteld ons dat er verschillende redenen voor “crowding” zijn. Kortweg hebben de belangrijkste redenen ermee te maken dat patiënten te lang op een SEH blijven. We gaan zo dadelijk analyseren in welke fase van het spoedeisende zorgproces deze vertraging zit, maar eerst brengen we de SEH in beeld. De SEH is recentelijk verbouw in 2016 en heeft nu de beschikking over 12 behandelbedden. Gedurende de onderzoeksperiode hebben in totaal 3640 patiënten een bezoek gebracht aan de SEH. Het meest geraadpleegde specialisme was chirurgie (n=1449). Doorverwijzing door huisarts of huisartsen post kwam in meer dan helft van de gevallen voor (n=1916), gevolgd door ambulance (n=654). Het aantal zelfverwijzers, gezien als een mogelijk probleem en oorzaak van “crowding”, wordt berekend op 4% (n=163). De meeste patiënten (n=1551) worden ingeschaald in de niet urgente triage code volgens de Nederlands Triage Standard. De gemiddelde leeftijd van de patiënten was 50 jaar. Mannen en vrouwen waren gelijkmatig verdeeld. We zien dat 41% (n=1443) van alle patiënten opgenomen wordt in het ziekenhuis. Percentagegewijs worden geriatrische patiënten het meeste opgenomen (85%) gevolgd door neurologie (73%) en de longgeneeskunde (68%). Patiënten van de interne geneeskunde vormen numeriek het hoogste aantal (n=357) en bedragen 25% van het totale aantal patiënten dat opgenomen moet worden.

De berekeningen van de bezettingsgraad tonen aan dat met name in de middag een onbalans te zien is tussen de zorgvraag en het zorgaanbod. Dit is vooral een probleem doordeweeks. Voor de >1.0 drempelwaarde wordt deze doordeweeks structureel tussen 14:00 en 16:00 overschreden. Bij de >0.85 drempelwaarde is dit tussen 12:00 en 17:00. De piek wordt bereikt om 15:00.

De prestatie van de instroom fase laat ons zien dat de wachttijd en de tijd voordat een arts de patiënt fysiek ziet, laag is. De doorstroom fase voor patiënten die de SEH verlaten is ook geen probleem indien de patiënt met ontslag gaat. Echter wanneer de patiënt opgenomen moet worden neemt de verblijftijd aanzienlijk toe en is dit vele malen hoger dan we in andere Nederlandse studies hebben gezien. Hier lijken we een probleem gevonden te hebben. De uitstroom fase laat zich lastig meten aangezien deze tijd niet geregistreerd wordt in het NEXUS systeem van de SEH. Aangezien het tijdens observatie opvalt dat de verpleegkundigen zelf het transport doen van de patiënt naar de verpleegafdelingen, wordt deze transporttijd in kaart gebracht. Het blijkt dat per dag de verpleegkundigen grofweg 7 uur kwijt zijn aan transport. Een inadequate inzet van de verpleegkundige middelen. De controle grafieken laten ons zien dat het hele zorgsysteem in balans is, maar dat vooral geriatrie en ook interne- en longgeneeskunde, meer behandeltijd nodig is dan dat statistisch kan worden geweten aan toeval. Hier is verder onderzoek en verbetering op z'n plaats.

Het wachtrijmodel laat ons zien dat met name doordeweeks er een hoge benuttingsgraad zichtbaar is. De rekenuitkomsten vertellen ons dat er met name problemen ontstaan in de ochtend vanaf 10.00. Het benuttingspercentage schiet dan voor zowel verpleegkundigen als artsen omhoog en het SEH systeem is in onbalans. Dit is met name duidelijk te zien bij de artsen die tevens in de avond ook nog een piekmoment hebben. Als we in herinnering de eerdere berekende bezettingsgraad nemen, waarbij een hoge benutting in de middag werd waargenomen, dan kunnen we stellen dat we eerst slechts naar het effect hebben gekeken. Het wachtrijmodel heeft ons laten zien dat de oorzaak eerder in de dag ligt. We gaan de bezetting van de verpleegkundigen en artsen wijzigen met verschillende alternatieve oplossingen en voeren deze opnieuw in het wachtrijmodel. Daaruit blijkt dat als de verpleegkundige tussendienst van 14:00 vooruit wordt geschoven naar 10:00, er zich geen problemen of momenten van onbalans voordoen. Voor de artsen is dit lastiger te realiseren met de huidige bezetting. De meeste optimale situatie wordt gevonden als de tussendienst van de artsen om 10:00 begint in plaats van 12:00. Ook is het beter als een arts die normaal om circa 16:00 zou beginnen, nu ook starts om 10:00. Nadeel is wel dat het wachtrijmodel ons verteld dat in de avond dan een probleem ontstaat. Beter zou zijn dat de arts de nu om 10:00 begint een 10-uurs dienst gaat draaien, of nog beter, dat er een extra arts bijkomt. Dit vraagt echter financieel meer van het ziekenhuis en daarom moet eerst onderzocht worden of hier draagvlak voor is voordat deze nieuwe bezetting getest kan worden.

Als we capaciteit berekeningen gaan maken met een 95% BI dan zien we dat met een extra capaciteit van 5 bedden de drempelwaarde van >0.85 niet wordt overschreden.

Conclusie

"Crowding" of de onbalans tussen zorgvraag en zorgaanbod is gemeten op de SEH van het Scheper Ziekenhuis Emmen. Met name in de middag is het systeem in onbalans. Als we kijken naar de doorlooptijden dan is de instroom fase geen probleem. Ook het aantal zelfverwijzers op de SEH is laag, vooral vergeleken met eerder Nederlands onderzoek. De doorstroom fase wordt een probleem wanneer de patiënten opgenomen moeten worden. Tevens gaat in de uitstroomfase veel verpleegkundige tijd verlopen aan transport. Verder weten we dat geriatrische patiënten, en die van de interne-, en longgeneeskunde, veel behandeltijd nodig hebben. Meer dan dat statisch kan worden toegewezen aan het toeval. Verder onderzoek hierin is wenselijk.

Hoewel bezettingsgraad zegt dat het zorgsysteem van de SEH in onbalans is gedurende de middag, laat het wachtrijmodel ons juist een hoge benutting van de verpleegkundigen en artsen zien in de ochtend. Dit is wederom doordeweeks en de weekenden lijken geen probleem te zijn. Tevens hebben de artsen ook nog een piekmoment in de avond. Om deze benuttingsgraad gelijkmatiger te verdelen en wat meer af te vlakken worden de diensten van de verpleegkundigen en artsen verschoven en weer ingevoerd in het wachtrijmodel. Daaruit blijkt dat als de verpleegkundige dienst van 14:00 wordt verschoven naar 10:00 de benuttingsgraad evenwijdig verdeeld is. Voor de artsen is dit lastiger, maar de oplossing waarbij de tussendienst van 12:00 om 10:00 begint en een arts van 16:00 ook naar 10:00 wordt verplaatst dit voor een betere benutting zorg gedurende de dag. Echter dit zorgt wel voor een extra piek in de avond. Een mogelijkheid zou zijn om een de lengte van de tussendienst te verlengen van 8 uur tot een 10 uur werkdag of een extra arts. Echter dit brengt extra kosten met zich mee en valt buiten de opdracht om binnen de huidige artsen bezetting tot een optimaal mogelijk resultaat te komen.

Met 5 extra bedden op de SEH komt de bezettingsgraad met een 95% BI niet boven de 0.85 drempelwaarde en doet de onbalans zicht niet voor.

De aanbevelingen zijn dan ook om de diensten te wijzigen zoals is onderzocht. Een extra capaciteit van vijf bedden te creëren voor de SEH. Dat systematisch en continue factoren die belangrijk zijn voor de doorlooptijden gemeten worden. Dat de verpleegkundigen niet meer het transport van de patiënten naar de verpleegafdeling verzorgen. Er verder onderzocht wordt waarom behandeltijden voor geriatrische patiënten en patiënten voor de interne – en longgeneeskunde onverklaarbaar lang zijn en er onderlinge afspraken gemaakt worden om het zorgproces van deze patiënten te versnellen en optimaliseren in de vorm van kort cyclisch verbeteren.

English summary

Introduction

Emergency departments (ED) worldwide are facing problems with staffing, capacity and ambulance diversion which are affecting the patient flow to stagnate or even fall still, causing the ED to close (temporarily). An undesirable situation that also occurs in the Netherlands. In the last quarter of 2015, a stop for ambulances was announced in the Amsterdam metropolitan area over 600 times because the EDs could no longer guarantee responsible care. This clogging of the ED is called "crowding" in international literature and has been documented frequently. Since the US publication Hospital-based Emergency Care: At the Breaking Point in 2006, more than a thousand articles about crowding appeared. We know that patients are worse off when they stay at an ED that is "crowded". They get less effective care and are at greater risk of death or complications. In addition, a "crowded” results in a high workload and reduces staff satisfaction. Since it is expected that demand for emergency care will only increase in the upcoming years, we want to deal with this problem. We can operationalize the concept of crowding towards an imbalance between supply and demand.

We performed a study into the patient flow at the ED of the Scheper Hospital Emmen that is part of Treant Zorggroep. In the Netherlands, few crowding studies have been conducted so far. The purpose of our research is to determine if and when this crowding happens. We also want to look for possible solutions for this. We restrict ourselves to the effective and efficient staffing of nurses and doctors at ED. In order to achieve the best possible result within the current availability of the staff at the ED. We also look at the capacity of the ED and investigate how many (extra) beds we need for optimal results so that the imbalance between supply and demand is no longer present.

Methods

We conducted data analyzes for the period from the 1st of February 2017 till the 30th of April 2017. Data was obtained from the electronic patient file of the ED called NEXUS. Observatory research was also conducted during March of 2017.

We start with a literature review of what we already know about crowding. We also look for methods and tools to measure the imbalance between supply and demand. Three measuring tools are documented frequently in international literature for crowding. We choose the method of the occupancy rate in connection with the retrospective data analysis we will carry out. Also the other measuring instruments have been developed in the US and are (yet) not validated for the Netherlands. We choose two thresholds, namely> 1.0 (or 100%) and> 0.85 (or 85%). If the threshold exceeds 1.0, then the demand of care clearly exceeds the supply that can be provided and we have shown an imbalance. However, operational research has shown us that if occupancy rates exceed 0.85, this is at the expense of the care process and it stagnates. Therefore, we also choose this threshold.

The current ED is mapped. We look at the patient's characteristics, how they enter the ED, what medical specialisms they are assigned too, what triage code and how they leave the ED. We make a conceptual model of our ED with an input, throughput and outflow phase. We are constructing key performance indicators to measure the different phases of the emergency care process. For the input phase, we calculate the waiting time and time before the physician has seen the patient. The throughput phase is calculated by measuring the length of stay. The output phase can be calculated by measuring the time from when the ED treatment end and the patient departs from the ED. In addition, we will construct control charts to test whether some medical specialties exceed the treatment time without statistically randomness. To get a fair picture, we split the patients by triage code so that we can analyze and compare the medical specialisms within the same urgency code.

To achieve improvement and optimization the staffing of the nurses and physicians, we need to transform the ED into a mathematical model. Although simulation is more common, we choose for simplicity reasons and because we want to know where there is room for improvement, for the queue model. As far as we know a novelty within the Dutch EDs. However, the queue model has already been tested successfully for consultation hours at the anesthesia clinic at an university hospital. Waiting systems are mathematically analyzed using probability with the purpose of finding the most effective measures against too long waiting time, or predicting and controlling the behavior of these systems. Queues often lead to much irritation. The queue theory is therefore also known as the math of the annoyance. Although there are several arrivals and patients can exit the ED in different ways, we choose not to do calculate these times separately. We calculate an average arrival per time period (which coincides with the different staffing time periods of nurses and doctors). In addition, no distinction is made between the patient's departure. The healthcare providers are divided into nurses separately. The current situation is first calculated with the current occupation of nurses and physicians. Further we will propose alternative solutions and test them with the same model. Main focus is the utilization of the staff.

Finally, regardless of the results of the mathematical queue model, we look at the capacity of the ED. How many (extra) beds do we need so that the imbalance does not happen. Again, we keep the threshold of> 1.0 and> 0.85. We look at when the upper limit of the 95% CI no longer surpasses this threshold.

Results

The literature review tells us there are several reasons of crowding. In summary, the main reasons are that patients stay at the ED too long. Later on we will analyze at which part of the ED care process this delay occurs, but first we will introduce the lay-out of the ED. The ED has recently been rebuilt in 2016 and now has 12 treatment beds. A total of 3640 patients visited the ED during the reserach period. The most consulted medical specialty was surgery (n = 1449). Referral by general practitioner or general practitioner post occurred in more than half of the cases (n = 1916), followed by ambulance (n = 654). The number of self-referrers, seen as a possible problem and cause of crowding, is calculated to be 4% (n = 163). Most patients (n = 1551) are assessed in the non-urgent triage code according to the Dutch Triage Standard. The average age of the patients was 50 years. Men and women were evenly divided. We see that 41% (n = 1443) of all patients are admitted to the hospital. Per percentage the highest percentage of patients that need admission are geriatric (85%) followed by neurology (73%) and pulmonology (68%). Patients of internal medicine are numerically the highest number (n = 357) and amount to 25% of the total number of patients that need admission.

The occupancy rate calculations show that an imbalance between the demand and supply can be seen, especially in the afternoon. This is mainly a problem during weekdays. The> 1.0 threshold is structurally exceeded between 02:00 PM and 16:00 PM. For the> 0.85 threshold, this is between 12:00 PM and 05:00 PM. The peak is reached at 03:00 PM.

The performance of the input phase shows us that the waiting time and time before a doctor sees the patient is low. The throughput phase for patients who are discharged from the ED is also not a problem. However, when the patient is to be admitted, the length of stay increases considerably and is many times higher than we have seen in other Dutch studies. Here we seem to have found a problem. The output phase is difficult to access, as this time is not registered in NEXUS. During observation it was noticed the nurses transport the patient from the ED to the ward, this so called transport time is mapped. It results that the nurses lose roughly 7 hours to transport a day. An inadequate deployment of the nursing resources. The control charts show us that the entire care system is in balance, but especially geriatrics and also internal medicine and pulmonology, have a longer treatment time than can statistically be contributed to randomness. Here further research and improvement is in place.

The queuing model shows us that a high utilization level is visible especially during weekdays. The results tell us that problems arise in the morning from 10:00 AM. The utilization level rises for both nurses and doctors and the ED system is in imbalance. This is particularly evident for the physicians who also have a peak moment in the evening. If we recall the previously calculated occupancy rates, which indicated a high utilization in the afternoon, then we can say thus far that we were looking at the effect not the cause of crowding. The queue model has shown us that the cause is earlier on in the day. We will change the staffing of nurses and physicians with different alternative solutions and re-enter this staffing in the queuing model. This shows that if the intermediary shift for the nurses starts at 10:00 AM instead of 02:00 PM, no problems or moments of imbalance are occurring. For the physicians this is harder to realize with the current staffing. The most optimal situation is found when the doctors start at 10:00 AM instead of 12:00 PM. Also, it is better if a physicians from the afternoon that usually starts at 4:00 PM, starts at 10:00 AM. The downside is that the queuing model tells us that in the evening a new problem arises. It would be better for the doctor to start a 10-hour shift from 10:00 AM, or better, that an additional physician may attend. However, this requires more financial resources for the hospital and therefore it is necessary to first investigate whether there is support for this new staffing.

If we calculate the additional capacity with a 95% CI then we see that with an extra capacity of 5 beds the threshold of> 0.85 is not exceeded.

Conclusion

Crowding or the imbalance between supply and demand is measured at the ED. Especially in the afternoon, the system is in an imbalance. If we look at the lead times then the input phase is not a problem. The number of self-referrals to the ED is low, especially compared to previous Dutch research. The throughput phase becomes a problem when the patients need to be admitted. Also, during the output phase, a lot of nursing time is wasted on transport time. Furthermore, we know that geriatric patients, and those of internal medicine and pulmonology, need extra treatment time. More than that, static can be assigned to randomness. Further research is desirable.

Although occupancy rates say that the ED system is in an imbalance during the afternoon, the queuing model shows us a high utilization level of nurses and physicians in the morning. This is mainly during weekdays and the weekends suggest not to be a problem. The physicians also have a peak moment during the evening. In order to spread this level of utilization more evenly, the staffing of nurses and physician are shifted and put through the queuing model. This shows that if the intermediary nurse is shifted from 02:00 PM to 10:00 AM the utilization level is distributed in parallel. For the physicans this is more difficult, but the solution when the physicians intermediary shift of 12:00 PM starts at 10:00 and a physician from the evening starts also at 10:00 AM, this results in better utilization levels throughout the day. However, this results in an extra peak in the evening. One possibility would be to extend the length of the intermediary service from 8 hours to a 10 hours working day or an additional physician. However, this entails additional costs and falls outside the assignment to achieve the best possible result within the current staffing.

With 5 extra beds on the ED, the occupancy rate with 95% CI does not exceed the 0.85 threshold and no imbalance or crowding occurs.

The recommendations are therefore to change the staffing as investigated. Create extra capacity for the ED with 5 additional beds. Systematic and continuous record factors that are important for the lead times. Nurses no longer take care of the transport of the patients to the wards. And further investigation is made why treatment times for geriatric patients and patients for internal medicine and pulmonology are statistically unexplained long so mutual agreements can made to improve and optimize the care process of these patients in the form of short cyclical improvement.

Table of Contents

List of symbols and abbreviations

Symbols

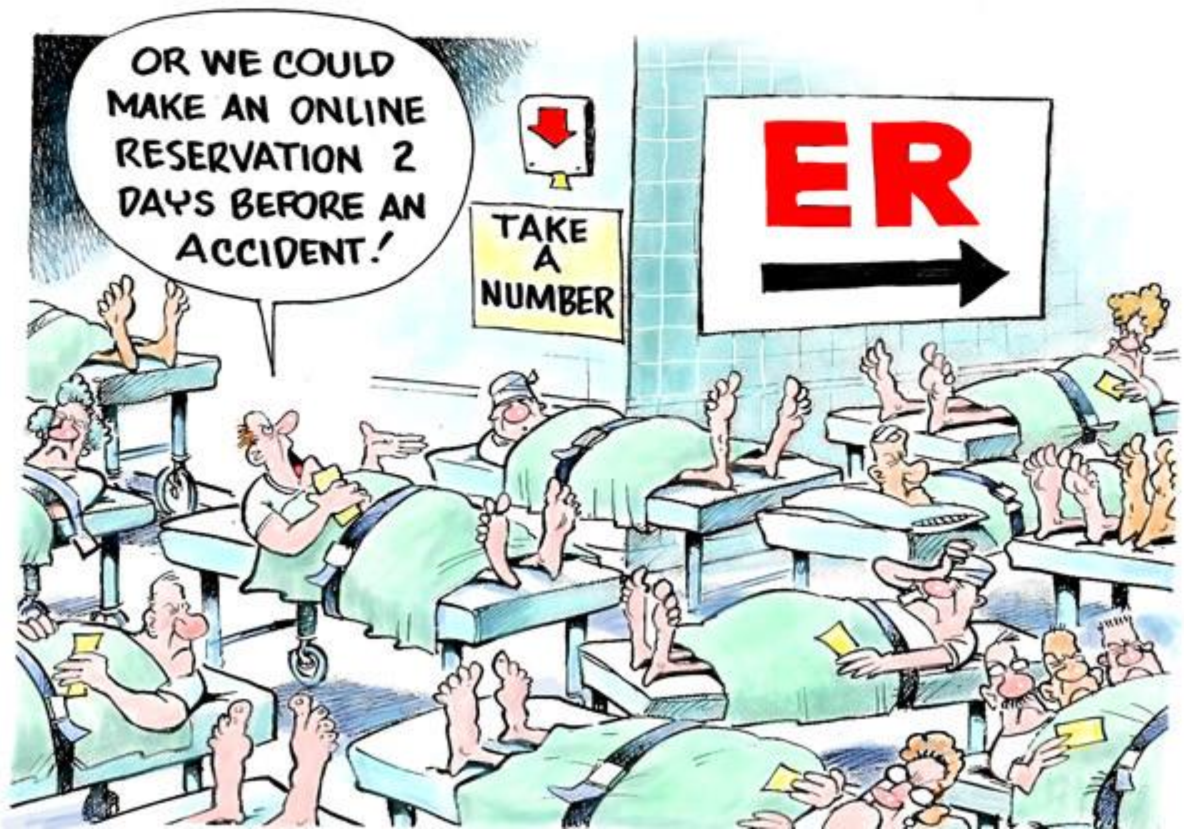
λ	Lambda, stand for the arrival rate
μ	Mu, stands for the service rate
L_q	Average number of patients waiting for service
L	Average number of patients in the system (waiting or being served)
W_q	Average time in hours patients wait in line
W	Average time in hours patients spend in the system
P	Rho, stands for system utilization
$1/\mu$	Service time
P_0	Probability of zero patients in system

Abbreviations

Arrival rate	Number of patients arriving at the ED per hour
AGP	Assistant of the General Practitioner
Boarding time	Time that a patient who remains in the ED after the patient has been admitted to the facility, but has not been transferred to a ward
CAR	Cardiology
CCU	Coronary Care Unit
CGP	Central General Practitioner Post
CHILD	Pediatrics
CI	Confidence Interval
CL	Control Limit (mean)
DTS	Dutch Triage Standard
ED	Emergency department
GP	General Practitioner
ICU	Intensive Care Unit
KPI	Key Performance Indicator
LCL	Lower control limit
Lead times	Number of minutes for the completion of an operation or process
LOS	Length of stay
M	Mean
Mean	Average
NC	Nurse coordinator with no direct patient care
NEU	Neurology
NEXUS	Electronic patient registry system of the ED
Optimization	The action of making the best or most effective use of a situation or resource
OR	Occupancy rate
ORT	Orthopedics
PC	Physician coordinator
PUL	Pulmonology

R	Range
R1	Referral emergency care
R2	Referral unscheduled urgent care
R3	Referral safety net care
SD	Standard deviation
Servers	Healthcare provider i.e. nurses and physicians
Service rate	Treatment time per server
SUR	Surgery
TTP	Time to physician
UCL	Upper Control Limit
URO	Urology
Utilization	The action of making practical and effective use of a resource or process
WT	Waiting time

CROWDING



at the

Emergency Department

1. General introduction

Like many hospitals in the Netherlands, the Scheper Hospital Emmen experiences negative influences of crowding according to staff and management. Although crowding seems to be getting increasing attention from healthcare professionals and government officials, few studies have been done in the Netherlands about the quantity, occurrence and potential solutions of this problem. With the use of quantitative research technique, the problems concerning crowding are analyzed concerning the lead times to find bottlenecks in the ED care process using Key Performance Indicators and control charts. This will lead to recommendations were improvement can be achieved. Also we fit our ED into a mathematical model to make various calculation resulting in alternative solutions for staffing optimization. We also focus on the capacity planning to find the most adequate number of beds needed for the emergency care at the Scheper Hospital Emmen.

This chapter provides background information of the Scheper Hospital in Section 1.1, 1.2, 1.3 and 1.4 and continues with the scope and goal of the research (Section 1.5), the problem definition (Section 1.6) and the research goal (Section 1.7). The chapter concludes by presenting the research questions in Section 1.8.

1.1 Background

This research was initiated on my own initiative as a master assignment for the Study Health Sciences at the University of Twente. I work at the Intensive Care Unit (ICU) of the Scheper Hospital since 2007. Although it might have seem logical to conduct my research at the ICU, I was very aware of potential bias. Therefore I was searching for a different research area. When I was talking with different healthcare providers in the hospital, the topic of high workload at the emergency department was mentioned often. My initially thought was, when talking to healthcare managers, to measure the workload of the nurses and physicians. Preliminary inquiry with Acute Zorgnetwerk Zwolle (in collaboration with the University of Antwerp) and supervisors from the University of Twente yielded that workload studies are at an early stage of development and conclusions thus far were little promising. When further deepening the underlying cause of high workload, the topic of crowding came to light. A topic that although in international literature is documented frequently, only few studies have been performed in the Netherlands. I became more interested in this topic and decided that this would be the focus of my study to further understand the underlying reason of the imbalance between the need for emergency care and the available resources. More important, to conduct reliable measures and develop adequate solutions to the problem. Therefor the emergency department was in my opinion the most suited place to conduct my research.

1.2 History of healthcare in Emmen

Emmen did not receive a hospital until 1938. At that time, much effort was made to build this hospital. In the 19th century Emmen lay at the border of vast, rugged soils consisting of sand and peat. Turf was the most important fuel in the Netherlands. Due to the many still untouched peat high fields in this part of Drenthe, there was a lot of employment in Emmen, which resulted in a large influx of (peat) workers. However, the importance of the peat decreased in the early 1900, as it was replaced by the must cheaper coal. As a consequence, a declining price of peat and reduced employment resulted in poverty which in turn led to a poor general health of the population.

The need for a local hospital was high, but nevertheless, the response to the grant application for the foundation of local hospital in Emmen was rejected. A new incentive was a serious traffic accident in 1934 involving a train and a bus, with a number of severely injured people unable to survive the long journey to the remote hospitals in the surrounding area. After this accident all effort was made to get a local hospital in Emmen.(1)

1.2.1 Reformed Deaconesses House of Emmen

It was professor dr. Slotemaker de Bruine who would prove to be the decisive factor that allowed the construction of a hospital. He was a professor of theology and politician for the Christian Historical Union. He used his contacts to persuade the government in The Hague for an approval to build a hospital in Emmen. Eventually the approval was given and construction began in 1937. The Dutch Reformed Deaconesses' House of Emmen was openend on the 29th of April in 1938. The hospital had cost over 250.000 guilders, an immense sum of money at the time and it was constructed with not a single penny from government subsidy.

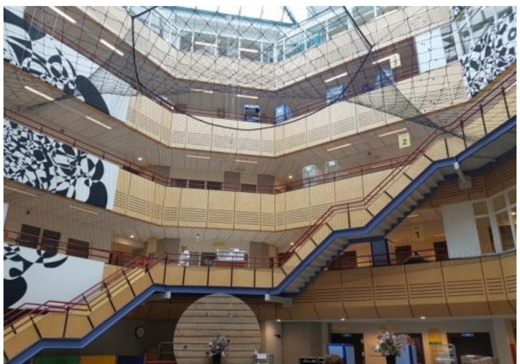
The hospital (picture 1.1) consisted of four wards and two single rooms with a total of 40 beds. It also had a laboratory, an operating room and an X-ray room. There worked and lived over 18 protestant nuns. The Deaconesses House was largely self-sufficient in the first years of its existence. It not only had a large vegetable garden with all kinds of greens, but there was also an orchard. In addition, there were chickens, pigs and sheep. In the beginning, two specialists practiced.

Picture 1.1 Deaconesses' House Emmen

From the beginning the hospitals' demand exceeded its capacity. Early plans were made to extend the hospital to 100 beds. Over the years, the building had to be expanded, and barracks were added. Finally it was decided to build a completely new hospital at the Boermarkeweg, with was across the road and had plenty of space.

1.3 Scheper Hospital Emmen

The newly build hospital was opened by Princess Margriet in 1973. This new building would carry the name Scheper Hospital. The name *Scheper* means sheep shepherd. Today at the entrance of the hospital there is still a statue of a shepherd with his dog in remembrance of the background of the name of the hospital. The hospital was sober and fairly cheaply build. The rooms or pavilions as they were called, where situated on a long hallway with a connecting service tunnel. The pavilions could easily be added or rebuild as the hospital grew, thus creating flexible capacity. In practice this would not happen and the wards remained as they were. Due to poor expansion capabilities of crucial departments it was decided that a new and modern hospital should be erected. In 1995, the hospital was completed and put into service. The old hospital was broken down and turned into the parking lot of the new hospital.(2)


Picture 1.2 Atrium of the Scheper Hospital

The current hospital has a greater capacity than the previous one. The current number of hospital beds is 333. The hospital can be categorized as a general hospital with some extra medical specialties. The hospital has a level 2 Intensive Care Unit which means that critically ill people with life threatening conditions can be treated at the hospital. The hospital is labeled as a cardio center which means that dotter procedures and the placement of stents in the coronary arteries (PCI) of the heart take place at the Scheper Hospital.

The hospital has modern research facilities such as a CT and MRI. Recently a Positron Emission Tomography scanner is purchased, enabling the body to be displayed in a special way. Especially helpful for the diagnosis of cancer, inflammations and cardiac conditions. Also the hospital is one of the largest dialysis centers in the Netherlands with 24 hemodialysis stations. In multiple areas such as pharmacy, training, medical technical innovations and medical practice, there is a collaboration with other hospitals. The hospital has a cooperation with the University Medical Center Groningen (UMCG) resulting in the status of teaching hospital for internal medicine and surgery specialties. This also led to the building of a radiotherapy center by the UMCG on the terrain of the hospital for the treatment of multiple kinds of cancer. When it comes to research the hospital has a scientific bureau which is responsible for the coordination, supervision and possible publication in many fields of science. It supports and advises researchers in all facets of research. The hospital has 8 operating rooms for general and orthopedic surgery. It also has the specialty for invasive and laparoscopic surgery to the abdomen, thorax, urogenital areas and mayor vascular interventions. There is a stroke unit for the treatment of a cerebrovascular accidents and plans are being made to provide intravascular thrombectomy in case of an ischemic stroke. A pediatric ward is present for the high care of sick infants with a maternity and gynecology ward. The care for geriatric patients is possible in a specialist geriatric department.(3)

The ED recently had a mayor rebuild and renovation to cope with the increasing demand of emergency care. The original ED was labeled to be too small and too outdated for the number of patients that needed treatment each day. Also little work space for the staff was available. To better accommodate emergency patients and regulate input, there is a collaboration with the Central GP Post (CGP). The rebuilding happened in different stages and the ED became fully operational again after the summer of 2016.(4)

Picture 1.3 Main entrance of the Scheper Hospital Emmen with the statue of the shepherd

1.4 Treant Zorggroep

Since the 1st of January 2015, Treant Zorggroep is founded. It is a merger of three hospital locations situated in Emmen (Scheper), Hoogeveen (Bethesda) and Stadskanaal (Refaja). Treant also has twenty places for elderly and nursing care in corresponding areas. The core of the strategy of Treant is summarized in the slogan: "together and connected". The starting point of Treant is that the inhabitants of the region must be assured from the best possible care. (5)

Figure 1.4 Logo of Treant Zorggroep

The name Treant is derived from the old geographical area that used to be from the Stellingwerven through North-East of Drenthe and the city of Groningen beyond Stadskanaal. This area largely corresponds to the service area of Treant Zorggroep and consists of approximately 300.000 inhabitants.

1.4.1 Mission, vision and core values

The mission of Treant is to organize care around its patients together with all other healthcare providers in the region. By connecting the care and cure divisions, Treant is aiming to deliver a coherent service. Together they form one organization who can deliver the whole body of care at every stage in life. For patients to benefit from access to care, Treant focuses on optimization of its resources.

The vision of Treant is to take the patient as the center of their actions and deliver appropriate care. Multidisciplinary cooperation between healthcare providers and the patients are considered to be important stakeholders in the healthcare process. The main philosophy is: nearby if possible, further away is necessary. Treant wants to organize this care as safe, qualitatively, efficiently and reliably as possible for all the patients in the service area.

Core values are transparency, entrepreneurship and involvement. The leadership style which Treant wants to scintillate can be categorized as human orientated and involved with their patients. The annual numbers, including the revenue and annual ED visits, can be found in table 1.1.

Table 1.1 Annual numbers Treant Zorggroep 2016

TREANT ZORGGROEP 2016	
Revenue	€455,429,000
Hospital admits	33691
Number of hospital beds	797
Number of beds nursing homes	1364
Employees	6097
Medical Specialists	303
Service acreage	$\pm$1000 km^2
Surgeries	46668
ED visits	32369

1.5 Scope and goal of the research

The scope of the research is limited to the ED of the Scheper Hospital Emmen which is a hospital of the Treant Zorggroep as mentioned before. The focus of the research is to investigate the different factors that lead to crowding. To be more specific, to focus on the patient flow at the ED analyzing retrospective registered time data . The goal of the research is to gain insight into how staffing, capacity and resources influence the patient flow and therefore the determine the degree of crowding. How can one measure a complex phenomenon like crowding methodically to identify the problem(s) leading to an imbalance between supply and demand. The ultimate goal is to come up with possible solutions in the emergency care process using analytical solutions. By using quantitative techniques from the field of operational research, the problems concerning crowding are studied, leading to different recommendations optimization of staffing and capacity planning of the emergency care processes. Not only by quantifying the current situation but defining and measuring the opportunities were improvement can be achieved. This is achieved by studying the system methodology according to Law and Kelton (6) as can be seen in figure 1.5 . The system is mapped to find bottlenecks in the care process and eventually come up with an analytical solutions model.

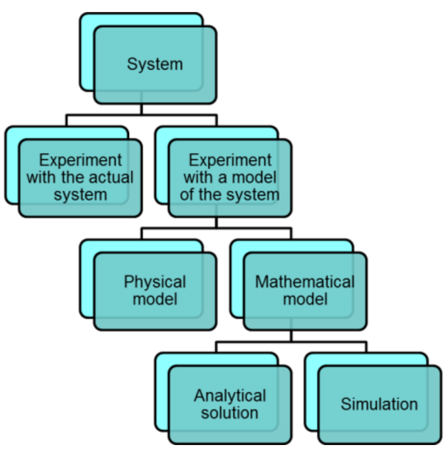


Figure 1.5 Ways to study a system by Law and Kelton

1.6 Problem definition

EDs worldwide are facing problems with staffing, capacity and ambulance diversion which are affecting the patient flow. The main culprit of this is described to be crowding. The most accepted published definition of crowding in scientific literature is that of the American College of Emergency Physicians (ACEP), which states that: *"crowding occurs when the identified need for emergency services exceeds available resources for patient care in the emergency department, hospital, or both"*.(7) To better operationalize this broad concept, crowding can be described as an imbalance between the need for emergency care and available resources. The Institute of Medicine in the US already described more than an decade ago that the hospital-based emergency care is at the breaking point. Nearly half of the EDs in the US report operating at or above capacity and nine out of ten hospitals report holding or boarding admitted patients in the ED while they await inpatient beds.(8) Since this publication in 2006 more than a thousand articles have appeared about crowding.

Also in the Netherlands there is an increasing interest in crowding of EDs. Especially when this has the consequence that an ED forces an admission stop and is temporarily closed. In 2013 an article was published in the NVSHV (The Professional Association for Acute Care), showing that 68% of the Dutch EDs struggle with frequent episodes, twice a week to even daily, of crowding.(9) In the last quarter of 2015 this happened over 600 times in the Amsterdam metropolitan area. Hospitals in North-Holland and Flevoland have written a pressing public letter back in 2016 to the Ministry of Public Health, stating that EDs cannot handle the increase in demand for emergency services anymore.(10) This growing demand has a restrictive effect on the patient flow of EDs during peak moments. This leads to long waiting times at the expense of good care, staff motivation and ultimately the efficiency, and more important, the safety at the ED. In order to cope with this problem, more knowledge is meaningful. What is challenging is to determine the extent and length of the crowding period(s). Measuring and assessing when crowding occurs. Crowding is not "static" but a dynamic process that cannot only change from day to day but from hour to hour. No studies on crowding have yet been performed in the Scheper Hospital Emmen or in rural areas of the Netherlands in general. We want to address the problem at the core that leads to crowding not finding solutions to counteract its effects. The causes in the literature that lead to crowding, will be discussed later, but first, the research goal is translated into the following main research questions:

Is there an imbalance between the need for emergency care versus the available resources, thus crowding, at the emergency department of the Scheper Hospital Emmen? How can we measure it, when does it happen and what are adequate solutions?

To reach this objective the following research questions are proposed:

1. *What does the literature mention about the causes and solutions for crowding at the ED?*
   In order to study if crowding is a problem at the ED the literature is checked to know how other researchers have dealt with imbalance problems in the healthcare sector and what their results have been so far. The literature review is done in Chapter 2.

2. *Which models for measuring crowding are available and suitable?*
   It is important to study which methodologies are fit to quantifying and measure episodes of crowding. Also their advantages and disadvantages will be evaluated. This is done in Chapter 2.

3. *How does is the current emergency care process work?*
Describing the current situation helps us as a starting point. The current situation will be described by analyzing the demand, capacity and staffing of the ED. Information will be gathered from observations and electronic data from the ED. A lay-out of the ED will be given along with a description of the various phases in the input, throughput and output of the ED patients. This will be presented in Chapter 3.

4. *What key performance indicators (KPI's) can be used to measure the current performance and lead times of the ED?*
When the current situation is outlined, the literature is reviewed to find suitable KPI's, to measure the performance of the ED. Also control charts are made to investigate if there are certain medical specialism that exceed the statistical expected treatment time per triage code. Also the control charts will tell us if the ED system is in control or not. This is done in Chapter 4. With the knowledge of the planning and control rules gathered from the literature, alternative solutions are developed that might improve the performance of ED.

5. *What mathematical modelling approach is suitable for a system-wide analysis of the staffing at ED?"*
After defining the designs of the ED an analytical solutions model is used to find the opportunities for improvement at the ED. Before doing so we must fit in our ED into a mathematical model. This is achieved by using Queuing Theory. The queuing model and its results will be further discusses in Chapter 5.

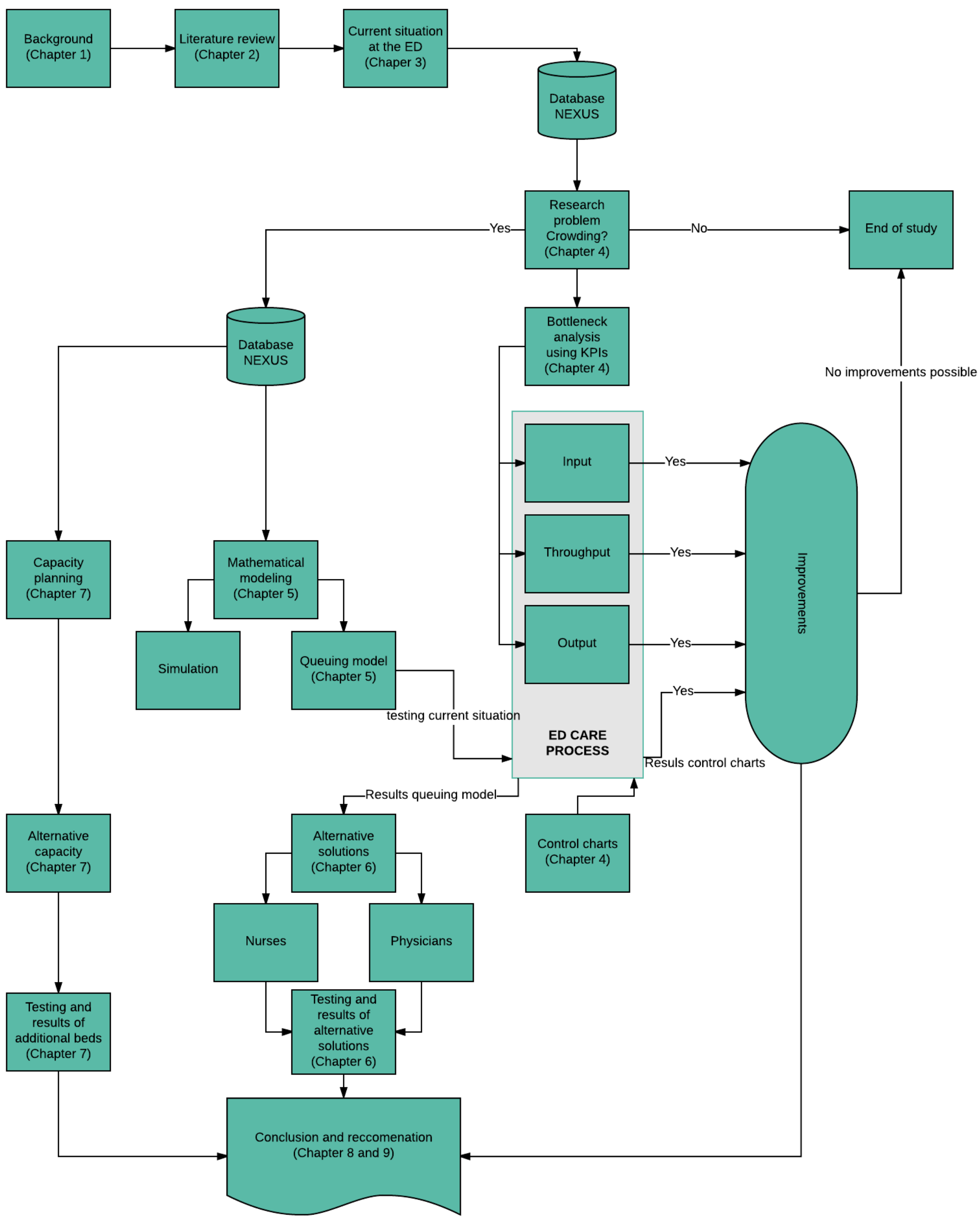
6. *What interventions are suitable to improve the current staffing of the ED for the solution approach according to the queuing model?*
In this chapter alternative solutions for the staffing are presented and tested with the queuing model. The possible and practical implementation of the developed alternative solutions are discussed together with an analysis of the results and recommendations for the implementation. This is presented in Chapter 6.

7. *What number of additional bed capacity provides the best possible outcome to balance out the need for emergency care versus the available resources of the ED?*
After chapter 4 has given an answer about the current performance of the ED, in this section the main focus will be on the capacity planning. We use the same dataset as before, but know we adjust the additional bed capacity (without the staffing optimization). Are there possibilities to alleviate stress on the so operations are not hindered. By using the results from chapter 4 we will discover the most optimal additional bed capacity. This will be done in Chapter 7.

1.7 Study design

The study design is visualized in the flow charts of figure 1.6. It shows the various steps that are being made to methodically analyze the ED system of the Scheper Hospital Emmen. The chapters were the answers are given to that part of the research are also presented in the flowchart.

Figure 1.6 Flowchart of the study design



2. Literature review

Having discussed the problem definition, this chapter reviews the literature for the definition of crowding (Section 2.1), the causes of crowding (Section 2.2), crowding in the Netherlands (Section 2.3), measuring tools of crowding (Section 2.4) and ending with the position of the research by looking into the framework for healthcare planning and control (Section 2.5). Leading to the final section of this chapter presenting the conclusions which can be drawn from the literature review in Section 2.6.

2.1 Definition of crowding

Healthcare is a business unlike all other due to many factors. For example, there is a differentiation in hospital types for example academic, general or specialized hospitals. Also in healthcare there more variability is present than in any other industry. Many stakeholder are involved in healthcare as well such as patients, doctors, nurses and managers, (sometimes) with conflicting goals. Further the patient is the consumer and product at the same time and patients cannot be refused. What makes it even more difficult is that the financial model does not reward efficiency in healthcare.(11) But things are changing because of the fact that healthcare is getting more expensive due to an ageing population. The TPG report of 2004 in the Netherlands showed that healthcare can be less costly. (12) Financial structures are changing and there is competition between hospitals. Also safety becomes more and more important. Logistical improvements go hand-in-hand with quality improvements: patients that have to visit the hospital less often, have shorter waiting times, and may count on more attention from nurses and physicians. (13)

The “need for care” is the highest at the emergency department of any hospital (ED). A hospitals’ ED is a hotspot and the place where new patients with acute illnesses or injuries receive initial diagnosis and treatment. The ED is responsible for assigning incoming patients to appropriate departments in the hospital, or referring them for further treatment. EDs demand continues to rise in almost all high-income countries. (4) EDs worldwide are facing problems with staffing, capacity and ambulance diversion which are affecting the patient flow.(14) The Institute of Medicine in the US already described more than an decade ago that the emergency care is at the breaking point. (15) Nearly half of the ED’s in the USA report operating at or above capacity and nine out of ten hospitals report holding or boarding admitted patients in the emergency department while they await inpatient beds.(16).

The main cause of impediments in patient flow is described to be crowding. (17) Crowding is defined as a situation in which the ED operations stalls when the number of patients waiting to be seen, undergoing assessment and treatment or waiting for departure, exceeds the staffing - or bed capacity of the ED. (18) Although there is a brought understanding that crowding has a negative influence on patient flow, there is no all-embracing description of crowding. Often the terms crowding and overcrowding are use vice versa but are referring to the same problem. (19) The most accepted published definition of crowding in scientific literature is that of the American College of Emergency Physicians (ACEP), which states that: “*crowding occurs when the identified need for emergency services exceeds available resources for patient care in the emergency department, hospital, or both”*.(7)

To better operationalize this broad concept, crowding can be described as *an imbalance between the need for emergency care and available resources*. This becomes an issue when inadequate resources to meet patient demands lead to a reduction in the care that is provided at the ED. It is also a problem when the resources are adequate but no patient arrive to be treated which means the system is idle and resources are lost. The supply and demand is uneven, thus hindering the operations of the ED. (20)

Not only is this imbalance inconvenient because patients must wait longer to receive treatment, it can also be dangerous and detrimental. Long waiting times in EDs not only reduce patients' perceived quality of care, but also increases the crowding which can adversely affect patients' outcomes. Waiting time has been found to affect patients' outcomes and is closely associated with delays in the provision of ancillary services to ED patients by the diagnostic and treatment laboratories. (21) The body of literature collectively and strongly suggests that ED crowding is associated with the potential of inadequate performance and results in adverse clinical outcomes. Also crowding correlates with poor quality of care, including increased length of stay for patients in the ED, patient dissatisfaction with emergency care, ambulance diversions, patients leaving the emergency department without treatment, delay in treatment, an increase in medical errors with higher complication rates and increased patient mortality. (22-27)

Crowding does not only effect patients but staff as well and is associated with higher absentee rates, staff sickness and decrease in physician productivity, lower staff morale and satisfaction because of high workload. (28) Crowding is also a system-wide problem of the entire hospital chain of care. Patients admitted through a crowded ED have longer hospital stays, leading to less inpatient capacity, further worsening access to emergency care.(29, 30) To sum it all up; crowding worsens outcomes, compromises quality of care and increases workload (31) There is an urgency to address patient flow bottlenecks at the ED by identifying them and find adequate solutions to reallocate a patient from emergency to inpatient care, or discharge, as soon as possible.(32)

2.2 Causes of crowding: patient flow

Crowding is a complex and multifactorial problem with not one probable cause because there is no general consensus as to what creates crowding.(33) It is helpful to look at the different stages of ED treatment. (29) The pathway of the ED patient can be broken down into a general conceptual model of input, throughput and output factors. (34) This will be discussed further in chapter 3. For now we highlight the most important findings in the different ED phases according to the international literature:

Input factors refer to conditions, events or system characteristics that contribute to the demand for ED services, including the volume, the acuity and type of patients. Contributing factors to the increase in ED presentations include rising community expectations regarding access to emergency care in acute hospitals, non-urgent visits , frequent flyer patients (seven or more times per year), self-reference, the influenza season and the ageing population. (35, 36)

Throughput factors refers to activities within the ED that can hinder patient flow. These include inadequate numbers of medical and nursing staff, waiting time for triage, waiting time for the physician's examination, waiting time for blood work, time away for radiological investigations, and poor ED design. (37-39)

Output factors are believed to be an important cause of ED crowding.(40) Time spent by ED providers to arrange appropriate follow-up undermines the efficiency of care and prolongs ED length of stay. Both admitted and discharged patients staying longer than 4 hours are associated with ED crowding. (41) Lack of hospital capacity may result in a mismatch between the time inpatient beds become available and the time that the patients requiring those beds present to the emergency department.(30) Boarding admitted patients until inpatient beds are available reduces the emergency departments' capacity to receive new patients. In fact a major cause for crowding is described to be the boarding of admitted patients. In other words patients that cannot be allocated to a hospital bed and therefore keep the ED bed unnecessarily occupied. The National Center for Health Statistics in the US found that the waiting and treatment time for boarding patients are longer than for discharged patients.(42) Admitted and discharged patients with prolonged ED stays contribute to crowding by utilizing beds and staff time that would otherwise be used for new patients.(43) Strategies used to help ease ED crowding require additional space and personnel resources, major process improvement interventions, or a combination of both.

2.3 Crowding in the Netherlands

Most of the earlier studies concerning crowding have been performed in North-America and Australia. In European countries ED crowding is not universally recognized. (35) Due to differences in regulations and legislation, the situation in the Netherlands is not the same as it international. (40, 41) One international factor concerning crowding, no access to primary care and therefore self-referral to the ED, does not suggest to be a large problem in the Netherlands. The Dutch health care system has a well-organized primary health which increasingly collaborates with the hospitals ED. (45, 46) (45, 46) (45, 46) (45, 46) (45, 46) Most Dutch citizens are registered by a local general practitioner (GP). GPs are obliged to organize a 24-hour care system of availability, in which both regular and acute care is provided during office hours and only acute care after working hours. (47,48)

However this does not imply that crowding is not a problems in the Netherlands. Several years ago an article was published which showed that 68% percent of the Dutch EDs regularly, twice a week or even daily, faces crowding.(9) Social developments, such as cuts to nursing home care, staff shortages, closures of emergency departments and medical developments, for example the expansion of treatment options in stroke care, the percentage of ED's who face crowding will likely to increase in the upcoming years. (48) In the last quarter of 2015 approximately 600 ambulances stops were promulgated in the Amsterdam metropolitan area because EDs could no longer guarantee responsible care. (49) Thus far crowding has only been observed and researched in populous areas of the Netherlands.

2.4 Measuring crowding

Perceptions of crowding vary among different healthcare providers and tend to be inaccurate.(50) To objectively determine if crowding happens (and when), one must first be able to measure it. To better understand and manage crowding, and to compare crowding levels, several quantitative and objective ED crowding measures have been developed. A number of crowding scores are proposed in the literature to quantify crowding using hospital and patient data as inputs for assisting healthcare professionals in anticipating imminent crowding problems. (51)

Several attempts have been made to measure the unbalance between the need for emergency care and the available resources, mainly in the US. The table bellows shows the three most commonly used me measuring tools along with its advantages and disadvantages. Also it is mentioned if retrospective detection is possible, with is important for our study.

Method	Working	Advantages	Disadvantages	Retrospective
The National Emergency Department Overcrowding Study (NEDOCS) is the most commonly used tool to estimate ED crowding. (50, 52)	A real-time linear regression model that associates five operational variables with the degree of crowding assessed by physicians and nurses. The variables are the number of admits, total hospital beds, number of ventilated patients in the ED, longest boarding time for admitted patient and longest wait in waiting room	The NEDOCS is considered to be a good tool to determine ED crowding	Inaccurate in an extremely high-volume ED setting. Developed in the US and is not validated for the Netherlands	No
Emergency Department Work Index (EDWIN) is another real-time crowding score (53, 54)	A real-time indicator which uses the number of patients in the ED per triage category, the number of attending physicians on duty, number of treatment bays, and the number of admitted patients from the ED.	EDWIN correlated well with staff assessment of ED crowding and diversion.(38) The EDWIN is able to identify fluctuations in ED occupancy. In addition, the EDWIN had high discriminatory power for identification of a busy ED.	Developed in the US and is not validated for the Netherlands	No
Occupancy rate (OR). (55, 56)	The number of patient using the OR are the sum of patients in the ED waiting room and in ED treatment beds. Number of ED treatment beds are all treatment facilities that are present at the ED. An OR >1.0 indicates that there are more patients in the ED then treatment beds. The higher the OR the more crowded the ED is	Easy to use Fairly high discriminatory power Can be used in Dutch ED setting	Urgency level, an important factor influencing workload of ED personnel, is not taken into consideration.	Yes

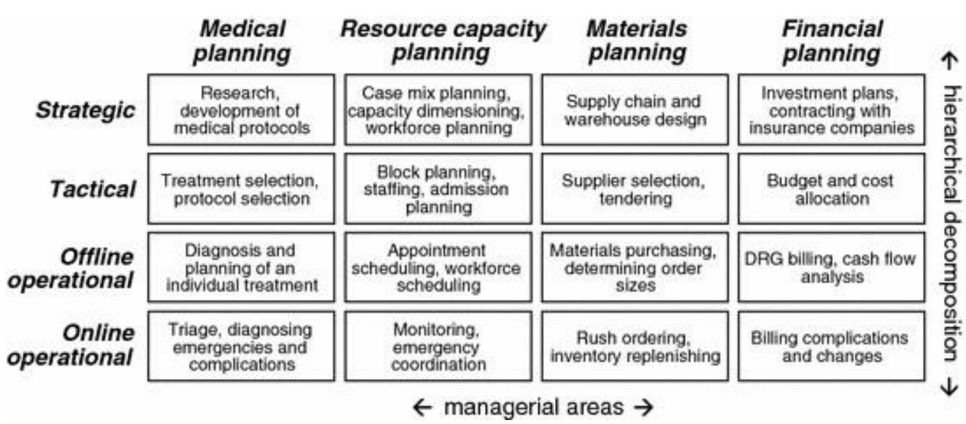
2.4.1 Summery measuring tools

The EDWIN, the NEDOCS and the OR have all been developed and validated in the US with an emergency care system characterized by high numbers of ED visits and ED boarding(44). Both EDWIN and NEDOCS are highly associated with physicians' perception of ED crowding (56). However, the NEDOCS quantifies ED crowding based on the number of respirators at the ED, longest admission time, and waiting room time of the last patient (52), which requires more detail than routinely stored in electronic hospital records. Also EDWIN is much more difficult to access because of its input data. The OR is based on the ratio of the total number of ED patients to the total number of licensed treatment beds per hour and is facile to use. However, urgency level, an important factor influencing workload of ED personnel, is not taken into consideration. Furthermore, studies concerning crowding measures have mostly been applied to settings in the North-America and Australia, and were conducted over a short period of time.(56) Although the ED occupancy rate is not ideal, its simplicity makes real-time and retrospective assessment of crowding feasible and easy.(39) For studies of crowding, occupancy rate may be the most useful metric for calculation.(57) In this thesis the OR will be used to determine retrospective when and how many time crowding occurred and there was an imbalance between the need for emergency care and the available resources.

2.5 Framework for healthcare planning and control

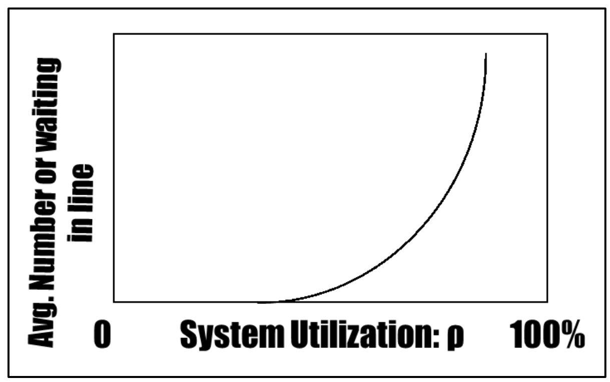
This study uses the principles of operations research. A discipline that deals with the application of advanced analytical methods to help make better decisions and gain knowledge and insight in planning and control of the different (healthcare) processes.(58) Planning and control in healthcare have received an increased amount of attention over the last years, both in practice and in the literature due to an increase in demand for healthcare and increasing expenditures. As a result, healthcare organizations are trying to re-organize processes for efficiency and effectiveness. It is therefore not surprising that the operational research community's interest in healthcare applications is rapidly increasing. To set the field for this study, the framework for healthcare planning and control to a general hospital in figure 2.1 is used.(58) In this thesis the focus is mainly on resource capacity planning at a strategic and tactical level.

Figure 2.1 Framework for healthcare planning and control to a general hospital



The horizontal axis of the framework presents the four managerial areas. The medical planning contains the medical decision making which is done by clinicians, for example, the definition of medical protocols. Resource capacity planning is the planning and control of renewable resources such as staff, equipment, and facilities. Materials planning addresses the planning and control of consumable materials. The last managerial area is the financial planning, which focuses on the coordination of the costs and revenues of the organization. On the vertical axis of the framework, the hierarchical levels are defined. The framework uses the hierarchical decomposition of the manufacturing planning and control, which consists three levels, namely strategic, tactical and operational. At a strategic level, structural decisions are made for the long-term. The decisions consist for example the capacity dimensioning and the patient mix. The tactical decisions are made for the mid-term and involve the organization of the operations, like the allocation of capacity over the specialties. The short-term decisions are taken at the operational level. The is a decomposition between online and the offline operational level. Offline decisions consist of the planning in advance. So the scheduling of the patients and the staff. Online decisions deal with the demand of reactive decisions making. It involves the monitoring of the processes as well the reaction to unforeseen events, like emergencies. This research will focus on resource capacity planning at all hierarchical levels. The results from operational research show that a higher system utilization utilization goes at the expense of the average number of waiting patients in line. Thus creating hold-ups in the patient flow. This is illustrated in figure 2.2.(59) The “operational rules” dictate that when the utilization level exceeds the 85% (or 0.85) threshold, the operation of the system stagnates. Thus waiting lines increase and workload among staff rises. This claim is supported by numerous article in the area of operational research.(60, 61)

Figure 2.2 Utilization versus number or waiting patients in line



2.5 Conclusions

The literature indicates that crowding does not have one simple cause but is a multifactorial problem. When studying crowding, we actually focus on patient flow, or better holdups or delay in this flow. The term crowding is vague and encapsulated many concepts and definitions. Therefore, when we talk about crowding, the term is operationalized as an imbalance between the need for emergency care and available resources. The first challenge is to determine the incidence of crowding. This means measuring (retrospective) the episodes of crowding. Then the care process at the ED needs to be analyzing why delay in the patient’s flow occurs by detecting bottlenecks. In addition objective models are needed to measure the performance of the system to see where there is room for improvement. This will be discussed later on in this study. The framework for healthcare planning and control is mentioned placing the focus of this research on resource capacity planning at all hierarchical levels.

3. Current situation

3.1 Introduction

In order to find answer to sub question 3, *" How does is the current emergency care process work?"*, the lay-out and operations of the ED at the Scheper Hospital Emmen is given in the results section of 3.3.
In 2016 the ED of the Scheper Hospital Emmen underwent a major renovation. Although the location and entrance have remained the same, everything else has been renewed. The new facility is designed for efficient use of space, staff and resources. Patients do not have to choose whether to report to the ED or GP because it is now integrated into one department . The waiting room for patients, the coffee room for the staff and the warehouse are all shared with both staff from the ED and the Central GP Post (CGP). Furthermore, the whole ED is reassigned and reequipped with renewed furniture, colors and light. The capacity and staffing of the ED is limited by certain factors. A separate paragraph is dedicated to the team post, as it places a central role in the coordination and execution of the EDs' operation. A floor map for spatial lay-out of the ED, with a cross-reference to the earlier section, is made in results section.

The number of treatment beds at the ED are restricted to the maximum number available. As is the staffing and number of nurses and physicians. The results will be discussed in section 3.5. Also the ED care process is mapped into the various steps of the ED care process using the conceptual input, throughput and output model of Asplin. (34) This is done in section 3.6.

The Dutch Triage Standard (DTS) is elaborated in section 3.7. The DTS is the standard for triage in the acute care chain and is used at the ED of the Scheper Hospital Emmen. The triage system is meant to determine the dynamic process of urgency plus the follow-up actions. The DTS is intended for ED nurses, GP assistants (AGP) and centralists from the emergency phone number 112 . The aim is to increase the safety and effectiveness of the triage in emergency care so that the patient comes to the right healthcare provider as soon as possible and gets the right treatment. Also the triage gives an warning and indication how sever the injury or illness is and gives a timeframe when treatment must start.

Not all patients that arrive to the ED have the same condition or urgency. Also treatment by medical specialism may vary. The patients are cataloged and labeled to gain insight into the different types of patients at the ED. Results of the patients' characteristics are given in section 3.8. This al leads to the conclusion and discussion in section 3.9. The ultimate goal of this chapter is to obtain more insight in the current care processes, which will support the problem analysis and gives answer to sub question 3.

3.2 Methods

For this study, the data was collected in several ways. First, data from the registration system of the ED (NEXUS) was retrieved, containing patient consults at the ED from the first of 1st of January 2017 to the 30th of April 2017. The patient characteristics, triage code and assigned medical specialism along with waiting and treatment times, where gathered for analysis. However, because a new registration system was introduced in the beginning of 2017, not all the data in the first month where complete, reliable or valid. Therefore the data from January 2017 was excluded for this study. Consequently, the historical data from the 1st of February 2017 till the 30th April 2017 was analyzed. With the collected data, the current situation is mapped and described with the help of Excel 2013 from Microsoft. Additional information was gathered from a non-participating and unconcealed observational study and by discussing with staff during March of 2017. A logbook was kept to note all the different findings from the observation. Staff was informed in advance that a crowding study would take place at the ED. Mainly the different care processes and proceeding in patient flow were the subject of observation. Observational study was made on nurse and physician performance.

The lay-out of the ED in the section 3.3 is made with the help of observations and is visualized using photographs, taken in April 2017. The current capacity and staffing was constructed by consulting the manager of the ED and by studying the working schedules for both the nurses and physicians. Not all the nurses at the ED are registered ER nurses. Some are still in training, but have their basic nursing degree. No distinction is made between the registered ER nurses and those in training, in the results section or later on during our study. All the physicians at the ED have finished, or almost finished, their basic medicine study. Also registered emergency physicians are present at different moments throughout the week. No distinction is made between the physicians in the results section or later on during our study.

The different steps in the care process are mapped and categorized into a flowchart. For simplicity reasons the conceptual model of Asplin is used for analysis and filled with data gathered from the NEXUS system of the ED. A more detailed flowcharts of the ED can be found in Appendix I.

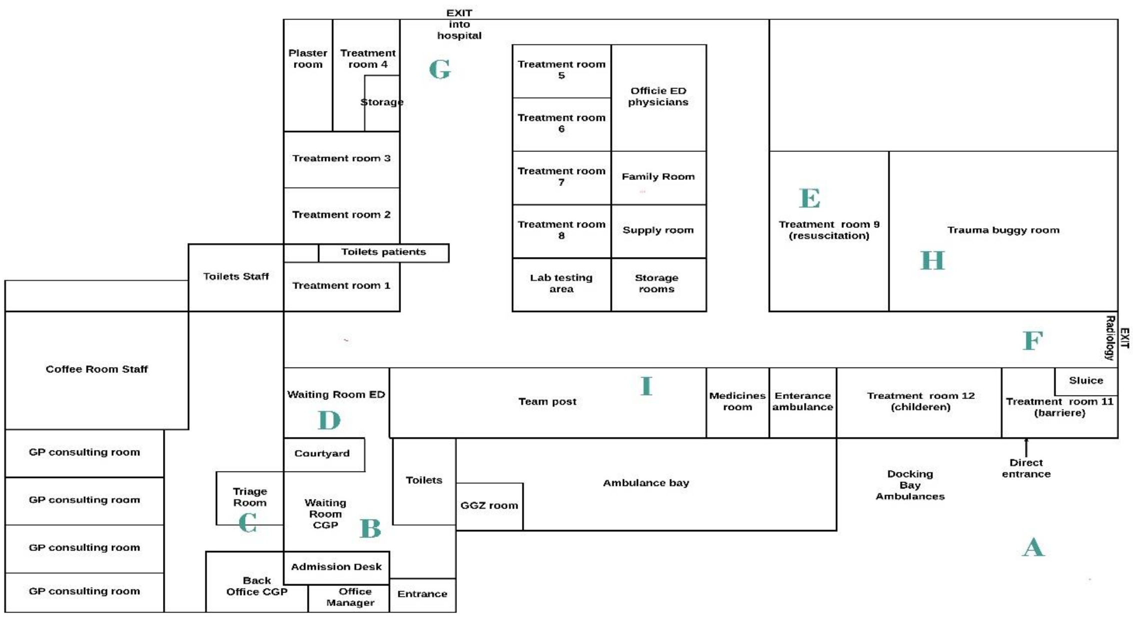
The characteristics of the patient at the ED are grouped into their total numbers and cataloged per medical specialism. Also their referral type is displayed to investigate how patients arrive at the ED. This was achieved through data analysis from the NEXUS registration system. General characteristics and per medical specialism where labeled into arrival, referral and admission following the conceptual model. The medical specialisms in the tables are abbreviated that are explained in the glossary. The various care steps are cataloged into input, throughput and output factors. The Dutch Triage Standard is explained with the help of available literature, placing the different codes into their urgency and maximum waiting time until treatment must start.

3.3 Results of the current situation

3.3.1 The floor map

The current situation of the ED is displayed in a floor map as shown in figure 3.1. The letters in the floor map, correspond with the letters of the pictures later on to depict what part of the ED is shown. The map is not drawn to scale and is intended to give an basic idea about the lay out of the ED.

Figure 3.1 Floor map of the emergency department at the Scheper Hospital Emmen and the CGP.



Picture A: Docking bay of the ambulance

Picture B: Waiting area CGP with front office

Picture C: The triage room

Picture D: Waiting room ED

Picture E: Treatment room (fit for resuscitation)

Picture F: View of the treatment rooms

Picture G: Hallways to the team post..

Picture H: Trauma bucky room

3.3.2 The emergency department

Our ED has recently been renovated, and fully reopened after the summer of 2016. The ED was redesigned to better accommodate patients and staff. A joint front office for both ED and CGP (B), separate waiting rooms and 12 treatment rooms were created. Also to start initial treatment and diagnostic as soon as possible, a special triage room (C) is constructed. The AGP behind the front office is responsible for these tasks. The AGP also has the ability for direct contact with the attending GP or with the nurse coordinator (NC) of the ED for consultation. So swift admission or consultation is possible when needed. The AGP uses the Dutch Triage Standard (table 3.3) and the guidelines of the ED, to determine with type of triage or initial treatment is required. The waiting rooms of the CGP and ED (D) are separated but also connected to each other. Once the patient takes place in the waiting room of the ED, the patients is admitted in the electronic patient registry system called Nexus. Nurses and physicians of the ED work with the same system and can see the patients data along with the triage code and possibly illness. The NEXUS system keeps track of the waiting times. NEXUS is a provider of healthcare software and claims to be specialized in IT solutions that allow the users to make patient throughput information or medical documentation simple. The NEXUS module records various patient data and keeps track of different lead times in de ED care process. (62)

If the patient is transferred to the ED, before entering, the patient is picked up by a nurse or physician and brought to an available treatment room. The treatment rooms at the ED are all similarly equipped. Al the rooms can monitor vital sign such as heart rate, blood pressure, oxygen saturation and body temperature. Tools at the treatment rooms are standardized. Some rooms are made fit to admit certain types of patients. For example, a resuscitation room is available for cardiopulmonary resuscitations.(E) To make multiple X-rays swiftly and timely, a special trauma bucky room (H) is designed. In theory all the rooms, with exception to the trauma bucky room, can be deployed to treat every patient if needed.

Team post

The team post is the operational center of the ED. It is intended to facilitate both nurses and the doctors in their work. At the post all the tasks are divided among staff. Screens on the wall show which patients have been assigned to a bed and which patients are seated in the waiting room. The NC and the physician coordinator (PC) supervise the operational level of the daily ED care process.

Picture I: Team post of the ED

To keep track of the bed capacity of the entire hospital, another system is used called *Hotflo*.(J) This is an integrated capacity management tool and claims to support hospitals in optimizing care processes and reducing costs.(63) It gives an update every minute about the current bed capacity of the hospital. It is dependent from input provided by the different wards.

Picture J: Green means available beds per ward, orange occupied beds, black are blocked beds and grey are beds that will possibly become available.

3.3.3 The current capacity and staffing of the ED

The total capacity of the ED is limited to 12 treatment rooms, as stated before. Also we already know that every patient can be treated at any random treatment room.

Because arrival rates vary as the day progresses, not a constant amount of staffing is present. In the current situation there are several shifts. The division of labor among staff is shown in tables 3.1 and table 3.2 for both nurses and physicians. Table 3.1 shows the number of healthcare providers and their shifts. Table 3.2 shows the staffing of the different time periods throughout the day.

When starting with the nurses, we can see that one nurse is allocated as the NC during the day and afternoon shift. The NC does not directly participate in the treatment of patients but oversees the overall operations of the ED, together with the PC. Therefore from 7:30 AM till 23:00 PM one nurse need to be less included. There is no difference between weekdays or weekends when it comes to staffing of the nurses.

Table 3.1 Staffing of nurses and physicians with their numbers and shift

Time of the day	**Number of nurses**	**Time of the day**	**Number of physicians**
07:30 AM - 03:30 PM	3 1 NC	7:45 AM - 4:00 PM	2
10:00 AM - 06:00 PM	1	12:00 PM - 08:00 PM	1
14:00 AM - 08:00 PM	1	12:00 PM - 04:45 PM (not on the weekends)	1
3:30 PM - 11:00 PM	3 1 NC	04:00 PM - 12:00 PM	3
11:00 PM - 07:30 AM	3	12:00 AM - 07:45 AM	2

Figure 3.2 Staffing throughout the different time periods of the day.

Time periods	Total number of nurses	Time periods	Total number of physicians
07:30 AM till 10:00 AM	2 1 NC	7:45 AM till 12:00 PM	2
10:00 AM till 02:00 PM	3 1 NC	12:00 AM till 04:00 PM (on weekends)	3
02:00 PM till 3:30 PM	4 1 NC	12:00 AM till 05:00 PM (on weekdays)	4
3:30 PM till 06:00 PM	5 1 NC	04:00 PM till 08:00 PM	4
06:00 PM till 08:00 PM	4 1 NC	08:00 PM till 12:00 AM	3
08:00 PM till 11:00 PM	3 1 NC	01:00 PM till 7:45 AM	3
11:00 PM till 07:30 PM	3		

In table 3.2 we observe the number of healthcare providers that are present during certain time period throughout the day. Beginning with the nurses, there is a dayshift that starts at 07:30 AM, with 2 nurses and 1 NC. Resulting in 2 nurses available for direct care between 07:30 AM and 10:00 AM. An intermediary shift starts at 10:00 AM, adding an extra nurse in the time frame from 10:00 AM till 02:00 PM. This is supplemented by another nurse from the intermediary shift that starts at 02:00 PM. Resulting in a total number of 4 nurses between 02:00 PM till 03:30 PM . The dayshift ends at 3:30 AM, thus the nursing staff changes, resulting in 2 nurses and the NC going home. For the afternoon shift 3 nurses and 1 NC start at 3:30 PM. The intermediary nurses remains until the end of their shift without replacements afterwards. So between 03:30 PM and 06:00 PM, 4 nurses are available for care duties along with 1 NC. At 06:00 PM the first intermediately shift leaves at, resulting in 4 nurses and 1 NC remaining. The last intermediately shift, that started at 02:00 PM, departs from the ED at 08:00 PM, thus 3 nurses and 1 NC stay present. They continue their shift till 11:00 PM. At this time the nightshift takes over till 7:30 the next morning, resulting into 2 nurses with no NC during this time period

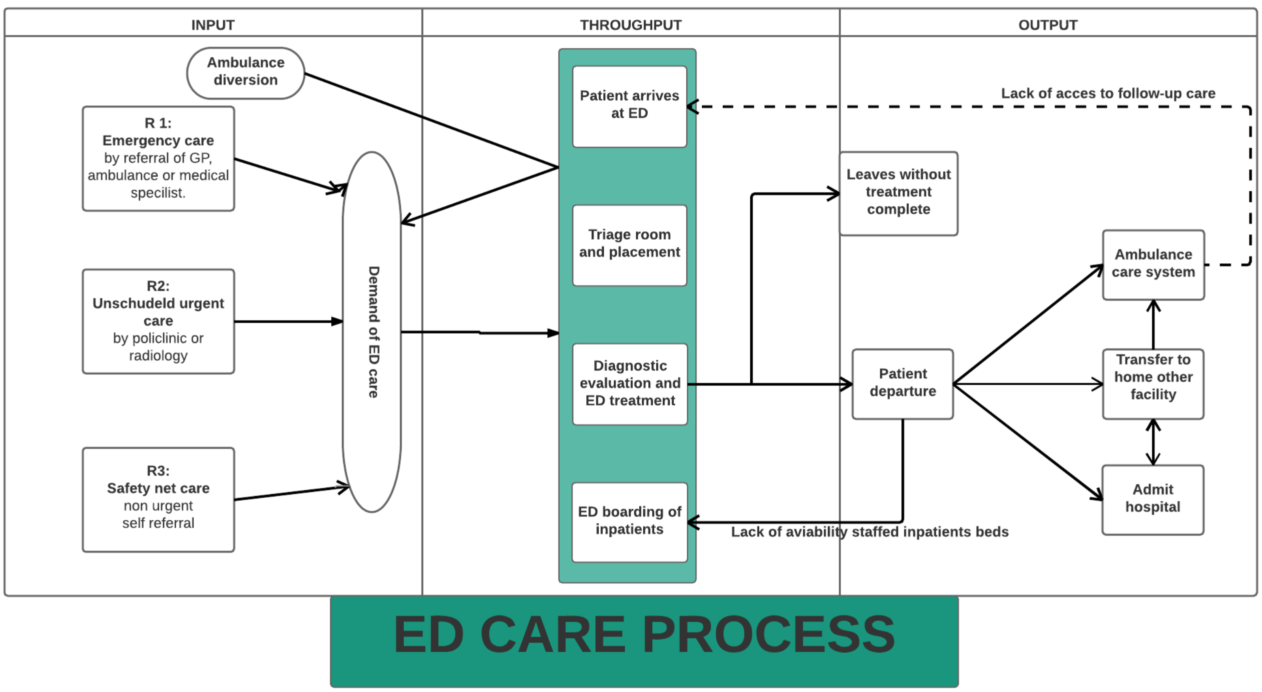
The staffing of physicians at the ED is somewhat different. We begin again with table 3.1, showing the number of providers and their shifts. In the morning 2 physicians start. Two intermediary shift start at 12:00 PM. One of these shifts represents a surgical resident. This is a physician who gets allocated to the ED during the afternoons and only during weekdays. This means one physician is less available during the weekends. The evening shift starts at 04:00 PM with 3 physician. This means the 2 physicians started in the morning, leave the ED. The intermediary shift also departs at 08:00 PM. At approximately 11:00 PM the nightshift takes over. The 2 physicians take over till 07:45 AM the following morning.

This yields the following results for the different time periods as we can see in table 3.2. We notice that during the morning from 7:45 AM till 12:00 PM, 2 physicians are present at the ED. An additional physician arrives at noon, for the intermediary shift, resulting in a total of 3 physicians between 12:00 PM and 04:00 PM. During weekdays there is also a surgical resident, causing a total number of 4 physician. In the evening at 04:00 PM the shift starts with 3 physicians, meaning the 2 physicians who began in the morning, depart from the ED. Resulting again in a total of 4 physicians during workdays and consequently 3 physicians at the weekends. After 08:00 PM, when the intermediary shift leaves the ED, 3 physicians remain. The nightshift, consisting of 2 physicians, take over at 11:00 PM till the next morning.

3.3.3 Conceptual model applied on the care process of the ED

We will begin by presenting the conceptual model in figure 3.2 and discuss the various phases of the ED care process.

Figure 3.2 Conceptual model of the ED care process



The *input phases* are labeled into emergency care (R1), unscheduled urgent care (R2) or safety net care (R3). The emergency care concerns patients who are seriously ill or injured. In other words the referral of patients with an urgent medical condition. This referral can be done by GP, CGP, ambulance or a medical specialist. Unscheduled urgent care consists the patients that want access to care due to convenience, conflict with job of family duties. In other words no emergency care that could be treated sufficiently by the GP during daily hours. Referral by medical specialist to the ED instead of the policlinic because of convince, can also be considered to the unscheduled urgent care. The safety net care patients are the vulnerable population in our society such as the elderly. They do not need direct emergency care or admission to the hospital, but are also not suited to stay at home. Also patient with access barriers such as financial reasons or lack of usual source of care, or better the self-referrers, are labeled in the safety net care. All these different referrals contributes to the demand in the input phase of the ED care process.

The *throughput phase* starts with the triage. The Dutch Triage Standard is used for both ambulance, CGP and the ED for emergency care optimization. The triage can be done by the AGP at the front office or by the ED nurse. In table 3.3 the criteria of the DTS are further explained and elaborated. If a patient is assigned to a certain medical specialism, the AGP takes blood works as stated in the ED guidelines related to the medical specialism. Also X-rays can be ordered and done in advance. Once a patient is transferred to the care of the ED there are two options to allocate the patient. First the patient can be seated in the waiting room. This especially happens with episodes of (early) crowding and with patients placed in a low or non-urgent triage code. Secondly the patient can be allocated to a treatment room right away. The happens when patient arrive per ambulance, priority policy, or when the ED is at a steady or idle situation where plenty of treatment rooms are available and allocation patients to the waiting room is nonsensical. After initial treatment has started and vital signs are checked by the nurse, a physician will visited the patients for diagnostics and come up with a treatment plan. This is the diagnostic and evaluation aspect of the throughput phase. Consultation by a medical specialist may be necessary or additional testing. If this process is completed the patient is ready for discharge from the ED. This is where the boarding time begin to starts and the patients move to the output phase of the ED care process.

At the *output phase* again there or two possibilities. The patient either is admitted to the hospital or they leave the ED and are discharged. Now and then a patient leaves without the throughput phase is fully completed. Admission is done by contacting the bed capacity planning of the hospital for an available bed. If no beds are immediate available the patients wait at the ED. If a bed is available the receiving ward is called for details about the transfer. This is primarily arranged by the nurse coordinator. Physical transport from the patient to the ward is done by the ER nurse. The ED nurse gives an spoken transferal to the nurse of the ward. With discharged patients there are other aspects. If the patient is fit enough, he or she will return home. It becomes more challenging if the patient needs transport to another facility. Especially if this requires the need for an ambulance. If follow-up care is not available or inadequate, it is likely the patients will return to the ED afterwards and thus the cycle repeats itself.

3.3.4 The Dutch Triage Standard

An elaboration about the triage code and the different time is given in table 3.3.(64). The codes are categorized between urgent and non-urgent. The urgent category starts with the red triage code, having the highest urgency of all, and immediately response is needed. The waiting time for the red triage is consequently zero minutes. The next triage code, orange, is labeled as highly urgent meaning waiting time must not be longer than 10 minutes. The yellow triage code, which is labeled urgent, calls for a maximum waiting time of 1 hours. The non-urgent category starts with the green code. This is labeled as a standard code and waiting time may rise to as long as 120 minutes. The following triage code blue, labeled non urgent, may even take up to 4 hours of waiting. The final triage code, white, is labeled to be unnecessary and there is no maximum to the waiting time.

	Color	**Urgency level**	**Response**	**Max waiting time in minutes**
Urgent				
	RED	U1	Immediately	0
	ORANGE	U2	Highly urgent	10
	YELLOW	U3	Urgent	60
Non-urgent				
	GREEN	U4	Standard	120
	BLUE	U5	Non urgent	240
	WHITE	U6	Unnecessary	No max time

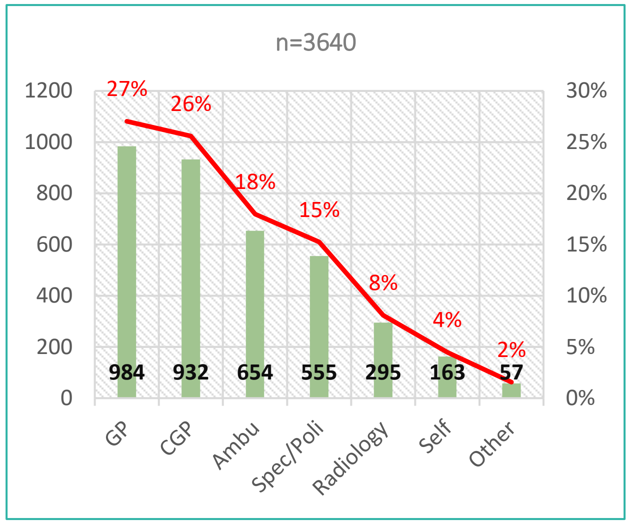
Table 3.3 Triage code with color, urgency level and maximum waiting time till start treatment.

3.3.4. Results patients characteristics and patient flow

Input: referral

The total number of patients that visited the ED during the research period is calculated to be n= 3640. Figure 3.3 shows that more than half of referrals to the ED are by the route of the primary care mainly the GP (n=984) during working hours and the CGP (n=932) after working hours (both R1 in figure 3.2). Arrival by ambulance takes up 18% (n=646) of the ED population (R1). Referral trough the policlinic (R2) takes up 15% of all patients (n=555). Radiology R2) also transfers 295 patients (8%) to ED. The self-referrals(R3), patient that arrive to the ED on their own initiative, are a small percentage of the total population with 163 patients (4%).

Figure 3.3 Referral by type



Throughput: arrival to medical specialty

As can be seen in tables 3.2 and figure 3.4, males and females are in balance. Each gender contributing about half of the EDs' population. Ages vary between young and old resulting in an average age of 50. The mayority of patient that arrives for treatment at the ED are those for surgery (n=1449). About 40% of all ED patients are for this specialism. Over 70% (n=1032) of the surgery patients have a green, blue or white triage code, indicating no urgency is required as visible in tables 3.4 and 3.5.

With internal medicine patients, about 55% (n=299) of the patients are given an orange or yellow treatment code which means urgent to very urgent medical care. The third specialism on the arrival list, orthopedics, 90% (n=317) of the patients have a low triage code, so no urgency is needed in most cases. When examining the data for pulmonology a different pattern is visible. More than three quarters of the patients (n=260, 76%) are placed in a high triage and urgency code, even as high as red which means life threatening. This also applies on neurology where 70% (n=242)

Table 3.2. Patient characteristics

Total population (n=3640)	**#**	**≈ %**
Gender:		
Male	1835	51
Female	1553	49
Age:		
Youngest	5 days	
Oldest	99 years	
Average	50 years	
Specialism:		
Surgery	1449	40
Internal	553	15
Orthopedics	360	10
Pulmonology	346	10
Neurology	346	10
Children	161	4
Urology	100	3
Geriatrics	72	2
Cardiology	69	2
Other	184	5

needs urgent care. When looking at the children or pediatrics patients also they have a high urgency code over 50% (n=84) of the cases.

Urology patients have a fairly high urgent code which is more than 40% (n=54). When it comes to the elderly patients who need geriatric care over 50% (n=37) need urgent care. The last patient category, cardiology, about 10% (n=7) have a red triage code this in combination with low admission rate. Overall this cardiology has a high urgency in more than 80% (n=56) of the cases. The remaining patients, contributing to the other category are the remaining specialisms like gynecology, plastic surgery and others but are separately too small for in-depth analysis.

Figure 3.4 Arrivals of patients per medical specialist

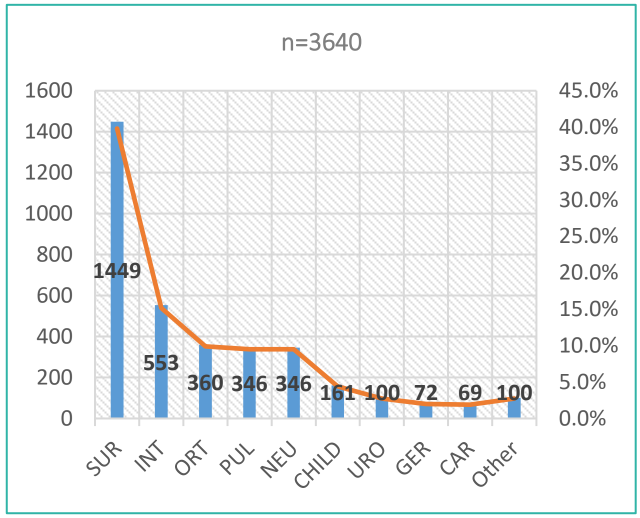
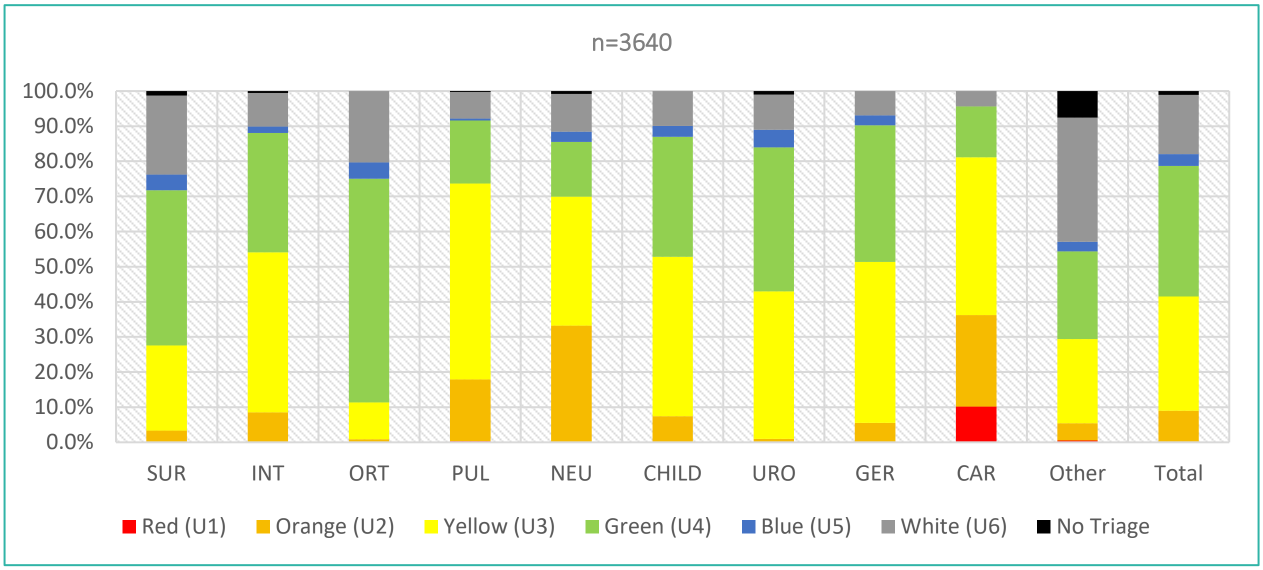


Table 3.3 Results of the number of patients per medical specialism and triage code

	Red (U1)	Orange (U2)	Yellow (U3)	Green (U4)	Blue (U5)	White (U6)	No Triage	Urgent (U1-U3)	Non-urgent (U4-U6)
Surgery **n =** **(%)**	1	47	351	641	64	327	18	399 (28)	1110 (78)
Internal **n =** **(%)**	0	47	252	188	10	53	3	299 (55)	254 (45)
Orthopedics **n =** **(%)**	0	3	38	229	17	73	0	317 (89)	43 (11)
Pulmonology **n =** **(%)**	1	61	193	62	2	26	1	260 (76)	86 (24)
Neurology **n =** **(%)**	0	115	127	54	10	37	3	242 (70)	104 (30)
Children **n =** **(%)**	0	12	73	55	5	16	0	84 (52)	77 (48)
Urology **n =** **(%)**	0	1	42	41	5	10	1	54 (54)	46 (46)
Geriatrics **n =** **(%)**	0	4	33	28	2	5	0	37 (51)	35 (49)
Cardiology **n =** **(%)**	7	18	31	10	0	3	0	56 (81)	13 (19)
Other **n =** **(%)**	1	9	44	46	5	65	14	54 (29)	130 (71)
Total **n =** **(%)**	10	317	1184	1354	120	615	40	1551 (42)	2089 (58)

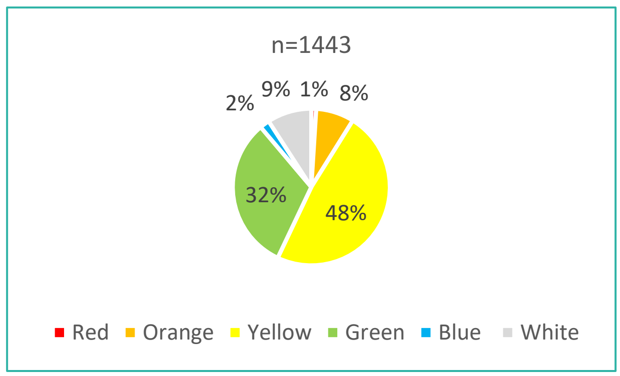
Figure 3.3. Block diagram of the distribution of triage codes per specialism



Output: admission or discharge

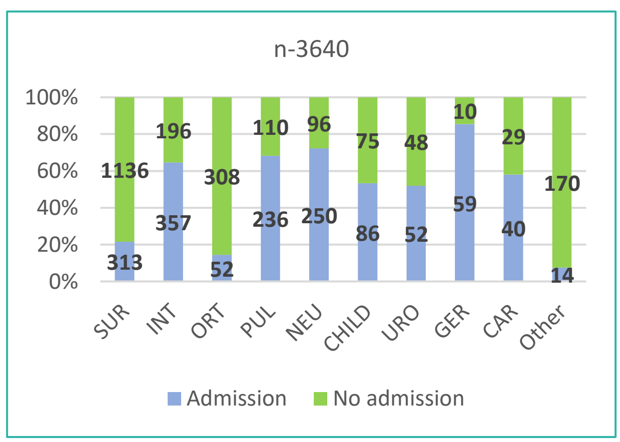
Not all patients that visit the ED need admission to the hospital. When looking at the data in the given research period, 41 % (n=1493) are being transferred to a ward. If those admitted patients are categorized by triage code as is displayed in figure 3.6 it can be noted that the bulk of patients that need admission have a green or yellow triage code. When divided between urgent (n=1551) and non-urgent (n=2089), respectively 57% (n=884) and 43% (n=898) of patients need admissions.

Figure 3.6 Admitted patients and their triage code



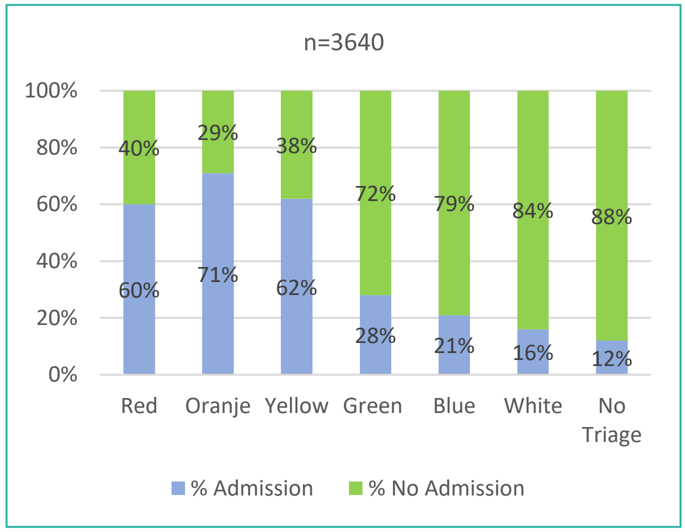
When looking at the admission per medical specialist in figure 3.7 the majority of the internal medicine, pulmonology, neurology and geriatric patient are admitted. For surgical and orthopedic patients this is the other way around where approximately 20% of the patients that visit the ED get admitted. For the remaining specialism the ratio is fairly fifty-fifty.

Figure 3.7 Admissions per medical specialist



When examining the admission per triage code in figure 3.8 there is a clear downward trend from a high urgency code to the lowest. The orange triage code needs most admissions calculated to be 71% followed by the yellow triage code which relates to 62% of the patients in this category. The red triage codes accumulates to 60% in need of admission The green and blue triage codes have an admission percentage of 28% and 21%. The patients with the white triage codes almost needs admission at 16%. Although no triage was made on some patients, 12% admission is needed.

Figure 3.8 Admission per triage code



3.9 Conclusion

The ED at the Scheper Hospital has recently been rebuild to better accommodate the treatment and diagnostic process of the patients. In total there is a capacity of 12 treatment rooms. Some treatment rooms have a dedicated function like for resuscitation, although this is not fixed when capacity is needed. In the time period from the 1st of February 2017 till the 30th of April 2017 a total of 3640 patient visited the ED. The average age of the patients was 50 years and male or female were equally divided. They were referred primarily by the GP. The second most common arrival was by ambulance. Policlinic patients, this means patients are in contact with the policlinic and then being transferred to the ED, come in as the third largest category. Reasons for this can be diverse, such as a worsening of the medical condition or for logistical reasons that swift consultation by a physicians is possible. Self-referral rate was low and does not seem contributing factor for crowding as stated in the literature review of chapter 2.

The most consulted medical specialism was surgery. The majority of ED patients have a low triage code indicating no urgency. The specialisms with the highest percentage of a high triages codes, thus suggesting urgency, are pulmonology, neurology and cardiology.

When looking at the admission another pattern if visible. Although surgical patient form the bulk of patients (n=1449) their admission rate is low, both numerical (n=313) as per percentage point (22%). In a way this is not strange. Minor injuries like cuts, stiches and small trauma are all done under the supervision of this specialism and do not call for admission. The internal medicine (n=553) patients form the greater number of admissions. In total 357 internal medicine patients needed admission making them the largest admitted medical specialism. This means 65% of the internal patients’ needs admission. An explanation of this might be that internal medicine patients generally need more treatment and are often fairly sick. Their condition is more worse than the surgery patients, hence the higher need for admission, both numerical and per percentage point. Also during the research period there was an influence epidemic in the Netherlands that lasted till the 13th of March 2017 (65), contributing the extra patients to internal medicine. This also applies on the medical specialisms geriatrics and pulmonology.

With the latter medical specialism pulmonology (n=346), patients with respiratory conditions like pneumonia and COPD are extra vulnerable when they are infected with the influenza virus. Thus admission is often needed for further treatment resulting in 68% (n=236). For geriatrics patients (n=69) again the influenza virus, in combination with low resistance for this population, gives an explanation for the relative high admission percentage of 86%. Neurology (n=346) also has a high admission ratio of 79% (n=250), which can be explained by of the high impact that a cerebral vascular accident can have on patients. Literally every minute counts for these patients, resulting in a high triage code with ditto admission. The high urgency of urology (n=100) can be contributed to the inability of urinating, leading to a full bladder and significant physical complaints. Consequently 54% (n=54) are labeled as urgent. The relative high admission (n=86) of children (n=161) can also be explained due to the flu season where children are prone to viral or bacterial infections. Cardiology (n=69) forms a separated category. Because the hospital has a specialized Coronary Care Unit for the diagnosis and treatment of patients will acute coronary syndrome, all patients are reallocated directly to this ward without first entering the ED. Only when this unit has reached it maximum capacity an cannot admit any more patients, the ED takes over. Also patient with a cardiac arrest are treated in the resuscitation room of the ED together with healthcare professionals from the ICU and CCU. Superfluously to say a condition of the highest urgency. For the cardiology patients that arrive by the ED, 58 % (n=40) need admission and 81% (n=56) is labeled to be urgent.

When looking at the overall admission ratio in relation to the triage code, of all admission (n=1443) the bulk of patients have a yellow (n=693) or green (n=462) triage code. In total 41% of the patients get admitted to a ward, the remaining patients (59%) leave the ED. It is noted that the higher the urgency code, the higher the admission rate. In other words the likelihood of admission correlates to the triage code that is given. We see that percentage of admission per triage codes, from orange (71%), to yellow (62%), green (28%), blue (21%) and white (16%), all have an downward trend. In other words the change of admission increases as the triage code, and thus the urgency, gets higher. A note can be placed when it comes to the red triage code. This code suggests, because it is the highest urgency, that almost all patient with the red triage need admission (60%), but because some of these patients died at the ED, admission was no longer an option.

4. Key Performance Indicators

4.1 Introduction

Now that the current situation is outlined as a starting point, we continue by reviewing the literature to find suitable key performance indicators (KPIs) for the ED. This is done to find the answer to the sub question: *"What key performance indicators (KPIs) can be used to measure the current performance and lead times of the ED?".* This chapter starts with a description of the relevant KPIs in the methods section of 4.2. The sequence of the conceptual model is again used to measure the lead times, categorizing the KPIs into input, throughput and output phase. In other words we dissect the ED system into its various parts and measure their separate lead times. Before doing so we begin by calculating the occupancy rate (OR). The OR was already determined to be a valuable tool to measure crowding, as was discussed in chapter 2. The OR has a fairly high distinctive power to detect crowding and can easily be used for retrospective analysis. Basically the goal of this chapter is to use the OR to discover if there is a problem at all. Does crowding happen at the ED or not? This is presented in section 4.3. If we have established that crowding does occur, then we want to investigate where the bottleneck(s) in the ED process can be found. Thus we further analyze the input, throughput and output phase using the KPIs. Also a bottleneck analysis is performed on the various medical specialists using control charts. Is it possible that some specialisms take up more treatment time than can be statistical explained? If so further investigation into why they take up longer time may be wise in the future. The chapter will end with the conclusion section in 4.4.

4.2 Methods

Data from the registration system of the ED (NEXUS) is used, containing patient visits to the ED from the 1st of January 2017 to the 30th of April 2017. Our dataset consists of $n = 89\ days\ \times 24\ hours = 2136$ observations. To determine whether our dataset, or sample size, for the occupancy of the ED follows a normal distribution, the kurtosis and skewness are calculated. For both measures, a perfectly normal distribution should return a score of 0. Otherwise a positive skewness value indicates positive (right) skew and a negative value indicates negative (left) skew. The values for asymmetry and kurtosis between -2 and +2 are considered acceptable in order to prove a normal distribution.(66). The normal distribution is necessary for the usage of the standard deviation and for calculating the additional capacity later on in chapter 7. The Jarque–Bera test is a goodness-of-fit test of whether sample data have the skewness and kurtosis matching a normal distribution. Because we have a large sample size (n=2136) we use the Jarque-Bara for a test of normality for the OR. (67) Total number of patients that visisted the ED during the research period were calculated to be n=3640.

We will describe separately per KPI how it is calculated. This is done with an example from our dataset. We will also show how we can compare our calculation with what is already know in literature . As mentioned before we will start with the OR as an overall performance indicator and a tool to detect crowding.

Overall performance

We will starts discussing with the occupancy rate as an overall performance indicator and as a tool to measure crowding.

Occupancy rate

The overall KPI that will be used to measure crowding is the occupancy rate (OR). The OR was already brought to our attention in chapter 2. (57, 68) In this study the OR is measured per full hour time so for example the number of patients present at the ED at 11:00 AM, or 12:00 PM, or 01:00 PM and so on. The OR is defined as:

$$OR = \frac{Number\ of\ patients\ at\ the\ ED\ (in\ treatment + waiting\ room)}{Total\ number\ of\ treatment\ beds}$$

The numerator counts all the patients that are present at the ED per hour (time period). Both the patients that have entered the ED and are being treated, as those who are awaiting allocation to a treatment room and are situated in the waiting room. The denominator is limited to the capacity or the number of treatment rooms. As stated before in chapter 3 the total number of treatment rooms, or beds, in our ED were determined to be 12. In the results section the frequency of a capacity >1.0, and >0.85 is given. These thresholds are chosen for the following reasons. A threshold greater than 1.0 suggest that the demand of care exceeds the capacity, thus crowding is present. The threshold of greater than 0.85 is chosen because operational research has shown that when the utilization level exceeds the 0.85 threshold, the operations of the organization stagnates and workload among staff increases as stated in chapter 2. In other words both an absolute threshold of >1.0 and a scientific threshold of >0.85 is chosen. To see if there is a difference between weekdays and weekends, and also recalling the difference in staffing as discussed in chapter 2, the data is presented accordantly. Results will be presented this order of weekdays and weekends hereafter. Standard deviation was calculated to compute the confidence intervals. The α was set on 0.05 creating a 95% confidence interval. Percentages where calculated where the stated thresholds where surpassed.

If we continue with our example of patient X, during the time this patient was at the ED several other patients required care as well. For instance at the 02:00 PM time period there were 9 patients in treatment and 2 patients in the waiting room. Resulting in:

$$OR = \frac{9\ patients + 2\ patients}{12\ treatment\ beds} = 0.92$$

If we compare this to our stated threshold, the >1.0 threshold is not surpassed so we can see that there is no crowding. However when we compare this to the >0.85 threshold, taking into account the results from operational research, we can say that there is crowding at the ED. Because there is a difference in results, both of the threshold will be discussed and visualized.

Input performance

The performance and lead times of the input phase will be measured by two indicators. We will starts with the KPI of waiting time.

Waiting time

Waiting time (WT) has been shown to be an important performance factor for both healthcare professionals and patients at the ED in a recently held preference study in the Netherlands.(69) The mean, SD, minimum and maximum in minutes of the WT are calculated. The calculations are compared to the stated maximum waiting time per triage code, as described in chapter 3. WT is defined as:

$$WT = time\ in\ waiting\ room$$

For example; in our dataset on Monday the 20th of February 2017 patient X arrived. This patient was categorized into the green triage code (U4) and assigned to surgery. The patient was logged into the electronic patient tracking system (NEXUS) of the ED at 01:30 PM and allocated to the waiting room. Thereafter the patients was transfer to an available treatment room at 01:45 PM. Thus resulting in a $WT = (1{:}45\ PM - 01{:}30\ PM) = 15\ minutes.$

Recalling the maximum waiting time for the U4 or green triage code, this time is well within the stated 120 minutes that the triage guidelines dictate.

Time to physician

Another KPI for the input phase according to the literature is the time to physician (TTP). (70) The TTP is defined as the time when a physician first sees the patient. The NEXUS system records when the physician has assigned himself to the patient. This is the time when diagnostics and treatment by a physician starts. If we subtract this time form the time when the patients arrived at the ED, we discover the TTP. Again the mean, SD, minimum and maximum of the TTP are calculated in minutes. Times are compared with Canadian results because data for the TTP in the Netherlands is lacking to this point. The mean in this study was calculated to be 59 minutes and is used as reference.(71) The TTP is defined as:

$$TTP = Arrival\ time\ patient\ to\ ED - \ arrival\ time\ physician$$

Again following our previous example of patient X, after this patient entered the ED at 01:30 PM the physician arrived at 02:00 PM to see the patients according to the Nexus system. Hence resulting in:

$$TTP = 02{:}00\ PM - 1{:}30\ AM = 30\ minutes.$$

Recalling our reference value in the Canadian study of 59 minutes, the TTP of this example is much faster and well within stated limits.

Throughput performance

The performance of the throughput phase of the ED care process will be measured on the basis of the length of stay.

Length of stay

An reliable throughput measures of crowding is ED length of stay (LOS). As stated before ED crowding is indicative to prolonged length of stay (LOS) at any ED. The LOS is an important indicators associated with crowding. (56) Length of stay is defined as the interval between patient registration and the moment the patient leaves the ED. The most commonly golden standard worldwide is the 4-hour treatment at an ED. Studies shown relationship between the 4-h standard performance and ED crowding as measured by occupancy. The 4-h standard is a meaningful quality metric and performance indicator.(72)Average length of stay at EDs in the Netherlands (119 minutes for discharged patients, 146 minutes for admitted patients) is short compared to published LOS in other countries.(73) In results section the numbers for the ED of the Scheper Hospital are shown and compared to the international standard and average time in the Netherlands.(70) Data is being presented into overall, admitted (ward and ICU) and discharged patients LOS. The maximum, minimum, mean and the SD of the LOS are calculated in minutes and benchmarked to the LOS in the Netherlands. The LOS is defined as:

$$LOS = (Departure\ time\ to\ the\ ED - Arrival\ time\ to\ the\ ED)$$

If we recall patient X in our example, this patient arrived at 01:30 PM and was logged into NEXUS. The patient was admitted and departed from the ED, or better was discharged from the NEXUS system, at 04:00 PM. Thus resulting in: $LOS = (04{:}00\ PM - 01{:}30\ PM) = 160\ minutes$. Again when comparing this to the LOS in the Netherlands for admitted patients, which was 146 minutes, this much longer and falls outside of the stated limits.

Output performance

Percentage of admissions

A KPI to measure the output phase of the ED care process is the percentage of admissions. The average admission percentage was already calculated in chapter3 . We can recapitulate that the overall average admission rate was 41%. We also noted before there was a connection between the triage code and the probability of admission. Stating the higher the urgency, the higher the likelihood of transfer to a ward in the hospital.

Boarding time

Boarding time (BT) tells us something about the capacity of the hospital. When diagnosis and treatment has ended at the ED, the patient is either admitted or discharged. For admission, a hospital bed in a ward is required. This is limited to the total number of beds in the hospital and their occupancy at that moment. BT can also be measured in minutes resulting mean, SD, minimum and maximum.

BT is defined as:

$$BT = waiting\ time\ from\ end\ of\ ED\ treatment\ till\ discharge\ to\ ward$$

We go back to patient X in our example. We will make the hypothetical statement that the ED treatment time ended at 03:30 PM. We already know that this patient needs admission to a ward. Then the results would be for a

$$BT = 04{:}00\ PM\ (Departure\ time) - 3{:}30\ PM\ \ (End\ of\ treatment\ at\ ED) = 30\ minutes.$$

However it is not possible for us at this time to verify if this is the actual boarding time for patient X. The end of the treatment at the ED is not registered in the electronic patient tracking system of Nexus. It only records when the patient is discharged from the ED, not if boarding time was preceded it. Our current dataset makes it impossible to calculated for this indicator. In order to make a statement for the output phase of the ED care process, we use another methods. A small-scale empirical study is done. We discussed with the nurses on average how much time it takes to transport a patients from the ED to the ward. A total of five nurses were ask an their mean estimated transport time was calculated along with the SD, minimum and maximum time. Although from a scientific point-of-view a time study or consulting more nurses would be more unambiguously, we believe this gives a good indication about how much time is required for transport. Thus giving a suggestion of a possible bottleneck and where improvement can be achieved.

Control charts

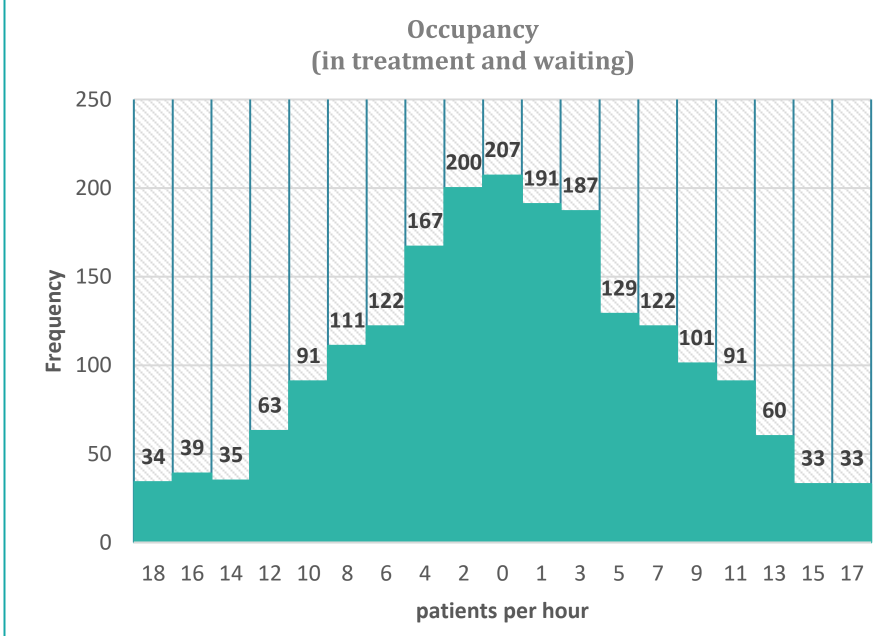
There is another way for a system wide performance analysis of the ED, namely control charts. A control chart is a scientific tool to display in graphic form the control limits on process outcomes.(74) In this study the treatment time per medical specialism is linked to the triage code. To our best knowledge thus far this has yet not been done in the Netherlands. Because time is a variable, the mean and range charts are used. Mean charts monitor a central tendency or process average and range charts monitor the dispersion of a process. These two charts are used together whether a process in in control and what observation fall outside de random control limits. For the mean charts the standard deviation approach was used so the averages of sample means $\bar{\bar{x}}$ and the standard deviation of sample distribution δ_x where used to construct confidence levels. Range charts where constructed using average ranges $\bar{R}$ and factors for D_3 and D_4 which were obtained from a factor charts based on the number of observations in the sample distribution. Once the charts where constructed to evaluate patterns for anomalies, even though observations might stay within the control limits, a Run-Based pattern test (A/B) and Up-and-Down patterns test (U/D) is performed.(75) A z-value within $\pm$ 1.96, which provides a 95% confidence interval was used what would show if the observations or runs were random or not. For the control charts both the mean with standard deviation approach and the range or both displayed in the same figure. Blue represents the mean and red the range charts. Limits are set for both chart with the letter M stands for the mean and the letter R for Range. Because control charts are not a common practice in healthcare, a further elaboration about its usage is given in appendix II.

4.3 Results of the Key Performance Indicators

4.3.1 The Jarque–Bera for goodness of fit test for normality of the occupancy

Before we can calculate the occupancy rates to measure crowding, we must first determine whether our dataset follows a normal distribution. This is also important to know for the solution approach that will be discussed later on in chapter 7. We begin by drafting up a histogram from our dataset for a visual inspection. In the histogram of figure 4.1 we can perceive the normal distribution.

Figure 4.1 Histogram of the patients per hour at the ED and their frequency.



If we look at the descriptive statistics computed by Excel yields the results as can be seen in table 4.1. Let's start by looking at our kurtosis. A kurtosis is the degree of peakedness of a distribution. Since the (excess) Kurtosis descriptive statistic is greater than zero. Skewness is usually described as a measure of a dataset's symmetry, or lack of symmetry. A perfectly symmetrical data set will have a skewness of 0. (since the normal distribution has a skewness of 0). In our table of 4.1 we can detect a positive skewness. What advocates even more that our dataset is normal distributed, is that the kurtosis and skewness both are within stated limits of +2 and -2. Also the mean and the median are closely together, again an sign of a normal distribution. The calculation of p-values for hypothesis testing typically is based on the assumption that the population distribution is normal. Therefore, a test of the normality assumption may be useful to inspect. A variety of tests of normality have been developed by various statisticians. As mentioned before our dataset is large, therefore we use the Jarque–Bera for goodness of fit test for normality of the occupancy.

n=2136	
Mean	6.2719
Standard error	0.0082
Median	5.9667
Standard deviation	4.5790
Excess kurtosis	0.2574
Skewness	0.1124

Table 4.1 Descriptive statistics

We consider testing the null hypothesis:

H_0 : The occupancy per hour follows a normal distribution

H_1: : The occupancy per hour does not follow a normal distribution

The Jarque-Bera test statistic is denoted as:

$$JB = n\left[\frac{S^2}{6} + \frac{(EK)^2}{24}\right]$$

Where n stand for the number of observations or sample size, S stand for the skewness and EK for the excess kurtosis This test statistic can be compared with a chi-square distribution ($\chi 2$) with 2 degrees of freedom. The null hypothesis of normality is rejected if the calculated test statistic exceeds a critical value from the $\chi 2_{\ (2)}$ distribution. The significance level is set at α 0.05 resulting in a critical value for the chi-square distribution of: $\chi 2=5.99$. The presentation of this test of normality is valid for 'large samples'. For 'small samples' the decision rule can be viewed as approximate. Our samples was already defined into n= 2136, representing a 'large dataset'. Our kurtosis (EK=0.2547) and skewness (S=0.1124) were already calculated. If we fill in the data into our formula, this results in JB=5.94.

Resulting in $\chi 2 = 5.94 < 5.99$ thus the decision is not to reject H^0.

Results of the occupancy rates

For the OR levels of the weekdays figure 4.2 is drawn up. The total number of records are n=63 weekdays in the period from the 1st of February 2017 till 30th of April 2017. If we multiply this by 24 time periods we get a total dataset of n=1512. We can already identify a trend or pattern in this figure. The mean with 95% CI in figure 4.3 captures this pattern even more. OR levels begin a steady rise at 08:00 AM. This upward trend increases and makes a jump at 10:00 AM reaching its peak around 03:00 AM. Then the OR levels are going down until 05:00 PM. At 06:00 PM the OR levels again are increasing until 9:00 PM after which the levels go down at a constant rate reaching an almost idle situation around 12:00 AM. When investigating the OR >0.85 threshold in figure 4.3 the limit is surpassed between 12:00 PM and 05:00 PM. The OR >1.0 is exceeded between 01:00 PM and 04:00 PM.

Figure 4.2 Daily OR levels for the weekdays

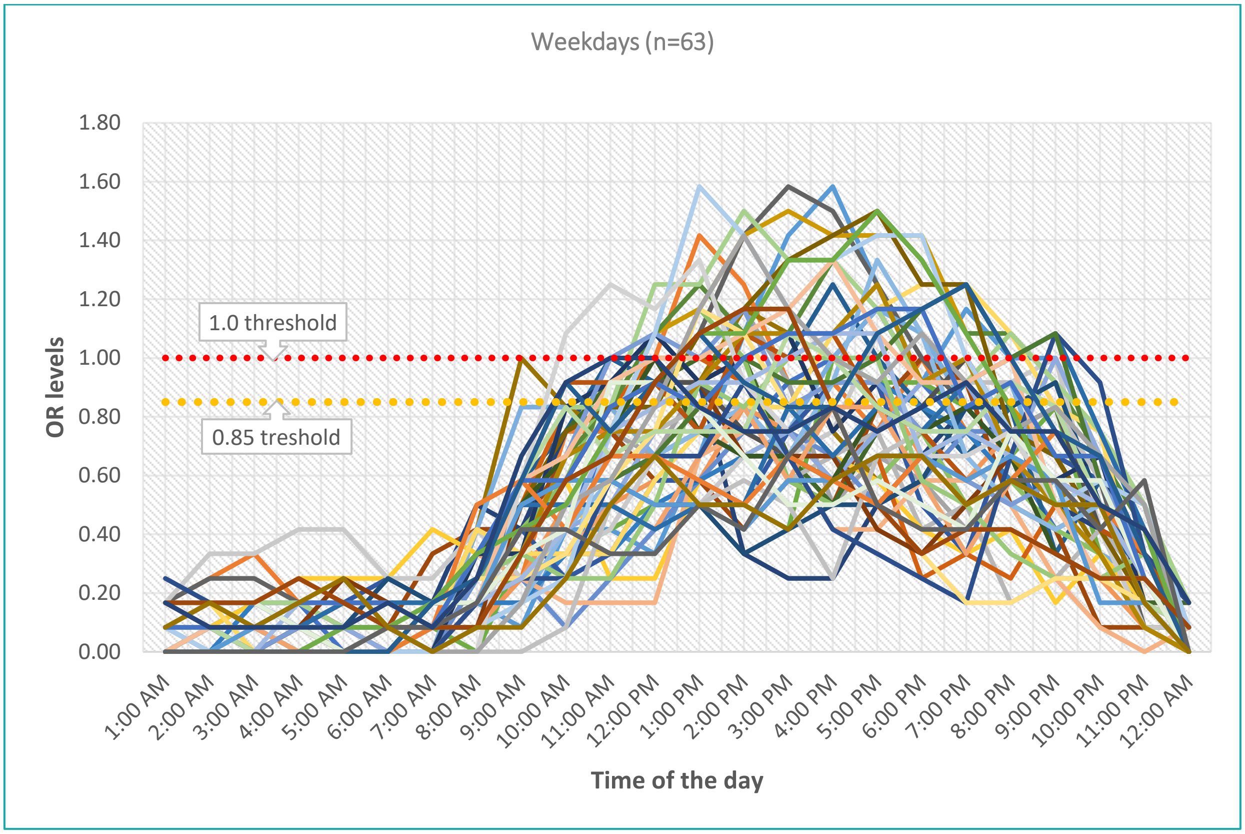
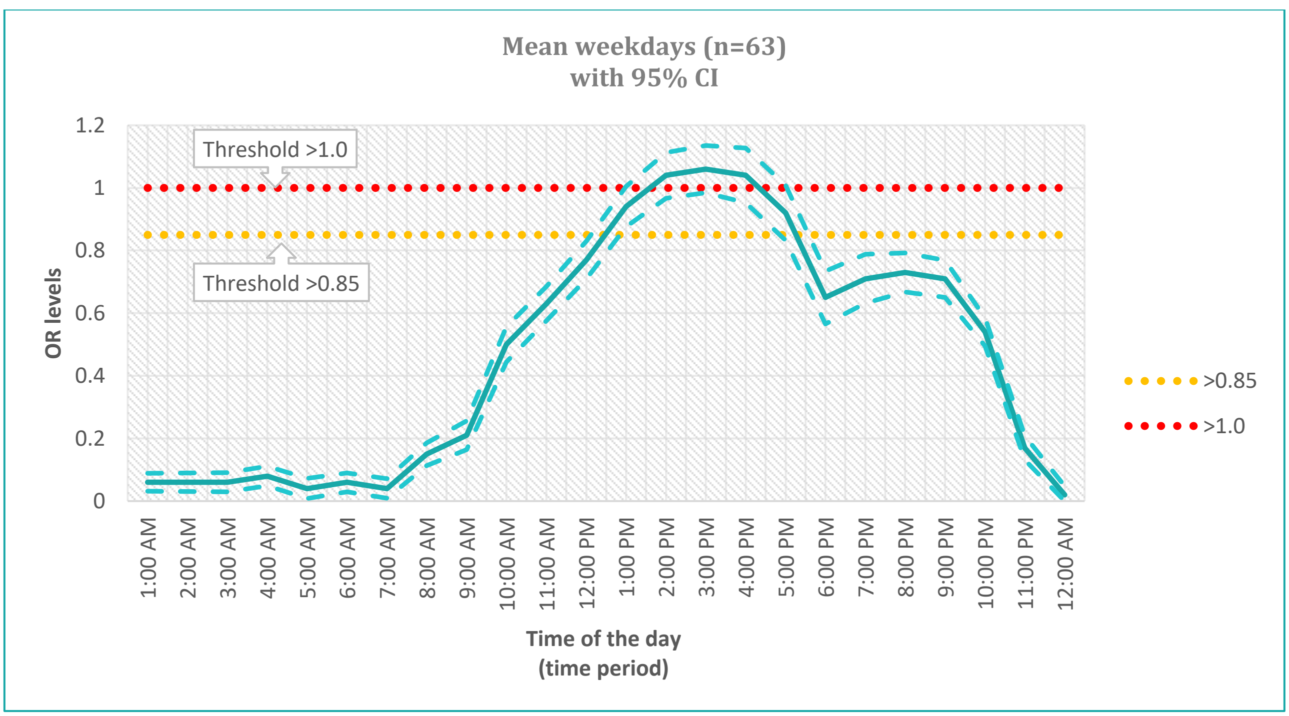


Figure 4.3 Mean OR levels with 95% confidence intervals for the weekdays



When calculating the ORs per day, as can be seen in figure 4.4, we count how many times the thresholds is surpassed. In total when we add up the frequencies of the >1.0 threshold, we calculate that this threshold is surpassed 145 times. Thus a total surpassing percentage of $\frac{145}{1512} \times 100\% = 9\%$. The >0.85 threshold is exceeded, when adding the frequency up, 270 times resulting in a percentage of $\frac{270}{1512} \times 100\% = 18\%$. However, when we make the same calculations for the different time periods we get another results. For example the >0.85 threshold is surpassed 33 times at 03:00 AM (which is also the highest frequency) as can be seen in figure 4.5. Taking into account the number of weekdays, this results in a surpassing percentage of $\frac{33}{63} \times 100\% = 52\%$. For the >1.0 threshold during that same time period we can calculate the surpassing percentage to be $\frac{22}{63} \times 100\% = 35\%$. When we compare the mean OR (figure 4.3) with the number of times when the OR exceeds the thresholds (figure 4.4), we calculate the total surpassing percentage during the time period of 12:00 PM and 05:00 PM for the >0.85 threshold. Resulting into $\frac{27+32+27+33+31+30}{63+63+63+63+63+63} \times 100\% = 57\%$. We also make the same calculation for the >1.0 threshold and taking the previously stated time period of 01:00 PM till 04:00 PM resulting in a surpassing percentage of $\frac{15+21+22+19}{63+63+63+63} \times 100\% = 31\%$.

Figure 4.4 Number of times the OR exceeds the thresholds for weekdays

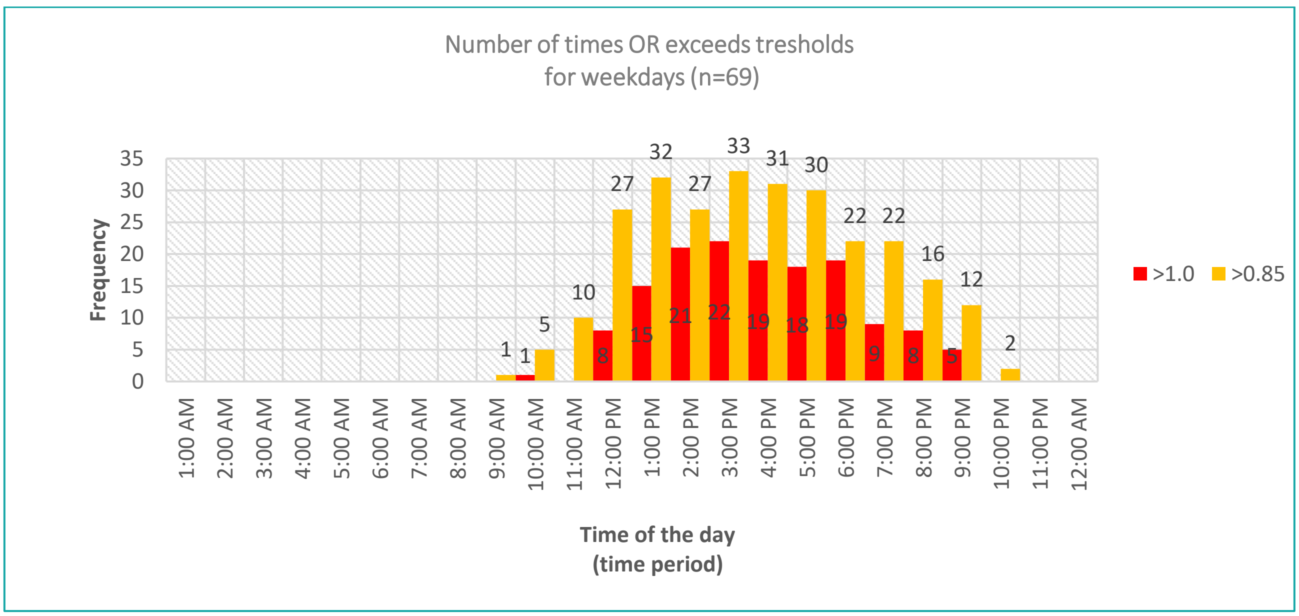
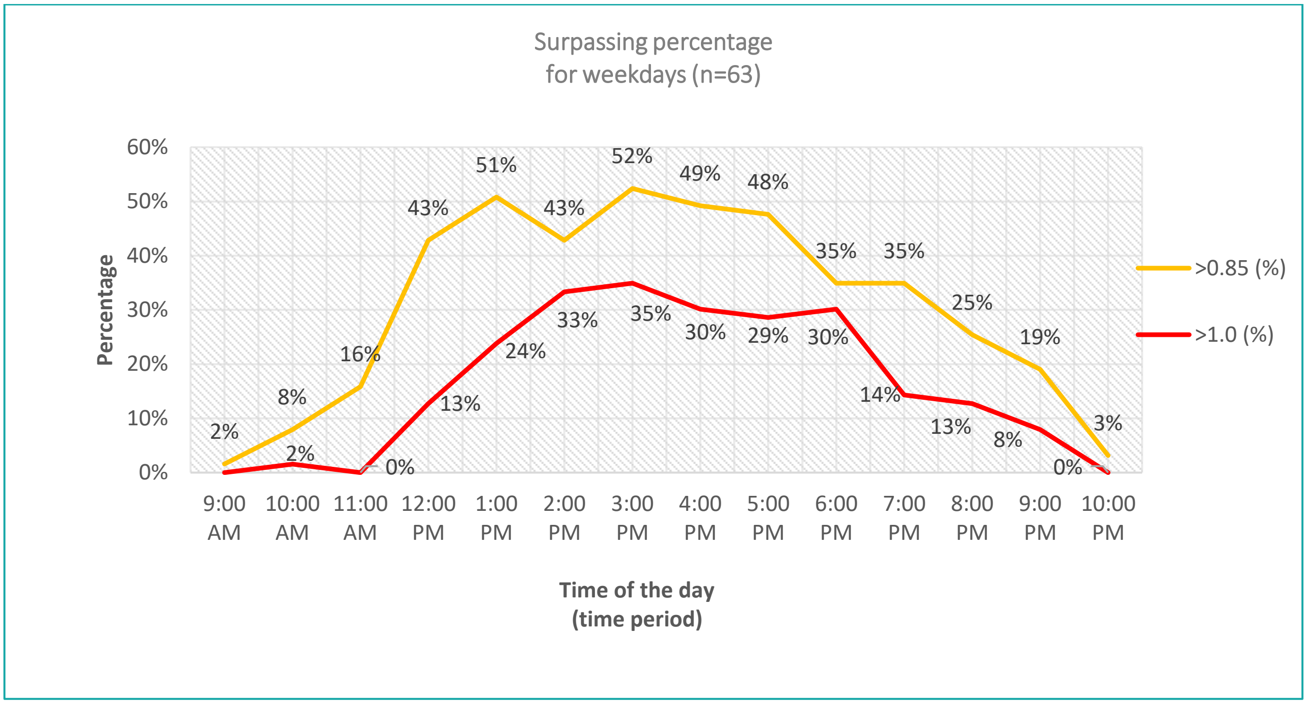


Figure 4.5 Surpassing percentage per time period for weekdays



A total of 26 weekend days were included into our study. Resulting in a total dataset, when multiplying by 24 time period, of n=624. Figure 4.6 shows the OR levels for the weekends. The same pattern is visible as for the weekdays. This is even more clear in figure 4.7. Although the time period when the ORs begin to climb are the same as for the weekdays, their intensity is less severe. Resulting in the mean utilization not exceeding the thresholds (only the upper confidence interval).

Figure 4.6 Daily OR levels for the weekends

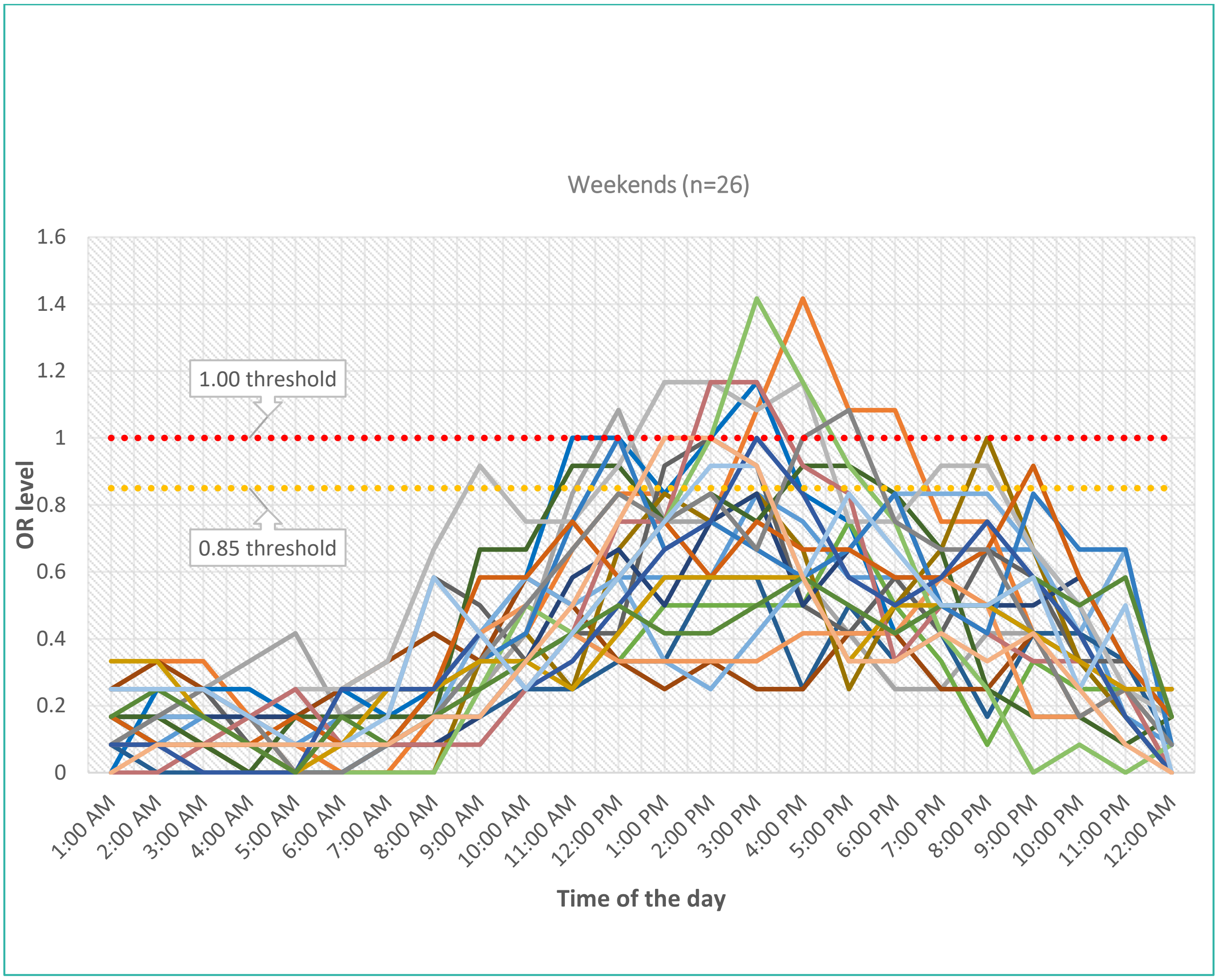


Figure 4.7 Mean OR levels with 95% confidence intervals for the weekends

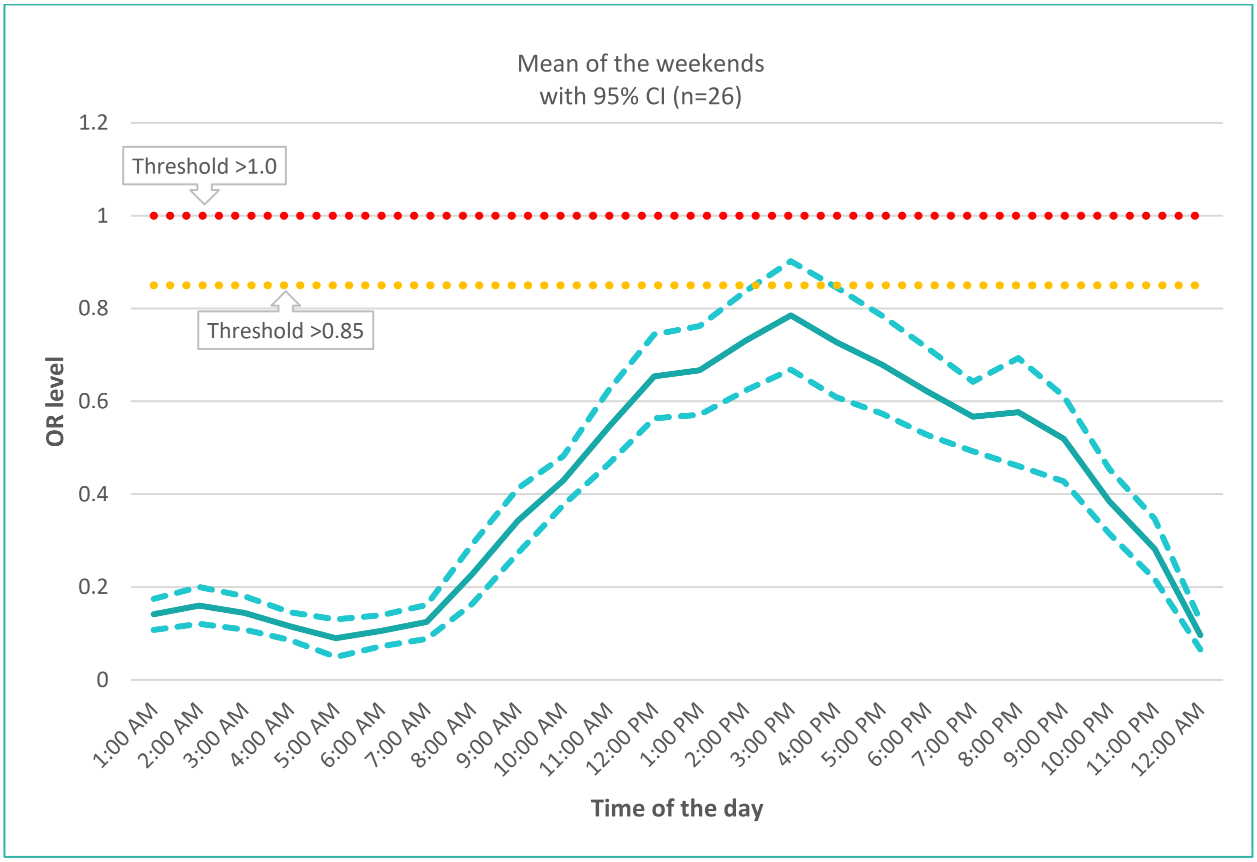


Figure 4.5 Mean OR levels with 95% confidence intervals of the weekends during the research period

This is also supported when we calculate the OR per day for the thresholds as can be seen in figure 4.8. On average the treshold of >0.85 is surpassed $\frac{41}{624} \times 100 = 7\%$ and the >1.0 threshold is calculated to be surpassed $\frac{15}{624} \times 100 = 2\%$ If we use the same example as with the ORs for the weekdays, we can calculate the surpassing percentage of the >0.85 threshold at 03:00 AM. Resulting in $\frac{10}{26} \times 100\% = 38\%$. For the OR >1.0 this percentage is calculated to be $\frac{6}{26} \times 100 = 23\%$. The results of the calculations for other time periods can be seen in figure 4.9. We can observer that crowding does not seem to be a big problem when it comes to the weekends.

Figure 4.8 Number of times the OR exceeds the thresholds for weekends

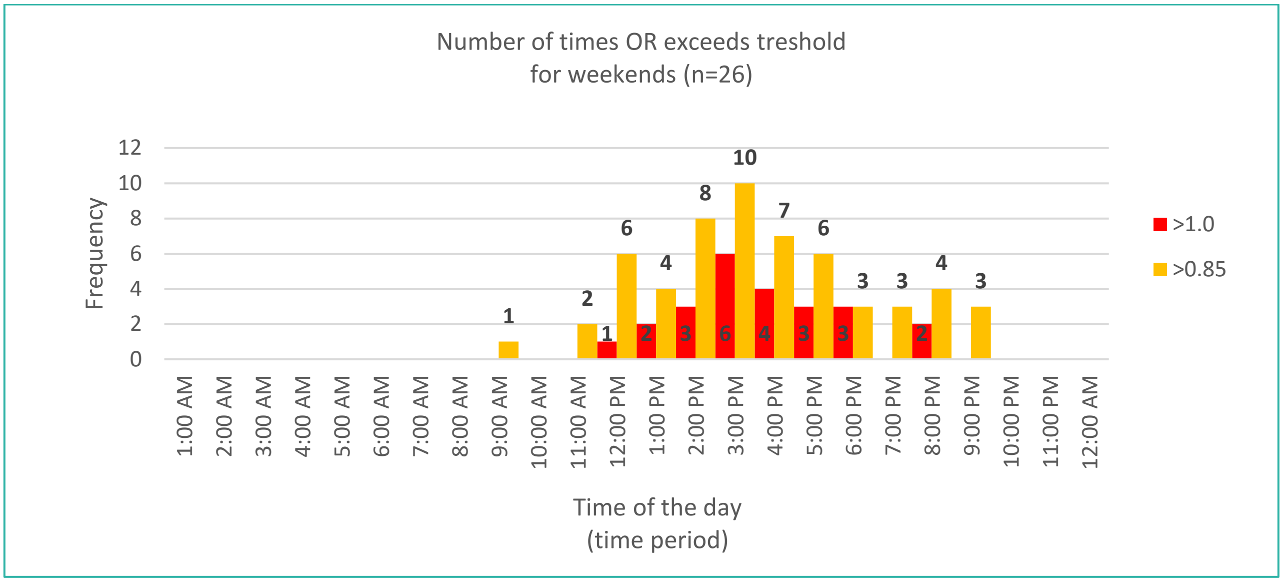
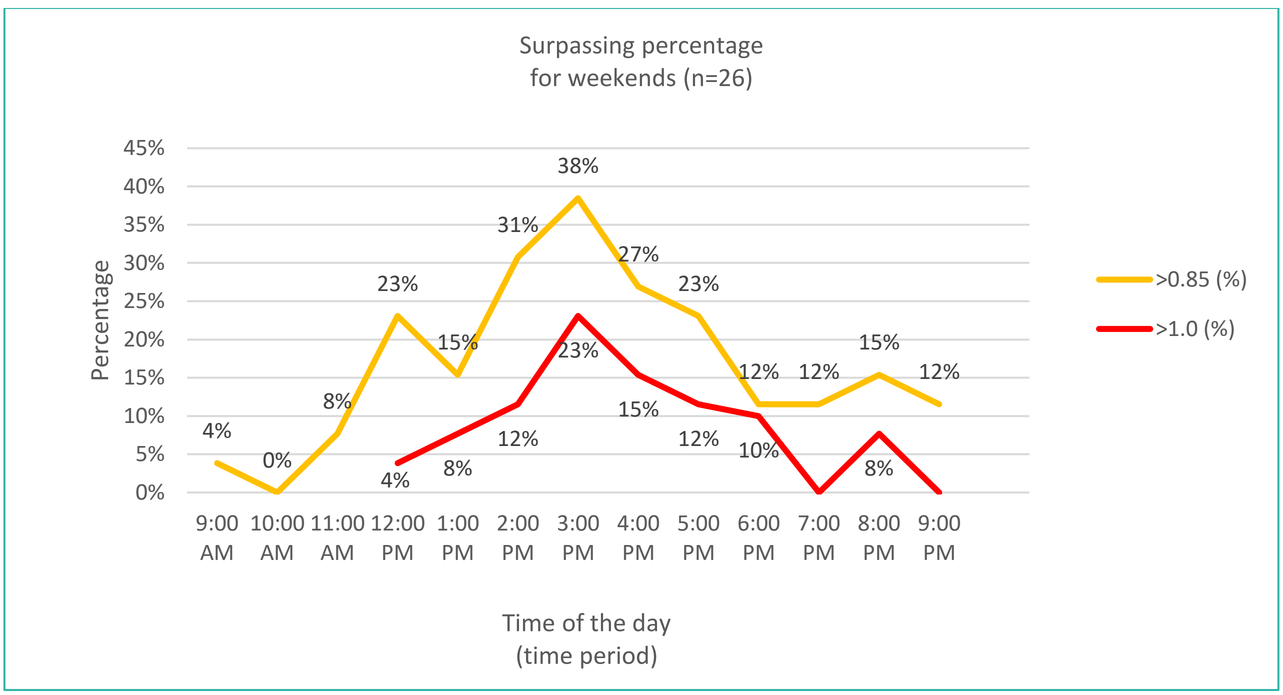


Figure 4.9 Surpassing percentage per time period for weekends



Since we have established that crowding seems to be a problem (mainly during weekdays), we further investigate the different phases of the ED care process to discover the bottleneck(s). This done by analyzing the input, throughput and output phase using KPIs.

Input results

Waiting time

Table 4.2 shows the results of the WT. The average waiting of the patients is not high and is calculated to be 9 minutes. The waiting times per triage code are calculated for a better in-depth analysis. If we compare this to the waiting times that are stated by the Dutch Triage Standard (DTS), we notice that for the yellow triage code, 30 patients were left waiting too long resulting in 9% of the total yellow triage population. Other triage levels show no noteworthy events or exciding of the triage time. A total of 44 patients waited too long before treatment started resulting into 1% which is low. Even when we add up the patients that received no triage code, this results in 2% so not notable. The only thing that is striking is the relatively long minimum waiting time for the green triage code. Although this still is within stated limits, it remains remarkably.

Table 4.2 Waiting time per triage code and overall

	Number of patients n=	Mean (min)	SD (min)	Triage time is exceeded per urgency code n (%)	Minimum in minutes	Maximum in minutes
Time per triage code (minutes)						
Red	10	1	18	1 (10)	0	2
Orange	317	5	40	30 (9)	0	194
Yellow	1184	3.2	74	6 (1)	0	132
Green	1354	11	88	7 (1)	52	177
Blue	120	18	81	0 (0)	8	153
White	615	32	92	0 (0)	2	162
No Code	40	19	10	- (-)	5	24
Overall waiting time (minutes)	3640	9	54	44 (1)	0	194

Time to physician

The mean time of the TTP is calculated to be 28 minutes represented in table 4.2 Differences can be observed in the TTP. From immediate physician arrival to extensive waiting time up to a maximum of 330 minutes. The fast bulk of patients is visited by a physician within the stated 59 minutes (82%) and 9 % must wait more than two hour. More than half of the patient are visited by the physician within 20 minutes after they arrived at the ED.

Table 4.3 Time to physician at the ED

	Number of patients	Mean in minutes	SD in minutes	Cumulative percentage (%)	Minimum in minutes	Maximum in minutes
<20 minutes	1905	-	-	(52)	-	-
21-29 minutes	599	-	-	(69)	-	-
30-59 minutes	482	-	-	(82)	-	-
60-119 minutes	318	-	-	(91)	-	-
120-359 minutes	336	-	-	(100)	-	-
>360 minutes	0	-	-	(-)	-	-
Total	3640	28	33	(100)	33	330

Throughput results

Length of stay

The results of the LOS calculation are displayed in table 4.4. Patients that are discharged from the ED have a mean waiting time of 123 minutes. Patient that needs admission to the ward have a longer LOS of 191 minutes. If patients go to the ICU the LOS is 79 minutes. The global golden standard of a 4-hours LOS is exceeded by 431 patients which corresponds to 12% of the patients. Maximum overall LOS was calculated to be 1050 minutes, or nearly 18 hours, with a minimum overall LOS of 5 minutes.

Table 4.4 Length of stay

N=3640	Mean In minutes	SD in minutes	Minimum in minutes	Maximum in minutes
Overall	145	86	5	1050
Admitted				
Ward	191	77	9	582
ICU	79	21	14	110
Discharged	123	78	5	1050
LOS >4 hours = n (%)	431 (12)			

Boarding time

Results of the boarding time are lacking due to the fact this time is not registered in the NEXUS system of the ED. To make a statement about this performance indicator we looked at the transport time, which is in essence part of the boarding time. Also because nurses of the ED transport the patients themselves, this means they cannot be deployed to the direct care or treatment of emergency patients. We asked the estimated transport time to 5 nurses during the research period. The results can be seen in table 4.5.

Table 4.5 Transport time

	Estimated transport time (in minutes)
Nurse 1	25
Nurse 2	30
Nurse 3	25
Nurse 4	20
Nurse 5	25
Mean	24
SD	3.53
Minimum	20
Maximum	30

Taking into account the admission rate of 41% for all the patients that visited the ED during the research period (n=3640) this results in 1493 patients being admitted. When using the mean of 24 minutes, this adds up to $1493 \times 24 = 35.832\ minutes$, or roughly 600 hours of labor going lost. This results in almost 7 hours of transport, and also boarding time, per day for an ED nurse. It was also noted that the physicians had good contact with the medical specialisms for consultation and swift admission if needed.

Summary of the KPIs results

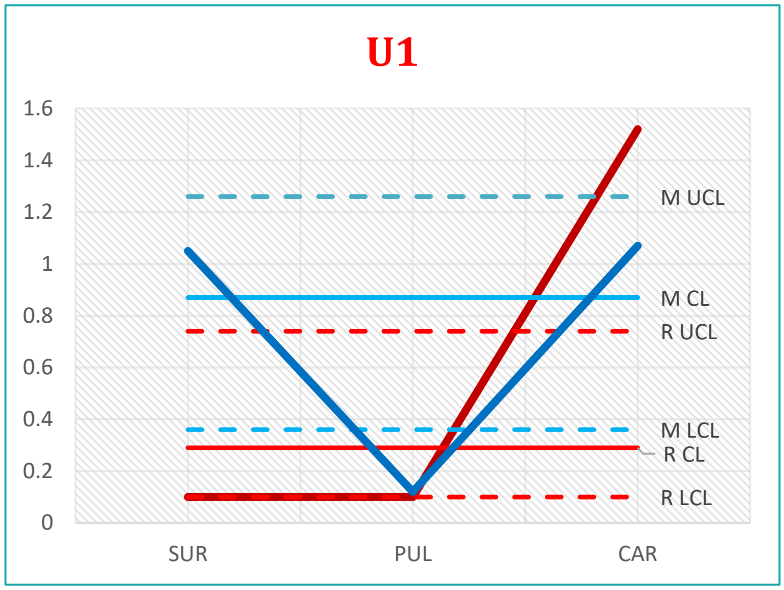
We have seen the results from the different KPIs per phase of the ED care process. The overall performance indicator of the occupancy rate showed us that crowding does happen at the ED. Especially during weekdays, the OR exceeds the >0.85 threshold between 12:00 PM and 05:00 PM. The threshold of >1.0 is surpassed between 01:00 PM and 04:00 PM. Thereafter we discovered that the input phase, measured by the waiting time and time to physician, does not seem to be a problem. No significant notable events were observed. The throughput phase, measured by the length of stay (LOS), suggest that when patients are discharged this is comparable with other LOS studies at EDs in the Netherlands. However when it comes to the admitted patients something is obvious, the mean LOS is significantly higher. Thus suggesting that there is a problem when it comes to the admitted patient in the throughput phase. The output phase was difficult to assess due to the fact that boarding time was not registered during the research period. We made an attempt to identify a bottleneck during this phase of the ED care process, by focusing on the transport time of the ED nurses. Transport time showed that labor is lost that could be deployed to direct ED patient care.

In summary, crowding does occur at the ED and is measured. The input phase does not suggest to be a problem, the throughput phase becomes a problem when patients need admission and the output phase was difficult to measure, although transport time seems to be a bottleneck. To further investigate the throughput phase, we analyses the treatment times per medical specialty and also per triage code. To discover if some specialisms stand out and have prolonged treatment times witch cannot be contributes to randomness. The α is set on 0.05 creating a 95% confidence interval. Consequently when we use the run-based pattern tests, results should be within -1.96 and 1.96. This states that the system in control and fluctuations in treatment time are contributed to statistical proven randomness. . If not we have found room for improvement and agreements on how to optimize the treatment time for a specific medical specialism is wise.

Control charts

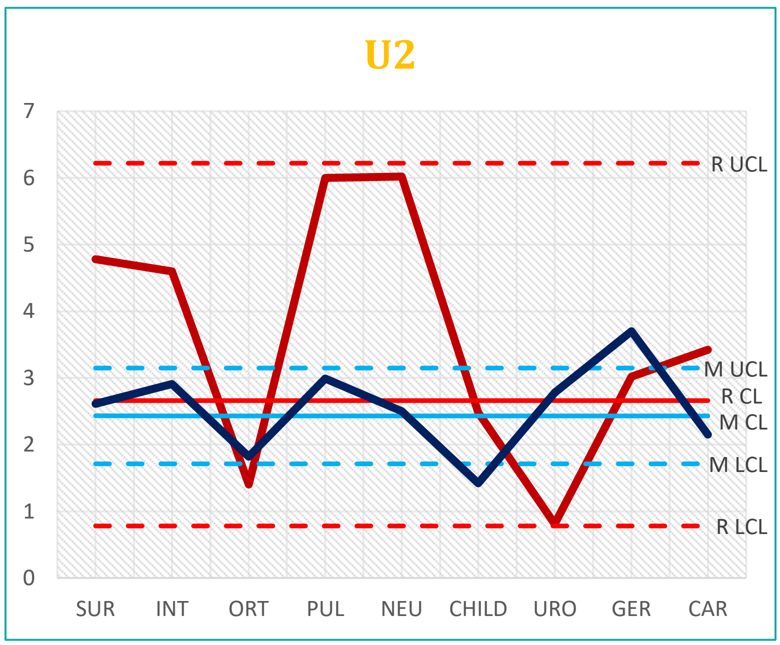
When looking at the mean and range charts for the *red* triage in figure 4.10 and investigating the standard deviation approach, no observations are outside of the calculated limits. The range charts tells us cardiology seems out of control, as the range is beyond the UCL. To discover if the system is in balance we perform a run-based pattern tests of the control charts showing $Z_{A/B}$ of $\bar{x}$= -1.15 and $\bar{R}$= 0. The up-and-down runs $Z_{U/D}$ yielded z-values of $\bar{x}$= 1.06 and $\bar{R}$ =0 showing both tests are within 95% confidence intervals and no anomalies are detected.

Figure 4.10 Mean and Range control charts for red triage code



If the pattern for the mean control chart for the *orange* triage code in figure 4.11 another pattern is noticed. Here we notice that the medical specialism of gereatrics falls outside of the confidence levels with a 95% CI. This variation can not be attributed to randomness suggesting that the treatment time for elderly patients is “out of controle”. Prolonged treatment times are not a result from randomness. However the range charts don’t underset this pattern. Here all observations are within confidence levels. What is striking is the big treatment range of pulmonology an neurology almost exceeding the Upper Control Limit.

Figure 4.11 Mean and Range control charts for orange triage code



When investigating the Run-based patterns for the mean and range charts the $Z_{A/B}$ is in control ($\bar{x}$ 1.78 and $\bar{R}$ 1.50) although the $Z_{U/D}$ runs tells that the system is not in control giving a z-value of $\bar{x}$ 2.70 and $\bar{R}$ 2.65 which is way above 2.0. In other words there are fluctuations in this triage considering the treatment time that fall outside of randomness. Further investigation is in place.

For the control charts in *yellow* triage, figure 4.12 is computed. In this figure we see that again the specialism of geriatrics is outside of the calculated limits. The same as it was in the orange triage. Also pulmonology is just outside the control limits and internal medicine remains (barley) within the calculated control limit. When examining the range charts, again internal medicine stands out. The range charts might give a distorted picture because for internal the range where a bit extreme. To further investigate this control chart again the run-based pattern tests were conducted. Test indicated for the mean chart ($\bar{x}$) that both $Z_{A/B}$ and $Z_{U/D}$ are not exceeding the 95% confidence interval with respectively a z value of 0.35 and 0.29, hence randomness is present. The tests for the range chart ($\bar{R}$) were also support this claim stating a value of $Z_{A/B}$ to be 1.06 and a $Z_{U/D}$ of 0.29. This is within the confidence interval, stating the overall system is not out of statistical control. Further investigation into especially geriatrics and also pulmonology and internal medicine why treatment time is statistically significantly higher, is wise.

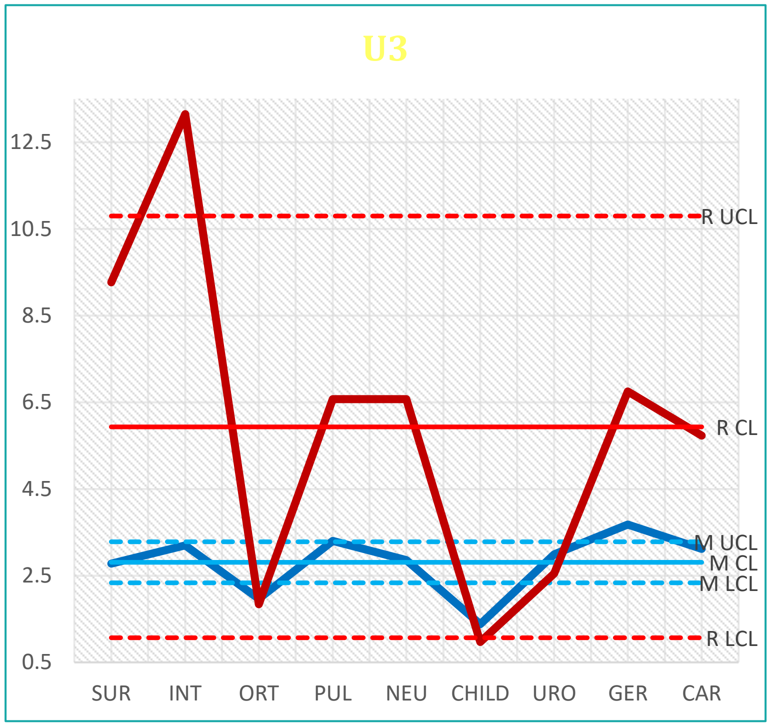
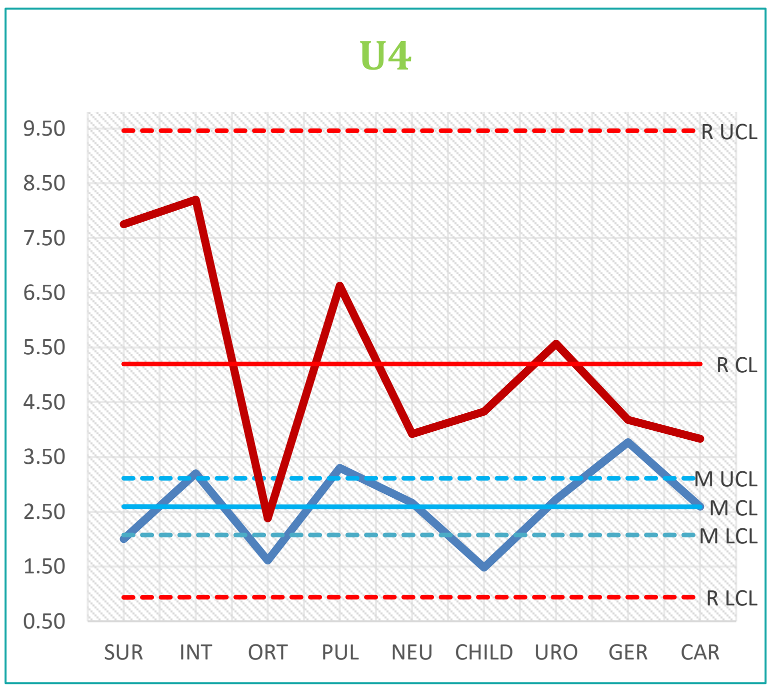


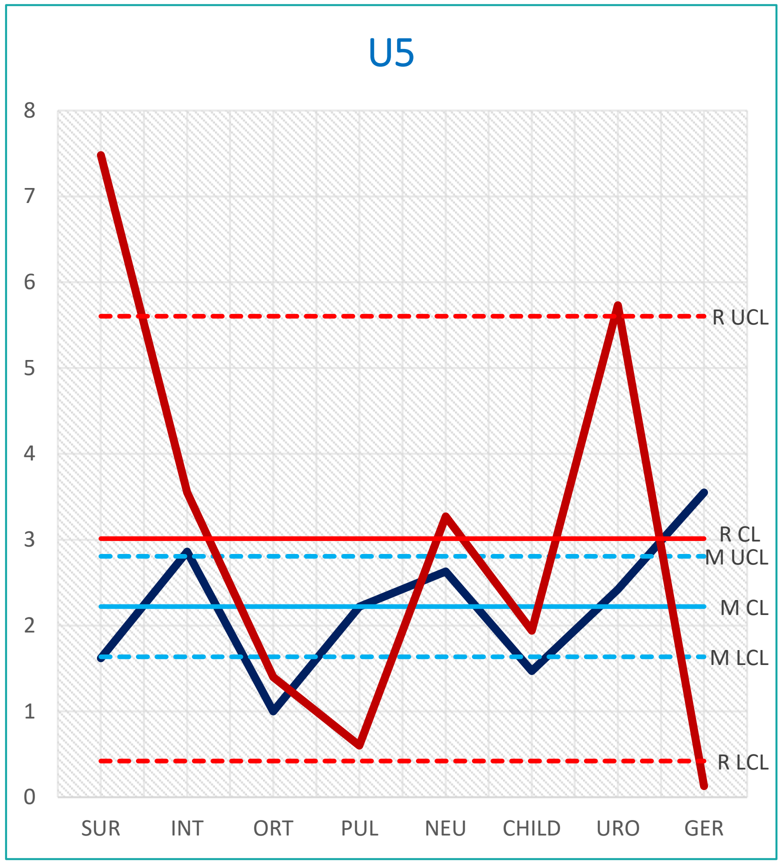
Figure 4.13 Mean and Range control charts for green triage code



Next we analyses the control chart constructed from the waiting time in the *green* triage code in figure 4.13. Again the same trend is visible in the mean chart as it was for the yellow triage code. Geriatrics stands out and is significantly outside the set control limit. Internal medicine and pulmonology are now clearly outside of the control limits as well. Indicating treatment time exceed the expected time, using the standard deviation approach. The range chart is within its calculated limits with no outliners detected. Run-based pattern tests are made to find out of more anomalies could be found. For mean ($\bar{x}$) and range ($\bar{R}$) charts the $Z_{A/B}$ the results where 1.06 and 0.35, so within statistical limits. For $Z_{U/D}$ the values where both o.29 so within confidence intervals indicating the overall system is not out of statistical control.

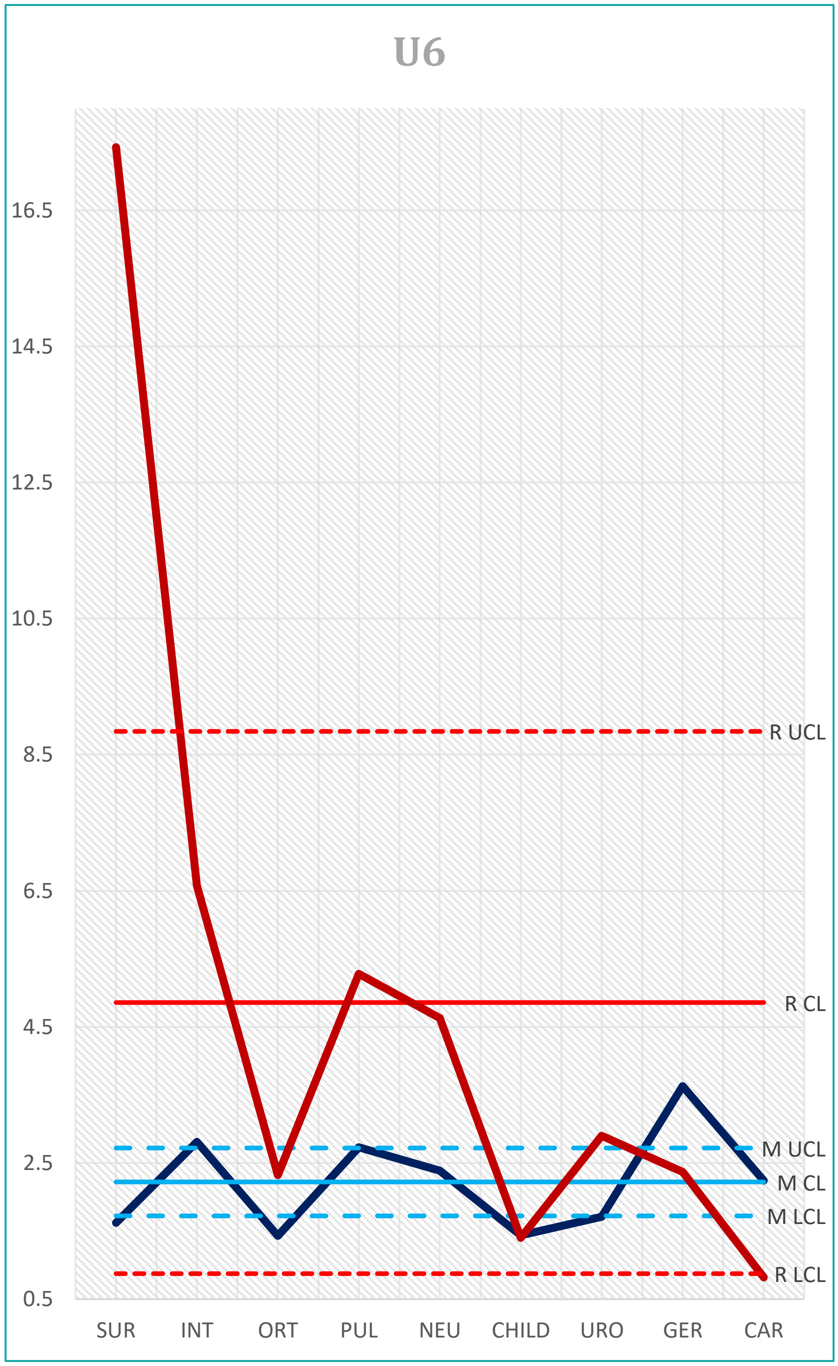
The following triage code that is plotted in the control charts for the blue triage code in figure 4.14. The mean charts tells us that again geriatrics is outside the calculated control limits. A pattern that was also visible in the previous discussed triage codes. Also internal medicine mean treatment time shows to be outside the calculated limits. When looking at the ranges it is striking that surgery falls outside of the upper range intervals. Again run-based pattern tests were conducted to check for anomalies. Beginning with the mean ($\bar{x}$) chart, $Z_{A/B}$ and $Z_{U/D}$ were calculated to be 0.75 and 0. For the range chart $\bar{R}$ the value of $Z_{A/B}$ and $Z_{U/D}$ found out to be 0.75 and 0.95. The test shows no abnormalities and fluctuation are due to randomness.

Figure 4.14 Mean and Range control charts for blue triage code



De last code that is under research, is the white triage in figure 4.15. Again geriatrics clearly stands out when looking at the mean chart and its calculated control levels. Also internal medicine and pulmonology or among the specialism that takes more treatment time then can statically be explained and are nonrandom. The range charts tells us surgery has an extremely high peak. This can be contributed to the great variety that is part of this medical specialism. Further all the specialism are within limits. Run-based patterns did not detect any abnormalities being the values for the mean $\bar{x}$ chart a $Z_{A/B}$ and $Z_{U/D}$ of respectively 1.06 and 1.17, well within limits. The range $\bar{R}$ also tell the same story, calculating $Z_{A/B}$ to be -1.06 and $Z_{U/D}$ is -0.59. Again well within the confidence interval of 95.5% and no surprises there. Notable are the reoccurring specialism that emerge as we computed different control charts per medical specialism. There seems to be a recurrent pattern and trend in the treatment time of certainly geriatrics and also pulmonology and internal medicine.

Figure 4.15 Mean and Range control charts for white triage code



Taking in mind that this is a low triage and thus long waiting time is possible, with a wide variation when treatment begins, may provide an explanation.

4.4 Conclusion

Several KPI's were constructed to determine the performance and calculate the lead times of the ED. KPI's were labeled into input, throughput and output indicators.

Before doing so, the occupancy rate (OR) was computed to discover if crowding is a problem at our ED. Calculations were made on our dataset (n=2136). The results showed that episodes of crowding do occur at the ED. The ORs per day during the research period show a similar trend, making the episodes of crowding predictable. The main problem, according to the ORs, are during weekdays. Although the same OR pattern is visible during the weekends, the intensity is less severe. In general, both for the weekends and weekdays, the ORs begin a steady climb at 09:00 AM reaching their peak between 01:00 PM and 05:00 PM. ORs decline having another short peak in the evening. The system reaches almost an idle situation from midnight until the next morning, beginning the same cycle again.

If we focus on the weekdays, the time period the >0.85 is surpassed mainly between 12:00 PM till 05:00 PM. We found that in 57% of the recorded cases (n=1218) this threshold was surpassed during this time period. We also make the same calculation for the >1.0 threshold resulting in a surpassing of 31% of the recorded cases (n=662). We can conclude that crowding does pose a problem at the ED.

To further investigate in the bottlenecks in the ED care process, we measured the different phases. KPI's measuring the input phase in the emergency care yielded that the average waiting time of the patients is not high and the mean is calculated to be 9 minutes. This is in line with other studies of the waiting time at EDs in the Netherlands, showing the mean to be 10 minutes. (73) What is even more important is that the waiting time is compared to the Dutch Triage Standard(DTS). We found that the waiting time does not significantly exceed the maximum waiting time, stated by the DTS per triage code. The overall exceeding waiting time of all the patients (n=3640) is calculated to be 2 %(n=68), negligibly low. What might need attention is that the green triage code patients, although well within stated limits, these patients had a fairly long minimum waiting time. Also the time to physician (TTP) was calculated as an input indicator. The majority of patients in visited by a physician within 30 minutes (n=2657)) and only 17% (n=619) must wait more than one hour. Mean TTP was calculated to be 28 minutes for our ED, making it much lower when comparing it with the Canadian study. All in all the input phase does not seem to be a significant bottleneck factor in the hold-up of patients which leads to crowding.

For the throughput phase, the LOS is an import indicator. For discharged patients the LOS in similar to the mean time found in other studies in the Netherlands. (73) However when looking at the LOS for the admitted patients, the mean at our ED is much higher (191 minutes) compared to earlier Dutch studies (146 minutes). The conclusion can be made that when it comes to patients that need admission, a delay a bottleneck presents itself. Further investigation if some medical specialisms take up longer treatment time then other, is presented with the control charts. These will be discussed later on in this section.

Although output factors could not be calculated due to the limitations of the electronic patient tracking systems, that does not register boarding time, we made an attempt to identify a potential bottleneck. We calculated an element of the boarding time, that is to say the transport time of admitted patient from the ED to the ward. Because the ED nurse transports the patients herself, this means the nurse cannot be deployed (temporarily) direct patients emergency care. We did this by asking five nurses how much time it takes to transport a patient and return to the ED. Our small-scale study suggested almost 7 hours of nursing labor is lost due to transport per day. A task that could be performed by the transport service of the hospital. In other words, we might potentially stumbled upon a straightforward way to improve in the output phase.

The control charts also gave insight in the reasons of crowding. To the best of our knowledge no previous attempts in the Netherland have been made to measure the treatment times at any ED and link them to the triage code on the basis of control charts. The control charts helped us to analyses the treatment times to determine if some medical specialism take up significantly longer time then can statically be explained to randomness. Range charts showed mainly the great distribution in treatment times per medical specialism, what could be expected. The run-based pattern tests determined that the overall performance of the ED was in control. It was calculated that the medical specialty of geriatrics had prolonged treatment times that could not statistically be explained. Also it could be noted that the demand for internal medicine and pulmonology also takes up longer time than what could be expected . During the research period the influenza infections were at their peak, resulting in a higher inflow of patient for these specialisms.

Now that we have established that crowding does happen at our ED and poses a problem, we have analyzed the lead times and discovered that the throughput time for admitted patients creates a bottleneck. This is especially true for geriatric, internal medicine and pulmonology patients. Also we found a quick fix for a component of the output phase. This will not result in an overall spoliation for the output phase, but will likely give an short-term improvement. Next we want to find adequate solutions to these bottlenecks in the ED care process and tests them. To do so we must fit our ED into a mathematical model. This will be done in the following chapter using a queuing model.

5. Mathematical modeling

5.1 Introduction

The goal of this chapter is to find answers to the sub question: "*What mathematical modelling approach is suitable for a system-wide analysis of the staffing at ED?".* According to Law and Kelton modeling be done physically or mathematically. (6) Because the impact of alternative solutions are not clear at this point, we prefer a mathematical model. There are two ways of mathematical modeling, by simulation or an analytical solution by using Queuing Theory.

Simulation is a more common way in this research area. One of the advantages of simulation compared with queuing modeling is the possibility to consider any desired system characteristic. This is, at the same time, also one of the major drawbacks of this method, because one might get lost in the details and lose sight of the real problem. Simulation modeling is a powerful tool but it is time-consuming due to the effort it takes to build the model into a simulation software program. Moreover, it requires detailed information on the input distribution. A simulation is often not generic and optimization is achieved by trial and error. Simulation can be used to determine the performance of the system, not directly guide us how the wanted performance can be reached.

An analytical queuing model has the advantages that it requires fewer data. For instance the queuing model used for this thesis only needs a mean arrival rate and a mean service rate (this will be discussed in the methods section). Queuing theory offers us a method to easily and definitely describe queues in mathematical terms. The queuing model enables a system-wide analysis of the ED and can easily be adjusted so that it represents one of the alternative solutions. It is also possible to adjust the model so that it represents a ED of another hospital. That a queuing model can work in the Netherlands is demonstrated by Zonderland et.al. by redesigning the preanesthesia evaluation clinic of a university hospital using the queuing modeling approach approach (76) The disadvatages of queuing lies in its assumptions and limitations. It assumes a steady state of arrival and service process and independence of arrival and service . Queuing modelling has little ability to incorporate important exceptions to the general flow. Also it makes it difficult to model more complicated processes. Although globally queuing models are widely used in healthcare, to the best of our knowledge a queuing mathematical model has not yet been used at any ED in the Netherlands thus far.

In our study we prefer the analytical queuing solution because of its simplicity and the advantage that the queuing model shows us were improvement can be achieved. Also we can easily test the alternative solutions with the same model to see if the results are adequate.

In de methods section we explain the basic concepts of Queuing Theory by its function, characteristics and usage in healthcare thus far. Also we will recall the conceptual model of the ED care process of the ED, as introduced and discussed in chapter 3. We identify the position of our queuing model and where it fits in the system of the ED process. A further conceptualization of our queuing system will be introduced along with additional explanation about the Markov chain. Because queuing models assume arrival rates that follows a Poisson distribution, we perform a Chi-Square goodness of fit test on our dataset. After this test the calculations of the input are demonstrate. Subsequently the outcomes from our queuing model for both nurses and physicians in the current situation will be presented in the results section.

Focus of this chapter will be on the staffing. Positioned at the tactical hierarchical level and in the managerial area of resource capacity planning. (58) The queuing model should provide us with a system-wide analysis so we can discover where there is room for improvement(s) in the staffing. For example, the ED may be responding to the needs of patients adequately during weekends, but difficulties arise over the weekdays and in certain hours of the day as we already have shown in chapter 4. The model should provide us the same answer and more important, shows us were during the day improvement can be achieved for the staffing of the ED. In other words, how can we redesign the staff of the ED so it accommodates better with the supply and demand of emergency care and thus reduce crowding. This will be discussed at the end in the conclusion section and elaborated in the next chapter.

5.1.1 Queuing models and capacity planning

Queueing theory is the study of queues as based on probability theory, statistics and other sub-fields of mathematics. The idea behind queueing theory is to propose models to apply to describe queues and the processes behind them. In queueing theory, queues tend to be modeled by stochastic processes, which are random functions based on probability distributions. In other words, queuing Theory is a mathematical approach for the analysis of waiting lines, or queues.

There are two elements that are important when using Queuing Theory i.e. patients and servers (in our case healthcare providers at the ED). There is a tradeoff between capacity and service delays. For example if capacity is high there are little waiting lines but resources are wasted and staff will be idle more often as they wait for patients. A vice versa situation is also true where limited capacity results into staff being (overwhelmingly) busy, leading to longer waiting lines and thus inevitable crowding. In other words an imbalance of the ED system can happen both ways. The goal of queuing is to achieve optimization of the available resources.

5.1.2 Waiting lines

A fundamental understanding when using Queuing Theory is the question why must we must wait in lines at all. The key words are average versus variability. Most service is planned on averages but in reality patients, especially at a ED, arrive at random intervals rather than at evenly spaced intervals. Also some patient requires more intensive treatment than others. As a result the ED becomes temporarily overloaded, thus crowded, and patients have to wait. At others times the ED is idle because there are no patients. Although a system may look manageable from a macro or average viewpoint, variability in patient arrival and medical service times causes the system to be crowded from a micro or looking at a certain time period viewpoint. This was also shown in chapter 4 when we used the occupancy rate,. In systems where variability can be minimized, waiting lines should ordinarily not form. (74)

5.1.3 Queuing System Characteristics.

Choosing the appropriate queuing model is obviously an important factor to address the imbalance of the system appropriately. Model selection depends on the characteristics of the system that is researched. The main queuing model characteristics are: the population source; (i) number of servers (healthcare providers, i.e. nurses and physicians; (ii) arrival patterns and service patterns (iii); and queue discipline (iv).

The population source (i) for the ED is infinite. In an infinite source situation, patient arrival is unrestricted and can greatly exceed system capacity at any given time. An infinite source exists when service or better the access to care, is unrestricted.

The capacity of queuing systems is determined by the treatment capacity of each server (ii), also known as a line or channel, and the number of servers being used. It is generally assumed that each channel can handle one customer at a time. Healthcare systems can be conceptualized as single-line or multiple-line, and may consist of phases (steps in a queuing system as shown in the conceptual model of the ED process).

Waiting lines occur random. Highly variable arrival and service patterns (iii) cause systems to be (temporarily) overloaded or crowded. The ED is a typical example of erratic arrival patterns causing such variability. The arrival patterns might be different on mornings and afternoons, and even more so after GPs close in the evening. The most commonly used models assume that the patient arrival rate can be described by a Poisson distribution and that the time between arrivals, inter-arrival time, can be described by a negative exponential distribution. Service, or treatment, to the arriving patients is another element that exhibits variability. Because of the varying nature or illnesses of the patients, the time required for clinical attention (service/treatment times) varies from patient to patient. Service rate and service times are also interchangeably, so that the Poisson distribution can characterize the service rate.

The Poisson and the negative exponential distribution are alternate ways of presenting the same information. If service time is exponential, then the service rate is Poisson. Further, if the customer arrival rate is Poisson, then the inter-arrival rate (the time between arrivals) is exponential.

Queue discipline (iv) refers to the order in which customers are processed. The assumption that service is provided on a first-come, first-served basis is probably the most commonly encountered rule. First-come first-served, which is seen in many businesses, has special adaptations in healthcare queue discipline and includes the critical first rule (based on the triage codes as mentioned in chapter 2) at the ED. Queuing models are identified by their characteristics. From a methods perspective, a nomenclature of A/B/C/D/E is used to describe them. Table 5.1 provides details for each component of the nomenclature. The last two components, D and E, of the nomenclature are not used unless there is a specific waiting room capacity or a limited population of patients. Since infinite-patient-source models are the main focus in this study, the nomenclature, “D and E,” will be omitted from discussion.

Table 5.1 Queuing model classification

A: Specification of arrival process, measured by inter-arrival time or arrival rate. M: Negative exponential or Poisson distribution. D: Constant value. K: Erlang distribution. G: A general distribution with known mean and variance. **B**: Specification of service process, measured by inter-service time or service rate. M: Negative exponential or Poisson distribution. D: Constant value. K: Erlang distribution. G: A general distribution with known mean and variance. **C:** Specification of number of servers—"s". **D:** Specification of queue or the maximum numbers allowed in a queuing system. **E:** Specification of customer population.

There are two commonly used infinite source models:

1. Single channel, M/M/1
2. Multiple channel, M/M/s >1

The "M" in the models stands for Markov. This will be explained later on. The "s" designates the number of channels (servers or healthcare providers). (74)

A queuing model needs input before calculation can be made. These models assume steady state conditions and a Poisson arrival rate. The most commonly used symbols in queuing models are shown in table 5.2.

Figure 5.2 Queuing model notation

$\boldsymbol{\lambda}$	Arrival rate
$\boldsymbol{\mu}$	Service rate
$\boldsymbol{L_q}$	Average number of patients waiting for service
$\boldsymbol{L}$	Average number of patients in the system (waiting or being served)
$\boldsymbol{W_q}$	Average time patients wait in line
$\boldsymbol{W}$	Average time patients spend in the system
$\boldsymbol{\rho}$	System utilization
$\boldsymbol{1/\mu}$	Service time
$\boldsymbol{P_0}$	Probability of zero patients in system

The simplest model represents a system that has one server called a single channel. The length of queue can be endless, just as the demand for medical services is. In M/M/1 queue models, arrival time cannot be greater than service time. Since there is only one server, the system can tolerate up to 100% utilization. If arrival rates are more than service rates, then a multi-channel queue system is appropriate (M/M/s >1). Again patients arrival rate can be approximated by a Poisson distribution, and service time by a negative exponential distribution, or Poisson service rate. The difference is with this system that multiple server are available in the system. Since the ED has more than 1 server (healthcare provider), the M/M/s>1 model is the appropriate one to use.

If we recall, the "M" in our model stands for Markov. A queuing model can be described as a continuous time Markov chain with a transition rate matrix on the state space {0,1,2,3,...}. This is the same continuous time Markov chain as in a birth–death process. The state space diagram for this chain in figure 5.1 shows the transitions states in the M/M/s>1 queue. A process satisfies the Markov property if one can make predictions for the future of the process based solely on its present state just as well as one could knowing the process's full history, hence independently from such history; that is conditional on the present state of the system, its future and past states are independent. A Markov chain is a type of Markov process that has either discrete state space or discrete index set, often representing time as is the case in our study.

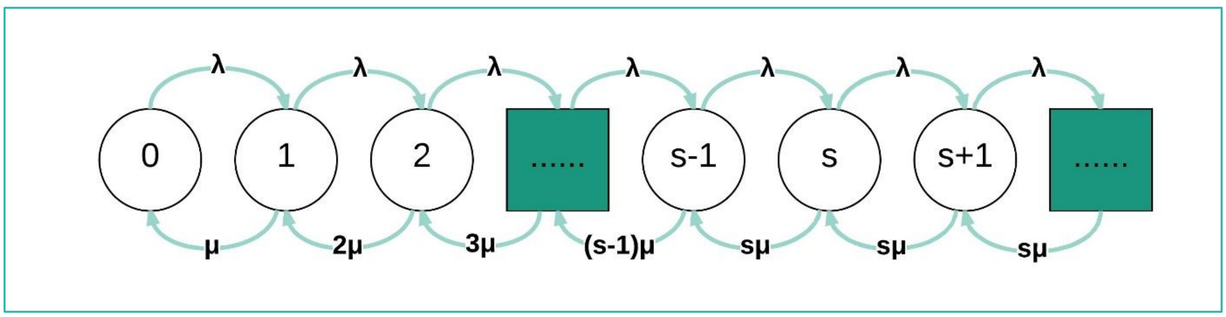


Figure 5.1 Transitions states in the M/M/s>1 queue

5.2 Methods

5.2.1 Data modeling

Data was used from the electronic tracking system of the ED at the Scheper Hospital Emmen from the 1st of February till the 30th of April 2017 (n=89 days). Data was split into weekends (n=24) and weekdays (n=65). This is done due to difference in arrival patterns and variation of staffing as shown in chapter 3 and 4. The staffing of nurses remains the same every day of the week. The staffing of the physicians differs between weekends and weekdays. Arrival rates for different time periods are calculated. The time periods are consistent with the current staffing at the different time frames as presented in chapter 3.

The total number of observation, or sample size, during the research period results into $\mathrm{n} = 89 \text{ days } \times 24 \text{ hours a day} = 2136$. The time periods for the queuing model were determined on the basis of the staff scheduling. the various calculation were made. We will focus primarily on the utilization levels as this is an indicator of crowding as stated in chapter 2. The other outcomes of the queuing model will also be presented. Data was analyzed using Excel 2013 from Microsoft and by installing the macro Queueing ToolPak 4.0. To make the assumption that arrival rates are Poisson distributed, a calculation is made in the results section using the Chi-Square goodness of fit test.

5.2.2 The queuing model

After this test we will show the position of our queuing model within the ED care process. We recall the conceptual model from figure 3.2 that was presented in chapter 3. The same conceptual model is again showed in the results section but with an additive. Our queuing model will overlaps the conceptual model thus showing what part of the ED care system is analyzed. After the position of the queuing model is identified, we will show the conceptualization of our multi-server queuing system. We use a multi-server channel denoted as a M/M/s>. In the model the “s” designates the number of servers. For this study the servers are separately categorized into nurses and physicians. Each server category is run through the queuing model, giving different outcomes for both the nurses and physicians. The reason for the use of this queuing model is its simplicity. Only limited amount of input data is needed. We will give an running example (example 5.1) that will be further used during this chapter.

Running example 5.1

> The arrivals of R1, R2 and R3 between 08:00 AM and 10:00 AM for the nurses in the weekends, all have a different arrival rate (λ). In the M/M/s>1 queuing model for the ED no distinction is made between these different arrival rates. This is done for reasons of simplicity. Instead a mean arrival rate is calculated that approaches the different arrivals. The number of nurses (*s*) is determined to be 2 in this example (thus representing a multi-server channel). Again not all the different service rates have to be known (μ) but instead the average service rate is required.

The example of the nurses is further clarified and explained in table 5.1 later on. In this table we will show how calculations are made that serve for the input of our queuing model. The SD is calculated to determine the upper and lower 95% confidence levels setting the α at 0.05. These levels are then again used as input for the queuing model. Calculations for the inputs of the model were made with the help of staff, collected from the electronic tracking system (NEXUS) and by means of observation. An average arrival was calculated for the different time periods along with a standard deviation. Example 5.1 for the nurses between 08:00 AM and 10:00 is again used to explain the transitions states in the M/M/s>1 queue. Also this example is used to demonstrates how the different outcomes of the queuing model are calculated.

5.2.3 Performance measurement

The performance focus will be primarily on the system utilization (ρ), recalling that a high utilization is related to crowding as stated in chapter 2. Also the other outcomes from the queuing model such as the average number of patients waiting for service (L_q), the average number of patients in the system (L), average time in line (W_q), average time in the system (W) and the probability of zero units in system (P_0) will be calculated and presented. Further, the mean utilization levels for every time period during the research period is calculated separately (not only the selected time periods). This is done to find out how many times during the research period the threshold of >0.85 or >1.0 (as mentioned in chapter 2) was surpassed. A further explanation using example 5.1 will later be given in table 5.3.

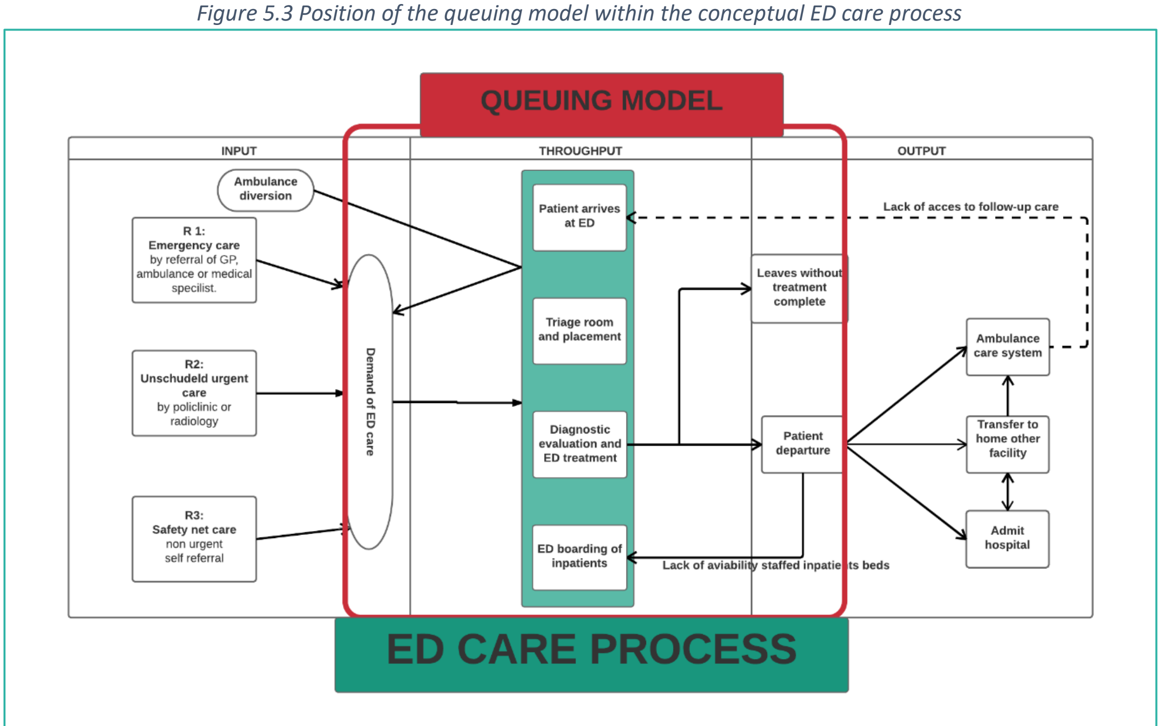
As mentioned before service time might varies due to the severity of the medical condition of the patient. One nurse stated then if the patients only had minor fractures she can treat up to 8, but when a mayor trauma comes, one patient is more than enough. To determine the average service rate, after discussing with staff and taking into account case mix adjustment, the average service time for nurses was set to be 4 patients per hour. For physicians the service rate was set on 3 patients per hour.

5.3 Results of the queuing model

5.3.1 The M/M/s >1 model

Recalling the conceptual model of figure 3.2, we are aware of the different phases of the ED care process. The queuing model overlaps the ED care process in figure 5.3. Although all the different phases of the care process are captured by the queuing model, no distinction is made between the different types of arrivals, R1 (i), R2 (ii) or R3 (iii). The main reason is simplicity because otherwise you have to investigate the networks of the queuing models, which falls outside of our scope. Also no difference is made which way the patients leave the ED. Basically we can consider the ED system to be a black box in terms of a single input and single output without reckoning of its internal workings (figure 5.4). This further conceptualization of the queueing model will be explained later on. Before we can look at this conceptualization of the queuing model we must first determine if arrivals follow a Poisson distribution at all, a key element as mentioned before.

Figure 5.3 Position of the queuing model within the conceptual ED care process



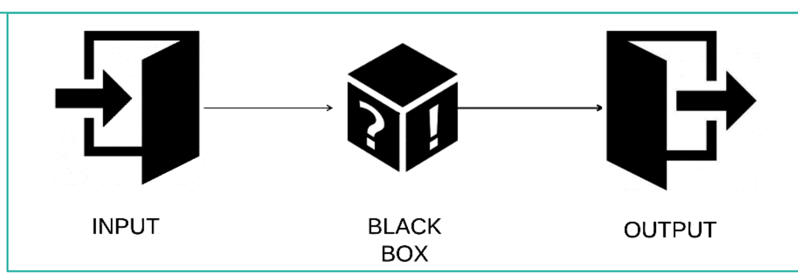


Figure 5.4 Black box system

5.3.2 Chi-Square for goodness of fit test for a Poisson distribution

We investigate if arrivals follow a Poisson distribution. We begin by making a histogram for a rough estimation. The histogram in figure 5.5 of the arrivals per hour suggests a Poisson distribution. To determine whether the number of arrivals per hour actually follows a Poisson distribution, the null and alternative hypotheses are drawn up followed:

H_0: The number of arrivals per hour follows a Poisson distribution

H_1: The number of arrivals per hour does not follow a Poisson distribution

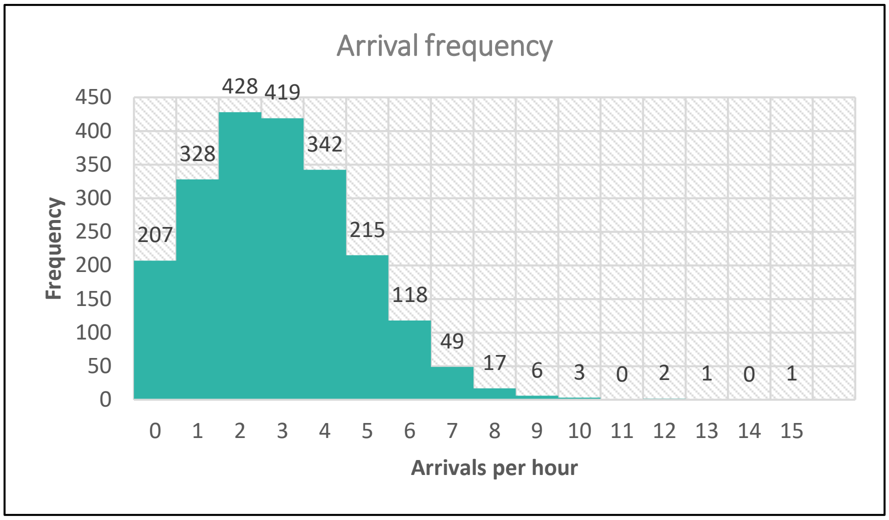


Figure 5.5 Histogram showing the frequency of arrivals per hour

Since the Poisson distribution has one parameter, its mean λ, either a specified value can be included as part of the null and alternative hypotheses, or the parameter can be estimated from the sample data. The result of the mean λ is calculated. This is done by summing up the frequency times the occurrence. After this the result is divided by the total number of observations which leads to λ = 2.9.

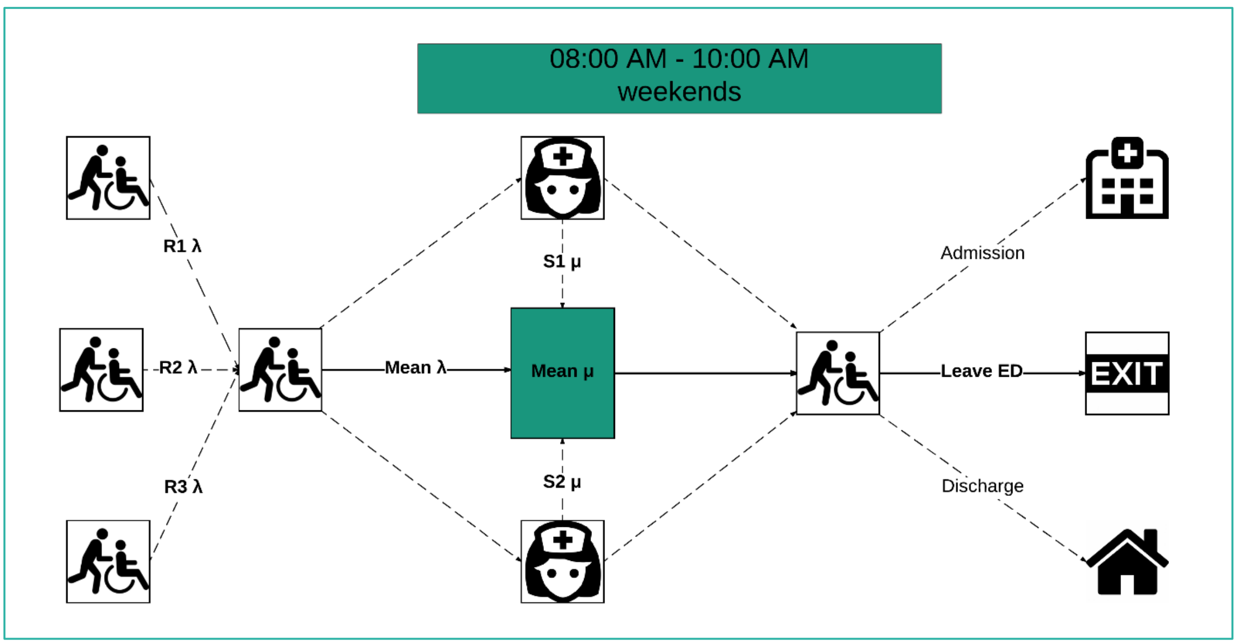
This value of the sample mean is used as the estimate of λ for the purposes of finding the probabilities from the tables of the Poisson distribution for λ = 2.9. Then the frequency of X successes can be determined. The theoretical frequency for each is obtained by multiplying the appropriate Poisson probability by the sample size (n =2136). The theoretical frequency of 9 or more arrivals is less than 1.0. In order to have all categories contain a frequency of 1.0 or greater, the frequency of 9 or more is combined with the category of 8 arrivals per hour. The chi-square test is then computed to be $\chi 2$ = 11.965

Since the mean of the Poisson distribution has been estimated from the data, the number of degrees of freedom are 7 (8-1). Using the 0.05 level of significance the critical value of χ2 with 7 degrees of freedom is 14.067. Resulting in χ2 = 11.965 < 14.067 thus the decision is not to reject H_0. There is insufficient evidence to conclude that the arrivals per hour do not fit a Poisson distribution.

5.3.3 Conceptualization of the M/M/s>1 model

Now that is calculated that arrivals are likely to have a Poisson distribution we look at the conceptualization of our M/M/S>1 model with the already given example from our dataset. Again we study the time period of the nurses between 08:00 AM and 10:00 AM during weekends. Table 5.3 gives more detailed information about this time frame. In this time period 2 nurses are available for service thus 2 servers. The conceptualization of our example is shown in figure 5.6. The dotted line shows the possible arrivals (R1, R2, R3), possible distribution among servers (S1, S2) and possible ways to depart from the ED. In our queuing model no distinction is made between the different arrival rates and instead a mean arrival rate is calculated for the given time period. This is pictured in the figure with the solid line. Following this line we also see the different service rates are combined into one average service rate. How the patients depart is not specified. Only when they exit the ED is deemed relevant, not their destination.

Figure 5.6 Conceptualization of the M/M/s>1 model



Input of the queuing model

Next, the calculations that are needed for the input of our model will be made. When we recall our example of the nurses during weekends at the time period 08:00AM – 10:00 AM we can derive the following data. The mean service rate is already stated and can be denoted as mean μ is 4 patients per hour for the nurses. The mean λ is calculated for the various time period. We continue with our earlier mentioned example and show how this mean λ is obtained. Table 5.3 elaborates how the different arrival rates per hour are summed up and divided by the total number of recorded time periods or days during the research period (n=24).

Table 5.3 Running example of how the mean arrival rate and the 95% CI of the mean arrival rate is calculated

Nurses on the weekends **n=26 time periods**					**Time period: 08:00AM - 10:00 AM**
dates of **February 2017:**	patients per hour **Arrival rate λ**	dates of **March 2017**	patients per hour **Arrival rate λ**	dates of **April 2017**	patients per hour **Arrival rate λ**
04/02	3.33	**04/03**	5.33	**01/04**	5.33
05/02	3.33	**05/03**	4.67	**02/04**	1.67
11/02	3.67	**11/03**	3.00	**08/04**	3.33
12/02	4.00	**12/03**	3.33	**09/04**	4.00
18/02	3.33	**18/03**	4.00	**15/04**	4.00
19/02	3.00	**19/03**	4.00	**16/04**	5.67
25/02	3.33	**25/03**	4.67	**22/04**	4.00
26/02	2.33	**26/03**	4.67	**23/04**	4.67
				29/04	3.67
				30/04	5.67
	$+$ 26.32		$+$ 33.67		$+$ 42.01
Cumulative $\sum \boldsymbol{\lambda}$	$26.32 + 33.67 + 40.01 = 104$				
Mean arrival rate λ Average patients per hour	$\bar{\lambda} = \frac{104}{26} = 4.0$				
SD	1.59				
μ	4				
s	2				
95% CI of the mean λ	(3.39, 4.61)				
Utilization threshold:					
>0.85 n= (%)	1		$\frac{1}{24} \times 100 =$ (4%)		
>1.0 n= (%)	0		(0%)		

We continue with our running example of 5.1. The calculations given in table 5.3 gives a mean λ of 4 person per hour for the input of our queuing model. All the different means of λ for the other time periods are calculated the same way. The 95% confidence interval of the mean arrival rate is calculated. For our example this results in a lower confidence interval of 3.39 and a upper confidence interval of 4.61. Again these results are used as input for the queuing model giving the confidence intervals for all the measured outcomes. Also the mean utilization levels per day in the research period for this time period were calculated. Our example shows that the number of times the threshold of >0.85 is exceeded is 1. Leading to a percentage of 4%. The >1.0 threshold was not surpassed thus resulting in a percentage of 0%.

Markov chain

Now that the position, conceptualization and the input parameters are described we can start with the calculations and discover what the results of our queuing model will be. Before rushing to the results, we first exhibit the different transitions states in the M/M/s>1 queue in figure 5.7. The transitions states can be described as a Markov chain and are essential for the use of our queuing model. We continue with our previously given example of the nurses between 08:00 AM and 10:00 AM in the weekends. As the average arrival rate is calculated to be 4 patients per hour and the average service time is determined to be 4 patients per hour we can demonstrate the transition states. Recalling figure 5.2 we can simply fill in the data as shown in figure 5.7.

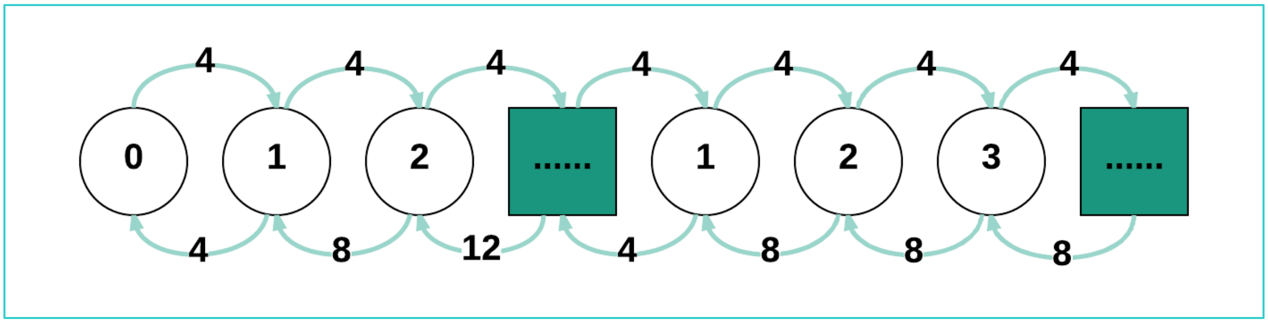


Figure 5.7 Transitions states of the modulated M/M/s>1 queue

Output of the M/M/s>1 model

For the output of the M/M/s>1 model we continue with our example. All the different calculations made with our queuing model are presented and explained. We use the known formulas of the Queuing Theory.(77) This gives an idea how the results for the various time periods are determined.

Utilization of nurses:

$$\rho = \frac{\lambda}{s\mu} = \frac{4}{2\times 4} = 0.5 = 50\ \%$$

Probability that the ED queue is empty:

$$P_0 = \frac{1}{\left[\sum_{n=0}^{s-1} \frac{\left(\frac{\lambda}{\mu}\right)^n}{n!} + \frac{\left(\frac{\lambda}{\mu}\right)^s}{s! - \frac{\lambda}{s\mu}}\right]} = \frac{1}{\left[\sum_0^1 \frac{\left(\frac{4}{4}\right)^0}{0!} + \frac{\left(\frac{4}{4}\right)^2}{2! - \frac{4}{4\times 4}}\right]} = 0.33 = 33\%$$

Persons waiting in the ED queue :

$$L_q = \frac{\lambda\mu\left(\frac{\lambda}{\mu}\right)^s}{(s-1)!(s\mu-\lambda)^2} P_0 = \frac{4\times4\left(\frac{4}{4}\right)^2}{(2-1)!\times(2\times4\times4)^2} \times P_0 = 0.33$$

Number of patients in the ED system:

$$L = L_q + \frac{\lambda}{\mu} = 0.33 + \frac{4}{4} = 1.33$$

Waiting time of the ED queue in hours:

$$W_q = \frac{L_q}{\lambda} = \frac{1.33}{4} = 0.08$$

Hours in the system (waiting and service):

$$W = W_q + \frac{1}{\mu} = 0.08 + \frac{1}{4} = 0.33$$

The calculations are repeated for the other time periods. Both for the nurses and the physicians. When applying the same methods and formula as described in this section on the other time periods, this lead to the following results as presented in tables 5.1 till 5.5. We will starts with the outcomes of our queuing model in the current situation for the nurses during weekends in table 5.1. Table 5.2 continues with the outcomes for the nurses during weekdays. The following tables 5.3, for the weekends, and 5.5, for the weekdays, show the calculations for the physicians.

Table 5.1 Queuing model with calculated outcomes for nurses during weekends

Nurses Weekends n=26	**Mean**	**SD**	**95% CI**	**Min**	**Max**		**Mean**	**SD**	**95% CI**	**Min**	**Max**
12.00 AM – 07:00 AM		1.37				**05:00PM-06:00PM**		2.9			
λ=2.7 μ= 4 s= 3						*λ=7.8 μ= 4 s= 5*					
ρ in %	22		(18, 27)	8	73	***ρ in %***	39		(33, 45)	15	80
L_q	0.01		(0.00, 0.02)	0.00	1.65	L_q	0.04		(0.02, 0.08)	0.00	2.22
L	0.68		(0.54, 0.82)	0.17	3.1	L	1.99		(1.69, 2.30)	0.75	6.21
W_q	0.04		(0.00, 0.01)	0.01	0.28	W_q	0.00		(0.00, 0.01)	0.00	0.14
W	0.24		(0.24, 0.26)	0.25	0.53	W	0.25		(0.25, 0.26)	0.25	0.39
$P(0)$ ***% empty***	0.50		(0.45, 0.45)	0.84	0.16	$P(0)$ ***% empty***	0.14		(0.19, 0.10)	0.47	0.01
ρ >0.85 n= (%)		0 (0)				***ρ >0.85 n= (%)***		0 (0)			
ρ >1.0 n= (%)		0 (0)				***ρ >1.0 n= (%)***		0 (0)			
08:00 AM – 10:00 AM		1.59				**07:00PM-08:00PM**		2.85			
λ=4.0 μ= 4 s= 2						*λ=6.9 μ= 4 s= 4*					
ρ in %	50		(42, 57)	21	116	**ρ in %**	43		(36, 50)	16	88
L_q	0.33		(0.19, 0.57)	0.02	-	$\mathrm{L_q}$	0.08		(0.04, 0.17)	0	4.06
L	1.33		(1.03, 1.72)	0.44	-	L	1.81		(2.47, 2.16)	0.63	7.47
W_q	0.08		(0.06, 0.12)	0.01	-	$\mathrm{W_q}$	0.01		(0.01, 0.02)	0	0.29
W	0.33		(0.31, 0.37)	0.26	-	W	0.26		(0.25, 0.27)	0.25	0.53
$P(0)$ ***% empty***	0.33		(0.41, 0.27)	0.65	-	$\mathrm{P(0)}$ **% empty**	0.27		(0.13; 0.23)	0.53	0.02
P >0.85 (n/%)		1 (4)				**ρ >0.85 n= (%)**		1 (4)			
P >1.0 (n/%)		1 (4)				**ρ >1.0 n= (%)**		0 (0)			
11.00 AM - 02:00 PM		3.41				**09:00PM-11:00PM**		2.03			
λ=7.3 μ= 4 s=3						*λ=4.7 μ= 4 s= 3*					
ρ in %	60		(34, 392)	35	95	***ρ in %***	39		(33, 46)	3	73
L_q	0.55		(1.95, 2.93)	0.06	17.3	L_q	0.09		(0.03, 0.17)	0.00	1.36
L	2.37		(0.05, 0.12)	1.11	20.8	L	1.27		(1.04, 1.55)	0.08	3.53
W_q	0.08		(0.30, 0.37)	0.01	1.52	W_q	0.02		(0.01, 0.03)	0.00	0.16
W	0.33		(0.18; 0.11)	0.26	1.76	W	0.27		(0.26, 0.28)	0.25	0.41
$P(0)$ ***% empty***	0.14		(0.45; 0.29)	0.35	0.02	$P(0)$ ***% empty***	0.31		(0.37, 0.24)	0.93	0.09
ρ >0.85 n= (%)		3 (12)				***ρ >0.85 n= (%)***		0 (0)			
ρ >1.0 n= (%)		0 (0)				***ρ >1.0 n= (%)***		0 (0)			
03:00 PM – 04:00 PM		2.89									
λ=9.1 μ= 4 s= 4											
ρ in %	57		(49, 65)	19	99						
L_q	0.34		(0.15, 0.66)	0.01	0						
L	2.59		(2.09, 3.26)	0.75	160						
W_q	0.04		(0.02, 0.06)	0.00	9.86						
W	0.03		(0.27, 0.31)	0.25	10.0						
$P(0)$ ***% empty***	0.09		(0.14, 0.06)	0.46	0.00						
ρ >0.85 n= (%)		3 (12)									
ρ >1.0 n= (%)		0 (0)									

Table 5.2 Queuing model with calculated outcomes for nurses during weekdays weekends

Nurses weekdays n=63	Mean	SD	95% CI	Min	Max		Mean	SD	95%CI	Min	Max
12.00 AM – 07:00 AM		1.07				**05:00PM-06:00PM**		4.07			
λ=1.5 μ= 4 s= 3						*λ=10.6 μ= 4 s= 5*					
ρ in %	12		(10; 14)	0	60	***ρ in %***	53		(48, 60)	18	120
L_q	0.00		(0.00, 0.01)	0	0.69	L_q	0.18		(0.10, 0.34)	0.00	-
L	0.25		(0.20, 0.33)	0	1.90	L	2.84		(2.51, 3.31)	0.88	-
W_q	0.00		(0.00, 0.00)	0	0.14	W_q	0.02		(0.01, 0.03)	0.00	-
W	0.25		(0.25, 0.26)	0	0.39	W	0.27		(0.26, 0.28)	0.25	-
$P(0)$ ***% empty***	0.70		(0.75, 0.65)	100	0.25	$P(0)$ ***% empty***	0.07		(0.09, 0.05)	0.41	-
ρ >0.85 n= (%)		0 (0)				***ρ >0.85 n= (%)***		1 (2)			
ρ >1.0 n= (%)		0 (0)				***ρ >1.0 n= (%)***		3 (5)			
08.00 PM – 10:00 AM		1.70				**07:00PM-08:00PM**		3.24			
λ=4.7 μ= 4 s= 2						*λ=9.1 μ= 4 s= 4*					
ρ in %	59		(54, 64)	4	112	***ρ in %***	57		(52, 62)	13	115
L_q	0.63		(0.54, 0.91)	0.00	-	L_q	0.32		(0.21, 0.50)	0.00	-
L	1.81		(1.51, 2.20)	0.08	-	L	2.60		(2.28, 2.98)	0.50	-
W_q	0.14		(0.10, 0.18)	0.00	-	W_q	0.04		(0.03, 0.05)	0.00	-
W	0.39		(0.35, 0.43)	0.25	-	W	0.29		(0.28, 0.30)	0.25	-
$P(0)$ ***% empty***	0.26		(0.30, 0.22)	0.92	-	$P(0)$ ***% empty***	0.10		(0.12, 0.08)	0.60	-
ρ >0.85 n= (%)		6 (10)				***ρ >0.85 n= (%)***		2 (3)			
ρ >1.0 n= (%)		2 (3)				***ρ >1.0 n= (%)***		4 (6)			
11.00 AM 02:00 PM		2.49				**09:00PM-11:00PM**		1.85			
λ=9.5 μ= 4 s= 3						*λ=5.5 μ= 4 s= 3*					
ρ in %	79		(72, 87)	42	125	***ρ in %***	46		(42, 50)	11	81
L_q	2.40		(1.23, 3.00)	0.11	-	L_q	0.17		(0.12, 0.23)	0.00	2.72
L	4.78		(3.35, 5.46)	1.36	-	L	1.55		(0.38, 1.72)	0.33	5.14
W_q	0.25		(0.21; 0.43)	0.02	-	W_q	0.03		(0.02, 0.04)	0.00	0.28
W	0.50		(0.39, 0.56)	0.27	-	W	0.28		(0.27, 0.29)	0.25	0.53
$P(0)$ ***% empty***	0.06		(0.09, 0.05)	0.28	-	$P(0)$ ***% empty***	0.24		(0.27, 0.21)	0.71	0.05
ρ >0.85 (n/%)		24 (38)				***ρ >0.85 n= (%)***		0 (0)			
ρ >1.0 (n/%)		5 (8)				***ρ >1.0 n= (%)***		0 (0)			
03.00 PM -04:00 PM		3.83									
λ=11.9 μ= 4 s= 4											
ρ in %	75		(70, 80)	19	144						
L_q	1.74		(1.17, 2.67)	0.00	-						
L	4.00		(3.27, 5.10)	0.75	-						
W_q	0.19		(0.14, 0.28)	0.00	-						
W	0.44		(0.36; 0.53)	0.25	-						
$P(0)$ ***% empty***	0.07		(0.10; 0.06)	0.47	-						
ρ >0.85 n= (%)		12 (19)									
ρ >1.0 n= (%)		5 (8)									

5.3.4 Results of the nurses

The outcomes for the weekends of the nurses in table 5.4. show that the mean utilization levels is low are during the night. Utilization level increases during the 08:00 AM till 10:00 AM time period. The mean is calculated to be 59% (54 64 Utilization levels begin to climb following the next time period between

11.00 AM and 02:00 PM were the mean utilization reaches its highest peak at 60%. The number of times the utilization levels exceed the 0.85 threshold is 3 times or 12%. The >1.0 threshold is not surpassed. In the next time period of 03:00 PM till 04:00 PM and 05:00 PM till 06:00 PM the utilization levels have a downward trend with no signs of a system-wide overload. In the 03:00 PM till 04:00 time period a surpassing of the >0.85 is also recorded 3 times. During the 05:00 PM till 06:00 PM time period no surpassing of the thresholds is measured. Utilization levels have a minor increases in the 07:00 PM till 08:00 PM time period, but thresholds are not exceeded at any given time during the research period. In the next time period of 09:00 PM till 11:00 PM, utilization levels lower even further and are well within manageable limits.

If we investigate the results of our queuing model for the nurses during weekdays, we notice that utilization levels during the nightshift (time period 12:00 AM till 07:00 AM) are low. Utilization levels begin to rise as the day progresses. The 08:00 AM till 10:00 AM time period shows an increase in utilization levels with an average of 59% . The utilization threshold of >0.85 exceeds it stated limit 6 times or 10%. The >1.0 threshold was surpassed 2 times with correspond to 2%. The utilization level reaches its peak during the 11:00 AM till 02:00 PM time period. Mean utilization is calculated to be 79%. The >0.85 threshold are exceeded 24 times (38%) during the research period, the highest calculated results. Also the >1.0 threshold is surpassed 5 times, corresponding to 8% of the recorder cases. Utilization levels have a downward trend going into the next time frame of 03:00 PM and 04:00 AM. Our thresholds are surpassed 12 times (19%) for the >0.85 threshold and 5 times (8%) for the >1.0 threshold. During the time frame from 05:00 PM till 06:00 PM, utilization levels decrease even more till an average utilization of 53%. The two thresholds show little overrun during this time period. This continues into the next time period of 07:00 PM till 08:00 PM, still the utilization mean being well within manageable limits with 57% (52, 62). In the following time period of 09:00 PM till 11:00 PM the utilization levels continue with their descending trend, reaching an average utilization of 46 %. Thresholds were not surpassed during the research period. Maximum utilization levels of more than 100% where recorded in almost every time frame. The periods from 08:00 AM till 11:00 PM recorded the highest number of time the system was overloaded (37%). The highest maximum is detected between 03:00 PM and 04:00 PM reaching a peak utilization of 144%.

In summary, both during weekdays as in the weekends, the utilization levels are higher during the recorded time period between 11.00 AM till 02.00 PM. These time frames are prone to reach peaks of a utilization greater than 0.85. Although weekends tend to be more busy during evenings and nights, the queuing model calculated with a confidence of 95% that the system seems to be in control.

We will continue with the results of the queuing model for the physicians. We begin with presenting the results for the weekends in table 5.3, followed by the outcomes of the weekdays for physicians in table 5.4.

Table 5.3 Queuing model with calculated outcomes for physicians during weekends

Physicians weekends n=26	Mean	SD	95% CI	Min	Max		Mean	SD	95% CI	Min	Max
12.00 PM - 07:00 AM		0.74				**05:00PM-08:00PM**		2.56			
λ=2.7 μ= 3 s= 2						*λ=7.3 μ= 3 s= 4*					
ρ in %	35		(21, 30)	4	50	***ρ in %***	61		(54, 69)	33	119
L_q	0.23		(0.02, 0.06)	0.00	0.33	L_q	0.48		(0.23, 0.95)	0.03	-
L	1.13		(0.43, 0.66)	0.09	1.33	L	2.92		(2.34, 3.71)	1.36	-
W_q	0.85		(0.02, 0.03)	0.00	0.11	W_q	0.06		(0.04, 0.11)	0.01	-
W	0.42		(0.35, 0.37)	0.33	0.44	W	0.40		(0.37, 0.45)	0.34	-
$P(0)$ ***% empty***	0.38		(0.66, 0.54)	0.92	0.33	$P(0)$ ***% empty***	0.08		(0.53, 0.05)	0.26	-
ρ >0.85 n= (%)		0 (0)				***ρ >0.85 n= (%)***		3 (13)			
ρ >1.0 n= (%)		0 (0)				***ρ >1.0 n= (%)***		2 (8)			
08.00 PM – 12:00 AM		1.55				**09:00PM-11:00PM**		2.03			
λ=5.3 μ= 3 s= 2						***λ=4.6 μ= 3 s= 3***					
ρ in %	88		(81, 98)	47	161	***ρ in %***	53		(44, 61)	6	144
L_q	6.04		(3.13, 43.7)	0.26	-	L_q	0.30		(0.14, 0.59)	0.00	-
L	7.80		(4.75, 45.7)	1.19	-	L	1.88		(1.46, 2.53)	0.11	-
W_q	1.14		(0.65, 7.44)	0.09	-	W_q	0.07		(0.04, 0.11)	0.00	-
W	1.47		(0.97, 7.78)	0.42	-	W	0.40		(0.37, 0.44)	0.33	-
$P(0)$ ***% empty***	0.06		(0.10, 0.01)	0.36	-	$P(0)$ ***% empty***	0.27		(0.18, 0.14)	0.90	-
ρ >0.85 n= (%)		3 (13)				***ρ >0.85 n= (%)***		2 (8)			
ρ >1.0 n= (%)		1 (4)				***ρ >1.0 n= (%)***		0 (0)			
01.00 PM - 04:00 PM		2.86									
λ=6.4 μ= 3 s= 3											
ρ in %	71		(62, 80)	28	118						
L_q	1.11		(0.51, 248)	0,01	-						
L	3.96		(3.00, 5.70)	0.15	-						
W_q	0.13		(0.07, 0.26)	0.00	-						
W	0.36		(0.40, 0.59)	0.37	-						
$P(0)$ ***% empty***	0,05		(0.08, 0.03)	0.32	-						
ρ >0.85 n= (%)		1 (4)									
ρ >1.0 n= (%)		1 (4)									

Table 5.4 Queuing model with calculated outcomes for physicians during weekdays

Physicians weekdays n=63	**Mean**	**SD**	**95% CI**	**Min**	**Max**		**Mean**	**SD**	**95% CI**	**Min**	**Max**
12.00 AM - 07:00 AM		0.64				**05:00PM-08:00PM**		3.49			
λ=1.5 μ= 3 s= 2						*λ=9.8 μ= 3 s= 4*					
ρ in %	25		(16, 21)	0	62	***ρ in %***	82		(24, 90)	29	178
L_q	0.03		(0.00, 0.01)	-	0.77	L_q	2.90		(0.01, 6.70)	0.01	-
L	0.53		(0.25, 0.35)	-	2.01	L	6.19		(0.96, 10.3)	1.18	-
W_q	0.02		(0.00, 0.01)	-	0.21	W_q	0.30		(0.00, 0.62)	0.00	-
W	0.36		(0.31, 0.34)	-	0.54	W	0.63		(0.34, 0.96	0.34	-
$P(0)$ ***% empty***	0.60		(0.78, 0.71)	-	0.24	$P(0)$ ***% empty***	0.02		(0.39, 0.01)	0.31	-
ρ >0.85 n= (%)		0 (0)				***ρ >0.85 n= (%)***		33 (52)			
ρ >1.0 n= (%)		0 (0)				***ρ >1.0 n= (%)***		33 (52)			
08.00 AM – 12:00 PM		1.83				**09:00PM-11:00PM**		1.85			
λ=6.2 μ= 3 s= 2						***λ=5.5 μ= 3 s= 3***					
ρ in %	102		(98, 111)	43	163	***ρ in %***	61		(56, 66)	22	107
L_q	-		(57.5, -)	0.20	-	L_q	0.59		(0.40,0.87)	0.02	-
L	-		(59.5, -)	1.07	-	L	2.53		(2.08, 2.86)	0.47	-
W_q	-		(9.75, -)	0.08	-	W_q	0.11		(0.08, 0.15)	0.02	-
W	-		(10.1, -)	0.41	-	W	0.44		(0.41, 0.48)	0.35	-
$P(0)$ ***% empty***	-		(0.02, -)	0.26	-	$P(0)$ ***% empty***	0.14		(0.31, 0.12)	0.64	-
ρ >0.85 n= (%)		20 (32)				***ρ >0.85 n= (%)***		12 (19)			
ρ >1.0 n= (%)		20 (32)				***ρ >1.0 n= (%)***		2 (3)			
01.00 PM - 04:00 PM		2.96									
λ=8.3 μ= 3 s= 4											
ρ in %	69		(74, 29)	36	128						
L_q	0.79		(0.01, 1.22)	0.02	-						
L	4.23		(1.47, 4.91)	1.82	-						
W_q	0.08		(0.00, 0.11)	0.00	-						
W	0.41		(0.34, 0.44)	0.34	-						
$P(0)$ ***% empty***	0.03		(0.23, 0.02)	0.17	-						
ρ >0.85 n= (%)		5 (8)									
ρ >1.0 n= (%)		5 (8)									

5.3.5 Results physicians

We start discussing the results from the weekend for the physicians in table 5.3. Overall the utilization of the physicians is higher than that of the nurses. When it comes to the weekends, the nightshift seems not to be overwhelmingly busy between 12:00 AM and 07:00 AM resulting in a low utilization. This changes when the dayshift takes over at the time period of 08.00 AM till 12:00 PM. Utilization levels climb to an average of 88% (81, 98). The utilization threshold of >0.85 and >1.0 were both surpassed 20 times with corresponds to 31% of the recorded cases. Also the highest maximum utilization peak is detected during this time frame i.e. 161%. The utilization level lowers between the following time period of 01.00 PM till 04:00 PM. Reaching a mean utilization of 71 %. The next time period of 05:00 PM till 08:00 PM also shows a utilization level within manageable limits.

We continue with the results of the queuing model in table 5.4 for the physicians on weekdays. Similar trends as for the weekends are visible but are more distinct. We will begin with the time period of 12:00 AM till 07:00 AM. Al levels seem to be within controllable limits, showing a low average utilization. This changes when the dayshift starts in the time period from 08:00 AM till 12:00 PM. The mean utilization rises to 102% (98, 111) showing an overload of the system. Both he thresholds are exceeded 20 times or 32% of the recorded cases. The system seems to recover in the unfollowing time period of 01:00 PM till 04:00 PM. The average utilization drops to 69% and also the thresholds are surpassed less frequently, both account for 8% of the recorded cases. During the next time period the utilization level goes up again, reaching an mean of 82%). What is notable in this time frame, is the surpassing of the thresholds. The pair of thresholds are exceeded both 33 times what comes down to 52%. The highest of the day. In the time frame from 09:00 PM till 11:00 PM the mean utilization improves, showing a mean to be 61%. Also the two thresholds are surpassed less frequent, With the exception of the 12:00 AM till 07:00 AM time period, all the other time periods have recorded peak moments where the maximum utilization exceeds the 100% limit of the system.

In summary, the results of the queuing model suggest that both during weekdays and weekends the system has a tendency to overload in the time period 08:00 till 12:00 for the physicians . The outcomes for the weekdays are more distinct then for the weekends. The mean utilization is significant and suggests overloading of the system. Also the higher frequency of peak moments, measured with the thresholds, are frequently present during the research period.

5.3.6 Results of the occupancy rate and the queuing calculations

Lastly we can compare the earlier determined ORs with our utilization outcomes per hour calculated with the help of our queuing model. In figure 5.8 we see the results for the weekends and figure 5.9 for the weekdays. It can be noted that utilization levels show a different trend then the ORs. We can recall that high ORs usually happen during the afternoon, both for the weekends and weekdays, between 02:00 PM and 05:00 PM. The utilization levels tell us that the overloading, or the imbalance of the system, happens earlier on during the day. For both the nurses and the physicians the bottleneck seems to be in the morning between 10:00 AM and 12:00 PM. Ideally we want to level off the peaks of the utilization, and thus the variability, to optimize the staffing of the ED.

Figure 5.8 Mean occupancy rates versus mean utilization per recorded hour during weekends.

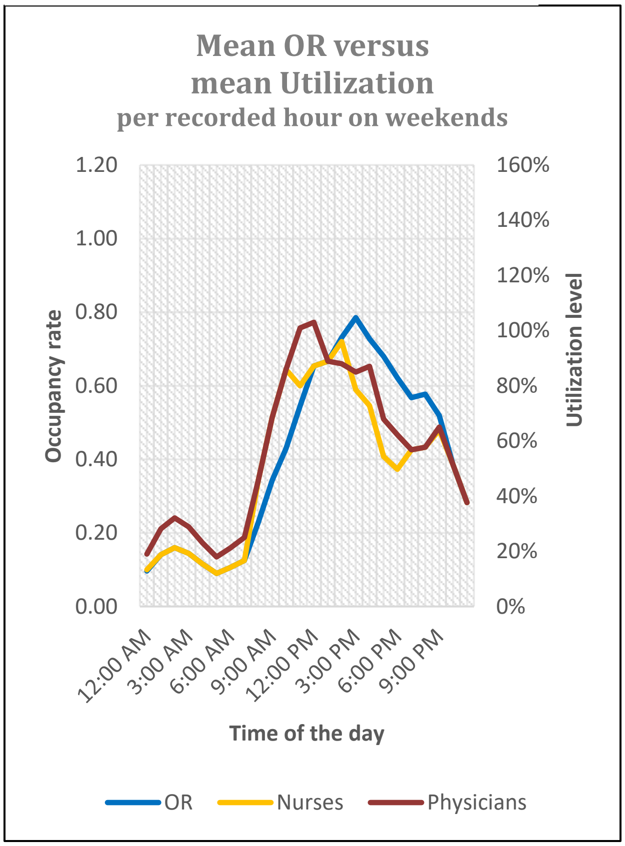
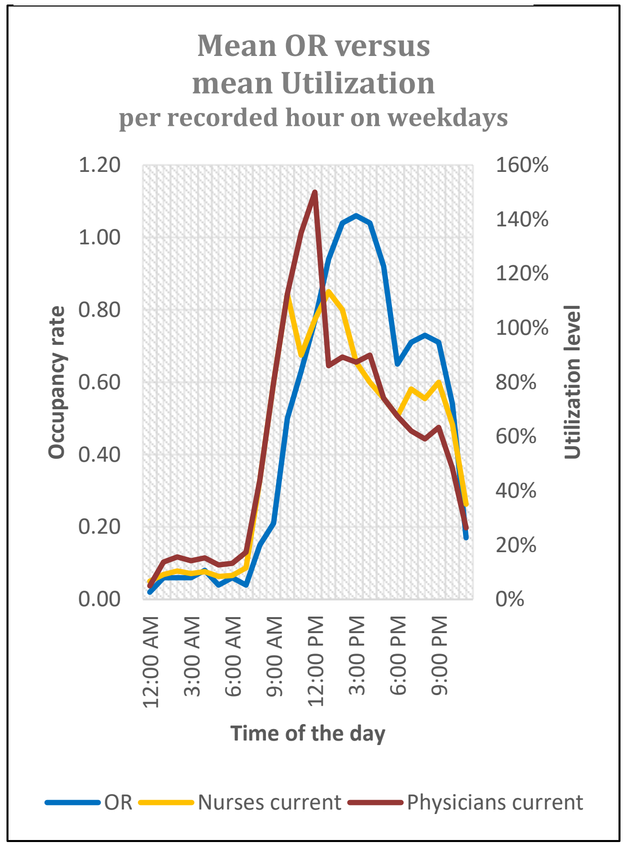


Figure 5.9 Mean occupancy rates versus mean utilization per recorded hour during weekdays.



5.4 Conclusion

The conclusion of the sub question: *" Which mathematical modelling approach is suitable for a system-wide analysis of the staffing at ED?,* is as follow. We decided to use an analytical approach to construct a queing model for the ED. Simulation is a more common approach in this area. Drawbacks of a simulation are the detailed information that is required for the input distribution, it is time-consuming and one might get lost in the details and lose sight of the real problem. An analytical queuing model requires fewer data. The queuing model enables a system-wide bottleneck analysis of the processes at the ED and can easily be adjusted so that it represents one of the alternative solutions that will be discussed later during the alternative solution process in chapter 6.

For the ED of the Scheper Hospital Emmen a queuing model was constructed using a multiple channel, M/M/s>1, where "s" designates the number of servers or healthcare providers. The servers where categorized into nurses and physicians. An elaboration about Queuing Theory and its characteristics was presented in the introduction section. We used the conceptual model of the ED process to identify the position of our queuing model. An average arrival and average service time was computed. We further conceptualized our queuing model on the basis of an example. In essence our queuing model represent a black box system in terms of a single input and single output without reckoning of the internal workings of the throughput phase. The example was further used to provide insight into how the outcomes of our model are calculated.

We determined that the number of arrivals per hour are likely to follow a Poisson distribution. Main focus of the outcomes of our model were the utilization levels. During the weekends the staffing of nurses seems to be adequate and only minor signs of overloading where detected. During the time period from 11.00 AM till 02:00 PM the system tends to be the most busy resulting in a higher but manageable utilization. If we recall the results from the occupancy rates in chapter 4, we can conclude that the weekends do not seem to be a problem for the staffing of the nurses and physicians.

During weekdays the same pattern as discussed for the weekends manifests itself, but more profoundly during the time period of 11:00 AM till 02:00 PM. Thus resulting in longer time patients wait in the queue, increased average number of patients in the system and longer average time in line and the system. The other time periods, give or take some peak moments, seem to be in control.

The utilization of the physicians is more troubling. The weekends suggest to be in control with manageable utilization levels. The utilization levels for the nurses during the morning (88%) and evening (61%) are high but seems to be controllable. It is when looking at the results for the physician during weekdays when we observer different problems. During the 12:00 AM till 08:00 AM the system does not suggest to be busy. This changes during the morning when investigating the time period form 08:00 AM till 12:00 AM. Mean utilization is high (102%), resulting in an overload of the system. Also episodes of crowding are detected in 33% of the cases, or days. The system recovers somewhat the following time period in the afternoon, but again utilization levels go up as the evening progresses.

In summary the queuing model suggests that problems in overloading of the systems happens earlier on during the day then when we recall the results from the occupancy rate, that told us that during the afternoon there are problems. This is especially true when it comes to the results for the physicians. When further examining the ORs versus the utilization levels we can conclude that the high ORs in the afternoon are a result of the high utilization levels in the morning. There is an imbalance of the system during this time of the day. Because crowding has a stacking effect with a build-up of patients, we can draw the conclusion that thus far we were looking at the effect, not the leading cause of crowding. Our queuing model has provided us with this answer and given us a bottleneck in the staffing of the ED. Thus the analytical queueing model suggests to be a robust method to analyze the system of the ED and has the ability to detect bottlenecks. To counteract the negative influences of this imbalance, several alternative solutions are proposed and tested using the same queuing model and the identical input data to measure their effects. This will be discussed in the next chapter.

6. Testing alternative solutions

6.1 Introduction

Since we have pointed out the problems, thus an imbalance in the system, in chapter 5 during the day, and by which type of healthcare professional, the alternative solutions can be drafted and tested using the queuing model with the same dataset. Goal and aim is to combat crowding as early as possibly to reduce, or ideally to even prevent overloading and peak moments from happening. How this is done will be researched and discussed in this chapter. The focus will be on the weekdays for both nurses and physicians because that is when most of the problems occur according to our queuing model. The weekends showed to be less problematic.

6.2 Methods

In this chapter we are going to make changes to the staffing of the ED to find an optimal solution. In other words turning the wheels of staffing. This is done by using the same original data as before but with alternative staffing ways. Optimization and improvement is also attempted to be achieves with the help of capacity planning with the same (original) dataset. Or to remain in the same metaphor, turning the wheels of the capacity. This will be discussed in chapter 7 and is separated from the impact of the (alternative) staffing. Staff is divided between nurses and physicians. First the alternative solution for the nurses will be calculated and discussed. To cope with the demand and capacity of the ED some nurses are already working intermediary shifts. As pointed out in table 5.2 the main problem when it comes to a high utilization and a longer time patients wait in the queue, increased average number of patients in the system and longer average time in line and the system, happen during the time period from 11:00 PM till 02:00 AM. Nursing staff will be shifted to determine the most optimal solution. Although it might seem logical, given the results from our queuing model in chapter 5, to allocate nurses from the nightshift this alternative solutions is not tested. Discussing with staff yielded that the nightshift is used for additional tasks such as reviling of equipment. Tasks that can't be measured with our queuing model. Hence this alternative solution is dropped beforehand.

Alternative solution 1

In the first alternative solution it is proposed that the nurse that start at 02:00 PM start earlier at 10:00 AM (thus there will be no shift that starts at 02:00 PM) . The current situation and alternative 1 are shown in table 6.1.

Alternative solution 2

In this situation a nurse from the evening shift that starts at 03:30 PM will start at 10:00 AM thus resulting into one nurse that is less available during the last part of the evening. The current situation and alternative 2 are shown in table 6.1.

Alternative solution 3

In this situation a nurse from the afternoon shift that starts at 02:00 PM will start at 12:00 AM the 02:00 PM shift will expire. The current situation and alternative 3 are shown in table 6.1.

Table 6.1 Staffing of the alternative solutions in comparison to the current situation for the nurses

Numbers of nurses	*Current situation*	*Alternative solution 1.*	*Alternative solution 2.*	*Alternative solution 3.*
07:30 AM till 10:00 AM	2 1 NC	2 1 NC	2 1 NC	2 1 NC
10:00 AM till 12:00 PM	3 1 NC	4 ↑ 1 NC	4 ↑ 1 NC	3 1 NC
01:00 PM till 02:00 PM	3 1 NC	4 ↑ 1 NC	4 ↑ 1 NC	4 ↑ 1 NC
03:00 PM till 3:30 PM	4 1 NC	4 1 NC	5 ↑ 1 NC	4 1 NC
3:30 PM till 06:00 PM	5 1 NC	5 1 NC	5 1 NC	5 1 NC
07:00 PM till 08:00 PM	4 1 NC	3 ↓ 1 NC	2 ↓ ↓ 1 NC	4 1 NC
09:00 PM till 11:00 PM	3 1 NC	3 1 NC	2 ↓ 1 NC	3 1 NC
12:00 PM till 07:00 PM	2	2	2	2

6.3.1 Results alternative staffing nurses

The calculated results using the queuing model are shown in table 6.2. The solution are separately calculated and ranked next to each other for comparison. At the end of the section the results of the model will be discussed.

Table 6.2. Alternative solutions for nurses with the calculated results

Nurses weekdays N=63	**Sol. 1 Mean**	**95% CI**	**Sol 2 Mean**	**95% CI**	**Sol. 3 Mean**	**95% CI**
08:00 AM – 10:00 AM						
λ=1.4 μ= 4	*s=3*		*s=3*		*s=3*	
SD		1.70		1.70		1.70
ρ in %	12	(10; 14)	12	(10; 14)	12	(10; 14)
L_q	0.00	(0.00, 0.01)	0.00	(0.00, 0.01)	0.00	(0.00, 0.01)
L	0.35	(0.20, 0.53)	0.35	(0.20, 0.33)	0.35	(0.20, 0.53)
W_q	0.00	(0.00, 0.00)	0.00	(0.00, 0.00)	0.00	(0.00, 0.00)
W	0.25	(0.25, 0.26)	0.25	(0.25, 0.26)	0.25	(0.25, 0.26)
$P(0)$ ***% empty***	0.70	(0.75, 0.65)	0.70	(0.75, 0.65)	0.70	(0.75, 0.65)
P >0.85 n (%)	0 (0)		0 (0)		0 (0)	
P >1.0 n (%)	0 (0)		0 (0)		0 (0)	
11.00 AM – 12:00 AM						
λ=9.5 μ= 4	*s=4*		*s=4*		*s=3*	
SD		2.69		2.69		2.69
ρ in %	59	(50; 68)	59	(50; 68)	79	(67; 85)
L_q	0.26	(0.18; 0.38)	0.26	(0.18; 0.38)	1.38	(0.90; 2.17)
L	2.43	(2.18; 2.71)	2.43	(2.18; 2.71)	3.55	(2.90; 4.50)
W_q	0.03	(0.02; 0.04)	0.03	(0.02; 0.04)	0.16	(0.11; 0.23)
W	0.28	(0.27; 0.29)	0.28	(0.27; 0.29)	0.41	(0.36; 0.48)
$P(0)$ ***% empty***	0.11	(0.18; 0.09)	0.11	(0.18; 0.09)	0.09	(0.11; 0.06)
P >0.85 n (%)	1 (2)		1 (2)		22 (34)	
P >1.0 n (%)	0 (0)		0 (0)		4 (6)	

01.00 PM – 02:00 PM						
λ=10.6 μ= 4	*s=4*		*s=4*		*s=4*	
SD		3.18		3.18		3.18
ρ in %	66	(61; 71)	66	(61; 71)	66	(61; 71)
L_q	0.70	(0.46; 1.06)	0.70	(0.46; 1.06)	0.70	(0.46; 1.06)
L	3.33	(2.90; 3.89)	3.33	(2.90; 3.89)	3.33	(2.90; 3.89)
W_q	0.07	(0.05; 0.09)	0.07	(0.05; 0.09)	0.07	(0.05; 0.09)
W	0.32	(0.30; 0.34)	0.32	(0.30; 0.34)	0.32	(0.30; 0.34)
$P(0)$ ***% empty***	0.07	(0.08; 0.05)	0.07	(0.08; 0.05)	0.07	(0.08; 0.05)
P >0.85 n (%)	12 (19)		12 (19)		12 (19)	
P >1.0 n (%)	5 (8)		12 (8)		5(8)	
03:00 PM – 03:30 PM						
λ=10.4 μ= 4	*s=4*		*s=5*		*s=4*	
SD		3.19		3.19		3.19
ρ in %	65	(60; 71)	52	(48; 56)	65	(60; 71)
L_q	0.70	(0.43; 1.11)	0.17	(0.10; 0,23)	0.70	(0.43; 1.11)
L	3.33	(2.82; 3.96)	2.79	(2.50; 3.01)	3.33	(2.82; 3.96)
W_q	0.07	(0.04; 0.10)	0.02	(0.01; 0.02)	0.07	(0.04; 0.10)
W	0.32	(0.30; 0.35)	0.27	(0.26; 0.27)	0.32	(0.30; 0.35)
$P(0)$ ***% empty***	0.07	(0.08; 0.05)	0.15	(0.09; 0.06)	0.07	(0.08; 0.05)
P ***n must wait***	0.36	(0.29; 0.45)	0.07	(0.11; 0.18)	0.36	(0.29; 0.45)
P >0.85 n (%)	13 (2)		3 (34)		13 (2)	
P >1.0 n (%)	4 (0)		1 (6)		4 (0)	
04.00 PM – 06:00 PM						
λ=10.6 μ= 4	*s=5*		*s=5*		*s=5*	
SD		3.83		3.83		3.83
ρ in %	53	(49; 58)	53	(49; 58)	53	(49; 58)
L_q	0.18	(0.11; 0.30)	0.18	(0.11; 0.30)	0.18	(0.11; 0.30)
L	2.84	(2.54; 3.18)	2.84	(2.54; 3.18)	2.84	(2.54; 3.18)
W_q	0.07	(0.01; 0.03)	0.07	(0.01; 0.03)	0.07	(0.01; 0.03)
W	0.27	(0.26; 0.28)	0.27	(0.26; 0.28)	0.27	(0.26; 0.28)
$P(0)$ ***% empty***	0.07	(0.09; 0.05)	0.07	(0.09; 0.05)	0.07	(0.09; 0.05)
P >0.85 n (%)	5 (8)		5 (8)		5 (8)	
P >1.0 n (%)	3 (5)		3 (5)		3 (5)	
07.00 PM – 08:00 PM						
λ=9.1 μ= 4	*s=3*		*s=2*		*s=4*	
SD		3.24		3.24		3.24
ρ in %	76	(69; 82)	113	(103; 124)	57	(49; 62)
L_q	1.81	(1.07; 3.22)	-	(-; -)	0.33	(0.11; 0.50)
L	4.08	(3.14; 5.69)	-	(-; -)	2.60	(2.54; 2.98)
W_q	0.20	(0.13; 0.33)	-	(-; -)	0.04	(0.01; 0.05)
W	0.45	(0.38; 0.58)	-	(-; -)	0.29	(0.26; 0.30)
$P(0)$ ***% empty***	0.07	(0.10; 0.05)	-	(-; -)	0.10	(0.11; 0.08)
P >0.85 n (%)	20 (31)		46 (73)		4 (6)	
P >1.0 n (%)	8 (13)		38 (60)		2 (3)	

09.00 PM – 11:00 PM						
λ=5.5 μ= 4	*s=3*		*s=2*		*s=3*	
SD		1.84		1.84		1.84
ρ in %	46	(42; 49)	69	(64; 75)	46	(42; 49)
L_q	0.17	(0.12; 0.23)	1.25	(0.84; 1.88)	0.17	(0.12; 0.23)
L	1.55	(1.38; 1.72)	2.63	(2.11; 3.37)	1.55	(1.38; 1.72)
W_q	0.03	(0.03; 0.04)	0.23	(0.17; 0.31)	0.03	(0.03; 0.04)
W	0.28	(0.27; 0.29)	0.48	(0.42; 0.56)	0.28	(0.27; 0.29)
$P(0)$ ***% empty***	0.24	(0.28; 0.21)	0.18	(0.23; 0.15)	0.24	(0.28; 0.21)
P >0.85 n (%)	0 (0)		14 (23)		0 (0)	
P >1.0 n (%)	0 (0)		6 (10)		0 (0)	

When the current situation was analyzed using Queuing Theory it was already clear that especially in the morning between 11:00 AM and 02:00 PM there was a problem with a fairly high utilization and peak moments surpassing the stated utilization threshold of >0.85 and >1.0.

The *alternative solution 1* shows that improvement and optimization is possible in this “troubling” time period but at the expense of relative higher utilization later on in the afternoon in the 07:00 PM - 08:00 PM time period. Thus resulting in longer time patients have to wait in the queue, increased average number of patients in the system and longer average time in line and the system. Although calculation are within acceptable limits and on average the systems seems to be in control with a sizeable lower mean of respectively 54% at 11:00 AM and 66% at 02:00 AM. Also the calculations do not exceeding the >0.85 threshold with a 95% confidence interval. The peak during the 07:00 PM - 08:00 PM time period dissipates in the next time period of 09:00 PM and 11:00 PM as well and exist for a short period of time.

With *alternative solution 2* the time period between 11:00 AM and 02:00 PM is also leveled off but to a significant high expense later on at 07:00 PM - 08:00 PM. Because there is one nurse less available the systems overloads thus resulting in a utilization of 113% and also both confidence intervals surpassing 100%. Not something that is desirable. Peak moment increase considerably to as high as 73% of the cases with the >0.85 threshold. This trends goes on and continues in the next time period of 09:00 PM and 11:00 PM resulting the previously mentioned threshold to be exceeded in 23% of the cases. This only happens with solution 2 and is not visible with the other solutions.

Alternative solution 3 shows also that utilization levels lowers. There is however a negative side effect if the nurse starts at 12.00 AM instead of 10:00 AM. Peak moments tend to build up resulting in prolonged peak moments of respectively 34% and 19% with the >0.85 threshold in the time between 10:00 AM and 02:00. Benefits are that in the 07:00 PM - 08:00 PM time period no significant peak moments occur, surpassing the >0.85 threshold only 6% and confidence intervals for utilization and waiting time are low. But again also an alternative solution with significant disadvantages.

Second the alternative solution for the physicians will be calculated and discussed. Finding an optimal solution for the physicians is more challenging. There are multiple period during the weekdays that utilization and thus waiting times are high as was displayed in table 5.4. The time period between 08.00 PM –12:00 AM causes evidently the most problems, showing a mean overload with high peak surpassing the >0.85 and >1.0 both 32% of the cases. Also the time period 09:00PM - 11:00PM and to a lower but significant degree the time period 05:00PM - 08:00PM tend to overload, with confidence intervals already surpassing both previously mentioned threshold to a considerable degree respectively 19% and 37% of the cases.

Again existing duty shifts will be exchanged and calculated using the queuing model. The solutions are ranked next to each other for comparison. At the end of the section the results of the model will be discussed.

Alternative solution 4

The intermediary shift that currently starts at 12.00 AM will start earlier at 10.00 AM to counteract the peak moments and high utilization in the morning. What effect this have on the evening, because the shift will end at 06:00 PM instead of 08:00 PM, has to be calculated. The current situation and alternative solution 1 are shown in table 5.6.

Alternative solution 5

The intermediary shift at 12:00 AM remains yet a physician from the evening starts at 10:00 AM instead of 04:00 PM. This results in one less physicians after 08:00 PM then in the current situation. The queuing model will test the results of alternative solution 2 in table 5.6.

Alternative solution 6

Again a physician from the evening starts at 10:00 AM instead of 04:00 PM but also the intermediary shift start at the same time, thus resulting that there is no shift that start at 12:00 AM. This will also results in viewer physicians during the evenings. Results of alternative solution 3, along with the other alternative solutions and the current situation, as depicted in table 6.3

Table 6.3 Staffing of the alternative solutions in comparison to the current situation of the physicians

Numbers of physicians	*Current situation*	*Alternative solution 1.*	*Alternative solution 2.*	*Alternative solution 3.*
08:00 AM till 10:00 AM	2	2	2	2
11:00 AM till 12:00 PM	2	3 ↑	3	4 ↑↑
01:00 PM till 02:00 PM	4	4	5 ↑	5 ↑
03:00 PM till 4:00 PM	4	4	5 ↑	5 ↑
5:00 PM till 06:00 PM	4	4	4	5 ↑
07:00 PM till 08:00 PM	4	3 ↓	3 ↓	2 ↓↓
09:00 PM till 12:00 PM	3	3	2 ↓	2 ↓
12:00 PM till 07:00 PM	2	2	2	2

6.3.2 Results alternative staffing physicians

The calculated results using the queuing model are shown in table 5.6. The solution are separately calculated and ranked next to each other for comparison. At the end of the section the results of the model will be discussed.

Physicians weekdays	**Sol. 4 Mean**	**95% CI**	**Sol 5 Mean**	**95% CI**	**Sol. 6 Mean**	**95% CI**
08:00 AM – 10:00 AM						
λ=1.0 μ= 3	*s=2*		*s=2*		*s=2*	
SD		1.70		1.70		1.70
ρ in %	18	(17; 12)	18	(17; 12)	18	(17; 12)
L_q	0.69	(0.01; 0.00)	0.69	(0.01; 0.00)	0.69	(0.01; 0.00)
L	0.01	(0.35; 0.25)	0.01	(0.35; 0.25)	0.01	(0.35; 0.25)
W_q	0.37	(0.01; 0.00)	0.37	(0.01; 0.00)	0.37	(0.01; 0.00)
W	0.26	(0.34; 0.31)	0.26	(0.34; 0.31)	0.26	(0.34; 0.31)
$P(0)$ **% empty**	0.69	(0.71; 0.78)	0.69	(0.71; 0.78)	0.69	(0.71; 0.78)
P **n must wait**	0.06	(0.05; 0.03)	0.06	(0.05; 0.03)	0.06	(0.05; 0.03)
P >0.85 n (%)	0 (0)		0 (0)			0 (0)
P >1.0 n (%)	0 (0)		0 (0)			0 (0)
11.00 AM – 12:00 AM						
λ=8.7 μ= 3	*s=3*		*s=3*		*s=4*	
St.dev		2.69		2.69		2.69
ρ in %	96	(89; 104)	96	(89; 104)	72	(67; 78)
L_q	25.3	(6.53; -)	25.3	(6.53; -)	1.22	(0.80; 1.97)
L	28.2	(9.20; -)	28.2	(9.20; -)	4.11	(3.49; 5.01)
W_q	2.92	(0.82; -)	2.92	(0.82; -)	0.14	(0.10; 0.21)
W	3.25	(1.15; -)	3.25	(1.15; -)	0.47	(0.43; 0.55)

$P(0)$ % empty	0.01	(0.03; -)	0.01	(0.03; -)	0.04	(0.06; 0.03)
P n must wait	0.94	(0.80; 1.07)	0.94	(0.80; 1.07)	0.47	(0.39; 0.56)
P >0.85 n (%)	41 (65)		41 (65)		12 (19)	
P >1.0 n (%)	30 (48)		30 (48)		4 (6)	
01.00 PM – 02:00 PM						
$\lambda=10.5$ $\mu= 3$	s=4		s=5		s=5	
St.dev		3.18		3.18		3.18
ρ in %	87	(81; 94)	70	(65; 75)	70	(65; 75)
L_q	5.28	(2.66; 14.4)	0.89	(0.56; 1.44)	0.89	(0.56; 1.44)
L	8.77	(5.90; 18.1)	4.40	(3.80; 5.21)	4.40	(3.80; 5.21)
W_q	0.50	(0.27; 1.27)	0.09	(0.06; 0.13)	0.09	(0.06; 0.13)
W	0.83	(0.61; 1.60)	0.42	(0.39; 0.46)	0.42	(0.39; 0.46)
$P(0)$ % empty	0.02	(0.03; 0.01)	0.03	(0.04; 0.02)	0.03	(0.04; 0.02)
P n must wait	0.74	(0.62; 0.88)	0.38	(0.30; 0.47)	0.38	(0.30; 0.47)
P >0.85 n (%)	8 (13)		2 (3)		2 (3)	
P >1.0 n (%)	3 (5)		0 (0)		0 (0)	
03:00 PM – 04:00 PM						
$\lambda=10.6$ $\mu= 3$	*s=4*		*s=5*		*s=5*	
St.dev		3.83		3.83		3.83
ρ in %	88	(81; 97)	71	(65; 77)	71	(65; 77)
L_q	5.97	(2.56; 26.0)	0.96	(0.54; 1.71)	0.96	(0.54; 1.71)
L	9.52	(5.79; 29.9)	4.51	(3.78; 5.57)	4.51	(3.78; 5.57)
W_q	0.56	(0.26; 2.25)	0.09	(0.06; 0.15)	0.09	(0.06; 0.15)
W	0.89	(0.60; 2.58)	0.42	(0.39; 0.48)	0.42	(0.39; 0.48)
$P(0)$ % empty	0.01	(0.03; 0.00)	0.02	(0.04; 0.02)	0.02	(0.04; 0.02)
P n must wait	0.76	(0.61; 0.93)	0.39	(0.30; 0.50)	0.39	(0.30; 0.50)
P >0.85 n (%)	29 (46)		15 (24)		15 (24)	
P >1.0 n (%)	19 (30)		9 (14)		9 (14)	
05.00 PM – 06:00 PM		4.07		4.07		4.07
$\lambda=10.7$ $\mu= 3$	*s=4*		*s=4*		*s=5*	
ρ in %	89	(80; 97)	89	(80; 97)	71	(64; 78)
L_q	5.83	(2.41; 28.9)	5.83	(2.41; 28.9)	0.95	(0.52; 1.75)
L	9.37	(5.62; 32.8)	9.37	(5.62; 32.8)	4.49	(3.72; 5.62)
W_q	0.55	(0.25; 2.48)	0.55	(0.25; 2.48)	0.09	(0.05; 0.15)
W	0.88	(0.58; 2.82)	0.88	(0.58; 2.82)	0.42	(0.39; 0.48)
$P(0)$ % empty	0.01	(0.03; 0.00)	0.01	(0.03; 0.00)	0.03	(0.04; 0.02)
P n must wait	0.76	(0.60; 0.93)	0.76	(0.60; 0.93)	0.39	(0.29; 0.51)
P >0.85 n (%)	29 (46)		29 (46)		18 (8)	
P >1.0 n (%)	20 (32)		20 (32)		8 (5)	

07.00 PM – 08:00 PM							
λ=8.9 μ= 3		s=3		s=3		s=2	
St.dev		3.24		3.24		3.24	
ρ in %	99	(92; 109)	99	(92; 109)	151	(139; 165)	
L_q	447	(9.47; -)	447	(9.47; -)	-	(-; -)	
L	450	(12.2; -)	450	(12.2; -)	-	(-; -)	
W_q	49.8	(1.15; -)	49.8	(1.15; -)	-	(-; -)	
W	50.1	(1.48; -)	50.1	(1.48; -)	-	(-; -)	
$P(0)$ **% empty**	0.00	(0.02; -)	0.00	(0.02; -)	-	(-; -)	
P **n must wait**	0.99	(0.85; 1.17)	0.99	(0.85; 1.17)	1.82	(1.60;2.05)	
P >0.85 n (%)	20 (31)		20 (31)		56 (89)		
P >1.0 n (%)	8 (13)		8 (13)		53 (84)		
09.00 PM – 11:00 PM		1.84		1.84		1.84	
λ=8.9 μ= 3	*s=2*		*s=2*		*s=2*		
ρ in %	61	(56; 66)	92	(84; 99)	92	(84; 99)	
L_q	0.59	(0.40; 0.87)	9.89	(4.17; 228)	9.89	(4.17; 228)	
L	2.43	(2.09; 2.86)	11.7	(4.86; 230)	11.7	(4.86; 230)	
W_q	0.11	(0.08; 0.15)	1.79	(0.82; 38.2)	1.79	(0.82; 38.2)	
W	0.44	(0.41; 0.48)	2.13	(1.16; 38.5)	2.13	(1.16; 38.5)	
$P(0)$ **% empty**	0.14	(0.17; 0.11)	0.04	(0.09; 0.00)	0.04	(0.09; 0.00)	
P **n must wait**	0.37	(0.31; 0.44)	0.88	(0.77; 0.99)	0.88	(0.77; 0.99)	
P >0.85 n (%)	12 (19)		36 (57)		36 (57)		
P >1.0 n (%)	2 (3)		21 (33)		21 (33)		

Table 5.7. Alternative solutions for physicians with the calculated data.

Alternative solution 4 shows that by reallocation the 02:00 PM shift to start at 10.00 AM it relives the tendency of the system to overload in the morning. It can be noted that utilization and waiting times are still high even with an extra physician. The confidence levels in the time period 10:00 AM till 12:00 AM show that there still yet a situation of overloading the system. Also peak moment surpassing the set threshold of >0.85 and >1.0 are quite high reaching respectively 65% and 48% of the recorded episodes. Utilization and waiting times reduces following the next time period but are still fairly high and can impede the workflow. This situation continues throughout the day reaching a "new peak" between 07:00 PM and 08:00 PM with a high mean of utilization and confidence levels show and overload.

With *alternative solution 5*, where a physician form the evening shifts starts at 10:00 AM the same situation can be noticed as with alternative solution 4, with some exceptions. The time period between 10:00 AM and 12:00 AM show the same pattern with high mean utilization and waiting times and confidence levels tell a situation of overloading of the system. Peak moments as described before are at the same height. Then the system seems to recover at time period 01:00 PM till 02:00 PM with utilization and waiting times being mediate. This stable situation is maintained till the time period 05:00 PM – 06:00 PM where utilization levels make an upward leap showing confidence level at near overload. Also the peak moments tend to increase significantly resulting in an exceeding of the >0.85 and >1.0 threshold in respectively 46% and 43% of the recorded cases. The utilization levels and waiting times even increases unfollowing the next time period of 07:00 PM and 08:00 PM although peak moments are lower and less frequent (31%-19%).

For *alternative solution 6* the queuing model show a fast improvement during the “troubling” time period of 10:00 AM and 12:00 AM. Utilization levels and waiting times are within suitable limits and peak moment have significantly dropped to respectively 19% and 8%. The system of physicians stay in control throughout the day with suitable levels and peak moments. This changes at the 07:00 PM -08:00 PM time period. Utilization levels take a giant leap causes the system to go in a full overload. Also with the confidence levels there is no sigh of a possible system recovery. Peak levels are excessive high reaching the exceeded thresholds to be respectively 89% and 84% of the cases.

6.3.3 Results of the alternative solutions versus the current situation

Figure 6.1 visualizes the OR versus the current utilization levels and the utilization levels that are calculated when testing the alternative solutions for both nurses and physicians. We again notice that the utilization for nurses is divided more proportionally with no high peak or variation between 10:00 AM and 12:00 AM. Also for the physicians the utilization levels more proportional but a peak arises between 07:00 PM and 08:00 PM as was discussed earlier on.

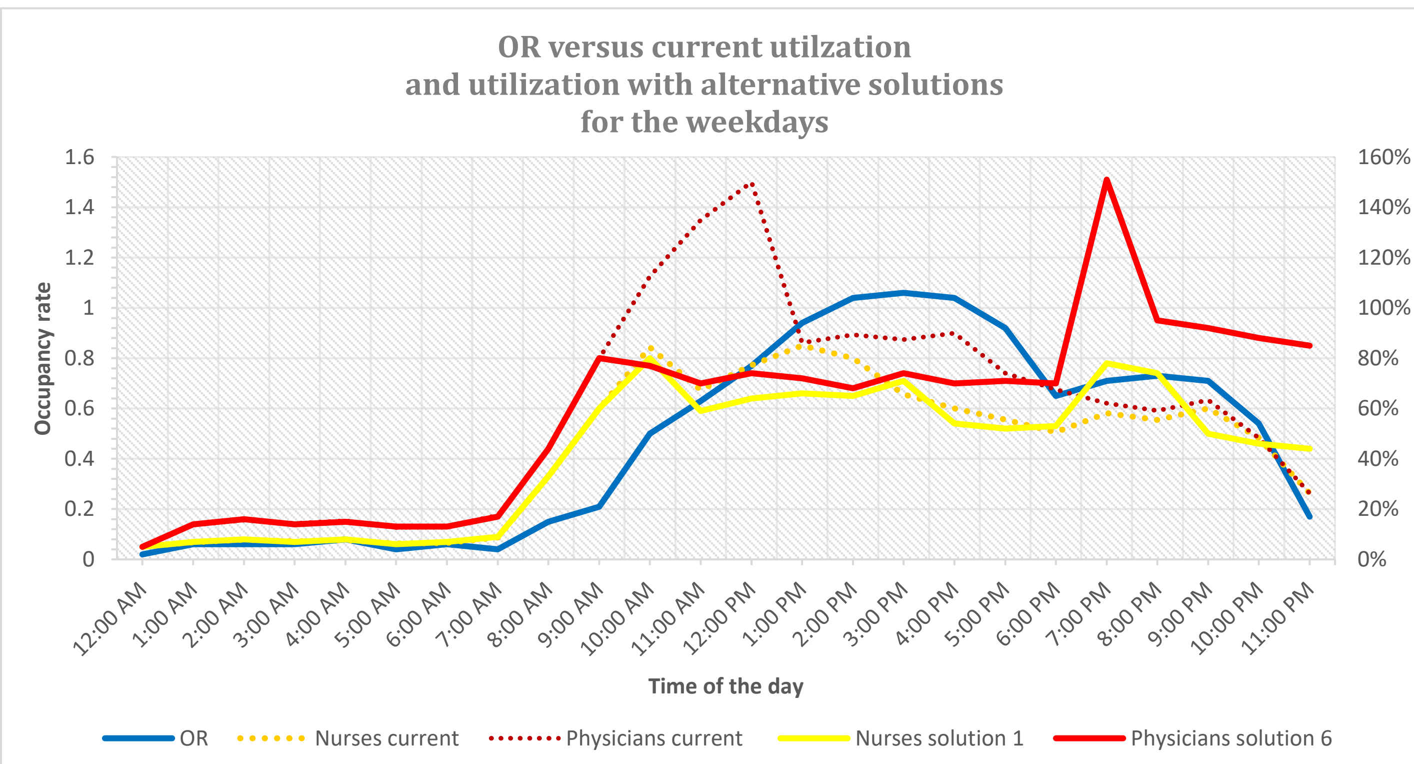


Figure 6.1 Results of the alternative solutions versus the current situation and the occupancy rate

6.4 Conclusion alternatives solutions staffing

The staffing of the nurses and physicians and tested using the proposed alternative solutions. First the nurses where analyzed and three alternative solutions where proposed. In chapter 5 it was already clear that the main problem when it comes to a high utilization, this mainly happens during the time period from 11:00 PM till 02:00 AM. Alternative solution 1, when the intermediary shift of the nurse starts at 10:00 AM instead of 02:00 PM, gave the best results according to our queuing model. The results from the queuing model showed that improvement and optimization is possible in this “troubling” time period but at the expense of relative higher but manageable utilization later on in the afternoon in the 07:00 PM - 08:00 PM time period. Although calculation are within acceptable limits and on average the systems seems to be in control with a sizeable lower mean. Also the calculations do not exceeding the set thresholds with a 95% confidence interval. Alternative solution 2 created a significant bottleneck between 07:00 PM and 08:00 PM resulting in a mean utilization of 113% and can be excluded from the improvement possibilities. Alternative solution 3, where a nurse form the evening shift start at 12:00 AM also gave good results but the peak moment during the morning remains.

Taking this al into account the conclusion for the staffing of the nurses can be made that alternative solution 1 offers to be the most optimal solution by reasoning that crowding, or the imbalance and overloading of the system, tends to have a stacking effect. By counteracting this effect at the beginning of the day, and thus tackling the origin of the problem, one might suggest that problems or stacking of patient will not happen or at least at a lower degree then in the current situation. To further test alternative solution 1 a simulation test can be recommended although this requires heaps of data.

Secondly the staffing for the physicians was analyzed and three alternative solutions where proposed. Before the alternatives solutions were tested it was already shown in chapter 5 that realizing an optimal situation with the current resources would prove to be difficult. The results from the queuing model support this claim. There are many “troubling” time period for the physician when it comes to the queuing model. Both during the morning as in the evening, which makes planning and control more challenging.

Again three alternative solutions (i.e. 4, 5 and 6) were proposed and tested. Alternative solution 4 shows that by reallocation the 02:00 PM shift to start at 10.00 AM, it relives the tendency of the system to overload in the morning. It can be noted that utilization and waiting times are still high even with an “extra” physician” in the morning by allocation. Also significant problems occur as the day progresses resulting in significant overload and extensive peak moment. So alternative solution 4 can be excluded from the improvement possibilities.

Alternative solution 5, where a physician from the evening starts at 10:00 AM instead of 04:00 PM , creates a stable situation and this is maintained until 05:00 PM where utilization levels make an upward leap showing confidence level at near overload (99%). Also the peak moments tend to increase significantly, even increases in the next time period. An undesirable situation. Also alternative solution 5 can be excluded as a possibility.

Alternative solution 6, where the intermediary shift starts at 10:00 and a physician from the evening starts at 10:00 AM instead of 04:00 PM, started very promising. Utilization levels and waiting times where low with acceptable peak moment. Everything looks fine and the system performance at a stable pace. Unfortunately the day does not stop at 07:00 PM because that when the trouble starts. Utilization levels and peak moments rice tremendously creating a total overload of the system. A swift recovery is achieved in the following time period of 09:00 PM and 11:00 PM. Also not eligible. All in all it seems that alternative solution 6 shows to have the most promise when looking at the utilization levels.. Although there is a problem at the end of the day during 07:00 PM and 08:00 PM, the system of physicians is at a constant rate for the remainder of the day. Taking into account was concluded earlier with the staffing of the nurses, crowding has a stacking effect, the origin of the problem is intercepted with this solution. So it is the indecipherable if the problem in the evening will happen at all if this solution is implemented.

There is however another more unconventional solution. Till now we only explored the possibility of alternative staffing with the current number of available physicians. If for example the physicians were willing to extend there working hours from 8 to 10 hours a whole new solution comes to light that would provide an optimal improvement within the queuing model. When using alternative solution 6 and augment the working day to 10 hours for the physician to start at 10:00 AM and end at 08:00 PM, the system will not overload. Before this “alternative solution 7” is tested, or a simulation is made, first it must be checked is physician are willing to extend their workday and if this can be considered to be an option at all. Also the possibility of an extra physician needs further research. An additional physician during the evening for solution 6 would probably alleviate the high utilization in the evening. But this requires more resource and thus is more costly. Senior management must first decide if they are willing to bear these costs before calculation can be made in the future.

7. Capacity planning with additional beds

7.1 Introduction

As was pointed out in the literature review, an buffer capacity often referred as an acute admission unit, might work to alleviate the patient flow at the ED and thus reduce crowding. To answer to the sub question *”What number of additional bed capacity provides the best possible outcome to balance out the need for emergency care versus the available resources of the ED?”,* is given in this chapter. We recall that figure 3.8 pointed out that the stated threshold for planning and control, set to be >0.85 and >1,0, was exceeded respectively between 01:00 PM and 17:00 PM and for the latter threshold between 02:00 PM and 04:00 PM. Confidence levels of 95% showed more spread and calculated a OR >0.85 between 12:00 AM and 05:00 PM. The goal and aim of this section is to find a solution to create additional capacity with a given confidence level. If this should be achieved by an acute admission unit or in another way is a point of discussion and will be contemplated at the recommendation section.

7.2 Methods

We use the same original NEXUS dataset from the 1st of February 2017 till the 30th of April 2017. Starting point of the calculation are again the OR rates as described in chapter 3. This time the capacity would be augmented with 3, 4, or 5 additional beds and OR’s were recalculate to detect the most optimal solution. In chapter 4 we already tested with the help of the Jarque–Bera for goodness of fit test that the OR follow a normal distribution. Thus we can use the standard deviation approach to calculated the confidence intervals. The α was set on 0.05 creating a CI of 95% for each new calculation. We use the same original dataset as before. We already know that the current bed capacity of the ED is 12 if we recall chapter 2.

7.3 Results

Figure 5.1 displays the OR rate per recorded time period per hour with the capacity being augmented with 2 additional beds (thus a total of $12 + 2 = 14$ beds). It is visible that the >1.0 is not surpassed at any given time even with the 95% confidence intervals. The >0.85 threshold is still exceeded between 02:00 PM and 04:00 PM and with the upper confidence level among 01:00 PM and 05:00 PM. In the other time periods there are no problems with the available capacity and the concerning demand from patients.

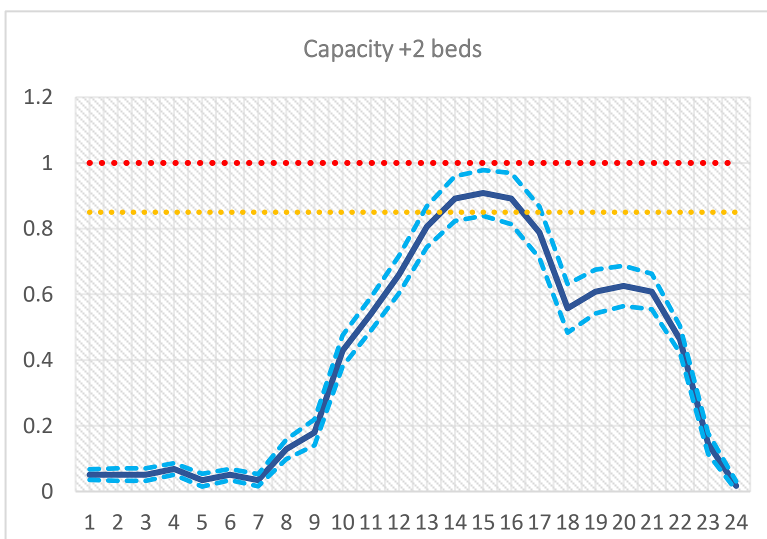


Figure 5.1 OR with capacity of 2 additional beds

Next the OR's with a capacity of 3 can be shown in figure 5.2. Superfluous to mention that the >1.0 threshold with an additional capacity of 3 beds is not surpassed. However more meaningful, again the >0.85 threshold is exceeding although the surface area is less wide. Now the threshold is surpassed only at 03:00 PM. The higher confidence levels indicate a trespassing among 02:00 PM and 04:00 PM. In other words the time band when the capacity exceeds the demand is narrowing.

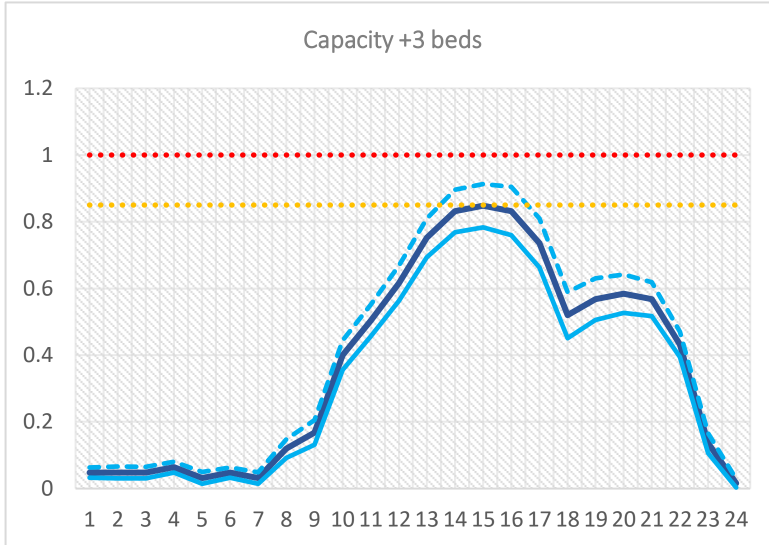


Figure 5.2 OR with capacity of 3 additional beds

In figure 5.3 the additional capacity is raised with 4 beds. The results from the calculation show that only the upper confidence level exceed the stated threshold of >0.85. This happens at 03:00 PM. The other time periods are all within control limits and supply and demand are in balance. While the system almost seems to be in control with a 95% confidence the optimal solution is not yet reached.

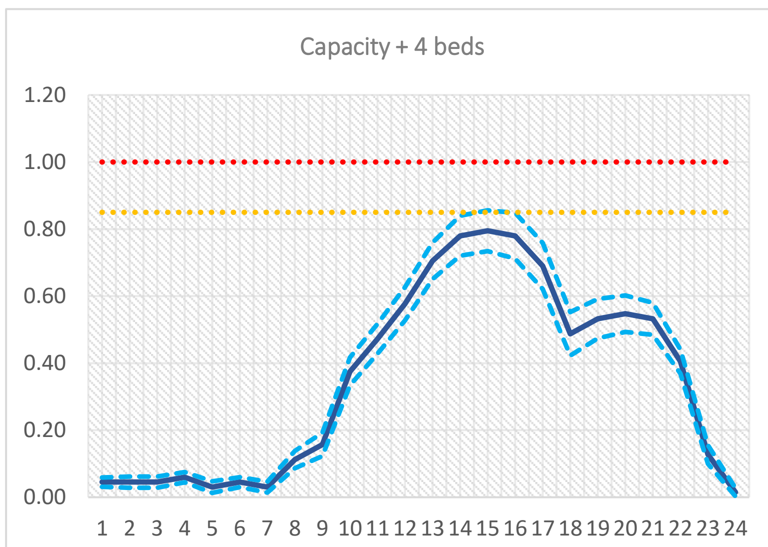


Figure 5.3 OR with capacity of 4 additional beds

In the final chart displayed in figure 5.4 the capacity is augmented with 5 additional beds. The calculation show that with a confidence of 95% the OR's do not surpass the >0.85 threshold and naturally also not the >1.0. Al OR's per time period are under the thresholds with no exceptions.

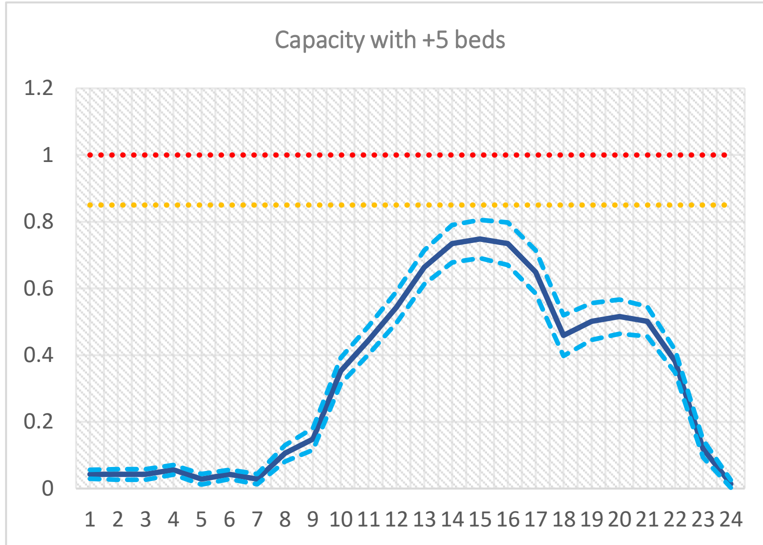


Figure 5.4 OR with capacity of 5 additional beds

7.4 Conclusion capacity

Although the capacity calculation that are made are at a somewhat high conceptual level, they give a good basic idea how much buffer capacity is needed to alleviate the stress on the ED. OR's will stay below the >0.85 threshold resulting in a stable throughput of patients and not hindering the overall operations of the ED. With a 95% confidence interval is can be concluded that a buffer capacity of 5 additional beds would be sufficient and create an optimal solution with the given dataset. In other words with 5 extra beds, the crowding will not happen. With the additional beds we do not factor in the possible advantages of the staffing optimization as proposed in chapter 6. However if we do not factor in the optimization of the staffing and maintain the current lead times of the patients, 5 additional beds would be sufficient. Again a simulation to determine the exact optimal condition may be prudent. On the other hand the high conceptual model does not lead to an extreme high calculation bed augmentation.. All-in-all we believe that 5 additional beds is not unrealistic and showed promising results, although of course also additional nurses and physicians are needed for staffing to treat the patients at these extra beds.

8. Conclusion and discussion

During the 1st of February 2017 and 30th of April 2017, a crowding study was done at the ED of the Scheper Hospital Emmen. We further operationalized the concept of crowding and stated that crowding is an system-wide imbalance between supply and demand. The goal was to measure the incidence of crowding and asses it intensity. Not only by quantifying the current situation, but coming up with adequate solutions to counteract this imbalance. This resulted in the following research question,

"Is there an imbalance between the need for emergency care versus the available resources, thus crowding, at the emergency department of the Scheper Hospital Emmen? How can we measure it, when does it happen and what are adequate solutions?

The data told us that a total of n=3640 visited the ED during this research period. The population that visited the ED has an average age of 50 and sexes were evenly distributed. The overall admission rate was 41%. The majority of patients were labeled to be non-urgent (n=2089) according to the Dutch Triage Standard and surgery was the most consulted medical specialism (n=1449). This is all in line what we already know from other EDs in the Netherlands.(78)

The self-referral was low and calculated to be 4%. Although international literature suggested that self-referral can be a cause of crowding, this does not seem to be a problem at our ED. This finding is much lower than what we find with other crowding studies in the Netherlands in more densely populated areas were 60% of the ED patients were self-referred.(79)

Episodes of crowding have been detected mainly during weekdays. The occupancy rate showed that the episodes when the demand exceed the supply, generally happens during the afternoon. This is also what we know from other EDs in the Netherlands. Most patients visit the ED during afternoons and weekdays. (78)

When examining the performance of the ED with the help of key performance Indicators, several things comes to light. The input phase turned out to perform well within limits. For the throughput phase the length of stay of patients that are discharged is comparable to that found in earlier studies in the Netherlands. However when a patients needs admission the length of stay is significantly longer. Suggesting that there is a problem with the admitted patients.(73) The output phase was more difficult to access because data was lacking. The transport time done by nursing, which is part of the boarding time, yielded that every day approximately 7 hours of nurse labor is lost.

A further in-depth analysis was made with the help of control charts, to discover if this was a system wide problem, or if some medical specialist would stick out when treatment times exceeded the control limits and thus are non-random. Especially geriatrics and also to a large degree internal medicine and pulmonology, have prolonged treatment times. Further research and improvement for these specialisms is urged.

Because the goal was not only to define and measure the current situation and find bottlenecks, but we also wanted to comes up with adequate solutions, the ED was entered into a mathematical model. Although simulation is a more common approach, we using a queuing model. Main reason for the queuing model is its simplicity and ability to show where during the day there is room for improvement. To the best of our knowledge no previous studies have been done using a queuing model for mathematical analyze an ED in the Netherlands, making it hard for comparison to other hospitals. A queuing model was used in the Netherlands redesigning a university hospital preanesthesia evaluation clinic. (76) That study also did a check afterwards how the outcomes and alternative solutions of the queuing model performed in 'real-life'. They found although patient arrivals increased sharply, the solutions worked and Queuing theory provides a robust methods to evaluate alternative solutions.

A queuing model was designed to measure the current situation and find ways to improve. Further we could test the alternative solutions with the same queuing model. Although the occupancy rates yielded that crowding occurs in the afternoon, the queuing model showed that in problems in the utilization levels start earlier on during the day at 10:00 AM. The crowding in the afternoon is merely an effect from delay in the patient flow earlier on. Thus far with the occupancy rate we were seeing the effect, not the cause of crowding as the queuing model showed. Staffing optimization could be achieved when the intermediary shift of 02:00 AM for the nurses would starts at 10:00 AM. For physician realizing an optimal solution proved to be more difficult because of two episodes of high utilization, in the morning at 10:00 AM and the evening at 08:00 PM. The best alternative showed to be when a physician from the evening starts at 10:00 AM instead of 04:00 PM. Also the intermediary shift should start at the same time. There is however a catch. This results in a significant overload during the evening. This can be counteracted if the physician who takes on this new shift would augment their workday to 10 hours, thus the system will not overload. Also an additional physician staring at 10:00 AM would likely alleviate the high utilizations.

However there are some disadvantages using a queuing model. The Queuing Theory assumes a steady state of arrival and service process. This is not true at our ED. We have tried to counteract this by measuring time periods instead of the average arrival per day. Also an independence of arrival and service is assumed and a queuing model has little ability to incorporate important exceptions to the general flow. We have simplified our queuing model with an average arrival and an average exit although in reality this is not true. Queuing theory makes it difficult to model more complicated processes such as the ED. Simulation may be more in place but requires large and reliable data. Also we wanted to discover were improvement and optimization could be achieved. This is not possible with a simulation model that only tell us the performance of the current situation. All-in-all we believe that the queuing model provides al robust way for staffing optimization but the proposed alternative solution must be tested if it works in 'real-life' before we can validate this claim.

When looking at the capacity planning an additional capacity of 5 additional beds would be sufficient and creates an optimal solution. This results should be considered separately and does no factor in the staffing optimization as discussed before.

ED crowding can be seen as a local manifestation of a systemic disease. It is not a problem that results solely from problems in the ED or one that can be addressed using only ED-based solutions. For example, there is a reasonable body of evidence correlating hospital occupancy with ED crowding as was observed during this research. (70)The lack of consistent collection of standardized ED data at an institutional and national levels impairs the ability to measure ED flow issues and ultimately take control before crowding escalates. What do we want to know and more important, what are we going to do with this data to regain control? Emergency care is likely to increase in the Netherlands the upcoming years demanding mayor changes in our healthcare system. This study has been the starting point for quantifying crowding factors at the Scheper Hospital Emmen but this does not tell the complete regional or national story. Crowding is a lot bigger then only measuring its causes and effect in one hospital. Hopefully this study will be a tool to create means of steering in the right direction. And that this thesis is not the end but only the beginning to stay in the flow. The recommendation in the next chapter

9. Recommendations

The following recommendations are proposed to address the various problems that are associated with crowding and thus resulting in an imbalance the need for emergency care versus the available resources of the ED.

1. Transport of patients to the ward should not been done by transport service of the hospital. It can be considered as a waste of labor and restricts the available resources if this is done by the nurses. During observations it was noticed that a verbal consigning by phone was sufficient for the receiving ward. This can be done by the nurse coordinator who is mainly relived from direct patient care. The physical transfer of the patient can then be done by the Patient Transport Service, that is already present at the Scheper Hospital Emmen. It may be wise to first consult the manager of this service if current resources can cope with this increase in transfer requests or if additional staff is needed with an additional cost-benefit analysis.
2. The intermediary shift for nurse that starts at 12:00 PM should start at 10:00 AM. The queuing model showed that this would significantly decrease the utilization levels and waiting time. There is however a slim change that this will cause problems in the evening.
3. Start measuring input, throughput and output factors in the electronic patient system especially boarding time. This is an important time indicator and can give a lot of information about possible improvement and what their affects might be. Also continues measuring of occupancy rate or, when validated for the Dutch emergency care, other crowding measuring tools. Crowding has a buildup tendency and a measuring tool can give warning in advance to make preventive adjustments to regain control. This also applies on the occupancy and bed capacity of the hospital, or even better, the entire Treant organization.
4. Further investigation into the reasons of the non-random prolonged waiting time of geriatric, pulmonology and internal medicine patients. Find ways in collaboration with the medical specialist to improve the diagnostic and initial treatment of these patient at the ED. Further diagnostic and treatment can be done at the ward not the ED and thus hindering the patient flow. In other words optimize the care for these patients with the help of short-cyclic improvements.
5. Create additional capacity. Calculations have shown that an additional capacity of 5 beds would be sufficient. If we study the charts intently, the extra capacity is not needed throughout the day. During the night there is no need for a buffer and according to the queuing model this urgency for additional starts at 10:00 AM.

6. Explore the possibilities of continuously improving the care pathways at the ED along with all the different healthcare professionals. Investigate how the processes can be done more effectively and efficiently and using the rules of operational research to reduce waste (eliminate unnecessary acts during the care process), reduce variability (capacity management and control for planned ED care) and reduce complexity (often the most simple solution is the best solution). The concept of Lean is becoming more and more into practice in daily healthcare and may prove to be an meaningful method.(61, 80). The disadvantages of big improvements in the care chains always intrigues unevenness in comparison with other parts of the value chain in question or even the broader system. Often the so-called side effects appear with some delay so that cause and effect are not easily seen. If the lean improvements are not seen holistically the benefit will be minimal or even counterproductive. In other words, it is an hospital wide problem not only that of the ED.

Further research

In this section endorsements for further research are made. In general further research can be done into the staffing and capacity planning of the ED at the Scheper Hospital Emmen. The queuing model does not take into account what happens if crowding is counteracted at the very beginning of its formation. A mathematical simulation gives more answers in this area and might provide a more detailed answers. Also they can further support the recommendation for an urgent and non-urgent treatment area and the effect. The Center for Healthcare Operations Improvement and Research (CHOIR) at the University of Twente has a lot of experience in this field and can assigning PhD students to carry out this simulations and are able to investigate an complex problem such as crowding longer and more intensive. A lot of reliable data in essential for the input of the simulation model thus again emphasizing the need to register the time factors important when it comes to crowding in the electronic patient system.

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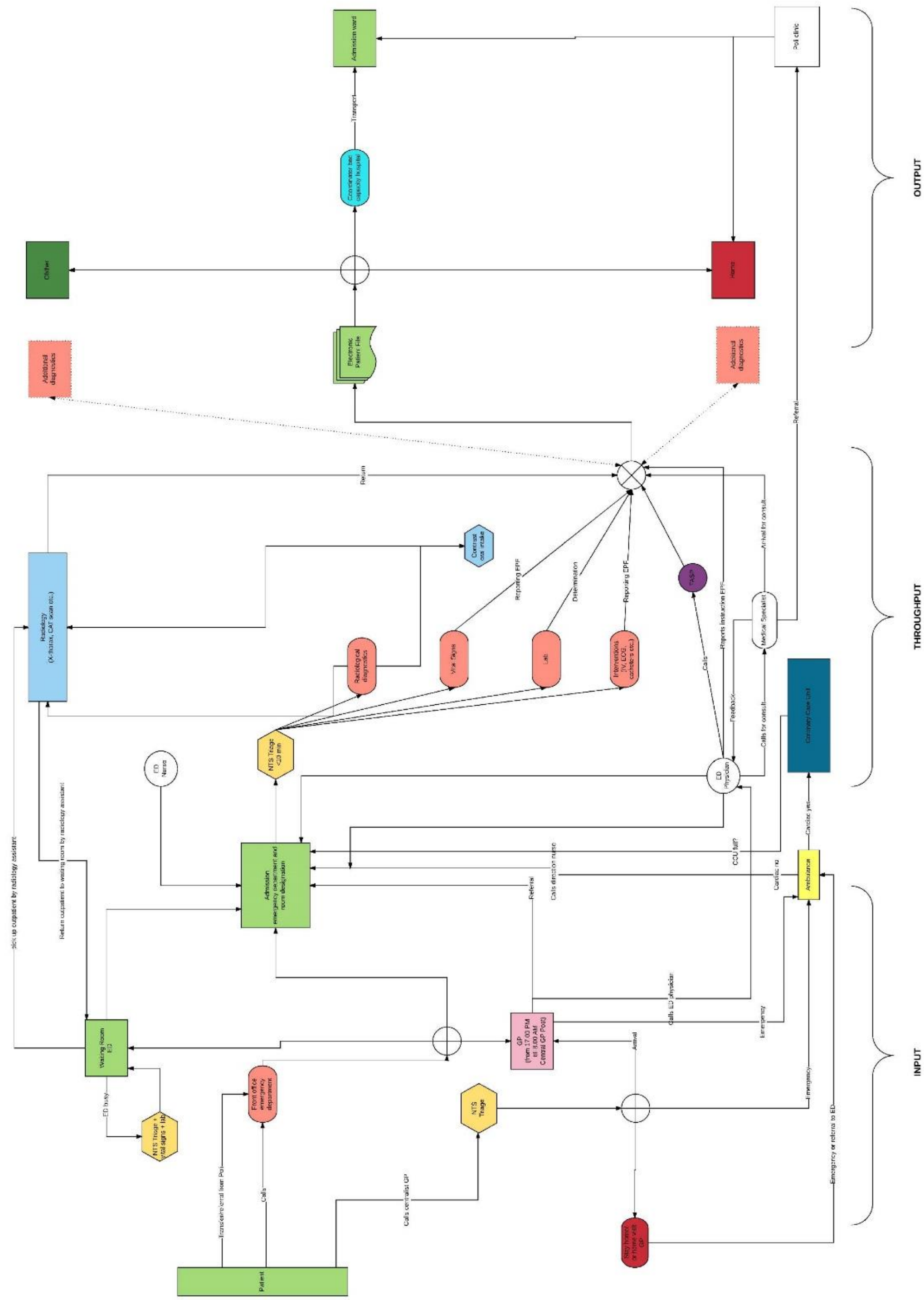
Appendix I: Detailed flowchart ED care process



Appendix I detailed flow chart of the various care processes at the ED of the Scheper Hospital Emmen

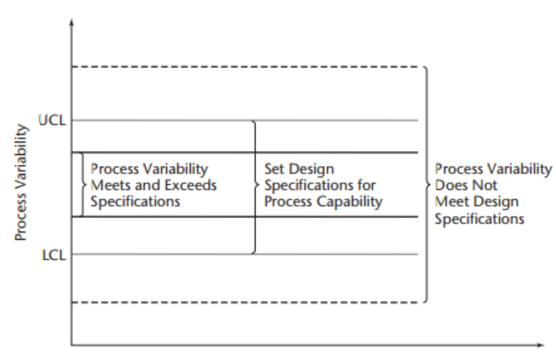
Appendix II: Control charts explanation

Quality Measurement and Control Techniques

For a further elaboration about the usage and application of control charts we give an overview from Quantitative Methods in Health Care Management textbook of Ozcan.

Process Variability In the delivery of health care, there are many occasions when an error can happen in the tasks performed by physicians, nurses, or allied health professionals such as radiation or physical therapists. Often the same task may not even be performed the same way for all patients, though minor alterations within defined limits can be acceptable. When, however, provider performance falls beyond acceptable limits, the errors that occur require investigation and correction. In order to detect noteworthy variations in process, or tendencies that may cause unacceptable levels of errors, health care managers must monitor the processes for quality, using various charts. The intent of the monitoring is to distinguish between random and nonrandom variation. The common variations in process variability that are caused by natural incidences are in general not repetitive, but various minor factors due to chance and are called random variation. If the cause of variation is systematic, not natural, and the source of the variation is identifiable, the process variation is called nonrandom variation. In health care, nonrandom variation may occur by not following procedures, using defective materials, fatigue, carelessness, or not having appropriate training or orientation to the work situation, among many reasons. Process variation is the range of natural variability in a process for which health care managers use control charts to monitor the measurements. If the natural variability or the presence of random variation exceeds tolerances set by control charts, then the process is not meeting the design specifications. Figure 12.3 shows a chart with design specifications to achieve a certain level of quality as determined by the lower confidence level (LCL) and the upper confidence level (UCL).

FIGURE 12.3. PROCESS CAPABILITY.

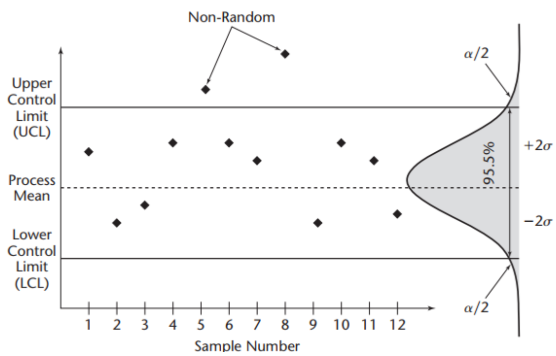


(We will show later how the LCL and UCL can be determined.) From this chart, three possible outcomes can be seen to occur. First, the actual outcomes can be so good that process variability would be contained in a narrower band than the design specifications. That may be due to an excellent quality program, or on the other hand, to design specification being too lax. In the second scenario outcomes could occur within LCL and UCL so that the expected quality would be achieved. However, in the third scenario, outcomes could occur beyond the design specifications, not meeting the expected quality outcomes. Then, health care managers should focus on the causes that create such variation by conducting investigations. Such outcomes are generally not random but systematic, and the sources in systematic factors must be found and corrected. In such situations, the health care manager usually must consider redesigning the system that causes such nonrandom outcomes. For example, high turnover and improperly trained new staff could be one of the sources for the process variation in nursing care units. Therefore, the health care manager may have to redesign and enforce the in-service training as well as having to attack problems causing high staff turnovers.

Monitoring Variation through Control Charts

A control chart is a tool to display in graphic form the control limits on process outcomes. In the hospitals, the outcomes can be staff response to patient requests, accuracy of medications, infections, accuracy of laboratory tests, and expedience of admissions and discharge processes, to name just some among the many that can be monitored with control charts. The health care manager has to use the appropriate type of control chart for the process being monitored, and that depends on how the process is measured. For example, how many times a staff member did not respond within the appropriate time to a patient request is a counting process, and the variables used to measure this outcome are attributes. Thus a c-chart for attributes is the appropriate control chart for such count-type measurements. Similarly, if the process is measured by the percentage of the responses received by patients that were inappropriate, or the percentage of design specifications that were not met (for example, percentage of discharges that are not processed within two hours of discharge orders), then the appropriate attribute based control chart is a p-chart. The other two commonly used charts are mean and range charts, which monitor process mean and range. Note that mean and range charts must be used together to monitor process variation. Although the construction of control charts depends on the measurement variable (monitoring attribute versus process mean/range), all control charts have common characteristics. Each chart has a process mean and lower and upper control limits that are calculated according to the type of measurement variable. The control limits theoretically separate random variation from nonrandom variation. Samples taken from the process in a time order are shown in Figure 12.4, where the variation within ± 2 sigma level—95.5 percent probability—can be described as random variation. However, we must approach this determination with caution. If all points appear within the LCL-UCL, we are sure about this with only 95.5 percent con- fidence; that means there is a 4.5 percent chance that we may be erroneously concluding the process is random, when it is not. This is called Type II error. Similarly, consider the two points (samples 5 and 8) beyond the UCL in the graph, where we conclude the variation is nonrandom. Again, we are able say this with only 95.5 percent confidence, and 4.5 percent of the time we may commit the error of concluding non randomness when randomness is present; that is called Type I error, or risk. Since Type I error can occur above or below the confidence levels, the risk is divided evenly for each part, ± 2. One can reduce Type I error by using wider limits such as ± 3 sigma. However, then detection of nonrandom variations would become more difficult, leading to greater Type II error of concluding that nonrandom variations are random. In practice, ± 2 sigma level is usually used to determine LCL and UCL for control charts.

FIGURE 12.4. CONTROL LIMITS, RANDOM AND NONRANDOM SAMPLE OBSERVATIONS.



Control Charts for Attributes

When process characteristics can be counted, attribute-based control charts are the appropriate way to display the monitoring process. However, counting can be conceptualized in different ways. If the number of occurrences per unit of measure can be counted, or there can be a count of the number of bad occurrences but not of non occurrences, then a c-chart is the appropriate tool to display monitoring. Counting also can occur for a process with only two outcomes, good or bad (defective); in such cases, p-chart is the appropriate control chart. The p-chart arises from binomial distribution where only two outcomes are possible. c-Chart. Certain processes require counting bad occurrences as quality defects. For example, the number of wrong medications delivered in one thousand patient days, or the number of infections occurring during a month are such occurrences. Remember that counting occurs over a sample or over time, and that occurrences can be counted per unit of measure. The theoretical conceptualization of this process is described by Poisson distribution, with a mean of c and standard deviation of c. When there are enough samples in the quality control process, by invoking central limit theorem we can use normal approximation to Poisson and define the control limits of the c-chart as follows: [12.2]

$$\mathrm{UCL} = c + z\sqrt{c} \qquad [12.1]$$

$$\mathrm{LCL} = c - z\sqrt{c} \qquad [12.2]$$

where c represents the population mean for the number of defects over a unit (or time period). In the absence of population parameters, estimates of the sample mean and standard deviation can be used by replacing c with c, and confidence limits can be established as:

$$\mathrm{UCL} = \bar{c} + z\sqrt{\bar{c}} \qquad [12.3]$$

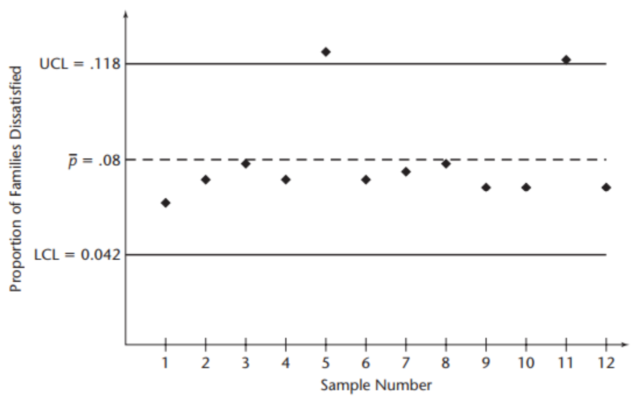
$$\mathrm{LCL} = \bar{c} - z\sqrt{\bar{c}} \qquad [12.4]$$

If LCL values are negative, for practical reasons they should be set to zero.

Control Charts for Variables

Mean and range charts are for variables measured continuously, such as “time” it takes to admit or discharge a patient. Mean charts monitor a central tendency or process average, and range charts monitor the dispersion of a process. These two charts are used together to determine whether a process is in control. Figure 12.7 displays two situations where neither chart alone can detect anomalies in the process quality. The upper chart in the figure shows that the process mean is stable, but that dispersion (variability) in the process is increasing.

FIGURE 12.6. HOLISTIC CARE CORPORATION’S QUALITY MONITORING.



In this situation the mean chart would not detect the shift in process variability, but the range chart would, as the range indicator increases steadily. The lower chart shows a process with stable range; however, the process mean increases. In this situation, the range chart would not detect the increasing trend in the process average; however, the mean chart would.

Mean Charts

Depending upon the available information, a mean chart can be constructed using either standard deviation or range information. Standard Deviation Approach. In general the population standard is unknown, and so the average of sample means x and the standard deviation of sample distribution x are used to construct the confidence limits as:

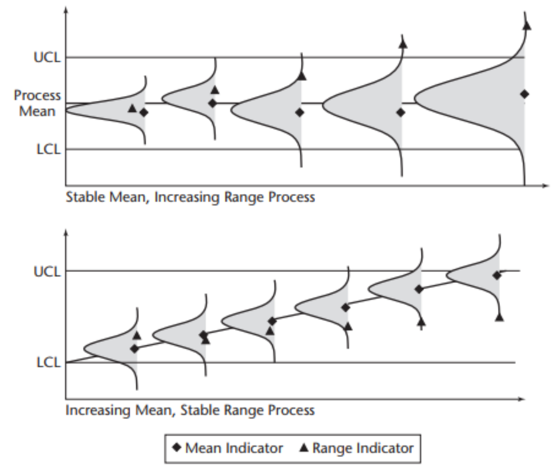
$$\mathrm{UCL} = \bar{\bar{x}} + z\sigma_{\bar{x}} \quad [12.9]$$

$$\mathrm{LCL} = \bar{\bar{x}} - z\sigma_{\bar{x}} \quad [12.10]$$

where

$$\sigma_{\bar{x}} = \frac{s}{\sqrt{n}}.$$

FIGURE 12.7. USE OF MEAN AND RANGE CHARTS.



Range Charts

Process dispersion is best monitored by range charts. The control limits for range charts are constructed using factors. To calculate LCL, factor score D3 is obtained from a factor chart based on the number of observations in the sample distributions. Similarly, to calculate UCL, factor score D4 is required. Control limits for range charts using these factor scores are then constructed as follows:

$$\mathrm{UCL} = D_4\overline{R} \qquad [12.13]$$

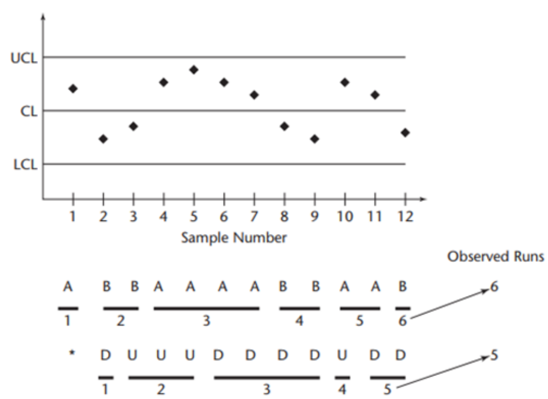
$$\mathrm{LCL} = D_3\overline{R}. \qquad [12.14]$$

Investigation of Control Chart Patterns

It is necessary to evaluate control chart patterns for anomalies, even though the observations stay within the confines of control limits. Although quality managers expect the sample variations to occur around the average line, sometimes consistent patterns can occur within control limits that are due to nonrandom causes and may require investigation. Such behavior can be characterized as consistent observations above or below the average (or center line); persistent zigzagging above and below the center line may signal disturbances in the system. Furthermore, high magnitude jumps from LCL to UCL or even beyond those limits may suggest nonrandomness and invokes investigation. Run-Based Pattern Tests. A pattern in a control chart described by a sequence of observations that have similar characteristics is called a "run." A simple classification of sample observations with respect to the center line that identify consecutive patterns is called an Above/Below run, or A/B run. For example, twelve observations shown in Figure 12.8 are classified as being above or below (A/B) the center line (CL).

If their classification is consecutive, it constitutes a run.

FIGURE 12.8. IDENTIFICATION OF RUNS.



In this example, an above (A) observation is followed by two consecutive below (B) observations, which are followed by four consecutive above observations, and so on. Whenever there is a switch in a classified observation, a new run starts. Hence there are six such A/B runs in this chart. Up (U) and down (D) runs is another way to classify and observe patterns. To classify sample observations as U or D, the first observation is used as a reference point, shown with "*" in Figure 12.8. Starting with the second observation one can classify each observation with respect to its predecessor. Here the second observation as compared to the first observation has a lower value, so its position is classified as down (D). The third observation as compared to the second observation has a higher value, so its position is classified as up (U). Ensuing observations are classified similarly. Once all observations are classified, the runs are identified by checking the consecutive patterns. In this example, the second observation is a stand-alone run. The next three observations are classified as up and constitute another run. The third run is a down run containing four observations. In total, there are five observed U/D runs in this example. Control chart patterns identified by runs require statistical testing of whether the runs are within expectations and hence the patterns are random, or beyond expectations and hence nonrandomness is present. It has been shown that runs are distributed approximately normally and using the z-test the significance of too few or too many observed runs can be determined as follows:

$$z = \frac{\text{Observed runs} - \text{Expected runs}}{\text{Standard deviation of runs}}. \qquad [12.15]$$

A z-value within ±2, which provides 95.5 percent confidence level, would show that the runs are random; however, beyond these values ±2 , a nonrandom presence would be shown. We already know how to determine observed runs, from an earlier discussion (Figure 12.8). It is necessary to calculate the expected runs and their standard deviations. The formulas for expected A/B or U/D runs and their standard deviations are as follows:

$$E(\text{run})_{\text{A/B}} = \frac{N}{2} + 1 \qquad [12.16]$$

$$\sigma(\text{run})_{\text{A/B}} = \sqrt{\frac{N-1}{4}} \qquad [12.17]$$

$$E(\text{run})_{\text{U/D}} = \frac{2N-1}{3} \qquad [12.18]$$

$$\sigma(\text{run})_{\text{U/D}} = \sqrt{\frac{16N-29}{90}}. \qquad [12.19]$$

Appendix III: Additional notes

Additional notes are added to the appendix who were made known to the researcher by the staff of the ED. Due to the inability to properly investigates these claims, but because they can be meaningful is a later stage of research or policy guidelines, they are added. Also a possibility which type of further research can be done is joined.

- *There is not a good mix between the senior and junior staff for both the nurses and doctors. The general feeling is that quality of staff is sometimes lacking and there is a mismatch between them.*
  One suggestion might be use work adjustment index. Claim needs further investigation.

- *Many patients are transferred to the ED of the Scheper Hospital Emmen from other hospitals with no clear need for this.*
  Suggestion might be to make agreements when and why a patient need transport.
  Claim needs further in-depth analysis.

- *Sometimes patients are referred to the ED because of convenience by the medical specialist and this unnecessary adds to the workload of the ED.*
  Again the suggestion might be to make agreements with medical specialism.
  Claim need further research.

- *Many additional task in the hospital like taking blood cultures from admitted patients. This hinders the operations at the ED.*
  Suggestion might be to add this time to the CoreLevel FTE's metric.
  Claim needs further investigation.

- *The coronary care unit benefits from us when they are busy but not vice versa. This creates an unfair working atmosphere.*
  Again agreements can be a solution or combining all the acute services at one location for passages of staff during peak moments. Claim needs further analysis.

- *Why can't the medical specialist themselves during peak moments diagnose and treatment at the ED. This would improve the treatment time considerably.*
  It is known to the researcher that the Hospital Bernhoven at Uden has medical specialists working and designated to the ED. The hospital is taken over by the health insurer VGZ and they redesigned the whole ED as an example for other hospitals in the Netherlands. Results thus far are promising and are worth further research.