Technische Universiteit
Eindhoven
University of Technology

Health Care Management and Modelling

Ivo Adan

Tools

Tools

- Main site for simulation language χ 3.0 is http://chi.se.wtb.tue.nl including:
  - Tool manual (installation, use of software)
  - Tutorial
  - Reference manual (details of χ 3.0)

Tools

- Main site for simulation language $\chi 3.0$ is http://chi.se.wtb.tue.nl including:
  - Tool manual (installation, use of software)
  - Tutorial
  - Reference manual (details of $\chi 3.0$)
- Software package R software is recommended for statistical computing (distribution plots, histograms, ...)

Objectives

Objectives

- Able to model, simulate and analyze health care systems

Objectives

- Able to model, simulate and analyze health care systems
- Able to construct and analyze elementary queueing models

Objectives

- Able to model, simulate and analyze health care systems
- Able to construct and analyze elementary queueing models
- Getting hands-on experience with simulation language χ 3.0

Objectives

- Able to model, simulate and analyze health care systems
- Able to construct and analyze elementary queueing models
- Getting hands-on experience with simulation language χ 3.0
- Develop intuition and understanding of critical logistical parameters

Objectives

- Able to model, simulate and analyze health care systems
- Able to construct and analyze elementary queueing models
- Getting hands-on experience with simulation language χ3.0
- Develop intuition and understanding of critical logistical parameters
- Develop understanding of the power and limitations of stochastic models for health care systems

Modeling: basic steps

Modeling: basic steps

- Identify the issues to be addressed

Modeling: basic steps

- Identify the issues to be addressed
- Learn about the system

Modeling: basic steps

- Identify the issues to be addressed
- Learn about the system
- Choose a modeling approach

Modeling: basic steps

- Identify the issues to be addressed
- Learn about the system
- Choose a modeling approach
- Develop and test the model

Modeling: basic steps

- Identify the issues to be addressed
- Learn about the system
- Choose a modeling approach
- Develop and test the model
- Verify and validate the model

Modeling: basic steps

- Identify the issues to be addressed
- Learn about the system
- Choose a modeling approach
- Develop and test the model
- Verify and validate the model
- Experiment with the model (what can you learn?)

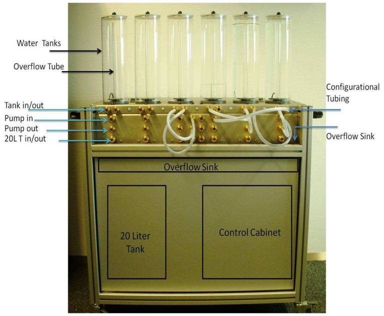
Modeling: basic steps

- Identify the issues to be addressed
- Learn about the system
- Choose a modeling approach
- Develop and test the model
- Verify and validate the model
- Experiment with the model (what can you learn?)
- Present the results!

Modeling: Types of models

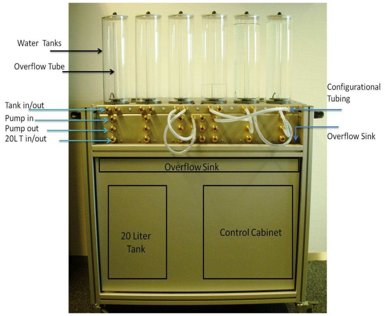
Modeling: Types of models

- (Small scale) Physical models (Water emulator Liquitrol)



Modeling: Types of models

- (Small scale) Physical models (Water emulator Liquitrol)

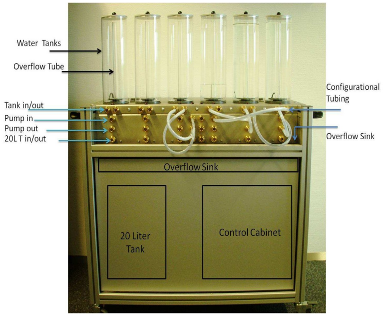


- Simulation models (χ3.0 code)

```
model result GRSE():
    chan patient a, b, c;
    run G(a, exponential(6.0)),
        R(a, b),
        S(b, c, gamma(4.0,1.0)),
        E(c, 6000.0)
end
```

Modeling: Types of models

- (Small scale) Physical models (Water emulator Liquitrol)



- Simulation models (χ 3.0 code)

```
model result GRSE():
    chan patient a, b, c;
    run G(a, exponential(6.0)),
        R(a, b),
        S(b, c, gamma(4.0,1.0)),
        E(c, 6000.0)
end
```

- Analytical models (Queueing formulas)

$$E(W) = \frac{1}{2}\,(1 + c_b^2)\,\frac{\rho}{1-\rho}\,E(B)$$

Modeling: Why?

Modeling: Why?

- Understanding

Modeling: Why?

- Understanding
- Intuition building

Modeling: Why?

- Understanding
- Intuition building
- Improvement

Modeling: Why?

- Understanding
- Intuition building
- Improvement
- Optimization

Modeling: Why?

- Understanding
- Intuition building
- Improvement
- Optimization
- Support decision making

Modeling: Issues

Modeling: Issues

- Trade-off between complexity and simplicity

Modeling: Issues

- Trade-off between complexity and simplicity
- Flexibility

Modeling: Issues

- Trade-off between complexity and simplicity
- Flexibility
- Data requirements

Modeling: Issues

- Trade-off between complexity and simplicity
- Flexibility
- Data requirements
- Transparency

Modeling: Issues

- Trade-off between complexity and simplicity
- Flexibility
- Data requirements
- Transparency
- Effective modeling requires intuition, analytical and simulation capability

Modeling: Issues

- Trade-off between complexity and simplicity
- Flexibility
- Data requirements
- Transparency
- Effective modeling requires intuition, analytical and simulation capability
- Art of modeling is in the selection of the right model for a given situation

Modeling: Critical logistical parameters

Modeling: Critical logistical parameters

- Throughput: Number of patients treated per time unit

Modeling: Critical logistical parameters

- Throughput: Number of patients treated per time unit
- Flow time or cycle time: Time it takes a patient to go through the system

Modeling: Critical logistical parameters

- Throughput: Number of patients treated per time unit
- Flow time or cycle time: Time it takes a patient to go through the system
- Cycle time factor: Cycle time divided by service time

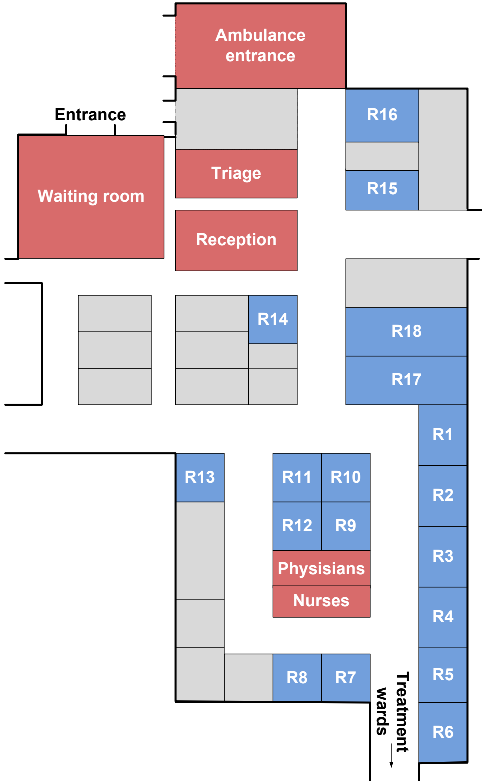
Modeling: Critical logistical parameters

- Throughput: Number of patients treated per time unit
- Flow time or cycle time: Time it takes a patient to go through the system
- Cycle time factor: Cycle time divided by service time
- Utilization: Fraction of time resource (bed, room, nurse, ...) is being used

Emergency Department

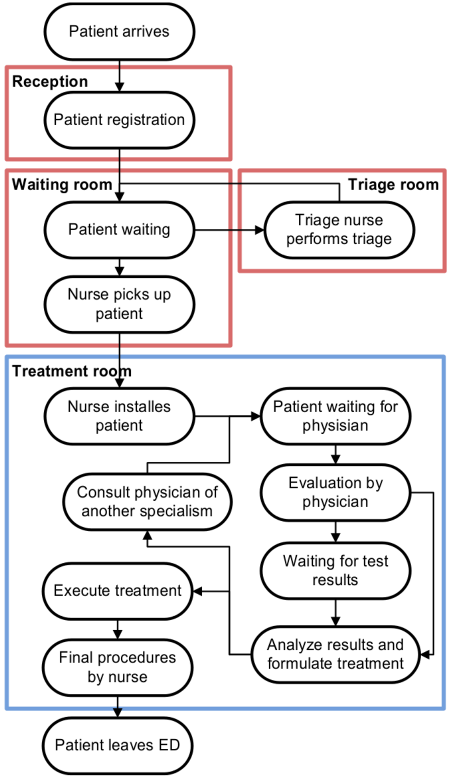
Emergency department (ED) of Catherina Hospital Eindhoven

Emergency Department



Layout of ED

Emergency Department



Patient flow through ED

Goal

Goal

- Develop model to support decision making in LEAN process improvement programs

Goal

- Develop model to support decision making in LEAN process improvement programs
- Address questions such as:
  - What capacity is required to meet target maximal waiting times?
  - How much does waiting time decrease by increasing nursing staff?
  - What is the effect of an increase in inflow due to the aging population?

Queueing model: Basic elements

Queueing model: Basic elements

- Patient arrivals

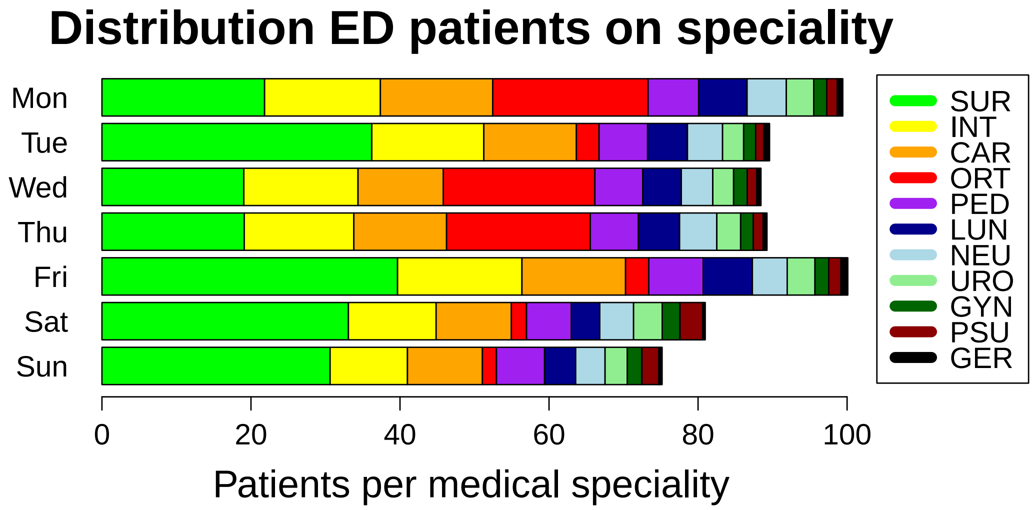
Queueing model: Basic elements

- Patient arrivals
- Treatment times

Queueing model: Basic elements

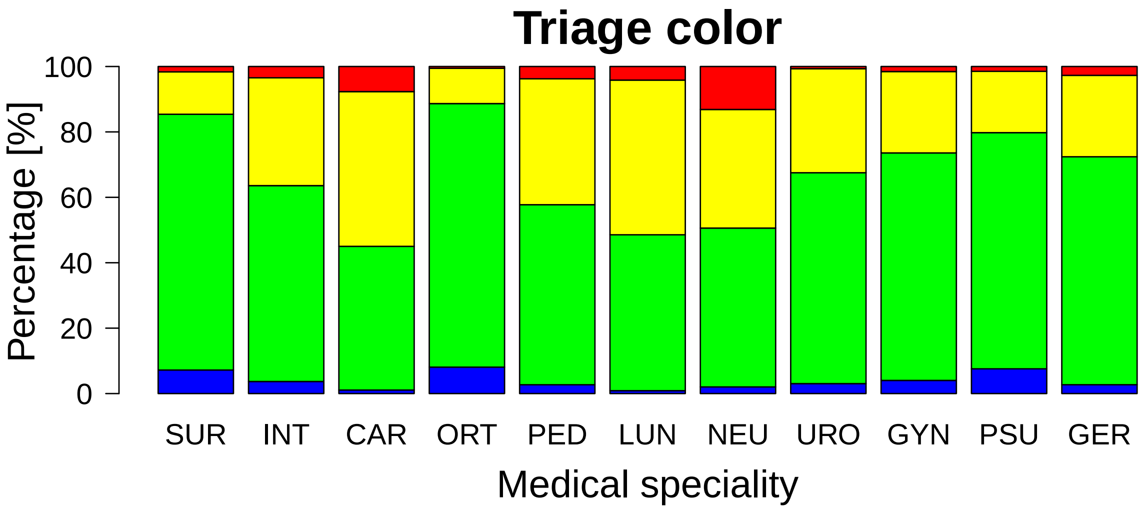
- Patient arrivals
- Treatment times
- Resource capacities

Arrivals and diversity

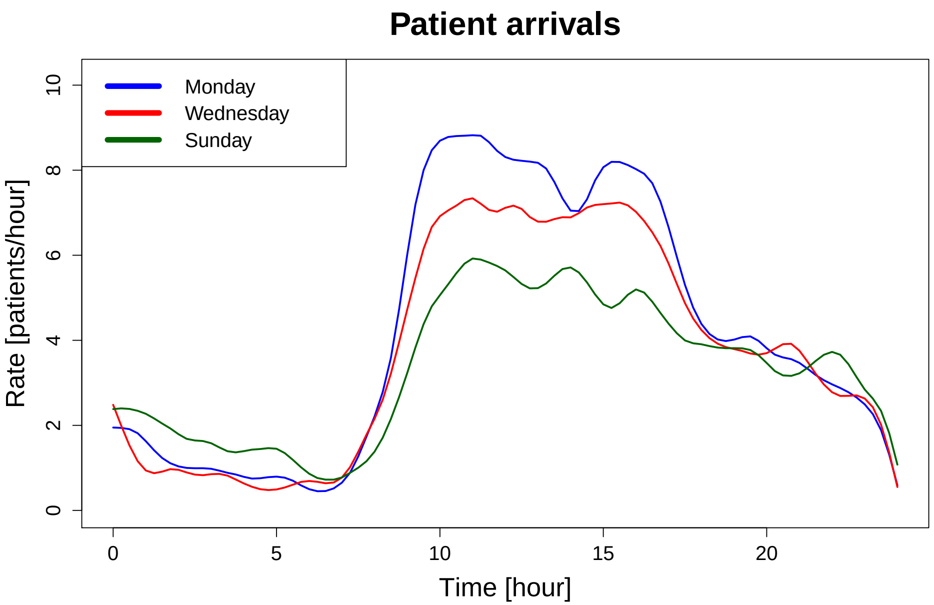


Technische Universiteit
Eindhoven
University of Technology

Arrivals and diversity



Arrivals and diversity



Arrival flow variability

Arrival flow variability

- Flow refers to arrival of patients

Arrival flow variability

- Flow refers to arrival of patients
- t_a and σ_a are mean and standard deviation of time between arrivals

Arrival flow variability

- Flow refers to arrival of patients
- t_a and σ_a are mean and standard deviation of time between arrivals
- Arrival rate

$$r_a = \frac{1}{t_a}$$

Arrival flow variability

- Flow refers to arrival of patients
- t_a and σ_a are mean and standard deviation of time between arrivals
- Arrival rate

$$r_a = \frac{1}{t_a}$$

- Coefficient of variation of time between arrivals

$$c_a = \frac{\sigma_a}{t_a}$$

Low c_a arrivals

High c_a arrivals

Poisson arrival flow

Poisson arrival flow

- Times between arrivals are independent and Exponential with rate λ

Poisson arrival flow

- Times between arrivals are independent and Exponential with rate λ
- So

$$t_a = \frac{1}{\lambda}, \quad r_a = \lambda, \quad c_a = 1$$

Properties of Poisson arrival flow: Memoryless

Properties of Poisson arrival flow: Memoryless

- Memoryless property

$$\mathsf{P}(\text{arrival in } (t, t+\Delta)) = 1 - e^{-\lambda\Delta} \approx \lambda\Delta$$

So in each small interval Δ there is an arrival with probability $\lambda\Delta$!

Properties of Poisson arrival flow: Memoryless

- Memoryless property

$$\mathrm{P}(\text{arrival in } (t, t+\Delta)) = 1 - e^{-\lambda\Delta} \approx \lambda\Delta$$

  So in each small interval Δ there is an arrival with probability $\lambda\Delta$!

- This means: “truly unpredictable arrivals”

Properties of Poisson arrival flow: Binomial and Poisson

Properties of Poisson arrival flow: Binomial and Poisson

- Dividing $(0, t)$ into intervals of length Δ, the number of arrivals in $(0, t)$ is Binomial with $n = \frac{t}{\Delta}$ and $p = \lambda\Delta$

Properties of Poisson arrival flow: Binomial and Poisson

- Dividing $(0, t)$ into intervals of length Δ, the number of arrivals in $(0, t)$ is Binomial with $n = \frac{t}{\Delta}$ and $p = \lambda\Delta$
- Since n is large and p is small, this number is Poisson distributed with parameter $np = \lambda t$

$$\mathrm{P}(k \text{ arrivals in } (0, t)) = e^{-\lambda t}\frac{(\lambda t)^k}{k!}, \quad k = 0, 1, 2, \ldots$$

This explains the name “Poisson process”

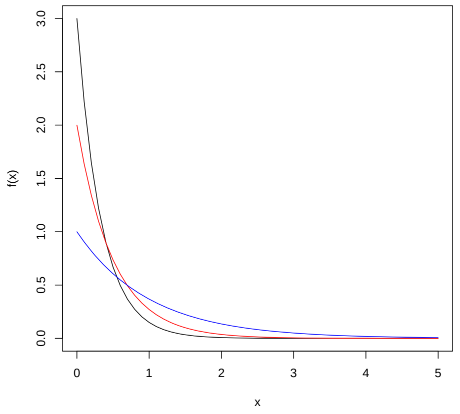
Properties of Poisson arrival flow: Clustered arrivals

Properties of Poisson arrival flow: Clustered arrivals

- Since Exponential density

$$f(x) = \lambda e^{-\lambda x}$$

is maximal for $x = 0$, short inter-arrival times occur more frequently than long ones

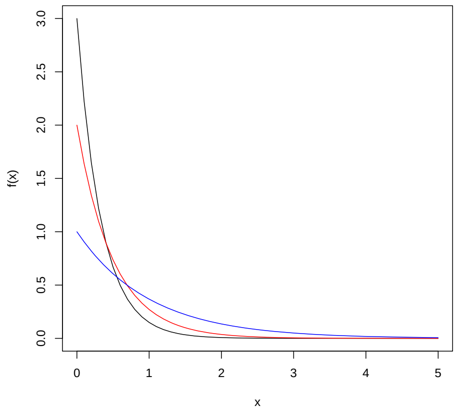


Properties of Poisson arrival flow: Clustered arrivals

- Since Exponential density

$$f(x) = \lambda e^{-\lambda x}$$

is maximal for $x = 0$, short inter-arrival times occur more frequently than long ones



- So arrivals tend to cluster:

Properties of Poisson arrival flow: Many rare arrival flows

Properties of Poisson arrival flow: Many rare arrival flows

- Superposition of many independent rarely occurring arrival flows is (close to) Poisson

Properties of Poisson arrival flow: Many rare arrival flows

- Superposition of many independent rarely occurring arrival flows is (close to) Poisson
- This explains why Poisson flows so often occur in practice!

Properties of Poisson arrival flow: Merging and splitting

Properties of Poisson arrival flow: Merging and splitting

- Merging of two Poisson flows with rates λ_1 and λ_2 is again Poisson with rate $\lambda_1 + \lambda_2$, since

$$\mathrm{P}(\text{arrival in } (t, t+\Delta)) \approx \lambda_1\Delta + \lambda_2\Delta = (\lambda_1 + \lambda_2)\Delta$$

Given there is an arrival in $(t, t+\Delta)$, it is of type 1 with probability

$$\begin{aligned}
\mathrm{P}(\text{type } 1 \text{ arrival in } (t, t+\Delta) | \text{arrival in } (t, t+\Delta)) &= \frac{\mathrm{P}(\text{type } 1 \text{ arrival in } (t, t+\Delta))}{\mathrm{P}(\text{arrival in } (t, t+\Delta))} \\
&= \frac{\lambda_1\Delta}{(\lambda_1+\lambda_2)\Delta} \\
&= \frac{\lambda_1}{\lambda_1+\lambda_2}
\end{aligned}$$

Properties of Poisson arrival flow: Merging and splitting

- Merging of two Poisson flows with rates λ_1 and λ_2 is again Poisson with rate $\lambda_1 + \lambda_2$, since

$$\mathrm{P}(\text{arrival in } (t, t+\Delta)) \approx \lambda_1 \Delta + \lambda_2 \Delta = (\lambda_1 + \lambda_2)\Delta$$

Given there is an arrival in $(t, t+\Delta)$, it is of type 1 with probability

$$\begin{aligned}
\mathrm{P}(\text{type 1 arrival in } (t, t+\Delta) | \text{arrival in } (t, t+\Delta)) &= \frac{\mathrm{P}(\text{type 1 arrival in } (t, t+\Delta))}{\mathrm{P}(\text{arrival in } (t, t+\Delta))} \\
&= \frac{\lambda_1 \Delta}{(\lambda_1 + \lambda_2)\Delta} \\
&= \frac{\lambda_1}{\lambda_1 + \lambda_2}
\end{aligned}$$

- Random splitting of Poisson flows with rate λ and splitting probability p is again Poisson with rate $p\lambda$, since

$$\mathrm{P}(\text{arrival in } (t, t+\Delta)) \approx p\lambda\Delta$$

Inhomogeneous Poisson arrival flow

Inhomogeneous Poisson arrival flow

- Arrival rate is not constant but time-dependent $\lambda(t)$

Inhomogeneous Poisson arrival flow

- Arrival rate is not constant but time-dependent $\lambda(t)$
- So

$$\mathrm{P}(\text{arrival in } (t, t+\Delta)) \approx \lambda(t)\Delta$$

Inhomogeneous Poisson arrival flow

- Arrival rate is not constant but time-dependent $\lambda(t)$
- So

$$\text{P(arrival in } (t, t+\Delta)) \approx \lambda(t)\Delta$$

- Question: How to simulate a realization of an inhomogeneous Poisson arrival flow?

Inhomogeneous Poisson arrival flow

- Arrival rate is not constant but time-dependent $\lambda(t)$
- So

$$\mathrm{P}(\text{arrival in } (t, t+\Delta)) \approx \lambda(t)\Delta$$

- Question: How to simulate a realization of an inhomogeneous Poisson arrival flow?
- Answer: Suppose there is a maximum rate $\Lambda = \max_{t \geq 0} \lambda(t)$

Inhomogeneous Poisson arrival flow

- Arrival rate is not constant but time-dependent $\lambda(t)$
- So

$$\mathrm{P}(\text{arrival in } (t, t+\Delta)) \approx \lambda(t)\Delta$$

- Question: How to simulate a realization of an inhomogeneous Poisson arrival flow?
- Answer: Suppose there is a maximum rate $\Lambda = \max_{t \geq 0} \lambda(t)$
  - Simulate Poisson flow with constant rate Λ

Inhomogeneous Poisson arrival flow

- Arrival rate is not constant but time-dependent $\lambda(t)$
- So

$$\mathrm{P}(\text{arrival in } (t, t+\Delta)) \approx \lambda(t)\Delta$$

- Question: How to simulate a realization of an inhomogeneous Poisson arrival flow?
- Answer: Suppose there is a maximum rate $\Lambda = \max_{t \geq 0} \lambda(t)$
  - Simulate Poisson flow with constant rate Λ
  - When arrival at time t, then:
    - ▶ accept arrival with probability $\frac{\lambda(t)}{\Lambda}$
    - ▶ reject arrival otherwise

Treatment times

Treatment times

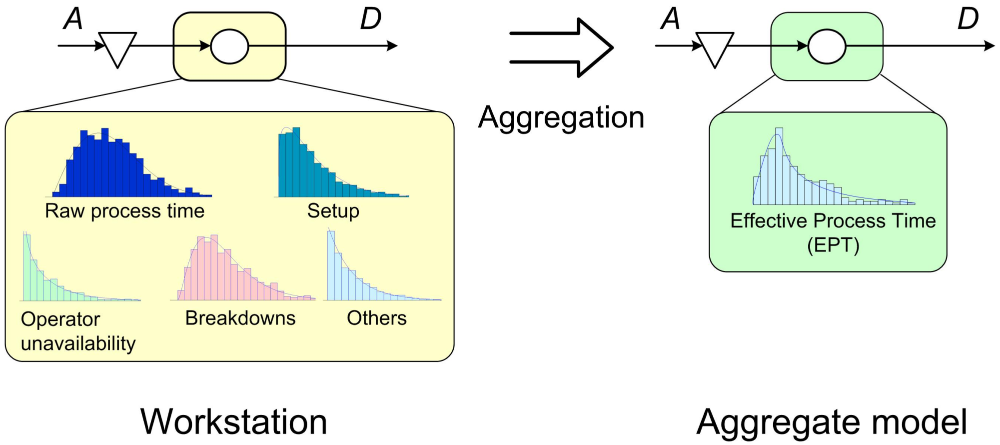
- Limited data available on activities in treatment rooms

Treatment times

- Limited data available on activities in treatment rooms
- Entrance and exit times in treatment rooms are accurately recorded

Treatment times

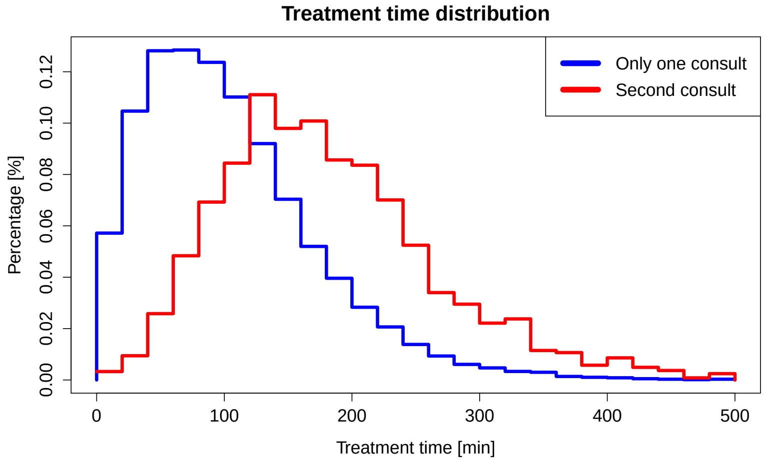
- Limited data available on activities in treatment rooms
- Entrance and exit times in treatment rooms are accurately recorded
- Employ the concept of Effective Process Times



Treatment times

Treatment times

- Treatment times of patients depend on patient characteristics such as:
  - Medical speciality
  - Triage color
  - Age
  - Type of attending physician



Technische Universiteit Eindhoven University of Technology

Treatment times

Treatment times

- Patient charateristics lead to almost 7000 treatment time groups!

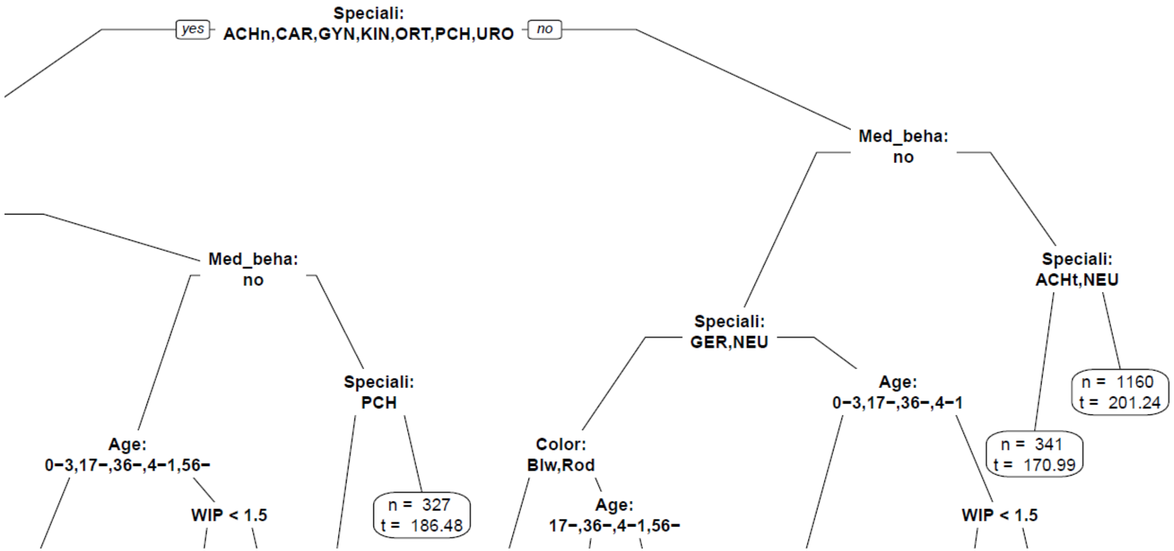
Technische Universiteit Eindhoven University of Technology

Treatment times

- Patient charateristics lead to almost 7000 treatment time groups!
- Only 34000 measurements: this calls for lumping

Treatment times

- Patient charateristics lead to almost 7000 treatment time groups!
- Only 34000 measurements: this calls for lumping
- Recursive partitioning leads to 34 groups of treatment times on which a distribution can be reliably fitted



Resource capacity and use

Resource capacity and use

- Simultaneous resource use: Patient needs room, nurse and physician

Resource capacity and use

- Simultaneous resource use: Patient needs room, nurse and physician
- Multi-processing feature: Nurses and physicians are capable of handling multiple patients simultaneously

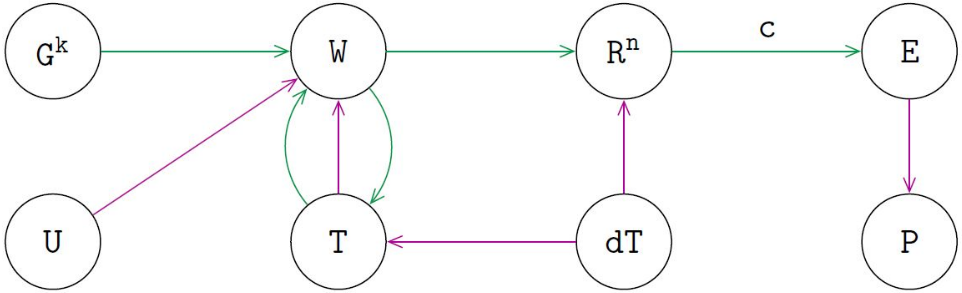
Resource capacity and use

- Simultaneous resource use: Patient needs room, nurse and physician
- Multi-processing feature: Nurses and physicians are capable of handling multiple patients simultaneously
- These features are modeled by a token system:
  - Every nurse is represented by 4 tokens (treat max 4 patients)
  - Every patient needs 1 nurse token
  - Same token mechanism used for triage nurse and physicians

Resource capacity and use

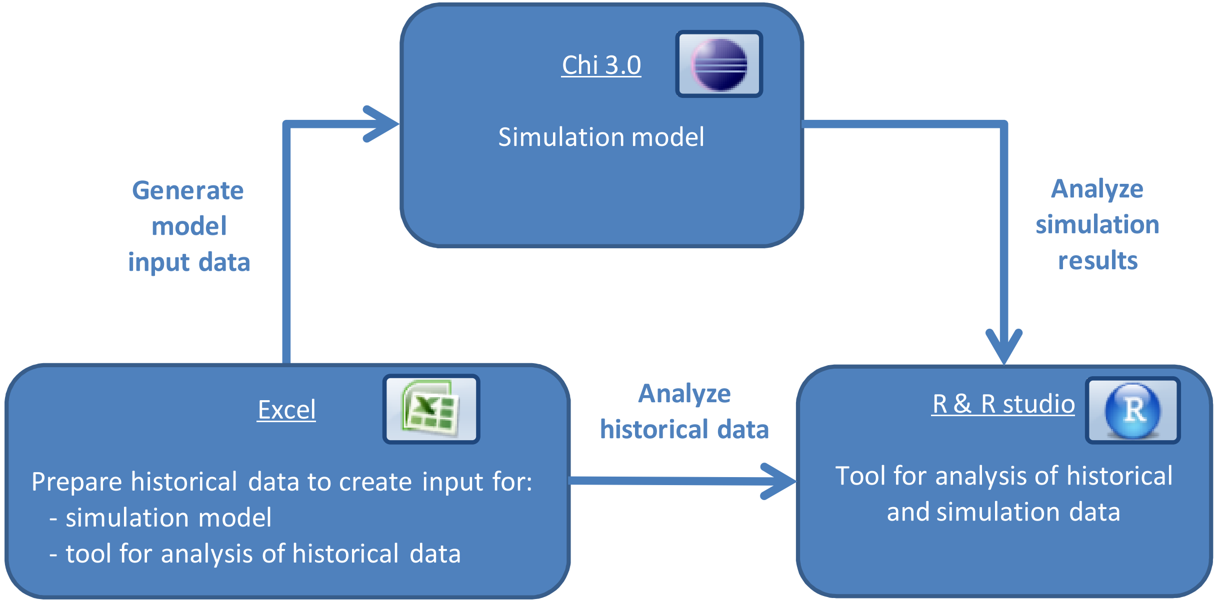
- Simultaneous resource use: Patient needs room, nurse and physician
- Multi-processing feature: Nurses and physicians are capable of handling multiple patients simultaneously
- These features are modeled by a token system:
  - Every nurse is represented by 4 tokens (treat max 4 patients)
  - Every patient needs 1 nurse token
  - Same token mechanism used for triage nurse and physicians
- Staffing levels adapted to workload during the day:
  Working rosters for each weekday specifying the available capacity at each point in time during the day

Simulation model

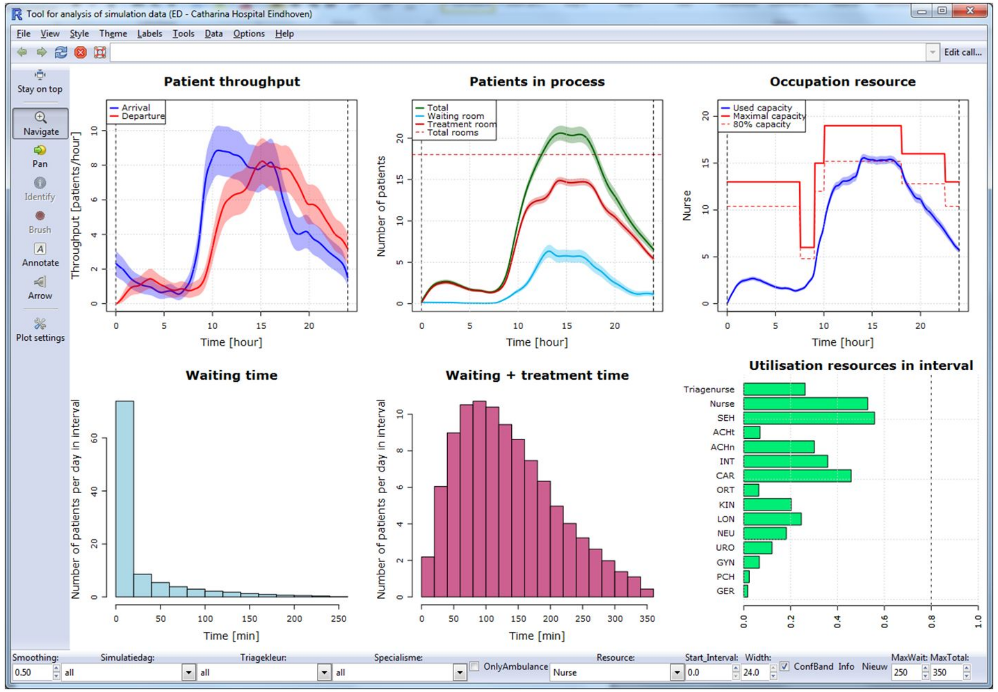


High level χ 3.0 model of ED: Green is patient flow, Purple information flow

Software package

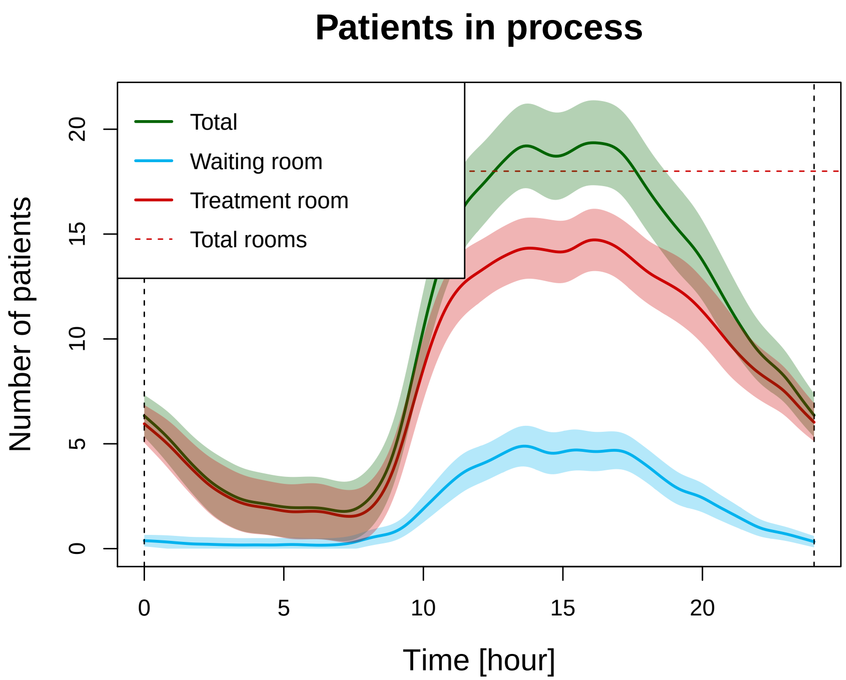


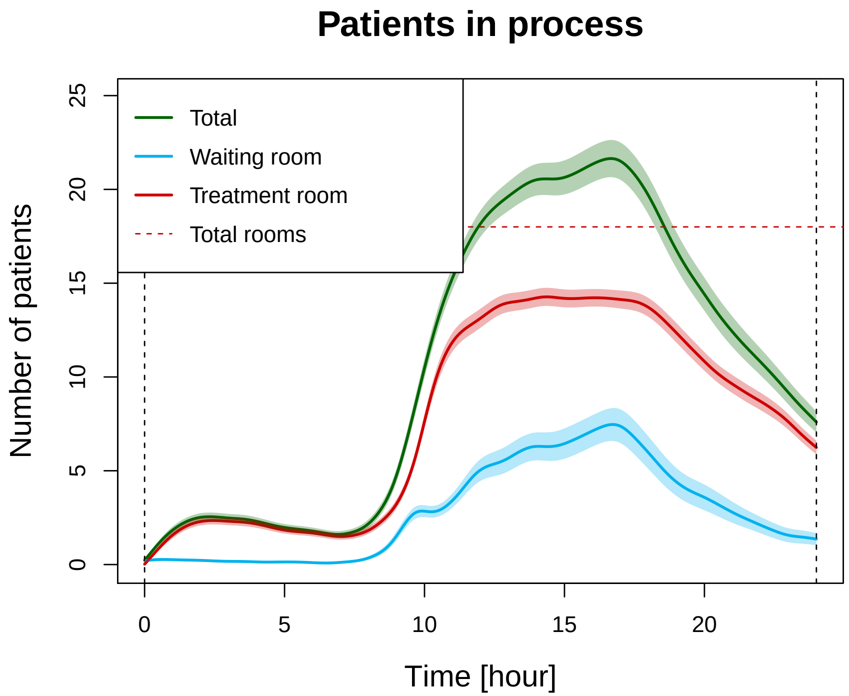
Emergency Department



Snapshot of simulation output of χ3.0 model

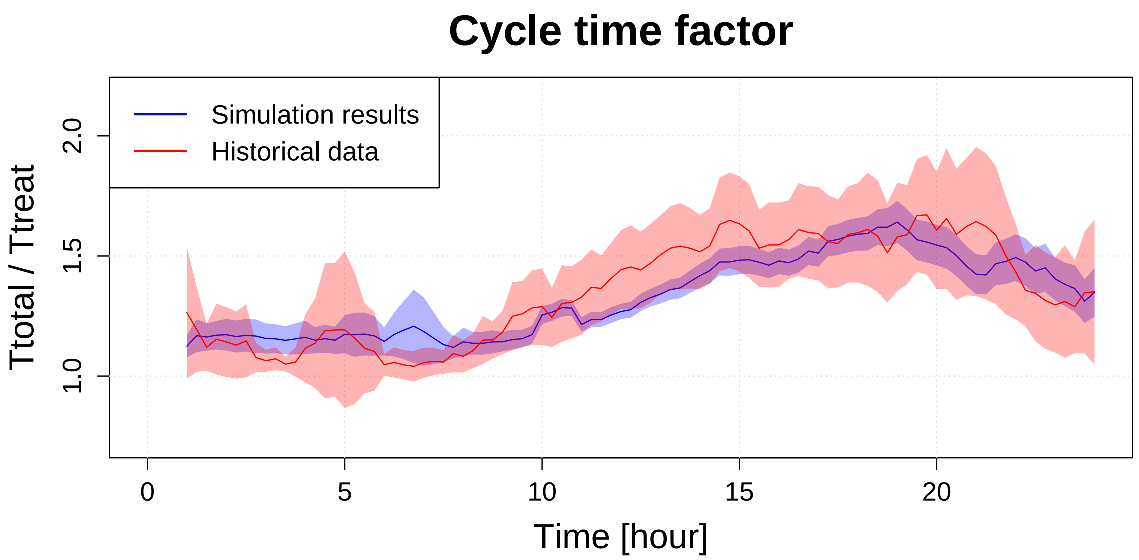
Validation





Historical (left) and simulated (right) average occupation on Monday

Validation



Cycle time factor for historical and simulated patients on Monday

Decision support

Improvement opportunities:

Decision support

Improvement opportunities:

- Reduce waiting times or number of patients waiting

Decision support

Improvement opportunities:

- Reduce waiting times or number of patients waiting
- Increase utilization of resources (rooms, nurses, ...)

Options:

Decision support

Improvement opportunities:

- Reduce waiting times or number of patients waiting
- Increase utilization of resources (rooms, nurses, ...)

Options:

- More treatment rooms

Decision support

Improvement opportunities:

- Reduce waiting times or number of patients waiting
- Increase utilization of resources (rooms, nurses, ...)

Options:

- More treatment rooms
- No priority for ambulance patients

Decision support

Improvement opportunities:

- Reduce waiting times or number of patients waiting
- Increase utilization of resources (rooms, nurses, ...)

Options:

- More treatment rooms
- No priority for ambulance patients
- More nursing capacity

Decision support

Improvement opportunities:

- Reduce waiting times or number of patients waiting
- Increase utilization of resources (rooms, nurses, ...)

Options:

- More treatment rooms
- No priority for ambulance patients
- More nursing capacity
- More physician capacity

Decision support

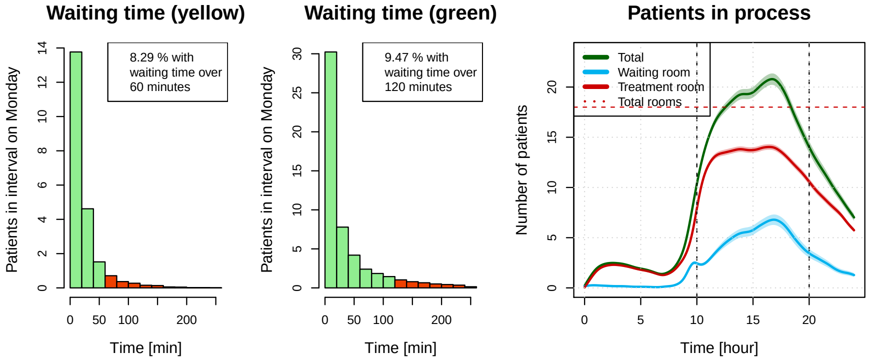
Improvement opportunities:

- Reduce waiting times or number of patients waiting
- Increase utilization of resources (rooms, nurses, ...)

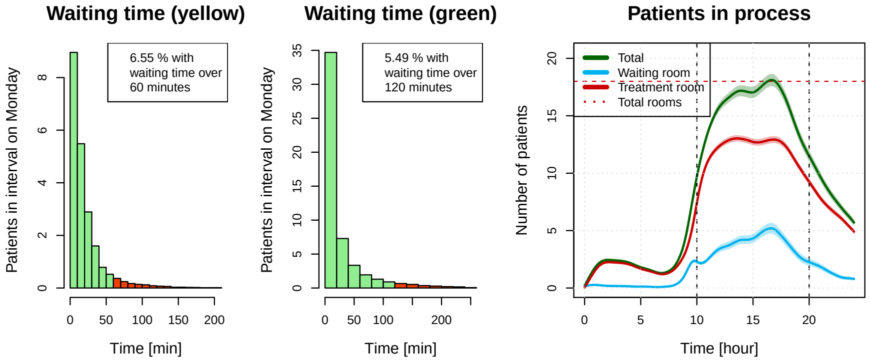
Options:

- More treatment rooms
- No priority for ambulance patients
- More nursing capacity
- More physician capacity
- Treatment time reduction (by shortening time to hospitalization)

Treatment time reduction (10 mins)



Simulation output on Monday for unadapted treatment time



Simulation output for 10 minutes treatment time reduction

Scenario analysis

Scenario analysis

- What effect has an increase of ED visits by elderly patients?

Scenario analysis

- What effect has an increase of ED visits by elderly patients?
- What extra capacity is needed if neighboring ED closes?

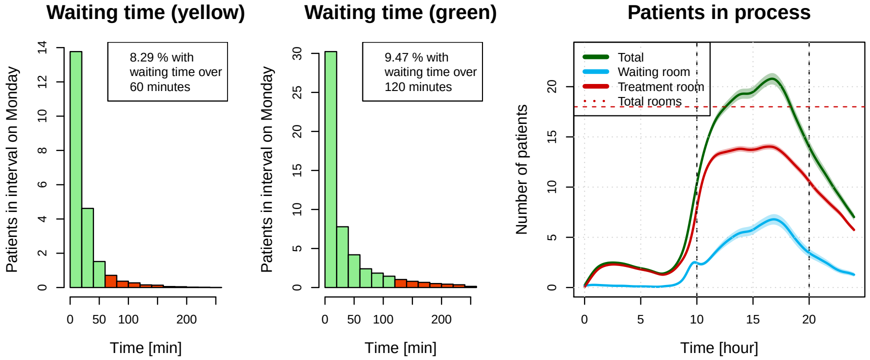
Scenario analysis

- What effect has an increase of ED visits by elderly patients?
- What extra capacity is needed if neighboring ED closes?
- What if average urgency of patients increases (due to less self-referrals)?

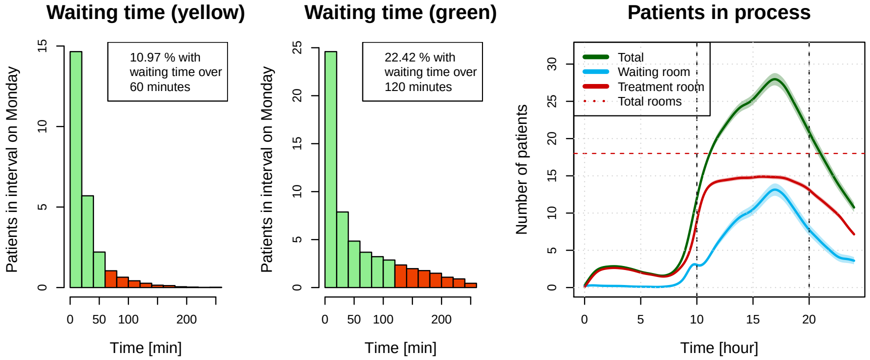
Scenario analysis

- What effect has an increase of ED visits by elderly patients?
- What extra capacity is needed if neighboring ED closes?
- What if average urgency of patients increases (due to less self-referrals)?
- What is more accurate triage results in less second consults?

Scenario: growth arrival rate (15%)



Simulation output on Monday for unadapted arrival rate



Simulation output for 15% growth of patient arrivals

References

References

- Aggregate model based performance analysis of an emergency department

References

- Aggregate model based performance analysis of an emergency department
- Aggregate modeling of semiconductor equipment using effective process times

References

- Aggregate model based performance analysis of an emergency department
- Aggregate modeling of semiconductor equipment using effective process times
- Aggregate simulation modeling of an mri department using effective process times