

Workforce Behaviours in Healthcare Systems

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THIS.

Supervisors:

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Thesis structure

1. Introduction
2. Literature review
3. Queueing theoretic model
4. Game theoretic model
5. Numerical results
6. Agent-based model
7. Conclusions

1. Introduction - Congestion in Healthcare

Patients forced to wait for 24 hours in ambulances, data shows

Ambulance crews forced to wait outside A&Es for 24 hours, according to chiefs

Rebecca Thomas Health Correspondent • Tuesday 17 May 2022 08:26 • Comments



(AFP/Getty)

'Appalling' waits for ambulances in England leaving lives at risk

Exclusive: Royal College of Emergency Medicine president says NHS is breaking its agreement to treat sickest in a timely way
The staff, this is heart-breaking - senior doctor's view on crisis
I feel so let down - long waits for ambulances on the south-west



Ambulance handover delays highest since start of winter
© iStockphoto.com



NHS 'on its knees' as ambulance response times for life-threatening calls rise to record high

Average response time to deal with Category 1 cases – such as cardiac arrest – is now nine minutes and 20 seconds, with rises across all categories.



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1. Introduction - Research contributions

- ▶ Queueing model with 2 consecutive waiting spaces.
- ▶ Performance measure formulas for queueing model.
- ▶ Game theoretic model between the EMS and two EDs.
- ▶ Numerical experiments showing emergent behaviour of gaming between EDs and the EMS.
- ▶ Reinforcement learning algorithm on ED staff to optimise their behaviour.

2. Literature Review

OR in Healthcare

**Game Theory and
Queueing Theory**

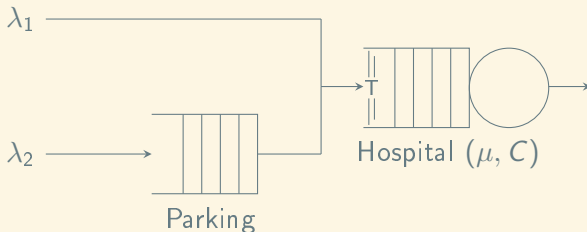
**Game Theory in
Healthcare**

Behavioural OR

3. Queueing theoretic model - Motivation



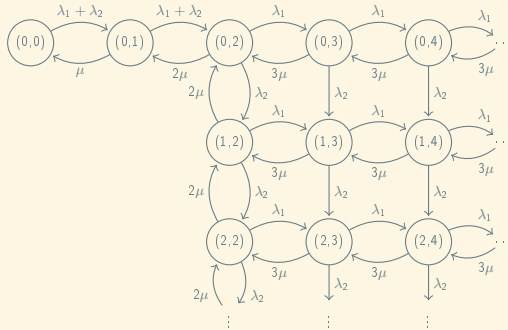
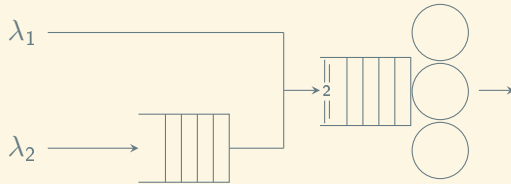
3. Queueing theoretic model - Diagrammatic representation



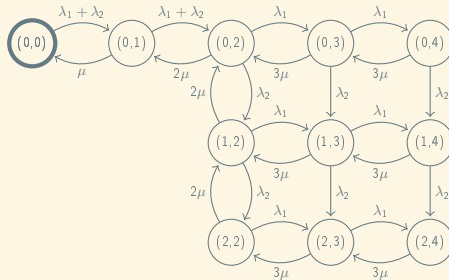
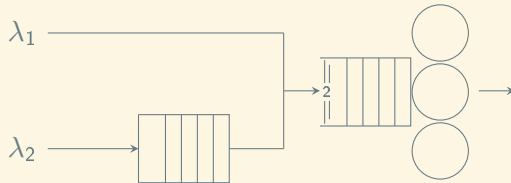
Parameters:

- ▶ λ_1 : Arrival rate of type 1 individuals
- ▶ λ_2 : Arrival rate of type 2 individuals
- ▶ μ : Service rate
- ▶ C : Number of servers
- ▶ T : Threshold

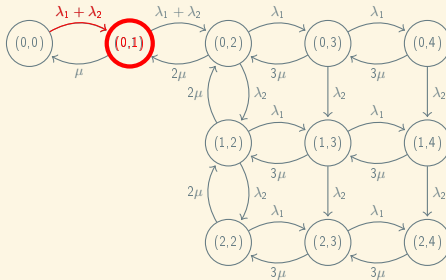
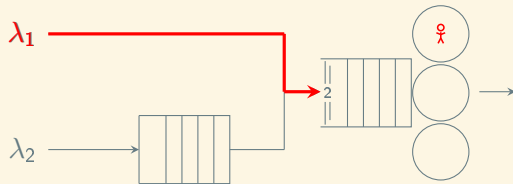
3. Queueing theoretic model - Markov Chain model



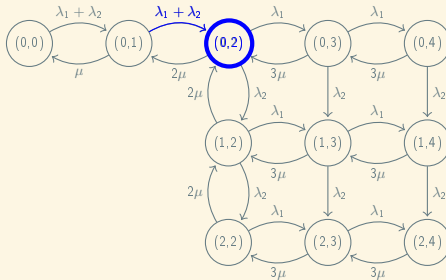
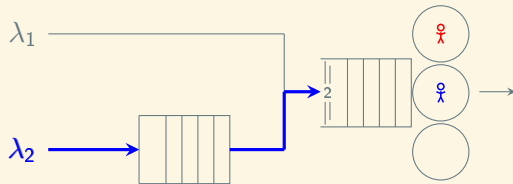
3. Queueing theoretic model - Markov Chain model



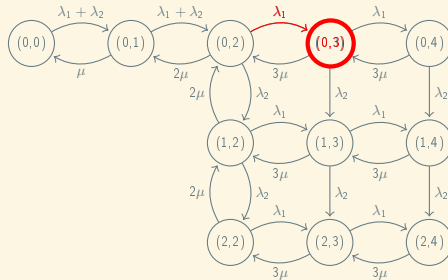
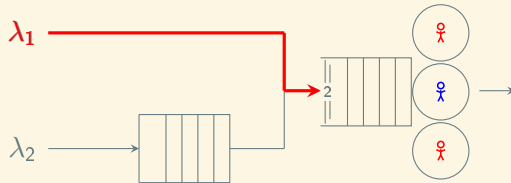
3. Queueing theoretic model - Markov Chain model



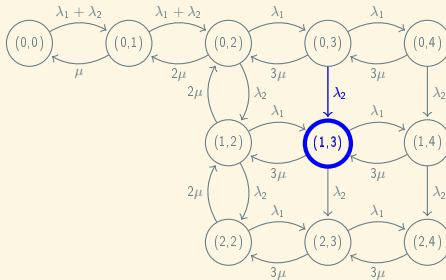
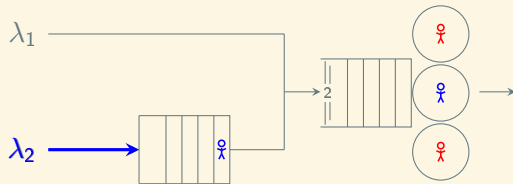
3. Queueing theoretic model - Markov Chain model



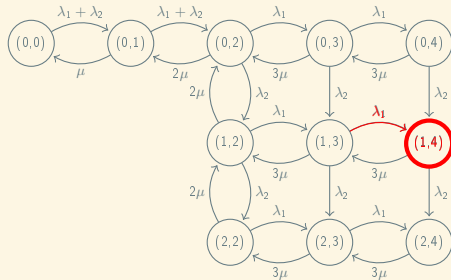
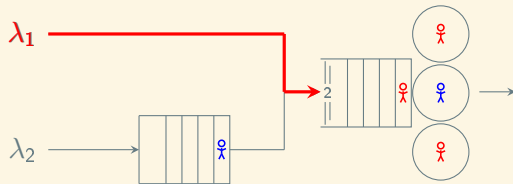
3. Queueing theoretic model - Markov Chain model



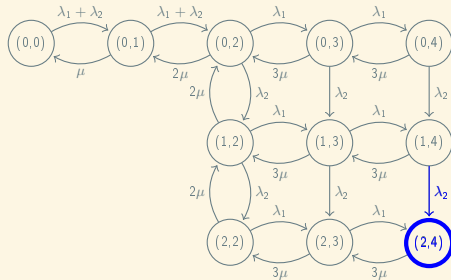
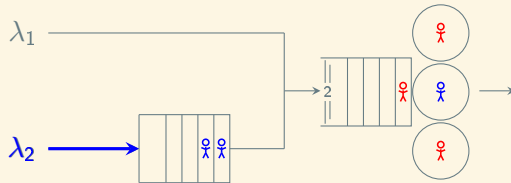
3. Queueing theoretic model - Markov Chain model



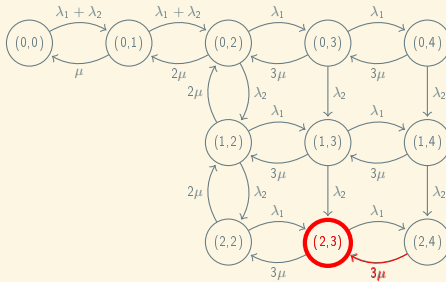
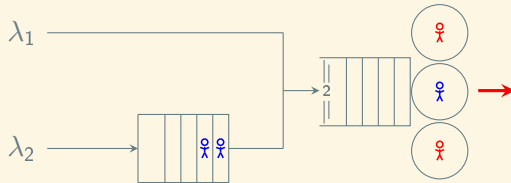
3. Queueing theoretic model - Markov Chain model



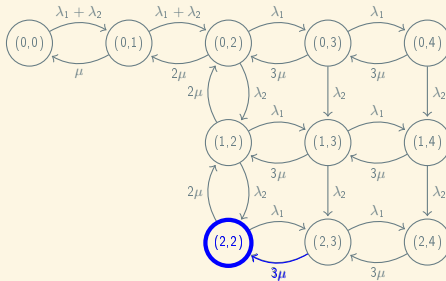
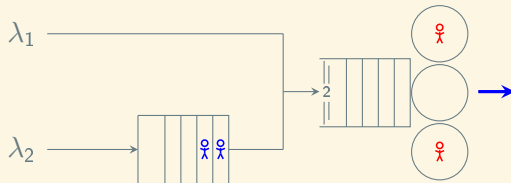
3. Queueing theoretic model - Markov Chain model



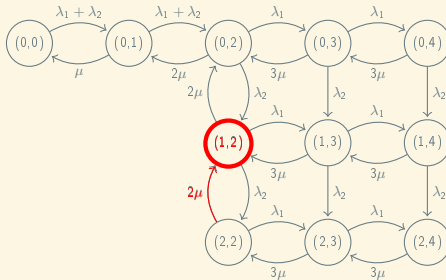
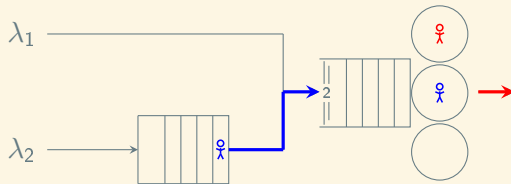
3. Queueing theoretic model - Markov Chain model



3. Queueing theoretic model - Markov Chain model



3. Queueing theoretic model - Markov Chain model



3. Queueing theoretic model - Steady state probabilities

From \ To	(0,0)	(0,1)	(0,2)		(2,3)	(2,4)
(0,0)	$-\lambda_1 - \lambda_2$	$\lambda_1 + \lambda_2$	0	...	0	0
(0,1)	μ	$-\mu - \lambda_1 - \lambda_2$	$\lambda_1 + \lambda_2$...	0	0
(0,2)	0	2μ	$-2\mu - \lambda_1 - \lambda_2$...	0	0
	\vdots	\vdots	\vdots	\ddots	\vdots	\vdots
(2,3)	0	0	0	...	$-\lambda_1 - 3\mu$	λ_1
(2,4)	0	0	0	...	3μ	-3μ

$$\frac{d\pi}{dt} = \pi Q = 0, \quad \sum \pi_{(u,v)} = 1$$

- ▶ Numerical integration
- ▶ Linear algebraic method
- ▶ Least squares method
- ▶ Closed-form approach

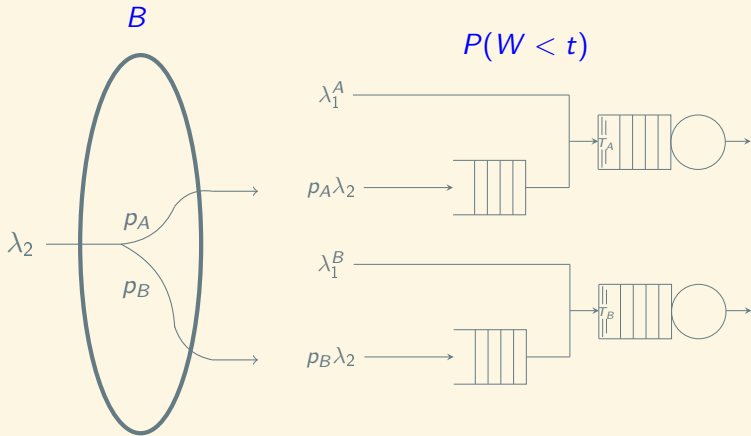
3. Queueing theoretic model - Performance measures

- ▶ **Waiting time**
 - ▶ Recursive formula
 - ▶ Direct formula
 - ▶ Closed-form formula
- ▶ **Blocking time**
 - ▶ Direct formula
 - ▶ Closed-form formula
- ▶ **Proportion of individuals within target**
 - ▶ Generic Ψ function
 - ▶ Specific Ψ function

4. Game theoretic model - Outline



4. Game theoretic model - Outline

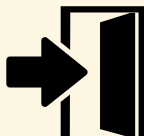


4. Game theoretic model - Players, Strategies, Objectives



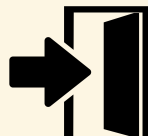
$$p_A, p_B \in [0, 1]$$
$$p_A + p_B = 1$$

$\min B$



$$T_A \in [1, N_A]$$

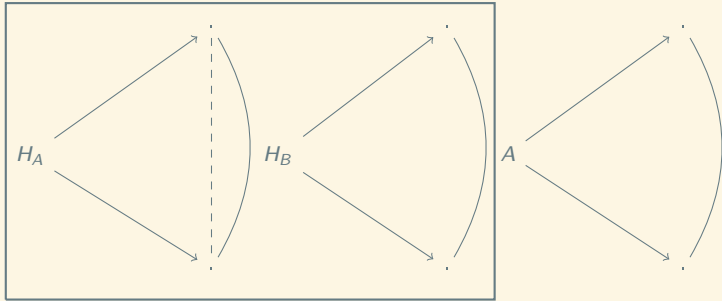
$$P(W^{(A)} < t) > 0.95$$



$$T_B \in [1, N_B]$$

$$P(W^{(B)} < t) > 0.95$$

4. Game theoretic model - Imperfect information game



4. Game theoretic model - Utilities

$$U_{T_A, T_B}^{(i)} = 1 - \left[(P(W^{(i)} < t) - 0.95)^2 \right]$$

$$A = \begin{pmatrix} U_{1,1}^A & U_{1,2}^A & \cdots & U_{1,N_B}^A \\ U_{2,1}^A & U_{2,2}^A & \cdots & U_{2,N_B}^A \\ \vdots & \vdots & \ddots & \vdots \\ U_{N_A,1}^A & U_{N_A,2}^A & \cdots & U_{N_A,N_B}^A \end{pmatrix}, \quad B = \begin{pmatrix} U_{1,1}^B & U_{1,2}^B & \cdots & U_{1,N_B}^B \\ U_{2,1}^B & U_{2,2}^B & \cdots & U_{2,N_B}^B \\ \vdots & \vdots & \ddots & \vdots \\ U_{N_A,1}^B & U_{N_A,2}^B & \cdots & U_{N_A,N_B}^B \end{pmatrix}$$

$$R = \begin{pmatrix} p_{1,1} & p_{1,2} & \cdots & p_{1,N_B} \\ p_{2,1} & p_{2,2} & \cdots & p_{2,N_B} \\ \vdots & \vdots & \ddots & \vdots \\ p_{N_A,1} & p_{N_A,2} & \cdots & p_{N_A,N_B} \end{pmatrix}$$

4. Game theoretic model - Asymmetric replicator Dynamics

$$\frac{dx}{dt}_i = x_i((f_x)_i - \phi_x), \quad \text{for all } i$$

$$\frac{dy}{dt}_i = y_i((f_y)_i - \phi_y), \quad \text{for all } i$$

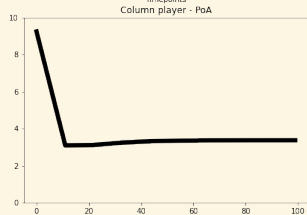
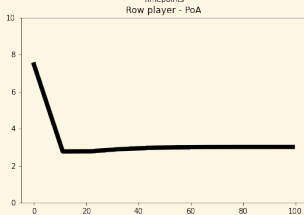
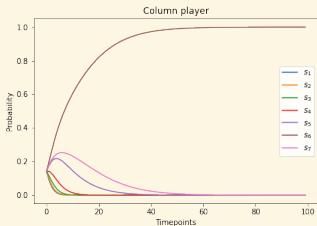
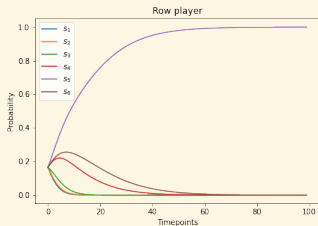
4. Game theoretic model - Compartmentalised price of anarchy

$$PoA = \frac{\max_{s \in E} Cost(s)}{\min_{s \in S} Cost(S)}$$

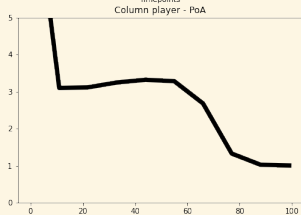
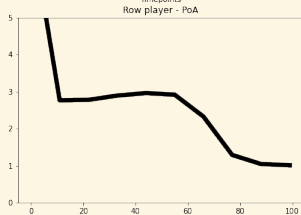
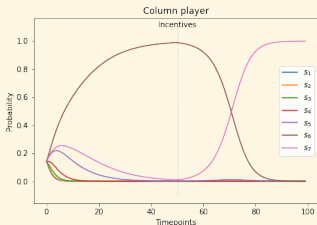
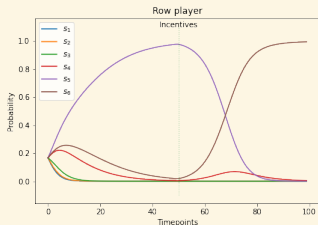
$$PoA_A(s_r) = \frac{Cost(s_r)}{\min_{s \in S} Cost(S)},$$

$$PoA_B(s_c) = \frac{Cost(s_c)}{\min_{s \in S} Cost(S)}$$

5. Numerical results - Asymmetric replicator dynamics



5. Numerical results - Asymmetric replicator dynamics



6. Agent-based model - Server's priority



1



2



2



3

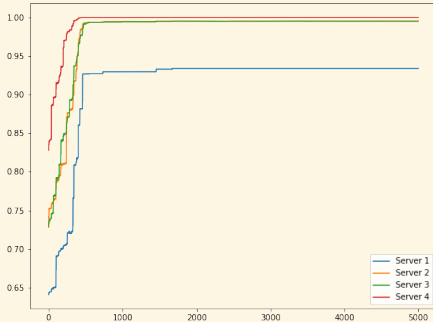
Utility

Idle time

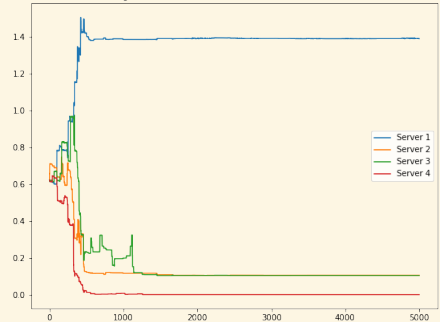
Served individuals

6. Agent-based model - Reinforcement learning

Utilities of all servers over all iterations

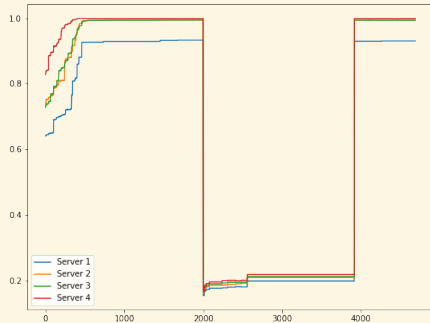


Weighted mean rates of all servers over all iterations

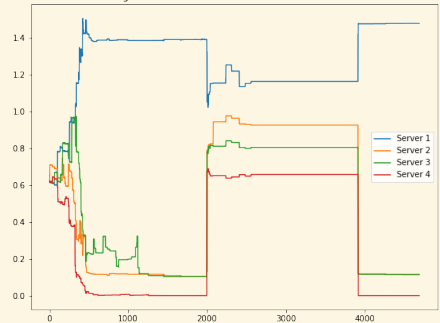


6. Agent-based model - Reinforcement learning

Utilities of all servers over all iterations



Weighted mean rates of all servers over all iterations



7. Conclusions

Inefficient behaviour can be learned and emerge naturally

Targeted incentivisation of behaviours can help escape learned inefficiencies.

Thank you!

Michalis Panayides, Vince Knight, and Paul Harper. *A game theoretic model of the behavioural gaming that takes place at the EMS - ED interface*. European Journal of Operational Research, 305(3):1236–1258, 2023.

\$ pip install ambulance_game
<https://github.com/11michalis11/AmbulanceDecisionGame>

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🐦 @Michalis_Pan

🗣 @MichalisPanayides