An Incomplete Overview of Some Applications of Game Theory to Patient Flow

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ABSTRACT

Individual behaviour has an effect on the optimal control of queueing systems, which is an idea that sits at the intersection of queueing theory and game theory. The role of this paper is to discuss some work in this area applied to healthcare systems.

One aspect considered is the effect of patient behaviour when choosing between service facilities. Various pieces of work will be discussed that have looked at this area.

A second aspect is the effect that managers may have when acting rationally in their control of queueing systems.

Thoughts for future directions of work are also considered.

KEYWORDS. Patient Flow, Game Theory, Queueing Theory

Main Area: Healthcare

1. Introduction

The best known work applying Game Theory to Healthcare is Roth's Noble prize winning work [**?**]. This work uses matching game algorithms to match medical interns to hospitals. The purpose of this paper is to discuss some work relevant to a different area of healthcare: congestion.

Understanding the effect of selfish individuals in queueing systems can be traced back to a series of short communications between Leeman [11, 12] and Saaty [18].

In [1, 2, 4, 9, 13, 14, 21] a variety of models are discussed that obtain optimal and equilibrium behaviour in situations where individuals can choose between a best queue to join. Most of the work considers these systems in a theoretical context but often comes to a common conclusion:

Selfish users make busier systems.

Most research where game theory is applied in healthcare has mainly concentrated on Emergency Departments (EDs) and how to deal with diversions of patients and ambulances. In [5] cooperative strategies for hospitals are considered, in order to reduce occurrences when ambulances are turned away due to the ED being full. In [3] a queueing network model of two EDs is proposed to study the network effect of ambulance diversion. Each ED aims to minimise the expected waiting time of its patients (walk-ins and ambulances) and chooses its diversion threshold based on the number of patients at its location. Decentralised decision making in the network is modelled as a non-cooperative game.

The degree of central control that should be exercised is a very important question to be considered by governments and/or policy makers. How do we measure the effect of selfish behaviour?

This is a question that is answered using the Game theoretical concept referred to as the *Price of Anarchy* (PoA). This was first defined in [10] but an excellent overview is given in [17]. The PoA is defined as the ratio of the selfish utility to the optimal utility.

Section 2 will discuss some PoA analysis applied to individuals choosing between queues. Section 3 will discuss similar analysis in the case of selfish behaviour related to the management of queues. Section 4 will conclude with a summary and thoughts for further work.

2. Choosing queues

This section describes how patient choices between various congestion affected services may be modelled. In particular the situation shown diagrammatically in Figure 1 is considered: patients have a choice amongst $M/M/c$ queues. Each $M/M/c$ queue corresponds to a (simple) model of a Hospital (or indeed any other public service facility).

The parameters of this system are shown in Table 2.

There are two approaches to solving this problem: assuming that patients observe or not the system states before choosing a facility. A rigorous comparison of these two approaches for individuals choosing to join an $M/M/1$ queue is given in [20].

An unobservable study is given in [6] where routing games [17] are used to study the system described. The routing game used is shown in 3.

The corresponding cost function for a given traffic flow λ is given by:

$$C(\lambda) = \sum_{i=1}^{m} \alpha_i \sum_{j}^{n} d_{ij}\lambda_{ij} + \sum_{j=1}^{n}\sum_{i=1}^{m} \lambda_{ij}w_j\left(\sum_{i=1}^{m}\lambda_{ij}\right) + \sum_{i=1}^{m}\beta_i\left(\Lambda_i - \sum_{j=1}^{n}\lambda_{ij}\right) \qquad (1)$$
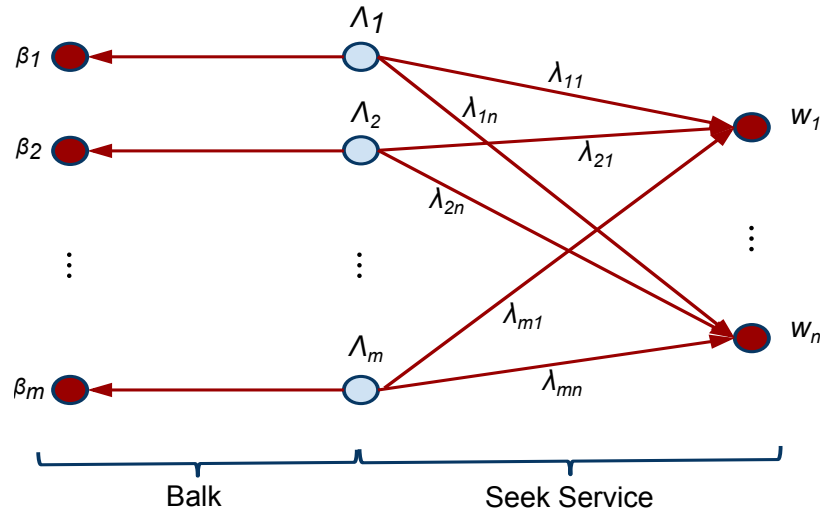
Figura 1: Routing patients from m hospitals to n services.

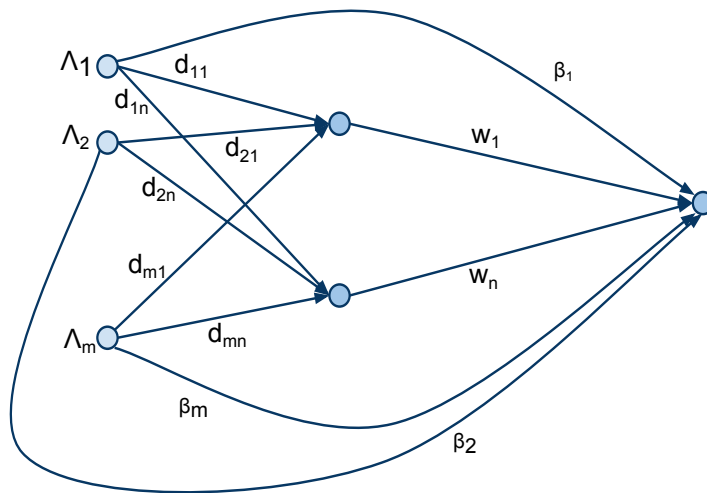| Parameter	Interpretation
$m \in \mathbb{Z}$	Number of sources
$n \in \mathbb{Z}$	Number of service centers
$\beta \in \mathbb{R}^m_{\geq 0}$	Worth of service
$\Lambda \in \mathbb{R}^m_{\geq 0}$	Demand rate
w_j for $j \in [n]$	A convex utility function
d_{ij} for $i \in [m],\ j \in [n]$	Distance from source i to service center j
λ_{ij} for $i \in [m],\ j \in [n]$	Traffic from source i to service center j

Figura 2: Parameters of model

Figura 3: Routing game: m hospitals to n services.

The constant $\alpha_i \in \mathbb{R}_{\geq 0}$ is simply a weighting statistic for the relative importance of travel distances to the other factors (once again allowing for this coefficient to be dependent on population partitioning). The Nash flow corresponding to the flow at which all traffic from a given source travels on minimal paths can be shown to be given by the flow that minimises the following function:

$$\Phi(\lambda) = \sum_{i=1}^{m} \alpha_i \sum_{j}^{n} d_{ij} \lambda_{ij} + \sum_{j=1}^{n} \int_{0}^{\sum_{i=1}^{m} \lambda_{ij}} w_j(x) dx + \sum_{i=1}^{m} \beta_i \left(\Lambda_i - \sum_{j=1}^{n} \lambda_{ij} \right) \qquad (2)$$

To be able to obtain the PoA for a given instance the following mathematical program must be solved:

OPTMP: NASHMP:
minimise (1)   minimise (2)

such that:

$$\sum_{j=1}^{n} \lambda_{ij} \leq \Lambda_i \text{ for all } i \in [m] \qquad (3)$$

$$\lambda_{ij} \in \mathbb{R}_{\geq 0}^{m \times n} \text{ for all } i \in [m], \ j \in [n] \qquad (4)$$

$$\sum_{i=1}^{m} \lambda_{ij} < c_j \mu_j \text{ for all } j \in [n] \qquad (5)$$

In [6] various theoretical results are proven with regards to the effect of worth of service on the PoA but also with regards to demand. The profile of Figure 4 is shown to hold in general.
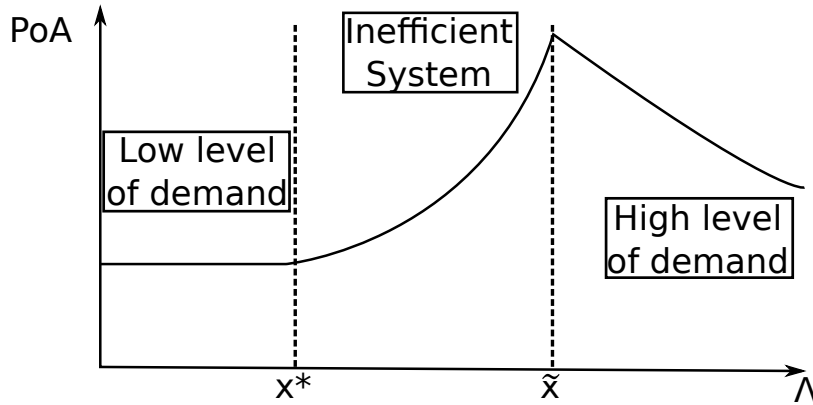

Figura 4: General profile of PoA.

Further to the theoretical consideration the PoA was calculated for a large case study using Hospital in Wales offering knee surgeries. A high PoA was calculated for the current demand.

To consider systems where individuals are able to observe the system there are two approaches: the first is to use a simulation based approach that allows individuals to choose their most desirable queue. One such approach that was considered specifically in the context of healthcare was considered in [8].

Given that individuals will consider a simple selfish decision rule this approach is relatively straightforward and can also be considered using straightforward analytical Markov models. The difficulty with this approach is appears when attempting to obtain the PoA.

In [19] various dynamic programming and approximate dynamic programming techniques are proposed that are able to not only give an optimal policy but also prove the following observation:

Selfish users make busier systems.

In the next section selfish congestion related decisions by managers will be considered.

3. Managing queues

Following the analysis of two critical care units (CCUs) it was found that the only a state dependent queueing model (where the demand rate to each CCU depended on the state of the CCU) would give a valid representation of the system. Upon discussion with the managers in question, it was acknowledged that certain behaviours took place. Indeed when one CCU was at high capacity it was likely to divert patients to the other CCU.

In [7] a normal form game consideration of this situation is given akin to the work on EDs in [3].

A pictorial representation of the situation considered is given in Figure 5 where each CCU can choose a capacity threshold at which to divert patients.
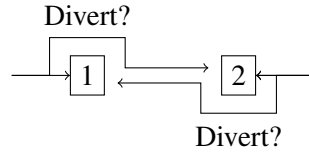

Figura 5: Diagrammatic representation of CCU interaction through patient diversion.

The capacity thresholds are denoted as $K_h \in \mathbb{Z}$ for $h \in \{1, 2\}$, once diverted the arrival rate is modified as shown in Figure 6. Note that $0 \leq K_h \leq c_h$.
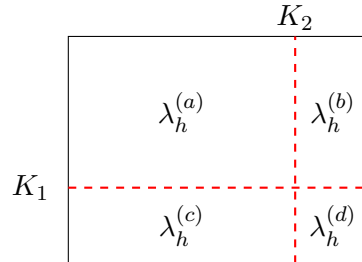

Figura 6: General arrival rates for each CCU at each region, where $h \in \{1, 2\}$

Utilities will be of interest when this queueing theoretical model will be inserted in the game theoretical model. Throughput of patients is a natural choice of utility given that most hospitals are financially rewarded per served patient [16]. For each threshold pair (K_1, K_2), the utilisation rate U_h and throughput T_h can easily be obtained for each CCU: $h \in \{1, 2\}$, using the following formulas:

$$U_h = \frac{\sum_{n=0}^{c_h} nP^{(h)}(n)}{c_h}$$
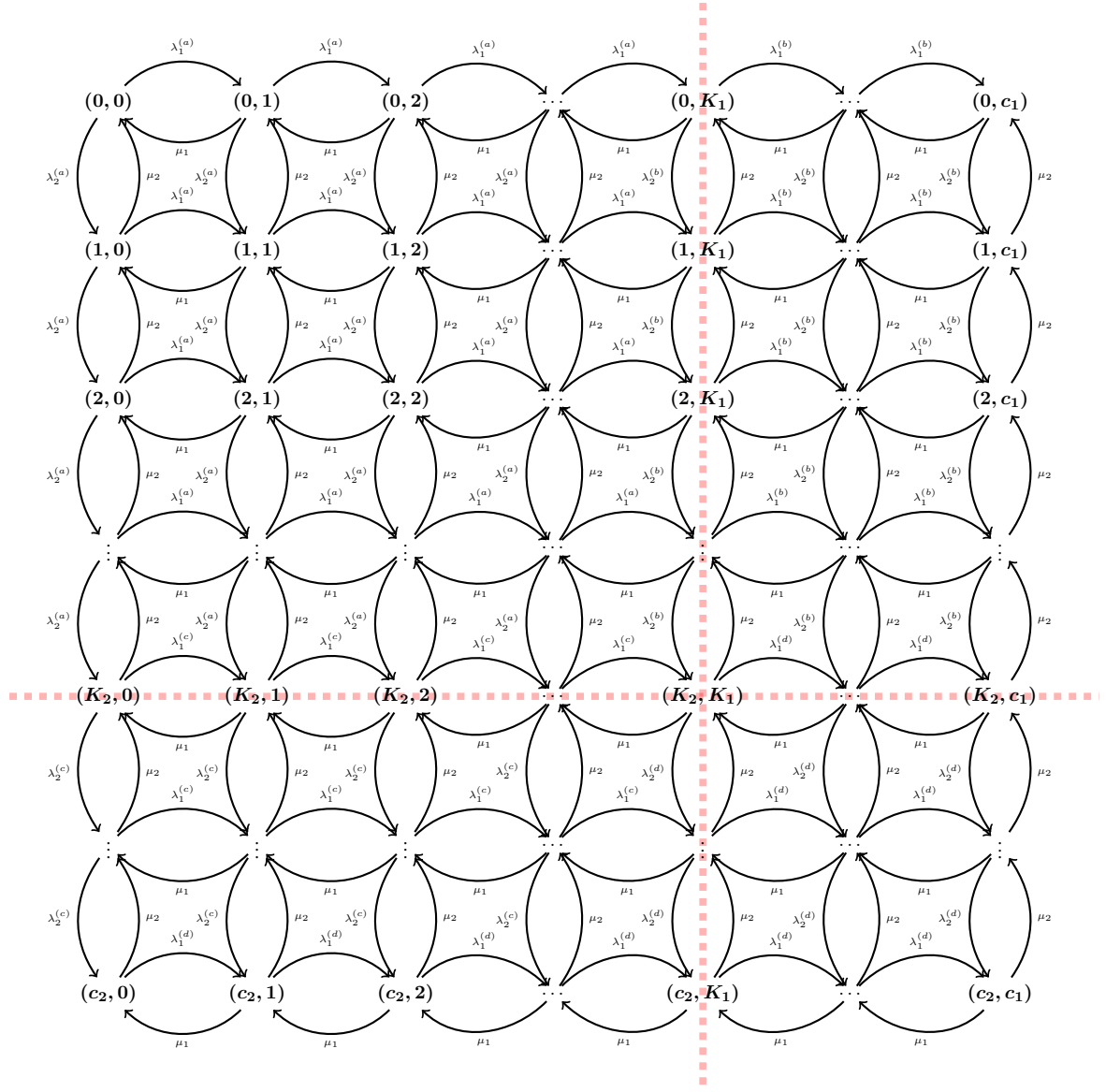
$$T_h = \mu_h \sum_{n=0}^{c_h} nP^{(h)}(n)$$

Figura 7: Generic Markov chain underpinning the queueing model of this paper

where $P^{(h)} = P^{(h)}(K_1, K_2)$ is the steady state probability distribution function (obtained from by analysing the Markov chain of Figure 7).

The optimisation problem faced by each hospital that gives rise to the game is shown in Figure 8.

For all $h \in \{1, 2\}$ minimise:

$$(U_h - t)^2$$

Subject to:

$$0 \leq K_h \leq c_h$$
$$K_h \in \mathbb{Z}$$

Figura 8: The optimisation problem underlying the game

This game is equivalent to a bi matrix game with restriction to pure strategies where both players aim to get their utilisation as close as possible to a certain target. As such a Nash Equilibrium is not guaranteed by traditional game theoretical results [15], but based on discussions with ABUHB, long term threshold policies are a realistic consideration. In [7] theoretical results are proved that guarentee pure strategy Nash equilibria in certain cases.

Using this and structural properties of the problem a Nash equilibria can be found. A variety of numerical results are shown giving the PoA for various scenarios but importantly this module can aid in the informed assignment of a policy t. Figure 9 show the smallest value of t that gives a PoA for a variation of demand ($x = 0$ corresponds to the actual demand of the system in consideration). We see that a value of $t = .72$ is sensible in our model.
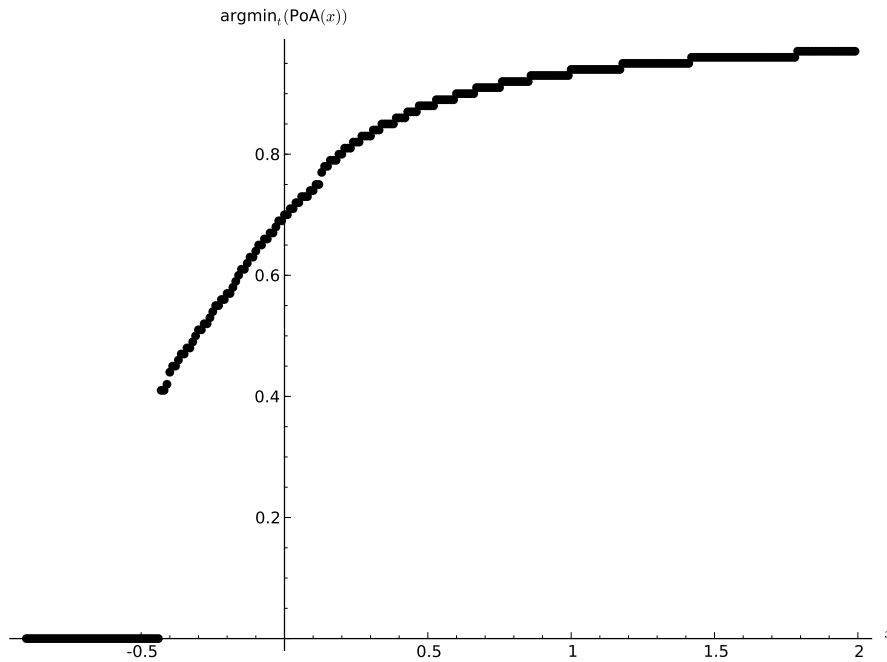

Figura 9: Lowest value of t ensuring PoA$= 1$

4. Conclusions

In this manuscript two game theoretic environments applied to healthcare have been considered:

- Modelling choices of patients;

- Modelling choices of managers.

The effect of stochasticity in healthcare systems is well understood and there is a wealth of research to match this. The effect of individual behaviour is less understood. Game theory and Price of Anarchy analysis offers one way to measure this effect.

Importantly, here are a variety of further avenues for this exciting area of research:

- Games involving players from different parts of a hospital and/or multiple hospitals;

- Machine loading games which can be applied to scheduling tasks;

- Further policy informing work.

With regards to methodological approaches there are a variety of tools available.

Firstly, one can model particular systems with parameters corresponding to the strategies of players (similar to the work described in Section [?]). Secondly, there are specific game theoretic models that can be applied directly to healthcare systems (similar to the work described in Section [?]). Finally there are also a variety of novel approaches that can be used such as using evolutionary game theoretic models. Specific heuristic approaches relevant to Markov Decision Process in both optimal and selfish calculations offer interesting avenues for research.

The fact that optimal behaviour and selfish behaviour are two sides of the same coin is well understood in unobservable queues. Finding similar connections in observable queues is an open research problem.

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