

Modelling patient flow and outcomes in community healthcare – a fluid approximation of a stochastic queueing system

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In recent decades, an ambition of healthcare policy has been to deliver more care in the community sector [6].

- ▶ Diverse range of services, operating in different physical locations
- ▶ Common for patients to use a range of services which they may re-use
- ▶ Considered to be crucial in meeting the current and future challenges that face modern health care services [3]

Challenge: how to organise and deliver these services given: physical distribution, patients using multiple services, increased referrals, case mix, and long term care requirements [7].

- ▶ Operational capability - waiting time, queue length, resource utilisation, capacity
- ▶ Outcome measures - aspects of a patient's health or experience, influenced by a care interaction
 - ▶ i.e. measurable behaviours, opinions, medical characteristics or health status
 - ▶ Used to monitor and evaluate the progression of patients and the quality of care received

Increasingly used by managers, clinicians and commissioners to inform quality improvement [2].

Uses in healthcare:

- ▶ Regularly evaluated as periodically calculated proportions
 - ▶ Misses time dependent variability in output of service and outcomes achieved
- ▶ Often considered in isolation from other services
- ▶ Misleading when considering dynamic patient flow of stochastic healthcare systems

Common modelling assumptions:

- ▶ Operational improvements positively affect outcomes
- ▶ Uniform patients

Understand dynamics of patient flow and use of patient outcomes in evaluating community healthcare

1. Unify two perspectives of quality in a single modelling framework
 - ▶ Account for flow of patients in different health states
 - ▶ Transition in health throughout queueing process important to understanding demand for and effect of system
2. Establish a concept of the flow of outcomes - how individual services contribute to a system's performance
 - ▶ Flow: bottlenecks, required capacity, waiting times
 - ▶ Outcomes: how they accrue over time through a combination of services

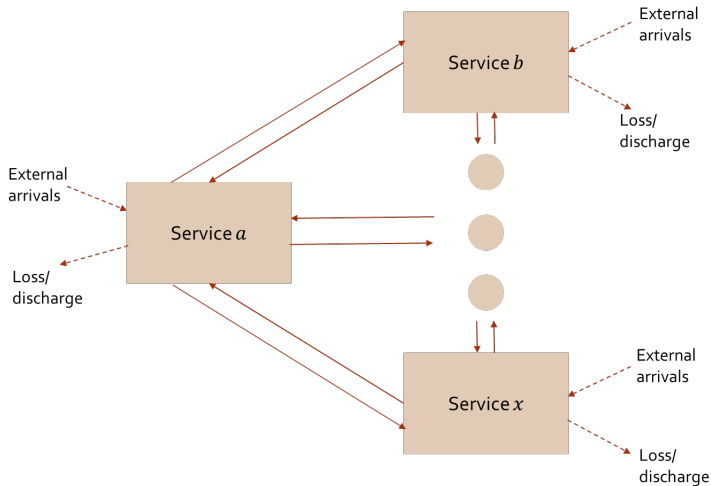
- ▶ Multiple services of varying configuration
- ▶ Patients reusing the same services - either sequentially or after care within another service
- ▶ Possibility of patients abandoning queue - impatient; seek healthcare in a non-community setting
- ▶ Patients arrive in different health states
 - ▶ Different capacity to benefit/resource requirement
 - ▶ Health may improve or decline throughout
- ▶ Time dependent demand

Traditional methods do not cope well with these dynamics - computationally expensive

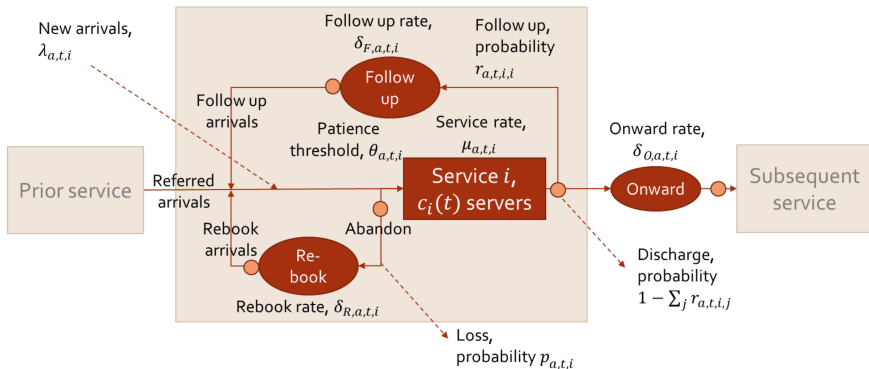
We present the application of a deterministic fluid and diffusion approximation for a stochastic queueing system. A novel application and extension of work by both S Ding et al. (2015)[1] and A Mandelbaum et al. (1998, 2002) [4, 5].

- ▶ Network of multiple services
- ▶ Health states - different parameters
- ▶ Application of diffusion equation

The system - a series of stochastic processes



The system - a series of stochastic processes



Indicates points at which a patient's health state may change
 $s_{a,b,m,t,i}, m \in \{R, F, S, l, O\}$



Finite server, service node – where patients obtain care



Infinite server, orbit node – waiting space until arriving at service

Number of servers split across A parallel queues

For analytical tractability, patients served first come first serve in parallel queues according to health state, $a \in A$.

Capacity $C_{a,i}(t)$ allocated to each queue at time t , with $\sum_{a \in A} C_{a,i}(t) = c_i(t)$.

$$C_{a,i}(u, \mathbf{Z}(u)) = \begin{cases} \frac{c_i Z_{a,Q,i}(u)}{\sum_{b=1}^A Z_{b,Q,i}(u)}, & \text{if } c_i < \sum_{b=1}^A Z_{b,Q,i}(u) > 0 \\ 0, & \text{otherwise} \end{cases} \quad (1)$$

$$C_{a,i}(u, \mathbf{Z}(u)) = \begin{cases} \frac{c_i \mu_{a,i} Z_{a,Q,i}(u)}{\sum_{b=1}^A \mu_b Z_{b,Q,i}(u)}, & \text{if } c_i < \sum_{b=1}^A Z_{b,Q,i}(u) > 0 \\ 0, & \text{otherwise} \end{cases} \quad (2)$$

$$C_{a,i}(u, \mathbf{Z}(u)) = \frac{Z_{a,Q,i}(0) + \lambda_{a,i}}{\sum_{b=1}^A Z_{b,Q,i}(0) + \lambda_{b,i}} \times c_i \quad (3)$$

- ▶ Work within Skorokhod space with J1 metric: intuitively provides wiggle space within both space and time.
- ▶ A natural and convenient formalism for describing trajectories of stochastic processes that may admit discontinuities, i.e. trajectories of Poisson processes.

Consider a sequence of models where the n -th model denoted by the superscript (n) has an arrival rate of $\lambda_{a,i}n$ for new patients in health state a and the total number of servers is nc_i . The scaled fluid process is defined as:

$$\bar{Z}_{a,m,i}(t) := \frac{Z_{a,m,i}^{(n)}(t)}{n},$$

where $a \in \{1, \dots, A\}$, $i = 1, \dots, J$ and $m \in \{Q, R, F, O, D, L\}$

Within this space and scaling the system for $n \rightarrow \infty$, we can define the fluid limit:

$$\begin{aligned} z_{a,Q,i}(t) &= z_{a,Q,i}(0) + \lambda_{a,i}t + \sum_{b=1}^A s_{b,a,R,i} \delta_{b,R,i} \int_0^t z_{b,R,i}(u) du \\ &+ \sum_{b=1}^A s_{b,a,F,i} \delta_{b,F,i} \int_0^t z_{b,F,i}(u) du \\ &+ \sum_{b=1}^A s_{b,a,O,i} \delta_{b,O,i} \int_0^t z_{b,O,i}(u) du \\ &- \mu_{a,i} \int_0^t \min(z_{a,Q,i}(u), C_{a,i}(u, \mathbf{z}(u))) du \\ &- \theta_{a,i} \int_0^t (z_{a,Q,i}(u) - C_{a,i}(u, \mathbf{z}(u)))^+ du \end{aligned}$$

$$\begin{aligned}z_{a,R,i}(t) &= z_{a,R,i}(0) - \delta_{a,R,i} \int_0^t z_{a,R,i}(u) du \\ &\quad + p_{a,i} \sum_{b=1}^A s_{b,a,l,i} \theta_{b,i} \int_0^t (z_{b,Q,i}(u) - C_{b,i}(u, \mathbf{z}(u)))^+ du \\ z_{a,F,i}(t) &= z_{a,F,i}(0) - \delta_{a,F,i} \int_0^t z_{a,F,i}(u) du \\ &\quad + r_{a,i,i} \sum_{b=1}^A s_{b,a,s,i} \int_0^t \mu_{b,i} \min(z_{b,Q,i}(u), C_{b,i}(u, \mathbf{z}(u))) du\end{aligned}$$

$$z_{a,O,i}(t) = z_{a,O,i}(0) - \delta_{a,O,i} \int_0^t z_{a,O,i}(u) du$$

$$+ \sum_{j=1; j \neq i}^J \sum_{b=1}^A s_{b,a,s,j} r_{a,j,i} \int_0^t \mu_{b,j} \min(z_{b,Q,j}(u), C_{b,j}(u, \mathbf{z}(u))) du$$

$$z_{a,L,i}(t) = z_{a,L,i}(0)$$

$$+ (1 - p_{a,i}) \sum_{b=1}^A s_{b,a,l,i} \theta_{b,i} \int_0^t (z_{b,Q,i}(u) - C_{b,i}(u, \mathbf{z}(u)))^+ du$$

$$z_{a,D,i}(t) = z_{a,D,i}(0) + r_{a,i,D} \sum_{b=1}^A s_{b,a,s,i} \mu_{b,i} \int_0^t C_{b,i}(u, \mathbf{z}(u)) du$$

Analytical expressions cannot be found for the above, however can be solved iteratively using common numerical schemes.

- ▶ Rewrite

$$z_{a,Q,i}(t), z_{a,R,i}(t), z_{a,F,i}(t), z_{a,O,i}(t), \quad i = 1, \dots, J, \quad a = 1, \dots, A$$

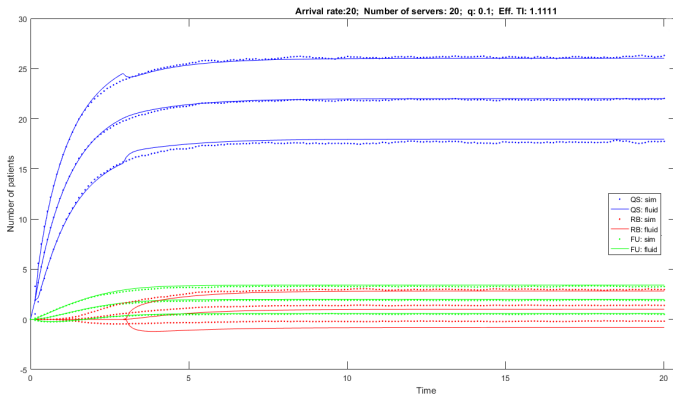
as $z(t) = \phi(z(t))$

- ▶ Let $z^{(0)}(0) = 0$
- ▶ Calculate $z^{(k+1)} = \phi(z^{(k)})$, $k = 0, 1, \dots$ using a common numerical scheme
- ▶ Stop when difference between $z^{(k+1)}$ and $z^{(k)}$ is deemed sufficiently small

Computed in MATLAB, produced a Discrete Event Simulation for the basic stochastic system and extension with health states

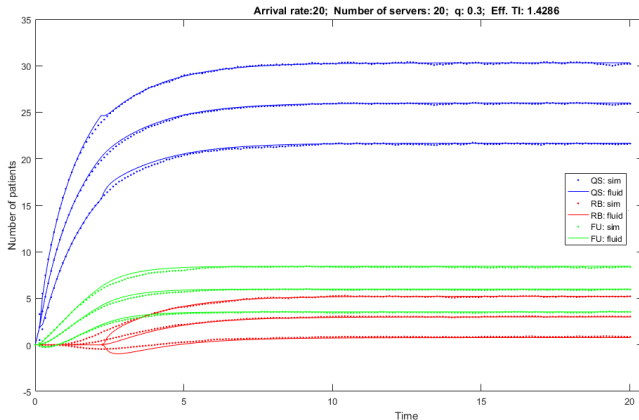
- ▶ Compare fluid model to simulation
- ▶ Basic model - rebook and follow up [1]
 - ▶ Explore parameter space for community healthcare
 - ▶ Triangulation of models
- ▶ Extended to include health states - single service
 - ▶ Assess accuracy of extension

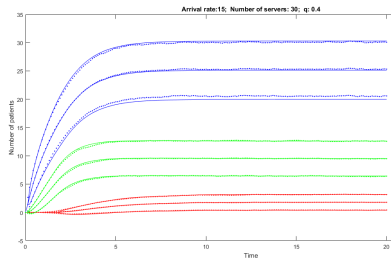
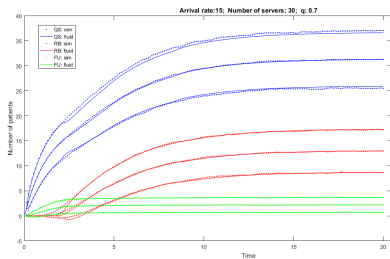
Effective traffic intensity: $\hat{\rho} = \frac{\lambda}{c\mu(1-q)}$



Simulations - Basic case

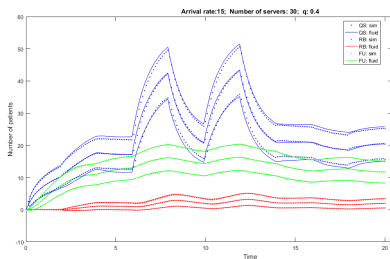
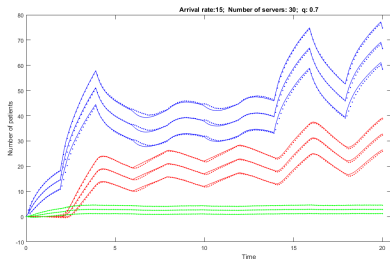
Larger probability of re-use





Simulations - System with outcomes

Time dependent behaviour - arrival spikes



- ▶ Number of patients, over time, in:
 - ▶ Services (or orbits)
 - ▶ Health states
- ▶ Waiting times, number in the system, waiting time distribution - using Erlang A or R, Virtual Waiting Time [5]
 - ▶ Per service
- ▶ Production of outcomes: number of patients discharge from a service/system in a given health state over time
- ▶ Loss over time

- ▶ Capacity allocation - i.e. optimisation:
 1. Balance across queues for equitable wait times
 2. Reduce net loss
 3. Prevent resource intensive re-joins

- ▶ Production of outcomes:
 1. Begin to understand how a network of services work together to "produce" patients with good health
 2. Seek balance across multiple services
 - ▶ Identify bottlenecks
 - ▶ Holistic view of operational measures

Limitations:

- ▶ A deterministic analogue of a stochastic system
- ▶ Errors for none heavily loaded systems
- ▶ Less accurate for smaller systems

Future directions:

1. Joint use of services - could an extension capture this?
2. Can the patient flow and outcomes of patients with multiple morbidities be informatively modelled?
3. Combining with optimisation methods - can useful information be gained for service planning?

Extending a fluid approximation of stochastic systems to a network of services, including patient health, is beneficial since:

- ▶ Model key dynamics of community healthcare
- ▶ Overcomes computational burden and time expense of other methods
- ▶ Provides time dependent analysis of system outputs

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Thank you for your attention

Are there any questions?