# On some fixed-point problems connecting branching and queueing 

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## Markov Chain Fixed-Point Equation

$X_{n}$ Markov chain, state space $E$
Recursion $X_{n+1}=\varphi\left(X_{n}, U_{n}\right)$
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GI/G/1 waiting time: $W \stackrel{\mathcal{D}}{=}(W+S-T)^{+}$
Stable distributions:

$$
X \stackrel{\mathcal{D}}{=} \frac{1}{n^{1 / \alpha}}\left(X_{1}+\cdots+X_{n}\right)
$$

## M/G/1 Busy Period



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FIFO (First in First Out)
Children: arrivals during service

## Sub-busy periods



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Fixed-point equation $B \stackrel{d}{=} S+\sum_{i=1}^{N} B_{i}$

## Sub-busy periods



Fixed-point equation $B \stackrel{d}{=} S+\sum_{i=1}^{N} B_{i}$
Can be reinterpreted in terms of LIFO (Last in First Out) Preemptive Resume

## LIFO Preemptive-Resume Family Tree



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Two variants:
LIFO-Preemptive-Repeat-Different LIFO-Preemptive-Repeat-Identical

## LIFO-Preemptive-Repeat

Initial service requirement $S_{0}^{*}$; busy period $B\left(S_{0}^{*}\right)$
$S_{k}$ service requirement of $k$ th interrupting customer $S_{k}^{*}$ service requirement after $k$ th interruption;


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Preemptive-Resume

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Preemptive-Repeat-Different: $S_{0}^{*}, S_{1}^{*}, \ldots$ i.i.d.
In Repeat-Different, must wait for interarrival time $>S_{k}^{*}$

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Children: all new arrivals preemptying during service
$\mathbb{P}($ restart $\mid S=s)=\mathbb{P}(T \leq s)=\mathrm{F}(\mathrm{S})$
$N$ : \# of children; geometric $(F(s))$ given $S=s$
Offspring mean $m=\mathbb{E} N=\mathbb{E} \frac{F(S)}{1-F(S)}=\mathbb{E} \frac{1}{\bar{F}(S)}-1$

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## Theorem

LIFO Preemptive-Repeat-Identical FPE is stable iff $\mathbb{E} \frac{1}{\bar{F}(S)} \leq 2$. With Poisson arrivals, $F(s)=1-\mathrm{e}^{-\lambda s}$ : iff $\mathbb{E} \mathrm{e}^{\lambda S} \leq 2$.

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\text { Proof: } \mathrm{GW}, N=0 \text { or } 2, \mathbb{P}(N=2)=\mathbb{P}(T \leq S)
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$\mathbb{E} \mathrm{e}^{\lambda S} \leq 2 \Rightarrow \mathbb{E}^{-\lambda S} \geq 1 / 2$ (Jensen to $1 / x$ )

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F IFR $\Rightarrow$ smaller stability region than for M/G/1
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Proof: \# customers at arrival epochs forms random walk

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Example:
$G$ Erlang(2) with density $s \mathrm{e}^{-s} \Rightarrow U_{G}(t)=3 / 4+t / 2+\mathrm{e}^{-2 t} / 4$ Stability: $2 \mathbb{E} T+\mathbb{E} \mathrm{e}^{-2 T} \geq 5$

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LIFO Pr-Repeat-Identical: ???
Will present approach covering phase-type $T$
In fact treat more general MAP arrivals
Multitype Galton-Watson but ...

## Markovian arrival process:

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Includes PH renewal processes
Dense

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Compute $\bar{p}_{i j}=\mathbb{P}_{i}\left(J_{B}=j\right)$
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Related MA work (preemptive-repeat-different)
Bini, D.A.,Latouche, G. and Meini, B. (2003)
Solving nonlinear matrix equations arising in tree-Like stochastic processes.
Linear Algebra and its Applications. 366, 39-64
He, Q.-M and Alfa, A.S. (1998)
The MMAP $[\mathrm{K}] / \mathrm{PH}[\mathrm{K}] / 1$ queues with a last-come-first-served preemptive service discipline
Queueing Systems 29, 269-291.

$$
\delta=\left|1-\frac{1}{d} \sum_{i, j=1}^{d} \bar{p}_{i j}\right|
$$




Figure: $\mathrm{H}_{2}$ arrivals, $\theta=1 / 8, \eta=14.6$

## Stability region for $E_{q} / M / 1$ and $H_{2} / M / 1$

Comparison: for $\mathrm{M} / \mathrm{M} / 1$, stability $\Longleftrightarrow \mathbb{E e}^{\lambda S} \leq 2 \Longleftrightarrow \rho \leq 1 / 2$

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$\mathrm{E}_{q} / \mathrm{M} / 1$ is IFR so region should be larger

| $\theta$ | $\eta_{1}$ | $\eta_{2}$ | $\eta_{3}$ | $\eta_{4}$ | $\eta_{5}$ |
| ---: | :---: | :---: | :---: | :---: | :---: |
| $1 / 8$ | 0.430 .58 | 0.310 .66 | 0.210 .72 | 0.120 .78 | 0.040 .84 |
| $3 / 8$ | 0.490 .53 | 0.430 .58 | 0.360 .62 | 0.250 .66 | 0.110 .71 |
| $5 / 8$ | 0.500 .52 | 0.480 .54 | 0.460 .56 | 0.430 .58 | 0.370 .60 |
| $7 / 8$ | 0.500 .50 | 0.500 .51 | 0.500 .52 | 0.490 .53 | 0.490 .53 |

## Back to FPE for FIFO/LIFO Busy Period $R$

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R \stackrel{d}{=} Q+\sum_{i=1}^{N} R_{i}
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Other examples:
weighted branching
Google PageRank Algorithm $R=Q+\sum_{i=1}^{N} A_{i} R_{i}$

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de Meyer \& Teugels 1980, Zwart 2000: $N \mid Q=q \operatorname{Poisson}(\lambda q)$ Light tails: Palmowski \& Rolski

## Existence and uniqueness of solution

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\begin{aligned}
& R=Q+\sum_{i=1}^{N} R_{i} \\
& Q, N, R \geq 0, \quad \bar{q}=\mathbb{E} Q<\infty, \bar{n}=\mathbb{E} N<1, \\
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$\Rightarrow$ total weight $R$ in tree is solution
Minimal solution $\geq 0$
Unique non-negative solution with $\bar{r}=\mathbb{E} R<\infty ; \quad \bar{r}=\frac{\bar{q}}{1-\bar{n}}$

## One Big Jump Heuristics

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## Theorem

If tail of $a_{0} Q+a_{1} N$ is $R V$ for all $a_{0}, a_{1}$, then

$$
\mathbb{P}(R>x) \sim \frac{1}{1-\bar{n}} \mathbb{P}(Q+\bar{r} N>x)
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Upper bound by RW argument; omitted

## Multitype Version of FPE

$$
R(i)=Q(i)+\sum_{k=1}^{K} \sum_{j=1}^{N_{k}(i)} R_{j}(k), \quad i=1, \ldots, K
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Motivating example multiclass queue in Ernst-SA-Hasenbein 2018: arrival rate $\lambda_{i k}$ of class $k$ when class $i$ customer in service

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$R(i)<\infty$ : offspring mean matrix $\mathbf{M}=\left(m_{i k}\right)$ has spr. $<1$
$m_{i k}=\mathbb{E} N_{k}(i)$
Uniqueness then easy when $\mathbb{E} Q(i)<\infty$

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Precisely (polar $L_{1}$ coordinates)

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& \|\mathbf{V}(i)\|=Q(i)+N_{1}(i)+\cdots+N_{K}(i) \\
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Reference RV tail $\bar{F}(x)=\frac{L(x)}{x^{\alpha}}$
$\mathbb{P}(\|\mathbf{V}(i)\|>x) \sim b_{i} \bar{F}(x)$ where either
(1) $b_{i}=0$ or
(2) $b_{i}>0, \mathbb{P}(\boldsymbol{\Theta}(i) \in \cdot \mid\|\mathbf{V}(i)\|>x) \rightarrow \mu_{i}(\cdot)$ for some measure $\mu_{i}$ on $\mathcal{B}$

## Outline of approach

No extension of random walk argument found

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No extension of random walk argument found Instead induction $K-1 \mapsto K ; \quad K=1$ done in first part Idea: Foss 1980, 84 reduces problems for $K$-class queues to $K-1$ by serving all class $K$ customers first

Constants don't need to be identified in each step
Enough to get $\mathbb{P}(R(i)>x) \sim d_{i} \bar{F}(x), i=1, \ldots, K-1$

## Reducing from 2 types to 1


green: type 1
red: type 2 descendants of the ancestor in direct line blue: the rest of type 2

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Use "one big jump heuristics" together with

$$
\begin{array}{r}
R(i)=Q(i)+\sum_{i=1}^{N_{1}(i)} R_{i}(1)+\sum_{i=1}^{N_{2}(i)} R_{2}(k), \quad i=1,2 \text { to get } \\
d_{i}=a_{i}+\bar{n}_{1}(i) d_{1}+\bar{n}_{2}(i) d_{2} \quad \text { where } \\
a_{i}=\lim _{x \rightarrow \infty} \frac{\mathbb{P}\left(Q(i)+\bar{r}_{1} N_{1}(i)+\bar{r}_{2} N_{2}(i)>x\right)}{\bar{F}(x)}
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Two equations, two unknowns
$\left(^{*}\right)$ helps to make "one big jump heuristics" rigorous

$$
R(i)=Q(i)+\sum_{k=1}^{K} \sum_{i=1}^{N_{k}(i)} R_{i}(k), \quad i=1, \ldots, K
$$

## Theorem

Assume that $\operatorname{spr}(\mathbf{M})<1, \int_{0}^{\infty} \bar{F}(x) \mathrm{d} x<\infty$ and that MRV holds. Then

$$
\begin{equation*}
\mathbb{P}(R(i)>x) \sim d_{i} \bar{F}(x) \text { as } x \rightarrow \infty, \tag{1}
\end{equation*}
$$

with the $d_{i}$ given as the unique solution to the set

$$
d_{i}=a_{i}+\sum_{k=1}^{K} m_{i k} d_{k}, \quad i=1, \ldots, K
$$

of linear equations where

$$
a_{i}=\lim _{x \rightarrow \infty} \frac{\mathbb{P}\left(Q(i)+\bar{r}_{1} N_{1}(i)+\bar{r}_{2} N_{2}(i)>x\right)}{\bar{F}(x)}
$$

and the $\bar{r}_{i}$ solve

$$
\bar{r}_{i}=\bar{q}_{i}+\sum^{k} m_{i k} \bar{r}_{k}, \quad i=1, \ldots, K .
$$

## Lemma

Let $Z_{1}, Z_{2}, \ldots$ be i.i.d. and $R V$ with finite mean $\bar{z}$ and define $S_{k}=Z_{1}+\cdots+Z_{k}$. Then for any $\delta>0$

$$
\sup _{y \geq \delta k}\left|\frac{\mathbb{P}\left(S_{k}>k \bar{z}+y\right)}{k \bar{F}(y)}-1\right| \rightarrow 0, k \rightarrow \infty
$$

## Corollary

For $0<\epsilon<1 / \bar{z}, d(F, \epsilon)=\limsup _{x \rightarrow \infty} \sup _{k<\epsilon x} \frac{\mathbb{P}\left(S_{k}>x\right)}{k \bar{F}(x)}<\infty$

## Lemma

Let $\mathbf{N}=\left(N_{1}, \ldots, N_{p}\right)$ be MRV with $\mathbb{P}(\|\mathbf{N}\|>x) \sim c_{N} \bar{F}(x)$ and let $Z_{m}^{(i)}$ be independent with $Z_{i}^{(j)} \sim F_{j}$ for $Z_{i}^{(j)}$ and $\bar{z}_{j}=\mathbb{E} Z_{m}^{(j)}$. Define $S_{m}^{(j)}=Z_{1}^{(j)}+\cdots+Z_{m}^{(j)}$. If $\bar{F}_{j}(x) \sim c_{j} \bar{F}(x)$, then

$$
\mathbb{P}\left(S_{N_{1}}^{(1)}+\cdots+S_{N_{p}}^{(p)}>x\right) \sim \mathbb{P}\left(\bar{z}_{1} N_{1}+\cdots+\bar{z}_{1} N_{p}>x\right)+c_{0} \bar{F}(x)
$$

where $c_{0}=c_{1} \mathbb{E} N_{1}+\cdots+c_{0} \mathbb{E} N_{0}$

## Theorem

Let $\mathbf{V}=(\mathbf{T}, N) \in[0, \infty)^{p} \times \mathbb{N}$ be $\operatorname{MRV}(F)$, let $\mathbf{Z}, \mathbf{Z}_{1}, \mathbf{Z}_{2}, \ldots \in[0, \infty)^{q}$ be i.i.d., independent of $(\mathbf{T}, N)$ and $\operatorname{MRV}(F)$, and define $\mathbf{S}=\sum_{1}^{N} \mathbf{Z}_{i}$. Then $\mathbf{V}^{*}=(\mathbf{T}, N, \mathbf{S})$ is $M R V(F)$.

