## Matrix-Geometric Analysis and Its Applications

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Introduction
Why we need the Matrix-Geometric Technique?
Matrix-Geometric in Action
Key Idea
General Matrix-Geometric Solution
General Concept
Application of Matrix-Geometric
Performance Analysis of Multiprocessing System
Properties of Solutions
Properties
Computational Properties of $\boldsymbol{R}$
Algorithm for solving $\boldsymbol{R}$

## Outline

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- Closed-form solution is hard to obtain.

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- Need to seek efficient, numerical stable solutions.
- Can be viewed as a generalization of conventional queueing analysis.
- A Special way to solve a Markov Chain.


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- Example: a modified $M / M / 1, \lambda^{*}$ if the system is empty, else $\lambda$. Customers require two exponential stages of service, $\mu_{1}$, and $\mu_{2}$
$S:\{(i, s) \mid i \geq 0$ and it is the no. of customer in the queue, $\}$ $s$ is the current stage of service, $s \in(1,2)\}$



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- Well, let us proceed to specify the state transition diagram, then the $\boldsymbol{Q}$ matrix.


Let $a_{i}=\lambda+\mu_{i}, i=1,2$. Arrange states lexicographically, $(0,0),(0,1),(0,2),(1,1),(1,2), \ldots$.

The transition rate matrix $\mathbf{Q}$ is:

$$
\boldsymbol{Q}=\left[\begin{array}{ccc|cc|cc|cc|c}
-\lambda^{*} & \lambda^{*} & 0 & 0 & 0 & 0 & 0 & 0 & 0 & \cdots \\
0 & -a_{1} & \mu_{1} & \lambda & 0 & 0 & 0 & 0 & 0 & \cdots \\
\mu_{2} & 0 & -a_{2} & 0 & \lambda & 0 & 0 & 0 & 0 & \cdots \\
\hline 0 & 0 & 0 & -a_{1} & \mu_{1} & \lambda & 0 & 0 & 0 & \cdots \\
0 & \mu_{2} & 0 & 0 & -a_{2} & 0 & \lambda & 0 & 0 & \cdots \\
\hline 0 & 0 & 0 & 0 & 0 & -a_{1} & \mu_{1} & \lambda & 0 & \cdots \\
0 & 0 & 0 & \mu_{2} & 0 & 0 & -a_{2} & 0 & \lambda & \cdots \\
\hline \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \cdots
\end{array}\right.
$$

Let us re-write the $\mathbf{Q}$ in matrix form:

$$
\begin{gathered}
\boldsymbol{A}_{0}=\left[\begin{array}{cc}
\lambda & 0 \\
0 & \lambda
\end{array}\right] ; \boldsymbol{A}_{1}=\left[\begin{array}{cc}
-a_{1} & \mu_{1} \\
0 & -a_{2}
\end{array}\right] ; \boldsymbol{A}_{2}=\left[\begin{array}{cc}
0 & 0 \\
\mu_{2} & 0
\end{array}\right] \\
\boldsymbol{B}_{00}=\left[\begin{array}{ccc}
-\lambda^{*} & \lambda^{*} & 0 \\
0 & -a_{1} & \mu_{1} \\
\mu_{2} & 0 & -a_{2}
\end{array}\right] ; \boldsymbol{B}_{01}=\left[\begin{array}{cc}
0 & 0 \\
\lambda & 0 \\
0 & \lambda
\end{array}\right] ; \boldsymbol{B}_{10}=\left[\begin{array}{ccc}
0 & 0 & 0 \\
0 & \mu_{2} & 0
\end{array}\right] \\
\boldsymbol{Q}=\left[\begin{array}{ccc|c|c|c}
\boldsymbol{B}_{00} & \boldsymbol{B}_{01} & \mathbf{0} & \mathbf{0} & \mathbf{0} & \cdots \\
\boldsymbol{B}_{10} & \boldsymbol{A}_{1} & \boldsymbol{A}_{0} & \mathbf{0} & \mathbf{0} & \cdots \\
\hline \mathbf{0} & \boldsymbol{A}_{2} & \boldsymbol{A}_{1} & \boldsymbol{A}_{0} & \mathbf{0} & \cdots \\
\mathbf{0} & \mathbf{0} & \boldsymbol{A}_{2} & \boldsymbol{A}_{1} & \boldsymbol{A}_{0} & \cdots \\
\vdots & \vdots & \vdots & \vdots & \vdots & \cdots
\end{array}\right.
\end{gathered}
$$

Let us solve it. For the repetitive portion

$$
\begin{equation*}
\boldsymbol{\pi}_{j-1} A_{0}+\boldsymbol{\pi}_{j} A_{1}+\boldsymbol{\pi}_{j+1} \boldsymbol{A}_{2}=\mathbf{0} \quad j=2,3, \ldots \tag{1}
\end{equation*}
$$

This is similar to the solution of $M / M / 1$. Therefore, $\pi_{j}$ is a function only of the transition rates between states with $j-1$ queued customers and states with $j$ queued customers.

$$
\begin{align*}
\boldsymbol{\pi}_{j} & =\boldsymbol{\pi}_{j-1} \boldsymbol{R} \quad j=2,3, \ldots \\
\text { or } \quad \boldsymbol{\pi}_{j} & =\boldsymbol{\pi}_{1} \boldsymbol{R}^{j-1} \quad j=2,3, \ldots \tag{2}
\end{align*}
$$

Putting (2) into (1), we have:

$$
\boldsymbol{\pi}_{1} \boldsymbol{R}^{j-2} \boldsymbol{A}_{0}+\boldsymbol{\pi}_{1} \boldsymbol{R}^{j-1} \boldsymbol{A}_{1}+\boldsymbol{\pi}_{1} \boldsymbol{R}^{j} \boldsymbol{A}_{2}=\mathbf{0} \quad j=2,3, \ldots
$$

Since it is true for $j=2,3, \ldots$, substitute $j=2$, we have:

$$
\boldsymbol{A}_{0}+\boldsymbol{R} \boldsymbol{A}_{1}+\boldsymbol{R}^{2} \boldsymbol{A}_{2}=\mathbf{0}
$$

For the initial portion:

$$
\begin{array}{r}
\boldsymbol{\pi}_{0} \boldsymbol{B}_{00}+\boldsymbol{\pi}_{1} \boldsymbol{B}_{10}=\mathbf{0} \\
\boldsymbol{\pi}_{0} \boldsymbol{B}_{01}+\boldsymbol{\pi}_{1} \boldsymbol{A}_{1}+\boldsymbol{\pi}_{2} \boldsymbol{A}_{2}=\mathbf{0}
\end{array}
$$

or

$$
\left[\boldsymbol{\pi}_{0}, \boldsymbol{\pi}_{1}\right]\left[\begin{array}{cc}
\boldsymbol{B}_{00} & \boldsymbol{B}_{01} \\
\boldsymbol{B}_{10} & \boldsymbol{A}_{1}+\boldsymbol{R} \boldsymbol{A}_{2}
\end{array}\right]=\mathbf{0}
$$

We also need:

$$
\begin{aligned}
1= & \boldsymbol{\pi}_{0} \boldsymbol{e}+\boldsymbol{\pi}_{1} \sum_{j=1}^{\infty} \boldsymbol{R}^{j-1} \boldsymbol{e}=\boldsymbol{\pi}_{0} \boldsymbol{e}+\boldsymbol{\pi}_{1}(\boldsymbol{I}-\boldsymbol{R})^{-1} \boldsymbol{e} \\
{\left[\boldsymbol{\pi}_{0}, \boldsymbol{\pi}_{1}\right] \quad } & {\left[\begin{array}{ccc}
\boldsymbol{e} & \boldsymbol{B}_{00}^{*} & \boldsymbol{B}_{01} \\
(\boldsymbol{I}-\boldsymbol{R})^{-1} \boldsymbol{e} & \boldsymbol{B}_{10}^{*} & \boldsymbol{A}_{1}+\boldsymbol{R} \boldsymbol{A}_{2}
\end{array}\right]=[1, \mathbf{0}] }
\end{aligned}
$$

where $\boldsymbol{M}^{*}$ is $\boldsymbol{M}$ with first column being eliminated.
$\bar{N}_{q}=\mathrm{E}[q u e u e d$ customers]

$$
=\sum_{j=1}^{\infty} j \boldsymbol{\pi}_{j} \boldsymbol{e}=\sum_{j=1}^{\infty}(j) \boldsymbol{\pi}_{1} \boldsymbol{R}^{j-1} \boldsymbol{e}=\boldsymbol{\pi}_{1}(\boldsymbol{I}-\boldsymbol{R})^{-2} \boldsymbol{e}
$$

Note: $\quad \boldsymbol{S}=\sum_{j=1}^{\infty} \boldsymbol{R}^{j-1}=\boldsymbol{I}+\boldsymbol{R}+\boldsymbol{R}^{2}+\cdots$

$$
\begin{aligned}
\boldsymbol{S} \boldsymbol{R} & =\boldsymbol{R}+\boldsymbol{R}^{2}+\boldsymbol{R}^{3}+\cdots \\
\boldsymbol{S}(\boldsymbol{I}-\boldsymbol{R}) & =\boldsymbol{I} \\
\boldsymbol{S} & =\boldsymbol{I}(\boldsymbol{I}-\boldsymbol{R})^{-1}=(\boldsymbol{I}-\boldsymbol{R})^{-1}
\end{aligned}
$$

This is true only when the spectral radius of $\boldsymbol{R}$ is less than unity.

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$$
\boldsymbol{Q}=\left[\begin{array}{cc|c|c|c|c}
\boldsymbol{B}_{00} & \boldsymbol{B}_{01} & \mathbf{0} & \mathbf{0} & \mathbf{0} & \cdots \\
\boldsymbol{B}_{10} & \boldsymbol{B}_{11} & \boldsymbol{A}_{0} & \mathbf{0} & \mathbf{0} & \cdots \\
\hline \boldsymbol{B}_{20} & \boldsymbol{B}_{21} & \boldsymbol{A}_{1} & \boldsymbol{A}_{0} & \mathbf{0} & \cdots \\
\hline \boldsymbol{B}_{30} & \boldsymbol{B}_{31} & \boldsymbol{A}_{2} & \boldsymbol{A}_{1} & \boldsymbol{A}_{0} & \cdots \\
\hline \boldsymbol{B}_{40} & \boldsymbol{B}_{41} & \boldsymbol{A}_{3} & \boldsymbol{A}_{2} & \boldsymbol{A}_{1} & \cdots \\
\hline \vdots & \vdots & \vdots & \vdots & \vdots & \vdots
\end{array}\right.
$$

We index the state by $(i, j)$ where $i$ is the level, $i \geq 0$ and $j$ is the state within the level, $0 \leq j \leq m-1$ for $i \geq 1$.

For the repetitive portion,

$$
\begin{align*}
\sum_{k=0}^{\infty} \boldsymbol{\pi}_{j-1+k} \boldsymbol{A}_{k} & =\mathbf{0} \quad j=2,3, \ldots  \tag{3}\\
\boldsymbol{\pi}_{j} & =\boldsymbol{\pi}_{1} \boldsymbol{R}^{j-1} \quad j=2,3, \ldots \tag{4}
\end{align*}
$$

putting (4) to (3), we have:

$$
\sum_{k=0}^{\infty} \boldsymbol{R}^{k} \boldsymbol{A}_{k}=\mathbf{0}
$$

For the boundary states, we have:

$$
\left[\boldsymbol{\pi}_{0}, \boldsymbol{\pi}_{1}\right]\left[\begin{array}{cc}
\boldsymbol{B}_{00} & \boldsymbol{B}_{01} \\
\sum_{k=1}^{\infty} \boldsymbol{R}^{k-1} \boldsymbol{B}_{k 0} & \sum_{k=1}^{\infty} \boldsymbol{R}^{k-1} \boldsymbol{B}_{k 1}
\end{array}\right]
$$

## Procedure (continue:)

Using the same normalization, we have
$\left[\boldsymbol{\pi}_{0}, \boldsymbol{\pi}_{1}\right]\left[\begin{array}{cc}\boldsymbol{e} & \boldsymbol{B}_{00}^{*} \\ (\boldsymbol{I}-\boldsymbol{R})^{-1} \boldsymbol{e} & {\left[\boldsymbol{B}_{01}\right.} \\ {\left[\sum_{k=1}^{\infty} \boldsymbol{R}^{k-1} \boldsymbol{B}_{k 0}\right]^{*}} & \sum_{k=1}^{\infty} \boldsymbol{R}^{k-1} \boldsymbol{B}_{k 1}\end{array}\right]=[1, \mathbf{0}]$
Therefore, it boils down to

1. Solving $\boldsymbol{R}$.

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\left[\boldsymbol{\pi}_{0}, \boldsymbol{\pi}_{1}\right]\left[\begin{array}{cc}
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\end{array} \begin{array}{c}
\sum_{k=1}^{\infty} \boldsymbol{R}^{k-1} \boldsymbol{B}_{k 1}
\end{array}\right]=[1, \mathbf{0}]
$$

Therefore, it boils down to

1. Solving $\boldsymbol{R}$.
2. Solving the initial portion of the Markov process.

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## Multiprocessing System

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- K homogeneous processors.
- Each processor is subjected to failure with rate $\gamma$.
- A single repair facility with repair rate $\alpha$.
- Jobs arrive at a Poisson rate $\lambda$.
- Whenever there is no processor available, all jobs are lost.


## Markov Model



Define $b_{i}=\lambda+i \gamma+\alpha$ for $i=1,2, \ldots, K$. We have:

$$
\boldsymbol{B}_{00}=[-\alpha] ; \boldsymbol{B}_{01}=[\alpha, 0, \cdots, 0] ; \boldsymbol{B}_{j 0}=\left[\begin{array}{c}
\gamma \\
0 \\
\vdots \\
0
\end{array}\right] ; \boldsymbol{B}_{0, j}=\mathbf{0} \quad j=2,3, \ldots,
$$

$$
\boldsymbol{B}_{1,1}=\left[\begin{array}{cccccccc}
-b_{1} & \alpha & 0 & 0 & \cdots & 0 & 0 & 0 \\
2 \gamma & -b_{2} & \alpha & 0 & \cdots & 0 & 0 & 0 \\
0 & 3 \gamma & -b_{3} & \alpha & \cdots & 0 & 0 & 0 \\
\vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\
0 & 0 & 0 & 0 & \cdots & (K-1) \gamma & -b_{K+1} & \alpha \\
0 & 0 & 0 & 0 & \cdots & 0 & K \gamma & -b_{K}
\end{array}\right]
$$

- The matrices of the repeating portion of the process are:

$$
\boldsymbol{A}_{0}=\lambda \boldsymbol{I} ; \boldsymbol{A}_{1}=\boldsymbol{B}_{1,1} ; \boldsymbol{A}_{2}=\left[\begin{array}{ccccc}
\mu & 0 & \cdots & 0 & 0 \\
0 & 2 \mu & \cdots & 0 & 0 \\
\vdots & \vdots & \cdots & \vdots & \vdots \\
0 & 0 & \cdots & (K-1) \mu & 0 \\
0 & 0 & \cdots & 0 & K \mu
\end{array}\right]
$$

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Computational Properties of $R$
Algorithm for solving $R$

- Informally, the stability of a process depends on the drift of the process for states in the repetitive portion.

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- For example, $M / M / 1$, the expected drift toward higher states is $\lambda 1$. The expected drift toward lower states is $\mu(-1)=-\mu$. The drift of the process is $\lambda-\mu$. Process is stable if the total expected drift is NEGATIVE, or $\lambda<\mu$ in our case.
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- For example, $M / M / 1$, the expected drift toward higher states is $\lambda 1$. The expected drift toward lower states is $\mu(-1)=-\mu$. The drift of the process is $\lambda-\mu$. Process is stable if the total expected drift is NEGATIVE, or $\lambda<\mu$ in our case.
- Now suppose the process can go up by 1 and go down by at most $K$ steps. Let the rate for $/$ steps be $r(I)$, $I=-K,-K-1, \ldots, 0,1$.

$$
r(1)+\sum_{l=1}^{K}(-l) r(-l) \rightarrow r(1)<\sum_{l=1}^{K} \operatorname{lr}(l)
$$

- Analogous to the scalar case, we can think of the drift of the process in terms of levels. Assume that for the repetitive portion, we have $m$ states, a transition from level $i, i \gg 0$, to level $i-k, 1 \leq k \leq K$

$$
-k \sum_{l=1}^{m} \boldsymbol{A}_{k+1}(j, l)
$$

where $A_{k+1}(j, I)$ is the transition from state $j$ in level $i$ to state $/$ in level $i-k$.


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$$

where $A_{k+1}(j, I)$ is the transition from state $j$ in level $i$ to state $/$ in level $i-k$.

- Let $f_{j}, 0 \leq j \leq m-1$ be the probability that the process is in inter-level $j$ of the repeating portion of the process of level $i \gg 0$. The average drift from level $i$ to level $i-k$ is

$$
-k \sum^{m-1} f_{j} \sum^{m-1} \boldsymbol{A}_{k+1}(j, I)
$$

- To get the total drift, we sum the previous equation for all $k$, $0 \leq k \leq K+1$.
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- But what is $f_{j}$ ? Let us define $\boldsymbol{A}=\sum_{l=0}^{K+1} \boldsymbol{A}_{l}$, we have $\boldsymbol{f}=\left(f_{0}, f_{1}, \ldots, f_{m-1}\right)$. Therefore:

$$
\boldsymbol{f} \boldsymbol{A}=0 \quad \& \quad \boldsymbol{f} \boldsymbol{e}=1
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- But what is $f_{j}$ ? Let us define $\boldsymbol{A}=\sum_{l=0}^{K+1} \boldsymbol{A}_{l}$, we have $\boldsymbol{f}=\left(f_{0}, f_{1}, \ldots, f_{m-1}\right)$. Therefore:

$$
f A=0 \quad \& \quad f e=1
$$

- The stability condition is:

$$
\boldsymbol{f} \boldsymbol{A}_{0} \boldsymbol{e}<\sum_{k=2}^{K+1}(k-1) \boldsymbol{f} \boldsymbol{A}_{k} \boldsymbol{e}
$$

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Computational Properties of $\boldsymbol{R}$
Algorithm for solving $\boldsymbol{R}$

- It is an iterative method. Let
$\boldsymbol{R}(0)=\mathbf{0}$

$$
\boldsymbol{R}(n+1)=-\sum_{l=0, l \neq 1}^{\infty} \boldsymbol{R}^{l}(n) \boldsymbol{A}_{l} \boldsymbol{A}_{1}^{-1} \quad n=0,1,2, \ldots
$$

The iterative process halts whenever entries in $R(n+$
and $R(n)$ differ in absolute value by less than a given
constant
The cecuence $\{R(n)\}$ are entry-wise non-decreasing and
converge monotonically to a non-negative matrix $R$.

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$$
\begin{aligned}
\boldsymbol{R}(0) & =\mathbf{0} \\
\boldsymbol{R}(n+1) & =-\sum_{I=0, l \neq 1}^{\infty} \boldsymbol{R}^{\prime}(n) \boldsymbol{A}_{l} \boldsymbol{A}_{1}^{-1} \quad n=0,1,2, \ldots
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- The sequence $\{\boldsymbol{R}(n)\}$ are entry-wise non-decreasing and converge monotonically to a non-negative matrix $\boldsymbol{R}$.

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\end{aligned}
$$

- The iterative process halts whenever entries in $\boldsymbol{R}(n+1)$ and $\boldsymbol{R}(n)$ differ in absolute value by less than a given constant.
- The sequence $\{\boldsymbol{R}(n)\}$ are entry-wise non-decreasing and converge monotonically to a non-negative matrix $\boldsymbol{R}$.
- the number of iteration needed for convergence increases as the spectral radius of $\boldsymbol{R}$ increases. This is similar to the scalar case where $\rho \rightarrow 1$. As the system utilization increases, it becomes computationally more difficult to get


## Replicated Database

- Poisson arrival with rate $\lambda$.


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- Probability it is a read request: $r$.

A read request can be served by any server.

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- A write request has to be served by BOTH servers.
- What is the proper state space?


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- What is the proper state space?

The state space $S=(i, j)$ where $i$ is the number of queued customers and $j$ is the number of replications that are involved in service. So $i \geq 0$ and $j=0,1,2$.


$$
\begin{aligned}
& \boldsymbol{Q}=\left[\begin{array}{ccc|cc|cc}
-\lambda & \lambda r & \lambda(1-r) & 0 & 0 & 0 & \cdots \\
\mu & -(\lambda+\mu) & \lambda r & \lambda(1-r) & 0 & 0 & \cdots \\
0 & 2 \mu & -(\lambda+2 \mu) & 0 & \lambda & 0 & \cdots \\
\hline 0 & 0 & \mu & -(\lambda+\mu) & 0 & \lambda & \cdots \\
0 & 0 & 2 \mu r & 2 \mu(1-r) & -(\lambda+2 \mu) & 0 & \cdots \\
\hline 0 & 0 & 0 & 0 & \mu & -(\lambda+\mu) & \cdots \\
\vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \cdots \\
\boldsymbol{B}_{00} & =\left[\begin{array}{ccc}
-\lambda & \lambda r & \lambda(1-r) \\
\mu & -(\lambda+\mu) & \lambda r \\
0 & 2 \mu & -(\lambda+2 \mu)
\end{array}\right] ; \boldsymbol{B}_{01}=\left[\begin{array}{cc}
0 & 0 \\
\lambda(1-r) & 0 \\
0 & \lambda
\end{array}\right] \\
\boldsymbol{B}_{10}=\left[\begin{array}{ccc}
0 & 0 & \mu \\
0 & 0 & 2 \mu r
\end{array}\right] ; \boldsymbol{B}_{11}=\boldsymbol{A}_{1}=\left[\begin{array}{ccc}
-(\lambda+\mu) & 0 \\
2 \mu(1-r) & -(\lambda+2 \mu)
\end{array}\right] ;
\end{array},\right.
\end{aligned}
$$

$$
\boldsymbol{A}_{0}=\left[\begin{array}{cc}
\lambda & 0 \\
0 & \lambda
\end{array}\right] ; \boldsymbol{A}_{2}=\left[\begin{array}{cc}
0 & \mu \\
0 & 2 \mu r
\end{array}\right]
$$

To determine the stability:

$$
\begin{gathered}
\boldsymbol{A}=\left[\begin{array}{cc}
-\mu & \mu \\
2 \mu(1-r) & -2 \mu(1-r)
\end{array}\right]=\boldsymbol{A}_{0}+\boldsymbol{A}_{1}+\boldsymbol{A}_{2} \\
f_{1}=\frac{2(1-r)}{3-2 r} ; \quad f_{2}=\frac{1}{3-2 r} \\
\boldsymbol{f} \boldsymbol{A}_{0} \boldsymbol{e}<\sum_{k=2}^{K+1}(k-1) \boldsymbol{f} \boldsymbol{A}_{k} \boldsymbol{e} \rightarrow \lambda<\frac{2 \mu}{3-2 r}
\end{gathered}
$$

