# A Series Expansion Approach to Risk Analysis of an Inventory System with Sourcing 

Joost Berkhout* Bernd Heidergott **<br>* Dept. Econometrics and Operations Research, VU University Amsterdam, the Netherlands, (e-mail: j2.berkhout@vu.nl)<br>** Tinbergen Institute and Dept. Econometrics and Operations Research, VU University Amsterdam, the Netherlands, (e-mail: bheidergott@feweb.vu.nl)


#### Abstract

In this paper we extend the series expansion approach for uni-chain Markov processes to a special case of finite multi-chains with possible transient states. We will show that multichain Markov models arise naturally in simple models such as a single item inventory system with sourcing, i.e., with the possibility to choose between different suppliers for replenishment. Numerical examples are provided to illustrate the performance of the series expansion algorithm to the risk analysis of this type of inventory systems.


Keywords: sensitivity analysis, perturbation analysis for Markov chains, multi-chains, series expansion algorithm

## 1. INTRODUCTION

Consider a Markov process $X_{\theta}=\left\{X_{\theta}(t): t \geq 0\right\}$ on some finite state-space $S$, where $\theta$ denotes a parameter of the system, such as the service rate in a queue or the arrival rate to a network. Let $Q_{\theta}$ denote the infinitesimal generator of $X_{\theta}$. The transition probability from $X_{\theta}(0)=i$ to $X_{\theta}(t)=j$, for $t>0$, is denoted by $P_{\theta}(i, j ; t)$, for $i, j \in S$ and it holds in matrix form $P_{\theta}(t)=e^{Q_{\theta} t}, t \geq 0$. Denote, for $i, j \in S$, by

$$
\lim _{t \rightarrow \infty} \frac{1}{t} \int_{0}^{t} P_{\theta}(i, j ; u) d u=\Pi_{\theta}(i, j)
$$

the ergodic projector of $Q_{\theta}$. For any initial distribution $\mu$ on $S$ it then holds that the limiting distribution of the process is $\mu \Pi_{\theta}$. A Markov process is called uni-chain if there exists only one ergodic class, and multi-chain otherwise. Provided that $X_{\theta}$ is uni-chain with possible transient states, then the stationary distribution $\pi_{\theta}$ of $X_{\theta}$ exists and can be found as the unique probability vector solving $\pi_{\theta} Q_{\theta}=0$. In this case, $\Pi_{\theta}$ is the matrix with rows equal to $\pi_{\theta}$.
Perturbation analysis of uni-chain Markov processes is a well developed theory that studies the effect of a perturbation $\Delta$ of $\theta$ has on $\pi_{\theta}$. For an early paper see Schweitzer [1968]. The series expansion algorithm introduced in Heidergott and Hordijk [2003], Heidergott et al. [2007, 2010] allows to obtain $\pi_{\theta+\Delta}$ as a polynomial in $\Delta$ and thus allows for a functional approximation of $\pi_{\theta}$ on an entire interval. See also Cao [1998] and Abbas et al. [2013].
This paper is devoted to perturbation analysis of multichains. We will show that the series expansion algorithm can be extended to a special multi-chain case, with possible transient states, provided that $Q_{\theta}$ and $Q_{\theta+\Delta}$ either have the same ergodic classes with some restrictions on the
transient states of $Q_{\theta+\Delta}$, or $Q_{\theta}$ is uni-chain. In addition we will show that, without extending the algorithm, it is not possible to develop $\pi_{\theta+\Delta}$ into a series at $\theta$ if $\Delta$ has an influence on the ergodic classes.

We will apply multi-chain version of the series expansion algorithm to perturbation analysis of a single-item inventory system with sourcing. Customers arrive to the inventory according to a Poisson $\lambda$ process and purchase one single time at a time. The inventory can be replenished by either ordering from a wholesaler, with lead time $\mu_{1}$, or directly from the producer, with lead time $\mu_{2}$ (throughout this paper 1 and 2 will be used to indicate orders from the wholesaler and from the producer, respectively). From the wholesaler items can be ordered in single units, whereas for the producer a bulk order has to be placed, i.e., the product can only be ordered in units of size $b>1$. When the inventory level drops below $s_{2}$ a bulk order is placed. Since, the lead time of a bulk order is relatively large, it can become necessary to order single items if the inventory reaches level $s_{1}>0$. The maximal capacity of the inventory is denoted by $N_{\max }$. If at inventory level $s_{2}$ a bulk order is placed, then maximal number of batches to be ordered is given by

$$
\left\lfloor\frac{N_{\max }-s_{2}}{b}\right\rfloor,
$$

and the inventory is replenished to level

$$
S_{2}:=\left\lfloor\frac{N_{\max }-s_{2}}{b}\right\rfloor b .
$$

If, single items are ordered, then we assume that the inventory is replenished to level $S_{1} \leq N_{\max }$. Thus, the system is described through $\left(s_{1}, S_{1}, s_{2}, S_{2}\right)$. To summarize, the system is specified by the set of uncontrollable parameters $\lambda, \mu_{1}, \mu_{2}$, and the set of controllable parameters $\left(s_{1}, S_{1}, s_{2}, S_{2}\right)$.

As we will illustrate by examples, the Markov processes modeling the inventory level together with the order list (to be defined presently) is typically a multi-chain with transient states. From our analysis of the multi-chain case, we will conclude that we cannot use the series expansion algorithm for analyzing the dependence of the ergodic projector on $\theta=\left(s_{1}, S_{1}, s_{2}, S_{2}\right)$. For this reason we focus in this paper on a series expansion of the ergodic projector $\Pi_{\theta}$ with respect to $\theta=\lambda, \mu_{1}, \mu_{2}$. More specifically, we will investigate the robustness of our model against the statistical insecurity in the parameter values for $\theta$. To this end we make the reasonable assumption that the "true" lead time $\mu_{1}$ is not revealed to us and for the model we have to rely on statistics for estimating $\mu_{1}$. For example letting $\theta=\mu_{1}$ we let $\theta=\theta_{0}+\Delta$ with $\theta_{0}$ being the mean value of the statistics and $\Delta$ representing the insecurity in predicting $\mu_{1}$ (typically, $\Delta$ is normally distributed with mean zero). Alternatively, $\Delta$ may be obtained by expert judgment, like, $\Delta$ uniformly distributed on $[-\epsilon, \epsilon]$ for some dispersion measure $\epsilon>0$.

The main idea of our analysis is to develop $\Pi_{\theta=\theta_{0}+\Delta}$ into a Taylor series with respect to $\Delta$ at $\Delta=0$, i.e., we will have

$$
\begin{align*}
\Pi_{\theta=\theta_{0}+\Delta} & \approx H\left(\theta_{0}, N ; \Delta\right) \\
& :=\Pi_{\theta_{0}} \sum_{n=0}^{N}\left(\left(Q_{\theta_{0}+\Delta}-Q_{\theta_{0}}\right) D_{\theta_{0}}\right)^{n}, \tag{1}
\end{align*}
$$

where $D_{\theta}$ is the deviation matrix associated with $Q_{\theta}$ and is given by

$$
D_{\theta}(i, j)=\lim _{t \rightarrow \infty} \frac{1}{t} \int_{0}^{t}\left(P_{\theta}(i, j, u)-\Pi_{\theta}(i, j)\right) d u
$$

for $i, j \in S$. For computation, the deviation matrix $D_{\theta}$ can be obtained as

$$
D_{\theta}=\left(\Pi_{\theta}-Q_{\theta}\right)^{-1}-\Pi_{\theta},
$$

assuming that $\left\|I+Q_{\theta}-\Pi_{\theta}\right\|<1$ for some operator norm $\|\cdot\|$ (which follows from the results on Neumann series). The series expansion in (1) allows to write $\Pi_{\theta}$ as a polynomial in the random variable $\Delta$. We will use this property to study the behavior of $\Pi_{\theta}$ as a random variable induced by $\Delta$. This provides a powerful analysis of the risk introduced by the insecurity about the actual value of $\theta$ on the model. Note that $\mathbb{E}[\theta]=\theta_{0}$, but, as $\Pi_{\theta}$ typically depends in a non-linear way on $\Delta$, it does not hold true that $\Pi_{\theta_{0}}=\mathbb{E}\left[\Pi_{\theta}\right]$.
The paper is organized as follows. In Section 2 we discuss the series expansion algorithm for a special case of finite multi-chain Markov processes. The risk analysis with respect to $\Delta$ is detailed in Section 3. Finally, in Section 4 we introduce the inventory model in more detail and we present numerical results.

## 2. SERIES EXPANSION ALGORITHM FOR MULTI-CHAINS

Let $Q$ have $I$ ergodic classes and $T$ transient states. After appropriate relabeling of the states, $\Pi_{Q}$ can be written as

$$
\left(\begin{array}{ccccc}
\Pi_{1} & 0 & \ldots & & 0  \tag{2}\\
0 & \Pi_{2} & 0 & \ldots & 0 \\
\vdots & & \ddots & & \vdots \\
0 & & & \Pi_{I} & 0 \\
R_{1} & \ldots & & R_{I} & 0
\end{array}\right)
$$

where $\Pi_{i}$ is the ergodic projector of the $i$-th ergodic class, which is given by a matrix with rows equal to $\pi^{i}$, the uniquely defined stationary distribution on class $i$, and $R_{i}(j, k)$ is the probability to go from transient state $j$ to state $k$ (which lies in ergodic class $i$ ). Note that it is typically possible to go from a transient state to several ergodic classes. In this case $R_{i}(i, k)$ is the probability of going from state $i$ to ergodic class $i$ times $\pi^{i}(k)$.
Remark 1. Computing the ergodic projector of a multichain with transient states is a non-trivial task. For computations, we apply the idea in E. P. C. Kao [1997] on page 172 for identifying the irreducible classes and transient states. Once the irreducible classes are identified, the corresponding stationary distributions $\Pi_{i}$ are computed in the standard way, i.e., we find the probability solution of $\pi_{i} Q_{i}=0$, where $Q_{i}$ is the restriction of the $Q$ matrix to states from ergodic class $i$, and $\Pi_{i}$ is a matrix with rows equal to $\pi_{i}$. The values of the transient components $R_{i}$ requires solving a set of balance equations. In particular, define the $T \times I$ matrix $P_{T_{1}}$ as the one step probabilities of the embedded Markov chain of going from a transient state to an ergodic class. More specifically, $P_{T_{1}}(i, c)$ is the one step probability of going from transient state $i$ to the ergodic class $c$. Similar, define the $T \times T$ matrix $P_{T_{2}}$ as the one step probabilities of moving from one transient state to another one. Then the probabilities of ending in ergodic class $c$ while starting in transient state $i$ is given by the (i,c)-th element in the $(T \times I)$-matrix $\left(I_{T}-P_{T_{2}}\right)^{-1} P_{T_{1}}$, where $I_{T}$ is the $T \times T$ identity matrix. The rows in the ergodic projector that correspond with the transient states can then be calculated using these probabilities and $\Pi_{i}$.

We say that a Markov process $X$ (resp. a infinitesimal generator $Q$ ) dominates a Markov process $X^{\prime}$ (resp. an infinitesimal generator $Q^{\prime}$ ) if $X$ and $X^{\prime}$ are defined on a common state space and (i) the ergodic classes of $X^{\prime}$ are subsets of the ergodic classes of $X$, and (ii) it must hold for any transient state in $Q^{\prime}$ that the set of ergodic class(es) that can be reached with a positive probability is a subset of the only ergodic class that can be reached from the same state in $Q$ (observe that the transient state in $Q^{\prime}$ is not necessarily transient in $Q$ ). Taking the explicit form in (2) into consideration we can proof the following result in case of domination.
Lemma 2. If $Q$ dominates $Q^{\prime}$, then $\Pi_{Q^{\prime}} \Pi_{Q}=\Pi_{Q}$.
Proof: In order to rephrase the domination definition above in mathematical terms and to prove the lemma we need some definitions. Define $E(Q)$ as the set of ergodic states of $Q$, similar, define $T(Q)$ as the set of transient states of $Q$. More specifically, define $[i]_{Q}$ as the set of states belonging to the ergodic class in $Q$ which contains $i \in E(Q)$. Furthermore, define $T E(Q ; i)$ as the ergodic states in $Q$ which have a positive probability of being reached from state $i$. Using this notation, the domination definition satisfies:
(i) $\forall i \in E\left(Q^{\prime}\right):[i]_{Q^{\prime}} \subseteq[i]_{Q}$.

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