

**DIFFERENTIABILITY OF THE MATRICES  $R$  AND  $G$   
IN THE MATRIX-ANALYTIC METHOD**

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**ABSTRACT**

The differentiability, with respect to a parameter of the model, of the matrices  $R$  and  $G$  that arise in the matrix-analytic method is studied. Some conditions for the differentiability of  $R$  and  $G$  are given.

**Key Words:** Differentiability, matrix-analytic method, queueing theory.

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## 1. Introduction

Let  $\Omega$  be an open set of real numbers. For  $x \in \Omega$ , let  $\{A_n(x), n \geq 0\}$  be a sequence of nonnegative square matrices of order  $m$  such that the matrix  $A(x) = \sum_{n=0}^{\infty} A_n(x)$  is an irreducible stochastic or substochastic matrix.  $R(x)$  is the minimal nonnegative solution to the equation

$$X = \sum_{n=0}^{\infty} X^n A_n(x), \quad (1)$$

and  $G(x)$ , the minimal nonnegative solution to

$$X = \sum_{n=0}^{\infty} A_n(x) X^n. \quad (2)$$

We study the differentiability of  $R(x)$  and  $G(x)$  under certain conditions on the sequence  $\{A_n(x), n \geq 0\}$ , especially when  $\{A_n(x), n \geq 0\}$  have only finitely many nonzero matrices.

$R(x)$  and  $G(x)$  are two important matrices in the matrix-analytic method (see Neuts [3], [4]; Ramaswami [5], [6]). They are useful in the computation of the distributions of queue lengths, waiting times and busy periods of *GI/MAP/1* and *MAP/G/1* queues.  $R(x)$  arises in the study of *GI/MAP/1* queues and  $G(x)$  of *MAP/G/1* queues.  $\{A_n(x)\}$  are blocks in the transition matrices of the embedded Markov chains, either at arrivals or departures, and  $x$  is a system parameter. In He and Neuts [2], the differentiability of  $R(x)$  and  $G(x)$  is discussed for a special quasi birth-and-death process. The present results are used there to derive second order expansions of some system descriptors.

In Section 2, we study the differentiability of  $R(x)$  in irreducible cases. In Section 3, the differentiability of  $G(x)$  is discussed. In Section 4, the technical details associated with reducible cases and cases related to continuous parameter Markov processes are discussed. In Section 5, we summarize the results obtained.

## 2. Differentiability of the Matrix $R$

Let  $\pi(x)$  be the left eigenvector corresponding to the maximal eigenvalue,  $sp(A(x))$ , of  $A(x)$ .  $\pi(x)$  is nonnegative and normalized by  $\pi(x)\mathbf{e} = 1$ , where  $\mathbf{e}$  is the column vector with all components one. Clearly,  $sp(A(x)) \leq 1$ . Let

$\beta(x) = \sum_{n=0}^{\infty} nA_n(x)\mathbf{e}$ . We define the matrix

$$M_r(x_1, x_2) = \sum_{n=1}^{\infty} \sum_{i=0}^{n-1} [R^i(x_1)]^T \otimes [R^{n-i-1}(x_2)A_n(x_2)], \quad x_1, x_2 \in \Omega, \quad (3)$$

where the superscript  $T$  denotes transpose and  $\otimes$  is the *Kronecker product* of matrices (see Graham [1]). The matrix  $M_r(x_1, x_2)$  exists since  $R(x_i)$ ,  $i = 1, 2$ , and  $\{A_n(x_2)\}$  are nonnegative matrices. Furthermore, the next lemma shows that  $M_r(x_1, x_2)$  is finite and its maximum eigenvalue is less than 1.

**Lemma 2.1.** Assume that  $A(x)$  is an irreducible stochastic or substochastic matrix. If  $A(x_i)\mathbf{e} < \mathbf{e}$ , or if  $A(x_i)\mathbf{e} = \mathbf{e}$  and  $\pi(x_i)\beta(x_i) > 1$ ,  $i = 1, 2$ , we have that

$$sp(M_r(x_1, x_2)) < 1, \quad x_1, x_2 \in \Omega.$$

**Proof.** By Corollary 1.3.1, Lemmas 1.3.4 and 1.3.5 in Neuts [3],  $sp(R(x_i)) < 1$ ,  $i = 1, 2$ . We rewrite  $M_r(x_1, x_2)$  as

$$M_r(x_1, x_2) = \sum_{n=0}^{\infty} [R^n(x_1)]^T \otimes B_n(x_2),$$

where  $B_n(x_2) = \sum_{i=0}^{\infty} R^i(x_2)A_{n+i+1}(x_2)$ ,  $n \geq 0$ . Since  $A(x_2)\mathbf{e} \leq \mathbf{e}$ ,

$$\begin{aligned} \sum_{n=0}^{\infty} B_n(x_2)\mathbf{e} &= \sum_{n=1}^{\infty} \left[ \sum_{i=0}^{n-1} R^i(x_2) \right] A_n(x_2)\mathbf{e} \\ &= (I - R(x_2))^{-1} (A(x_2) - R(x_2))\mathbf{e} \leq \mathbf{e}, \end{aligned}$$

so that  $sp(\sum_{n=0}^{\infty} B_n(x_2)) \leq 1$ .

If  $sp(R(x_1)) = 0$ ,  $R(x_1)$  has the Jordan canonical decomposition

$$R(x_1) = P \begin{pmatrix} 0 & * & \cdots & * \\ & \ddots & \ddots & \vdots \\ & & \ddots & * \\ & & & 0 \end{pmatrix} P^{-1},$$

where  $P$  is an invertible matrix. Hence, we have

$$\sum_{n=0}^{\infty} [R^n(x_1)]^T \otimes B_n(x_2) = [(P^{-1})^T \otimes I] \begin{pmatrix} 0 & & & \\ * & \ddots & & \\ \vdots & \ddots & \ddots & \\ * & \cdots & * & 0 \end{pmatrix} (P^T \otimes I).$$

Therefore,  $sp(M_r(x_1, x_2)) = 0$ .

If  $sp(R(x_1)) > 0$ , since  $A(x_1)$  is irreducible, then by Lemma 1.3.2 in Neuts [3], the left eigenvector  $\mathbf{u}$  of  $R(x_1)$  corresponding to  $sp(R(x_1))$  may be chosen to be positive. Hence, we have

$$\begin{aligned} [\sum_{n=0}^{\infty} (R^n(x_1))^T \otimes B_n(x_2)](\mathbf{u}^T \otimes \mathbf{e}) &= \sum_{n=0}^{\infty} [(sp(R(x_1)))^n \mathbf{u}^T] \otimes (B_n(x_2)\mathbf{e}) \\ &< \mathbf{u}^T \otimes [(\sum_{n=0}^{\infty} B_n(x_2))\mathbf{e}] \\ &\leq \mathbf{u}^T \otimes \mathbf{e}. \end{aligned}$$

Therefore, since  $\mathbf{u}$  is positive, we have  $sp(M_r(x_1, x_2)) < 1$ .  $\square$

Set

$$A^*(z, x) = \sum_{n=0}^{\infty} z^n A_n(x). \quad 0 < z < 1, \quad x \in \Omega.$$

It is obvious that  $A(x) = \lim_{z \rightarrow 1} A^*(z, x)$ .

**Lemma 2.2.** If the sequence  $\{A_n(x)\}$  satisfy the conditions of Lemma 2.1 for all  $x$  in  $\Omega$  and its terms are continuous in  $\Omega$ , then  $R(x)$  is continuous in  $\Omega$ .

**Proof.** Let  $\rho(x) = sp(R(x))$ . First, we claim that for  $x_0 \in \Omega$ , there exists a neighborhood  $S(x_0)$  of  $x_0$  such that  $\rho(x) < \delta(x_0) < 1$ , for  $x \in S(x_0)$ .

Suppose that the claim is false, then there exists a nondecreasing subsequence  $\rho(x_n) \rightarrow 1$ , with  $\lim_{n \rightarrow \infty} x_n = x_0$ . Let  $\mathbf{u}(x)$  be the left eigenvector of  $R(x)$  corresponding to  $\rho(x)$  with  $\mathbf{u}(x)\mathbf{e} = 1$ . Since  $R(x_n)$  satisfies equation (1), we have that

$$\mathbf{u}(x_n)R(x_n) = \mathbf{u}(x_n)\rho(x_n) = \mathbf{u}(x_n)A^*(\rho(x_n), x_n). \quad (4)$$

Furthermore, there exists a subsequence  $\{x_{n_i}\}$  of  $\{x_n\}$  such that  $\{\mathbf{u}(x_{n_i})\}$  converges to a nonnegative vector  $\mathbf{u}$  with  $\mathbf{u}\mathbf{e} = 1$ . Therefore  $\mathbf{u} = \mathbf{u}A(x_0)$ . Since  $A(x_0)$  is irreducible, we know that  $\mathbf{u} = \pi(x_0)$ . For  $\{R(x_n)\}$ , there exists a subsequence  $\{R(x_{n_i})\}$  such that  $\{R(x_{n_i})\}$  converges to a nonnegative matrix  $\hat{R}$  with  $\mathbf{u}\hat{R} = \mathbf{u}$ .

By Lemma 2.1,  $\sum_{i=0}^{\infty} B_i(x_n)\mathbf{e} \leq \mathbf{e}$  so that  $\mathbf{u}(x_n) \sum_{i=0}^{\infty} B_i(x_n)\mathbf{e} \leq \mathbf{u}(x_n)\mathbf{e} = 1$ . Therefore,

$$\sup_{n \rightarrow \infty} \mathbf{u}(x_n) \sum_{i=0}^{\infty} B_i(x_n)\mathbf{e} \leq 1. \quad (5)$$

On the other hand,

$$\mathbf{u}(x_n) \sum_{i=0}^{\infty} B_i(x_n) = \mathbf{u}(x_n) \sum_{i=1}^{\infty} \sum_{j=0}^{i-1} \rho^j(x_n) A_i(x_n).$$

Since  $\lim_{x_n \rightarrow x_0} \rho(x_n) = 1$ ,  $\lim_{x_n \rightarrow x_0} \mathbf{u}(x_n) = \mathbf{u}$  and  $\lim_{x_n \rightarrow x_0} A_i(x_n) = A_i(x_0)$ , it follows that

$$\sup_{n \rightarrow \infty} \mathbf{u}(x_n) \sum_{i=0}^{\infty} B_i(x_n) \mathbf{e} \geq \mathbf{u} \sum_{i=1}^{\infty} i A_i(x_0) \mathbf{e} = \pi(x_0) \beta(x_0) > 1.$$

This contradicts equation (5). Therefore, the claim is true.

For any subsequence  $\{x_m\}$  of  $\{x_n\}$  such that  $\lim_{x_m \rightarrow x_0} R(x_m) = \hat{R}$ , there exists a subsequence  $\{x_{m_i}\}$  such that  $\{\rho(x_{m_i})\}$  converges to a nonnegative number  $\hat{\rho}$  ( $< \delta(x_0) < 1$ ). Since  $\rho(x_n) < \delta(x_0) < 1$ ,  $\{R^i(x_n)\}$  converges to the zero matrix uniformly in  $n$ . Hence, it can be proved that  $\hat{R} = \sum_{i=0}^{\infty} \hat{R}^i A_i(x_0)$ . By (4), we have  $\mathbf{u} A^*(\hat{\rho}, x_0) = \mathbf{u} \hat{\rho}$ . By Theorem 1.3.3 in Neuts [3], we know that the solution  $X$  to equation (1) with  $sp(X) < 1$  at  $x_0$  is unique. Therefore, we have  $\hat{R} = R(x_0)$ . This implies that  $\lim_{x_n \rightarrow x_0} R(x_n) = R(x_0)$ .  $\square$

For a matrix  $C$  of dimensions  $m_1 \times m_2$ ,  $\phi(C)$  is the  $m_1 m_2$ -vector obtained by forming the *direct sum* of the rows of  $C$ . Call  $\phi$  the *direct sum transform* of matrices. If  $X, Y$  and  $Z$  are matrices and their product  $XYZ$  is well defined, then  $\phi(XYZ) = \phi(Y)X^T \otimes Z$ . This property is used in the proof of Theorem 2.3.

**Theorem 2.3.** Suppose that, for all  $x$  in  $\Omega$ ,  $A_n(x) = 0$  for  $n > N > 0$  and  $\{A_n(x), n \leq N\}$  are differentiable up to order  $K (\geq 1)$  and satisfy the conditions of Lemma 2.1. If  $\{A_n^{(K)}(x)\}$  are continuous, the minimal nonnegative solution,  $R(x)$ , of (1) is differentiable in  $\Omega$  up to order  $K$ .

**Proof.** From (1), we have, for  $x_0 \in \Omega$ ,

$$\begin{aligned} R(x) - R(x_0) &= \sum_{n=1}^N \sum_{i=0}^{n-1} R^i(x_0) [R(x) - R(x_0)] R^{n-i-1}(x) A_n(x) \\ &\quad + \sum_{n=0}^N R^n(x_0) [A_n(x) - A_n(x_0)]. \end{aligned}$$

Taking direct sum transforms of both sides, we have, by the property of the transform  $\phi$ , that

$$\phi(R(x_0) - R(x)) = \phi\left(\sum_{n=0}^N R^n(x_0) (A_n(x) - A_n(x_0))\right) \cdot [I - M_r(x_0, x)]^{-1}. \quad (6)$$

By virtue of the proofs of Lemmas 2.1 and 2.2,  $[I - M_r(x_0, x)]^{-1}$  exists and is continuous at  $x_0$  in  $x$ . Dividing both sides of (4) by  $x - x_0$  and letting  $x \rightarrow x_0$ , it follows that

$$\phi(R'(x_0)) = \phi\left(\sum_{n=0}^N R^n(x_0)A'_n(x_0)\right) \cdot [I - M_r(x_0, x_0)]^{-1}. \quad (7)$$

Therefore,  $R(x)$  is differentiable at  $x_0$ .

Suppose that  $R(x)$  is differentiable up to order  $i < K$ . We shall show that  $R(x)$  is differentiable up to order  $i + 1$ . By induction,  $R^{(i)}(x)$  satisfies

$$R^{(i)}(x) = \sum_{n=1}^N \sum_{j=0}^{n-1} [R(x)]^j R^{(i)}(x) [R(x)]^{n-j-1} A_n(x) + f_i(x), \quad (8)$$

where

$$f_i(x) = \sum_{n=0}^N \left[ \sum_{\substack{j_1 + \dots + j_{n+1} = i \\ 0 \leq j_1, \dots, j_n < i}} \frac{i!}{j_1! \dots j_{n+1}!} R^{(j_1)}(x) \dots R^{(j_n)}(x) A_n^{(j_{n+1})}(x) \right], \quad i \geq 1,$$

Then, similar to (6), we have

$$\begin{aligned} & \phi(R^{(i)}(x_0) - R^{(i)}(x)) \\ &= \phi\left(\sum_{n=0}^N \sum_{j=0}^{n-1} [R(x_0)]^j R^{(i)}(x_0) [(R(x_0))^{n-j-1} A_n(x_0) - [R(x)]^{n-j-1} A_n(x)] \right. \\ & \quad + \sum_{n=0}^N \sum_{j=0}^{n-1} [(R(x_0))^j - (R(x))^j] R^{(i)}(x) (R(x))^{n-j-1} A_n(x) \\ & \quad \left. + f_i(x_0) - f_i(x)\right) \cdot [I - M_r(x_0, x)]^{-1}. \end{aligned}$$

Dividing both sides by  $x - x_0$  and letting  $x \rightarrow x_0$ , we obtain

$$\phi(R^{(i+1)}(x_0)) = \phi(f_{i+1}(x_0)) \cdot [I - M_r(x_0, x_0)]^{-1}, \quad (9)$$

and, since the  $\{A_n(x)\}$  are differentiable at  $x_0$  up to order  $K$ , so is  $R(x)$ .  $\square$

**Note 2.1.** Theorem 2.3 also holds for  $N = \infty$  if  $f_i(x)$  (defined in the proof of Theorem 2.3) exists,  $1 \leq i \leq K$ . However, we have

$$f_1(x) = \sum_{n=0}^{\infty} R^n(x) A'_n(x). \quad (10)$$

and  $f_i(x)$  is much more complicated for  $i \geq 2$ . So, it is next to impossible to verify the existence of  $\{f_i(x)\}$  when  $N = \infty$ .

**Note 2.2.** We consider an  $M/M/1$  queue with an arrival rate  $\lambda(x)$  and a service rate 1. Routine calculations give that

$$R(x) = \begin{cases} \lambda(x), & \text{if } \lambda(x) \leq 1; \\ 1, & \text{if } \lambda(x) > 1. \end{cases} \quad (11)$$

Equation (11) shows that for any  $x_0$  with  $\lambda(x_0) = 1$  and  $\lambda'(x_0) \neq 0$ ,  $R(x)$  may not be differentiable at  $x_0$ . Therefore,  $\Omega$  is assumed to be an open set.

To compute the derivatives of  $R(x)$ , we solve equation (8). We can use an iterative process to obtain approximation solutions. Alternately, we use the direct sum transformation (9), which gives the explicit solution for  $\{R^{(i)}(x), i \geq 1\}$ , provided that  $R(x)$  is known.

### 3. Differentiability of the Matrix $G$

We define

$$M_g(x_1, x_2) = \sum_{n=1}^{\infty} \left( \sum_{i=0}^{n-1} A_n(x_1) G^i(x_1) \right)^T \otimes G^{n-1-i}(x_2), \quad x_1, x_2 \in \Omega. \quad (12)$$

As in the case with the matrix  $M_r(x_1, x_2)$ , the invertibility of the matrix  $M_g(x_1, x_2)$  is the key to the differentiability of the matrix  $G(x)$ .

**Lemma 3.1.** Assume that  $A(x)$  is an irreducible stochastic or substochastic matrix. If  $A(x_i)\mathbf{e} < \mathbf{e}$ , or if  $A(x_i)\mathbf{e} = \mathbf{e}$  and  $\pi(x_i)\beta(x_i) < 1$ ,  $i = 1, 2$ , we have that

$$sp(M_g(x_1, x_2)) < 1, \quad x_1, x_2 \in \Omega.$$

**Proof.** (12) may be rewritten as

$$M_g(x_1, x_2) = \sum_{n=0}^{\infty} [\bar{B}_n(x_1)]^T \otimes G^n(x_2),$$

where  $\bar{B}_n(x_1) = \sum_{i=0}^{\infty} A_{n+i+1}(x_1) G^i(x_1)$ ,  $n \geq 0$ .

When  $A(x_1)\mathbf{e} < \mathbf{e}$ ,  $sp(G(x_1)) < 1$ . By routine calculations, we have

$$\sum_{n=0}^{\infty} \bar{B}_n(x_1) = [A(x_1) - G(x_1)][I - G(x_1)]^{-1}.$$

Therefore,  $\pi(x_1) \sum_{n=0}^{\infty} \bar{B}_n(x_1) < \pi(x_1)$ , so that  $sp(\sum_{n=0}^{\infty} \bar{B}_n(x_1)) < 1$ .

When  $A(x_1)\mathbf{e} = \mathbf{e}$ , we have  $sp(G(x_1)) = 1$ . Denote by  $\mathbf{g}$ , the left invariant vector of  $G(x_1)$ . By routine calculations,

$$\sum_{n=0}^{\infty} \bar{B}_n(x_1) = (A(x_1) - G(x_1) + \beta(x_1)\mathbf{g})(I - G(x_1) + \mathbf{e}\mathbf{g})^{-1}.$$

The matrix  $I - G(x_1) + \mathbf{e}\mathbf{g}$  is invertible since  $\pi(x_1)\beta(x_1) < 1$ . Hence,

$$\pi(x_1) \left( \sum_{n=0}^{\infty} \bar{B}_n(x_1) \right) = \pi(x_1) + (\pi(x_1)\beta(x_1) - 1)\mathbf{g} < \pi(x_1).$$

Therefore, since every component of  $\pi(x_1)$  is positive,  $sp(\sum_{n=0}^{\infty} \bar{B}_n(x_1)) < 1$ .

Combining the results of the two cases, we have  $sp(\sum_{n=0}^{\infty} \bar{B}_n(x_1)) < 1$ . By applying the  $T_c$  transform (see Appendix) to the matrix  $M_g(x_1, x_2)$ ,

$$T_c(M_g(x_1, x_2)) = \sum_{n=0}^{\infty} T_c((\bar{B}_n(x_1))^T \otimes G^n(x_2)) = \sum_{n=0}^{\infty} G^n(x_2) \otimes [\bar{B}_n(x_1)]^T.$$

The proof that  $sp(T_c(M_g(x_1, x_2))) < 1$  is similar to that of Lemma 2.1. Since  $sp(T_c(M_g(x_1, x_2))) = sp(M_g(x_1, x_2))$ , we have  $sp(M_g(x_1, x_2)) < 1$ .  $\square$

As in Lemma 2.2 and Theorem 2.3, the following results hold for  $G(x)$ .

**Lemma 3.2.** If  $\{A_n(x)\}$  satisfy the conditions given in Lemma 3.1 for all  $x$  in  $\Omega$  and are continuous in  $\Omega$ , then  $G(x)$  is continuous in  $\Omega$ .  $\square$

**Theorem 3.3.** Suppose that, for all  $x$  in  $\Omega$ ,  $A_n(x) = 0$  for  $n > N > 0$  and  $\{A_n(x)\}$  are differentiable up to order  $K (\geq 1)$  and satisfy the conditions given in Lemma 3.1. If  $\{A_n^{(K)}(x)\}$  are continuous, the minimal nonnegative solution,  $G(x)$ , to equation (2) is differentiable up to order  $K$ .  $\square$

#### 4. Discussion

The results given by Theorems 2.3 and 3.3 can be generalized to the cases where  $A(x)$  is reducible. Suppose that  $A(x)$  has the structure

$$A(x) = \begin{pmatrix} A(1, x) & \cdots & * \\ & \ddots & \vdots \\ & & A(k, x) \end{pmatrix},$$



where the diagonal blocks  $A(i, x)$ ,  $1 \leq i \leq k$ , are irreducible matrices. Then  $\{A_n(x)\}$  have the same structure as  $A(x)$  and we denote their corresponding diagonal blocks by  $\{A_n(i, x), 1 \leq i \leq k\}$ . The minimal nonnegative solution  $R(x)$  to the matrix equation (1) has the same structure as  $A(x)$ . The diagonal blocks of  $R(x)$ ,  $R(i, x)$ ,  $1 \leq i \leq k$ , satisfy

$$R(i, x) = \sum_{n=0}^{\infty} R^n(i, x)A_n(i, x), \quad 1 \leq i \leq k.$$

By routine calculations, we have

$$M_r(x_1, x_2) = \begin{pmatrix} \sum_{n=0}^{\infty} (R^n(1, x_1))^T \otimes B_n(x_2) & & & \\ & \vdots & \ddots & \\ & * & \cdots & \sum_{n=0}^{\infty} (R^n(k, x_1))^T \otimes B_n(x_2) \end{pmatrix}.$$

If  $\{A_n(i, x)\}$ ,  $1 \leq i \leq k$ , satisfy the conditions in Lemma 2.1 and Theorem 2.3, we obtain the results in Theorem 2.3 for  $R(x)$ .

There is an entirely analogous theory for the cases where  $A_n(x)$ ,  $n \geq 0$  and  $n \neq 1$ , are nonnegative matrices,  $A_1(x)$  has nonnegative off-diagonal elements and negative diagonal elements, and  $A(x)\mathbf{e} \leq 0$ . The matrix  $R(x)$  is here defined as the minimal nonnegative solution to the equation

$$0 = \sum_{n=0}^{\infty} X^n A_n(x). \quad (13)$$

If there is an analytic function  $\tau(x)$  satisfying

$$\tau(x) > 1 + \max_{1 \leq j \leq m} \{-(A_1(x))_{jj}\},$$

for  $x \in \Omega$ , then (13) may be rewritten as

$$X = \sum_{n=0}^{\infty} X^n \tilde{A}_n(x), \quad (14)$$

where  $\tilde{A}_n(x) = A_n(x)/\tau(x)$ ,  $n \geq 0$  and  $n \neq 1$ , and  $\tilde{A}_1(x) = I + A_1(x)/\tau(x)$ . Equation (14) is the same as equation (1), so Theorem 2.3 is applicable. Similar results hold for the matrix  $G(x)$ .

## 5. Conclusions

We have proved that, under certain conditions on  $\{A_n(x)\}$ , the matrices  $R(x)$  and  $G(x)$  are differentiable. Let us use  $R(x)$  as an example. For the first order differentiability,  $R(x)$  is differentiable when  $\{A'_n(x), n \geq 0\}$  exist and are continuous, and  $\sum_{n=0}^{\infty} R^n(x)A'_n(x)$  exists (see Lemma 2.1, Theorem 2.3 and (10)). For  $\{A_n(x)\}$  with only finitely many nonzero matrices,  $R(x)$  is differentiable up to order  $K$  when  $\{A_n(x)\}$  are differentiable up to order  $K$  and  $\{A_n^{(K)}(x)\}$  are continuous (see Lemma 2.1 and Theorem 2.3).

Although we obtained some conditions for the differentiability of  $R(x)$  and  $G(x)$ , this paper raises more questions than it has solved. For example, when  $\{A_n(x)\}$  have infinitely many nonzero matrices, for higher order differentiability, the conditions imposed on  $\{f_i(x)\}$  are too complicated to be explicitly checked. More tangible conditions in terms of  $\{A_n(x)\}$  are required in applications.

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## APPENDIX

We define a transform,  $T_c$ , on the Kronecker product of matrices  $A$  and  $B$  by

$$T_c(A \otimes B) = B \otimes A,$$

where  $A$  and  $B$  are square matrices of orders  $m_1$  and  $m_2$  respectively.

**Lemma A.** There exists a permutation matrix  $P_{m_1 m_2}$ ,  $P_{m_1 m_2}^2 = I$ , satisfying

$$T_c(A \otimes B) = P_{m_1 m_2}(A \otimes B)P_{m_1 m_2}. \quad (15)$$

Hence,  $T_c(A \otimes B)$  and  $A \otimes B$  are similar.

**Proof.** See (2.14), Graham [1].

□

Using Lemma A, we can define a generalized  $T_c$  on sums of Kronecker products of matrices, i.e., the transform  $T_c(A_1 \otimes B_1 + A_2 \otimes B_2)$  is well-defined and

$$T_c(A_1 \otimes B_1 + A_2 \otimes B_2) = T_c(A_1 \otimes B_1) + T_c(A_2 \otimes B_2),$$

where  $A_1$  and  $A_2$  are of the same dimension and so are  $B_1$  and  $B_2$ . Lemma A still holds for the generalized transformation.