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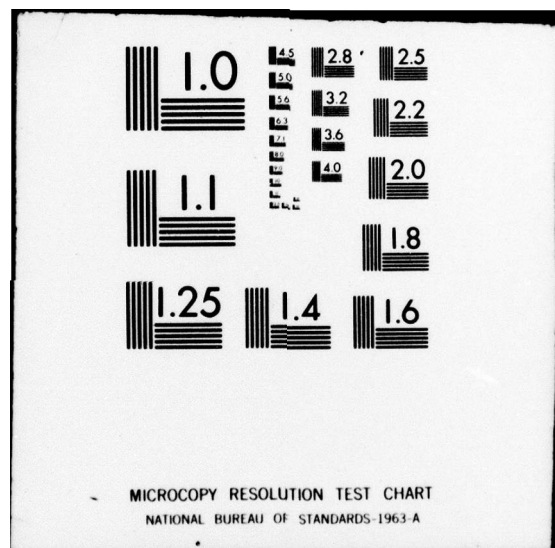
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LEAST SQUARES PREDICTION FOR MIXED AUTOREGRESSIVE MOVING AVERAG--ETC(U)
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LEAST SQUARES PREDICTION FOR MIXED AUTOREGRESSIVE MOVING AVERAGE TIME SERIES

By N. Joseph Newton and Marcello Pagano
Institute of Statistics, Texas A&M University and
Dept. of Biostatistics, Harvard University, U.S.A.

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26. ABSTRACT (Continue on reverse side if necessary and identify by block number)		27. ABSTRACT (Continue on reverse side if necessary and identify by block number)	28. ABSTRACT (Continue on reverse side if necessary and identify by block number)
A computer subroutine is given for computing predictors of any specified horizon's ahead.			

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Keywords: Mixed Time Series, Toeplitz Matrix, Modified Cholesky Decomposition

ISO Fortran

LANGUAGE

DESCRIPTION AND PURPOSE

Let $y(1), \dots, y(T)$ be a sample realization of a mixed autoregressive moving average process $y(t), t = 0, 1, \dots$ of order (p, q) , i.e., $y(t)$ satisfies

$$\sum_{j=0}^p a(j)y(t-j) = \sum_{k=0}^q b(k)e(t-k), \quad t = 0, 1, \dots$$

for constants $p, q, a(0) = b(0) = 1, a(1), \dots, a(p), b(1), \dots, b(q)$, where $e(\cdot)$ is a white noise time series of zero mean, uncorrelated random variables with variance σ^2 . The zeros of the complex polynomials $g(z) = \sum_{j=0}^p a(j)z^j$ and $h(z) = \sum_{k=0}^q b(k)z^k$ are assumed outside the unit circle.

Subroutine NORD calculates least squares predictors $y(t+v|t)$ of $y(t+v)$ given $y(1), \dots, y(t)$ for

$$v = v_p, \dots, v_L \text{ for } t = t_p, \dots, t_L. \quad (1)$$

NUMERICAL METHOD

The algorithm given by Pagano and Parzen (1973) (based on the work of Whittle (1963)) is used. Let $X(t) = \sum_{j=0}^p a(j)y(t-j), t = p+1, \dots, T$.

Then the $X(\cdot)$ are a sample realization of a pure moving average process of order q and $X^T = (X(p+1), \dots, X(T))$ has the symmetric Toeplitz correlation matrix Γ where

$$\Gamma_{jk} = \begin{cases} 1 & j = k \\ \rho(|j-k|) & |j-k| = 1, \dots, q \\ 0 & |j-k| > q \end{cases}$$

$$\text{and } \rho(v) = \sum_{k=0}^q b(k)b(k+v) / \sum_{k=0}^q b^2(k) = R(|v|)/R(0), \quad |v| \leq q.$$

Let $\Gamma = L\Lambda L^T$ be the modified Cholesky decomposition (Wilkinson (1967)) of Γ , i.e., L is a unit lower triangular $(T-p) \times (T-p)$ matrix (L_{jk}) and D is a $(T-p) \times (T-p)$ diagonal matrix (D_{jj}) . Define $\tilde{\Gamma} = (e(p+1), \dots, e(T))$ by $\tilde{\Gamma} = X(t) - \sum_{k=1}^{T-p-t+q} L_{t-p-k, t-k} e(t-k), t = p+1, \dots, T$, i.e., $\tilde{\Gamma} = \tilde{X}$.

Then $y(t+v|t) = X(t+v|t) - \sum_{j=1}^p a(j)y(t+v-j|t)$ where

$$X(t+v|t) = \begin{cases} \sum_{k=0}^q b(k)e(t+v-k), & v = 1, \dots, q \\ 0 & v > q \end{cases}$$

and $y(t|t) = y(t)$ if $t \leq p$.

Thus the algorithm essentially consists of finding successive rows of the matrix L , using as little storage space as possible. This is done by noting:

- 1) the k^{th} row of L has $n_k = \max(k-q-1, 0)$ leading zero elements followed by $n_k = \min(k-1, q)$ elements, followed by a 1, followed by $T-p-n_k-n_k-1$ zeros. Thus only n_k elements need be stored for any row.

- 2) to find the k^{th} row of L , at most the previous q rows are necessary.

- 3) Bauer (1955) has shown that as k gets large, $L_{k,k-j} \rightarrow b(j)$ and $D_{kk} \rightarrow \sigma^2/R(0)$. Thus for a fixed δ , there should be an integer N such that

$$\begin{aligned} |L_{k,k-j} - b(j)| &< \delta \\ |D_{kk} - \sigma^2/R(0)| &< \delta \end{aligned} \quad (2)$$

for $j = 1, \dots, q, k \geq N$. Thus only the first N rows of L need be computed.

NORD calls auxiliary subroutine NORTN to find $e(p+1), \dots, e(T)$ using only a $(q+1) \times (q+1)$ work space for computing L . NORTN is designed so that it can be used also for performing Bauer's algorithm or to find the modified Cholesky decomposition of the symmetric Toeplitz matrix whose first row is $(1, \rho(1), \dots, \rho(q))$.

NORD is designed to perform prediction for pure autoregressive time series if $q = 0$ and for pure moving average time series if $p = 0$.

Subroutine MACV1 (M0, M1A, SIGSQ, R, M0, IFAULT)

Description: MACV1 calculates moving average autocovariances corresponding to moving average parameters.

Formal parameters

M0 Integer input: order of moving average
M1A Real Array (M0) input: moving average coefficients
SIGSQ Real input: variance of $\epsilon(\cdot)$
R Real Array (M0) output: autocovariances for lags 1, ..., M0
M0 Real output: variance of moving average
IFAULT Integer output: faulty indicator, equal to:
0 if proper execution
1 if $M0 < 1$

RESTRICTIONS, TIME, NECESSARY STORAGE

If the zeros of $h(z)$ are not outside the unit circle, the correlation matrix r is not positive definite. This is manifested by a diagonal element of its modified Cholesky decomposition becoming nonpositive. Subroutine MAORTH tests for this by checking for diagonal elements being $< \epsilon$ (specified in data statement). If one is found, IFAULT is set to 5 and execution stops.

Subroutine MTRD requires $(p+1) + (q+4)(q+1) + 3T + MM$ storage locations. The number of operations is approximately $(t_L - p)(p+q) + M(q+1)/2 + (t_L - t_p + 1)[v_L p + q + (q-1) + \dots + \max(1, q - v_L + 1)]$, where M is the number of rows of L before convergence. M increases as the smallest zero of $h(z)$ approaches the unit circle.

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Outline of Algorithm for Subroutine MAORTH

Subroutine MAORTH is used to find a vector $\xi = (\xi(1), \dots, \xi(T))^T$, by $L\xi = Y$, where $Y^T = (Y(1), \dots, Y(T))$ is a sample realization of a moving average process of order q with coefficients $\beta(1), \dots, \beta(q)$ and noise variance σ^2 , and L is the $(T \times T)$ unit lower triangular matrix of the modified Cholesky decomposition $r_{q,T} = LDL^T$ of the $T \times T$ symmetric band Toeplitz correlation matrix $r_{q,T}$ of Y . Thus the (j, k) th element of $r_{q,T}$ is given by

$$(r_{q,T})_{jk} = \begin{cases} 1 & \text{if } j = k \\ \rho(|j - k|) & |j - k| = 1, \dots, q \\ 0 & |j - k| > q \end{cases}$$

where $\rho(v) = R(v)/R(0)$ and

$$R(v) = \sigma^2 \sum_{k=0}^{q-v} \beta(k)\beta(k+v), \quad v = 0, \dots, q$$

(Subroutine MACV1 calculates $R(0), R(1), \dots, R(q)$ given $q, \sigma^2, \beta(1), \dots, \beta(q)$)

Subroutine MAORTH can also be used to calculate $\sigma^2, \beta(1), \dots, \beta(q)$ if $R(0), R(1), \dots, R(q)$ are inputted. Thus if IOPTB = 1, the R 's are input while if IOPTB = 0, the β 's and σ^2 are input.

Further, one need not calculate the ϵ 's if the subroutine is used only for Beuer's algorithm (IOPTB = 1). Thus if IOPTC = 1, the ϵ 's are calculated (and the Y 's are input), while if IOPTC = 0, the ϵ 's are not calculated (and the Y 's need not be inputted). The dimension of E and Y (the mnemonics for ϵ, Y) is IROMS1 which can be 1 if IOPTC = 0.

Finally, subroutine MAORITE can be used to merely find the modified Cholesky decomposition of $\Gamma_{q,T}$ by inputting $R(0)$, $R(1)$, ..., $R(q)$, 0, ..., 0, letting $NQ = T - 1$, $ITER9 = T$, $IOPTS = 1$, and $IOPT8 = 0$.

Let $A = (A_{ij})$ be a real symmetric $(T \times T)$ matrix and $L = (L_{ij})$, $D = \text{diag}(d_1, \dots, d_T)$ be the factors in the Modified Cholesky decomposition of A , i.e., $A = LDL^T$. Then

$$\begin{aligned} L_{11} &= 1, \quad d_1 = A_{11} \\ A_{ki} &= \sum_{j=1}^{i-1} d_j L_{kj} L_{ji} \\ L_{ki} &= \frac{A_{ki} - \sum_{j=1}^{i-1} d_j L_{kj} L_{ji}}{d_i} \quad i < k = 2, \dots, T \\ d_k &= A_{kk} - \sum_{j=1}^{k-1} d_j L_{kj} L_{kj} \end{aligned}$$

For $A = \Gamma_{q,T}$, $L_{ki} = 0$ if $k - i > q$; in fact the nonzero elements of row k of L are

$$L_{k, m_1+1}, \dots, L_{k, m_1+m_2}, \quad L_{kk} = 1$$

where $m_1 = \max(k - q - 1, 0)$, $m_2 = \min(k - 1, q)$.

The equations given above become

$$L_{k, m_1+j} = \frac{\rho(k-m_1-j) - \sum_{i=m_1+1}^{m_1+j-1} d_i L_{ki} L_{m_1+i, j}}{d_{m_1+j}}, \quad j = 1, \dots, m_2$$

$$d_k = 1 - \sum_{j=1}^{m_2} d_{m_1+j} L_{k, m_1+j}^2$$

From these equations it is possible to note:

$$L_{k, m_1+1} = \frac{\rho(k-m_1-1)}{d_{m_1+1}}$$

Thus in calculating row k of L and d_k , one needs only rows $m_1 + 2, \dots, m_1 + m_2 = k - 1$ of L and $d_{m_1+1}, \dots, d_{m_1+m_2}$, i.e., at most the previous q rows of L and the previous q elements of D . However, $q + 1$ rows are stored so that the decomposition of $\Gamma_{q, q+1}$ can be obtained.

Let $NQ \equiv q$, $NQP1 \equiv q + 1$. Subroutine MAORITE uses the constant DK and the arrays $D(NQP1)$, $WKL(NQP1)$, $AL(NQP1)$, $NQP1$ to determine the rows of L and the diagonal elements of D :

Step 1: initialize $D(1) = 1$, $AL(1, 1) = 1$, $I = 1$, $NQP1$
Calculate $R(1) = R(1)/M9$, i.e. the autocorrelations

Step K:

Calculate $L_{k, m_1+1}, \dots, L_{k, m_1+m_2}, d_k$ and store in $WKL(1), \dots, WKL(M3)$,
DK

If $K \leq NQP1$: put WKL into K^{th} row of AL , DK into $D(K)$, and go to next row

If $K > NQP1$: shift down by 1 the 2nd through $NQP1^{\text{th}}$ rows of AL and 2nd through $NQP1^{\text{th}}$ elements of D . Put WKL into $NQP1^{\text{th}}$ row of AL and DK into $D(NQP1)$.

Thus the key point of the subroutine is knowing where L_{Lj} and d_{Lj} are located in AL and D when calculating the K^{th} step.

If $K \leq NQ + 2$, no shifting of AL and D has been done since shifting is done after calculating WKL , DK and only for $K > NQ + 1$. Thus the I^{th} row of L is in the I^{th} row of AL and d_I is in $D(I)$. If $K = NQ + 2 + M$ the $NQ + 1$ rows of AL are the M^{th} through $(NQ + M)^{\text{th}}$ rows of L . In general then the I^{th} row of L and d_I are in the $(I - NQ)$ row of AL and in $D(I - NQ)$, where $NQ = \max(K - NQ - 2, 0)$.

It remains to determine where the j^{th} element of row I of L is located at step K . The elements of the i^{th} row of L that aren't identically zero or one are $L_{i, M_1}, \dots, L_{i, M_2}$ where $M_1 = \max(I - M_0, 1)$. They are stored in the first through $\min(I - 1, M_0)$ elements of row $(I - M_0)$ of AL at step K , i.e., $L_{i, M_1 + M_0 - 1}$ is in $AL(I - M_0, M_1)$ or $L_{i, J}$ is in $AL(I - M_0, J - M_0 + 1)$ at step K .

Thus the equations given above can be written:

For step $K \geq 2$: Let $M_1 = M_1 = \max(K - M_0 - 1, 0)$, $M_2 = M_2 = \min(K - 1, M_0)$,
 $M_3 = \max(K - M_0 - 2, 0)$.

$$WEL(1) = \frac{\rho(K - M_1 - 1)}{d_{M_1 + 1}} = \frac{R(K - M_1 - 1)}{D(M_1 + 1 - M_0)}$$

If $M_3 < 2$, go to d

$$WEL(J) = \frac{\rho(K - M_1 - J) - \sum_{I=1}^{J-1} d_{M_1 + J} L_{I, M_1 + J}^2}{d_{M_1 + J}}$$

$$= \frac{R(K - M_1 - J) - \sum_{I=1}^{J-1} D(M_1 + J - M_0) * WEL(I) * AL(M_1 + J - M_0, M_1 + J - \max(M_1 + J - M_0, 1) + 1)}{D(M_1 + J - M_0)}$$

$J = 2, \dots, M_3$

$$*MK = 1 - \sum_{J=1}^{M_3} d_{M_1 + J} L_{I, M_1 + J}^2$$

$$= 1 - \sum_{J=1}^{M_3} D(M_1 + J - M_0) * WEL(J) * WEL(J)$$

Summary of MAORTH (Let E represent c)

Initialize:
 $EFS = 1.E - 10$
 If $IOPTB = 0$, calculate M_0 , $R(1)$, ..., $R(M_0)$ via MACV1
 Store $\rho(1)$, ..., $\rho(M_0)$ in $R(1)$, ..., $R(M_0)$
 $D(1) = 1$
 $AL(1, 1) = 1$, $I = 1$, $MQP1$
 If $IOPTB = 1$, $E(1) = Y(1)$
Do 130 K = 2, ITERB
Calculate WEL , DK
 If $IOPTB = 1$, calculate $E(K)$
 If $DK < EFS$, Γ not positive definite. Go to 199
 $K < MQP1$: put WEL , DK into AL , D . Go to 130
 $K > MQP1$: do shifting
 $IOPTB = 1$: check convergence of rows of AL
 Yes: Form $BETA$, $SIGSQ$. Go to 150
 No: Go to 130
 $IOPTB = 0$: check convergence of AL to $BETA$
 Yes: Go to 150
 No: Go to 130
 130 CONTINUE
 If Loop is performed for all K , then the algorithm is done except if
 $IOPTB = 1$ in which case $BETA$, $SIGSQ$ are assigned values from last row
 of AL and D and Go to 199
 150 CONTINUE
 If $IOPTB = 1$, calculate the rest of the E 's using $BETA$
 199 Reform autocovariances
 RETURN

Outline of Algorithm for Subroutine MIXPD

Let $Y(1), \dots, Y(T)$ be a sample realization of length T of a mixed autoregressive moving average time series of order (p, q) with autoregressive parameters $\alpha(1), \dots, \alpha(p)$ and moving average parameters $\beta(1), \dots, \beta(q)$, and σ^2 .

Subroutine MIXPD calculates the least squares predictors

$$\begin{aligned} YPD(1) &= Y(t_f + v_f | t_f), YPD(2) = Y(t_f + v_f + 1 | t_f), \dots, YPD(N1) = Y(t_f + v_f | t_f), \\ YPD(N1 + 1) &= Y(t_f + 1 + v_f | t_f + 1), YPD(N1 + 2) = Y(t_f + 1 + v_f + 1 | t_f + 1), \dots, \\ YPD(2 \cdot N1) &= Y(t_f + 1 + v_f | t_f + 1), \end{aligned}$$

;

$$YPD(N2 - 1) \cdot N1 + 1 = Y(t_f + v_f | t_f), \dots, YPD(NN) = Y(t_f + v_f | t_f),$$

where $N1 = v_f - v_f + 1$, $N2 = t_f - t_f + 1$, $NN = N1 \cdot N2$.

The predictor $Y(t + v | t)$ is given by

$$Y(t + v | t) = \begin{cases} X(t + v | t) - \sum_{j=1}^p \alpha(j)Y(t + v - j | t) & p \neq 0, q \neq 0 \\ - \sum_{j=1}^q \beta(j)Y(t + v - j | t) & p \neq 0, q = 0 \\ X(t + v | t) & p = 0, q \neq 0 \\ 0 & p = 0, q = 0 \end{cases}$$

where:

$$(a) Y(t | a) = Y(t)$$

$$\text{if } t \leq a$$

$$(b) X(t + v | t) = \begin{cases} \sum_{k=1}^q \beta(k) \epsilon(t + v - k) & v = 1, \dots, q \\ 0 & v > q \end{cases}$$

$$(c) \xi = (\epsilon(p + 1), \dots, \epsilon(T))^T = L_{q, T-p}^{-1} \bar{X}, \text{ where}$$

$L_{q, T-p}$ is the unit lower triangular matrix in the modified Cholesky decomposition of the $(T - p) \times (T - p)$ correlation matrix $\Gamma_{q, T-p} \bar{X}$.

$$(d) \bar{X} = (X(p + 1), \dots, X(T))^T, \text{ where}$$

$$X(t) = \sum_{j=0}^p \alpha(j)Y(t - j), \quad t = p + 1, \dots, T.$$

Note that $NPP1 = p + 1$ and $NQP1 = q + 1$ are input rather than p and q so that the dimension of $ALPHA = \alpha$ and $BETA = \beta$ can't be zero without stopping execution.

If $q = 0$, the $X(t + v | t)$ (and thus the ϵ 's) are not needed.

The predictors $Y(t + v | t)$ satisfy a difference equation for fixed t .

$$\text{Thus } Y(t + 1 | t), \dots, Y(t + v - 1 | t), X(t + 1 | t), \dots, X(t + v - 1 | t),$$

$$Y(t | t) = Y(t), \dots, Y(t - p + 1 | t) = Y(t - p + 1), \text{ and } \epsilon(t - q + 1),$$

$$\dots, \epsilon(t) \text{ are required to calculate } Y(t + v_f | t). \text{ If } t = q + 1 \leq p + 1$$

or $t - p + 1 < 1$ these values cannot be obtained. This is also true if

$t > T$. Thus if $t < p + q$ or $t < p$ or $t > T$ or $p + q = 0$, the predictors

$Y(t + v_f | t), \dots, Y(t + v_L | t)$ are assigned the value zero.

Summary of MIXPD

If $NQ \neq 0$ calculate $E(NP + 1), \dots, E(NOBS)$ via MAORTH

Do $150 \text{ NT} = \text{NT}, \text{NTL}$

If $\text{NT} < NP + NQ$ or $\text{NT} < NP$ or $\text{NT} > T$ or $NP + NQ = 0$ set predictors equal to zero and go to 150

If $NP \neq 0$ put $Y(\text{NT} - NP + 1), \dots, Y(\text{NT})$ into $X(1), \dots, X(NP)$.

Calculate $Y(\text{NT} + 1 | \text{NT}), \dots, Y(\text{NT} + \text{NVL} | \text{NT})$ and store in $X(NP + 1),$

$\dots, X(NP + \text{NVL})$.

Put X(NP + NVF), ..., X(NP + NVL) into YPD((NT - NTF)*NI + 1),
 ..., YPD((NT - NTF + 1)*NI), where NI = NVL - NVF + 1.
 150 CONTINUE

```

      SUBROUTINE MXPD(NPP1,NQP1,ALPHA,BETA,SIGSQ,NOBS,Y,DEL,NTF,
C      INTL,NVF,NVL,NN,IROWS1,IROWS2,AL,D,WKL,R,R0,E,X,YPD,IFAU
C      THIS SUBROUTINE CALCULATES LEAST SQUARES PREDICTORS FOR A MIXED
C      AUTOREGRESSIVE MOVING AVERAGE PROCESS OF ORDER (NP,NQ)
C
C      DIMENSION ALPHA(NPP1),BETA(NQP1),Y(NOBS),AL(IROWS1,IROWS1),
C      ID(IROWS1),WKL(NQP1),R(NQP1),E(IROWS2),X(NOBS),YPD(NN)
C      DATA ZERO,IOPTR,IOPTE/0.0,0,1/
C
C      TEST FOR INVALID PARAMETERS
C
C      IFAULT=1
C      IF(NPP1.LT.1) GO TO 160
C      IFAULT=2
C      IF(NQP1.LT.1) GO TO 160
C      IFAULT=3
C      IF((INTL-NTF+1)*(NVL-NVF+1).GT.NN) GO TO 160
C      IFAULT=4
C      IF(IROWS1.LT.NQP1) GO TO 160
C
C      FIND E ARRAY
C
C      NQ=NQP1-1
C      NP=NPP1-1
C      NPPNQ=NP+NQ
C      IF(NQ.EQ.0) GO TO 40
C      NX=NOBS-NP
C      DO 20 I=1,NX
C      NPPI=NP+I
C      C=Y(NPPI)
C      DO 10 J=1,NP
C      NPPIM=NPPI-J
C      C=C+ALPHA(J)*Y(NPPIM)
10      CONTINUE
C      X(I)=C
20      CONTINUE

```

```

C      CALL MAORTH(IOPTR,IOPT,E,NQ,DEL,NX,NX,X,BETA,SIGSQ,IROWS1,
C      1R,R0,WKL,D,AL,E,IF1)

```

```

C      IFAULT=5
C      IF(IF1.EQ.5) GO TO 160
C      DO 30 I=1,NX
C      N1=NOBS-I+1
C      N2=N1-NP
C      E(N1)=E(N2)
C 30    CONTINUE

```

```

C      FIND PREDICTORS
C

```

```

C 40    CONTINUE
C      N1=NVL-NVF+1
C      N2=NP+NVF
C      DO 150 NT=NTF,NTL
C      N3=(NT-NTF)*N1
C      NTEMP1=NT-NP-NQ
C      NTEMP=NT-NP
C      IF((NPPNQ.EQ.0).OR.(NT.LT.1).OR.(NT.GT.NOBS)) GO TO 55
C      IF((NP.NE.0).AND.(NT.LT.NPPNQ)) GO TO 55
C      GO TO 60
C 55    CONTINUE
C      DO 50 I=1,N1
C      N3PI=N3+I
C      YPD(N3PI)=ZERO
C 50    CONTINUE
C      GO TO 150
C 60    CONTINUE
C      IF(NP.EQ.0) GO TO 80
C      DO 70 I=1,NP
C      N4=NTEMP+I
C      X(I)=Y(N4)
C 70    CONTINUE

```

```

C 80    CONTINUE
C      DO 130 NV=1,NVL
C      C=ZERO
C      IF((NQ.EQ.0).OR.(NV.GT.NQ)) GO TO 100
C      NTPNV=NT+NV
C      IF((NP.EQ.0).AND.(NTPNV.LE.NQ)) GO TO 100
C      DO 90 K=NV,NQ
C      KK=NTPNV-K
C      C=C+BETA(K)*E(KK)
C 90    CONTINUE
C 100   CONTINUE
C      NPPNV=NP+NV
C      IF(NP.EQ.0) GO TO 120
C      DO 110 I=1,NP
C      NP1=NPPNV-I
C      C=C-ALPHA(I)*X(NP1)
C 110   CONTINUE
C 120   CONTINUE
C      X(NPPNV)=C
C 130   CONTINUE
C      DO 140 NV=1,N1
C      N3PNV=N3+NV
C      N5=N2+NV-1
C      YPD(N3PNV)=X(N5)
C 140   CONTINUE
C 150   CONTINUE

```

```

C      IFAULT=0
C 160   CONTINUE
C      RETURN
C      END
C      SUBROUTINE MAORTH(IOPTR,IOPT,E,NQ,DEL,ITERS,IROWS1,Y,BETA,
C      1SIGSQ,IROWS2,R,R0,WKL,D,AL,E,IFAU)

```

```

C      THIS SUBROUTINE CALCULATES THE MODIFIED CHOLESKY FACTORS OF THE
C      ITERS ORDER CORRELATION MATRIX FOR A MOVING AVERAGE PROCESS OF
C      ORDER NQ. IT IS USED TO CALCULATE THE CORRESPONDING COEFFICIENTS
C      AND/OR AN ORTHOGONAL TRANSFORMATION OF INPUTTED MOVING AVERAGE DATA.
C

```

```

      DIMENSION Y(IROWS1),BETA(NQ),R(NQ),WKL(NQ),D(IROWS2),
      1AL(IROWS2,IROWS2),E(IROWS1)
      DATA ONE/1.0/
      DATA EPS/1.E-10/
C
C   EPS IS CRITERION FOR TESTING FOR ZERO DIAGONAL
C
C   TEST FOR INVALID PARAMETERS
C
      IFAULT=1
      IF(NQ.LT.1) GO TO 299
      IFAULT=2
      IF((IOPTB.NE.0).AND.(IOPTB.NE.1)) GO TO 299
      IFAULT=3
      IF((IOPTB.NE.0).AND.(IOPTB.NE.1)) GO TO 299
      IFAULT=4
      IF(IROWS2.LE.NQ) GO TO 299
C
C   AUTOCORRELATIONS AND INITIALIZATION
C
      IF(IOPTB.EQ.0) CALL MACV1(NQ,BETA,SIGSQ,R,R0,IF1)
      D(1)=ONE
      NQP1=NQ+1
      DO 5 I=1,NQ
        R(I)=R(I)/R0
      5 CONTINUE
      DO 10 I=1,NQP1
        AL(I,I)=ONE
      10 CONTINUE
      IF(IOPTB.EQ.1) E(1)=Y(1)
C
C   ROW K OF FACTORIZATION
C
C   M1 IS NUMBER OF LEADING ZEROS
C   M3 IS NUMBER OF ELEMENTS TO CALCULATE
C   MR IS SHIFTING FACTOR IN STORAGE OF PREVIOUS ROWS
C   INDD+J-1 IS ROW NUMBER OF AL FOR CALCULATING WKL(J)
C

```

```

      DO 130 K=2,ITERS
      M1=MAX0(K-NQ-1,0)
      M3=MIN0(K-1,NQ)
      INDR=K-M1-1
      MR=MAX0(K-NQ-2,0)
      INDD=M1+1-MR
      WKL(1)=R(INDR)/D(INDD)
      IF(M3.LT.2) GO TO 40
      DO 30 J=2,M3
        JM1=J-1
        INDR1=INDR-JM1
        C=R(INDR1)
        INDLR=INDD+JM1
        M4=-MAX0(M1+J-NQ,1)+M1+1
        DO 20 I=1,JM1
          INDD1=INDD+I-1
          INDL1=M4+I
          C=C-D(INDD1)*WKL(I)*AL(INDLR,INDL1)
        20 CONTINUE
        WKL(J)=C/D(INDLR)
      30 CONTINUE
      40 CONTINUE
      DK=ONE
      DO 50 J=1,M3
        INDD=M1+J-MR
        DK=DK-D(INDD)*WKL(J)*WKL(J)
      50 CONTINUE
      IF(IOPTB.EQ.0) GO TO 65
      C=Y(K)
      DO 60 I=1,M3
        INDWKL=M3-I+1
        INDE=K-I
        C=C-WKL(INDWKL)*E(INDE)
      60 CONTINUE
      E(K)=C

```

```

65  CONTINUE
    IFAULT=5
    IF(DK.LT.EPS) GO TO 199
    IF(N.GT.NQP1) GO TO 80
    D(K)=DK
    DO 70 I=1,NQ
        AL(K,I)=WKL(I)
70  CONTINUE
    GO TO 130
80  CONTINUE
    DO 82 I=1,NQ
        IP1=I+1
        D(I)=D(IP1)
        DO 81 J=1,NQ
            AL(I,J)=AL(IP1,J)
81  CONTINUE
82  CONTINUE
    D(NQP1)=DK
    DO 83 I=1,NQ
        AL(NQP1,I)=WKL(I)
83  CONTINUE
C
C  DEL IS CONVERGENCE CRITERION
C
    IF(IOPTR.EQ.0) GO TO 110
    DO 90 I=1,NQ
        IF(ABS(AL(NQP1,I)-AL(NQ,I)).GE.DEL) GO TO 130
90  CONTINUE
    IF(R0*ABS(D(NQP1)-D(NQ)).GE.DEL) GO TO 130
    DO 100 I=1,NQ
        INDWKL=NQ-I+1
        BETA(I)=WKL(INDWKL)
100 CONTINUE
    SIGSQ=R0*D(NQP1)
    IFAULT=0
    GO TO 150

```

```

110 CONTINUE
    DO 120 I=1,NQ
        INDB=NQ-I+1
        IF(ABS(WKL(I)-BETA(INDB)).GE.DEL) GO TO 130
120 CONTINUE
    IF(ABS(D(NQP1)*R0-SIGSQ).LT.DEL) GO TO 150
130 CONTINUE
    IFAULT=6
    IF(IOPTR.EQ.0) GO TO 199
    DO 140 I=1,NQ
        INDWKL=NQ-I+1
        BETA(I)=WKL(INDWKL)
140 CONTINUE
    SIGSQ=R0*DK
    GO TO 199
150 CONTINUE
    IFAULT=0
    IF(IOPTE.EQ.0) GO TO 199
    IF(K.EQ.ITER5) GO TO 199
    KP1=K+1
    DO 170 J=KP1,ITERS
        C=Y(J)
        DO 160 I=1,NQ
            INDE=J-I
            C=C-BETA(I)*E(INDE)
160 CONTINUE
        E(J)=C
170 CONTINUE
    IFAULT=0
199 CONTINUE
    DO 200 I=1,NQ
        R(I)=R(I)*R0
200 CONTINUE
299 RETURN
    END
    SUBROUTINE MACV1(NQ,BETA,SIGSQ,R,R0,IFAU)

```

C THIS SUBROUTINE CALCULATES AUTOCOVARIANCES OF A MOVING AVERAGE
C PROCESS OF ORDER NQ GIVEN ITS COEFFICIENTS AND RESIDUAL VARIANCE.
C

```
      DIMENSION BETA(NQ),R(NQ)
      DATA ONE /1.0/
      IFAULT=1
      IF(NQ.LT.1) GO TO 40
      C=ONE
      DO 10 I=1,NQ
      C=C+BETA(I)*BETA(I)
10    CONTINUE
      R0=SIGSQ*C
      DO 20 IV=1,NQ
      NQMIV=NQ-IV
      C=BETA(IV)
      DO 30 I=1,NQMIV
      IVPI=IV+I
      C=C+BETA(I)*BETA(IVPI)
30    CONTINUE
      R(IV)=C*SIGSQ
20    CONTINUE
C
C      IFAULT=0
40    RETURN
      END
```