

LEAST-SQUARES SPECTRAL ANALYSIS REVISITED

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PREFACE

In order to make our extensive series of technical reports more readily available, we have scanned the old master copies and produced electronic versions in Portable Document Format. The quality of the images varies depending on the quality of the originals. The images have not been converted to searchable text.

LEAST SQUARES SPECTRAL ANALYSIS REVISITED

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PREFACE

The original version of this report appeared in 1978 under the Report Series (Report BI-R-78-8) of the Bedford Institute of Oceanography, Dartmouth, Nova Scotia, when the first author was working there. It was authored by the first two authors of the present version. The third author has been mainly responsible for the changes and improvements in the present version of the software.

This revised version is being issued for three reasons:

- (i) The original report is out of print.
- (ii) Students not exposed to functional analysis have had some difficulty in reading the report, so that the original report has been extended to include a more elementary description of least-squares spectral analysis.
- (iii) Since 1978 the software has been modified, both to eliminate some "bugs" and to be more versatile.

The changes, program listings of the new version, and a user's guide are in PART B.

The authors are grateful to the Bedford Institute of Oceanography for permission to reprint herewith parts of the original Report BI-R-78-8.

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PART A

LEAST-SQUARES SPECTRAL ANALYSIS

ABSTRACT

An algorithm is described to compute the optimum least-squares spectrum of an unequally or equally spaced generally non-stationary and coloured time series for which some of the shapes of the constituents (systematic noise) are known. Known constituents of four kinds are provided for: datum biases, linear trend, periodic constituents with known periods, and arbitrary user-specified constituents. An alternative, more efficient algorithm is described for piecewise equally-spaced time series with possible gaps.

INTRODUCTION

Observed time series are often composed of constituents that are of interest (which we will call the signal), and constituents that obscure the signal (which we will call the noise). Often we know the general form of a noise constituent, but not its magnitude (we will call such constituents systematic noise).

One class of such time series is that dominated by a few periodic constituents (the systematic noise) and smaller amplitude periodic constituents (the signal) whose presence is obscured by the noise--coloured series. Extracting the signal from this series has been called the hidden periodicity problem. In general, the systematic noise may contaminate but not totally obscure the signal.

If all the constituents of a time series are periodic, then we can say that it is a colour time series; that the noise is coloured noise; that the signal is a coloured signal; and that the extent to which the noise obscures the signal is the extent to which the noise discolours the signal.

A property of a time series is the degree to which it is stationary. Strict sense (or strong) stationarity requires that all statistical properties of the time series (mean value, autocorrelation function, and all higher order moments) be independent of the choice of the time origin. Wide sense (or weak) stationarity requires that only the mean value and autocorrelation function be independent of the choice of the time origin [Bendat and Piersol, 1971]. One common violation of stationarity is the presence of datum shifts in the time series: that is, the mean value is shifted from time to time. Another common violation is the presence of a trend (perhaps linear) in the time series: the "mean" value changes linearly with time.

Both these kinds of non-stationarity-inducing constituents (datum shifts and trends) can also be considered as systematic noise, as long as we know their general form, that is, the time at which datum shifts occurred, and the kind of trend (linear, quadratic, exponential, etc.).

Another property of a time series is its spacing. Are all the data values equally spaced in time? Are there data gaps between otherwise equally-spaced segments of the series? Or are all the values in the time

series unequally spaced in time? Ideally we would like to have only equally spaced time series, but this is rarely the case in practice.

A specific example of this situation is a time series of ocean tide gauge records, from which we are interested in the long period (> 1 year) constituents. Three kinds of systematic noise may contaminate this time series from our point of view. Firstly, there may be step functions due to sudden changes in the tide gauge datum (caused by alterations to the tide gauge or to its supporting structure, or possibly caused by vertical co-seismic displacements). The dates of such step functions are usually well documented, but it can be difficult to document their magnitudes. Secondly, there may be a gradual change in the tide gauge datum (due, for example, to changes in the mean sea level, or to land subsidence including the gauge), which is most simply modelled as a linear trend. Thirdly, the tide gauge time series are dominated by short (in our context) periodic constituents (i.e., tidal constituents) for which the periods are precisely known, but the magnitudes are not. In addition to these problems, there is almost certain to be data gaps due to equipment failures. It is this kind of series that we will analyse at the end of PART A as an example.

To obtain an undistorted spectral image of the signal, we must somehow remove the influence of the systematic noise, both the "colours" and the non-stationarity. The usual way of dealing with this problem is to first find the magnitudes of the components of the noise, subtract the noise from the time series, and perform a spectral analysis on the "corrected" time series. It is known, however, that such a treatment affects the location of spectral peaks arising from the rest of the time series [Taylor and Hamilton, 1972]. We must somehow deal with the data gaps as well. When the data is piecewise equally spaced, as in the example given at the end of PART A, the two usual options are to treat each piece separately, or to somehow manufacture data to fill in the gaps. Neither is satisfactory. The problem is even more difficult when the time series is completely unequally spaced, rather than merely gappy.

An alternative is the least-squares spectral analysis [Vaníček, 1971]. This alternative provides two advantages: systematic noise, including both colours and non-stationarity, can be rigorously accounted for (suppressed) without producing any shift of the existing spectral peaks [Taylor and Hamilton, 1972]; and time series with unequally spaced data can

be analysed [Maul and Yanaway, 1978].

The purpose of this report is to present a brief exposition of the method, for unequally spaced time series, and to describe how the spectrum computation can be made much faster if the time series is equally, or at least piecewise equally, spaced.

Capitalized parameter names longer than one letter refer to identifiers used in FORTRAN subroutines SPECUN and SPECEQ which respectively compute the least-squares spectrum for unequally spaced and equally spaced time series (see PART B for program listings).

SPECTRUM COMPUTATION

There are many definitions of a spectrum, and many ways of computing a spectrum from a time series. Here we simply state the problem in a general way: Given

- (a) $\underline{t} = \{t_i\}$, $i=1,2,\dots,n$, a vector of observation times,
- (b) $\underline{f}(\underline{t}) = \{f_i\} = \{f(t_i)\}$, a vector of observed values,
- (c) $\underline{\omega} = \{\omega_j\}$, $j=1,2,\dots,m$, a vector of frequencies for which spectral values are desired,

then find

$$\underline{s}(\underline{\omega}) = \{s_j\} = \{s(\omega_j)\}, \text{ a vector of spectral values.}$$

Note that

- (a) $\underline{f}(\underline{t})$ or $\{f_i, t_i\}$ together define a time series.
- (b) $s(\omega_j)$ must be some measure of the fractional content of $\underline{f}(\underline{t})$ which is represented by the frequency ω_j .

Here we consider only one specific technique for computing $s(\omega_j)$, which is the Least-Squares Spectral Analysis (LSSA). This technique is an application of Least-Squares Approximation (LSA) [Vaníček and Wells, 1972], which is closely related to the Linear Least-Squares Parametric Adjustment (LLSPA) [Wells and Krakiwsky, 1971; Vaníček and Krakiwsky, 1982].

LSA and LLSPA use the same algorithm, but they have different purposes, and different interpretations of the quantities involved. Those parts of the algorithm which we are interested in are, in our notation,

$$\underline{\hat{c}} = (\underline{\phi}^T \underline{W} \underline{\phi})^{-1} \underline{\phi}^T \underline{W} \underline{f} \quad (1)$$

$$\underline{\hat{v}} = \underline{f} - \underline{\phi} \underline{\hat{c}} \quad (2)$$

For LLSPA, we are given

\underline{f} = a vector of observations

$\underline{\phi}$ = the design matrix which models the physical relationship between the observations \underline{f} and the vector of unknown parameters \underline{c} via the observation equation $\underline{f} = \underline{\phi} \underline{c}$

$\underline{W} = \underline{C}_f^{-1}$ where \underline{C}_f is the covariance matrix of \underline{f} , a statistical quantity,

and the problem solved in part by (1) and (2) is to obtain an estimate for some physical parameters \underline{c} , based on the observations \underline{f} . What we want here is $\underline{\hat{c}}$ (plus its covariance matrix).

For LSA we are given

\underline{f} = a known vector to be approximated, not necessarily based on observations,

$\underline{\phi}$ = a matrix considered to consist of several column vectors

$\underline{\phi} = [\phi_1, \phi_2, \dots, \phi_m]$ called base functions, each of which is a known function of the same dimension as \underline{f} . Note that $\underline{\phi}$ does not necessarily model any physical dependence of \underline{f} .

$\underline{W} =$ a weight function with no statistical meaning. Here we assume $\underline{W} = \underline{I}$ (often the case in LSA).

For LSA it is usual to rewrite $\underline{f} = \underline{\phi} \underline{c}$ in the form

$$\underline{f} = \sum_{i=1}^m c_i \phi_i \quad (3)$$

and to state the LSA problem as finding the best fitting approximant \underline{p} to \underline{f} , that is

$$\underline{p} = \sum_{i=1}^m \hat{c}_i \phi_i \quad (4)$$

such that the residuals $\underline{\hat{v}} = \underline{f} - \underline{p}$ are minimized in the least-squares sense. Note that for LSA we are more interested in \underline{p} than in the coefficients $\underline{\hat{c}}$, although $\underline{\hat{c}}$ is still given by (1).

Specifically for LSSA we know $\underline{f}(t)$ and we use

$$\begin{aligned}\phi_1 &= \cos \omega_j t \\ \phi_2 &= \sin \omega_j t\end{aligned}\quad (5)$$

For each ω_j for which we want $s(\omega_j)$ we compute

$$\underline{p}(\omega_j) = \hat{c}_1 \cos \omega_j t + \hat{c}_2 \sin \omega_j t \quad (6)$$

where $\underline{\hat{c}} = \begin{vmatrix} \hat{c}_1 \\ \hat{c}_2 \end{vmatrix}$ is determined from (1), that is

$$\underline{\hat{c}} = (\underline{\phi}^T \underline{\phi})^{-1} \underline{\phi}^T \underline{f} \quad (7)$$

Now when $\underline{p}(\omega_j)$ fits \underline{f} perfectly ($\hat{v} = 0$), then the fractional content of \underline{f} represented by \underline{p} is 1 (all of \underline{f} is represented by \underline{p}). On the other hand, it is possible that $\underline{\hat{c}} = 0$ (that is \underline{f} is orthogonal to $\underline{\phi}$) and $\underline{p} = 0$. In this case, the fractional content of \underline{f} represented by \underline{p} is 0. In general we will see below that the fractional content of \underline{f} represented by \underline{p} can be measured by the ratio

$$s = \frac{\text{length of the orthogonal projection of } \underline{p} \text{ onto } \underline{f}}{\text{length of } \underline{f}} \quad (8)$$

and that this can be computed from

$$s = \frac{\underline{f}^T \underline{p}}{\underline{f}^T \underline{f}} \quad (9)$$

Note that since from (6) $\underline{p} = \underline{p}(\omega_j)$, so also

$$s(\omega_j) = \frac{\underline{f}^T \underline{p}(\omega_j)}{\underline{f}^T \underline{f}} \quad (10)$$

that is, for each spectral value $s(\omega_j)$ we must separately compute the least-squares approximant $\underline{p}(\omega_j)$. Therefore to compute the least-squares spectrum $\underline{s}(\omega) = \{s_j, \omega_j\}$ we must compute m spectral values $s(\omega_j)$ $j=1,2,\dots,m$ which involves performing the least-squares approximation m times, each time to get $\underline{p}(\omega_j)$ for a different frequency ω_j .

So far we have dealt only with the problem of computing the spectrum of a complete time series. This is one major application of LSSA. A second major application is to first remove some constituents from the time series, and then to compute the spectrum of the residual time series. This is more complicated, and is more easily described (and hopefully understood) using the language of functional analysis.

REQUISITE ELEMENTS OF FUNCTIONAL ANALYSIS

Functional analysis is the analysis of functionals [Luenberger, 1969; Kreyszig, 1978; Oden, 1979]. A functional is a scalar function of vector quantities. We are interested in three functionals called the scalar product, the norm, and the metric. First we define some spaces.

In this report we will speak solely of spaces of finite dimensions. A vector space L of dimension $n = \dim L$ is a space of all possible n -tuples $\{\ell_1, \ell_2, \dots, \ell_n\}$ of real numbers $\ell_1, \ell_2, \dots, \ell_n$. It is required that a linear combination of any elements is also an element, that is if $\forall i: \underline{a}_i \in L$ and $\alpha_i \in \mathbb{R}$ (scalars), then

$$\underline{b} = \sum_i \alpha_i \underline{a}_i \quad (11)$$

is also from L . A Hilbert (finite) space H is a vector space on which the scalar product is defined. If $\underline{a}, \underline{b} \in H$ then we denote their scalar product by $\langle \underline{a}, \underline{b} \rangle$ and define the norm (or length or magnitude) of $\underline{a} \in H$ as

$$||\underline{a}|| = (\langle \underline{a}, \underline{a} \rangle)^{1/2} \quad (12)$$

and the metric (or distance) between $\underline{a}, \underline{b} \in H$ as

$$d(\underline{a}, \underline{b}) = ||\underline{a} - \underline{b}|| = [\langle \underline{a} - \underline{b}, \underline{a} - \underline{b} \rangle]^{1/2} \quad (13)$$

There are many ways of specifying a particular expression for the scalar product, some involving weight functions, some involving integrals. Here we use the most familiar and simplest expression

$$\langle \underline{a}, \underline{b} \rangle = \underline{a}^T \underline{b} = \sum_i a_i b_i \quad (14)$$

We will use concepts of linear independence, basis, and manifold. An n-tuple of vectors $\underline{a}_i \in L$ is linearly independent when the equation

$$\sum_{i=1}^n \alpha_i \underline{a}_i = 0 \quad , \quad \forall i: \alpha_i \in \mathbb{R} \quad (15)$$

is satisfied if and only if $\forall i: \alpha_i = 0$. That is none of the \underline{a}_i can be expressed as a linear combination of the others. Given a linearly independent n-tuple $\{\underline{a}_i, \forall i\} \subset L$ then the set of all vectors

$$\underline{b}_j = \sum_i \alpha_i \underline{a}_i \quad (16)$$

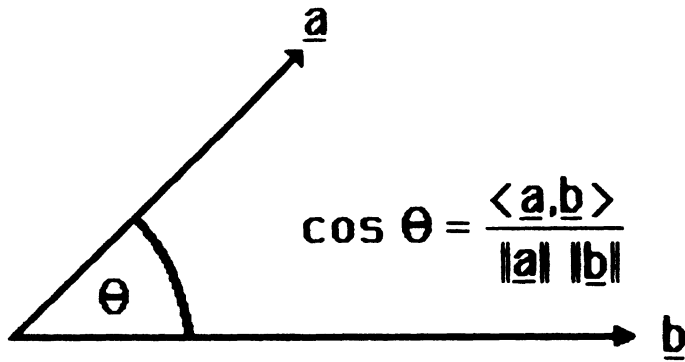
(where all possible combinations of scalar values α_i are used to generate different \underline{b}_j) form a manifold S of L, and $\{\underline{a}_i, \forall i\}$ is said to generate S, or to be a basis of S. The number n of vectors in $\{\underline{a}_i, \forall i\}$ is the dimension of S.

We will also use concepts of orthogonality, and orthogonal projection. Let us explore how these concepts are intimately related to the scalar product. For illustration we will consider two vectors \underline{a} and \underline{b} in the real plane. If these two vectors intersect at a right angle then their scalar product is zero, $\langle \underline{a}, \underline{b} \rangle = 0$. In this case we say that \underline{a} and \underline{b} are orthogonal (denoted $\underline{a} \perp \underline{b}$). In more general Hilbert spaces, the following statements also all mean the same thing, although "intersection at a right angle" can no longer be visualized:

$\langle \underline{a}, \underline{b} \rangle = 0$ means the same as
 $\underline{a} \perp \underline{b}$, which means the same as
 \underline{a} and \underline{b} are orthogonal.

So much for the special case of orthogonality. In general \underline{a} and \underline{b} will not intersect at a right angle. What then is the geometrical meaning of the scalar product? Let us say they intersect at some angle θ (see Figure 1). We recall

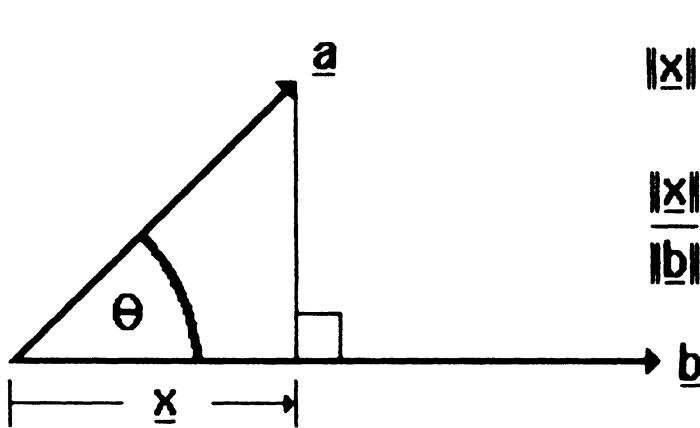
$$\langle \underline{a}, \underline{b} \rangle = ||\underline{a}|| \ ||\underline{b}|| \ \cos \theta \quad . \quad (17)$$



$$\cos \theta = \frac{\langle \underline{a}, \underline{b} \rangle}{\|\underline{a}\| \|\underline{b}\|}$$

ORTHOGONAL
PROJECTIONS

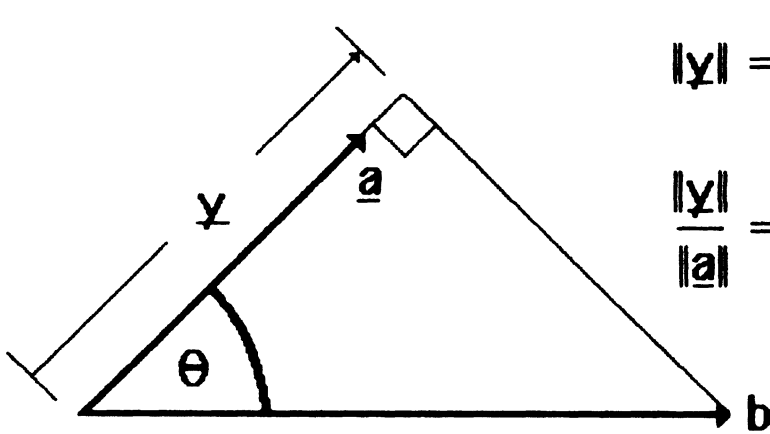
Definition of angle



$$\|\underline{x}\| = \|\underline{a}\| \cos \theta = \frac{\langle \underline{a}, \underline{b} \rangle}{\|\underline{b}\|}$$

$$\frac{\|\underline{x}\|}{\|\underline{b}\|} = \frac{\langle \underline{a}, \underline{b} \rangle}{\langle \underline{b}, \underline{b} \rangle}, \quad \underline{x} = \frac{\langle \underline{a}, \underline{b} \rangle}{\langle \underline{b}, \underline{b} \rangle} \underline{b}$$

Orthogonal Projection of \underline{a} onto \underline{b}



$$\|\underline{y}\| = \|\underline{b}\| \cos \theta = \frac{\langle \underline{a}, \underline{b} \rangle}{\|\underline{a}\|}$$

$$\frac{\|\underline{y}\|}{\|\underline{a}\|} = \frac{\langle \underline{a}, \underline{b} \rangle}{\langle \underline{a}, \underline{a} \rangle}, \quad \underline{y} = \frac{\langle \underline{a}, \underline{b} \rangle}{\langle \underline{a}, \underline{a} \rangle} \underline{a}$$

Orthogonal Projection of \underline{b} onto \underline{a}

FIGURE 1.

Orthogonality is such a useful concept that even in this case we want somehow to construct a right angle. There are two possibilities. Either we can drop a perpendicular from \underline{a} onto \underline{b} or we can drop a perpendicular from \underline{b} onto \underline{a} . In Figure 1, the vector \underline{x} is called the orthogonal projection of \underline{a} onto \underline{b} , and \underline{y} is the orthogonal projection of \underline{b} onto \underline{a} . From (17) we see that the lengths of these vectors are

$$\begin{aligned} \|\underline{x}\| &= \|\underline{a}\| \cos \theta = \frac{\langle \underline{a}, \underline{b} \rangle}{\|\underline{b}\|} \quad , \\ \|\underline{y}\| &= \|\underline{b}\| \cos \theta = \frac{\langle \underline{a}, \underline{b} \rangle}{\|\underline{a}\|} \quad . \end{aligned} \tag{18}$$

To obtain expressions for the vectors themselves, we note that unit vectors in the direction of \underline{a} (and \underline{y}) and in the direction of \underline{b} (and \underline{x}) are given by $\frac{\underline{a}}{\|\underline{a}\|}$ and $\frac{\underline{b}}{\|\underline{b}\|}$ respectively. Hence, using (12), we have

$$\begin{aligned} \underline{x} &= \|\underline{x}\| \frac{\underline{b}}{\|\underline{b}\|} = \frac{\langle \underline{a}, \underline{b} \rangle}{\langle \underline{b}, \underline{b} \rangle} \underline{b} \quad , \\ \underline{y} &= \|\underline{y}\| \frac{\underline{a}}{\|\underline{a}\|} = \frac{\langle \underline{a}, \underline{b} \rangle}{\langle \underline{a}, \underline{a} \rangle} \underline{a} \quad , \end{aligned} \tag{19}$$

from which we see that the ratio of the length of \underline{x} to the length of \underline{b} (and similarly of \underline{y} to \underline{a}) is given by the ratio of two scalar products. Finally we note that (18) and (19) are not restricted to the simple example here, but are valid in any Hilbert space.

THE PROJECTION THEOREM

The shortest distance between a point and a plane is the perpendicular from the point to the plane. This is the projection theorem.

We can rephrase this theorem, substituting the terms

"minimum norm" for	"shortest distance";
"(vector) element of Hilbert space" for	"point";
"manifold of Hilbert space" for	"plane"; and
"orthogonal" for	"perpendicular".

Given $\underline{f} \in H$ (point) and $S \subset H$ (plane), then of all the elements $\underline{s} \in S$, there is one element $\underline{p} \in S$ such that $d(\underline{f}, \underline{p}) \leq d(\underline{f}, \underline{s})$ (shortest distance). This element \underline{p} is given by the orthogonal projection of \underline{f} onto S , that is $(\underline{f} - \underline{p}) \perp S$ (perpendicular) (see Figure 2).

In order to invoke this theorem, we need first to specify \underline{f} and S . We can specify \underline{f} in several ways, for example, as an ordered sequence of real numbers, or using an analytic functional expression. We can also specify S in many ways. Let us choose to specify S by specifying a basis $\{\underline{\phi}_i, \forall i\}$ which generates S . Figure 2 illustrates the geometrical relationships between \underline{f} , S , \underline{p} , and $\{\underline{\phi}_i, \forall i\}$ for the simple case of a three-dimensional \underline{f} and a two-dimensional S . Then any $\underline{s} \in S$ can be expressed as

$$\underline{s} = \sum_i c_i \underline{\phi}_i \quad . \quad (20)$$

That is, there is some relationship between each n-tuple $\{c_i, \forall i\}$ and the corresponding \underline{s} . Let the particular n-tuple of scalars $\{c_i, \forall i\}$ corresponding to \underline{p} be denoted $\{\hat{c}_i, \forall i\}$. Then

$$\underline{p} = \sum_i \hat{c}_i \underline{\phi}_i \quad . \quad (21)$$

Now we can write the condition we must satisfy, $(\underline{f} - \underline{p}) \perp S \equiv (\underline{f} - \underline{p}) \perp \underline{\phi}_j; \forall j$, in terms of $\{\hat{c}_i, \forall i\}$ corresponding to \underline{p} , that is

$$\forall j: \langle (\underline{f} - \sum_i \hat{c}_i \underline{\phi}_i), \underline{\phi}_j \rangle = 0 \quad (22)$$

This can be rewritten

$$\sum_i \hat{c}_i \langle \underline{\phi}_i, \underline{\phi}_j \rangle = \langle \underline{f}, \underline{\phi}_j \rangle \quad j=1,2,\dots,n \quad . \quad (23)$$

If we define

$$\underline{N} = \begin{bmatrix} \langle \underline{\phi}_1, \underline{\phi}_1 \rangle & \langle \underline{\phi}_2, \underline{\phi}_1 \rangle & \dots & \langle \underline{\phi}_n, \underline{\phi}_1 \rangle \\ \langle \underline{\phi}_1, \underline{\phi}_2 \rangle & \langle \underline{\phi}_2, \underline{\phi}_2 \rangle & \dots & \langle \underline{\phi}_n, \underline{\phi}_2 \rangle \\ \cdot & \cdot & \dots & \cdot \\ \langle \underline{\phi}_1, \underline{\phi}_n \rangle & \langle \underline{\phi}_2, \underline{\phi}_n \rangle & \dots & \langle \underline{\phi}_n, \underline{\phi}_n \rangle \end{bmatrix}$$

$$\underline{u} = \begin{bmatrix} \langle \underline{f}, \underline{\phi}_1 \rangle \\ \langle \underline{f}, \underline{\phi}_2 \rangle \\ \cdot \\ \langle \underline{f}, \underline{\phi}_n \rangle \end{bmatrix}$$

$$\underline{\hat{c}} = \begin{bmatrix} \hat{c}_1 \\ \hat{c}_2 \\ \cdot \\ \hat{c}_n \end{bmatrix}$$

then (23) becomes

$$\underline{N} \underline{\hat{c}} = \underline{u} \quad (24)$$

the normal equations ($\underline{f} - \underline{p}$ is normal or orthogonal to S). In fact if we define

$$\underline{\phi} = [\underline{\phi}_1, \underline{\phi}_2, \dots, \underline{\phi}_n] \quad (25)$$

then $\underline{N} = \underline{\phi}^T \underline{\phi}$ and $\underline{u} = \underline{\phi}^T \underline{f}$ so that

$$\underline{\hat{c}} = \underline{N}^{-1} \underline{u} = (\underline{\phi}^T \underline{\phi})^{-1} \underline{\phi}^T \underline{f} \quad (26)$$

which was equation (7). The approximant \underline{p} is then

$$\underline{p} = \underline{\phi} \underline{\hat{c}} = \sum_i \hat{c}_i \underline{\phi}_i \quad (27)$$

and the residual vector is

$$\underline{\hat{v}} = \underline{f} - \underline{p} = \underline{f} - \underline{\phi} \underline{\hat{c}} = \underline{f} - \underline{\phi} (\underline{\phi}^T \underline{\phi})^{-1} \underline{\phi}^T \underline{f} . \quad (28)$$

Note that $\underline{\hat{v}} \perp \underline{p}$. This follows from the projection theorem, where $\underline{\hat{v}} = (\underline{f} - \underline{p}) \perp S$, that is $\underline{\hat{v}}$ is orthogonal to all vectors in S , in particular the column vectors of $\underline{\phi}$ (which generate S). Thus $\underline{\hat{v}}$ is orthogonal to \underline{p} which is a linear combination of $\underline{\phi}$, and hence also lies in S . Thus the projection theorem (or LSA or LLSPA) decomposes \underline{f} into two orthogonal components \underline{p} (the orthogonal projection of \underline{f} onto S) and $\underline{\hat{v}}$ (the perpendicular from \underline{f} to S).

To compute something akin to the spectral value, we must perform a second orthogonal projection. However, this one is simpler. So far we have projected \underline{f} onto the manifold S , in which case many projections are possible, and we used the minimum norm, or perpendicularity condition to select the one we want. For the second projection, we simply project \underline{p} back onto \underline{f} . Figure 3 illustrates this for the simple case corresponding to Figure 2.

The length of this orthogonal projection is, from (18)

$$\frac{\langle \underline{f}, \underline{p} \rangle}{\|\underline{f}\|} .$$

The ratio of the length of this orthogonal projection to the length of \underline{f} is, from (19)

$$\frac{\langle \underline{f}, \underline{p} \rangle}{\langle \underline{f}, \underline{f} \rangle} = \frac{\underline{f}^T \underline{p}}{\underline{f}^T \underline{f}} . \quad (29)$$

This then is a measure of the fractional part of \underline{f} which is represented by \underline{p} .

Since \underline{p} is a special element of S (the orthogonal projection of \underline{f} onto S), this ratio also tells us something about how much of \underline{f} is "contained" in S . The "closer" to S that \underline{f} lies, the closer to 1 will the ratio (29) become. If \underline{f} lies in S , the ratio is 1. If \underline{f} is orthogonal to S , the ratio is 0.

Now let us apply this to spectral analysis. For each spectral frequency ω_j , $j=1,m$, we have a different manifold S spanned by

$$\underline{\phi} = [\cos \omega_j t, \sin \omega_j t] . \quad (30)$$

Consequently, the orthogonal projection $\underline{p}(\omega_j)$ of \underline{f} onto S will be different for each ω_j . Due to the properties of the ratio (29) described above, we choose that ratio to be the least-squares spectral value of \underline{f} for frequency ω_j

**PROJECTION
THEOREM**

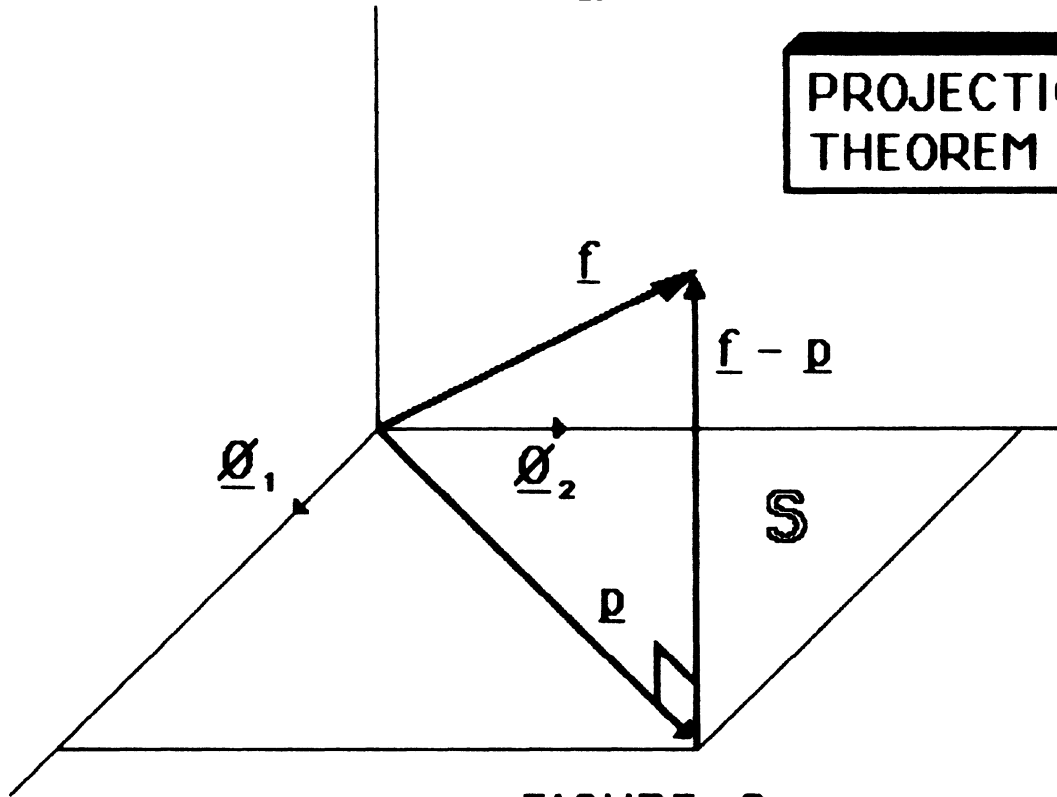


FIGURE 2.

**SECOND PROJECTION
IN SPECTRAL ANALYSIS**

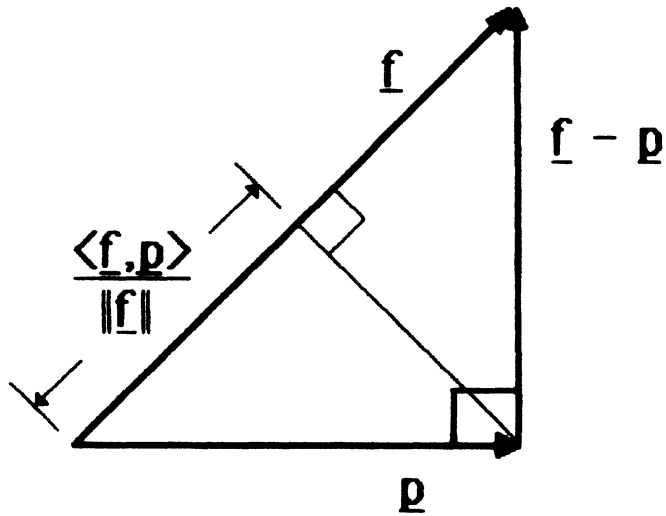


FIGURE 3.

$$s(\omega_j) = \frac{\underline{f}^T \underline{p}(\omega_j)}{\underline{f}^T \underline{f}} \quad (31)$$

The least-squares spectrum of \underline{f} is the collection of spectral values for all (desired) frequencies ω_j ,

$$\underline{s}(\omega) = \{s(\omega_j); j=1,m\} \quad (32)$$

LEAST-SQUARES SPECTRAL ANALYSIS WITH KNOWN CONSTITUENTS

For some applications we can consider a time series as consisting of two kinds of constituents: those which we are interested in studying (and having represented in the spectrum), i.e., the signal, and those which we are not interested in, or which obscure the constituents we want to study, i.e., the noise. The noise can be either periodic, rendering the series "coloured" or other, rendering the series non-stationary, or both.

In both cases, we must know something about the constituent in order to deal with it. Here we restrict ourselves to the case where we know the noise base functions $\underline{\phi}_i(t)$, but do not know what the magnitude of the contribution is to the time series; that is if we represent

$$\underline{f}(t) = \sum_i^{NK} c_i \underline{\phi}_i(t) \quad (33)$$

we know $\underline{f}(t)$ and all the $\underline{\phi}_i(t)$, and do not know the coefficients c_i . So far this is similar to the previous case.

Now, however, we partition $\underline{\phi}$ into the known constituents $\hat{\underline{\phi}}$, and the spectral functions, $\cos \omega_j t$, $\sin \omega_j t$, we used before, so that

$$\underline{\phi} = [\hat{\underline{\phi}}_1, \hat{\underline{\phi}}_2, \dots, \hat{\underline{\phi}}_{NK}, \cos \omega_j t, \sin \omega_j t] \quad (34)$$

It was shown by Vaníček [1971] that the known constituents do not have to be removed from \underline{f} before evaluating the spectrum. It speeds the computations up, however, if the least-squares estimate $\hat{\underline{p}} = \hat{\underline{c}}\hat{\underline{\phi}}$ is removed before the

spectrum is evaluated. This simply means we decompose $\underline{f}(t)$ into its orthogonal projection $\hat{\underline{p}} \in \{c\hat{\underline{\phi}}\}$ and the residual $\underline{f} - \hat{\underline{p}}$ (which is orthogonal to $\hat{\underline{p}}$). We then have the residual time series

$$\underline{g}(t) = \underline{f}(t) - \hat{\underline{p}}(t) \quad (35)$$

and it is this that we compute the spectrum for. We then orthogonally project \underline{g} onto the manifold $M(\underline{\phi})$ spanned by $\underline{\phi} = [\hat{\underline{\phi}}, \cos \omega t, \sin \omega t]$ and obtain the projection $\underline{r} = \underline{p} - \hat{\underline{p}}$ and residual $\hat{\underline{v}} = \underline{g} - \underline{r} = \underline{f} - \underline{p}$. Note that whether we project \underline{f} onto $M(\underline{\phi})$ directly, or \underline{f} onto $M(\hat{\underline{\phi}})$ and then $\underline{f} - \hat{\underline{p}}$ onto $M(\underline{\phi})$, we obtain the same final residual. Finally, we orthogonally project \underline{r} onto \underline{g} and compute the ratio of the length of the projection to the length of \underline{g} as our spectral value.

In summary:

- (a) LSA and LLSPA involve one orthogonal projection: \underline{f} onto $M(\underline{\phi})$.
- (b) LLSA with no known constituents involves two orthogonal projections
 - (i) \underline{f} onto $M(\underline{\phi})$ to obtain \underline{p}
 - (ii) \underline{p} onto \underline{f} to obtain the spectral value.
- (c) LSSA with known constituents involves three orthogonal projections
 - (i) \underline{f} onto $M(\hat{\underline{\phi}})$ to eliminate the known constituents and obtain \underline{g}
 - (ii) \underline{g} onto $M(\underline{\phi})$ to obtain \underline{r}
 - (iii) \underline{r} onto \underline{g} to obtain the spectral value.

In order to geometrically illustrate the concept of these three orthogonal projections as in Figure 4, we have to unrealistically restrict $\underline{\phi}$ to two dimensions. If we let $\hat{\underline{\phi}} = \underline{\phi}_1$ be one dimensional, that leaves only one dimension, $\underline{\phi}_2$, to represent the spectral functions (of which we have in actuality two). If we can live with this limitation in order to look at the three projections conceptually, then the top part of Figure 4 shows the first and second projections (\underline{f} onto $M(\hat{\underline{\phi}})$, and \underline{g} onto $M(\underline{\phi})$), and the bottom part of the figure shows the second and third projections (\underline{g} onto $M(\underline{\phi})$, and \underline{r} onto \underline{g}).

By analogy with (29) the spectral value is

$$s(\omega_j) = \frac{\underline{g}^T \underline{r}(\omega_j)}{\underline{g}^T \underline{g}} \quad (36)$$

where $\underline{g} = \underline{f} - \hat{\underline{p}}$ and $\underline{r} = \underline{p} - \hat{\underline{p}}$. We must compute $\underline{r}(\omega_j)$ for each spectral frequency ω_j , however we need compute only once the quantities (from (28))

$$\underline{g} = \underline{f} - \hat{\underline{\phi}} (\hat{\underline{\phi}}^T \hat{\underline{\phi}})^{-1} \hat{\underline{\phi}}^T \underline{f} \quad (37)$$

and $\underline{g}^T \underline{g}$. Then the projection of \underline{g} onto $M(\underline{\phi})$ has the form

$$\underline{r} = \underline{\phi} (\underline{\phi}^T \underline{\phi})^{-1} \underline{\phi}^T \underline{g} \quad (38)$$

so that

$$\underline{g}^T \underline{r} = \underline{g}^T \underline{\phi} (\underline{\phi}^T \underline{\phi})^{-1} \underline{\phi}^T \underline{g} \quad (39)$$

Now $\underline{g}^T \underline{\phi}$ can be written

$$\underline{g}^T \underline{\phi} = \underline{g}^T [\hat{\underline{\phi}}, \cos \omega_j t, \sin \omega_j t] \quad (40)$$

But $\underline{g}^T \hat{\underline{\phi}} = 0$ (\underline{g} is orthogonal to $M(\hat{\underline{\phi}})$), so that

$$\underline{g}^T \underline{\phi} = [0, 0, \dots, 0, \underline{g}^T \cos \omega_j t, \underline{g}^T \sin \omega_j t] \quad (41)$$

Hence in (39) only the south-east 2 by 2 submatrix of $(\underline{\phi}^T \underline{\phi})^{-1}$ need be computed.

More specifically, denoting $\underline{\phi}^T \underline{\phi}$ by \underline{A} , we have

$$\underline{A} = \begin{vmatrix} \hat{\underline{A}} & \underline{u} & \underline{v} \\ \underline{u}^T & CC & CS \\ \underline{v}^T & CS & SS \end{vmatrix}$$

where the NK by NK matrix $\hat{\underline{A}} = \hat{\underline{\phi}}^T \hat{\underline{\phi}}$, the NK -vectors \underline{u} and \underline{v} are given by $\underline{u}_j = \underline{\phi}_{j-NK+1}^T$, $j = 1, 2, \dots, NK$ and $\underline{v}_j = \underline{\phi}_{j-NK+2}^T$, $j = 1, 2, \dots, NK$, and the elements

$CC = \underline{\phi}_{NK+1}^T \underline{\phi}_{NK+1}$, $CS = \underline{\phi}_{NK+1}^T \underline{\phi}_{NK+2}$, and $SS = \underline{\phi}_{NK+2}^T \underline{\phi}_{NK+2}$. (Note that alternatives to the normal equations such as the Householder transformation could be used; however, they would probably involve penalties in computation times over the algorithm we have chosen.) Since the matrix \hat{A} is positive definite symmetric, it is most conveniently inverted by the Choleski method. The residual time series then is $\underline{g} = \underline{f} - \hat{\phi}(\hat{\phi}^T \hat{\phi})^{-1} \hat{\phi}^T \underline{f}$ and its quadratic norm is $FNORM = \underline{g}^T \underline{g} = \underline{f}^T (\underline{I} - \hat{\phi}(\hat{\phi}^T \hat{\phi})^{-1} \hat{\phi}^T) \underline{f}$.

The orthogonal projection \underline{r} of \underline{g} onto $\underline{\phi}$ is $\underline{r} = \underline{\phi} \underline{c}$, where the coefficient vector \underline{c} satisfies the normal equations $\underline{A} \underline{c} = \underline{b}$, where $\underline{A} = \underline{\phi}^T \underline{\phi}$ and $\underline{b} = \underline{\phi}^T \underline{g}$ are known. Then $\underline{g}^T \underline{r} = \underline{g}^T \underline{\phi} \underline{c} = \underline{b}^T \underline{c} = \underline{b}^T \underline{A}^{-1} \underline{b}$, and $\underline{s}(\omega) = \underline{b}^T \underline{A}^{-1} \underline{b} / FNORM$. From (2) the first NK components of the $(NK+2)$ -vector \underline{b} are zero, the last two being $FCOS = \underline{g}^T \underline{\phi}_{NK+1}$ and $FSIN = \underline{g}^T \underline{\phi}_{NK+2}$. Hence we really need only determine the lower right-hand 2 by 2 submatrix of \underline{A}^{-1} .

It is easily shown that the lower right-hand 2 by 2 submatrix of \underline{A}^{-1} is:

$$\frac{1}{DET} \begin{bmatrix} (SS-VAV), & -(CS-UAV) \\ -(CS-UAV), & (CC-UAU) \end{bmatrix},$$

where $UAU = \underline{u}^T \underline{A}^{-1} \underline{u}$, $VAV = \underline{v}^T \underline{A}^{-1} \underline{v}$, $UAV = \underline{u}^T \underline{A}^{-1} \underline{v}$, and $DET = (CC-UAU)(SS-VAV) - (CS-UAV)^2$. Hence the algorithm for computing the spectrum of \underline{f} is:

$$s(\omega) = [(SS-VAV)FCOS^2 - 2(CS-UAV)FCOS \cdot FSIN + (CC-UAU)FSIN^2] / (DET \cdot FNORM). \quad (42)$$

RELATIONSHIP TO OTHER SPECTRAL FUNCTIONS

To relate this spectrum to the Fourier spectrum, a basis for other kinds of spectra, note that in the absence of known constituents $UAU = VAV =$

$UAV = 0$ and $\underline{g} = \underline{f}$. If the time series is equally spaced and symmetrical about the time origin, then $CS = 0$ and $s(\omega) = (1/FNORM)[(FCOS^2/CC) + (FSIN^2/SS)]$. Letting the time series length increase beyond all limits as the time series spacing decreases to zero, and introducing the compact definition of the scalar product,

$$\underline{x}^T \underline{y} = \int_{-\infty}^{\infty} \underline{x}(t) \underline{y}(t) dt,$$

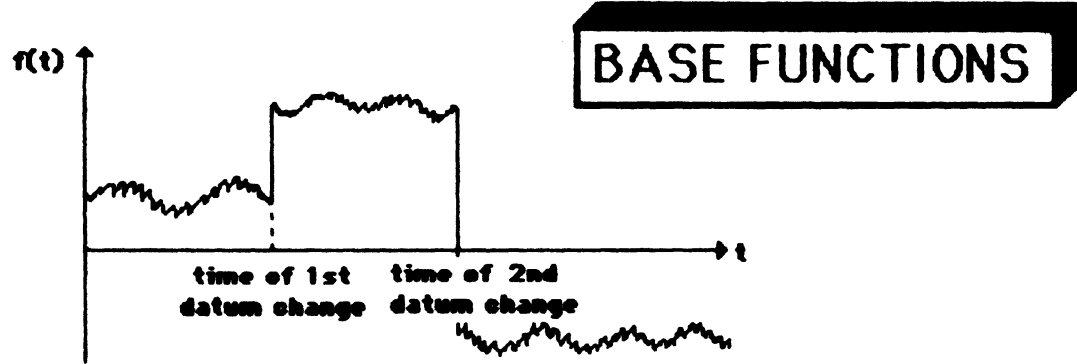
then in our notation the square of the absolute value of the Fourier transform of \underline{f} , $|C(\omega)|^2 = (1/2\pi)(FCOS^2 + FSIN^2)$, can be compared with the above expression for the least-squares spectrum.

There are other possibilities to define a least-squares spectrum, namely, $s(\omega) = (\alpha^2 + \beta^2)/\|\underline{f}\|^2$, where α , β are evaluated (a) from the orthogonal projection $\hat{c} + \alpha \cos(\omega t) + \beta \sin(\omega t)$ of \underline{f} onto $M(\hat{\phi})$, or (b) from the orthogonal projection $\alpha \cos(\omega t) + \beta \sin(\omega t)$ of $\underline{g} = \underline{f} - \hat{p}$ onto the two-dimensional manifold spanned by $\{\cos(\omega t), \sin(\omega t)\}$. In the first case, the spectrum is not defined for values of ω which are present in the known constituents. The second case (equivalent to the standard Fourier analysis approach) distorts the spectrum by forcing it to go to zero for the frequencies present in the known constituents. Both cases are discussed by Taylor and Hamilton [1972] and neither is found to be advantageous from the spectral accuracy point of view.

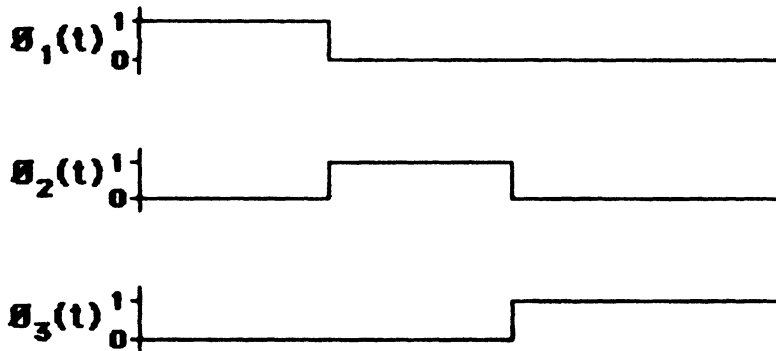
TYPES OF KNOWN CONSTITUENTS

We now turn to the specific software implementation of LSSA documented in this report. In this software, the known constituent base functions $\hat{\phi}$ can be of several types.

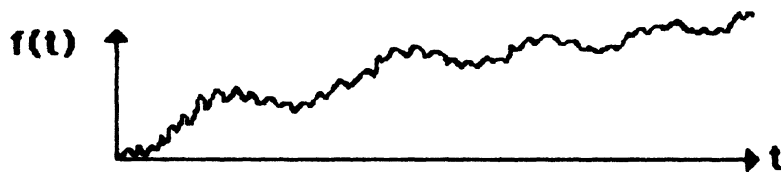
(a) $\phi(t) = 1$ for datum bias. For example, say a tide gauge was moved twice in 10 years and the times of the move were known, but the vertical relationship of the different locations was not known. The time series would look like that shown in the top part of Figure 5. The three datum bias known constituent base functions in Figure 5 would be used.



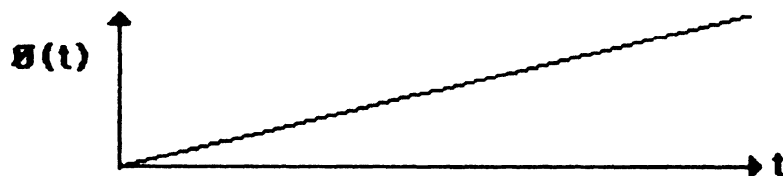
Time Series Containing Datum Biases



Base Functions to Remove Datum Biases



Time Series Containing Linear Trend



Base Function to Remove Linear Trend

FIGURE 5.

(b) $\phi(t) = t$, for linear trend. For example, say a tide gauge was situated on a dock which was slowly (or uniformly) sinking into the seabed. Then the time series would look like that in the bottom part of Figure 5. The linear trend constituent base function in Figure 5 would be used to remove this linear trend.

$$\begin{array}{l} \text{(c) } \phi_1(t) = \cos \mu_i t \quad | \\ \quad \quad \quad \quad \quad \quad \quad | \text{ for } \underline{\text{forced periodic}} \text{ constituents, with} \\ \quad \quad \quad \quad \quad \quad \quad | \text{ frequencies } \mu_i. \\ \phi_2(t) = \sin \mu_i t \quad | \end{array}$$

For example, we know that a given time series contains the tidal frequencies M_2 and K_1 (perhaps from a previous spectral analysis), so we want to remove these peaks from the spectrum and see what is left.

(d) $\phi(t) =$ "anything else" for user defined constituents. For example, instead of a linear trend we may believe that some nonlinear trend (say exponential) exists.

INPUT AND OUTPUT PARAMETERS

The input parameters for computing the spectrum (5) must specify the time series, the limits and density of the spectral band to be produced, and the known constituents $\hat{\Phi}$.

The time series is defined by the vectors (F_i, T_i) $i=1,2,\dots,NF$ where the values T_i are in units of time, and for SPECUN (the version used for unequidistant series) are unrestricted as to spacing. For SPECEQ (the version used for equidistant series) the time series is assumed to consist of a specific number (NIVL) of subintervals, each of which consists of equally spaced data points separated by a time increment STEP common to all subintervals. The subintervals need not be separated by integral multiples of STEP. Separation of subintervals is specified as detected by the software when two consecutive elements are not separated by STEP. The value for STEP is defined by the difference between the first and second elements in the time series.

The spectrum is defined by the vectors (S_i, P_i) $i=1,2,\dots,NW$, where the values P_i are specified spectral periods in the same units as T_i , and the values S_i are the computed spectral values.

The known constituents. Rather than requiring the user to specify the form of $\hat{\phi}$, it is useful to build some common types of known constituents into the algorithm leaving the user free to ignore them and specify his own functions if he so desires. This algorithm, therefore, provides four optional types of known constituents:

- (a) Datum Bias. Let the time series consist of $NDAT$ segments, each referred to a different datum. Then for $NDAT \geq 1$

$$\phi_i(\underline{t}) = \begin{cases} 1 & \text{if } t \text{ is in the } i\text{th datum segment} \\ 0 & \text{otherwise} \end{cases} \quad i=1,2,\dots,NDAT$$

In the program in this case

$NDAT = 3$ (number of segments of total time series separated by datum shifts)

$DAT(1) = t_0$ (start time of first datum = start time of time series)

$DAT(2) = t_1$ (start time of second datum)

$DAT(3) = t_2$ (start time of third datum).

If there are no datum biases we set $NDAT = 0$, and the contents of DAT are not used. On input to routines $SPECUN$ and $SPECEQ$, if $NDAT$ is negative, a warning message is produced, $NDAT$ is set to zero, and the program continues. If $NDAT$ is positive and $DAT(1) \neq t_0$, a fatal message is produced and the program aborts.

- (b) Linear Trend. If used, this known constituent is of the form

$$\phi_i(\underline{t}) = \underline{t}, \quad i = NDAT + 1 \quad (LT = 1 \text{ if used, } LT = 0 \text{ otherwise}).$$

On input to routines $SPECUN$ and $SPECEQ$, if LT is not either 0 or 1, a warning message is produced, LT is set to 0, and the program continues.

- (c) Forced Periods. For $NPER \geq 1$ known periods PER_j (and frequencies $\mu_j = 2\pi/PER_j$), the known constituents are the periodic functions

$$\phi_i(\underline{t}) = \cos(\mu_j t)$$

$$i = NDAT + LT + 2j - 1, \quad j=1,2,\dots,NPER.$$

$$\phi_{i+1}(\underline{t}) = \sin(\mu_j t)$$

In the program in this case we set

$NPER = 2$ (number of frequencies to be removed)

$PER(1) = 12.42$ hours (for M_2) (period of first frequency)

$PER(2) = 23.93$ hours (for K_1) (period of second frequency).

If we do not want to remove any periodic constituents before computing the spectrum we set $NPER = 0$, and the contents of PER are not used. On input to routines $SPECUN$ and $SPECEQ$, if $NPER$ is negative, a warning message is produced, $NPER$ is set to zero, and the program continues. On input to routine $SPECEQ$ only, if $NPER$ is greater than the dimension of the arrays required ($NPERDM$), a fatal message is produced and the program aborts.

- (d) User-specified. These known constituents are of arbitrary form (for example, quadratic trend or exponential trend, a numerical function) chosen by each user

$$\phi_i(t) = ?, \quad i = NDAT + LT + 2*NPER + j, \quad j = 1, 2, \dots, NBASE.$$

In the example at the end of PART A we set

$NBASE = 1$ (number of user defined constituents to be removed)

and add the appropriate code in subroutine $BASE$ to implement the user-defined function. This particular user defined function is an exponential trend and the code reads:

$BASE = EXP(-T/25.)$.

If there are no user defined constituents to be removed, set $NBASE = 0$. On input to routines $SPECUN$ and $SPECEQ$, if $NBASE$ is negative, a warning message is produced, $NBASE$ is set to zero, and the program continues.

The total number of known constituents then is:

$$NK = NDAT + LT + 2*NPER + NBASE, \quad (43)$$

which may also equal to 0 (for $NDAT = LT = NPER = NBASE = 0$).

On input to routines $SPECUN$ and $SPECEQ$, if (43) is not satisfied, a warning message is produced, NK is set equal to the right hand side of (43), and the computation continues. If NK is greater than the dimensions of the arrays required ($NKDIM$), a fatal message is produced, and the program aborts.

The next two input parameters, MODE and EQORUN, specify whether a sequential or batch solution is desired (MODE) and if SPECEQ or SPECUN should be used. Standard deviations of and correlations between a priori estimates \hat{c} are also evaluated from the usual statistical formulae. Their values are printed if they are considered significant. The significance level for standard deviations (in percents) is another input parameter, PCENT; for correlation, the level is called CLEVEL.

Two more statistical parameters are produced by the software: the mean spectral value for white noise (see Vaníček [1971]):

$$RS = 2/(NF - NK) * 100\% \quad , \quad (44)$$

and the critical percentage variance on 95% for detecting statistically significant peaks in the spectrum [Steeves, 1981]:

$$RS95 = (1 - \alpha^{2/(NF-NK-2)}) * 100\% \quad , \quad (45)$$

where $\alpha = 0.95$. These are printed together with the spectrum.

GENERAL SCALAR PRODUCT ALGORITHM FOR EQUALLY SPACED DATA

The spectrum (5) requires evaluation of the scalar products FNORM, FCOS, FSIN, CC, CS, SS, and U_i, V_i ($i=1,2,\dots,NK$). For an unequally spaced time series treated by SPECUN, all these scalar products must be evaluated directly from:

$$\underline{x}^T \underline{y} = \langle \underline{x}, \underline{y} \rangle = \sum_{t_i} x(t_i) y(t_i) \quad (46)$$

where, for convenience, we now introduce the bracket notation $\langle \underline{x}, \underline{y} \rangle$. Provided that the time series is at least piecewise equally spaced (as described in the previous section for input to SPECEQ), we can use much more efficient formulae to evaluate CC, CS, SS and those elements of the vectors \underline{U} and \underline{V} corresponding to datum bias, linear trend, and forced period known constituents. However, FNORM, FCOS, FSIN and those elements of \underline{U} and \underline{V} corresponding to user-defined known constituents must still be evaluated directly from (44).

For convenience we define the function $\text{trig}(x)$ as being either $\cos(x)$ or $\sin(x)$. We seek, to begin with, an algorithm for the scalar products

$$\langle 1, \text{trig}(\omega t) \rangle = \sum_{T_i} \text{trig}(\omega T_i) \quad i=1,2,\dots,NF. \quad (47)$$

Direct evaluation requires computing NF trigonometric functional values. We can reduce this number considerably by applying the identities [Korn and Korn, 1968, p. 981]:

$$\sum_{k=0}^n \text{trig}(2ak + b) = [1/\sin(a)] * \sin(an + a) * \text{trig}(an + b). \quad (48)$$

Let the j th subinterval of the time series F consist of equally spaced data points, separated by the time increment STEP , the first data point occurring at time TA_j and the last at time TB_j . Then setting

$$\begin{aligned} k &= (T_i - TA_j)/\text{STEP} = 0,1,\dots,n; \\ n &= (TB_j - TA_j)/\text{STEP}; \\ a &= (\omega/2)*\text{STEP}; \text{ and} \\ b &= \omega*TA_j; \end{aligned}$$

we have

$$\sum_{T_i=TA_j}^{TB_j} \text{trig}(\omega T_i) = [1/\sin(Q)] * \sin(N_j Q) * \text{trig}(L_j Q), \quad (49)$$

where $Q = (\omega/2)*\text{STEP}$; $N_j = 1 + (TB_j - TA_j)/\text{STEP}$; and $L_j = (TB_j + TA_j)/\text{STEP}$.

Summing over the $NIVL$ subintervals in F gives us the scalar product:

$$\langle 1, \text{trig}(\omega T) \rangle = \frac{1}{\sin(Q)} \sum_{j=1}^{NIVL} \sin(N_j Q) * \text{trig}(L_j Q), \quad (50)$$

which requires computing only $(2*NIVL+1)$ trigonometric functional values, where $NIVL$ is the number of subintervals.

SPECIFIC SCALAR PRODUCT EXPRESSIONS

It now simply remains to reduce the scalar products CC , CS , SS , \underline{U} , and \underline{V} to the form of (50). Using (46) it is easy to see that $CC = (NF/2) +$

$(1/2)* \langle 1, \cos 2\omega T \rangle$; $CS = (1/2)* \langle 1, \sin 2\omega T \rangle$; and $SS = (NF/2) - (1/2)* \langle 1, \cos 2\omega T \rangle$ where from (50) we can see that:

$$\langle 1, \text{trig}(2\omega T) \rangle = \frac{1}{\sin(2Q)} \sum_{j=1}^{\text{NIVL}} \sin(2N_j Q) * \text{trig}(2L_j Q) \quad . \quad (51)$$

The first NDAT elements of vectors \underline{U} and \underline{V} involve constituents of type (a) (datum biases). Let INTA_i and INTB_i be the first and last subintervals referred to the i th datum. Then

$$U_i = \frac{1}{\sin Q} \sum_{j=\text{INTA}_i}^{\text{INTB}_i} \sin N_j Q \cos L_j Q$$

$i=1, 2, \dots, \text{NDAT} \quad . \quad (52)$

$$V_i = \frac{1}{\sin Q} \sum_{j=\text{INTA}_i}^{\text{INTB}_i} \sin N_j Q \sin L_j Q$$

If $LT \neq 0$, the next element of \underline{U} and \underline{V} involves the known constituent of type (b) (linear trend). Then

$$U_{\text{NDAT}+1} = \frac{\partial}{\partial \omega} \langle 1, \sin \omega T \rangle = \frac{\partial Q}{\partial \omega} \frac{\partial}{\partial Q} \left(\frac{1}{\sin Q} \sum_{j=1}^{\text{NIVL}} \sin N_j Q \sin L_j Q \right) \quad (53)$$

$$V_{\text{NDAT}+1} = - \frac{\partial}{\partial \omega} \langle 1, \cos \omega T \rangle = - \frac{\partial Q}{\partial \omega} \frac{\partial}{\partial Q} \left(\frac{1}{\sin Q} \sum_{j=1}^{\text{NIVL}} \sin N_j Q \cos L_j Q \right) \quad .(54)$$

After some development, we get

$$U_{\text{NDAT}+1} = \frac{\text{STEP}}{2} \frac{1}{\sin Q} \sum_{j=1}^{\text{NIVL}} -\cot Q \sin N_j Q \sin L_j Q + N_j \cos N_j Q \sin L_j Q + L_j \sin N_j Q \cos L_j Q \quad (55)$$

$$V_{\text{NDAT}+1} = \frac{\text{STEP}}{2} \frac{1}{\sin Q} \sum_{j=1}^{\text{NIVL}} +\cot Q \sin N_j Q \cos L_j Q - N_j \cos N_j Q \cos L_j Q + L_j \sin N_j Q \sin L_j Q \quad .(56)$$

The next $(2*\text{NPER})$ elements of \underline{U} and \underline{V} involve constituents of type (c) (forced periods). Using (46), it is easy to see that:

$$U_i = \frac{1}{2} \langle 1, \cos(\mu_k + \omega)T \rangle + \frac{1}{2} \langle 1, \cos(\mu_k - \omega)T \rangle \quad (57)$$

$$U_{i+1} = \frac{1}{2} \langle 1, \sin(\mu_k + \omega)T \rangle + \frac{1}{2} \langle 1, \sin(\mu_k - \omega)T \rangle \quad (58)$$

$$V_i = \frac{1}{2} \langle 1, \sin(\mu_k + \omega)T \rangle - \frac{1}{2} \langle 1, \sin(\mu_k - \omega)T \rangle \quad (59)$$

$$V_{i+1} = -\frac{1}{2} \langle 1, \cos(\mu_k + \omega)T \rangle + \frac{1}{2} \langle 1, \cos(\mu_k - \omega)T \rangle \quad (60)$$

$$i = \text{NDAT} + \text{LT} + 2*k-1$$

$$k = 1, 2, \dots, \text{NPER}.$$

Letting $P_k = (\mu_k/2)*\text{STEP}$, we see from (50) that

$$\langle 1, \text{trig}(\mu_k \pm \omega)T \rangle = \frac{1}{\sin(P_k \pm Q)} \sum_{j=1}^{\text{NIVL}} \sin N_j(P_k \pm Q) \text{trig} L_j(P_k \pm Q). \quad (61)$$

We note that the functions of sums of angles in (51) and (61) can be expressed in terms of functions of angles only. Hence the scalar products CC, CS, SS and those elements of \underline{U} , \underline{V} which refer to known constituents of types (a), (b), and (c) can be computed from the $(2*\text{NPER} + 4*\text{NPER}*\text{NIVL})$ functions $\text{trig}(P_k)$, $\text{trig}(N_j P_k)$, $\text{trig}(L_j P_k)$ (which need only be computed once for a given $\hat{\omega}$) and from the $(2 + 4*\text{NIVL})$ functions $\text{trig}Q$, $\text{trig}(N_j Q)$, $\text{trig}(L_j Q)$ (which must be computed for each desired spectral frequency ω).

EXAMPLES

As a model of many time series encountered in practice, we have generated the following time series:

$$f(t) = c_i + 0.01t + 3*\exp(-t/25) + \sum_{j=1}^5 (a_j \cos \mu_j t + b_j \sin \mu_j t), \quad (62)$$

(where t is in years) that may represent a typical, say geophysical, (coloured) time series. Three hundred values of f were generated spanning 50 years and grouped into four subintervals consisting of equally spaced data, that is $t \in D_k$, $k=1, 2, 3, 4$, where

$$\begin{aligned}
D_1 &\equiv [0.1, 0.2, \dots, 10.0] \text{ years} && (100 \text{ values}) \\
D_2 &\equiv [20.1, 20.2, \dots, 25.0] \text{ years} && (50 \text{ values}) \\
D_3 &\equiv [28.1, 28.2, \dots, 40.0] \text{ years} && (120 \text{ values}) \\
D_4 &\equiv [47.1, 47.2, \dots, 50.0] \text{ years} && (30 \text{ values}) .
\end{aligned}$$

The datum biases were $c_1 = 1$, $t \in D_1$; $c_2 = -1$, $t \in D_2$; and $c_3 = 3$, $t \in D_3$, D_4 . The amplitudes and periods of the trigonometric terms were $a_j = 1/2, 1, 0, 1.2, -1.4$; $b_j = 1, 1/2, 1, -1, 0$; and $p_j = 2\pi/\mu_j = (2.759, 3.636, 5.714, 40, 16)$ years. The graph of this time series is shown in Figure 6.

The time series (62) was analysed using both SPECEQ and SPECUN. In addition, a second unequally spaced time series was generated from (62) by adding to the linearly increasing t a sinusoidal variation of period 50 years and amplitude 0.5 years. The second time series was analysed using SPECUN only.

Nine runs were made for each of these three analyses, increasing the number of known constituents from zero to 15. The SPECEQ results are shown in Figure 7. The top four spectra illustrate the influence the datum biases and the linear and exponential trends, and their removal, have on the spectra. The next four spectra illustrate how the technique can be used in searching for hidden periodicities. By suppressing the effect of the periodic constituent which was the most prominent in the previous run, we enhance the remaining peaks, revealing the existence of "weaker" periodic constituents. The ninth run suppressed the effect of all constituents of (62), in which case the residual time series consisted of round-off error only, no spectrum was computed, and, as expected, the computed amplitudes of the known constituents agreed within round-off with those used in (62). The SPECUN generated results were identical to the SPECEQ generated results. As expected for the unequally spaced SPECUN results, the computed amplitudes of the known constituents and the height of the spectral peaks differed slightly from the equally spaced analyses. However, there was no shift in the position of the spectral peaks.

The execution times of Table 1 were obtained using the FORTRAN 77 compiler on an IBM 3081 computer. The equally spaced SPECEQ and unequally spaced SPECUN execution times were essentially equal for small numbers of

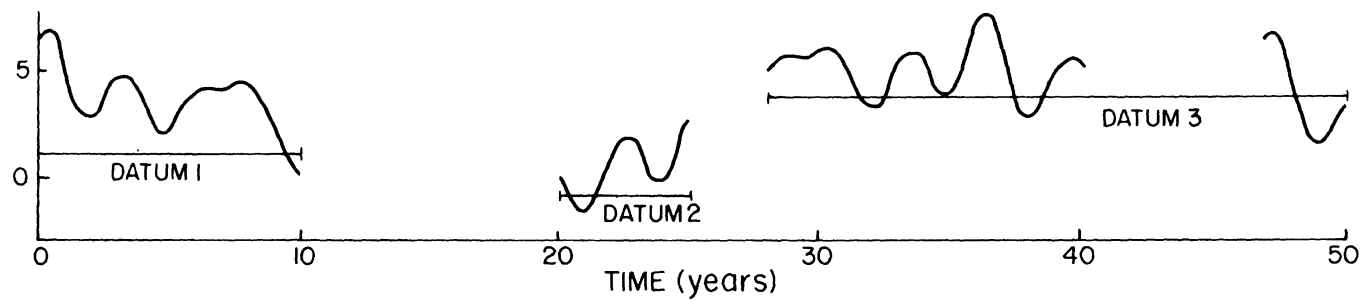


Figure 6. Graph of test time series of 300 values generated by Equation (62).

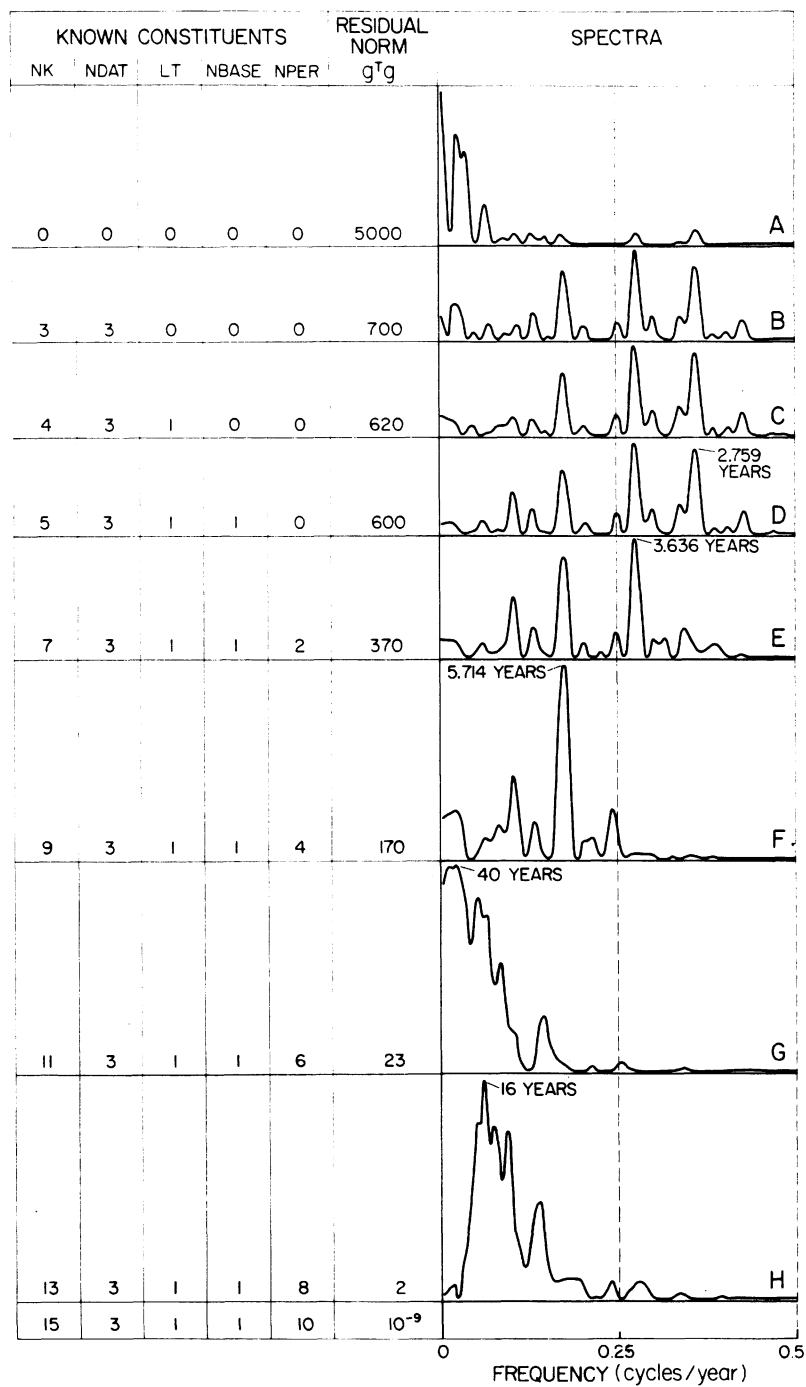


Figure 7. Results from nine runs of program SPECEQ, analyzing the time series of Figure 6. The number of known constituents suppressed in each run are specified by NK, NDAT, LT, NBASE, and NPER, respectively, giving the total number of constituents, the number of datum biases, the linear trend, the number of user-defined constituents, and the number of forced periods.

TABLE 1

IBM 3081 CPU Times for Test Time Series Containing 300 Values.

Number of Known Constituents NK	CPU Times (sec)	
	SPECEQ	SPECUN
0	5.77	5.83
3	5.82	6.95
4	6.04	7.32
5	6.72	8.19
7	6.90	10.23
9	7.04	12.19
11	7.28	14.22
13	7.53	16.35

constituents. However, for longer time series and larger numbers of constituents the difference in execution times increases considerably in favour of equally spaced execution time.

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PART B

USER'S GUIDE AND PROGRAM LISTINGS

INTRODUCTION

This version of the Least-Squares Spectral Analysis software has been modified from the version published with the original version of this report. Some modifications were made to correct errors in the original version. Other modifications were made to expand the information provided on output.

STRUCTURE OF THE SOFTWARE

The software has been modularized into 16 routines, shown in Figure 1. Three of these specify the input:

TSPEC Main program. Calls TIMSER, DRIVER and FPLOT.
 TIMSER Reads input time series.
 DRIVER Calls SPECUN or SPECEQ.

Five of these compute the known constituents, the spectrum, and the residual time series

SPECUN Computes least squares spectrum of unequally-spaced time series.
 SPECEQ Computes least squares spectrum of equally-spaced time series.
 BASE Computes known constituent functional values.
 RESID Computes residual time series after removing known constituents.
 CHOLS Inverts matrix in place using Cholesky decomposition.
 EPS Determines smallest ϵ such that $1 + \epsilon$ is distinguishable from 1.

Four of these report the results on the lineprinter:

FPLOT Plots input time series.
 AMPL Lists sine and cosine least-squares estimated coefficients of known constituents.
 AMPHAS Lists least-squares estimated amplitude and phase (and their standard deviations) of known constituents.
 COVAR Lists covariance matrix of unknown constituents.
 SPLOT Plots output spectrum.
 ERROR Prints error message. Stops if fatal error.

The central routine is either SPECUN or SPECEQ. Both have the following parameter list:

T = input vector of time series times $\{t_i\}$
 F = input vector of time series values $\{f_i\}$
 output vector of residual time series values $\{g_i\}$
 NF = input length of T and F
 FNORM = output $\underline{g}^T \underline{g}$
 NK = input total number of known constituents to be removed from F

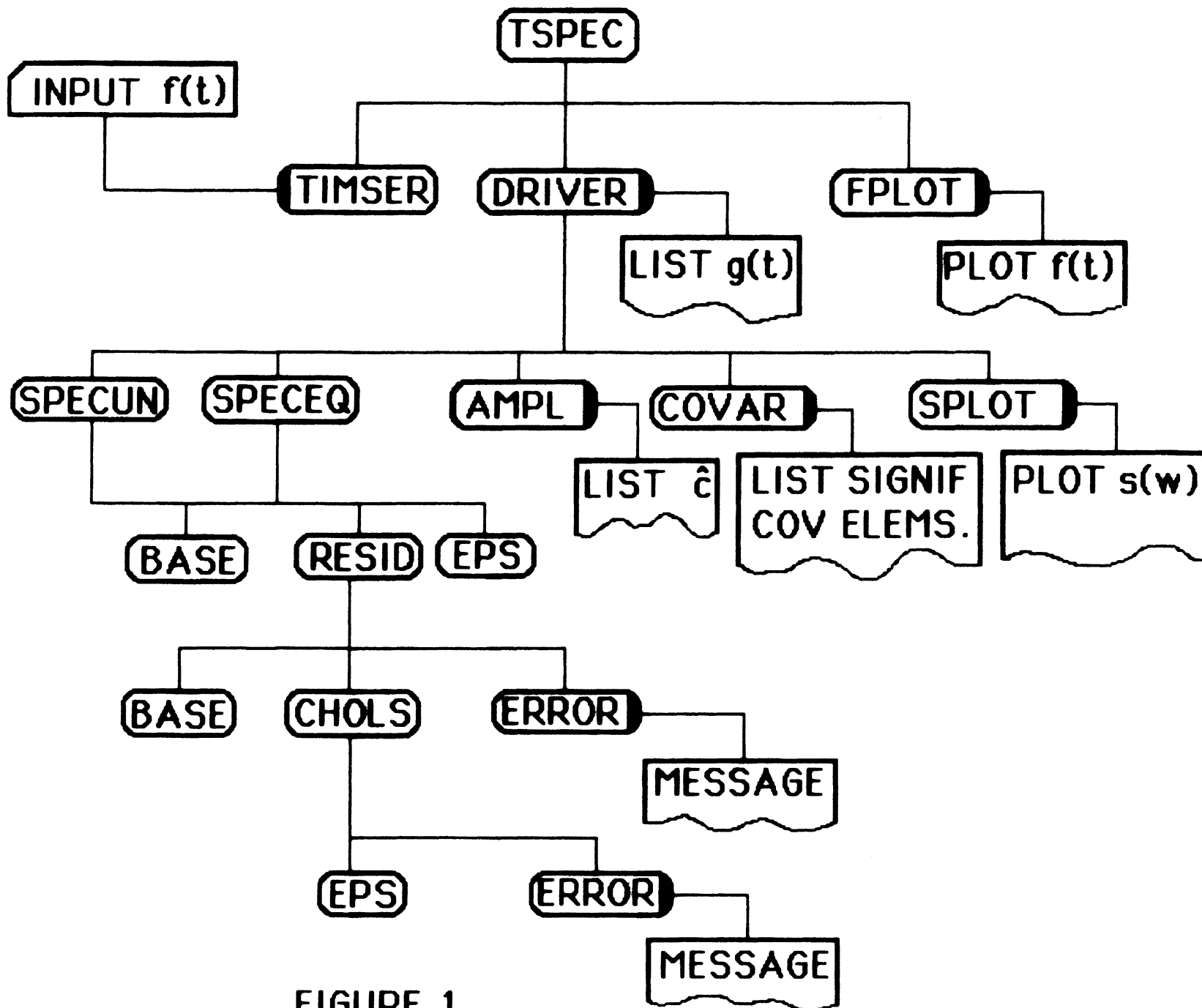


FIGURE 1

DAT = input vector of time new datum bias begins
 NDAT = input number of datum biases (length of DAT)
 LT = input linear trend switch
 PER = input forced periods
 NPER = input number of forced periods (length of PER)
 NBASE = input number of user defined constituents
 C = output vector of amplitudes (coefficients) of removed known constituents \hat{c} . NK values.
 P = input vector of periods for which spectral values will be computed
 S = output vector of spectral values
 NW = input length of P, S.
 IB = input spectral band label. If only one spectral band is to be computed, set IB = 1. If more than one spectral band is to be computed from same time series, set IB = 1 for first band, during which \underline{g} and $\underline{g}^T \underline{g}$ are computed. For subsequent bands set IB > 1, and the previous values of \underline{g} and $\underline{g}^T \underline{g}$ are used, rather than recomputing.

Thus SPECUN and SPECEQ accept inputs specifying

- (a) the time series $\{t_i, f_i\}$, $i=1,2,\dots,NF$
- (b) the known constituents $\hat{\phi}_i(t)$, $i=1,2,\dots,NK$ to be removed from \underline{f}
- (c) the periods P_i , $i=1,2,\dots,NW$ for which spectral values are wanted

and provides outputs specifying

- (a) the residual time series $\{g_i\}$ $i=1,2,\dots,NF$ and its norm $\underline{g}^T \underline{g}$
- (b) the amplitudes of the known constituents $\{\hat{c}_i\}$ $i=1,2,\dots,NK$
- (c) the spectral values $\{s_i\}$, $i=1,2,\dots,NW$.

SPECEQ has four main blocks of code:

- (a) error checking
- (b) identification of equally spaced subintervals, and precomputation of trigonometric functions
- (c) computation of \underline{g} and $\underline{g}^T \underline{g}$ (done by subroutine RESID)
- (d) computation of $s(\omega_j) = \underline{g}^T \underline{r}(\omega_j) / \underline{g}^T \underline{g}$ for each ω_j .

SPECUN omits the second of these four blocks of code.

MODIFYING THE SOFTWARE

The only routines that need be changed to accommodate new time series, known constituents, or spectral periods are

TSPEC (main)
TIMSER
DRIVER
SPECUN
BASE

(a) The only change to BASE is to add more user defined base functions, if required.

(b) The only change to SPECUN is to redimension the following arrays if there are more than 15 known constituents ($NK > 15$):

A(NK,NK)
B(NK)
U(NK)
V(NK)
reset NKDIM = NK

(c) The only changes to TSPEC (Main) are as follows:

Redimension FF(NF), T(NF) if $NF > 500$
Redimension PER(NPER) if $NPER > 5$
Redimension DAT(NAT) if $NDAT > 3$

(d) DRIVER generates the input specification of the periods for which spectral values are wanted, and passes the parameters P, NW, IB to SPECUN. If these are to be changed then the parameters PL, PS, NW, and IB in the DATA statement must be changed.

In addition, DRIVER must be changed under the following circumstances:

Redimension F(NF) for $NF > 500$
Redimension P(NW), S(NW) for $NW > 500$
Redimension C(NK) for $NK > 15$

(e) TIMSER generates the inputs specifications for

- (i) the time series, passing T, F, NF to SPECUN
- (ii) the known constituents to be removed, passing DAT, NDAT, LT, PER, NPER, NBASE, to SPECUN.

If the time series is to be read in as data, replace the DO 10 loop in TIMSER by a READ statement. If a different artificial time series is to

be generated by TIMSER, change the vectors A, B,C, P, NB, NE, IVL and the scalars NIVL and STEP to appropriate values, taking care to redimension as required.

If different known constituents are to be removed (including none to be removed) change DAT, NDAT, LT, PER, NPER, and NBASE as required. Take care to redimension DAT(NDAT) and PER(NPER) in TSPEC as required.

General redimensioning rules are, for TIMSER, to redimension

C(NK) if $NK > 5$

A(NPER), B(NPER), P(NPER) if $NPER > 5$

IVL(NDAT+1), NB(NDAT+1), NE(NDAT+1) if $NDAT > 3$.


```

PROGRAM TSPEC
IMPLICIT DOUBLE PRECISION (A-H,O-Z)
CHARACTER *2 EQORUN
CHARACTER *5 MODE
DIMENSION DAT(3), FF(500), PER(5), T(500)
DATA IPR /6/
C
C FUNCTION: TSPEC CALLS TIMSER TO GENERATE TEST TIME SERIES
C AND CALLS DRIVER TO COMPUTE SEVERAL
C LEAST SQUARES SPECTRA OF THE TEST
C TIME SERIES
C
C UNIT NUMBER: IPR = 6 = LISTING OF INPUT AND OUTPUT
C
C EXTERNALS: DRIVER,FPLOT,TIMSER
C
C SUMMARY:
C CALL TIMSER
C CALL FPLOT TO PLOT INPUT TIME SERIES
C CALL DRIVER ADDING DATUM BIAS, LINEAR TREND, USER-DEFINED
C CONSTITUENTS AND FORCED FREQUENCIES SIMULTANEOUSLY (MODE=BATCH)
C CALL DRIVER WITH NO KNOWN CONSTITUENTS
C CALL DRIVER ADDING DATUM BIAS CONSTITUENTS
C CALL DRIVER ADDING LINEAR TREND CONSTITUENT
C CALL DRIVER ADDING USER-DEFINED CONSTITUENTS
C CALL DRIVER ADDING ONE FORCED FREQUENCY AT A TIME
C CALL TIMSER(T, FF, NF, DAT, MDAT, MT, PER, MPER, MBASE, MODE,
$ EQORUN, PCENT, CLEVEL)
CALL FPLOT(T, FF, NF, DAT, MDAT, EQORUN, IPR)
IF (MODE .EQ. 'SQNTL') GO TO 1
IF (MODE .EQ. 'BATCH')
$CALL DRIVER(T, FF, NF, DAT, MDAT, MT, PER, MPER, MBASE, IPR,
$ EQORUN, PCENT, CLEVEL)
STOP
1 NDAT = 0
LT = 0
NBASE = 0
NPER = 0
CALL DRIVER(T, FF, NF, DAT, NDAT, LT, PER, NPER, NBASE, IPR,
$ EQORUN, PCENT, CLEVEL)
IF(MDAT .EQ. 0) GO TO 5
NDAT = MDAT
CALL DRIVER(T, FF, NF, DAT, NDAT, LT, PER, NPER, NBASE, IPR,
$ EQORUN, PCENT, CLEVEL)
5 IF(MT .EQ. 0) GO TO 10
LT = MT
CALL DRIVER(T, FF, NF, DAT, NDAT, LT, PER, NPER, NBASE, IPR,
$ EQORUN, PCENT, CLEVEL)
10 IF(MBASE .EQ. 0) GO TO 15
NBASE = MBASE
CALL DRIVER(T, FF, NF, DAT, NDAT, LT, PER, NPER, NBASE, IPR,
$ EQORUN, PCENT, CLEVEL)
15 IF(MPER .EQ. 0) GO TO 25
DO 20 NPER = 1,MPER
20 CALL DRIVER(T, FF, NF, DAT, NDAT, LT, PER, NPER, NBASE, IPR,
$ EQORUN, PCENT, CLEVEL)
25 STOP
END

```

```

TSPE 001
TSPE 002
TSPE 003
TSPE 004
TSPE 005
TSPE 006
TSPE 007
TSPE 008
TSPE 009
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TSPE 050
TSPE 051
TSPE 052
TSPE 053
TSPE 054
TSPE 055
TSPE 056
TSPE 057
TSPE 058

```

```

SUBROUTINE AMPL(A, NF, NK, FNORM, DAT, NDAT, LT, PER, NPER,
$           NBASE, C, IPR)
IMPLICIT DOUBLE PRECISION (A-H,O-Z)
DIMENSION A(100,100), C(1), DAT(1), PER(1)
DATA PI/3.141592653589793D0/
C
C FUNCTION: AMPL LISTS PRELIMINARY COSINE AND SINE
C           COEFFICIENTS.
C
C CALLED FROM: DRIVER
C
C ARGUMENTS: A           = INVERTED MATRIX OF NORMAL EQUATIONS
C               NK       = TOTAL NUMBER OF KNOWN CONSTITUENTS
C               DAT(NDAT) = TIMES NEW DATUM BEGINS
C               LT       = LINEAR TREND SWITCH (1 = INCLUDED)
C               PER(NPER) = FORCED PERIODS
C               NBASE    = NUMBER OF USER-DEFINED CONSTITUENTS
C               C(NK)    = PRELIMINARY AMPLITUDES OF KNOWN
C                       CONSTITUENTS
C               IPR      = UNIT NUMBER FOR OUTPUT
C
C EXTERNALS: DSQRT, DATA2, DMOD
WRITE(IPR,1001) NDAT,LT,NPER,NPER,NPER,NBASE
IF(NDAT .GE. 1) WRITE(IPR,1002) (K,C(K),K=1,NDAT)
K = NDAT + 1
IF(LT .EQ. 1) WRITE(IPR,1003) K,C(K)
IF(NPER .EQ. 0) GO TO 10
DO 5 I = 1, NPER
  K = NDAT + LT + 2 * I - 1
  K1 = K + 1
  AMP = DSQRT(C(K)*C(K) + C(K1)*C(K1))
  GPL = DATAN2(C(K1),C(K)) * 180.DO / PI
  GPL = DMOD(GPL + 360.DO, 360.DO)
  ESTSD = DSQRT(FNORM / (NF - NK))
  SIGAMP = DSQRT(C(K) * C(K) * A(K,K) + C(K1) * C(K1) *
$           A(K1,K1) + 2.DO * C(K) * C(K1) * A(K,K1)) *
$           ESTSD / AMP
  SIGPL = DSQRT(C(K1) * C(K1) * A(K,K) +
$           C(K) * C(K) * A(K1,K1) -
$           2.DO * C(K) * C(K1) * A(K,K1)) *
$           (ESTSD / (AMP * AMP)) * (180.DO / PI)
  WRITE(IPR,1004) K,K1,PER(I),C(K),C(K1),AMP,SIGAMP,GPL,SIGAPL
5 CONTINUE
10 IF(NBASE .EQ. 0) RETURN
DO 15 I = 1,NBASE
  K = NDAT + LT + 2 * NPER + I
15 WRITE(IPR,1005) K, C(K)
RETURN
1001 FORMAT(1H1,2X,31HSOLUTION FOR KNOWN CONSTITUENTS,///,
$ 14X,5HDATUM,4X,6HLINEAR,4X,6HFORCED,4X,6HCOSINE,6X,
$ 4HSINE,8X,4HUSER,/,15X,4HBIAS,5X,5HTREND,
$ 4X,6HPERIOD,4X,4HTERM,8X,4HTERM,5X,7HDEFINED,2X,
$ 9HAMPLITUDE,3X,7H(SIGMA),4X,5HPHASE,2X,7H(SIGMA),///,
$ 2X,6HNUMBER,5X,I5,5(7X,I3),//)
1002 FORMAT(7X,I3,E11.3)
1003 FORMAT(7X,I3,10X,E11.3)
1004 FORMAT(3X,I3,1H-,I3,18X,F11.3,2E11.3,10X,E10.3,1X,1H(,E10.3,
$ 1H),1X,F6.2,1X,1H(,F6.2,1H))
1005 FORMAT(7X,I3,51X,E11.3)
END
AMPL 001
AMPL 002
AMPL 003
AMPL 004
AMPL 005
AMPL 006
AMPL 007
AMPL 008
AMPL 009
AMPL 010
AMPL 011
AMPL 012
AMPL 013
AMPL 014
AMPL 015
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AMPL 058
AMPL 059
AMPL 060

```

DOUBLE PRECISION FUNCTION BASE(I, T, DAT, NDAT, LT, PER, NPER)	BASE 001
IMPLICIT DOUBLE PRECISION (A-H,O-Z)	BASE 002
DIMENSION DAT(1), PER(1)	BASE 003
DATA PI/3.141592653589793D0/	BASE 004
C	BASE 005
C FUNCTION: BASE COMPUTES KNOWN CONSTITUENT FUNCTIONAL	BASE 006
C VALUES.	BASE 007
C	BASE 008
C CALLED FROM: RESID	BASE 009
C	BASE 010
C ARGUMENTS: I = INDEX OF KNOWN CONSTITUENT TO BE COMPUTED	BASE 011
C T = TIME AT WHICH KNOWN CONSTITUENT COMPUTED	BASE 012
C DAT(NDAT) = INPUT TIMES NEW DATUM BEGINS	BASE 013
C LT = INPUT LINEAR TREND SWITCH (1 = INCLUDED)	BASE 014
C PER(NPER) = INPUT FORCED PERIODS	BASE 015
C	BASE 016
C EXTERNALS: DCOS, DEXP, DSIN	BASE 017
C	BASE 018
C LIMITATION: USER MUST SUPPLY CODING TO COMPUTE EACH	BASE 019
C USER-DEFINED CONSTITUENT. AS AN EXAMPLE,	BASE 020
C THIS VERSION CONTAINS THE EXPONENTIAL	BASE 021
C TREND EXP(-T/25).	BASE 022
C	BASE 023
C DATUM BIAS	BASE 024
IF(I .GT. NDAT) GO TO 5	BASE 025
BASE = 1.0D0	BASE 026
IF(I .EQ. NDAT .AND. T .GE. DAT(I)) RETURN	BASE 027
IF(I .LT. NDAT .AND. T .GE. DAT(I)	BASE 028
\$.AND. T .LT. DAT(I+1)) RETURN	BASE 029
BASE = 0.0D0	BASE 030
RETURN	BASE 031
C	BASE 032
C LINEAR TREND	BASE 033
5 IF(I .GT. NDAT + LT) GO TO 10	BASE 034
BASE = T	BASE 035
RETURN	BASE 036
C	BASE 037
C FORCED PERIODS	BASE 038
10 IF(I .GT. NDAT + LT + 2 * NPER) GO TO 20	BASE 039
IND = (I - NDAT - LT + 1) / 2	BASE 040
IF(I - NDAT - LT .EQ. IND * 2) GO TO 15	BASE 041
BASE = DCOS(2.D0 * PI * T / PER(IND))	BASE 042
RETURN	BASE 043
15 BASE = DSIN(2.D0 * PI * T / PER(IND))	BASE 044
RETURN	BASE 045
C	BASE 046
C EXPONENTIAL TREND	BASE 047
20 IF(I .GT. NDAT + LT + 2 * NPER + 1) GO TO 25	BASE 048
BASE = DEXP(-T / 25.D0)	BASE 049
RETURN	BASE 050
C	BASE 051
C ADD ADDITIONAL USER-DEFINED FUNCTIONS HERE	BASE 052
25 BASE = 0.D0	BASE 053
RETURN	BASE 054
END	BASE 055

```

SUBROUTINE CHOLS(A, IRDA, NA)                                CHOL 001
IMPLICIT DOUBLE PRECISION (A-H,O-Z)                        CHOL 002
DIMENSION A(IRDA, NA)                                     CHOL 003
DATA ROUND /500.DO/                                       CHOL 004
C                                                           CHOL 005
C FUNCTION: CHOLS INVERTS MATRIX A IN PLACE                CHOL 006
C              USING CHOLESKY DECOMPOSITION                CHOL 007
C                                                           CHOL 008
C CALLED FROM: RESID                                       CHOL 009
C                                                           CHOL 010
C ARGUMENTS: A(IRDA,NA) = ARRAY CONTAINING POSITIVE DEFINITE CHOL 011
C              SYMMETRIC INPUT MATRIX, WITH ROW DIMENSION CHOL 012
C              IRDA. THE INPUT MATRIX SIZE IS (NA,NA)      CHOL 013
C              AND IS INVERTED IN PLACE, DESTROYING THE   CHOL 014
C              INPUT, RETURNING THE INVERSE.              CHOL 015
C                                                           CHOL 016
C EXTERNALS: EPS, ERROR, DSQRT                             CHOL 017
C                                                           CHOL 018
C ERROR CONDITIONS:                                       CHOL 019
C 101 = FATAL. DIMENSION OF A .LT. 1                      CHOL 020
C 102 = FATAL. NEGATIVE SQUARE ROOT. A PROBABLY SINGULAR. CHOL 021
C 103 = FATAL. DIAGONAL ELEMENT OF CHOLESKY DECOMPOSITION CHOL 022
C              NEGLIGIBLY SMALL COMPARED TO DIAGONAL ELEMENT OF A. CHOL 023
C              A PROBABLY SINGULAR.                       CHOL 024
C              ("NEGLIGIBLY SMALL" MEANS LESS THAN EPS*ROUND, CHOL 025
C              WHERE EPS IS THE SMALLEST NUMBER SO THAT   CHOL 026
C              1. + EPS .GT. 1., AND ROUND ACCOUNTS FOR   CHOL 027
C              ACCUMULATED ROUND OFF)                     CHOL 028
C                                                           CHOL 029
C MATRIX DIMENSION CHECK                                  CHOL 030
C   IF(NA .LT. 1)                                         CALL ERROR(101) CHOL 031
C                                                           CHOL 032
C INVERSION OF 1X1 MATRIX                                  CHOL 033
C   IF(NA .GT. 1) GO TO 5                                  CHOL 034
C   A(1,1) = 1.0DO / A(1,1)                               CHOL 035
C   RETURN                                                 CHOL 036
C                                                           CHOL 037
C CHOLESKY DECOMPOSITION OF INPUT MATRIX                  CHOL 038
C   5 A(1,1) = DSQRT(A(1,1))                                CHOL 039
C   DO 10 I = 2, NA                                       CHOL 040
C 10  A(I,1) = A(I,1) / A(1,1)                              CHOL 041
C   DO 30 J = 2, NA                                       CHOL 042
C     SUM = 0.0DO                                          CHOL 043
C     DO 15 K = 2, J                                       CHOL 044
C 15  SUM = SUM + A(J,K-1) ** 2                             CHOL 045
C     IF(A(J,J) .LT. SUM)                                  CALL ERROR(102) CHOL 046
C     SUM = DSQRT(A(J,J) - SUM)                            CHOL 047
C     IF(SUM/A(J,J) .LT. EPS(ARG)*ROUND) CALL ERROR(103) CHOL 048
C     A(J,J) = SUM                                         CHOL 049
C     IF(J .EQ. NA) GO TO 30                               CHOL 050
C     J2 = J + 1                                           CHOL 051
C     DO 25 I = J2, NA                                     CHOL 052
C       SUM = 0.0DO                                        CHOL 053
C       DO 20 K = 2, J                                     CHOL 054
C 20  SUM = SUM + A(I,K-1) * A(J,K-1)                       CHOL 055
C 25  A(I,J) = (A(I,J) - SUM) / A(J,J)                     CHOL 056
C 30  CONTINUE                                             CHOL 057
C                                                           CHOL 058
C INVERSION OF LOWER TRIANGULAR MATRIX                   CHOL 059
C   DO 35 I = 1, NA                                       CHOL 060
C 35  A(I,I) = 1.0DO / A(I,I)                              CHOL 061

```

DO 45 J = 2, NA	CHOL 062
DO 45 I = J, NA	CHOL 063
SUM = 0.000	CHOL 064
DO 40 K = J, I	CHOL 065
40 SUM = SUM + A(I,K-1) * A(K-1,J-1)	CHOL 066
45 A(I,J-1) = - A(I,I) * SUM	CHOL 067
C	CHOL 068
C CONSTRUCTION OF INVERSE OF INPUT MATRIX	CHOL 069
DO 65 J = 1, NA	CHOL 070
IF(J .EQ. 1) GO TO 55	CHOL 071
DO 50 I = 2, J	CHOL 072
50 A(I-1,J) = A(J,I-1)	CHOL 073
55 DO 65 I = J, NA	CHOL 074
SUM = 0.000	CHOL 075
DO 60 K = I, NA	CHOL 076
60 SUM = SUM + A(K,I) * A(K,J)	CHOL 077
65 A(I,J) = SUM	CHOL 078
RETURN	CHOL 079
END	CHOL 080

```

SUBROUTINE COVAR(FNORM, NF, NK, A, C, PCENT, CLEVEL, IPR)
IMPLICIT DOUBLE PRECISION (A-H,O-Z)
DIMENSION A(100,1), COV(1,1), C(1)
C
C FUNCTION: COVAR COMPUTES THE VARIANCE-COVARIANCE MATRIX
C           OF THE UNKNOWN CONSTITUENTS, THE CORRELATION
C           MATRIX AND PRINTS RESULTS.
C
C CALLED FROM: DRIVER
C
C EXTERNALS: DSQRT, DABS
C
C   IF (NK .LE. 0) RETURN
C
C COMPUTE THE STANDARD DEVIATIONS STD, CHECK IF
C EXCEED PCENT+C(I) AND PRINT ALL OUTSTANDING
C STANDARD DEVIATIONS
C   SIGMA2 = FNORM / (NF - NK)
C   WRITE (IPR,1000) PCENT
C   NSTD = 0
C   DO 25 I = 1, NK
C     STD = DSQRT(SIGMA2 * A(I,I))
C     IF (STD .LT. DABS(PCENT+C(I) / 100.0D0)) GO TO 25
C     WRITE (IPR,1001) I, STD
C     NSTD = NSTD + 1
C 25 CONTINUE
C   IF(NSTD .EQ. 0) WRITE (IPR, 1004)
C
C CHECK IF ANY CORRELATION EXCEEDS CLEVEL AND PRINT
C ALL OUTSTANDING CORRELATIONS
C   WRITE(IPR,1002) CLEVEL
C   NLEVEL = 0
C   DO 35 I = 1, NK
C     DO 30 J = 1, NK
C       IF(I .GE. J) GO TO 30
C       COR = A(I,J) / DSQRT(A(I,I) * A(J,J))
C       IF(DABS(COR) .LT. CLEVEL) GO TO 30
C       WRITE (IPR,1003) I, J, COR
C       NLEVEL = NLEVEL + 1
C 30 CONTINUE
C 35 CONTINUE
C   IF(NLEVEL .EQ. 0) WRITE (IPR, 1004)
C
C 1000 FORMAT(1H1, 5X,
C $          53HOUTSTANDING STANDARD DEVIATIONS OF KNOWN CONSTITUENTS
C $          ,/,5X,12H(LARGER THAN, 1X, F5.1, 1X,
C $          25H% OF ESTIMATED MAGNITUDE),//, 5X, 6HNUMBER,
C $          2X, 18HSTANDARD DEVIATION,/)
C 1001 FORMAT(6X, I3, 9X, E9.3)
C 1002 FORMAT(1H1, 5X,
C $          51HOUTSTANDING CORRELATIONS BETWEEN KNOWN CONSTITUENTS,/,
C $          5X, 30H(LARGER IN ABSOLUTE VALUE THAN, 1X, F4.2,1H),//,
C $          6X,6HNUMBER, 6X, 11HCORRELATION,/)
C 1003 FORMAT(5X, I3, 1H-, I3, 5X, F11.8)
C 1004 FORMAT(10X, 14HNONE WAS FOUND)
C   END

```

COVA 001
COVA 002
COVA 003
COVA 004
COVA 005
COVA 006
COVA 007
COVA 008
COVA 009
COVA 010
COVA 011
COVA 012
COVA 013
COVA 014
COVA 015
COVA 016
COVA 017
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COVA 036
COVA 037
COVA 038
COVA 039
COVA 040
COVA 041
COVA 042
COVA 043
COVA 044
COVA 045
COVA 046
COVA 047
COVA 048
COVA 049
COVA 050
COVA 051
COVA 052
COVA 053
COVA 054
COVA 055

```

SUBROUTINE DRIVER(T, FF, NF, DAT, NDAT, LT, PER, NPER, NBASE, IPR, DRIV 001
$      EQORUN, PCENT, CLEVEL) DRIV 002
IMPLICIT DOUBLE PRECISION (A-H,O-Z) DRIV 003
CHARACTER *2 EQORUN DRIV 004
DIMENSION A(100,100), C(100), DAT(1), F(2000), FF(1), DRIV 005
$      P(2000), PER(1), S(2000), T(1) DRIV 006
DATA PL/ 200.DO/, DRIV 007
$      PS/ 2.DO/, DRIV 008
$      NW/125/, DRIV 009
$      IB/ 1/ DRIV 010
C DRIV 011
C FUNCTION: DRIVER CALLS SPECEQ OR SPECUN TO COMPUTE A DRIV 012
C LEAST SQUARES SPECTRUM (P,S) FOR THE INPUT DRIV 013
C TIME SERIES (T,F). DRIV 014
C DRIV 015
C CALLED FROM: TSPEC DRIV 016
C DRIV 017
C ARGUMENTS: T(NF) = INPUT TIME SERIES TIMES DRIV 018
C FF(NF) = INPUT TIME SERIES VALUES DRIV 019
C DAT(NDAT) = INPUT TIMES NEW DATUM BEGINS DRIV 020
C LT = INPUT LINEAR TREND SWITCH (1 = INCLUDED) DRIV 021
C PER(NPER) = INPUT FORCED PERIODS DRIV 022
C NBASE = NUMBER OF USER-DEFINED CONSTITUENTS DRIV 023
C IPR = UNIT NUMBER FOR OUTPUT DRIV 024
C EQORUN = FLAG FOR EQUALLY OR UNEQUALLY SPACED SERIES DRIV 025
C PCENT = PERCENTAGE LEVEL FOR DETECTING OUTSTANDING DRIV 026
C STANDARD DEVIATIONS OF UNKNOWNNS DRIV 027
C CLEVEL = CRITICAL LEVEL FOR DETECTING OUTSTANDING DRIV 028
C CORRELATIONS IN THE SOLUTION DRIV 029
C DRIV 030
C EXTERNALS: AMPL, DFLOAT, SPECEQ, SPECUN, PLOT, ERROR(108) DRIV 031
C DRIV 032
C SUMMARY: DRIV 033
C COMPUTE SPECTRAL PERIODS, P DRIV 034
C PL = LONGEST PERIOD IN P DRIV 035
C PS = SHORTEST PERIOD IN P DRIV 036
C NW = NUMBER OF PERIODS IN P DRIV 037
C COPY VECTOR F (MODIFIED BY SPECEQ AND SPECUN) DRIV 038
C COMPUTE NK = TOTAL NUMBER OF KNOWN CONSTITUENTS DRIV 039
C CALL SPECEQ OR SPECUN TO COMPUTE SPECTRUM DRIV 040
C CALL AMPL TO LIST KNOWN CONSTITUENT AMPLITUDES DRIV 041
C CALL COVAR TO LIST ALL OUTSTANDING STANDARD DEVIATIONS DRIV 042
C AND CORRELATIONS DRIV 043
C LIST RESIDUAL TIME SERIES AND ITS QUADRATIC NORM DRIV 044
C COMPUTE RS = MEAN SPECTRAL VALUE FOR WHITE NOISE DRIV 045
C COMPUTE RS95 = CRITICAL PERCENTAGE VARIANCE AT 95% DRIV 046
C CONFIDENCE LEVEL FOR DETECTING STATISTICALLY DRIV 047
C SIGNIFICANT PEAKS IN THE SPECTRUM DRIV 048
C DRIV 049
C PLOT SPECTRUM DRIV 049
DO 5 I = 1,NW DRIV 050
5 P(I) = DFLOAT(NW-1)/(DFLOAT(NW-I)/PL + DFLOAT(I-1)/PS) DRIV 051
DO 10 I = 1,NF DRIV 052
10 F(I) = FF(I) DRIV 053
NK = NDAT + LT + NBASE + 2 * NPER DRIV 054
IF(EQORUN.EQ.'EQ') DRIV 055
$CALL SPECEQ(T, F, NF, FNORM, DRIV 056
$      NK, DAT, NDAT, LT, PER, NPER, NBASE, A, C, DRIV 057
$      P, S, NW, IB, ICRIT) DRIV 058
IF(EQORUN.EQ.'UN') DRIV 059
$CALL SPECUN(T, F, NF, FNORM, DRIV 060
$      NK, DAT, NDAT, LT, PER, NPER, NBASE, A, C, DRIV 061

```

\$	P, S, NW, IB, ICRIT)	DRIV 062
	CALL AMPL(A, NF, NK, FNORM, DAT, NDAT, LT, PER, NPER,	DRIV 063
\$	NBASE, C, IPR)	DRIV 064
	CALL COVAR(FNORM, NF, NK, A, C, PCENT, CLEVEL, IPR)	DRIV 065
	RS = 200.000 / (NF - NK)	DRIV 066
	RS95 = 100.000 / (1.000 / (0.0500 + (-2.000 / (NF - NK - 2)) - 1) + 1)	DRIV 067
	WRITE(IPR, 1001) (F(I), I=1, NF)	DRIV 068
	WRITE(IPR, 1002) FNORM	DRIV 069
	IF(ICRIT .EQ. 0) CALL ERROR(108)	DRIV 070
	CALL SPLOT(P, S, NW, RS, RS95, IB, IPR)	DRIV 071
	RETURN	DRIV 072
1001	FORMAT(1H1, 9X, 20HRESIDUAL TIME SERIES//110(11E10.2/))	DRIV 073
1002	FORMAT(9X, 35HRESIDUAL TIME SERIES QUADRATIC NCRM, E15.5)	DRIV 074
	END	DRIV 075


```
      DOUBLE PRECISION FUNCTION EPS(ARG)
      IMPLICIT DOUBLE PRECISION (A-H,O-Z)
C
C FUNCTION: EPS SETS FUNCTIONAL VALUE EPS AND ARGUMENT ARG
C           BOTH EQUAL TO THE SMALLEST NUMBER SO THAT
C           1. + EPS .GT. 1.
C CALLED FROM: CHOLS, SPECUN, SPECEQ
C
      EPS = 1.0D0
10  EPS = EPS / 2.0D0
      IF ((1.0D0 + EPS) - 1.0D0 .EQ. EPS) GO TO 10
      EPS = EPS * 2.0D0
      ARG = EPS
      RETURN
      END
```

EPS	001
EPS	002
EPS	003
EPS	004
EPS	005
EPS	006
EPS	007
EPS	008
EPS	009
EPS	010
EPS	011
EPS	012
EPS	013
EPS	014
EPS	015
EPS	016

SUBROUTINE ERROR(IER)	ERRO 001
INTEGER IER,IPR	ERRO 002
DATA IPR /6/	ERRO 003
C	ERRO 004
C FUNCTION: ERROR DETECTS WHETHER ERROR IS WARNING	ERRO 005
C OR FATAL, AND PRINTS MESSAGE	ERRO 006
C	ERRO 007
C CALLED FROM: DRIVER, CHOLS, SPECUN, SPECEQ	ERRO 008
C	ERRO 009
C ARGUMENT: IER = ERROR INDEX	ERRO 010
C WARNINGS HAVE INDICES 1 - 99	ERRO 011
C FATAL ERRORS HAVE INDICES 100 AND OVER.	ERRO 012
C	ERRO 013
IF(IER .GT. 100) GO TO 10	ERRO 014
WRITE(IPR,1001) IER	ERRO 015
RETURN	ERRO 016
10 WRITE(IPR,1002) IER	ERRO 017
STOP	ERRO 018
1001 FORMAT(11H ***WARNING,I5)	ERRO 019
1002 FORMAT(15H ***FATAL ERROR,I5)	ERRO 020
END	ERRO 021

```

SUBROUTINE FPLOTT(T, F, NF, DAT, NDAT, EQORUN, IPR)
IMPLICIT DOUBLE PRECISION (A-H,O-Z)
CHARACTER *1 IBLANK, ISTAR, IPLOT
CHARACTER *2 EQDRUN
DIMENSION DAT(1), F(1), IPLOT(100), T(1)
DATA IBLANK /' '/,
      ISTAR /'*'/
$
C
C FUNCTION: FPLOTT PLOTS TIME SERIES F
C           DETECTING TIMES OF NEW DATUM BIASES
C
C CALLED FROM: TSPEC
C
C ARGUMENTS: T(NF) = INPUT TIME SERIES TIMES
C            F(NF) = INPUT TIME SERIES VALUES
C            DAT(NDAT) = INPUT TIMES NEW DATUM BEGINS
C            IPR = UNIT NUMBER FOR OUTPUT
C
C EXTERNALS: DMAX1, DMIN1, IFIX
C
C SUMMARY:
C INITIALIZE PLOT ARRAY
C COMPUTE MAXIMUM AND MINIMUM VALUES IN F
C SCAN THROUGH TIME SERIES
C CHECKING FOR NEW DATUM
C PLOTTING TIME SERIES VALUES
C
      WRITE(IPR,1001)
      DO 5 I = 1,100
5     IPLOT(I) = IBLANK
      FMIN = F(1)
      FMAX = F(1)
      DO 10 I = 2,NF
          FMIN = DMIN1(FMIN,F(I))
10     FMAX = DMAX1(FMAX,F(I))
      IDAT = 1
      STEP = T(2) - T(1)
      NGAP = 0
      DO 20 I = 1,NF
          IF (I.EQ. 1 .OR. EQORUN.EQ. 'UN') GO TO 12
          IF (T(I)-T(I-1) .LT. 1.500*STEP) GO TO 12
          NGAP = NGAP + 1
          NPNT = (T(I) - T(I-1)) / STEP - 1
          WRITE (IPR, 1004) NGAP, NPNT
12     IF(NDAT.EQ. 0 .OR. IDAT.GT. NDAT) GO TO 15
          IF(DAT(IDAT).GT. T(I)) GO TO 15
          WRITE(IPR,1002) IDAT
          IDAT = IDAT + 1
15     KF= 1 + (99.000 * (F(I) - FMIN) / (FMAX - FMIN))
          IF(KF.LT. 1) KF = 1
          IF(KF.GT. 100) KF = 100
          IPLOT(KF) = ISTAR
          WRITE(IPR,1003) I,T(I),F(I),IPLOT
20     IPLOT(KF) = IBLANK
      RETURN
1001 FORMAT(1H1,9X,11HTIME SERIES//
$         5X,1HI,8X,4HT(I),8X,4HF(I)//)
1002 FORMAT(/,30X,38(1H-),18HBEGINNING OF DATUM,I5,39(1H-),/)
1003 FORMAT(2X,I4,2E12.4,100A1)
1004 FORMAT(/,30X,37(1H-),5HGAP #,I4,1X,2HOF,I6,1X,6HPOINTS,38(1H-))
END

```

FPLD 001
 FPLD 002
 FPLD 003
 FPLD 004
 FPLD 005
 FPLD 006
 FPLD 007
 FPLD 008
 FPLD 009
 FPLD 010
 FPLD 011
 FPLD 012
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 FPLD 047
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 FPLD 051
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 FPLD 056
 FPLD 057
 FPLD 058
 FPLD 059
 FPLD 060
 FPLD 061


```

SUBROUTINE SPLOT(P, S, NW, RS, RS95, IB, IPR)
IMPLICIT DOUBLE PRECISION (A-H,O-Z)
CHARACTER *1      IBLANK, ISTAR, IPLOT
DIMENSION        IPLOT(100), P(1), S(1)
DATA             IBLANK /' '/,
                ISTAR  /'*'/
$
C
C FUNCTION:  SPLOT PLOTS SPECTRUM S
C
C CALLED FROM: DRIVER
C
C ARGUMENTS: P(NW) = INPUT SPECTRAL PERIODS
C             S(NW) = INPUT SPECTRAL VALUES
C             IPR  = UNIT NUMBER FOR OUTPUT
C
C EXTERNALS: IFIX
C
C SUMMARY:
C   INITIALIZE PLOT ARRAY
C   SCAN THROUGH SPECTRUM
C   PLOTTING SPECTRAL VALUES (PERCENTAGE VARIANCES)
C
WRITE(IPR,1001) IB, NW, P(1), P(NW), RS, RS95
DO 5 I = 1,100
5  IPLOT(I) = IBLANK
DO 10 I = 1, NW
  KS=S(I)
  IF(KS .LT. 1) KS = 1
  IF(KS .GT. 100) KS = 100
  IPLOT(KS) = ISTAR
  WRITE(IPR,1002) P(I), S(I), IPLOT
10 IPLOT(KS) = IBLANK
RETURN
1001 FORMAT(1H1,10X,13HSPECTRAL BAND,I5,/,/,
$ 10X,I5,24H SPECTRAL VALUES BETWEEN,2F14.6,/,/,
$ 12X,35HMEAN SPECTRAL VALUE FOR WHITE NOISE,F11.2,/,/,
$ 12X,35HCRITICAL PERCENTAGE VARIANCE AT 95%,/,/,
$ 12X,35HCONFIDENCE LEVEL FOR DETECTING,/,/,
$ 12X,35HSIGNIFICANT PEAKS IN THE SPECTRUM,F11.2,/,/,
$ 10X,6HPERIOD,6X,19HPERCENTAGE VARIANCE/)
1002 FORMAT(5X,F10.5,F12.3,100A1)
END

```

SPLD 001
SPLD 002
SPLD 003
SPLD 004
SPLD 005
SPLD 006
SPLD 007
SPLD 008
SPLD 009
SPLD 010
SPLD 011
SPLD 012
SPLD 013
SPLD 014
SPLD 015
SPLD 016
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SPLD 030
SPLD 031
SPLD 032
SPLD 033
SPLD 034
SPLD 035
SPLD 036
SPLD 037
SPLD 038
SPLD 039
SPLD 040
SPLD 041
SPLD 042

```

SUBROUTINE TIMSER(T, F, NF, DAT, NDAT, LT, PER, NPER, NBASE, TIMS 001
$          MODE, EQORUN, PCENT, CLEVEL) TIMS 002
IMPLICIT DOUBLE PRECISION (A-H,O-Z) TIMS 003
CHARACTER *2 EQORUN, EQ, UN TIMS 004
CHARACTER *5 MODE, SQNTL, BATCH TIMS 005
DIMENSION X(5), Y(5), Z(5), DAT(3), F(500), IVL(4), TIMS 006
$          NB(4), NE(4), P(5), PER(5), T(500) TIMS 007
DATA X / 0.500D0, 1.000D0, 0.000D0, 0.500D0, -0.250D0/, TIMS 008
$      Y / 1.000D0, 0.500D0, 1.000D0, -0.500D0, 0.000D0/, TIMS 009
$      Z / 1.000D0, -1.000D0, 3.000D0, 0.010D0, 3.000D0/, TIMS 010
$      P / 2.759D0, 3.636D0, 5.714D0, 40.000D0, 16.000D0/, TIMS 011
$      NB / 1, 201, 281, 471/, TIMS 012
$      NE /100, 250, 400, 500/, TIMS 013
$      IVL/ 1, 2, 3, 3/, TIMS 014
$      NIVL/ 4/, TIMS 015
$      STEP/ 0.1D0/, TIMS 016
$      PI / 3.141592653589793D0/ TIMS 017
DATA EQ / 'EQ' /, TIMS 018
$      UN / 'UN' /, TIMS 019
$      SQNTL / 'SQNTL' /, TIMS 020
$      BATCH / 'BATCH' / TIMS 021
C TIMS 022
C TIMS 023
C FUNCTION: TIMSER GENERATES A TEST TIME SERIES WITH TIMS 024
C          3 DATUM BIASES, A LINEAR TREND, TIMS 025
C          SIN/COSINE TERMS FOR 5 FREQUENCIES, TIMS 026
C          AND AN EXPONENTIAL TREND TIMS 027
C TIMS 028
C CALLED FROM: TSPEC TIMS 029
C TIMS 030
C          F(NF) = TEST TIME SERIES VALUES TIMS 031
C          DAT(NDAT) = TIMES NEW DATUM BEGINS TIMS 032
C          LT = LINEAR TREND SWITCH (1 = INCLUDED) TIMS 033
C          PER(NPER) = PERIODS FOR TRIGONOMETRIC TERMS TIMS 034
C          NBASE = NUMBER OF USER-DEFINED CONSTITUENTS TIMS 035
C          EQORUN = EQUAL OR UNEQUAL SPACED TIME SERIES TIMS 036
C          EQORUN = EQ: EQUAL SPACED TIME SERIES TIMS 037
C          (SUBROUTINE SPECEQ IS USED) TIMS 038
C          EQORUN = UN: UNEQUAL SPACED TIME SERIES TIMS 039
C          (SUBROUTINE SPECUN IS USED) TIMS 040
C          MODE = BATCH OR SEQUENTIAL FORCING OF UNKNOWNNS TIMS 041
C          MODE = SQNTL: SEQUENTIAL SOLUTION TIMS 042
C          MODE = BATCH: BATCH SOLUTION TIMS 043
C          PCENT = PERCENTAGE LEVEL FOR DETECTING TIMS 044
C          OUTSTANDING STANDARD DEVIATIONS OF UNKNOWNNS TIMS 045
C          CLEVEL = CRITICAL LEVEL FOR DETECTING OUTSTANDING TIMS 046
C          CORRELATIONS IN THE SOLUTION TIMS 047
C TIMS 048
C EXTERNALS: DCOS,DEXP,DFLOAT,DSIN TIMS 049
C TIMS 050
C          NDAT = 3 TIMS 051
C          LT = 1 TIMS 052
C          NPER = 5 TIMS 053
C          NBASE = 1 TIMS 054
C          EQORUN = EQ TIMS 055
C          MODE = SQNTL TIMS 056
C          PCENT = 25.0D0 TIMS 057
C          CLEVEL = 0.50D0 TIMS 058
C          DO 5 I = 1,NPER TIMS 059
C          5 PER(I) = P(I) TIMS 060
C TIMS 061

```

C EQUAL SPACING RUN		TIMS 062
DT1 = 0.DO		TIMS 063
DT2 = 1.DO		TIMS 064
C		TIMS 065
C UNEQUAL SPACING RUN		TIMS 066
DT1 = 0.5DO		TIMS 067
DT2 = 50.0DO		TIMS 068
C		TIMS 069
NF = 0		TIMS 070
DO 10 K = 1,NIVL		TIMS 071
I1 = NB(K)		TIMS 072
I2 = NE(K)		TIMS 073
DO 10 I = I1,I2		TIMS 074
NF = NF + 1		TIMS 075
T(NF) = DFLOAT(I) * STEP +		TIMS 076
DT1 * DSIN(PI * DFLOAT(I) / DT2)		TIMS 077
F(NF) = Z(IVL(K)) + Z(NDAT+1) * T(NF) +		TIMS 078
Z(NDAT+2) * DEXP(-T(NF) / 25.DO)		TIMS 079
DO 10 J = 1,NPER		TIMS 080
F(NF) = F(NF) + X(J) * DCOS(2.DO * PI * T(NF) / P(J))		TIMS 081
+ Y(J) * DSIN(2.DO * PI * T(NF) / P(J))		TIMS 082
DAT(1) = T(1)		TIMS 083
DAT(2) = T(101)		TIMS 084
DAT(3) = T(151)		TIMS 085
RETURN		TIMS 086
END		

```

SUBROUTINE SPECEQ(T, F, NF, FNORM,                                SPCQ 001
$      NK, DAT, NDAT, LT, PER, NPER, NBASE, A, C,                SPCQ 002
$      P, S, NW, IB, ICRIT)                                     SPCQ 003
IMPLICIT DOUBLE PRECISION (A-H,O-Z)                             SPCQ 004
DIMENSION A(100,100), B(100), C(1), CLP(60,50),                SPCQ 005
$      CNP(60,50), CP(50), DAT(1), F(1), IVL(60), P(1),        SPCQ 006
$      PER(1), S(1), SLP(60,50), SNP(60,50), SP(50),          SPCQ 007
$      SPMQ(50), SPPQ(50), T(1), U(100), V(100),              SPCQ 008
$      XL(60), XN(60)                                           SPCQ 009
DATA PI/3.141592653589793D0/,                                   SPCQ 010
$      ROUND /100000./,                                         SPCQ 011
$      NKDIM /100/,                                             SPCQ 012
$      NPERDM /50/,                                            SPCQ 013
$      IVLDIM /60/                                             SPCQ 014
C                                                                    SPCQ 015
C FUNCTION: SPECEQ COMPUTES THE LEAST SQUARES SPECTRUM OF      SPCQ 016
C      A PIECEWISE EQUALLY SPACED TIME SERIES                SPCQ 017
C      AFTER SUPPRESSING KNOWN CONSTITUENTS                   SPCQ 018
C                                                                    SPCQ 019
C CALLED FROM: DRIVER                                         SPCQ 020
C                                                                    SPCQ 021
C ARGUMENTS:                                                  SPCQ 022
C   SPECIFYING THE INPUT TIME SERIES                          SPCQ 023
C     T(NF) = INPUT TIME SERIES TIMES                          SPCQ 024
C     F(NF) = INPUT TIME SERIES VALUES                       SPCQ 025
C           = OUTPUT RESIDUAL TIME SERIES VALUES            SPCQ 026
C     FNORM = OUTPUT QUADRATIC NORM OF RESIDUAL F             SPCQ 027
C                                                                    SPCQ 028
C   SPECIFYING THE KNOWN CONSTITUENTS                         SPCQ 029
C     NK      = INPUT TOTAL NUMBER OF KNOWN CONSTITUENTS     SPCQ 030
C     DAT(NDAT) = INPUT TIMES NEW DATUM BEGINS                SPCQ 031
C     LT      = INPUT LINEAR TREND SWITCH (1 = USE TREND)     SPCQ 032
C           (0 = DO NOT USE)                                  SPCQ 033
C     PER(NPER) = INPUT FORCED PERIODS                         SPCQ 034
C     NBASE    = INPUT NUMBER OF USER-DEFINED CONSTITUENTS  SPCQ 035
C     A(NKDIM,NKDIM) = OUTPUT NORMAL EQUATION MATRIX RESULTING SPCQ 036
C                   FROM SUPPRESSION OF KNOWN CONSTITUENTS  SPCQ 037
C     C(NK)    = OUTPUT PRELIMINARY AMPLITUDES OF KNOWN      SPCQ 038
C                   CONSTITUENTS                             SPCQ 039
C                                                                    SPCQ 040
C   SPECIFYING THE OUTPUT SPECTRUM                            SPCQ 041
C     P(NW) = INPUT SPECTRAL PERIODS                           SPCQ 042
C     S(NW) = OUTPUT SPECTRAL VALUES                          SPCQ 043
C     IB    = INPUT SPECTRAL BAND LABEL                         SPCQ 044
C     ICRIT = ROUNDOFF FLAG                                    SPCQ 045
C           (1 = OK. CONTINUE ANALYSIS)                        SPCQ 046
C           (0 = RESIDUAL TIME SERIES CONSISTS ONLY OF ROUNDOFF) SPCQ 047
C                                                                    SPCQ 048
C EXTERNALS: DABS, DMAX1, BASE, DCOS, EPS, ERROR, DFLOAT, RESID, DSIGN, SPCQ 049
C           DSIN, DSQRT                                         SPCQ 050
C                                                                    SPCQ 051
C ERROR CONDITIONS:                                           SPCQ 052
C   1 = WARNING. ARGUMENT NDAT .LT. 0. (SET TO 0.)           SPCQ 053
C   2 = WARNING. ARGUMENT LT NOT 0 OR 1. (SET TO 0.)         SPCQ 054
C   3 = WARNING. ARGUMENT NPER .LT. 0. (SET TO 0.)           SPCQ 055
C   4 = WARNING. ARGUMENT NBASE .LT. 0. (SET TO 0.)          SPCQ 056
C   5 = WARNING. ARGUMENT NK .NE. NDAT+LT+2*NPER+NBASE.     SPCQ 057
C           (SET TO NDAT + LT + 2 * NPER + NBASE.)            SPCQ 058
C   104 = FATAL. LESS THAN 3 TIME SERIES VALUES INPUT.     SPCQ 059
C   105 = FATAL. T ELEMENT VALUES NOT MONOTONIC INCREASING SPCQ 060
C   106 = FATAL. NK TOO LARGE FOR DIMENSIONS OF A,B,U,V     SPCQ 061

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C	(LIMITATION NO. 2 BELOW)	SPCQ 062
C	107 = FATAL. DAT(1) .NE. T(1). (REQUIREMENT NO. 2 BELOW)	SPCQ 063
C	108 = FATAL. RESIDUAL TIME SERIES CONSISTS OF ROUND OFF	SPCQ 064
C	(NOW CALLED IN DRIVER)	SPCQ 065
C	109 = FATAL. NPER TOO LARGE FOR DIMENSIONS OF	SPCQ 066
C	CLP,CNP,CP,SLP,SNP,SP,SPMQ,SPPQ.	SPCQ 067
C	110 = FATAL. NIVL TOO LARGE FOR DIMENSIONS OF	SPCQ 068
C	CLP,CNP,IVL,SLP,SNP,XL,XN.	SPCQ 069
C	111 = FATAL. PER CONTAINS FORCED PERIOD .LT. 2. * STEP.	SPCQ 070
C	112 = FATAL. P CONTAINS SPECTRAL PERIOD .LT. 2. * STEP.	SPCQ 071
C		SPCQ 072
C	CALLING ROUTINE REQUIREMENTS:	SPCQ 073
C	1. WHEN NO KNOWN CONSTITUENTS ARE TO BE SUPPRESSED, THE	SPCQ 074
C	CALLING ROUTINE MUST PASS ZERO VALUES FOR NK,NDAT,	SPCQ 075
C	LT,NPER AND NBASE.	SPCQ 076
C	2. WHEN NDAT .GT. 0, THE CALLING ROUTINE MUST SET	SPCQ 077
C	DAT(1) = T(1)	SPCQ 078
C	3. THE CALLING ROUTINE MUST SET	SPCQ 079
C	NK = NDAT + LT + 2 * NPER + NBASE.	SPCQ 080
C	4. WHEN NBASE .GT. 0, THE USER MUST SUPPLY CODING IN	SPCQ 081
C	FUNCTION BASE TO COMPUTE EACH USER-DEFINED	SPCQ 082
C	CONSTITUENT.	SPCQ 083
C	5. ON INITIAL CALL, CALLING ROUTINE MUST SET IB = 1 TO	SPCQ 084
C	COMPUTE RESIDUAL TIME SERIES. MANY SPECTRAL BANDS	SPCQ 085
C	FOR THE SAME SPECTRUM CAN THEN BE COMPUTED BY	SPCQ 086
C	SETTING IB .NE. 1, AND CALLING REPEATEDLY,	SPCQ 087
C	CHANGING ONLY P(NW).	SPCQ 088
C	6. CALLING ROUTINE MUST DIMENSION ARGUMENT ARRAYS .GE.	SPCQ 089
C	T(NF),F(NF),DAT(NDAT),PER(NPER),C(NK),P(NW),S(NW).	SPCQ 090
C	7. T ELEMENT VALUES MUST CONSIST OF NIVL SUBINTERVALS,	SPCQ 091
C	EACH SUBINTERVAL CONTAINING EQUALLY SPACED DATA	SPCQ 092
C	SEPARATED BY A TIME INCREMENT STEP COMMON TO ALL	SPCQ 093
C	SUBINTERVALS. THE GAPS BETWEEN SUBINTERVALS NEED	SPCQ 094
C	NOT BE INTEGRAL MULTIPLES OF STEP. THE FIRST DATA	SPCQ 095
C	POINT MUST NOT BE ISOLATED (MUST NOT BE FOLLOWED	SPCQ 096
C	BY A GAP). T ELEMENT VALUES MUST INCREASE	SPCQ 097
C	MONOTONICALLY. DAT, P AND PER ELEMENT VALUES MUST	SPCQ 098
C	BE IN THE SAME UNITS AS T.	SPCQ 099
C	8. THE FORCED PERIODS IN PER AND SPECTRAL PERIODS IN P	SPCQ 100
C	MUST BE SHORTER THAN 2 * STEP, EQUIVALENT TO THE	SPCQ 101
C	MAXIMUM INTERVAL USED IN FOURIER ANALYSIS.	SPCQ 102
C		SPCQ 103
C	LIMITATIONS:	SPCQ 104
C	1. WHEN CALLED WITH IB = 1, AND NK .GT. 0, THE CONTENTS	SPCQ 105
C	OF THE TIME SERIES F IS REPLACED BY THE RESIDUAL	SPCQ 106
C	TIME SERIES VALUES.	SPCQ 107
C	2. WHEN NK .GT. NKDIM, A,B,U AND V MUST BE REDIMENSIONED	SPCQ 108
C	.GE. NK, AND NKDIM CHANGED TO THE NEW DIMENSION.	SPCQ 109
C	3. WHEN NPER .GT. NPERDM THEN SP,CP,SPMQ,SPPQ AND THE	SPCQ 110
C	SECOND INDEX OF CLP,SLP,CNP,SNP MUST BE	SPCQ 111
C	REDIMENSIONED .GE. NPER, AND NPERDM CHANGED TO THE	SPCQ 112
C	NEW DIMENSION.	SPCQ 113
C	4. WHEN NIVL (= NDAT + NUMBER OF GAPS IN T BETWEEN DATUM	SPCQ 114
C	CHANGES) .GT. IVLDIM THEN XN,XL,IVL AND THE FIRST	SPCQ 115
C	INDEX OF CLP,SLP,CNP,SNP MUST BE REDIMENSIONED .GE.	SPCQ 116
C	NIVL, AND IVLDIM CHANGED TO THE NEW DIMENSION.	SPCQ 117
C		SPCQ 118
C	IF(IB .NE. 1) GO TO 65	SPCQ 119
C		SPCQ 120
C	PROCESS INPUT ARGUMENTS	SPCQ 121
C	CHECK NF .GE. 3	SPCQ 122

C	CHECK T INCREASES MONOTONICALLY	SPCQ 123
C	COMPUTE FMAX = MAXIMUM ABSOLUTE VALUE IN F	SPCQ 124
C	CHECK VALUES OF NDAT,LT,NPER,NBASE,AND NK	SPCQ 125
C	CHECK DAT(1) .EQ. T(1)	SPCQ 126
	IF(NF .LT. 3)	CALL ERROR(104) SPCQ 127
	DO 5 I = 2,NF	
	IF(T(I) .LE. T(I-1))	CALL ERROR(105) SPCQ 128
5	CONTINUE	SPCQ 129
	FMAX = DABS(F(1))	SPCQ 130
	DO 10 I = 2,NF	SPCQ 131
10	FMAX = DMAX1(FMAX,DABS(F(I)))	SPCQ 132
	IF(NDAT .GE. 0) GO TO 15	SPCQ 133
	CALL ERROR(1)	SPCQ 134
	NDAT = 0	SPCQ 135
15	IF(LT .EQ. 0 .OR. LT .EQ. 1) GO TO 20	SPCQ 136
	CALL ERROR(2)	SPCQ 137
	LT = 0	SPCQ 138
20	IF(NPER .GE. 0) GO TO 25	SPCQ 139
	CALL ERROR(3)	SPCQ 140
	NPER = 0	SPCQ 141
25	IF(NBASE .GE. 0) GO TO 30	SPCQ 142
	CALL ERROR(4)	SPCQ 143
	NBASE = 0	SPCQ 144
30	IF(NK .EQ. NDAT + LT + 2 * NPER + NBASE) GO TO 35	SPCQ 145
	CALL ERROR(5)	SPCQ 146
	NK = NDAT + LT + 2 * NPER + NBASE	SPCQ 147
35	IF(NK .GT. NKDIM)	CALL ERROR(106) SPCQ 148
	IF(NDAT .GE. 1 .AND. DAT(1) .NE. T(1))	CALL ERROR(107) SPCQ 149
	IF(NPER .GT. NPERDM)	CALL ERROR(109) SPCQ 150
	EPSARG = EPS(ARG)	SPCQ 151
C		SPCQ 152
C	COMPUTE STEPSIZE IN T	SPCQ 153
	STEP = T(2) - T(1)	SPCQ 154
C		SPCQ 155
C	COMPUTE CRITICAL VALUE OF STEP FOR DETECTING GAPS IN T	SPCQ 156
	STEP1 = 1.5DO * STEP	SPCQ 157
C		SPCQ 158
C	INITIALIZE ARGUMENTS IDAT, NIVL, NGAP, TA	SPCQ 159
	IDAT = 1	SPCQ 160
	NIVL = 0	SPCQ 161
	NGAP = 0	SPCQ 162
	TA = T(1)	SPCQ 163
C		SPCQ 164
C	FIND SUBINTERVAL BOUNDARIES (GAPS OR NEW DATUM SHIFTS) IN T	SPCQ 165
	DO 45 N = 2,NF	SPCQ 166
	NEWIVL = 0	SPCQ 167
	IF(N .NE. NF) GO TO 39	SPCQ 168
	NEWIVL = NGAP	SPCQ 169
	IF(NEWIVL .EQ. 0) GO TO 45	SPCQ 170
	GO TO 42	SPCQ 171
C		SPCQ 172
C	CHECK IF THERE IS GAP AND DATUM SHIFT IN T	SPCQ 173
39	IF((T(N) - T(N-1)) .GT. STEP1 .AND.	SPCQ 174
\$	DABS(DAT(IDAT+1)-T(N)) .LT. EPSARG*ROUND) GO TO 40	SPCQ 175
C		SPCQ 176
C	CHECK IF THERE IS ONLY GAP IN T	SPCQ 177
	IF((T(N) - T(N-1)) .GT. STEP1) GO TO 41	SPCQ 178
C		SPCQ 179
C	CHECK IF THERE IS ONLY DATUM SHIFT IN T	SPCQ 180
	IF (DABS(DAT(IDAT+1)-T(N)) .LT. EPSARG*ROUND) GO TO 40	SPCQ 181
	IF (NEWIVL .EQ. 0) GO TO 45	SPCQ 182
		SPCQ 183

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      GO TO 42
C
C COMPUTE NEWIVL, IDAT AND NGAP WHEN THERE IS DATUM SHIFT REGARDLESS
C OF PRESENCE OF GAP IN T
  40  NEWIVL = NGAP + 1
      DAT(IDAT+1) = T(N)
      IDAT = IDAT + 1
      GO TO 42
C
C COMPUTE NEWIVL, IDAT AND NGAP WHEN THERE IS ONLY GAP IN T
  41  NEWIVL = NGAP + 1
      NGAP = NGAP + 1
      IF(NEWIVL .EQ. 0) GO TO 45
C
C COMPUTE XL, XN, IVL FOR EACH SUBINTERVAL IN T
  42  TB = T(N-1)
      IF (N .EQ. NF) TB = T(NF)
      NIVL = NIVL + 1
      IF(NIVL .GT. IVLDIM) CALL ERROR(110)
      XN(NIVL) = 1.000 + (TB - TA) / STEP
      XL(NIVL) = (TB + TA) / STEP
      IVL(NIVL) = IDAT - NEWIVL + NGAP
      TA = T(N)
  45  CONTINUE
      IF (NPER.LE.0) GO TO 52
C
C COMPUTE TRIG(PK), TRIG(XN*PK), TRIG(XL*PK) FOR EACH SUBINTERVAL IN T
  DO 50 I = 1,NPER
    IF(PER(I) .LT. 2.000 * STEP) CALL ERROR(111)
    PK = PI * STEP / PER(I)
    SP(I) = DSIN(PK)
    CP(I) = DCOS(PK)
    DO 50 J = 1,NIVL
      XNPK = XN(J) * PK
      XLPK = XL(J) * PK
      SNP(J,I) = DSIN(XNPK)
      CNP(J,I) = DCOS(XNPK)
      SLP(J,I) = DSIN(XLPK)
      CLP(J,I) = DCOS(XLPK)
  50  CONTINUE
C
C CHECK VALUES IF P .GE. 2*STEP
  52  DO 55 I = 1,NW
      IF(P(I) .LT. 2.000 * STEP) CALL ERROR(112)
  55  CONTINUE
C
C SUPPRESS KNOWN CONSTITUENTS
C REPLACE F WITH RESIDUAL TIME SERIES
C COMPUTE QUADRATIC NORM OF F
C CHECK IF RMS VALUE OF RESIDUAL F IS LESS
C THAN EPS * FMAX * ROUND, WHERE
C EPS = EPSARG = SMALLEST NUMBER SO 1 + EPS .GT. 1
C FMAX = MAXIMUM ABSOLUTE VALUE OF ORIGINAL F
C ROUND ACCOUNTS FOR ACCUMULATED ROUND OFF IN
C COMPUTING RESIDUAL F
  IF(NK .GT. 0) CALL RESID(T, F, NF,
$ NK, DAT, NDAT, LT, PER, NPER, NBASE,
$ A, B, C, NKDIM)
  FNORM = 0.000
  DO 60 I = 1,NF
    FNORM = FNORM + F(I) ** 2

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60	CONTINUE	SPCQ	245
C		SPCQ	246
C	CHECK IF RESIDUAL F CONSISTS OF ROUND OFF	SPCQ	247
	ICRIT = 1	SPCQ	248
	IF(DSQRT(FNORM/DFLOAT(NF)) .LT.	SPCQ	249
	\$ EPSARG*FMAX*ROUND) ICRIT = 0	SPCQ	250
C		SPCQ	251
C	FOR EACH SPECTRAL PERIOD P(I), COMPUTE SPECTRAL VALUE S(I)	SPCQ	252
C	COMPUTE SCALAR PRODUCTS FCOS, FSIN, CC, CS, SS, U, V	SPCQ	253
C	COMPUTE BILINEAR FORMS UAU, UAV, VAV	SPCQ	254
C	COMPUTE PERCENTAGE VARIANCE S	SPCQ	255
	65 DO 130 I = 1, NW	SPCQ	256
	OMEGA = 2.0DO * PI / P(I)	SPCQ	257
	FCOS = 0.0DO	SPCQ	258
	FSIN = 0.0DO	SPCQ	259
	CC = 0.0DO	SPCQ	260
	CS = 0.0DO	SPCQ	261
	SS = 0.0DO	SPCQ	262
	IF(NK .EQ. 0) GO TO 75	SPCQ	263
	DO 70 J = 1, NK	SPCQ	264
	U(J) = 0.0DO	SPCQ	265
	V(J) = 0.0DO	SPCQ	266
70	CONTINUE	SPCQ	267
75	DO 85 J = 1, NF	SPCQ	268
	WT = OMEGA * T(J)	SPCQ	269
	COSWT = DCOS(WT)	SPCQ	270
	SINWT = DSIN(WT)	SPCQ	271
	FCOS = FCOS + F(J) * COSWT	SPCQ	272
	FSIN = FSIN + F(J) * SINWT	SPCQ	273
	IF(NBASE .EQ. 0) GO TO 85	SPCQ	274
	DO 80 L = 1, NBASE	SPCQ	275
	K = NDAT + LT + 2 * NPER + L	SPCQ	276
	FUNC = BASE(K, T(J), DAT, NDAT, LT, PER, NPER)	SPCQ	277
	U(K) = U(K) + FUNC * COSWT	SPCQ	278
	V(K) = V(K) + FUNC * SINWT	SPCQ	279
80	CONTINUE	SPCQ	280
85	CONTINUE	SPCQ	281
	Q = 0.5DO * OMEGA * STEP	SPCQ	282
	SQ = DSIN(Q)	SPCQ	283
	CQ = DCOS(Q)	SPCQ	284
	IF(NPER .EQ. 0) GO TO 95	SPCQ	285
	DO 90 J = 1, NPER	SPCQ	286
	SPMQ(J) = SP(J) * CQ - CP(J) * SQ	SPCQ	287
	IF(DABS(SPMQ(J)) .LT. EPSARG) SPMQ(J) = DSIGN(EPSARG, SPMQ(J))	SPCQ	288
	SPPQ(J) = SP(J) * CQ + CP(J) * SQ	SPCQ	289
	IF(DABS(SPPQ(J)) .LT. EPSARG) SPPQ(J) = DSIGN(EPSARG, SPPQ(J))	SPCQ	290
90	CONTINUE	SPCQ	291
95	DO 115 J = 1, NIVL	SPCQ	292
	XNQ = XN(J) * Q	SPCQ	293
	XLQ = XL(J) * Q	SPCQ	294
	SNQ = DSIN(XNQ)	SPCQ	295
	CNQ = DCOS(XNQ)	SPCQ	296
	SLQ = DSIN(XLQ)	SPCQ	297
	CLQ = DCOS(XLQ)	SPCQ	298
	CC = CC + SNQ * CNQ * CLQ * CLQ - SNQ * CNQ * SLQ * SLQ	SPCQ	299
	CS = CS + SNQ * CNQ * SLQ * CLQ	SPCQ	300
	IF(NK .EQ. 0) GO TO 115	SPCQ	301
	IF(NDAT .EQ. 0) GO TO 100	SPCQ	302
	K = IVL(J)	SPCQ	303
	U(K) = U(K) + SNQ * CLQ / SQ	SPCQ	304
	V(K) = V(K) + SNQ * SLQ / SQ	SPCQ	305

100	IF(LT .EQ. 0) GO TO 105	SPCQ 306
	K = NDAT + 1	SPCQ 307
	SSCS = - SNQ * SLQ * CQ / SQ	SPCQ 308
	SCCS = SNQ * CLQ * CQ / SQ	SPCQ 309
	XNCS = XN(J) * CNQ * SLQ	SPCQ 310
	XNCC = - XN(J) * CNQ * CLQ	SPCQ 311
	XLSC = XL(J) * SNQ * CLQ	SPCQ 312
	XLSS = XL(J) * SNQ * SLQ	SPCQ 313
	STSQ = 0.5D0 * STEP / SQ	SPCQ 314
	U(K) = U(K) + STSQ * (SSCS + XNCS + XLSC)	SPCQ 315
	V(K) = V(K) + STSQ * (SCCS + XNCC + XLSS)	SPCQ 316
105	IF(NPER .EQ. 0) GO TO 115	SPCQ 317
	DO 110 L = 1, NPER	SPCQ 318
	K = NDAT + LT + 2 * L - 1	SPCQ 319
	SNPMQ = (SNP(J,L) * CNQ - CNP(J,L) * SNQ) / SPMQ(L)	SPCQ 320
	SNPPQ = (SNP(J,L) * CNQ + CNP(J,L) * SNQ) / SPPQ(L)	SPCQ 321
	SINM = (SLP(J,L) * CLQ - CLP(J,L) * SLQ) * SNPMQ	SPCQ 322
	SINP = (SLP(J,L) * CLQ + CLP(J,L) * SLQ) * SNPPQ	SPCQ 323
	COSM = (CLP(J,L) * CLQ + SLP(J,L) * SLQ) * SNPMQ	SPCQ 324
	COSP = (CLP(J,L) * CLQ - SLP(J,L) * SLQ) * SNPPQ	SPCQ 325
	U(K) = U(K) + 0.5D0 * (COSP + COSM)	SPCQ 326
	U(K+1) = U(K+1) + 0.5D0 * (SINP + SINM)	SPCQ 327
	V(K) = V(K) + 0.5D0 * (SINP - SINM)	SPCQ 328
	V(K+1) = V(K+1) + 0.5D0 * (-COSP + COSM)	SPCQ 329
110	CONTINUE	SPCQ 330
115	CONTINUE	SPCQ 331
	SQCQ = SQ * CQ	SPCQ 332
	CCSQCQ = CC / SQCQ	SPCQ 333
	SS = 0.5D0 * (DFLOAT(NF) - CCSQCQ)	SPCQ 334
	CC = 0.5D0 * (DFLOAT(NF) + CCSQCQ)	SPCQ 335
	CS = CS / SQCQ	SPCQ 336
	UAU = 0.0D0	SPCQ 337
	UAV = 0.0D0	SPCQ 338
	VAV = 0.0D0	SPCQ 339
	IF(NK .EQ. 0) GO TO 125	SPCQ 340
	DO 120 J = 1, NK	SPCQ 341
	DO 120 K = 1, NK	SPCQ 342
	UAU = UAU + U(J) * A(J,K) * U(K)	SPCQ 343
	UAV = UAV + U(J) * A(J,K) * V(K)	SPCQ 344
	VAV = VAV + V(J) * A(J,K) * V(K)	SPCQ 345
120	CONTINUE	SPCQ 346
125	S(I) = 0.0D0	SPCQ 347
	DET = (CC-UAV) * (SS-VAV) - (CS-UAV) * (CS-UAV)	SPCQ 348
	IF(DABS(DET) .LT. EPSARG) GO TO 130	SPCQ 349
	S(I) = 100.0D0 * ((SS - VAV) * FCOS * FCOS -	SPCQ 350
	2.0D0 * (CS - UAV) * FCOS * FSIN +	SPCQ 351
	(CC - UAU) * FSIN * FSIN) /	SPCQ 352
	(DET + FNORM)	SPCQ 353
	\$	SPCQ 354
	\$	SPCQ 355
	\$	SPCQ 356
130	CONTINUE	
	RETURN	
	END	

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SUBROUTINE SPECUN(T, F, NF, FNORM,
$           NK, DAT, NDAT, LT, PER, NPER, NBASE, A, C,
$           P, S, NW, IB, ICRIT)
IMPLICIT DOUBLE PRECISION (A-H,O-Z)
DIMENSION A(100,100), B(100), C(1), DAT(1), F(1), P(1),
$          PER(1), S(1), T(1), U(100), V(100)
DATA      PI      /3.141592653589793D0/,
$          ROUND  /100000./,
$          NKDIM  /100/
C
C FUNCTION:  SPECUN COMPUTES THE LEAST SQUARES SPECTRUM OF
C           AN UNEQUALLY SPACED TIME SERIES
C           AFTER SUPPRESSING KNOWN CONSTITUENTS
C
C CALLED FROM: DRIVER
C
C ARGUMENTS:
C SPECIFYING THE INPUT TIME SERIES
C   T(NF) = INPUT TIME SERIES TIMES
C   F(NF) = INPUT TIME SERIES VALUES
C           = OUTPUT RESIDUAL TIME SERIES VALUES
C   FNORM = OUTPUT QUADRATIC NORM OF RESIDUAL F
C
C SPECIFYING THE KNOWN CONSTITUENTS
C   NK      = INPUT TOTAL NUMBER OF KNOWN CONSTITUENTS
C   DAT(NDAT) = INPUT TIMES NEW DATUM BEGINS
C   LT      = INPUT LINEAR TREND SWITCH (1 = USE TREND)
C           (0 = DO NOT USE)
C   PER(NPER) = INPUT FORCED PERIODS
C   NBASE    = INPUT NUMBER OF USER-DEFINED CONSTITUENTS
C   A(NKDIM,NKDIM) = OUTPUT NORMAL EQUATION MATRIX RESULTING
C           FROM SUPPRESSION OF KNOWN CONSTITUENTS
C   C(NK)    = OUTPUT PRELIMINARY AMPLITUDES OF KNOWN
C           CONSTITUENTS
C
C SPECIFYING THE OUTPUT SPECTRUM
C   P(NW) = INPUT SPECTRAL PERIODS
C           DSIN,DSQRT
C   S(NW) = OUTPUT SPECTRAL VALUES
C   IB    = INPUT SPECTRAL BAND LABEL
C   ICRIT = OUTPUT ROUNDOFF FLAG
C           (1 = OK. CONTINUE ANALYSIS)
C           (0 = RESIDUAL TIME SERIES CONSISTS ONLY OF ROUNDOFF)
C
C EXTERNALS: DABS, DMAX1, BASE, DCOS, EPS, ERROR, DFLOAT, RESID,
C
C ERROR CONDITIONS:
C   1 = WARNING. ARGUMENT NDAT .LT. 0. (SET TO 0.)
C   2 = WARNING. ARGUMENT LT NOT 0 OR 1. (SET TO 0.)
C   3 = WARNING. ARGUMENT NPER .LT. 0. (SET TO 0.)
C   4 = WARNING. ARGUMENT NBASE .LT. 0. (SET TO 0.)
C   5 = WARNING. ARGUMENT NK .NE. NDAT+LT+2*NPER+NBASE.
C       (SET TO NDAT + LT + 2 * NPER + NBASE.)
C 104 = FATAL. LESS THAN 3 TIME SERIES VALUES INPUT.
C 105 = FATAL. T ELEMENT VALUES NOT MONOTONIC INCREASING
C 106 = FATAL. NK TOO LARGE FOR DIMENSIONS OF A,B,U,V
C       (LIMITATION NO. 2 BELOW)
C 107 = FATAL. DAT(1) .NE. T(1). (REQUIREMENT NO. 2 BELOW)
C 108 = FATAL. RESIDUAL TIME SERIES CONSISTS OF ROUNDOFF
C       (NOW CALLED IN DRIVER)

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C	CALLING ROUTINE REQUIREMENTS:	SPUN 062
C	1. WHEN NO KNOWN CONSTITUENTS ARE TO BE SUPPRESSED, THE	SPUN 063
C	CALLING ROUTINE MUST PASS ZERO VALUES FOR NK,NDAT,	SPUN 064
C	LT,NPER AND NBASE.	SPUN 065
C	2. WHEN NDAT .GT. 0, THE CALLING ROUTINE MUST SET	SPUN 066
C	DAT(1) = T(1)	SPUN 067
C	3. THE CALLING ROUTINE MUST SET	SPUN 068
C	NK = NDAT + LT + 2 * NPER + NBASE.	SPUN 069
C	4. WHEN NBASE .GT. 0, THE USER MUST SUPPLY CODING IN	SPUN 070
C	FUNCTION BASE TO COMPUTE EACH USER-DEFINED	SPUN 071
C	CONSTITUENT.	SPUN 072
C	5. ON INITIAL CALL, CALLING ROUTINE MUST SET IB = 1 TO	SPUN 073
C	COMPUTE RESIDUAL TIME SERIES. MANY SPECTRAL BANDS	SPUN 074
C	FOR THE SAME SPECTRUM CAN THEN BE COMPUTED BY	SPUN 075
C	SETTING IB .NE. 1, AND CALLING REPEATEDLY,	SPUN 076
C	CHANGING ONLY P(NW).	SPUN 077
C	6. CALLING ROUTINE MUST DIMENSION ARGUMENT ARRAYS .GE.	SPUN 078
C	T(NF),F(NF),DAT(NDAT),PER(NPER),C(NK),P(NW),S(NW).	SPUN 079
C	7. T ELEMENT VALUES ARE UNRESTRICTED AS TO SPACING, BUT	SPUN 080
C	MUST MONOTONICALLY INCREASE. P,DAT AND PER ELEMENT	SPUN 081
C	VALUES MUST BE IN THE SAME UNITS AS T.	SPUN 082
C	LIMITATIONS:	SPUN 083
C	1. WHEN CALLED WITH IB = 1, AND NK .GT. 0, THE CONTENTS	SPUN 084
C	OF THE TIME SERIES F IS REPLACED BY THE RESIDUAL	SPUN 085
C	TIME SERIES VALUES.	SPUN 086
C	2. WHEN NK .GT. NKDIM, A,B,U AND V MUST BE REDIMENSIONED	SPUN 087
C	.GE. NK, AND NKDIM CHANGED TO THE NEW DIMENSION.	SPUN 088
C	IF(IB .NE. 1) GO TO 65	SPUN 089
C	PROCESS INPUT ARGUMENTS	SPUN 090
C	CHECK NF .GE. 3	SPUN 091
C	CHECK T INCREASES MONOTONICALLY	SPUN 092
C	COMPUTE FMAX = MAXIMUM ABSOLUTE VALUE IN F	SPUN 093
C	CHECK VALUES OF NDAT,LT,NPER,NBASE,AND NK	SPUN 094
C	CHECK DAT(1) .EQ. T(1)	SPUN 095
	IF(NF .LT. 3)	CALL ERROR(104)
	DO 5 I = 2, NF	SPUN 099
	IF(T(I) .LE. T(I-1))	CALL ERROR(105)
	5 CONTINUE	SPUN 101
	FMAX = DABS(F(1))	SPUN 102
	DO 10 I = 2, NF	SPUN 103
	10 FMAX = DMAX1(FMAX, DABS(F(I)))	SPUN 104
	IF(NDAT .GE. 0) GO TO 15	SPUN 105
	CALL ERROR(1)	SPUN 106
	NDAT = 0	SPUN 107
	15 IF(LT .EQ. 0 .OR. LT .EQ. 1) GO TO 20	SPUN 108
	CALL ERROR(2)	SPUN 109
	LT = 0	SPUN 110
	20 IF(NPER .GE. 0) GO TO 25	SPUN 111
	CALL ERROR(3)	SPUN 112
	NPER = 0	SPUN 113
	25 IF(NBASE .GE. 0) GO TO 30	SPUN 114
	CALL ERROR(4)	SPUN 115
	NBASE = 0	SPUN 116
	30 IF(NK .EQ. NDAT + LT + 2 * NPER + NBASE) GO TO 35	SPUN 117
	CALL ERROR(5)	SPUN 118
	NK = NDAT + LT + 2 * NPER + NBASE	SPUN 119
	35 IF(NK .GT. NKDIM)	CALL ERROR(106)
	IF(NDAT .GE. 1 .AND. DAT(1) .NE. T(1))	CALL ERROR(107)
		SPUN 120
		SPUN 121
		SPUN 122

C		SPUN 123
C	SUPPRESS KNOWN CONSTITUENTS	SPUN 124
C	REPLACE F WITH RESIDUAL TIME SERIES	SPUN 125
C	COMPUTE QUADRATIC NORM OF F	SPUN 126
C	CHECK IF RMS VALUE OF RESIDUAL F IS LESS	SPUN 127
C	THAN EPS * FMAX * ROUND, WHERE	SPUN 128
C	EPS = EPSARG = SMALLEST NUMBER SO 1 + EPS .GT. 1	SPUN 129
C	FMAX = MAXIMUM ABSOLUTE VALUE OF ORIGINAL F	SPUN 130
C	ROUND ACCOUNTS FOR ACCUMULATED ROUND OFF IN	SPUN 131
C	COMPUTING RESIDUAL F	SPUN 132
	IF(NK .GT. 0) CALL RESID(T, F, NF,	SPUN 133
	\$ NK, DAT, NDAT, LT, PER, NPER, NBASE,	SPUN 134
	\$ A, B, C, NKDIM)	SPUN 135
	FNORM = 0.000	SPUN 136
	EPSARG = EPS(ARG)	SPUN 137
	DO 60 I = 1, NF	SPUN 138
	60 FNORM = FNORM + F(I) * F(I)	SPUN 139
C		SPUN 140
C	CHECK IF RESIDUAL F CONSISTS OF ROUND OFF	SPUN 141
	ICRIT = 1	SPUN 142
	IF(DSQRT(FNORM/DFLOAT(NF)) .LT.	SPUN 143
	\$ EPSARG+FMAX+ROUND) ICRIT = 0	SPUN 144
C		SPUN 145
C	FOR EACH SPECTRAL PERIOD P(I), COMPUTE SPECTRAL VALUE S(I)	SPUN 146
C	COMPUTE SCALAR PRODUCTS FCOS, FSIN, CC, CS, SS, U, V	SPUN 147
C	COMPUTE BILINEAR FORMS UAU, UAV, VAV	SPUN 148
C	COMPUTE PERCENTAGE VARIANCE S	SPUN 149
	65 DO 130 I = 1, NW	SPUN 150
	OMEGA = 2.000 * PI / P(I)	SPUN 151
	FCOS = 0.000	SPUN 152
	FSIN = 0.000	SPUN 153
	CC = 0.000	SPUN 154
	CS = 0.000	SPUN 155
	SS = 0.000	SPUN 156
	IF(NK .EQ. 0) GO TO 75	SPUN 157
	DO 70 J = 1, NK	SPUN 158
	U(J) = 0.000	SPUN 159
	V(J) = 0.000	SPUN 160
	70 DO 85 J = 1, NF	SPUN 161
	WT = OMEGA * T(J)	SPUN 162
	COSWT = DCOS(WT)	SPUN 163
	SINWT = DSIN(WT)	SPUN 164
	FCOS = FCOS + F(J) * COSWT	SPUN 165
	FSIN = FSIN + F(J) * SINWT	SPUN 166
	CC = CC + COSWT * COSWT	SPUN 167
	CS = CS + COSWT * SINWT	SPUN 168
	SS = SS + SINWT * SINWT	SPUN 169
	IF(NK .EQ. 0) GO TO 85	SPUN 170
	DO 80 K = 1, NK	SPUN 171
	FUNC = BASE(K, T(J), DAT, NDAT, LT, PER, NPER)	SPUN 172
	U(K) = U(K) + FUNC * COSWT	SPUN 173
	V(K) = V(K) + FUNC * SINWT	SPUN 174
	80 CONTINUE	SPUN 175
	UAU = 0.000	SPUN 176
	UAV = 0.000	SPUN 177
	VAV = 0.000	SPUN 178
	IF(NK .EQ. 0) GO TO 125	SPUN 179
	DO 120 J = 1, NK	SPUN 180
	DO 120 K = 1, NK	SPUN 181
	UAU = UAU + U(J) * A(J, K) * U(K)	SPUN 182
	UAV = UAV + U(J) * A(J, K) * V(K)	SPUN 183

120	VAV = VAV + V(J) * A(J,K) * V(K)	SPUN 184
125	S(I) = 0.0DO	SPUN 185
	DET = (CC-UAU) * (SS-VAV) - (CS-UAV) * (CS-UAV)	SPUN 186
	IF(DABS(DET) .LT. EPSARG) GO TO 130	SPUN 187
	S(I) = 100.0DO * ((SS - VAV) * FCOS * FCOS -	SPUN 188
	2.0DO * ((CS - UAV) * FCOS * FSIN +	SPUN 189
	(CC - UAU) * FSIN * FSIN) /	SPUN 190
	(DET * FNORM)	SPUN 191
130	CONTINUE	SPUN 192
	RETURN	SPUN 193
	END	SPUN 194