# PROPAGATION OF UNCERTAINTY FOR AN INTERPOLATED RADIATION THERMOMETRY SCALE 

Peter Saunders<br>Measurement Standards Laboratory of New Zealand<br>PO Box 31-310, Lower Hutt, New Zealand<br>e-mail: p.saunders@irl.cri.nz


#### Abstract

An evaluation is made of the expected uncertainties that may be achieved by approximating ITS-90 in the range from the silver point up to $2500{ }^{\circ} \mathrm{C}$ by an interpolated scale based on the recently developed carbon-metal eutectic fixed points. Analytic expressions are derived for the sensitivity coefficients for the uncertainties in the measured signals and the estimated temperatures for a generalised non-linear interpolation equation, for both exact fitting and least-squares determinations of the free parameters. These formulae are applied to interpolation between the carbon-metal eutectic fixed points using a modified form of the Sakuma-Hattori interpolation equation. It is shown that in the interpolation region, the combined uncertainty in this approximation to ITS-90 can be kept below the uncertainty in the individual fixed points, provided that the interpolation equation is of sufficiently high order to ensure that the interpolation error is kept low. With expected improvements in the reproducibility of the carbon-metal eutectics, this uncertainty should be much smaller than the uncertainty in the current realisation of ITS-90. In the future, thermodynamics measurements of the fixed-point temperatures may allow ITS-90 to be redefined between the silver point and $3000^{\circ} \mathrm{C}$ in terms of this interpolation approach.


## 1. INTRODUCTION

The interpolation equation approach for primary radiation thermometry is currently only practicable in approximating ITS-90 in the temperature range below the copper point. The lack of fixed points above the copper points means that in this range the equations must be extrapolated, resulting in uncertainties that propagate as $T^{2}$ at best. However, the recent development of metal-carbon eutectic fixed points, e.g. [1], in the range $1100^{\circ} \mathrm{C}$ to $2500^{\circ} \mathrm{C}$ raises the interesting possibility of redefining the ITS-90 temperature scale above the silver point based on interpolation between defined temperatures of the eutectic points. Interpolation equations for radiation thermometers can be shown in principle [2] to be equivalent to the widespread practice of using a temperature-dependent mean effective wavelength in the integral signal ratio equation to solve the for the unknown temperature. In addition, interpolation equations obviate the need to measure the spectral responsivity of the pyrometer and are not prone to errors caused by unaccounted-for out-of-band transmission.

The narrow bandwidth of primary radiation thermometers allows interpolation equations to be developed that contain a small number of free parameters, typically only three or four. Since there are 12 fixed points, including the pure metal fixed points as well as the carbon-metal eutectic points, between the silver point and $2500^{\circ} \mathrm{C}$, least-squares techniques can be used to take advantage of the increased number of degrees of freedom available over the exact fitting case. This reduces the overall uncertainty using interpolation.

Lagrange (polynomial) interpolation is used in many of the ITS-90 sub-ranges below the silver point. White and Saunders [3] have shown how for these cases propagation of uncertainty formulae can be written down by inspection. However, interpolation equations for radiation thermometers are almost exclusively non-linear (see [4] for a special-case exception) and so cannot be expressed in the Lagrange formalism. In this paper we present analytic propagation of uncertainty formulae for a general non-linear equation for both the exact fitting case and the least-squares problem. These formulae are then applied to a specific example of a commonly used radiation thermometry interpolation equation, and numerical results are given.

## 2. PROPAGATION OF UNCERTAINTY FOR EXACT FITTING

The general form for a non-linear interpolation equation is

$$
\begin{equation*}
S=S\left(T, a_{1}, a_{2}, \ldots, a_{N}\right) \tag{1}
\end{equation*}
$$

where $S$ is the signal measured by the pyrometer, and is a function of temperature $T$ and a set of $N$ parameters $a_{i}$. In the exact fitting case the parameters $a_{i}$ are determined by requiring equation (1) to pass through $N$ measured temperature-signal pairs, $\left(T_{1}, S_{1}\right),\left(T_{2}, S_{2}\right), \ldots,\left(T_{N}, S_{N}\right)$. That is, each of the parameters $a_{i}$ is a function of all the measured pairs. Thus, equation (1) can be rewritten as

$$
\begin{equation*}
S=S\left(T, T_{1}, T_{2}, \ldots, T_{N}, S_{1}, S_{2}, \ldots, S_{N}\right) \tag{2}
\end{equation*}
$$

Because the interpolation equation is non-linear it is usually not possible to write it down explicitly in the form of equation (2), and the parameters $a_{i}$ are determined numerically. Nevertheless, application of the propagation of uncertainty formula requires the evaluation of each of the sensitivity coefficients $\partial S / \partial T_{i}$ and $\partial S / \partial S_{i}$.

Appendix A gives the derivation of the sensitivity coefficients for the exact fitting case. These can be written in the compact form

$$
\begin{equation*}
\frac{\partial S}{\partial T_{i}}=-\left.\frac{\partial S}{\partial T}\right|_{T=T_{i}} \sum_{j=1}^{N} \mathbf{M}_{i j}^{-1} \frac{\partial S}{\partial a_{j}} \tag{3}
\end{equation*}
$$

and

$$
\begin{equation*}
\frac{\partial S}{\partial S_{i}}=\sum_{j=1}^{N} \mathbf{M}_{i j}^{-1} \frac{\partial S}{\partial a_{j}} \tag{4}
\end{equation*}
$$

where $\mathbf{M}_{i j}^{-1}$ is the $i_{, j}{ }^{\text {th }}$ element of the inverse of the $N \times N$ square matrix $\mathbf{M}$ given by

$$
\mathbf{M}=\left[\begin{array}{cccc}
\left.\frac{\partial S}{\partial a_{1}}\right|_{T=T_{1}} & \left.\frac{\partial S}{\partial a_{1}}\right|_{T=T_{2}} & \cdots & \left.\frac{\partial S}{\partial a_{1}}\right|_{T=T_{N}}  \tag{5}\\
\left.\frac{\partial S}{\partial a_{2}}\right|_{T=T_{1}} & \left.\frac{\partial S}{\partial a_{2}}\right|_{T=T_{2}} & \cdots & \left.\frac{\partial S}{\partial a_{2}}\right|_{T=T_{N}} \\
\vdots & \vdots & \vdots & \vdots \\
\left.\frac{\partial S}{\partial a_{N}}\right|_{T=T_{1}} & \left.\frac{\partial S}{\partial a_{N}}\right|_{T=T_{2}} & \cdots & \left.\frac{\partial S}{\partial a_{N}}\right|_{T=T_{N}}
\end{array}\right]
$$

All the derivatives on the right-hand sides of equations (3) to (5) are easily evaluated from the form of the interpolation equation given by equation (1). The only difficult step is determining the inverse of the matrix $\mathbf{M}$; however, in practice this is most easily performed numerically, and needs only to be calculated once for a given interpolation equation and set of fixed-point temperatures. Note that unlike Lagrange interpolation, it is necessary to determine the values of the parameters before being able to calculate the sensitivity coefficients.

The propagation of uncertainty formula for the uncertainty in the pyrometer signal, $u_{S}$, in the absence of correlations, is [5]

$$
\begin{equation*}
u_{S}^{2}=\sum_{i=1}^{N}\left(\frac{\partial S}{\partial T_{i}}\right)^{2} u_{T_{i}}^{2}+\sum_{i=1}^{N}\left(\frac{\partial S}{\partial S_{i}}\right)^{2} u_{S_{i}}^{2}, \tag{6}
\end{equation*}
$$

where $u_{T_{i}}$ and $u_{S_{i}}$ are the uncertainties in the temperatures and measured signals, respectively, that define the interpolation equation. Equation (6) is converted to an uncertainty in $T$ through the equation

$$
\begin{equation*}
u_{S}=\frac{\partial S}{\partial T} u_{T} \tag{7}
\end{equation*}
$$

## 3. PROPAGATION OF UNCERTAINTY FOR LEAST-SQUARES FITTING

Least-squares fitting uses redundancy in the number of measured points, which provides assurance that the measurements are consistent and that the radiation thermometer interpolates well, and provides a measure of the interpolation error through the error of fit. The additional number of degrees of freedom allows a reduction in the total uncertainty by a factor of the order of $\sqrt{N / M}$ where $M$ measurements are used to determine $N$ parameters $(M>N)$.

For the least-squares problem, the parameters in equation (1) are all functions of the $M$ measurement pairs. Thus equation (2) becomes

$$
\begin{equation*}
S=S\left(T, T_{1}, T_{2}, \ldots, T_{M}, S_{1}, S_{2}, \ldots, S_{M}\right) \tag{8}
\end{equation*}
$$

For unweighted least squares, the parameters are determined by minimising the chi-squared function

$$
\begin{equation*}
\chi^{2}=\sum_{i=1}^{M}\left[S_{i}-S\left(T_{i}\right)\right]^{2} \tag{9}
\end{equation*}
$$

where, for the purpose of clarity, $S\left(T_{i}\right)$ is used to mean the value of $S$ obtained by substituting $\mathrm{T}=T_{i}$ into equation (1) or (8).

In Appendix B the sensitivity coefficients are derived using equation (9) as the starting point. The results, after applying a minor approximation, are

$$
\left[\begin{array}{c}
\frac{\partial S}{\partial T_{1}}  \tag{10}\\
\frac{\partial S}{\partial T_{2}} \\
\vdots \\
\frac{\partial S}{\partial T_{M}}
\end{array}\right]=\mathbf{B} \mathbf{H}^{-1}\left[\begin{array}{c}
\frac{\partial S}{\partial a_{1}} \\
\frac{\partial S}{\partial a_{2}} \\
\vdots \\
\frac{\partial S}{\partial a_{N}}
\end{array}\right]
$$

where the matrix elements of the $M \times N$ matrix $\mathbf{B}$ are

$$
\begin{equation*}
\mathbf{B}_{i j}=-\left.\left(\frac{\partial S}{\partial T} \frac{\partial S}{\partial a_{j}}\right)\right|_{T=T_{i}}+\left.\left[S_{i}-S\left(T_{i}\right)\right] \frac{\partial^{2} S}{\partial T \partial a_{j}}\right|_{T=T_{i}} \text { for } i=1 \text { to } M, j=1 \text { to } N, \tag{11}
\end{equation*}
$$

and

$$
\left[\begin{array}{c}
\frac{\partial S}{\partial S_{1}}  \tag{12}\\
\frac{\partial S}{\partial S_{2}} \\
\vdots \\
\frac{\partial S}{\partial S_{M}}
\end{array}\right]=\left[\begin{array}{cccc}
\left.\frac{\partial S}{\partial a_{1}}\right|_{T=T_{1}} & \left.\frac{\partial S}{\partial a_{2}}\right|_{T=T_{1}} & \cdots & \left.\frac{\partial S}{\partial a_{N}}\right|_{T=T_{1}} \\
\left.\frac{\partial S}{\partial a_{1}}\right|_{T=T_{2}} & \left.\frac{\partial S}{\partial a_{2}}\right|_{T=T_{2}} & \cdots & \left.\frac{\partial S}{\partial a_{N}}\right|_{T=T_{2}} \\
\vdots & \vdots & \vdots & \vdots \\
\left.\frac{\partial S}{\partial a_{1}}\right|_{T=T_{M}} & \left.\frac{\partial S}{\partial a_{2}}\right|_{T=T_{M}} & \cdots & \left.\frac{\partial S}{\partial a_{N}}\right|_{T=T_{M}}
\end{array}\right] \mathbf{H}^{-1}\left[\begin{array}{c}
\frac{\partial S}{\partial a_{1}} \\
\frac{\partial S}{\partial a_{2}} \\
\vdots \\
\frac{\partial S}{\partial a_{N}}
\end{array}\right],
$$

where $\mathbf{H}$ is a square symmetric matrix given by

$$
\mathbf{H}=\left[\begin{array}{ccc}
\sum_{i=1}^{M}\left(\left.\frac{\partial S}{\partial a_{1}}\right|_{T=T_{i}}\right)^{2} & \sum_{i=1}^{M}\left(\frac{\partial S}{\partial a_{1}} \frac{\partial S}{\partial a_{2}}\right)_{T=T_{i}} & \ldots  \tag{13}\\
\sum_{i=1}^{M}\left(\frac{\partial S}{\partial a_{2}} \frac{\partial S}{\partial a_{1}}\right)_{T=T_{i}} & \sum_{i=1}^{M}\left(\left.\frac{\partial S}{\partial a_{2}}\right|_{T=T_{i}}\right)_{i=1}^{2}\left(\frac{\partial S}{\partial a_{1}} \frac{\partial S}{\partial a_{N}}\right)_{T=T_{i}} \\
\vdots & \cdots & \sum_{i=1}^{M}\left(\frac{\partial S}{\partial a_{2}} \frac{\partial S}{\partial a_{N}}\right)_{T=T_{i}} \\
\sum_{i=1}^{M}\left(\frac{\partial S}{\partial a_{N}} \frac{\partial S}{\partial a_{1}}\right)_{T=T_{i}} & \sum_{i=1}^{M}\left(\frac{\partial S}{\partial a_{N}} \frac{\partial S}{\partial a_{2}}\right)_{T=T_{i}} & \vdots \\
\vdots \\
\vdots & \cdots & \sum_{i=1}^{M}\left(\left.\frac{\partial S}{\partial a_{N}}\right|_{T=T_{i}}\right)^{2}
\end{array}\right] .
$$

The dimensions of the vectors and matrices in equations (10) and (12) are $[M \times 1]=[M \times N] \times[N \times N] \times[N \times 1]$. Once again, all the derivatives on the right-hand sides of equations (10) to (13) are straightforward to evaluate. The matrix $\mathbf{H}$ is usually called the curvature matrix in the context of least-squares fitting (and is related to the Hessian). As expected, when $M=N$ equations (10) and (12) are identical to equations (3) and (4), respectively (although this is not immediately obvious!).

## 4. INTERPOLATION THROUGH METAL-CARBON EUTECTIC FIXED POINTS

In this section we demonstrate the application of the propagation of uncertainty formula (equation (6)), with the sensitivity coefficients given by equations (10) and (12), to simulated measurements made at several of the carbon-metal eutectic fixed points. The interpolation equation was chosen to be the Planck version of the Sakuma-Hattori equation,

$$
\begin{equation*}
\text { Signal }=\frac{C}{\exp \left(\frac{c_{2}}{A T+B}\right)-1}, \tag{14}
\end{equation*}
$$

where $A, B$, and $C$ are the fitted parameters. Because of the exponential nature of this equation, unweighted least-squares fitting tends to skew the residuals. This problem is largely overcome by fitting the logarithm of the signal as a function of temperature. Thus, we use the interpolation equation

$$
\begin{equation*}
S=a_{1}-\ln \left[\exp \left(\frac{c_{2}}{a_{2} T+a_{3}}\right)-1\right], \tag{15}
\end{equation*}
$$

where $a_{1}=\ln C, a_{2}=A, a_{3}=B$, and the values of the measurements $S_{i}$ are the logarithms of the simulated signals. The derivatives appearing in equations (10) and (12) are all easily calculated from equation (15).

### 4.1 Propagated Uncertainty

To simulate the measured signals the Planck function was integrated over a spectral responsivity curve with a centre wavelength of 650 nm and a bandwidth of 50 nm with a shape corresponding to that of a true interference filter, including a small secondary peak 200 nm from the main peak. The temperatures used for the carbon-metal eutectic points were rounded to the nearest degree, as given by Yamada et al. [1]. Equation (15) was fitted successively to $3,4,5$, and 10 fixed points. These points are summarised in Table 1. The first three sets of points are identical to those chosen by Yamada et al. [1] in their calculation of uncertainty using a Monte Carlo technique.

| Number of Points | Points Used | Fixed-Point Temperature ( ${ }^{\circ} \mathrm{C}$ ) |
| :---: | :---: | :---: |
| 3 | Cu | 1084.62 |
|  | Pt-C | 1738 |
|  | $\mathrm{Re}-\mathrm{C}$ | 2474 |
| 4 | Cu | 1084.62 |
|  | Pd-C | 1492 |
|  | Ru-C | 1953 |
|  | Re-C | 2474 |
| 5 | Cu | 1084.62 |
|  | Pd-C | 1492 |
|  | Pt-C | 1738 |
|  | Ir-C | 2290 |
|  | Re-C | 2474 |
| 10 | Ag | 961.78 |
|  | Cu | 1084.62 |
|  | $\mathrm{Fe}-\mathrm{C}$ | 1153 |
|  | $\mathrm{Ni}-\mathrm{C}$ | 1329 |
|  | Pd-C | 1492 |
|  | Rh-C | 1657 |
|  | Pt-C | 1738 |
|  | Ru-C | 1953 |
|  | Ir-C | 2290 |
|  | Re-C | 2474 |

Table 1. Fixed-points and their temperatures for the 3-point, 4-point, 5 -point, and 10 -point data sets used to illustrate the propagation of uncertainty equation.

Also, to be consistent with Yamada et al., the uncertainty in each fixed-point temperature was chosen to be $0.1^{\circ} \mathrm{C}$. However, here we also assume that there is a $0.05 \%$ uncertainty in each of the measured signals at the fixed points. Figure 1 shows the combined uncertainty in the interpolated temperature for each set of points.

Although each curve in Figure 1 was calculated using equation (10) and (12), the 3-point curve could be determined using the simpler equations (3) and (4), since for the case $M=N$ the two sets of equations are identical (for exact fitting the residuals are zero). It is clear that increasing the number of points reduces the uncertainty in the interpolated temperature, and the combined uncertainty can be well below the uncertainty in an individual measurement. However, in the extrapolation region the uncertainty increases quite rapidly. These conclusions are the same as those reached by Yamada et al., and indeed by assuming a zero uncertainty in each of the measured signal, the first three curves in Figure 1 are identical to the corresponding curves of Yamada et al. (notwithstanding slight differences in assumed spectral responsivity).


Figure 1. Combined uncertainty calculated using equations (6) and (7), with the sensitivity coefficients given by equations (10) and (12), for the 3-parameter interpolation equation (14). The fixed points used for each curve are listed in Table 1. The uncertainties in the temperature of each fixed point is assumed to be $0.1^{\circ} \mathrm{C}$ and the uncertainty in each of the measured signals is assumed to be $0.05 \%$.

### 4.2 Interpolation Error

An important consideration in the interpretation of Figure 1 is interpolation error. The uncertainty plotted in this figure describes how the interpolation equation varies with the uncertainties in its defining points. It does not account for differences between the interpolation equation and the true behaviour of the pyrometer. Equation (14) is semi-empirical and contains the implicit assumption that the extended effective wavelength [2] is a linear function of inverse temperature. This is a good approximation for narrow bandwidths and short temperature ranges. However, the temperature range here is quite large and this approximation may limit the performance of equation (14).


Figure 2. The interpolation error for each of the data sets for the interpolation equation (14). The curves for the 4- and 5point data sets are almost identical.

The interpolation error is plotted in Figure 2 for each set of points. Note that the interpolation error is given by the temperature calculated from the interpolation equation minus the true temperature. Even within the interpolation region the error is of a similar magnitude to, or larger than, the combined uncertainty shown in Figure 1. The extended effective wavelength is plotted in Figure 3 as a function of inverse temperature, and indeed there is significant curvature in the line, consistent with the interpolation error of Figure 2. Figure 4 shows the residuals for both a linear fit and a quadratic fit to the curve in Figure 3. For the linear fit, implicit in equation (14), the wavelength errors are of the order of several tenths of a nanometre. On the other hand, the quadratic fit performs within about $\pm 0.025 \mathrm{~nm}$ over most of the temperature range and would appear to offer significant improvement over the linear approximation.


Figure 3. Extended effective wavelength as a function of inverse temperature for the spectral responsivity assumed for the calculations. There is clearly some curvature over the relatively large temperature range used.


Figure 4. Residuals for a linear and a quadratic fit to the extended effective wavelength plotted in Figure 3.

Extending equation (14) to take account of this curvature yields

$$
\begin{equation*}
\text { Signal }=\frac{C}{\exp \left(\frac{c_{2}}{A T+B+D / T}\right)-1} \tag{16}
\end{equation*}
$$

where we have introduced the extra parameter $D$. To solve for the parameters of this interpolation equation we again use its logarithmic form:

$$
\begin{equation*}
S=a_{1}-\ln \left[\exp \left(\frac{c_{2}}{a_{2} T+a_{3}+a_{4} / T}\right)-1\right] \tag{17}
\end{equation*}
$$



Figure 5. Combined uncertainty as for Figure 1, but for the interpolation equation (16).


Figure 6. Interpolation error as for Figure 2, but for the interpolation equation (16).

Figures 5 and 6 give the combined uncertainty and interpolation error, respectively, for the 4-point, 5-point, and 10 -point data sets. The combined uncertainty for this 4-parameter interpolation equation is slightly higher than for the 3-parameter equation shown in Figure 1, mainly due to the reduced number of degrees of freedom. However, the interpolation error is significantly reduced over that shown in Figure 2, to the extent that it is now below the level of the combined uncertainty.

The interpolation error may be reduced further by finding a more suitable fit, than a simple polynomial, to the extended effective wavelength versus temperature relationship. A possible 3-parameter description of this relationship has been suggested by Schreiber [6]:

$$
\begin{equation*}
\lambda_{\mathrm{x}}=A+\frac{B}{T+C}, \tag{18}
\end{equation*}
$$

where $A, B$, and $C$ are the free parameters. This yields an interpolation equation of the form

$$
\begin{equation*}
S=\frac{a_{1}}{\exp \left(\frac{1+a_{4} / T}{a_{2} T+a_{3}}\right)-1} . \tag{19}
\end{equation*}
$$

Indeed, in the case considered here, equation (19) produces a marginally smaller error of fit than equation (16). However, an even better extended effective wavelength versus temperature relationship is

$$
\begin{equation*}
\lambda_{\mathrm{x}}=A+\frac{B}{T}+\frac{C}{T^{4}} . \tag{20}
\end{equation*}
$$

In this case the interpolation equation is

$$
\begin{equation*}
S=\frac{a_{1}}{\exp \left(\frac{c_{2}}{a_{2} T+a_{3}+a_{4} / T^{3}}\right)-1} . \tag{21}
\end{equation*}
$$

This equation gives almost identical combined uncertainty curves to those plotted in Figure 5, but the interpolation error is approximately 4 times smaller in magnitude than the curves in Figure 6 and has a similar shape.

## 5. CONCLUSIONS

This paper has provided an algebraic solution to the propagation of uncertainty problem for both exact-fitting and least-squares interpolation using non-linear interpolation equations. This gives a simple means of analysing the utility of an interpolated radiation thermometry scale, since interpolation equations for radiation thermometers are fundamentally non-linear. The recent development of carbon-metal eutectic fixed points between $1100{ }^{\circ} \mathrm{C}$ and $2500{ }^{\circ} \mathrm{C}$ provides conveniently spaced reference points for interpolation to be practicable over this temperature range.

The propagated uncertainty for an interpolated scale, within the interpolation region, is generally no greater than the uncertainty associated with the measurements at each of the fixed points. For least-squares fitting this combined uncertainty decreases with the number of measurements used. With future improvements in the reproducibility of the carbon-metal fixed points, this combined uncertainty will be easily below the uncertainty in the current ITS- 90 realisation, which is generally about $1^{\circ} \mathrm{C}$ to $2^{\circ} \mathrm{C}$ above $2000{ }^{\circ} \mathrm{C}$ [1]. By defining the temperatures of the fixed points, following their thermodynamic measurement, the uncertainty in the interpolated scale will be reduced even further. However, in the extrapolation region the uncertainties increase fairly rapidly, so an interpolated scale is only useful up to the temperature of the highest fixed point, and perhaps a bit higher.

To cover the full temperature from the silver point to $2500{ }^{\circ} \mathrm{C}$ requires a 4-parameter interpolation equation in order to ensure that interpolation errors are less than $0.05{ }^{\circ} \mathrm{C}$ for the $650 \mathrm{~nm}, 50 \mathrm{~nm}$ bandwidth spectral
responsivity used for the calculations presented here. Equation (21) reduces this interpolation error to $0.01^{\circ} \mathrm{C}$ and is maintained below $0.02^{\circ} \mathrm{C}$ with extrapolation up to $3000^{\circ} \mathrm{C}$. On the other hand, use of a 3-parameter equation results in errors as large as $0.2^{\circ} \mathrm{C}$; this is larger than the expected reproducibility of the fixed points. It should be noted that the pyrometer signals must be corrected for non-linearity and size-of-source effect for the interpolation error to be kept low. It may be that other interpolation equations are more suitable for pyrometers with different operating wavelengths, bandwidths, spectral responsivity shapes, and required to operate over different temperature ranges. This should be investigated in future work. It is likely that determining the best interpolation equation for a given pyrometer requires only a rough estimate of its spectral responsivity, not a detailed determination as required for the ITS-90 approach.

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## APPENDIX A - DERIVATION OF SENSITIVITY COEFFICIENTS FOR EXACT FITTING

For the exact fitting case the interpolation equation contains $N$ parameters, which are determined by requiring the equation to pass through $N$ measured temperature-signal pairs. Thus

$$
\begin{equation*}
S=S\left(T, a_{1}, a_{2}, \ldots, a_{N}\right), \tag{A1}
\end{equation*}
$$

where

$$
\begin{align*}
& a_{1}=a_{1}\left(T_{1}, T_{2}, \ldots, T_{N}, S_{1}, S_{2}, \ldots, S_{N}\right) \\
& a_{2}=a_{2}\left(T_{1}, T_{2}, \ldots, T_{N}, S_{1}, S_{2}, \ldots, S_{N}\right) \\
& \vdots  \tag{A2}\\
& a_{N}=a_{N}\left(T_{1}, T_{2}, \ldots, T_{N}, S_{1}, S_{2}, \ldots, S_{N}\right)
\end{align*}
$$

In addition, since we have exact fitting, the following equations hold:

$$
\begin{align*}
& S_{1}=S\left(T_{1}, a_{1}, a_{2}, \ldots, a_{N}\right) \\
& S_{2}=S\left(T_{2}, a_{1}, a_{2}, \ldots, a_{N}\right)  \tag{A3}\\
& \vdots \\
& S_{N}=S\left(T_{N}, a_{1}, a_{2}, \ldots, a_{N}\right)
\end{align*}
$$

To determine the sensitivity coefficients $\partial S / \partial T_{i}$ we differentiate both (A1) and each of the equations in (A3) with respect to each of the $T_{i}$, bearing in mind the dependencies given in (A2), and compare the results. Differentiating equation (A1) gives

$$
\begin{align*}
& \frac{\partial S}{\partial T_{1}}=\frac{\partial S}{\partial a_{1}} \frac{\partial a_{1}}{T_{1}}+\frac{\partial S}{\partial a_{2}} \frac{\partial a_{2}}{\partial T_{1}}+\ldots+\frac{\partial S}{\partial a_{N}} \frac{\partial a_{N}}{\partial T_{1}} \\
& \frac{\partial S}{\partial T_{2}}=\frac{\partial S}{\partial a_{1}} \frac{\partial a_{1}}{T_{2}}+\frac{\partial S}{\partial a_{2}} \frac{\partial a_{2}}{\partial T_{2}}+\ldots+\frac{\partial S}{\partial a_{N}} \frac{\partial a_{N}}{\partial T_{2}} .  \tag{A4}\\
& \vdots \\
& \frac{\partial S}{\partial T_{N}}=\frac{\partial S}{\partial a_{1}} \frac{\partial a_{1}}{T_{N}}+\frac{\partial S}{\partial a_{2}} \frac{\partial a_{2}}{\partial T_{N}}+\ldots+\frac{\partial S}{\partial a_{N}} \frac{\partial a_{N}}{\partial T_{N}}
\end{align*}
$$

This can be written conveniently in matrix form:

$$
\left[\begin{array}{c}
\frac{\partial S}{\partial T_{1}}  \tag{A5}\\
\frac{\partial S}{\partial T_{2}} \\
\vdots \\
\frac{\partial S}{\partial T_{N}}
\end{array}\right]=\mathbf{A}\left[\begin{array}{c}
\frac{\partial S}{\partial a_{1}} \\
\frac{\partial S}{\partial a_{2}} \\
\vdots \\
\frac{\partial S}{\partial a_{N}}
\end{array}\right],
$$

where the $N \times N$ square matrix $\mathbf{A}$ is given by

$$
\mathbf{A}=\left[\begin{array}{cccc}
\frac{\partial a_{1}}{\partial T_{1}} & \frac{\partial a_{2}}{\partial T_{1}} & \cdots & \frac{\partial a_{N}}{\partial T_{1}}  \tag{A6}\\
\frac{\partial a_{1}}{\partial T_{2}} & \frac{\partial a_{2}}{\partial T_{2}} & \cdots & \frac{\partial a_{N}}{\partial T_{2}} \\
\vdots & \vdots & \vdots & \vdots \\
\frac{\partial a_{1}}{\partial T_{N}} & \frac{\partial a_{2}}{\partial T_{N}} & \cdots & \frac{\partial a_{N}}{\partial T_{N}}
\end{array}\right] .
$$

In general we cannot directly evaluate the derivatives in equation (A6) because we cannot explicitly write the parameters $a_{i}$ in terms of the temperatures $T_{i}$. However, we can eliminate $\mathbf{A}$ from equation (A5) by differentiating each of the equations in (A3). This gives

$$
\begin{align*}
& \frac{\partial S_{1}}{\partial T_{1}}=\left.\frac{\partial S}{\partial a_{1}}\right|_{T=T_{1}} \frac{\partial a_{1}}{\partial T_{1}}+\left.\frac{\partial S}{\partial a_{2}}\right|_{T=T_{1}} \frac{\partial a_{2}}{\partial T_{1}}+\ldots+\left.\frac{\partial S}{\partial a_{N}}\right|_{T=T_{1}} \frac{\partial a_{N}}{\partial T_{1}}+\left.\frac{\partial S}{\partial T}\right|_{T=T_{1}} \\
& \frac{\partial S_{1}}{\partial T_{2}}=\left.\frac{\partial S}{\partial a_{1}}\right|_{T=T_{1}} \frac{\partial a_{1}}{\partial T_{2}}+\left.\frac{\partial S}{\partial a_{2}}\right|_{T=T_{1}} \frac{\partial a_{2}}{\partial T_{2}}+\ldots+\left.\frac{\partial S}{\partial a_{N}}\right|_{T=T_{1}} \frac{\partial a_{N}}{\partial T_{2}} \\
& \frac{\partial S_{1}}{\partial T_{N}}=\left.\frac{\partial S}{\partial a_{1}}\right|_{T=T_{1}} \frac{\partial a_{1}}{\partial T_{N}}+\left.\frac{\partial S}{\partial a_{2}}\right|_{T=T_{1}} \frac{\partial a_{2}}{\partial T_{N}}+\ldots+\left.\frac{\partial S}{\partial a_{N}}\right|_{T=T_{1}} \frac{\partial a_{N}}{\partial T_{N}} \\
& \frac{\partial S_{2}}{\partial T_{1}}=\left.\frac{\partial S}{\partial a_{1}}\right|_{T=T_{2}} \frac{\partial a_{1}}{\partial T_{1}}+\left.\frac{\partial S}{\partial a_{2}}\right|_{T=T_{2}} \frac{\partial a_{2}}{\partial T_{1}}+\ldots+\left.\frac{\partial S}{\partial a_{N}}\right|_{T=T_{2}} \frac{\partial a_{N}}{\partial T_{1}} \\
& \frac{\partial S_{2}}{\partial T_{2}}=\left.\frac{\partial S}{\partial a_{1}}\right|_{T=T_{2}} \frac{\partial a_{1}}{\partial T_{2}}+\left.\frac{\partial S}{\partial a_{2}}\right|_{T=T_{2}} \frac{\partial a_{2}}{\partial T_{2}}+\ldots+\left.\frac{\partial S}{\partial a_{N}}\right|_{T=T_{2}} \frac{\partial a_{N}}{\partial T_{2}}+\left.\frac{\partial S}{\partial T}\right|_{T=T_{2}} \\
& \text { : } \\
& \frac{\partial S_{N}}{\partial T_{1}}=\left.\frac{\partial S}{\partial a_{1}}\right|_{T=T_{N}} \frac{\partial a_{1}}{\partial T_{1}}+\left.\frac{\partial S}{\partial a_{2}}\right|_{T=T_{N}} \frac{\partial a_{2}}{\partial T_{1}}+\ldots+\left.\frac{\partial S}{\partial a_{N}}\right|_{T=T_{N}} \frac{\partial a_{N}}{\partial T_{1}} \\
& \frac{\partial S_{N}}{\partial T_{N}}=\left.\frac{\partial S}{\partial a_{1}}\right|_{T=T_{N}} \frac{\partial a_{1}}{\partial T_{N}}+\left.\frac{\partial S}{\partial a_{2}}\right|_{T=T_{N}} \frac{\partial a_{2}}{\partial T_{N}}+\ldots+\left.\frac{\partial S}{\partial a_{N}}\right|_{T=T_{N}} \frac{\partial a_{N}}{\partial T_{N}}+\left.\frac{\partial S}{\partial T}\right|_{T=T_{N}} \tag{A7}
\end{align*}
$$

Since all the $S_{i}$ values are constant, each of the left-hand sides is equal to zero. These equations can also be rearranged into matrix form:

$$
\left[\begin{array}{cccc}
-\left.\frac{\partial S}{\partial T}\right|_{T=T_{1}} & 0 & \cdots & 0  \tag{A8}\\
0 & -\left.\frac{\partial S}{\partial T}\right|_{T=T_{2}} & \cdots & 0 \\
\vdots & \vdots & \vdots & \vdots \\
0 & 0 & \cdots & -\left.\frac{\partial S}{\partial T}\right|_{T=T_{N}}
\end{array}\right]=\mathbf{A} \times \mathbf{M}
$$

where the matrix $\mathbf{A}$ is given by equation (A6) and $\mathbf{M}$ is an $N \times N$ square matrix given by

$$
\mathbf{M}=\left[\begin{array}{cccc}
\left.\frac{\partial S}{\partial a_{1}}\right|_{T=T_{1}} & \left.\frac{\partial S}{\partial a_{1}}\right|_{T=T_{2}} & \cdots & \left.\frac{\partial S}{\partial a_{1}}\right|_{T=T_{N}}  \tag{A9}\\
\left.\frac{\partial S}{\partial a_{2}}\right|_{T=T_{1}} & \left.\frac{\partial S}{\partial a_{2}}\right|_{T=T_{2}} & \cdots & \left.\frac{\partial S}{\partial a_{2}}\right|_{T=T_{N}} \\
\vdots & \vdots & \vdots & \vdots \\
\left.\frac{\partial S}{\partial a_{N}}\right|_{T=T_{1}} & \left.\frac{\partial S}{\partial a_{N}}\right|_{T=T_{21}} & \cdots & \left.\frac{\partial S}{\partial a_{N}}\right|_{T=T_{N}}
\end{array}\right] .
$$

A can now be determined by right-multiplying both sides of equation (A8) by $\mathbf{M}^{-1}$. The result is then substituted into equation (A5) to yield the required sensitivity coefficients:

$$
\left[\begin{array}{c}
\frac{\partial S}{\partial T_{1}}  \tag{A10}\\
\frac{\partial S}{\partial T_{2}} \\
\vdots \\
\frac{\partial S}{\partial T_{N}}
\end{array}\right]=\left[\begin{array}{cccc}
-\left.\frac{\partial S}{\partial T}\right|_{T=T_{1}} & 0 & \cdots & 0 \\
0 & -\left.\frac{\partial S}{\partial T}\right|_{T=T_{2}} & \cdots & 0 \\
\vdots & \vdots & \vdots & \vdots \\
0 & 0 & \cdots & -\left.\frac{\partial S}{\partial T}\right|_{T=T_{N}}
\end{array}\right] \mathbf{M}^{-1}\left[\begin{array}{c}
\frac{\partial S}{\partial a_{1}} \\
\frac{\partial S}{\partial a_{2}} \\
\vdots \\
\frac{\partial S}{\partial a_{N}}
\end{array}\right] .
$$

The other set of sensitivity coefficients, $\partial S / \partial S_{i}$, are derived in a similar fashion. This time we differentiate equations (A1) and (A3) with respect to each of the $S_{i}$. Differentiating (A1) yields equations identical to (A5) and (A6) but with each of the $T_{i}$ replaced by the corresponding $S_{i}$. Differentiating (A3) similarly gives equations (A8) and (A9) with the same replacements, but additionally the matrix on the left-hand side of equation (A8) is in this case the identity matrix. Following the same procedure as above, the equation for the sensitivity coefficients is simply

$$
\left[\begin{array}{c}
\frac{\partial S}{\partial S_{1}}  \tag{A11}\\
\frac{\partial S}{\partial S_{2}} \\
\vdots \\
\frac{\partial S}{\partial S_{N}}
\end{array}\right]=\mathbf{M}^{-1}\left[\begin{array}{c}
\frac{\partial S}{\partial a_{1}} \\
\frac{\partial S}{\partial a_{2}} \\
\vdots \\
\frac{\partial S}{\partial a_{N}}
\end{array}\right],
$$

where the square matrix $\mathbf{M}$ is again given by equation (A9). Note that equations (A10) and (A11) are given in equivalent form as equations (3) and (4) in the main text.

## APPENDIX B — DERIVATION OF SENSITIVITY COEFFICIENTS FOR LEAST SQUARES

For the least-squares fitting case the interpolation equation contains $N$ parameters, which are determined by fitting the equation to a set of $M$ measured temperature-signal pairs, where $M>N$. Thus

$$
\begin{equation*}
S=S\left(T, a_{1}, a_{2}, \ldots, a_{N}\right) \tag{B1}
\end{equation*}
$$

where

$$
\begin{align*}
& a_{1}=a_{1}\left(T_{1}, T_{2}, \ldots, T_{M}, S_{1}, S_{2}, \ldots, S_{M}\right) \\
& a_{2}=a_{2}\left(T_{1}, T_{2}, \ldots, T_{M}, S_{1}, S_{2}, \ldots, S_{M}\right) \\
& \vdots  \tag{B2}\\
& a_{N}=a_{N}\left(T_{1}, T_{2}, \ldots, T_{M} S_{1}, S_{2}, \ldots, S_{M}\right)
\end{align*}
$$

For least squares, an equation similar to equation (A3) does not hold.
In unweighted least squares the coefficients are solved for by minimising the function

$$
\begin{equation*}
\chi^{2}=\sum_{i=1}^{M}\left[S_{i}-S\left(T_{i}\right)\right]^{2} \tag{B3}
\end{equation*}
$$

which is achieved by setting each of the derivatives $\partial \chi^{2} / \partial a_{i}$ equal to zero and solving the resulting set of $N$ simultaneous equations:

$$
\begin{align*}
& \frac{\partial \chi^{2}}{\partial a_{1}}=-\left.2 \sum_{i=1}^{M}\left[S_{i}-S\left(T_{i}\right)\right] \frac{\partial S}{\partial a_{1}}\right|_{T=T_{i}}=0 \\
& \frac{\partial \chi^{2}}{\partial a_{2}}=-\left.2 \sum_{i=1}^{M}\left[S_{i}-S\left(T_{i}\right)\right] \frac{\partial S}{\partial a_{2}}\right|_{T=T_{i}}=0  \tag{B4}\\
& \vdots \\
& \frac{\partial \chi^{2}}{\partial a_{N}}=-\left.2 \sum_{i=1}^{M}\left[S_{i}-S\left(T_{i}\right)\right] \frac{\partial S}{\partial a_{N}}\right|_{T=T_{i}}=0
\end{align*}
$$

To determine the sensitivity coefficients $\partial S / \partial T_{i}$, each of the equations in (B4) is differentiated with respect to each of the $T_{i}$. For example, differentiating the first equation with respect to $T_{1}$ yields

$$
\begin{align*}
& \frac{\partial a_{1}}{\partial T_{1}} \sum_{i=1}^{M}\left\{\left(\left.\frac{\partial S}{\partial a_{1}}\right|_{T=T_{i}}\right)^{2}-\left.\left[S_{i}-S\left(T_{i}\right)\right] \frac{\partial^{2} S}{\partial a_{1}^{2}}\right|_{T=T_{i}}\right\} \\
& +\frac{\partial a_{2}}{\partial T_{1}} \sum_{i=1}^{M}\left\{\left.\frac{\partial S}{\partial a_{2}} \frac{\partial S}{\partial a_{1}}\right|_{T=T_{i}}-\left.\left[S_{i}-S\left(T_{i}\right)\right] \frac{\partial^{2} S}{\partial a_{2} a_{1}}\right|_{T=T_{i}}\right\} \\
& +\ldots  \tag{B5}\\
& +\frac{\partial a_{N}}{\partial T_{1}} \sum_{i=1}^{M}\left\{\left.\frac{\partial S}{\partial a_{N}} \frac{\partial S}{\partial a_{1}}\right|_{T=T_{i}}-\left.\left[S_{i}-S\left(T_{i}\right)\right] \frac{\partial^{2} S}{\partial a_{N} a_{1}}\right|_{T=T_{i}}\right\} \\
& =-\left.\left(\frac{\partial S}{\partial T} \frac{\partial S}{\partial a_{1}}\right)\right|_{T=T_{1}}+\left.\left[S_{1}-S\left(T_{1}\right)\right] \frac{\partial^{2} S}{\partial T \partial a_{1}}\right|_{T=T_{1}}
\end{align*}
$$

The full set of derivatives can be written in matrix form as

$$
\begin{equation*}
\mathbf{D} \times \mathbf{H}=\mathbf{B} \tag{B6}
\end{equation*}
$$

where

$$
\mathbf{D}=\left[\begin{array}{cccc}
\frac{\partial a_{1}}{\partial T_{1}} & \frac{\partial a_{2}}{\partial T_{1}} & \cdots & \frac{\partial a_{N}}{\partial T_{1}}  \tag{B7}\\
\frac{\partial a_{1}}{\partial T_{2}} & \frac{\partial a_{2}}{\partial T_{2}} & \cdots & \frac{\partial a_{N}}{\partial T_{2}} \\
\vdots & \vdots & \vdots & \vdots \\
\frac{\partial a_{1}}{\partial T_{M}} & \frac{\partial a_{2}}{\partial T_{M}} & \cdots & \frac{\partial a_{N}}{\partial T_{M}}
\end{array}\right] .
$$

The matrix elements of the $N \times N$ matrix $\mathbf{H}$ are

$$
\begin{equation*}
\mathbf{H}_{i j}=\sum_{k=1}^{M}\left\{\left(\frac{\partial S}{\partial a_{i}} \frac{\partial S}{\partial a_{j}}\right)_{T=T_{k}}-\left.\left[S_{k}-S\left(T_{k}\right)\right] \frac{\partial^{2} S}{\partial a_{i} \partial a_{j}}\right|_{T=T_{k}}\right\} \text { for } i=1 \text { to } N, j=1 \text { to } N, \tag{B8}
\end{equation*}
$$

and the matrix elements of the $M \times N$ matrix $\mathbf{B}$ are

$$
\begin{equation*}
\mathbf{B}_{i j}=-\left.\left(\frac{\partial S}{\partial T} \frac{\partial S}{\partial a_{j}}\right)\right|_{T=T_{i}}+\left.\left[S_{i}-S\left(T_{i}\right)\right] \frac{\partial^{2} S}{\partial T \partial a_{j}}\right|_{T=T_{i}} \text { for } i=1 \text { to } M, j=1 \text { to } N \tag{B9}
\end{equation*}
$$

If we now differentiate equation (B1) with respect to each of the $T_{i}$ (as we did in Appendix A for equation (A1)), we obtain

$$
\left[\begin{array}{c}
\frac{\partial S}{\partial T_{1}}  \tag{B10}\\
\frac{\partial S}{\partial T_{2}} \\
\vdots \\
\frac{\partial S}{\partial T_{M}}
\end{array}\right]=\mathbf{D}\left[\begin{array}{c}
\frac{\partial S}{\partial a_{1}} \\
\frac{\partial S}{\partial a_{2}} \\
\vdots \\
\frac{\partial S}{\partial a_{N}}
\end{array}\right] .
$$

From equation (B6), $\mathbf{D}=\mathbf{B} \times \mathbf{H}^{-1}$, so the sensitivity coefficients are given by

$$
\left[\begin{array}{c}
\frac{\partial S}{\partial T_{1}}  \tag{B11}\\
\frac{\partial S}{\partial T_{2}} \\
\vdots \\
\frac{\partial S}{\partial T_{M}}
\end{array}\right]=\mathbf{B ~ H}^{-1}\left[\begin{array}{c}
\frac{\partial S}{\partial a_{1}} \\
\frac{\partial S}{\partial a_{2}} \\
\vdots \\
\frac{\partial S}{\partial a_{N}}
\end{array}\right] .
$$

Note that the matrix $\mathbf{H}$ contains sums of residuals multiplied by second derivatives. In general, these terms are
small in comparison with the other terms, partly because the second derivatives are themselves small and partly because the residuals are small and random in sign. Thus we can approximate $\mathbf{H}$ by

$$
\mathbf{H} \approx\left[\begin{array}{cccc}
\sum_{i=1}^{M}\left(\left.\frac{\partial S}{\partial a_{1}}\right|_{T=T_{i}}\right)^{2} & \left.\sum_{i=1}^{M}\left(\frac{\partial S}{\partial a_{1}} \frac{\partial S}{\partial a_{2}}\right)\right|_{T=T_{i}} & \ldots & \sum_{i=1}^{M}\left(\frac{\partial S}{\partial a_{1}} \frac{\partial S}{\partial a_{N}}\right)_{T=T_{i}}  \tag{B12}\\
\sum_{i=1}\left(\left.\frac{\partial S}{\partial a_{2}} \frac{\partial S}{\partial a_{1}}\right|_{T=T_{i}}\right. & \sum_{i=1}^{M}\left(\left.\frac{\partial S}{\partial a_{2}}\right|_{T=T_{i}}\right)^{2} & \ldots & \sum_{i=1}^{M}\left(\frac{\partial S}{\partial a_{2}} \frac{\partial S}{\partial a_{N}}\right)_{T=T_{i}} \\
\vdots & \vdots & \vdots & \vdots \\
\sum_{i=1}^{M}\left(\frac{\partial S}{\partial a_{N}} \frac{\partial S}{\partial a_{1}}\right)_{T=T_{i}} & \left.\sum_{i=1}^{M}\left(\frac{\partial S}{\partial a_{N}} \frac{\partial S}{\partial a_{2}}\right)\right|_{T=T_{i}} & \ldots & \sum_{i=1}^{M}\left(\left.\frac{\partial S}{\partial a_{N}}\right|_{T=T_{i}}\right)^{2}
\end{array}\right] .
$$

Because the matrix $\mathbf{B}$ contains only individual residuals, these terms cannot be neglected.
The other set of sensitivity coefficients, $\partial S / \partial S_{i}$, are obtained by differentiating equation (B1) and each of equations (B4) with respect to each $S_{i}$. The result of differentiating the first of equations (B4) with respect to $S_{1}$, for example, is

$$
\begin{align*}
& \frac{\partial a_{1}}{\partial S_{1}} \sum_{i=1}^{M}\left\{\left(\left.\frac{\partial S}{\partial a_{1}}\right|_{T=T_{i}}\right)^{2}-\left.\left[S_{i}-S\left(T_{i}\right)\right] \frac{\partial^{2} S}{\partial a_{1}^{2}}\right|_{T=T_{i}}\right\} \\
& +\frac{\partial a_{2}}{\partial S_{1}} \sum_{i=1}^{M}\left\{\left.\frac{\partial S}{\partial a_{2}} \frac{\partial S}{\partial a_{1}}\right|_{T=T_{i}}-\left.\left[S_{i}-S\left(T_{i}\right)\right] \frac{\partial^{2} S}{\partial a_{2} a_{1}}\right|_{T=T_{i}}\right\} \\
& +. .  \tag{B13}\\
& +\frac{\partial a_{N}}{\partial S_{1}} \sum_{i=1}^{M}\left\{\left.\frac{\partial S}{\partial a_{N}} \frac{\partial S}{\partial a_{1}}\right|_{T=T_{i}}-\left.\left[S_{i}-S\left(T_{i}\right)\right] \frac{\partial^{2} S}{\partial a_{N} a_{1}}\right|_{T=T_{i}}\right\} \\
& =\left(\frac{\partial S}{\partial a_{1}}\right)_{T=T_{1}}
\end{align*}
$$

Following the same procedure as above, the sensitivity coefficients are

$$
\left[\begin{array}{c}
\frac{\partial S}{\partial S_{1}}  \tag{B14}\\
\frac{\partial S}{\partial S_{2}} \\
\vdots \\
\frac{\partial S}{\partial S_{M}}
\end{array}\right]=\left[\begin{array}{cccc}
\left.\frac{\partial S}{\partial a_{1}}\right|_{T=T_{1}} & \left.\frac{\partial S}{\partial a_{2}}\right|_{T=T_{1}} & \cdots & \left.\frac{\partial S}{\partial a_{N}}\right|_{T T T_{1}} \\
\left.\frac{\partial S}{\partial a_{1}}\right|_{T=T_{2}} & \left.\frac{\partial S}{\partial a_{2}}\right|_{T=T_{2}} & \cdots & \left.\frac{\partial S}{\partial a_{N}}\right|_{T=T_{2}} \\
\vdots & \vdots & \vdots & \vdots \\
\left.\frac{\partial S}{\partial a_{1}}\right|_{T=T_{M}} & \left.\frac{\partial S}{\partial a_{2}}\right|_{T=T_{N}} & \cdots & \left.\frac{\partial S}{\partial a_{N}}\right|_{T=T_{\mu}}
\end{array}\right] \mathbf{H}^{-1}\left[\begin{array}{c}
\frac{\partial S}{\partial a_{1}} \\
\frac{\partial S}{\partial a_{2}} \\
\vdots \\
\frac{\partial S}{\partial a_{N}}
\end{array}\right],
$$

where $\mathbf{H}$ is given by equation (B9) and is well approximated by equation (B12).

