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'WIGGLE MATCHING' RADIOCARBON DATES

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ABSTRACT. This paper covers three different methods of matching radiocarbon dates to the 'wiggles' of the calibration curve in those situations where the age difference between the ^{14}C dates is known. These methods are most often applied to tree-ring sequences. The simplest approach is to use a classical Chi-squared fit of the ^{14}C data to the ^{14}C curve. This gives the calendar date where the data fit best and allows tests of how good the fit is. The only drawback of this method is that it is difficult to ascertain the uncertainty in the date found in this way. An extension of this technique uses a Monte-Carlo simulation to sample possible ^{14}C concentrations consistent with the measurement made and for each of these possibilities performs a Chi-squared fit. This method yields a distribution of values in the calendrical time-scale, from which the overall dating uncertainty can be derived. A third, rather different approach, based on Bayesian statistics, calculates the relative likelihood of each possible calendar year fit. This can then be used to calculate a range of most likely dates in a similar way to the probability method of ^{14}C calibration. The theories underlying all three methods are discussed in this paper and a comparison made for the fitting of specific model sequences. All three methods are found to give consistent results and the application of any one of them depends on the nature of the scientific question being addressed.

INTRODUCTION

The calibration of a single radiocarbon date from the notional "^{14}C age" to the true "calendar age" almost always results in a considerable loss of precision. This is because the calibration curve, which can be interpolated as a function R of time t with an uncertainty δR :

$$r = R(t) \pm \delta R(t) \tag{1}$$

is not smooth and monotonic. There is, therefore, no single valued, differentiable, inverse function which can be used for calibration.

It has long been realized that if several different points on this curve are sampled, where the age relationship is well characterized, the ^{14}C data can be fitted to the shape of the function $R(t)$. This technique is often, loosely speaking, referred to as 'wiggle matching'. The simplest example of this is the case of tree rings where the age difference between the rings is known precisely and ^{14}C measurements can, in principle, be made over several hundred years. In practice 'wiggle matching' in the broadest sense can also be applied in cases where the relationships are described only in terms of sequences, phases and other similar constraints (see Bronk Ramsey 1994, 1995, 1998; Buck et al. 1991, 1992, 1998; Lange 1998; Manning and Weninger 1992; Weninger 1997; Jöris and Weninger 2000) but this is not the subject of this paper.

As a first approximation a series of ^{14}C dates made on material with known age separations can be matched to the calibration curve by eye. This will quickly show where the data fits to the curve, and indeed how good that fit is. It seems useful, however, to be able to define this fitting process in more mathematical terms, especially when the resulting fit is to be used in further statistical analysis or for something as important as extensions to the calibration curve itself.

In this paper, we will look at three statistical techniques, which although not an exhaustive list, cover the main approaches likely to be used.

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In all cases in this paper we will consider a series of samples that are related to an event that occurred at time t_s. This might, for example, be the date of the falling of a tree. The samples (numbered $i = 1 - n$) are all dated relative to this event by independent means (for example tree-ring counting) so that the age of each sample can be given by:

$$t_i = t_s + \Delta t_i .$$
(2)

The aim of the exercise is to determine a value for t_s given a series of ^{14}C measurements $R_i \pm \delta R_i$ made on the samples themselves.

The χ^2 Test

The most obvious classical statistical tool to apply to the wiggle matching of tree-ring sequences is the χ^2 test. To use such a test we can first define a suitable χ^2 function. In this case we chose this function to be:

$$F(t_s) = \sum_{i=1}^{n} \frac{(R_i - R(t_s + \Delta t_i))^2}{\delta R_i^2} .$$
(3)

This term can then be further modified to the reduced χ^2 distribution by dividing by $(n-1)$. This is the term calculated, for example by the program CAL25 (van der Plicht 1995). If the uncertainties in the calibration curve are also included this gives:

$$F(t_s) = \sum_{i=1}^{n} \frac{(R_i - R(t_s + \Delta t_i))^2}{\delta R_i^2 + \delta R(t_s + \Delta t_i)^2} .$$
(4)

Either of these functions $F(t_s)$ or $F'(t_s)$ then gives us an χ^2 value for all possible values of t_s. A minimum in this χ^2 value can then easily be obtained and this gives us both the best fit t_m and a χ^2 value for the goodness of fit at this point $(F(t_m))$.

Effectively this method is merely a minimization of the weighted sum of squares of the measured points from the calibration curve itself (a method used, for example, in Pearson 1986). In some cases it is possible that there will be two or more minima in the function $F(t_s)$ although, in general, for cases where $n > 2$, we would expect there to be one minimum that is lower than the others.

By its nature, this method normally only gives one answer. We can find, from statistical tables, the maximum value, F_{crit}, of $F(t_m)$ that is acceptable for any degree of confidence. It is tempting to use this to define a range of possible ages by looking at the range in which $F(t_s) < F_{crit}$. This does indeed define the range of possible values for which there is an acceptable fit, but it has the very unsatisfactory characteristic that the larger the scatter on the measurements, the narrower the uncertainty limits. It seems to us, therefore, that it would be unwise to use this to define uncertainties in the fit.

There are several attempts (for example Kilian et al. 1995, 2000) to add uncertainty limits using classical statistics and making some assumptions about the nature of the function $R(t)$. Many of these are quite complex and will not be discussed further here since either of the probabilistic approaches described here do give error limits without making any assumptions about the nature of the curve, or assuming that any such uncertainties will be normally distributed.

Monte Carlo Wiggle Matching

A direct extension of the fitting process described above is to consider, numerically, the range of ^{14}C values that are consistent with the measurements made.

Given the measurement made on any individual sample, $R_i \pm \delta R_i$, we can assume that the true value is likely to lie near this value and that the probability distribution for the true value is Normal:

$$p(R_{i1}) \propto \exp\left(-\frac{(R_{i1} - R_i)}{2\delta R_i^2}\right). \tag{5}$$

Using Monte-Carlo techniques we can produce a whole set of possible ^{14}C values for the samples measured, and possible points on the calibration curve. Then, using the χ^2 test outlined above, we can evaluate an optimal fit t_{m1}. The process can then be repeated a large number of times, p, to produce a whole series of possible solutions:

$$t_{m1}, t_{m2}, t_{m3}...t_{mp} \tag{6}$$

These solutions can then be plotted as a histogram, which will illustrate the range of possible values. To estimate a range at 95% probability, a range can be selected by numerical integration, which contains 95% of the area under the histogram. To check the goodness of fit the average value of the χ^2 function can be evaluated for all solutions. This method is then capable of using classical statistics, in conjunction with Monte-Carlo modeling to give us a goodness of fit and a realistic range of possible solutions.

There are a number of implementation problems that complicate this method. The most serious of these, from a theoretical standpoint, is that at each stage of the Monte-Carlo simulation, only one solution is chosen, although there could be two, almost equally good, fits. If in such circumstances the lowest or highest one is always chosen (or indeed the average between the two) this could introduce a significant bias. Care is needed in the detailed treatment of such cases. Another problem, of a more practical nature, is the large number of iterations needed to get a smooth distribution—this follows from the method being stochastic rather than analytical. In practice, using the GaussWM program (Weninger 1997; Lange 1998; Jöris and Weninger 2000), as we shall see, neither of these prevent this technique from giving reliable solutions.

It should be noted that the assumption underlying this technique, is that, during the Monte-Carlo simulation, *a priori* all possible ^{14}C measurements are assumed to be equally likely. During the χ^2 fit, all calendar dates are assumed to be equally likely.

A Bayesian Approach

A third approach which does not use Classical Statistics at all is the Bayesian, probabilistic approach. In this we make use of the probability distributions generated when calibrating single ^{14}C dates. If we consider the ^{14}C date on one of our samples, $R_i \pm \delta R_i$, this can be used to calculate a probability density function for the true calendar age of this single sample. This will be

$$P_i(t_i) \propto \frac{\exp(-(R_i - R(t_i))^2/2(\delta R_i^2 + \delta R^2(t_i)))}{\sqrt{\delta R_i^2 + \delta R^2(t_i)}} \tag{7}$$

This function, then, tells us about the age of the single sample. However, we know that $t_i = t_s + \Delta t_i$ and so we can use it to provide us with an estimate of the likelihood of different values of t_s:

$$P_i(t_s + \Delta t_i) \propto \frac{\exp(-(R_i - R(t_s + \Delta t_i))^2 / 2(\delta R_i^2 + \delta R^2(t_s + \Delta t_i)))}{\sqrt{\delta R_i^2 + \delta R^2(t_s + \Delta t_i)}}. \tag{8}$$

Using the Bayes theorem, we can then say that given all of the measurements made on the n different samples, we can arrive at a probability distribution for t_s given all of the available information:

$$P_s(t_s) \propto \prod_{i=1}^{n} P_i(t_s + \Delta t_i). \tag{9}$$

This calculation can be performed numerically without using stochastic Monte-Carlo techniques and generates a probability distribution for t_s similar to that generated by the Monte-Carlo technique. Again, a range containing 95% of the area of the curve can easily be deduced by numerical integration.

This is the method employed by OxCal (Bronk Ramsey 1994, 1995, 1998) and others (Christen and Litton 1995; Goslar and Madry 1998). Here, it should be noted that the *a priori* assumption is that all possible calendar ages for t_s are equally likely. It is not assumed that all ^{14}C measurements are equally likely. Given that $R(t)$ is a non-linear function, this assumption is different from that made using the Monte-Carlo technique.

In order to test for the goodness of fit, an overlap integral (essentially a pseudo-Bayes-Factor) can be calculated and this is the method employed in OxCal. This overlap integral relates the posterior probability distribution to the likelihood distribution for individual measurements:

$$A_i = \frac{\int P_s(t_s) P_i(t_s + \Delta t_i) dt_s}{\int P_i(t_s + \Delta t_i)^2 dt_s}. \tag{10}$$

This is expected, on average, to have a value close to 1 (expressed as 100% in the program output). The overall agreement, $A_{overall}$ is defined as a product of these terms, taken to a power of $1/\sqrt{n}$ on the grounds that, for independent distributions, the factor variation from 1 should be something like a random walk and so the power scale as $\sqrt{n}$.

$$A_{overall} = \left[\prod_{i=1}^{n} A_i \right]^{1/\sqrt{n}} \tag{11}$$

For independent distributions the threshold of acceptability for this overall agreement index does not depend on n. In the case of combinations of the type performed for wiggle matching, however, the posterior distributions are not all independent and the threshold which corresponds to the χ^2 test at 5% is:

$$A_n = \frac{1}{\sqrt{2n}}. \tag{12}$$

This threshold can be used to calculate whether the scatter of the measurements is larger (at 95% confidence) than would be expected (see OxCal manual and Bronk Ramsey 1995 for more details).

Comparison of the Techniques

In order to compare these three approaches, a series of tests has been performed on five data-sets. The χ^2 test was performed both using CAL25 (without uncertainty on the calibration curve) and with a development version of OxCal v3.5 (with uncertainty on the calibration curve). The Monte-Carlo technique was performed using GaussWM (Weninger 1997; Lange 1998; Jöris and Weninger 2000) and the Bayesian technique, OxCal v3.4 (Bronk Ramsey 1995).

Test Data-Sets

Two tests were performed on a linear "calibration curve" with one year error terms. In this case it is possible to calculate what the range of possible values ought to be. In both cases there were 16 data points with error terms of ±40 years with the last point being 1300 AD. In one case the points were exactly on the curve and in the second, more scattered than you would expect from a gaussian distribution. The results of the fits in these cases should have centred on 1300 AD with ranges of 1290–1310 AD for 68% probability and 1280–1320 AD for 95% probability, based on the reduced standard error.

Another three tests were performed on artificially generated sequences with the 1986 calibration curve. The first of these was chosen to be well behaved, the second to be more scattered than expected, and the third to give rise to two possible fits. The first two had sixteen points and the third only four. The data fitted are summarised in Table 1.

Table 1 Data to be 'wiggle matched'in the five tests

Test	Method	Fit for last point in series			Agreement
		Center point	**68% range**	**95% range**	
1) - 16 points	χ^2 fit[a]	1300			χ^2=0 (<25.0)
linear curve	χ^2 fit[b]	1300			χ^2=0 (<25.0)
linear points	Monte-Carlo	1300 ± 9.8	1289–1310	1280–1319	
	Bayesian		1289–1311	1280–1320	A=355% (>17.7%)
	Theoretical[a]	1300	1290–1310	1280–1320	χ^2=0 (<25.0)
2) - 16 points	χ^2 fit[1]	1299			χ^2=28.2 (>25.0)
linear curve	χ^2 fit[2]	1300			χ^2=28.1 (>25.0)
scattered points	Monte-Carlo	1300 ± 9.9	1289–1310	1280–1319	
	Bayesian		1289–1311	1280–1320	A=13.0% (<17.7%)
	Theoretical[a]	1300	1290–1310	1280–1320	χ^2=28.2 (>25.0)
3) - 16 points	χ^2 fit[a]	1299			χ^2=12.2 (< 25.0)
1986 curve	χ^2 fit[b]	1300			χ^2=10.7 (<25.0)
typical example	Monte-Carlo	1300 ± 4.9	1295–1304	1287–1313	
	Bayesian		1295–1304	1289–1310	A=111% (>17.7%)
4) - 16 points	χ^2 fit[a]	1302			χ^2=32.1 (>25.0)
1986 curve	χ^2 fit[b]	1303			χ^2=30.2 (>25.0)
scattered points	Monte-Carlo	1300 ± 3.6	1299–1307	1297–1310	
	Bayesian		12982–1308	1294–1312	A=13.2% (<17.7)
5) - 4 points	χ^2 fit[a]	1147			χ^2=0.08 (<7.8)
1986 curve	χ^2 fit[b]	1149			χ^2=0.003 (< 7.8)
bimodal solution	Monte-Carlo	1116 ± 27.1	1090–1156	1080–1166	
	Bayesian		1092–1119	1086–1163	A=128% (>35.4%)
			1140–1157		

[a]Ignoring uncertainty in calibration curve
[b]Taking account of the uncertainty in the calibration curve

Resulting Fits and Ranges

The results for all of these tests are shown in Table 2. As can be seen from this the agreement between the techniques is excellent. The minimum of the χ^2 fit always lies within the ranges give by the other two techniques. This is as one would expect. The Bayesian approach, which calculates a probability density $P_s(t_s)$, is approximately equal to a simple function of $F'(t_s)$:

$$P_s(t_s) \propto \exp(F'(t_s)/2) . \tag{13}$$

Thus the minimum in $F(t_s)$ or $F'(t_s)$ which occurs at t_m, will always be a maximum of $P_s(t_s)$ (as pointed out by Goslar and Madry 1998). In fact, this is only, strictly speaking, true if the error terms in the calibration curve, $\delta R(t)$, are either constant over the period of interest, or insignificant compared to the errors, δR_i of the measurements to be matched.

Table 2 Results of the "wiggle matching" tests using three different techniques

Test	Data to be fitted			Calibration curve
	^{14}C ages (BP)	±	Gaps	
1) - 16 points linear curve linear points	950, 930, 910, 890, 870, 850, 830, 810, 790, 770, 750, 730, 710, 690, 670, 650	40 ...	20 ...	Linear Gradient: 1 $1950 \equiv 0BP$ Uncertainty: 1 year
2) - 16 points linear curve scattered points	875, 930, 985, 890, 795, 850, 905, 810, 715, 770, 825, 730, 635, 690, 745, 650	40 ...	20 ...	Linear Gradient: 1 $1950 \equiv 0BP$ Uncertainty: 1 year
3) - 16 points 1986 curve typical example	1087, 1000, 997, 854, 927, 963, 907, 877, 902, 857, 829, 832, 786, 813, 637, 659	40 ...	20 ...	1986
4) - 16 points 1986 curve scattered points	1127, 1000, 937, 854, 987, 963, 847, 877, 962, 857, 769, 832, 846, 813, 577, 659	40 ...	20 ...	1986
5) - 4 points 1986 curve bimodal solution	1280, 1200, 1120, 930	30 ...	100, 100, 200	1986

It can also be seen that in the case of the linear calibration curve this is simply the reduced exponential function from the combination of all of the error terms.

Both the Bayesian approaches and the χ^2 fit sample the calendar date space. The Monte-Carlo wiggle match explores the possible ^{14}C space and fits a representative selection of possible values on to

the calendar axis. There is, therefore, no reason to expect the results to be in exact agreement. The fact that they are so close is therefore a good indication of the robustness of the deduced ranges to different underlying assumptions. To put this in Bayesian terms, the Monte-Carlo technique assumes, it *a priori* that all possible ^{14}C measurements are equally likely during the sampling procedure whereas the Bayesian approach used here only assumes that all calendar ages for the sequence are equally likely. The distinction is in fact very close to that between the intercept method of calibration and the probabilistic method. Both have their merits.

Diagnostics of Poor Fit

All of the methods examined here do have some form of diagnosis for how good the fit was. In the case of the Bayesian method, this is an overlap integral that is a pseudo-Bayes-factor. The thresholds, A_n, for the agreement index in these cases should be 17.7% for 16 points or 35.4% for 4 points. Using these correctly identifies the two test series that were more scattered than should be expected (tests 2 and 4).

The other two methods use the χ² value as a test of goodness of fit. For 16 points, in 95% of cases, this should fall below 25. For 4 points the test value is 7.8. Again, the series with excessively scattered values can be identified. From version 3.5 of OxCal, the minimum χ² value is also calculated and tested when performing a wiggle match.

Limits in Uncertainty

From the results outlined above, it seems that the agreement between the methods is good and that the error limits determined by two different methods are both very similar. These ranges also correspond to the theoretical ones where these are calculable and they are therefore probably realistic given the assumptions common to both. It is worth considering what these assumptions are and how they might affect our interpretation of such analyses.

Calendar Date Accuracy of Calibration Curve. Clearly, any match of this sort is only as accurate as the calendar dates of the calibration curve itself. For the periods where such a technique is likely to be used this is probably not a worry. In other cases, where the method is being applied to matches of floating chronologies, it must always be remembered that the match only gives a relative and not an absolute date.

Calibration Curve Interpolation and Span of Measurements. More significant is the fact that the calibration curve must usually be interpolated in order to perform any of these analyses. It is not easy to see, in general, what effect this might have but certainly changing between a linear and a cubic interpolation makes a difference of no more than a year or two.

A related but distinct point is that the measurements made for the calibration curves themselves are typically on tree rings spanning several years, whereas those which are being matched may be for single years, of for spans of different length. Ultimately, this comes down to the question of how different would an annual calibration curve be from one made on, for example, decadally averaged material. Clearly, the latter should be the average of the former and one would expect any such effects to be random rather than systematic across the points being matched. Thus, the overall accuracy of any match is not likely to be significantly compromised but the level of agreement might well be poorer than expected.

Density of Points. More serious consideration needs to be given to the density of sampled points being matched. The assumption underlying all of these techniques is that each measurement, and its

comparison to the calibration curve, is independent. Given that the curve is interpolated, this will clearly not be the case if the matched points are more densely clustered than the points on the calibration curve itself. In such cases, we would recommend matching the curve to the new data points rather than the usual match of data points to the curve.

Measurement Bias. Another serious concern is systematic offsets in the measurements on the calibration curve and those made on the samples to be matched. [14]C labs will usually keep a close eye on any such possible offsets by measuring standards of known ^{14}C composition, or indeed wood from the tree rings used to make the calibration curve. However, such biases will almost certainly exist even if they are well under 10 years. Similarly, geographical effects also cannot be ruled out.

This is a problem for ^{14}C dates more generally but given that the precisions obtainable by "wiggle-matching" are so very high, it needs special consideration here. Comparison of tests 1 and 3 illustrate the power of the method to achieve high precision. With a linear calibration curve, 16 points with uncertainties of ±40 will give a range at 95% of 40 years. With the real calibration curve this drops to only 20 years, since the data can be "keyed in" to the shape of the curve.

If we consider the potential effect of an overall bias in the measurements of 10 years, with the linear calibration curve this will clearly shift the resulting fit by 10 years. However, if we try this with test example 3, it turns out that the shift is only about 3 years. So we find that the matching of the data to the wiggles in the curve, in this case, not only improves the precision by a factor of two but it improves the robustness to minor offsets by an even greater factor. This is not entirely unexpected; where there is a good tight match, we are effectively using sections of the curve with a high gradient, and so we would expect changes in the measured ^{14}C concentration to have a reduced effect on the deduced calendar age.

CONCLUSIONS

The three methods of "wiggle-matching" [14]C dates in sequences with known gaps that we have looked at here all seem to give results which are in good agreement. We also find that the two methods that generate probable age ranges both produce similar ranges even though the underlying assumptions are different.

The ranges of dates obtainable by these techniques can be even tighter than the combined errors in the ^{14}C measurements. This is because the data can be fitted to the shape of the calibration curve. This enhanced precision is also associated with an increased robustness to minor measurement offsets and so we do believe that the ranges generated in this way can be trusted.

However, a number of considerations do limit the ultimate precision obtainable. The calibration curve accuracy on the calendar age axis is clearly fundamental. Care must also be taken to ensure that the data points being matched are not more closely spaced that the points on the calibration curve. Overall measurement biases seem to have only a minor effect but will provide a limit in accuracy at some point (probably of the order of 3–4 years). The implications of the interpolation of points on the calibration curve is difficult to quantify but would be expected to be less than 5 years. Overall, we would recommend that once the analyses have been performed, an extra latitude of about 5 years either way be allowed in any interpretation.

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