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Statistical modelling of the conditioning curve, and validation of the rapid conditioning criterion proposed in Report SG05 at Christchurch

By

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SUMMARY

Curve-fitting algorithms have been used on data from mass-time and diameter-time plots to find statistically-based models of the conditioning process. Whilst a near-optimum functional solution appears to have been found, the model obtained is neither practical nor easily applicable for determining "time to condition", especially under rapid conditioning. The method previously proposed in Christchurch is therefore judged the most physically appropriate and practical for determining the “time to condition” for rapid conditioning.

Data is presented on diameter and colour measurement that confirms the adequacy of the significantly-shortened rapid conditioning time indicated by the “theta” method previously proposed.

The proposals offered in Christchurch are therefore re-submitted for approval approval specifically in respect of the criterion for rapid conditioning in IWTO-52.

INTRODUCTION

This work follows on from that detailed in Report SG05 presented at Christchurch[1]. Following presentation of that report, it was requested that the criterion proposed for determining “time to condition”, especially in respect of rapid conditioning, be validated.

Additionally there was later discussion concerning the most appropriate model to describe the general shape of the conditioning curve (i.e. the mass versus time relationship, or diameter versus time relationship).

Both these issues are examined in this report.

CURVE-FITTING

Method

Separate files were obtained of the mass versus time data for the measurements summarized in the referenced paper, together with two diameter versus time datasets obtained using the OFDA 2000 instrument, and also mentioned in that paper. The primary aim was to fit the mass-time data, but the OFDA plots were included for interest since they provided a slightly different perspective on the conditioning process.

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[1] A new criterion for “time to condition”, with data on rapid conditioning of opened fibre assemblies, P. Baxter, IWTO Report SG05, Christchurch, April 2000.

Each file was then input to a commercial curve-fitting algorithm[2]. This program submits the data to 60 pre-defined nonlinear regression models, and ranks the performance based on a selection of goodness of fit criteria. User-defined models can also be tested and ranked against the pre-defined models.

In addition to the pre-defined models, two specific models that are commonly used for growth curve analyses (Gompertz and Logistic)[3] were also tested on one of the data sets, together with a range of variations on sigmoidal models documented by Ratkowsky[4].

Results

10 datasets, comprising 8 mass-time and 2 MFD-time sets were examined. These represented wool being conditioned from dry in various density conditions, from very open to tightly packed (in the range of approximately 7 to 337 kg/m³).

Various measures of goodness of fit are provided by the *DataFit* program, but for simplicity, the results are shown in residual sum of squares ranking order, up to rank 50, with R^2 values only in Appendix 1. Also included are the first 12 non-polynomial fits for the Shirleyed web sample for the higher ranked functions. The Gompertz and Logistic sigmoidal variation model results are not shown since they were evaluated subsequent to production of the table - however, they were poorly ranked (rank 15 and over), and therefore of no consequence in the ensuing discussion.

At this point it is worth briefly considering the philosophy behind the selection of models in work of this type. The datasets are, from one perspective, very detailed, since they include measurements of mass or MFD at one minute intervals over periods of up to 100 hours. However, in some cases it is necessary to ensure that the curve-fitting ignores significant perturbations to the “pure” form of the curves, arising from a variety of causes. (Such as small shifts in environmental conditions over the period, inadequate correction algorithms in the case of the coned yarns, “noise” due to balance oscillations in the conditioning airflow, or statistical sampling variances in the case of the MFD data.)

With such detailed data it is feasible to obtain precise fits on a wide range of functions. However, caution must be observed in the way these are interpreted. Firstly, it is possible to “over-fit” the available data – in other words, to select the function which best fits all 10 examples, including spurious perturbations, only to find later that it performs poorly on the 11th data set. Secondly, we must bear in mind the reason for doing this work – we are seeking a method which might be applicable as a working model in practice, but which would be applied in all probability to data with only limited numbers of observations. For example, in rapid conditioning work, there may be only 5 or 6 useful observations in the period prior to complete stability. In that case there is no point in considering a model with 10 unknown coefficients – it would be simply impossible to determine them. Even with only 3 coefficients in a model, the precision obtainable for the coefficients would be very poor in this case. Given sufficient time and resources, it may be possible to include a wider range of models, but given the limited return from the current selection, one must question the logic of such an approach.

Therefore it should be clear that we need to seek the most “elegant” function with the least number of unknown coefficients that gives a relatively low residual sum of squares. Additionally, there is one other constraint – we are primarily interested in the terminal fit (at large time), rather than the initial fit (at small time). In the case of the function family known generically as growth curves, the initial portion of the curve may have a significant effect on the residuals, and yet be irrelevant to the overall problem, and it is therefore vital to study the form of the curves and not simply the tabulated outcomes.

It will readily be seen from the tables in Appendix 1 that the best fits were generally obtained with high order polynomials. This should come as no surprise, but since such functions are of limited practical use in work of this type, they were ignored. All the models near the top of the table with only 2 unknown coefficients gave fits at large time which were not considered adequate.

Of the models with 3 unknown coefficients, none gave totally satisfactory fits on all 10 datasets. The optimum function from the selection tested seemed to be the following:

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[2] *DataFit*, version 7.0.36, Oakdale Engineering, 23 Tomey Road, Oakdale, PA 15071, USA

[3] Statistical Forecasting, Warren Gilchrist, John Wiley & Sons, 1976, Chapter 9.

[4] Choosing non-linear regression models, D.A. Ratkowsky, Symp. On Regression Analysis, NSW branch Stat. Soc. Aust. Aug 1979

$$y = x / (a + b.x + c.x^2) \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(1)$$

where x corresponds to the time variable, and y corresponds to the response – either regain or change in mean fibre diameter.

Examples of the levels of fit for equation 1 are shown in figures 1 and 2. Refer to Appendix 1 for fits to other functions with low residuals ranking. This specific function did not, however, provide a particularly good fit at large time on the broader of the two fibre samples measured on the OFDA 2000.

Figure 1: Model using equation 1 applied to fibre after Shirley analysing

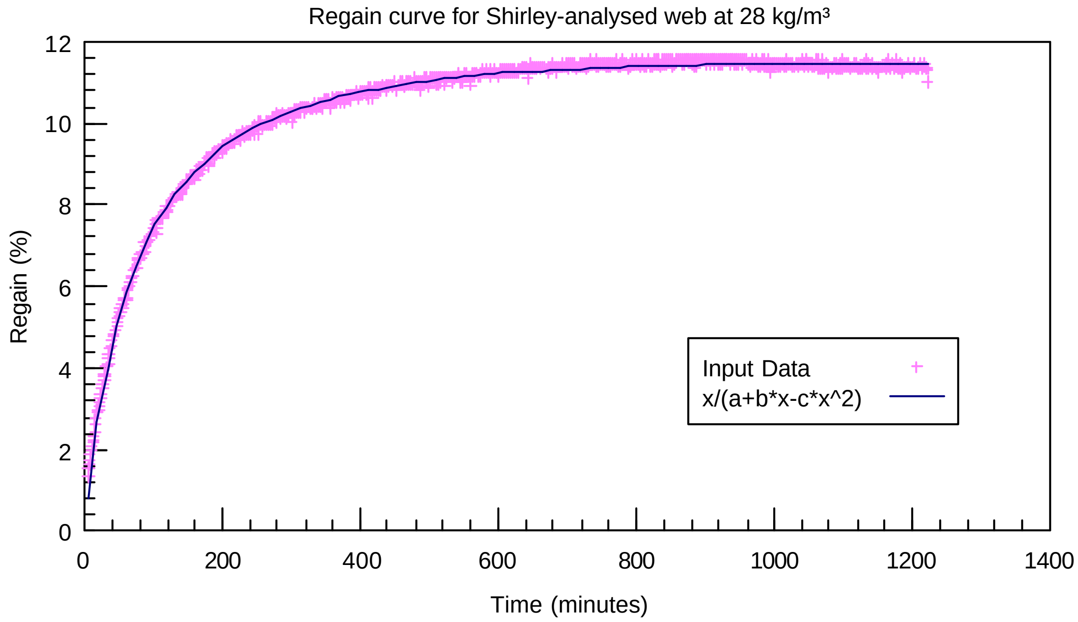
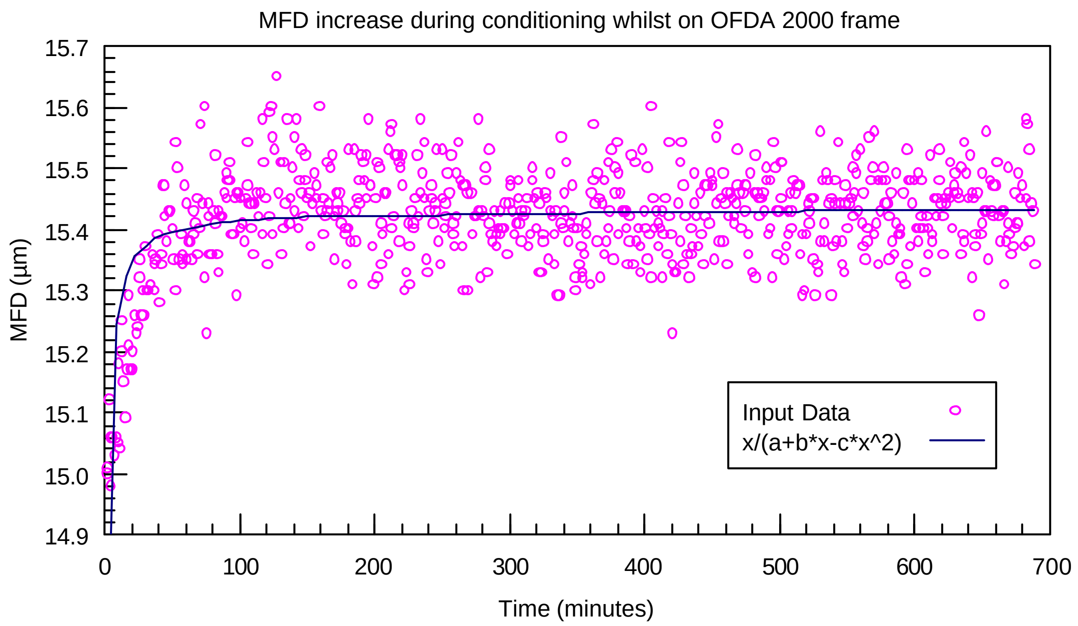


Figure 2: Model using equation 1 applied to 15 µm web measured on OFDA 2000



Comments and observations

The function shown in equation 1 is, unfortunately, far from ideal in terms of the main aim of this work. There are three unknown coefficients, which is regarded as one too many, especially for determining “time to condition” under rapid conditioning; and it does not readily lend itself to simplification so as to allow determination of an end-point, which is a reasonable pre-condition for deployment in a test method.

By comparison, the “theta” method outlined in the Christchurch report requires the determination of only one statistical parameter, and is based on sound physical principles. Its use was demonstrated to be both theoretically and practically much more precise in estimating the “time to condition” than the method currently given in the test method, since it uses a simple plotting method to minimise "noise". It therefore seems both logical and sound to continue with this approach.

VALIDATION OF THE “THETA” MODEL DURING RAPID CONDITIONING

Method

The “theta” model was outlined in the previous paper given at Christchurch. Table 2 in that paper indicated that for the rapid conditioners used in our laboratories, the “time to condition” could be reduced from 102 minutes to 44 minutes. As requested during discussion of the paper at Christchurch, this reduced conditioning time has been validated using MFD measurements on production samples.

Over a period of 5 separate days, spread over several weeks, 100 samples in total were measured for both airflow and colour after 44 minutes in the rapid conditioner. The test specimens were then recombined with the surplus material and replaced in the rapid conditioner for a further hour (bringing their total exposure up to the normal “time to condition”). After re-measurement they were again replaced in the rapid conditioner, the fan speed was reduced to about 1/3 of normal to retain circulation without excessive filtering, and the samples kept there for 24 hours before being re-measured.

Results

The characteristics of the samples used in the validation are summarized in Table 1:

Table 1: Characteristics of the sample set used to validate the “theta” method

Property	No. samples	Minimum	Maximum	Average
Airflow MFD µm	100	18.8	41.1	33.4
Colour Y units	100	45.3	67.6	61.7
Colour Y-Z units	100	-1.5	10.3	3.0

The samples covered virtually the full range of diameters and colours likely to be encountered routinely in New Zealand.

The measurement results at 24 hours were taken as the baseline, and for each sample the difference was calculated between this value and the 44 and 100 minutes exposures respectively. Analyses of variance were carried out to establish whether there were any effects attributable to the different days on which the work was carried out, or whether there was any level dependency in the differences. It was found that there was no detectable level-dependency for any of the parameters, but there was a small but detectable difference between the sets carried out on different days for diameter but not colour. On examination of the data sets, there was no physical explanation to be attributed to this observation, simply that the airflow measurements were sufficiently precise that small statistical differences could be detected between the 5 different averages of 20 paired observations.

The mean differences over the 100 samples, between the 24 hour measurements and the 44 and 100 minute exposures are detailed in table 2. Full analysis details as required by IWTO-0 are detailed in Appendix 2.

Table 2: Mean differences between baseline (24 hours) and 44 and 100 minute exposure times

Property	**44 minutes**	**100 minutes**	**44 to 100 diff.**
Airflow MFD µm	+0.04 (0.34) ns	-0.02 (0.29) ns	+0.06 (0.36) ns
Colour Y units	+0.45 (0.49) ***	+0.29 (0.26) ***	+0.16 (0.35) ***
Colour Y-Z units	+0.26 (0.23) ***	+0.11 (0.24) ***	+0.14 (0.20) ***

Discussion and comments

The results summarised in table 2 and detailed in Appendix 2 indicate that mean fibre diameter is as stable after 44 minutes of rapid conditioning as it is at both the standard "time to condition" and after the 24 hours extended period. It should be noted that the latter exposure was under conditions of airflow in excess of those normally encountered when samples are left on racks to condition, and therefore might reasonably be said to completely represent the long-term stable condition. In our diameter-colour conditioning room, the air velocities in most locations in the room are of the order of at least 0.05 m/sec, and with the rapid conditioners running there is no possibility of there being "dead space".

The colour results deserve some discussion. Positive differences indicate that the first measurement was higher on average. In other words, the Y results at 44 minutes were higher than at 100 minutes, which in turn were higher than at 24 hours. This suggests that the wool was getting duller the longer it was exposed to airflow. This is consistent with experience – the wool picks up minute particles of dust from the atmosphere as it effectively filters the air in the room[5]. From this perspective, the least time in the rapid conditioner the better.

The Y-Z differences are slightly harder to understand. Again, the positive differences indicate that the Y-Z values were higher at the start than at the end. If, as suggested, the dust in the room is responsible for the colour change, then it must have had a proportionately greater effect on Y than on Z. Indeed when the raw data was examined in detail, it was clear that the Z values on average did not change between 44 minutes and 100 minutes, but deteriorated by 0.2 units over the period from 100 minutes to 24 hours.

On this basis, it can be concluded that the predicted 44 minutes of exposure to rapid conditioning, as calculated using the "theta" method, is validated as satisfactory for diameter measurement. It is also considered valid for colour measurement, since the apparent deterioration in colour with prolonged conditioning is consistent with prolonged filtering of dust particles from the atmosphere by the samples.

CONCLUSIONS

1. The investigations outlined suggest that the complete conditioning process cannot be modeled by a simple or elegant function that lends itself to being easily used in a test method of this nature. It is therefore concluded that the process proposed in the Christchurch paper, based as it is on physical principles, relatively easy to apply, and precise in its results, should be accepted as the replacement criterion for rapid conditioning in IWTO-52.

2. The significantly-shortened rapid "time to condition" of 44 minutes, determined in our laboratory, has been validated by comparison with both the current "time to condition", and the long-term condition, for both mean fibre diameter and colour. The work confirms that prolonged exposure in a rapid conditioner can lead to an apparent slight deterioration of colour.

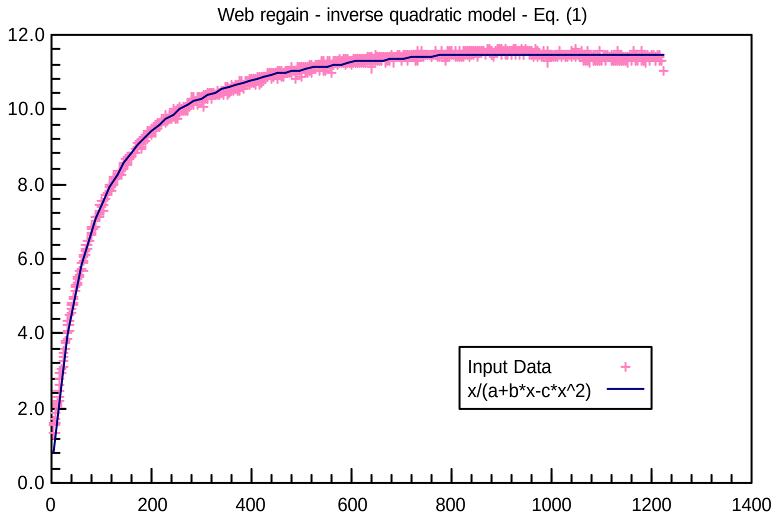
3. The committee is therefore requested to formally consider accepting the proposal first outlined at Christchurch, but now made specific to the rapid conditioning process only, with text modifications as detailed in Appendix 3.

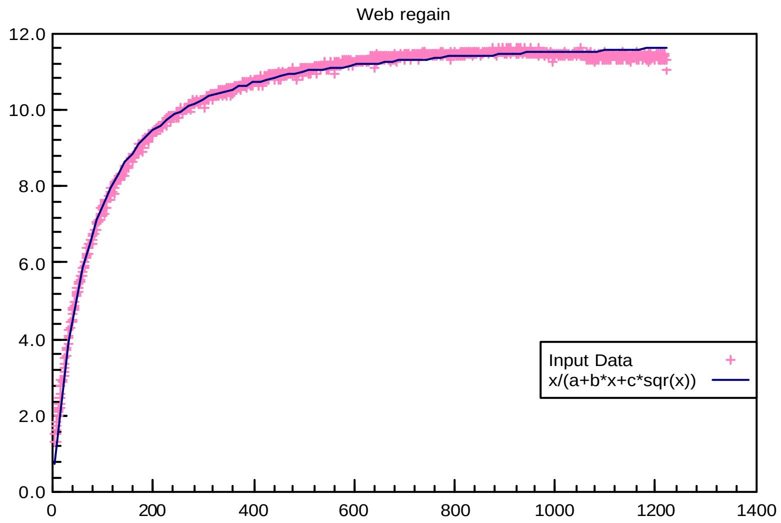
[5] S. Ranford, WRONZ, Pers. Comm.

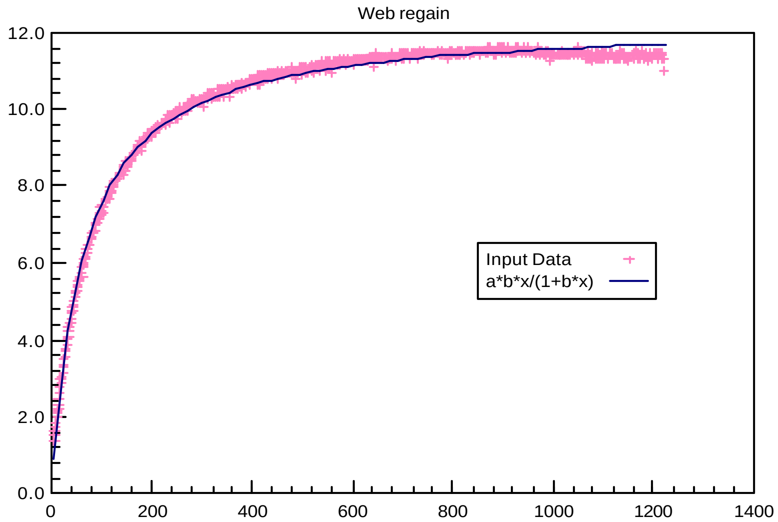
Appendix 1: Details of the outcome of regression ranking using 'DataFit'

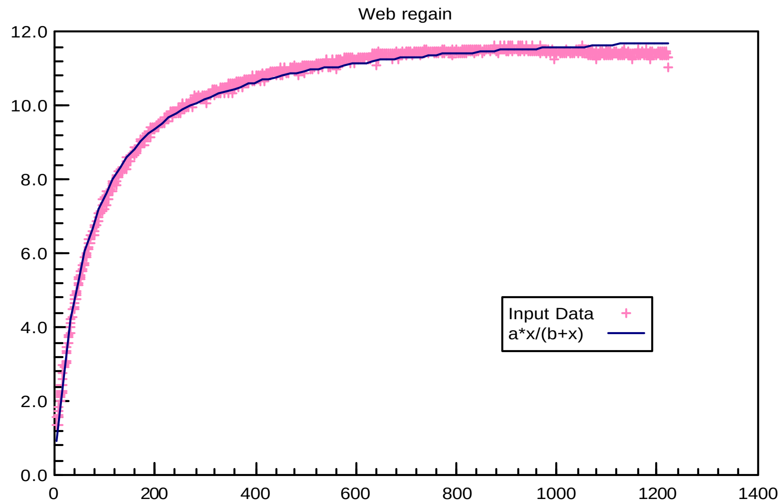
Rank	Coned yarn - 337 kg/m^3	R^2	Coned yarn - 192 kg/m^3	R^2	Loose Yarn - 25 kg/m^3	R^2	Worsted fabric - 183 kg/m^3	R^2	Woollen felt - 151 kg/m^3	R^2
1	Tenth order polynomial	0.993	Tenth order polynomial	0.987	x/(a+b*x-c*x^2)	0.990	Tenth order polynomial	1.000	Tenth order polynomial	1.000
2	Ninth order polynomial	0.992	Ninth order polynomial	0.987	x/(a+b*x+c*sqr(x))	0.987	x/(a+b*x-c*x^2)	0.999	Ninth order polynomial	1.000
3	Eighth order polynomial	0.985	Eighth order polynomial	0.987	Tenth order polynomial	0.987	Ninth order polynomial	0.999	Eighth order polynomial	0.999
4	exp(a+b/x+c*log(x))	0.970	Seventh order polynomial	0.961	Ninth order polynomial	0.982	Eighth order polynomial	0.999	Seventh order polynomial	0.999
5	a*exp(b/x)	0.969	x/(a+b*x-c*x^2)	0.919	Eighth order polynomial	0.978	x/(a+b*x+c*sqr(x))	0.999	Sixth order polynomial	0.999
6	Seventh order polynomial	0.961	a*x/(b+x)	0.915	a*x/(b+x)	0.975	Seventh order polynomial	0.997	x/(a+b*x+c*sqr(x))	0.998
7	x/(a+b*x-c*x^2)	0.960	x/(a*x+b)	0.915	a*b*x/(1+b*x)	0.975	Sixth order polynomial	0.994	a*x/(b+x)	0.998
8	x/(a*x+b)	0.955	a*b*x/(1+b*x)	0.915	x/(a*x+b)	0.975	x/(a*x+b)	0.992	a*x^5+b*x^4+c*x^3+d*x^2+e*x+f	0.997
9	a*x/(b+x)	0.955	exp(a+b/x+c*log(x))	0.909	Seventh order polynomial	0.972	a*b*x/(1+b*x)	0.992	a*x^4+b*x^3+c*x^2+d*x+e	0.992
10	a*b*x/(1+b*x)	0.955	a*exp(b/x)	0.908	a*b^(1/x)*x^c	0.964	a*x/(b+x)	0.992	a*x^3+b*x^2+c*x+d	0.973
11	a*x^(b/x)	0.944	a*b^(1/x)*x^c	0.906	exp(a+b/x+c*log(x))	0.964	a*x^5+b*x^4+c*x^3+d*x^2+e*x+f	0.988	a*(1+x)^b	0.908
12	Sixth order polynomial	0.896	a*x^(b/x)	0.901	a*exp(b/x)	0.964	exp(a+b/x+c*log(x))	0.988	a*x^2+b*x+c	0.899
13	a*x^5+b*x^4+c*x^3+d*x^2+e*x+f	0.800	Sixth order polynomial	0.862	Sixth order polynomial	0.952	a*exp(b/x)	0.987	a*exp((-(x-b)^2)/(2*c^2))	0.840
14	a*b^x*x^c	0.790	x^a*exp(b-c*x)	0.859	a*x^(b/x)	0.935	a*x^(b/x)	0.983	exp(a+b*x+c*x^2)	0.840
15	x^a*exp(b-c*x)	0.790	a*b^x*x^c	0.859	a*x^5+b*x^4+c*x^3+d*x^2+e*x+f	0.912	a*x^b*exp(-c*x)	0.972	a*(x-b)	0.644
16	a*x^b*exp(-c*x)	0.790	a*x^b*exp(-c*x)	0.859	a*x^b*exp(-c*x)	0.895	a*b^x*x^c	0.972	a*x+b	0.644
17	a*b^(1/x)*x^c	0.766	a*x^5+b*x^4+c*x^3+d*x^2+e*x+f	0.796	x^a*exp(b-c*x)	0.895	x^a*exp(b-c*x)	0.972	a*b^x	0.583
18	a*x^4+b*x^3+c*x^2+d*x+e	0.678	a*x^4+b*x^3+c*x^2+d*x+e	0.783	a*b^x*x^c	0.895	a*x^4+b*x^3+c*x^2+d*x+e	0.968	a*exp(b*x)	0.583
19	a+b*log(x)	0.660	a*x^3+b*x^2+c*x+d	0.736	a*x^4+b*x^3+c*x^2+d*x+e	0.838	a*x^3+b*x^2+c*x+d	0.918	exp(a+b*x)	0.583
20	log(a+b*x)	0.639	a+b*log(x)	0.719	a*x^3+b*x^2+c*x+d	0.699	a+b*log(x)	0.897	log(x-a)	0.062
21	a*x^b	0.594	log(a+b*x)	0.713	a+b*log(x)	0.699	a*x^b	0.813	a+b*cos(x)+c*sin(x)	0.000
22	a*(1+x)^b	0.592	a*x^b	0.650	log(a+b*x)	0.659	a*(1+x)^b	0.812	exp(-a*x^2)	0.000
23	a*x^3+b*x^2+c*x+d	0.554	a*(1+x)^b	0.648	a*x^b	0.630	a*b^(1/x)*x^c	0.799	x/(a*x+b)	0.000
24	a*x^2+b*x+c	0.414	1/(a+b*log(x))	0.598	a*(1+x)^b	0.625	a*x^2+b*x+c	0.782	exp(-exp(a-b*x))	0.000
25	exp(a+b*x+c*x^2)	0.394	a*x^2+b*x+c	0.553	1/(a+b*log(x))	0.578	log(a+b*x)	0.741	a/(1+b*x+c*x^2)	0.000
26	a*exp((-(x-b)^2)/(2*c^2))	0.394	a*exp((-(x-b)^2)/(2*c^2))	0.521	a*x^2+b*x+c	0.505	exp(a+b*x+c*x^2)	0.723	1/(a+b*x+c*x^2)	0.000
27	1/(a+b*x+c*x^2)	0.377	exp(a+b*x+c*x^2)	0.521	a*exp((-(x-b)^2)/(2*c^2))	0.475	a*exp((-(x-b)^2)/(2*c^2))	0.723	a/(1+b*x)	0.000
28	a/(1+b*x+c*x^2)	0.377	a/(1+b*x+c*x^2)	0.493	exp(a+b*x+c*x^2)	0.475	a/(1+b*x+c*x^2)	0.674	1/(x+a)	0.000
29	a+b*x+c/x^2	0.248	1/(a+b*x+c*x^2)	0.493	a/(1+b*x+c*x^2)	0.450	1/(a+b*x+c*x^2)	0.674	x/(a+b*x-c*x^2)	0.000
30	a*(x-b)	0.231	a+b*x+c/x^2	0.297	1/(a+b*x+c*x^2)	0.450	x^a	0.649	a*cos(x)+b*sin(x)	0.000
31	a*x+b	0.231	a*(x-b)	0.276	a+b*x+c/x^2	0.276	a+b*x+c/x^2	0.474	cos(x+a)	0.000
32	exp(a+b*x)	0.221	a*x+b	0.276	a+b/x	0.271	a*(x-b)	0.468	sin(x+a)	0.000
33	a*exp(b*x)	0.221	a*b^x	0.261	a*x+b	0.230	a*x+b	0.468	1/(1+a*x)	0.000
34	a*b^x	0.221	a*exp(b*x)	0.261	a*(x-b)	0.230	a*exp(b*x)	0.428	1/(a+b*x)	0.000
35	a/(1+b*x)	0.213	exp(a+b*x)	0.261	exp(a+b*x)	0.219	exp(a+b*x)	0.428		
36	1/(a+b*x)	0.213	1/(a+b*x)	0.247	a*b^x	0.219	a*b^x	0.428		
37	a*x^(b*x)	0.204	a/(1+b*x)	0.247	a*exp(b*x)	0.219	a*x^(b*x)	0.399		
38	log(x-a)	0.164	a*x^(b*x)	0.238	a/(1+b*x)	0.209	1/(a+b*x)	0.395		
39	a+b/x	0.152	a+b/x	0.169	1/(a+b*x)	0.209	a/(1+b*x)	0.395		
40	a+b*cos(x)+c*sin(x)	0.000	log(x-a)	0.024	a*x^(b*x)	0.196	log(x-a)	0.093		
41	x^a	0.000	a+b*cos(x)+c*sin(x)	0.000	log(x-a)	0.137	a+b/x	0.088		
42	exp(-a*x^2)	0.000	x^a	0.000	a+b*cos(x)+c*sin(x)	0.000	a+b*cos(x)+c*sin(x)	0.000		
43	a^(1/x)	0.000	exp(-a*x^2)	0.000	x^a	0.000	exp(-a*x^2)	0.000		
44	exp(-exp(a-b*x))	0.000	a^(1/x)	0.000	exp(-a*x^2)	0.000	a^(1/x)	0.000		
45	1-exp(-x^a)	0.000	exp(-exp(a-b*x))	0.000	a^(1/x)	0.000	exp(-exp(a-b*x))	0.000		
46	1-1/(x^a)	0.000	1-exp(-x^a)	0.000	exp(-exp(a-b*x))	0.000	1-exp(-x^a)	0.000		
47	exp(-x^a)	0.000	1-1/(x^a)	0.000	exp(-x^a)	0.000	1-1/(x^a)	0.000		
48	1-exp(-a*b^x)	0.000	exp(-x^a)	0.000	1-exp(-x^a)	0.000	exp(-x^a)	0.000		
49	x/(a+b*x+c*sqr(x))	0.000	1-exp(-a*b^x)	0.000	1-exp(-a*b^x)	0.000	1/(x+a)	0.000		
50	1/(x+a)	0.000	x/(a+b*x+c*sqr(x))	0.000	1/(x+a)	0.000	a*cos(x)+b*sin(x)	0.000		

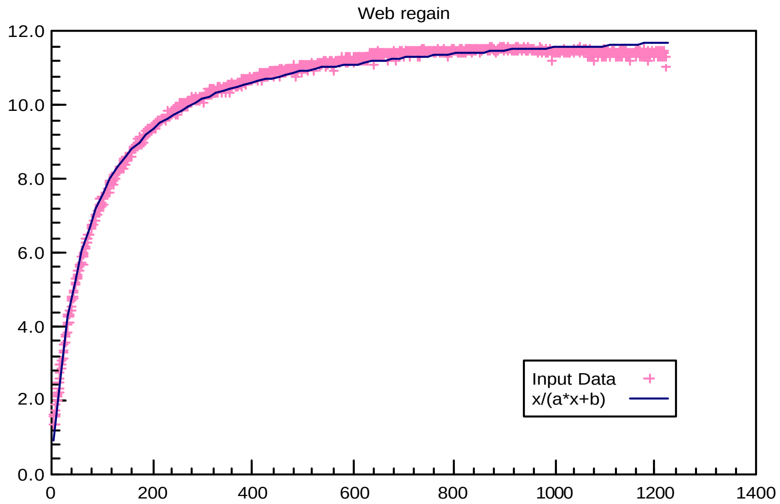
Rank	Shirleyed web - 28 kg/m³	R^2	Loose fibre - 7 kg/m³	R^2	Scoured log - 65 kg/m³	R^2	OFDA 2000 - 15 µm	R^2	OFDA 2000 - 36 µm	R^2
1	Tenth order polynomial	0.999	Tenth order polynomial	0.998	Tenth order polynomial	1.000	Tenth order polynomial	0.468	Tenth order polynomial	0.881
2	Ninth order polynomial	0.999	Ninth order polynomial	0.998	Ninth order polynomial	1.000	Ninth order polynomial	0.468	Ninth order polynomial	0.881
3	Eighth order polynomial	0.999	x/(a+b*x+c*sqr(x))	0.997	Eighth order polynomial	1.000	Eighth order polynomial	0.466	Eighth order polynomial	0.880
4	Seventh order polynomial	0.998	Eighth order polynomial	0.996	Seventh order polynomial	0.999	Seventh order polynomial	0.460	Seventh order polynomial	0.879
5	x/(a+b*x-c*x^2)	0.997	x/(a+b*x-c*x^2)	0.995	Sixth order polynomial	0.999	Sixth order polynomial	0.454	Sixth order polynomial	0.875
6	Sixth order polynomial	0.997	Seventh order polynomial	0.993	x/(a+b*x-c*x^2)	0.999	a*x^5+b*x^4+c*x^3+d*x^2+e*x+f	0.442	a*x^5+b*x^4+c*x^3+d*x^2+e*x+f	0.861
7	x/(a+b*x+c*sqr(x))	0.995	x/(a*x+b)	0.993	x/(a+b*x+c*sqr(x))	0.998	a*x^4+b*x^3+c*x^2+d*x+e	0.388	a*x^b*exp(-c*x)	0.841
8	a*x/(b+x)	0.993	a*b*x/(1+b*x)	0.993	a*b*x/(1+b*x)	0.998	a*x^(b/x)	0.384	x^a*exp(b-c*x)	0.841
9	a*b*x/(1+b*x)	0.993	a*x/(b+x)	0.993	x/(a*x+b)	0.998	a*b^x*x^c	0.366	a*b^x*x^c	0.841
10	x/(a*x+b)	0.993	a*b^(1/x)*x^c	0.990	a*x/(b+x)	0.998	a*x^b*exp(-c*x)	0.366	x/(a+b*x+c*sqr(x))	0.814
11	a*x^5+b*x^4+c*x^3+d*x^2+e*x+f	0.993	exp(a+b/x+c*log(x))	0.990	a*x^5+b*x^4+c*x^3+d*x^2+e*x+f	0.997	x^a*exp(b-c*x)	0.366	a*x^4+b*x^3+c*x^2+d*x+e	0.810
12	a*x^(b/x)	0.990	a*exp(b/x)	0.988	x^a*exp(b-c*x)	0.993	x/(a+b*x+c*sqr(x))	0.352	a*x^(b/x)	0.789
13	a*x^b*exp(-c*x)	0.984	Sixth order polynomial	0.987	a*b^x*x^c	0.993	a*b^(1/x)*x^c	0.322	a*x^3+b*x^2+c*x+d	0.722
14	a*b^x*x^c	0.984	a*x^5+b*x^4+c*x^3+d*x^2+e*x+f	0.974	a*x^b*exp(-c*x)	0.993	exp(a+b/x+c*log(x))	0.322	a*b^(1/x)*x^c	0.704
15	x^a*exp(b-c*x)	0.984	a*x^(b/x)	0.954	a*x^4+b*x^3+c*x^2+d*x+e	0.992	x/(a+b*x-c*x^2)	0.310	exp(a+b/x+c*log(x))	0.704
16	a*b^(1/x)*x^c	0.979	x^a*exp(b-c*x)	0.938	exp(a+b/x+c*log(x))	0.986	a*b*x/(1+b*x)	0.309	a+b*log(x)	0.676
17	exp(a+b/x+c*log(x))	0.979	a*b^x*x^c	0.938	a*x^(b/x)	0.976	x/(a*x+b)	0.309	a*x^b	0.672
18	a*x^4+b*x^3+c*x^2+d*x+e	0.978	a*x^b*exp(-c*x)	0.938	a*b^(1/x)*x^c	0.976	a*x/(b+x)	0.309	1/(a+b*log(x))	0.669
19	a*exp(b/x)	0.974	a*x^4+b*x^3+c*x^2+d*x+e	0.936	a*exp(b/x)	0.976	a*exp(b/x)	0.306	a*(1+x)^b	0.661
20	a*x^3+b*x^2+c*x+d	0.940	a+b*log(x)	0.871	a*x^3+b*x^2+c*x+d	0.974	a+b/x	0.303	a*x^2+b*x+c	0.548
21	a+b*log(x)	0.916	a*x^3+b*x^2+c*x+d	0.839	a+b*log(x)	0.960	a*x^3+b*x^2+c*x+d	0.266	a*exp((-(x-b)^2)/(2*c^2))	0.546
22	a*x^b	0.843	a*x^b	0.790	a*x^b	0.905	a+b*log(x)	0.212	exp(a+b*x+c*x^2)	0.546
23	a*x^2+b*x+c	0.842	a*(1+x)^b	0.784	a*(1+x)^b	0.904	a*x^b	0.211	a/(1+b*x+c*x^2)	0.543
24	a*(1+x)^b	0.840	log(a+b*x)	0.761	a*x^2+b*x+c	0.899	1/(a+b*log(x))	0.210	1/(a+b*x+c*x^2)	0.543
25	a*exp((-(x-b)^2)/(2*c^2))	0.789	1/(a+b*log(x))	0.725	x^a	0.859	a*(1+x)^b	0.205	x/(a+b*x-c*x^2)	0.527
26	exp(a+b*x+c*x^2)	0.789	a*x^2+b*x+c	0.693	a*exp((-(x-b)^2)/(2*c^2))	0.841	a+b*x+c/x^2	0.155	x/(a*x+b)	0.409
27	1/(a+b*log(x))	0.778	exp(a+b*x+c*x^2)	0.646	exp(a+b*x+c*x^2)	0.841	a*x^2+b*x+c	0.122	a*b*x/(1+b*x)	0.409
28	log(a+b*x)	0.750	a*exp((-(x-b)^2)/(2*c^2))	0.646	1/(a+b*x+c*x^2)	0.789	exp(a+b*x+c*x^2)	0.122	a*x/(b+x)	0.409
29	a/(1+b*x+c*x^2)	0.744	1/(a+b*x+c*x^2)	0.609	a/(1+b*x+c*x^2)	0.789	a*exp((-(x-b)^2)/(2*c^2))	0.122	a*exp(b/x)	0.395
30	1/(a+b*x+c*x^2)	0.744	a/(1+b*x+c*x^2)	0.609	a+b*x+c/x^2	0.646	1/(a+b*x+c*x^2)	0.121	a+b/x	0.382
31	a+b*x+c/x^2	0.633	a+b*x+c/x^2	0.476	a*x+b	0.640	a/(1+b*x+c*x^2)	0.121	a+b*x+c/x^2	0.349
32	a+b/x	0.588	a*(x-b)	0.432	a*(x-b)	0.640	log(a+b*x)	0.051	log(a+b*x)	0.329
33	a*(x-b)	0.527	a*x+b	0.432	a*b^x	0.579	a*(x-b)	0.049	a*x+b	0.276
34	a*x+b	0.527	a*exp(b*x)	0.403	a*exp(b*x)	0.579	a*x+b	0.049	a*(x-b)	0.276
35	exp(a+b*x)	0.484	exp(a+b*x)	0.403	exp(a+b*x)	0.579	a*exp(b*x)	0.049	a*b^x	0.275
36	a*b^x	0.484	a*b^x	0.403	a*x^(b*x)	0.547	a*b^x	0.049	exp(a+b*x)	0.275
37	a*exp(b*x)	0.484	1/(a+b*x)	0.378	1/(a+b*x)	0.530	exp(a+b*x)	0.049	a*exp(b*x)	0.275
38	a/(1+b*x)	0.447	a/(1+b*x)	0.378	a/(1+b*x)	0.530	a/(1+b*x)	0.049	a/(1+b*x)	0.274
39	1/(a+b*x)	0.447	a*x^(b*x)	0.370	a+b/x	0.100	1/(a+b*x)	0.049	1/(a+b*x)	0.274
40	a*x^(b*x)	0.447	a+b/x	0.304	log(x-a)	0.030	a*x^(b*x)	0.041	a*x^(b*x)	0.241
41	x^a	0.352	log(x-a)	0.005	a+b*cos(x)+c*sin(x)	0.000	a+b*cos(x)+c*sin(x)	0.003	a+b*cos(x)+c*sin(x)	0.003
42	log(x-a)	0.008	a+b*cos(x)+c*sin(x)	0.000	exp(-a*x^2)	0.000	log(x-a)	0.000	log(x-a)	0.000
43	a+b*cos(x)+c*sin(x)	0.000	x^a	0.000	a^(1/x)	0.000	x^a	0.000	x^a	0.000
44	exp(-a*x^2)	0.000	exp(-a*x^2)	0.000	exp(-exp(a-b*x))	0.000	exp(-a*x^2)	0.000	exp(-a*x^2)	0.000
45	a^(1/x)	0.000	a^(1/x)	0.000	1-exp(-x^a)	0.000	a^(1/x)	0.000	a^(1/x)	0.000
46	1-1/(x^a)	0.000	1-exp(-a*x^b)	0.000	1-1/(x^a)	0.000	1-1/(x^a)	0.000	1-exp(-a*x^2)	0.000
47	exp(-x^a)	0.000	exp(-exp(a-b*x))	0.000	exp(-x^a)	0.000	exp(-x^a)	0.000	1-exp(-a*b^x)	0.000
48	1-exp(-a*b^x)	0.000	1-exp(-a*x^2)	0.000	1/(x+a)	0.000	1-exp(-a*b^x)	0.000	exp(-x^a)	0.000
49	1/(x+a)	0.000	1-exp(-x^a)	0.000	a*cos(x)+b*sin(x)	0.000	1/(x+a)	0.000	1-1/(x^a)	0.000
50	a*cos(x)+b*sin(x)	0.000	exp(-x^a)	0.000	sin(x+a)	0.000	a*cos(x)+b*sin(x)	0.000	1/(x+a)	0.000

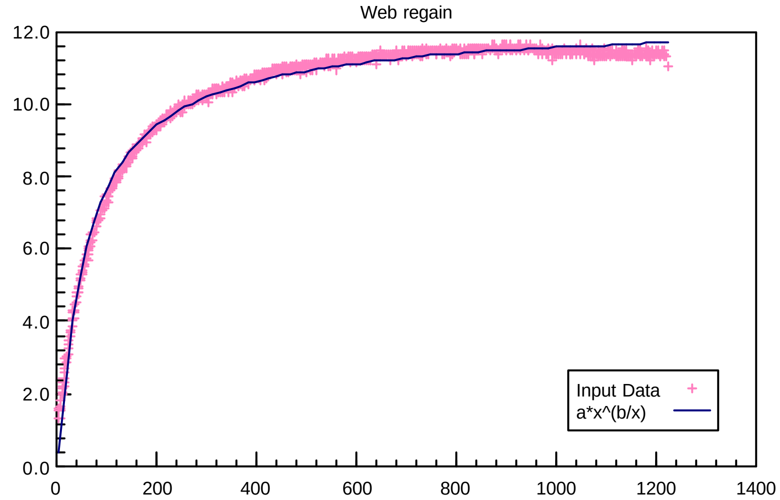

Web regain - inverse quadratic model - Eq. (1)
Input Data
x/(a+b*x-c*x^2)
12.0
10.0
8.0
6.0
4.0
2.0
0.0
0
200
400
600
800
1000
1200
1400

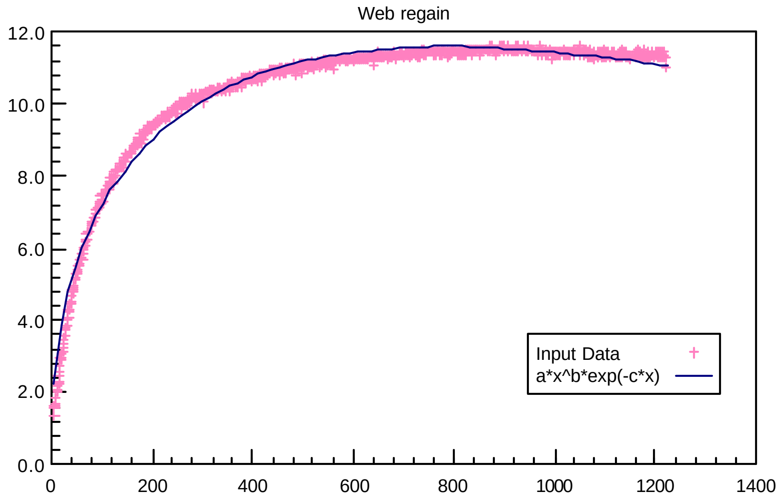

Web regain
Input Data
x/(a+b*x+c*sqr(x))
12.0
10.0
8.0
6.0
4.0
2.0
0.0
0
200
400
600
800
1000
1200
1400

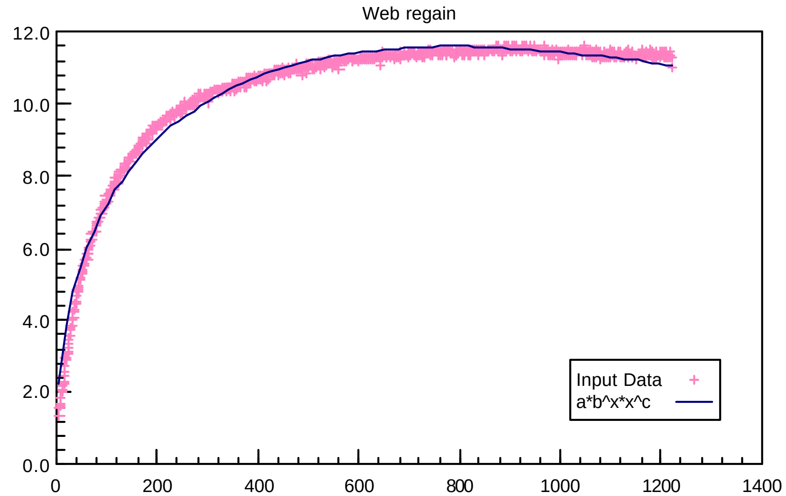

Web regain
Input Data
a*b*x/(1+b*x)
12.0
10.0
8.0
6.0
4.0
2.0
0.0
0
200
400
600
800
1000
1200
1400

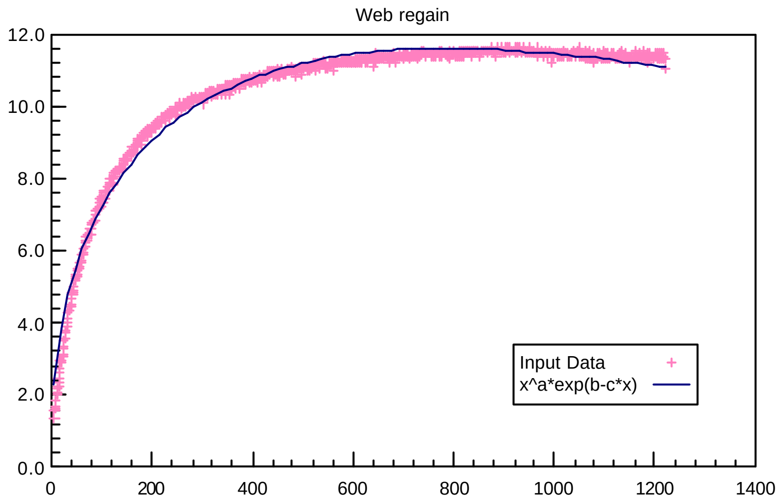

Web regain
Input Data
a*x/(b+x)
12.0
10.0
8.0
6.0
4.0
2.0
0.0
0
200
400
600
800
1000
1200
1400

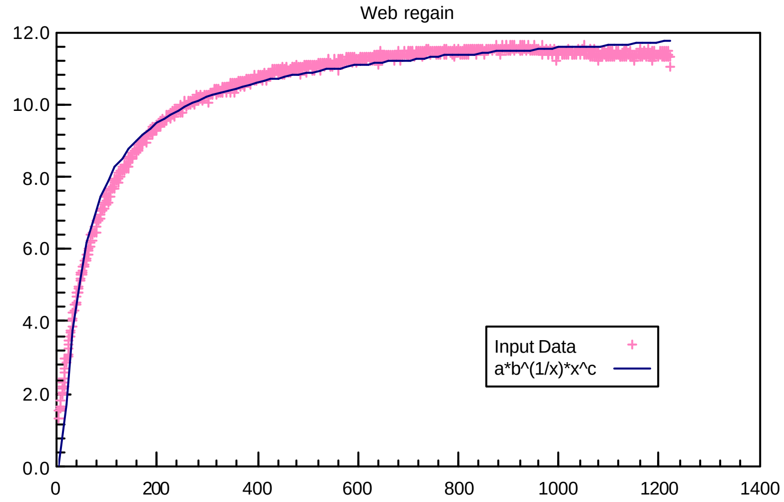

Web regain
Input Data
x/(a*x+b)
0.0
2.0
4.0
6.0
8.0
10.0
12.0
0
200
400
600
800
1000
1200
1400

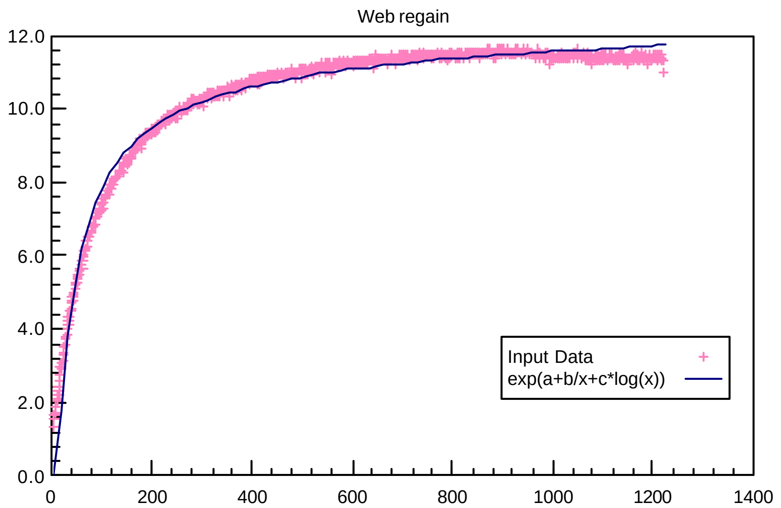

Web regain
Input Data
a*x^(b/x)
0.0
2.0
4.0
6.0
8.0
10.0
12.0
0
200
400
600
800
1000
1200
1400

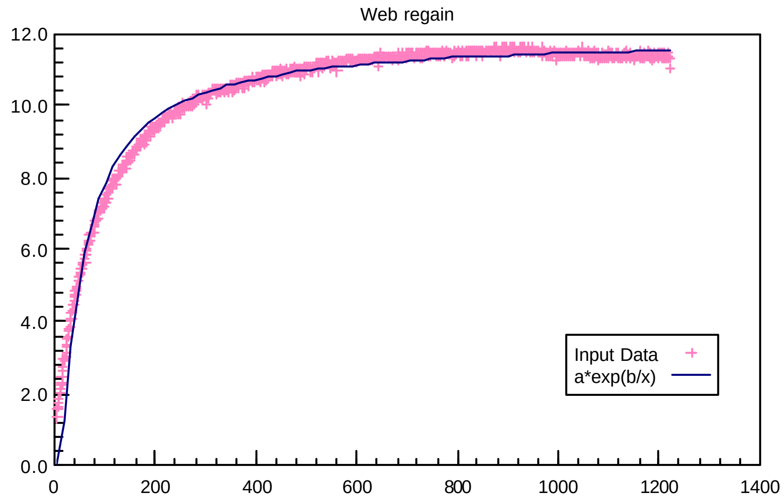

Web regain
Input Data
a*x^b*exp(-c*x)
0.0
2.0
4.0
6.0
8.0
10.0
12.0
0
200
400
600
800
1000
1200
1400


Web regain
Input Data
a*b^x*x^c
0.0
2.0
4.0
6.0
8.0
10.0
12.0
0
200
400
600
800
1000
1200
1400


Web regain
12.0
10.0
8.0
6.0
4.0
2.0
0.0
0
200
400
600
800
1000
1200
1400
Input Data
x^a*exp(b-c*x)


Web regain
12.0
10.0
8.0
6.0
4.0
2.0
0.0
0
200
400
600
800
1000
1200
1400
Input Data
a*b^(1/x)*x^c


Web regain
12.0
10.0
8.0
6.0
4.0
2.0
0.0
0
200
400
600
800
1000
1200
1400
Input Data
exp(a+b/x+c*log(x))


Web regain
12.0
10.0
8.0
6.0
4.0
2.0
0.0
0
200
400
600
800
1000
1200
1400
Input Data
a*exp(b/x)

<u>Appendix 2 – Data analyses in accordance with IWTO-0</u>

See Table 2 for summarised differences.

<u>Mean fibre diameter</u>:

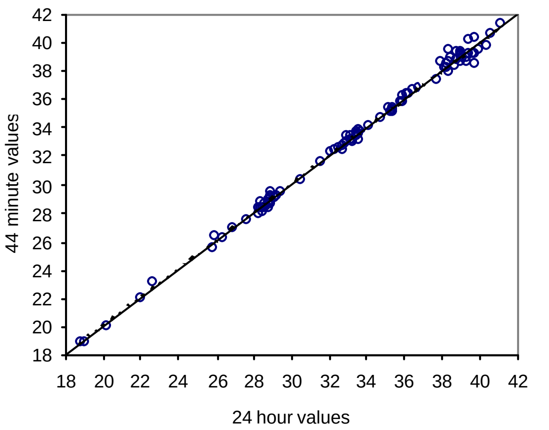
Comparison:		44 min to 24 hr		100 min to 24 hr		44 min to 100 min	
Statistic		GM	DVA	GM	DVA	GM	DVA
Estimated slope		1.0017	0.0015	0.9963	-0.0040	1.0054	0.0052
Standard error of slope		0.0066	0.0066	0.0055	0.0056	0.0069	0.0069
Significance of slope:	t-value	0.264	0.224	0.659	0.668	0.785	0.756
	Signif	ns	ns	ns	ns	ns	ns
Significance of correlation:	R value	0.9979	0.0226	0.9985	0.067	0.9977	0.076
	t-value	150.8	0.223	179.6	0.668	145.3	0.756
	Signif	***	ns	***	ns	***	ns

<u>Brightness</u> Y:

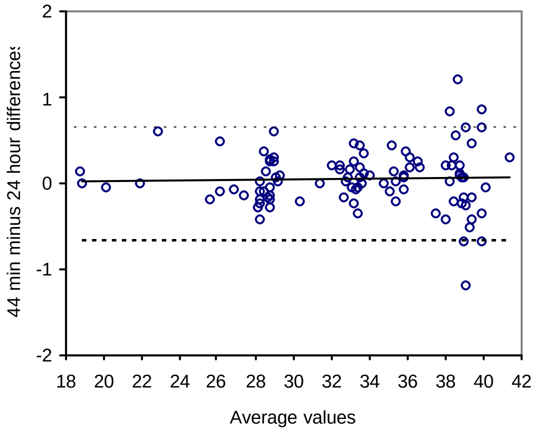
Comparison:		44 min to 24 hr		100 min to 24 hr		44 min to 100 min	
Statistic		GM	DVA	GM	DVA	GM	DVA
Estimated slope		1.0269	0.0264	1.0039	0.0042	1.0229	0.0222
Standard error of slope		0.0124	0.0121	0.0105	0.0104	0.0077	0.0076
Significance of slope:	t-value	2.177	2.185	0.375	0.410	2.987	2.932
	Signif	*	*	ns	ns	***	**
Significance of correlation:	R value	0.9929	0.2155	0.9947	0.0413	0.9972	0.2840
	t-value	82.5	2.185	95.5	0.410	133.1	2.932
	Signif	***	*	***	ns	***	**

<u>Yellowness</u>, Y-Z:

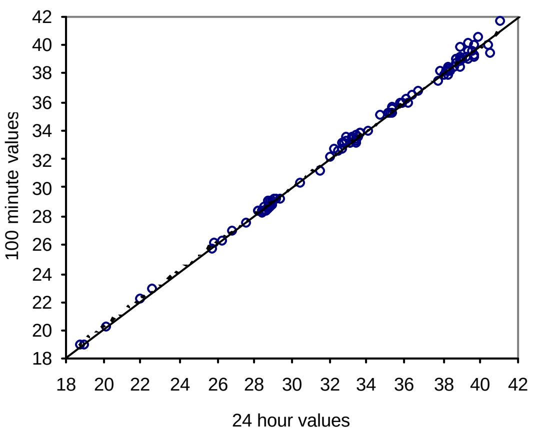
Comparison:		44 min to 24 hr		100 min to 24 hr		44 min to 100 min	
Statistic		GM	DVA	GM	DVA	GM	DVA
Estimated slope		1.0107	0.0058	1.0183	0.0135	0.9925	-0.0080
Standard error of slope		0.0143	0.0142	0.0139	0.0137	0.0076	0.0077
Significance of slope:	t-value	0.748	0.405	1.315	0.984	0.979	1.005
	Signif	ns	ns	ns	ns	ns	ns
Significance of correlation:	R value	0.9901	0.0409	0.9908	0.0989	0.9971	0.1010
	t-value	69.9	0.405	72.5	0.984	130.0	1.005
	Signif	***	ns	***	ns	***	ns



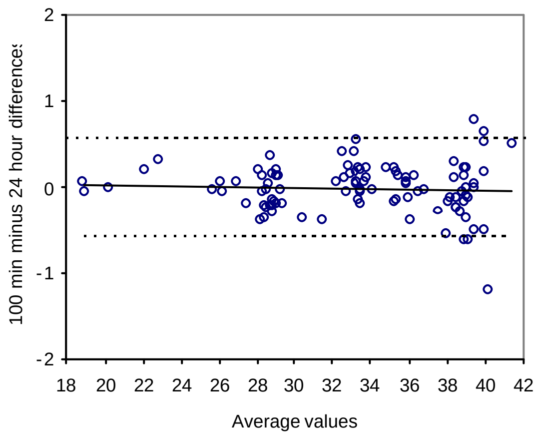
GM regression - MFD 44 minutes versus 24 hours



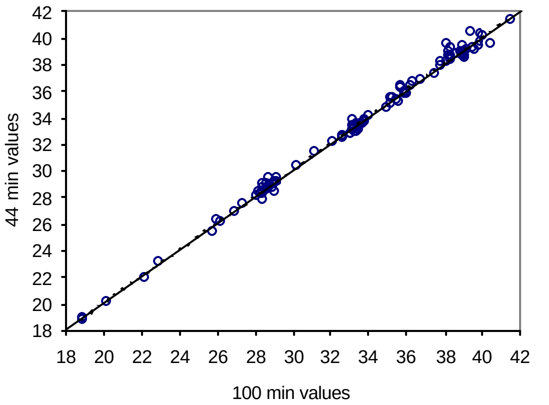
DVA regression - MFD 44 minutes minus 24 hours



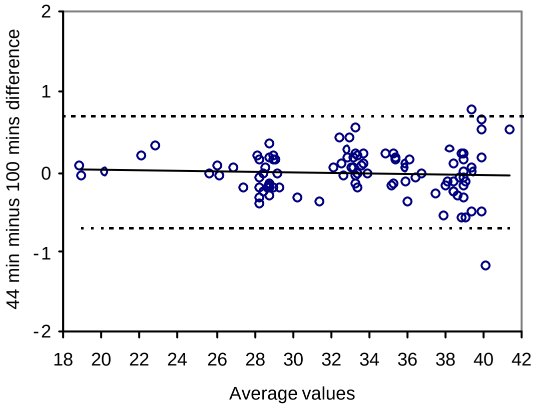
GM regression - MFD 100 minutes versus 24 hours



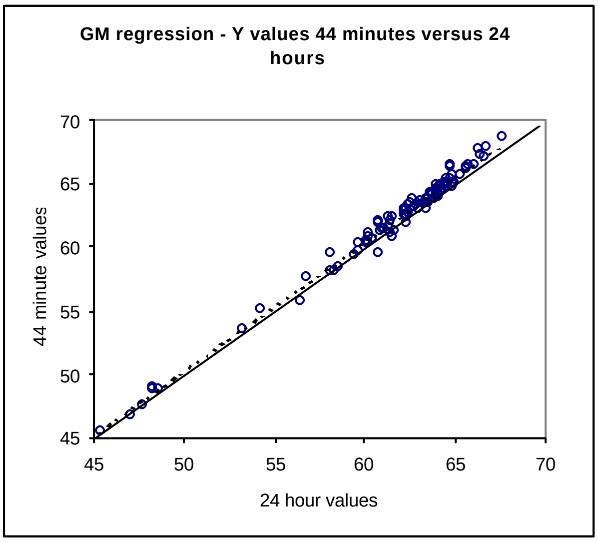
DVA regression - MFD 100 minutes minus 24 hours

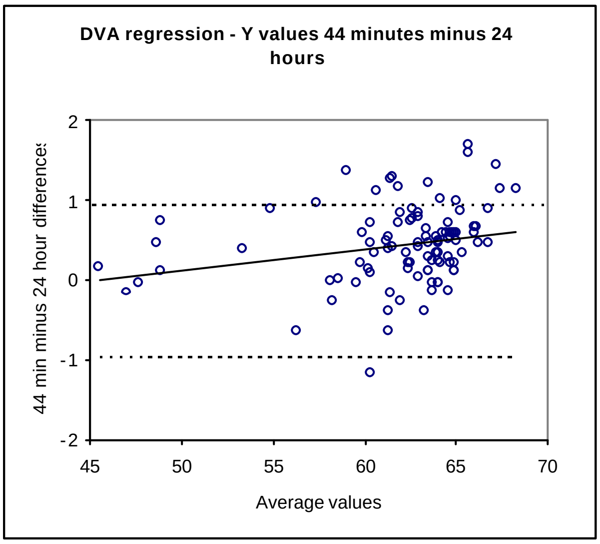


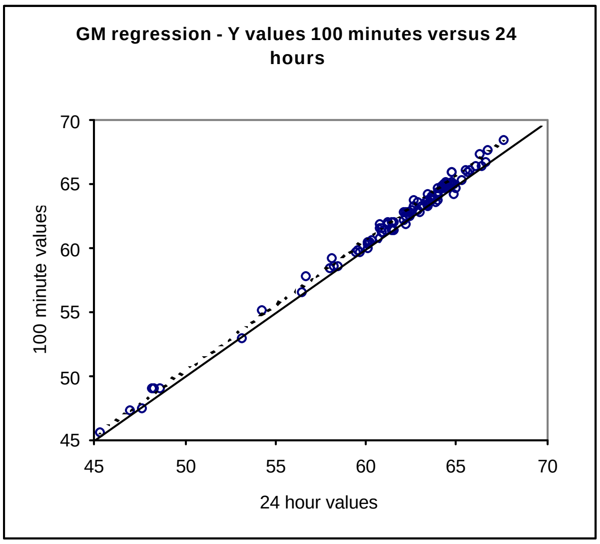
GM regression - MFD 44 minutes versus 100 minutes

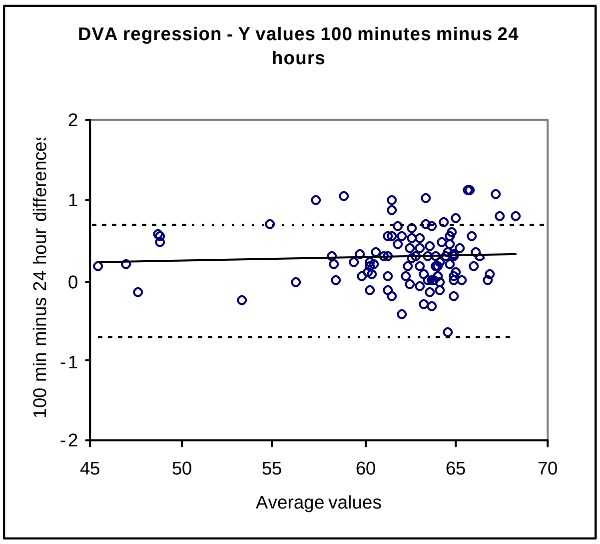


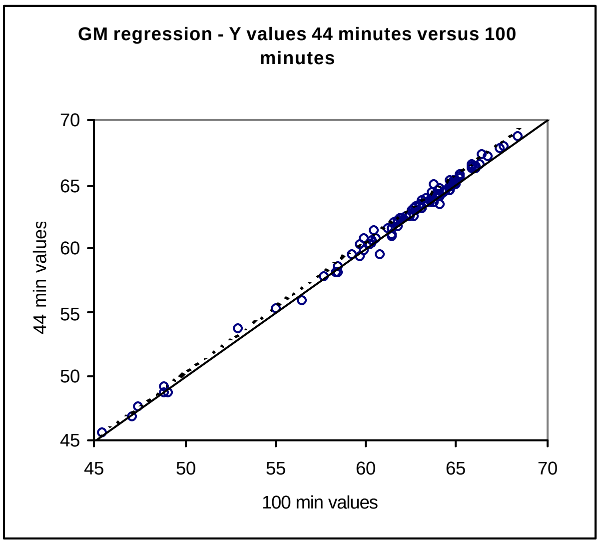
DVA regression - MFD 44 minutes minus 100 minutes

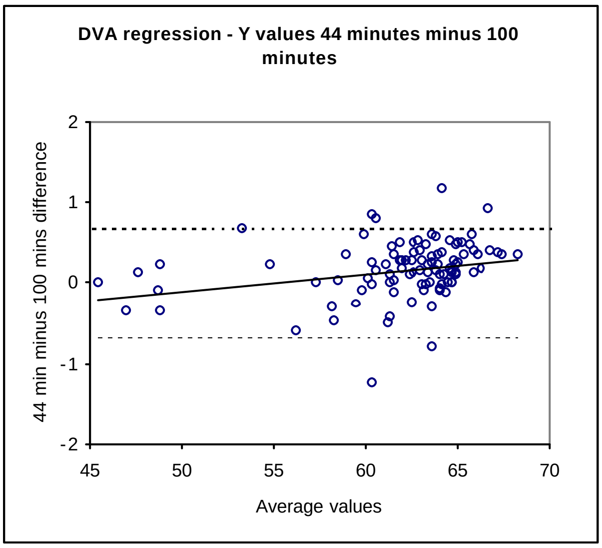

GM regression - Y values 44 minutes versus 24 hours
44 minute values
24 hour values
45
50
55
60
65
70

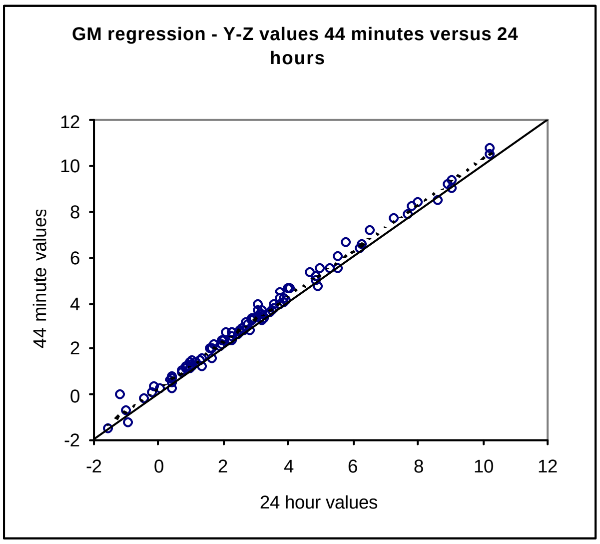

DVA regression - Y values 44 minutes minus 24 hours
44 min minus 24 hour differences
Average values
2
1
0
-1
-2
45
50
55
60
65
70

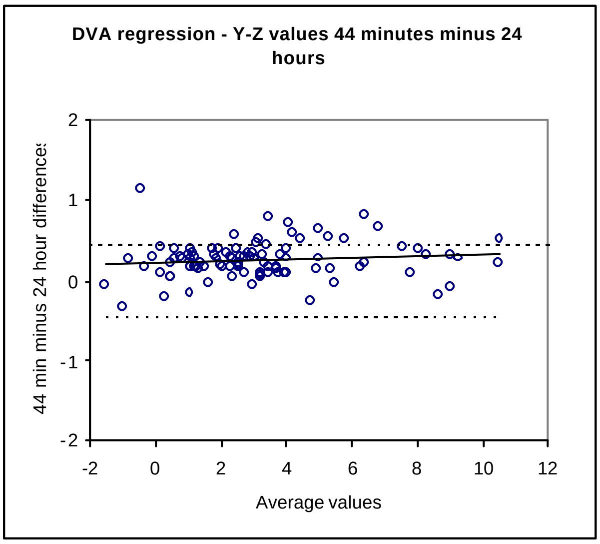

GM regression - Y values 100 minutes versus 24 hours
100 minute values
24 hour values
45
50
55
60
65
70

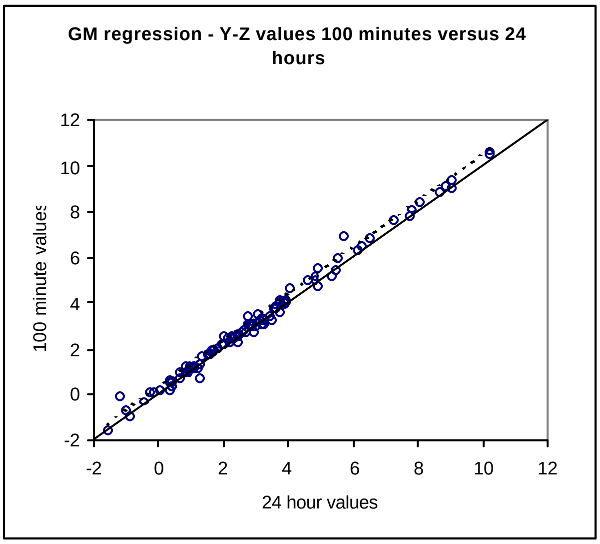

DVA regression - Y values 100 minutes minus 24 hours
100 min minus 24 hour differences
Average values
2
1
0
-1
-2
45
50
55
60
65
70

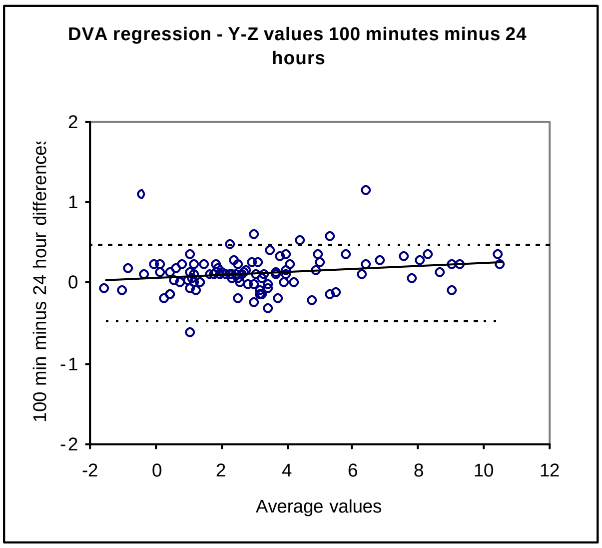

GM regression - Y values 44 minutes versus 100 minutes
44 min values
100 min values
45
50
55
60
65
70

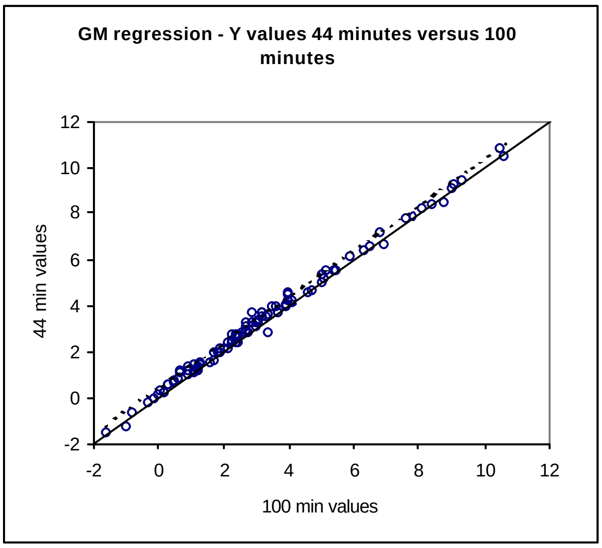

DVA regression - Y values 44 minutes minus 100 minutes
44 min minus 100 mins difference
Average values
2
1
0
-1
-2
45
50
55
60
65
70

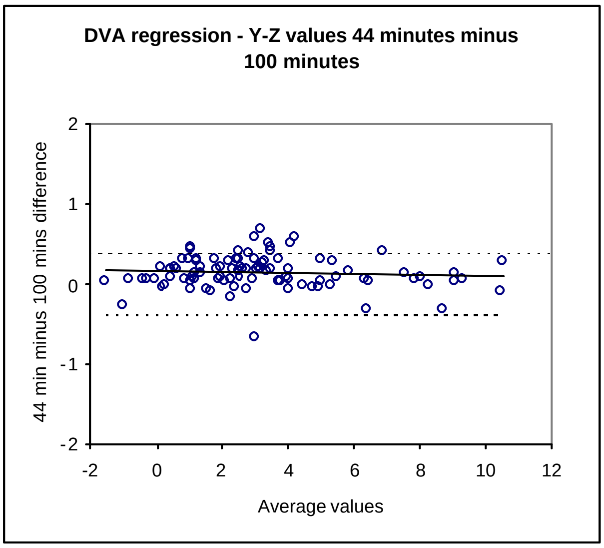

GM regression - Y-Z values 44 minutes versus 24 hours
44 minute values
24 hour values


DVA regression - Y-Z values 44 minutes minus 24 hours
44 min minus 24 hour differences
Average values


GM regression - Y-Z values 100 minutes versus 24 hours
100 minute values
24 hour values


DVA regression - Y-Z values 100 minutes minus 24 hours
100 min minus 24 hour differences
Average values


GM regression - Y values 44 minutes versus 100 minutes
44 min values
100 min values


DVA regression - Y-Z values 44 minutes minus 100 minutes
44 min minus 100 mins difference
Average values

Appendix 3 – Proposed text change for IWTO-52

Text to be deleted is shown in ~~strikethrough~~, whilst text to be added is underlined.

Clause 7.2.4 Method D - Method when conditioning is required rapidly

There may be circumstances when it is necessary to condition materials as rapidly as possible. This involves the use of ~~rapid pre-conditioners and~~ rapid conditioners, and may additionally involve the use of rapid preconditioners, where the samples or specimens have not already been dried as in procedures such as IWTO-19 or IWTO-33, and maintained on the dry side of 65% rh. When the samples or specimens are uniform in size and condition (usually associated with high volumes of testing), the procedure can be standardised and verified against the standard reference method.

Procedures (a) through (e) remain as current version.

(f) ~~The requirement for rapid conditioning shall be established by a procedure similar to that in Steps (a) to (e) but using the proposed conditioning apparatus in place of the preconditioning apparatus~~. Where samples or specimens have not already been dried, and maintained on the dry side of 65% rh, as in procedures such as IWTO-19 or IWTO-33, samples or specimens must first be preconditioned as described in Steps (a) through (e). The rapid conditioner shall pass air of standard atmosphere as in Clause 6.1(a) and Appendix B. The samples or specimens shall be weighed immediately after preconditioning (W_i), and thereafter at 5 minute intervals of rapid conditioning. The time of exposure (t) shall be recorded for each weighing. Weighing shall be repeated until 2 weighings at least 15 minutes apart show an increase in the mass of the sample of not more than 0.1% of the last mass recorded.

For each weight recorded whilst the sample was exposed (W), calculate the parameter θ from the initial weight (W_i) and the final weight (W_f) as follows:

$$\theta = (W_f - W) / (W_f - W_i)$$

For each recorded weight calculate the natural logarithm of exposed time, ln(t).

For each sample, plot ln(t) against θ for values of θ less than 0.85 and until the first value of zero is encountered. The plot should be almost a straight line. Either draw a best-fit straight line on the plot, or calculate the linear regression. In either case, record the intercept C on the ln(t) axis (for $\theta = 0$), and convert this back to a time to condition in minutes, by calculating the exponent, e^C.

Calculate the average (T_c) and standard deviation (s_c) of the time to condition for all samples. Calculate the standard exposure time (SET) as follows:

$$SET = T_c + 3.5\, s_c$$

(g) As current version