THE MODELLING OF MOISTURE CONTENT DISTRIBUTIONS ON CENSORED READINGS FROM A RESISTANCE METER

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INTRODUCTION

There are two prevalent methods for the non-destructive measurement of the moisture content of kiln-dried lumber:
- hand-held resistance meters
- in-line capacitance meters

It is important to ensure that reliable measurements are obtained from these meters. It is evident from this year's Dry Kiln Club technical program that there is continuing interest in achieving a highly reliable method to non-destructively determine moisture contents. For instance, Mr. Briener is here from California to discuss performance of in-line meters, while Messrs. Pfaff and Garrahan, from Forintek's Eastern Laboratory, are here to discuss the improvement of measurements from a resistance meter. My topic this morning will be on what to do with these moisture content measurements after we take them.

Improving moisture content measurement of boards will increase our ability to ensure the quality of our dried product. In-line moisture meters are capable of measuring all the boards going through the planer mill quickly and at a low cost to the producer. If an in-line moisture meter is not available, however, the quality of the charge is assessed by sampling boards with a hand-held moisture meter. In addition to improving the reliability of moisture measurements, attention must be focussed on decreasing sampling costs. One way to achieve this is to develop better models for the distribution of moisture contents for the dried boards in a kiln. This is the topic of today's talk.

There are problems associated with resistance and capacitance meters. These problems include:
- the requirement for temperature correction
- species correction
- grain orientation affects the reading, and finally
- the instrument is capable of measuring only a narrow range of moisture contents. Typical values for this range of moisture contents are 6-30 percent on a dry basis (Pfaff and Garrahan, 1984).

Because of the last point, if we take measurements with these meters, the resulting data can be regarded as censored. That is, we are incapable of measuring accurately beyond the upper and/or lower bounds of the meter. However, there exist statistical methods to evaluate censored data that are not commonly used in the forest industry. In statistical parlance, our measurements from the resistance meters are doubly Type I censored samples.
DISTRIBUTION OF MOISTURE CONTENT

It would be an advantage if one knew a priori what the distribution of the moisture contents is. The ultimate purpose of a sampling procedure is to provide a reliable method to determine some characteristic of the moisture content in a kiln charge (e.g., the mean) at the least possible sampling cost. In general, the more we know about the distribution of the moisture content of the boards in a typical kiln charge, the less sampling we have to do to achieve a reliable estimate. One can get a feel for the distribution by observing a histogram from the kiln charge (Figure 1). It is obvious that we don't have moisture contents less than zero percent, so there is a finite tail on the left side of the distribution. In addition, the distribution has a positive skew (a long tail on the right side). As a load becomes drier the skewness of the distribution generally increases. Currently, it is assumed that moisture content follows a normal distribution. It is evident, from the histogram, that the normal distribution (a symmetric distribution) may not be the best model for moisture content distributions.

There are statistical distributions that may be more appropriate for modelling moisture content distributions. Examples of distributions that reflect the properties of the observed histogram include the Weibull, gamma and lognormal distributions. Of these three distributions, the lognormal is relatively easy to work with because the same statistical methods for the normal distribution can be used to analyze the data from a lognormal distribution. This paper will discuss the use of the lognormal distribution (Figure 2).

The lognormal distribution is a flexible distribution capable of modelling a wide variety of engineering phenomena. As found in the moisture content data, the lognormal distribution has a finite left tail and a positive skew.

THEORY OF DOUBLE-CENSORED SAMPLES

As mentioned previously, we have data from moisture meters which is doubly Type I censored. Once a statistical model has been chosen, the theory of maximum likelihood (ML) with censored samples can be applied to the model.

The procedure for calculating the parameter estimates with censored data for the lognormal distribution can be found in Lawless (1982). A location parameter is used since the moisture content of a board can never be zero. The lowest moisture content board in the population would be at the equilibrium moisture content. A listing of the program to perform the analysis can be found in Appendix I.

EXPERIMENTAL DATA

In a mill study, a resistance meter was used to obtain 10 moisture content readings per board from 120 boards each in two kiln charges. The data were analyzed by first considering, and then disregarding, the censored data. Both the lognormal and the normal distributions were considered. Table 1 shows the results of estimating the mean and the 95th percentile for two kiln
charges. The 95th percentile is of use, for example, if we want to say that 95 percent of the boards fall below 19 percent moisture content. If the 95th percentile is above 19 percent moisture content then the boards do not conform to standard. For the lognormal case, it was assumed that the location parameter was at seven percent moisture content. This was based on the kiln schedule used which was developed from the final equilibrium moisture content.

Table 1. Moisture Content ML Point Estimates for Two Kiln Charges

<table>
<thead>
<tr>
<th>Charge 1</th>
<th>Charge 2</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>95th</td>
</tr>
<tr>
<td></td>
<td>Mean</td>
</tr>
<tr>
<td>Normal uncensored</td>
<td>9.7</td>
</tr>
<tr>
<td>Normal censored</td>
<td>9.7</td>
</tr>
<tr>
<td>Lognormal uncensored</td>
<td>12.2</td>
</tr>
<tr>
<td>Lognormal censored</td>
<td>12.3</td>
</tr>
</tbody>
</table>

Both cases of field data failed a statistical test for normality. However, they passed a lognormal test. Therefore, the assumption that moisture contents are distributed lognormally is consistent with data obtained in this particular field test. The point estimates of the mean for the normal and lognormal cases show that a difference does exist by using a different probability density function. In addition, the 95th percentile estimate was considerably different. An examination of Figure 3 shows that the lognormal estimate of the 95th percentile is considerably more accurate than the normal estimate.

SIMULATION DATA

Further investigation was done with some randomly-generated lognormal variables. The lognormal population had a mean of 12 percent moisture content with a large variance. The location parameter was at 0.0 percent moisture content. The intention was to look at heavily censored samples. The sample was censored at less than six percent and greater than 30 percent. The results are shown below in Table 2.

<table>
<thead>
<tr>
<th></th>
<th>Mean</th>
<th>95th Percentile</th>
</tr>
</thead>
<tbody>
<tr>
<td>True lognormal population</td>
<td>12.0</td>
<td>62.2</td>
</tr>
<tr>
<td>Censored lognormal estimate</td>
<td>12.1</td>
<td>60.1</td>
</tr>
<tr>
<td>Uncensored lognormal estimate</td>
<td>12.4</td>
<td>35.0</td>
</tr>
<tr>
<td>Uncensored normal estimate</td>
<td>19.9</td>
<td>24.4</td>
</tr>
<tr>
<td>Censored normal estimate</td>
<td>19.8</td>
<td>34.9</td>
</tr>
</tbody>
</table>

Examination of Table 2 shows that estimating the mean with the censored lognormal equations is very accurate, even in this particular case where more than a third of the random numbers happened to be censored. The table also shows that using the
uncensored lognormal model, the estimation of the mean is also reasonable. However, using the uncensored normal distribution, a discrepancy of over eight percent moisture content was observed! It must be noted that this is a hypothetical example, with the random numbers generated to highlight the different statistical procedures.

The 95th percentile comparisons are even more dramatic. When the censoring is taken into consideration, the lognormal distribution provides a reasonable conservative estimate of the 95th percentile. However, for this example, no consideration of censoring provides totally erroneous results.

DISCUSSION

The statistical procedures outlined here are complicated. However, they can be done with ease by computer. This paper presented a statistical method which could be used to analyze moisture content data sampled from a kiln charge. An accurate estimate of the mean can be made and, more importantly, an accurate continuous distribution can be modelled from the data. This would be particularly important for the specialty drying people, where they are concerned about the tails of the distributions.

Now, consider the problem we have at hand:
-- The moisture content distribution is non-normal.
-- The readings from a resistance or capacitance meter are censored.
-- Our kiln operators have a poor statistics background and are not even remotely interested in lognormal distributions.
-- We require a reliable, inexpensive and quick method to determine moisture contents in a charge.

We hope to provide a solution to these quality control problems and hopefully, by next year's meeting, a talk will be given on what we are doing to address these problems.

CONCLUSIONS

1. A theoretical foundation has been laid for estimating the moisture content distribution from resistance meter data.
2. A lognormal distribution can effectively model the data.
3. Taking into consideration censored data improves the estimation of the lognormal parameters.

REFERENCES


This program calculates the mu and sigma parameters of the Lognormal distribution, taking into account of censored data. It was written by Jean A. Cook, Statistician at Forintek Canada Corp. in April, of 1985, with some assistance from Robert L. Zwick. This program can easily be modified to estimate the mean and standard deviation of a normal distribution.

Character*4 ans, resp
INTEGER N,P,FLNM(10),inc,j
REAL Y(500,10),W(500,10),Etao(500),TA0(500),MU,MU1,LAMBDA,emc,
1 emcmin,emcmax,smu,x,vmax,div,sum,lgnrm,emsee
WRITE(5,26)
26 FORMAT('WHAT IS THE INPUT FILE?')
READ(5,30) (FLNM(I),I=1,10)
30 FORMAT(10A2)
OPEN(UNIT=1,NAME=FLNM,TYPE='OLD')
'OPEN(UNIT=2,NAME='ROB.OUT',TYPE='NEW')'
WRITE(5,*) ' Type in the number of readings per board - P'
C READ IN THE SIZE OF THE Y MATRIX
C READ(5,*) P
C READ IN THE DATA
C Write(5,*) ' What is the minimum emc value of the load?'
Read(5,*) emc
n=0
DO 1 1=1,1000
READ(1,*,end=1) (Y(I,J),J=1,P)
1 CONTINUE
write(5,11) n
11 format (' The number of boards read = ',15)
do 333 I=1,N
DO 222 J=1,P-
emsee=y(i,j)-emc
if (emsee.le.1.1) then
    y(i,j)=1.1
else
    y(i,j)=y(i,j)-emc
end if
Y(I,J)=ALOG(Y(I,J))
222 continue
333 continue
C COUNT THE NUMBER OF CENSORED OBSERVATIONS:R1 ARE CENSORED
FROM BELOW,R2 ARE CENSORED FROM ABOVE
C if (emc.ge.6.0) then
    emcmin=emc-6.0
else
    emcmin = 6.0-emc
end if
emcmax = 30.0-emc
R1=0.
R2=0.
DO 10 I=1,N
DO 10 J=1,P
10 continue
IF(Y(I,J).LT.ALOG(emcmin)) R1=R1+1.
IF(Y(I,J).GT.ALOG(emcmax)) R2=R2+1.

CC R IS THE NUMBER OF UNCENSORED OBSERVATIONS
C
R=N*P-R1-R2
10 CONTINUE
WRITE(2,*) 'THERE ARE ',R,' UNCENSORED OBSERVATIONS.
WRITE(2,*) R1,' ARE LESS THAN 6 AND ',R2,' ARE GREATER THAN 30'
WRITE(2,*)

CC WEIGHT IS THE DENOMINATOR FOR COMPUTING SIGMA HAT SQUARED
CC
if (p.eq.1) then
  weight=n*p
else
  WEIGHT=n*(p-1)
end if

CC COPY Y INTO W: TO CREATE A WORKING FILE
C
DO 2 I=1,N
  DO 2 J=1,P
  2 W(I,J)=Y(I,J)

CC START THE ITERATIONS, NCOUNT COUNTS THE NUMBER OF ITERATIONS
C
MU1=0.
NCOUNT=1
C
C CALCULATE THE ESTIMATES
C SUM CONTAINS THE SUM OF ALL THE OBSERVATIONS,SUM1 CONTAINS THE ROW (INDIVIDUAL BOARD) TOTALS
C
100 SUM=0.
  DO 3 I=1,N
    SUM1=0.
    DO 4 J=1,P
      SUM1=SUM1+W(I,J)
    4 CONTINUE
    SUM=SUM+W(I,J)
  3 CONTINUE

C MU IS THE OVERALL MEAN OF THE W(I,J)'S
C
MU=SUM/(N*P)
if (p.eq.1) go to 131
C
C TAO IS THE INDIVIDUAL BOARD MEANS MINUS MU
C (TAO(I) IS THE M.L.E. FOR THE ADDITIONAL CONTRIBUTION DUE TO THE ITH BOARD)
C
5 TAO(I)=TAO(I)-MU
  go to 112

131 do 113 I=1,n
  tao(I)=0.0
113
C
C SIGMA SQUARED IS THE SSE DIVIDED BY WEIGHT
C
112 SUM2=0.
DO 6 I=1,N
DO 6 J=1,P
6 SUM2=SUM2+(W(I,J)-MU-DAO(I))**2
SIGMA=SQRT(SUM2/WEIGHT)
SS=SUM2/WEIGHT
SMU=EXP(MU)+EMC
C
C WRITE OUT THE ESTIMATES
C
WRITE(2,*) 'THE ESTIMATES FOR THE ITH ITERATION ARE:'
WRITE(2,*) 'I = ',NCOUNT,'DENOM. OF SIGMA SQ.',WEIGHT
WRITE(2,*) 'MEAN=',SMU,'S SQUARED=',SS,'SIGMA= ',SIGMA
C
C CALCULATE THE NEW W(I,J)'S AND WEIGHT
C
C1=0.
C2=0.
DO 7 I=1,N
DO 7 J=1,P
IF(Y(I,J).EQ.5.) GO TO 16
IF(Y(I,J).EQ.31.) GO TO 17
GO TO 7
16 CALL F1(MU,TAO(I),SIGMA,WNEW,DELTA)
W(I,J)=WNEW
C1=C1+DELTA
GO TO 7
17 CALL F2(MU,TAO(I),SIGMA,WNEW,LAMBDA)
W(I,J)=WNEW
C2=C2+LAMBDA
7 CONTINUE
WEIGHT=R-C1+C2
C
C GO BACK FOR NEXT ITERATION
C
XM=ABS(MU-MUL)
WRITE(2,*) 'XM=',XM
IF(XM.LE.0.00001)GO TO 77
MUL=MU
NCOUNT=NCOUNT+1
GO TO 100
77 CONTINUE
98 STOP
END
SUBROUTINE F1(A,B,C,D,E)
ARG=6.-A-B/C
TEMP=WW(ARG)
D=A+B-C*TEMP
E=-1.*TEMP*(TEMP+ARG)
RETURN
END
SUBROUTINE F2(A,B,C,D,E)
ARG=30.-A-B/C
TEMP=WV(ARG)
D=A+B-C*TEMP
E=TEMP*(TEMP-ARG)
RETURN
END
FUNCTION WW(X)
PHI=(SQRT(1./(2.*3.1415926)))*EXP(-(X*X/2.))
CALL MDNOR(X,P)
IF(P.EQ.0.0)GO TO 39
WW=PHI/P
GO TO 40
39 WW=X
40 RETURN
END

FUNCTION V(X)
PHI=(SQRT(1./(2.*3.1415926)))*EXP(-(X*X/2.))
CALL MDNOR(X,P)
IF(P.EQ.1.0)GO TO 50
Q=1.-P
V=PHI/Q
GO TO 51
50 V=X
51 RETURN
END
Figure 1. Histogram of observed moisture contents in a kiln charge.

Figure 2. Log-normal p.d.f.'s with \( \mu = 0 \) and \( \sigma = 0.25, 0.5, 1.5 \) and 3.0.
Figure 3. Log-normal distribution fit to observed moisture contents in a kiln charge.