Managing lumber stiffness variation in a sawmill - A statistical quality control approach

by

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Declaration

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Summary

Several studies over the past two decades in South Africa showed that graded structural lumber from certain young pine resources did not conform to the stiffness requirements of SANS 10163-1(2003). The broad aim of this study was to propose a quality control system to South African sawmills, which will ensure the supply of structural lumber that is safe and reliable in its end-use application. The focus was on modulus of elasticity (MOE), since previous studies showed that this was the property most at risk of non-compliance to current standards. The specific objectives of this investigation were the following: (i) to quantify the amount of MOE variation within and between bundles of graded structural South African pine lumber from two sawmills, (ii) to attempt to define what is acceptable MOE variation for end-users of structural lumber in South Africa, and (iii) to evaluate the current proposed SANS 1783-5-2 quality assurance system and compare it with other possible systems in terms of its efficiency to ensure safe and reliable structural lumber in terms of lumber MOE.

Board MOEs from two anonymous sawmills (Sawmill A and B) in South Africa processing pine saw logs were measured for this study. Twelve months of data were available for Sawmill A and 2 months of data for Sawmill B. Only data for 38x114mm lumber from both sawmills graded as either utility grade / XXX (non-conforming), or structural grade S5 were used in the analysis. The dynamic MOE (MOE_{dyn}) for each board was measured using a resonance type stress grading device. The data was sorted into bundles using the intake bundles sizes (190 pieces per bundle). Variation in MOE was analysed and a reliability analysis performed. Various quality control methods were compared in terms of their ability to detect production periods where a large percentage of bundles did not conform to the reliability requirements in terms of both the serviceability and ultimate limit states.

Results showed that the mean MOE and 5th percentile MOE values of the full population of S5 graded 38x114 mm pieces were above the required SANS 10163 levels for both Sawmill A and Sawmill B. Over time and between bundles, however, there were fairly large changes in the MOE means and 5th percentile values between the two sawmills. In general, Sawmill A had higher mean bundle MOEs than Sawmill B. Sawmill B on the other hand had much lower variation in MOE and a much smaller range in bundle mean MOE values.

In terms of reliability, it was found that overall for all the bundles produced in the respective sampling periods, 1.38% of the bundles did not conform to the required reliability index for the serviceability limit state (152 bundles from a total of 11 046 bundles produced). Less than 0.1% of the bundles did not conform to the required reliability index for the ultimate limit state (8 bundles from a total of 11 046 bundles produced). It was observed that the variability of MOE played a relatively larger role in determining acceptable reliability than the mean MOE.

The EWMA chart seem to be the most effective quality control method at detecting production periods where a large percentage of bundles do not conform to reliability requirements. The current proposed quality control system based on a moving average (SANS 1783-5-2), as well as the CUSUM methods also seem to be able to effectively detect out-of-control production periods. However, the stop-production signal threshold in the current proposed quality control system (SANS 1783-5-2) may need to be changed in order to ensure an efficient system. The ARIMA method did not prove to be effective. Although increased sampling frequency enables quicker detection of out-of-control MOE, the current proposed sampling frequency of 1 out of 1 000 pieces seems to give acceptable results.

Additional research is recommended including a pilot study at several sawmills evaluating the lumber quality control procedure recommended from this study. In this case the static MOE values need to be measured instead of dynamic MOE.

Keywords: MOE, Structural lumber, Variation, Reliability, Load and resistance factors design, limit states, Quality control, moving average, CUSUM, EWMA.

Opsomming

Verskeie Suid Afrikaanse studies oor die afgelope twee dekades het getoon dat gegradeerde, strukturele hout vanaf sommige jong, denneboom-bronne nie voldoen aan die styfheidsvereistes van SANS 10163-1 (2003) nie. Die oorkoepelende doelwit van hierdie studie was om 'n kwaliteitsversekeringstelsel voor te stel vir Suid Afrikaanse saagmeulens wat sal verseker dat veilige en betroubare hout verskaf word aan die eindgebruiker. Die fokus van die studie was op die elastisiteitsmodulus (MOE), aangesien vorige studies gewys het dat dit die eienskap is wat die grootste risiko toon vir nie-nakoming van standaarde. Die doelwitte van die studie was: (i) om die variasie in MOE tussen bondels en binne bondels van gegradeerde Suid Afrikaanse dennehout vanaf twee saagmeulens te kwantifiseer, (ii) om te poog om te definieer wat aanvaarbare MOE variasie is vir eindgebruikers van strukturele hout in Suid Afrika, en (iii) om die huidige voorgestelde SANS 1783-5-2 kwaliteitsversekeringstelsel te evalueer en te vergelyk met ander moontlike stelsels in terme van die vermoë om veilige en betroubare strukturele hout te verseker in terme van MOE.

Plank MOE's vanaf twee anonieme Suid Afrikaanse denne-saagmeulens (Saagmeul A en B) is gemeet vir hierdie studie. Twaalf maande se data was beskikbaar vir Saagmeul A en 2 maande vir Saagmeul B. Slegs data van produksie van 38x114 mm planke wat gradeer is in algemene graad (XXX) of strukturele S5 graad is gebruik. Die dinamiese MOE (MOE_{dyn}) van elke plank is gemeet met behulp van 'n resonansie-tipe graderingsapparaat. Die data is sorteer in bondels van 190 stukke per bondel. Variasie in MOE is ge-analiseer en 'n betroubaarheidstudie is uitgevoer. Verskeie kwaliteitsversekeringsmetodes is vergelyk in terme van hulle vermoë om produksieperiodes te identifiseer waar 'n groot hoeveelheid bondels substandaard was.

Resultate het aangedui dat die gemiddelde MOE en 5de persentiel MOE van al die bondels gegradeerde S5 38x114 mm planke hoër was as die vereisde SANS 10163 waardes vir beide Saagmeul A en Saagmeul B. Oor tyd was daar egter redelike groot veranderinge in gemiddelde en 5de persentiel MOE waardes van elke saagmeul asook tussen die twee saagmeulens. Oor die algmeen het Saagmeul A hoër gemiddelde bondel MOE waardes gehad terwyl Saagmeul B laer variasie in MOE gehad het.

In terme van betroubaarheid is gevind dat 1.38% van alle bondels oor die studietydperk nie voldoen het aan die vereiste betroubaarheidsindeks vir die diensbaarheidslimietstaat nie (152 bondels uit 11046 bondels). Minder as 0.1% van die bondels het nie voldoen aan die uiteindelike ("ultimate") limietstaat nie (8 bondels uit 11 046). Daar is waargeneem dat die variasie in MOE 'n relatiewe groter rol speel in bepaling van aanvaarbare betroubaarheid as gemiddelde MOE.

Die EWMA grafiek lyk asof dit die mees effektiewe metode van kwaliteitsversekering is in terme van identifikasie van tye waar groot hoeveelhede bondels substandaard is ten opsigte van betroubaarheid. Die huidige voorgestelde kwaliteitsversekering-stelsel wat gebaseer is op 'n bewegende gemiddelde (SANS 1783-5-2), asook die CUSUM metode lyk ook asof dit buite-beheer omstandighede effektief kan identifiseer. Die stop-produksie sein van die huidige voorgestelde stelsel moet egter dalk verander om 'n effektiewe stelsel te verseker. Die ARIMA metode was nie gevind as 'n effektiewe metode nie. Alhoewel verhoogde bemonstering frekwensie vinniger opspoor van buite-beheer MOE moontlik maak, lyk dit asof die huidig voorgestelde frekwensie van 1 uit 1000 stukke aanvaarbare resultate verskaf.

Meer navorsing word aanbeveel insluitende 'n loodstudie by verskeie saagmeulens waar die aanbevole kwaliteitsbeheer prosedures getoets kan word. In hierdie geval moet die statiese en nie dinamiese MOE gemeet word.

Sleutelwoorde: Elastisiteitsmodulus, Strukturele hout, Variasie, Betroubaarheid, limietstate, Kwaliteitsversekering, bewegende gemiddelde, CUSUM, EWMA.

This thesis is dedicated to

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Table of contents

Declaration ... ii
Summary ... iii
Opsomming ... v
Acknowledgements ... viii
Table of contents ... ix
List of figures ... xi
List of tables ... xv
List of abbreviations ... xvi
List of symbols ... xvii
Chapter 1 : Introduction ... 1
1.1 Background ... 1
1.2 Objectives ... 2
1.3 Key questions ... 2
1.4 Research procedure and structure ... 3
Chapter 2 : Literature review ... 4
2.1 Wood characteristics ... 4
2.1.1 Wood properties ... 4
2.1.2 Wood property variation ... 5
2.2 Structural lumber ... 5
2.2.1 Lumber grading ... 5
2.2.2 Design with structural lumber ... 6
2.3 Quality control and improvement ... 9
2.3.1 Quality definition ... 9
2.3.2 Customer satisfaction ... 10
2.3.3 Variation ... 10
2.3.4 Cost of quality and financial impacts ... 11
2.3.5 Quality control and improvement ... 11
2.3.6 Output control ... 14
Chapter 3 : Materials and Methodology ... 25
3.1 Materials ... 25
3.1.1 Production process ... 25
3.2 Methodology ... 26
3.2.1 MOE_{dyn} measurement ... 26
3.2.2 Data preparation ... 28

3.2.3 Data analysis 28
Chapter 4 : RESULTS AND DISCUSSION 37
4.1 MOE variation of structural lumber. 37
4.1.1 Overall MOE variation in the boards for the 2 sawmills 37
4.1.2 MOE variation between the individual boards. 38
4.1.3 The variation in MOE within and between the bundles 40
4.1.4 General discussion on MOE variability 50
4.2 Acceptable MOE mean and variation. 53
4.3 Statistical quality control system for structural lumber 60
4.3.1 Key performance measures 60
4.3.2 Measuring the performance of the quality control method in SANS 1783-5-2 using data collected. 60
4.3.3 Testing different control charts and sampling strategies. 64
4.3.4 Control chart comparison 76
Chapter 5 : Conclusions and recommendations 81
5.1 Conclusions 81
5.2 Recommendations 82
References 83
Appendix A 87
Appendix B 91
Appendix C 92

List of figures

Figure 2-1: Load and resistance factor probability diagram. Adapted from Burdekin (2007)............................ 9
Figure 2-2: DMAIC model for continuous improvement. The different phases in an improvement process... 12
Figure 2-3: Steps followed in a control process. 15
Figure 2-4: Diagram showing procedure on choosing the right control chart for your process. Adapted from Montgomery (2009). .... **Error! Bookmark not defined.**
Figure 3-1: Supplier-input-process-output-customer (SIPOC) diagram showing the supply chain of the lumber manufacturing process. 25
Figure 3-2: Schematic diagram showing Sawmills A and B lumber production system. 26
Figure 3-3: Pictures showing MOE_{dyn} measuring system using a Microtec Viscan stress grading machine. Retrieved from https://microtec.eu/. 27
Figure 3-4: The quality control method proposed in SANS 1783-5-2 showing the moving average chart. The samples were sampled at 1 in a 1000 samples sampling intervals and the moving average averaged over 20 samples. The different target lines are also displayed on the graph.. 34
Figure 3-5: The quality control method proposed in SANS 1783-5-2 showing the running total number of tests with a value less than 4 630 MPa. The target lines provide a warning and a signal to stop production.... 34
Figure 4-1: Histogram of individual board MOE for 38x114 mm S5 graded boards from both sawmills. The blue vertical line represents the target mean MOE (7 800 MPa). 37
Figure 4-2: Histogram of individual board MOE for Month 1, Sawmill A. The blue vertical line represents the target mean MOE (7 800 MPa). 38
Figure 4-3 : Histogram of individual board MOE for Month 1, Sawmill B. The blue vertical line represents the target mean MOE (7 800 MPa). 38
Figure 4-4: Boxplots of mean MOE of the individual S5 graded boards for Sawmill A over 12 months showing the median, upper quantile and lower quantile values. The blue horizontal line shows the target mean for the bundles at 7 800 MPa and the circular data points are outliers. 39
Figure 4-5: Boxplots of mean MOE of the individual S5 graded boards for Sawmill B over 2 months showing the median, upper quantile and lower quantile values. The blue horizontal line shows the target mean for the bundles at 7 800 MPa and the circular data points are outliers. 39
Figure 4-6: Histogram showing mean MOE for bundles for Month 1, Sawmill A. The blue vertical line represents the target mean MOE (7 800 MPa). 40
Figure 4-7: Histogram showing mean MOE for bundles for Month 1, Sawmill B. The blue vertical line represents the target mean MOE (7 800 MPa). 40
Figure 4-8: Boxplots of bundle MOE characteristics of Sawmill A over 12 months showing the median, upper quantile and lower quantile values. The blue horizontal line shows the target mean for the bundles at 7 800 MPa and the circular data points are outliers. 41
Figure 4-9: Boxplots of bundle MOE characteristics of Sawmill B over 2 months showing the median, upper quantile and lower quantile values. The blue line shows the target mean for the bundles at 7 800 MPa. 41
Figure 4-10: Xbar chart to monitor the mean MOEs of bundles for Month 1, Sawmill A. The MOE values in MPa are plotted on the y-axis and the summary of the data is shown on the graph. The chart shows the centreline (CL) as well as the upper and lower control limits marked by UCL and LCL, respectively. 46

Figure 4-11: S chart to monitor the standard deviation of MOE within bundles for Month 1, Sawmill A. The MOE values in MPa are plotted on the y-axis and the summary of the data is shown on the graph. The chart shows the centreline (CL) as well as the upper and lower control limits marked by UCL and LCL, respectively. 46

Figure 4-12: Xbar chart to monitor the MOE means of bundles for Month 1, Sawmill B. The MOE values in MPa are plotted on the y-axis and the summary of the data is shown on the graph. The chart shows the centreline (CL) as well as the upper and lower control limits marked by UCL and LCL, respectively. 47

Figure 4-13: S chart to monitor the standard deviation of MOE within bundles for Month 1, Sawmill B. The MOE values in MPa are plotted on the y-axis and the summary of the data is shown on the graph. The chart shows the centreline (CL) as well as the upper and lower control limits marked by UCL and LCL, respectively. 47

Figure 4-14: The variation observed within a bundle with a low mean MOE value (mean MOE = 6 688 MPa) from Sawmill B, Month 1. The blue points represent the samples within the bundles. The green line is the target line at 7 800 MPa. 49

Figure 4-15: The variation observed within a bundle with an average mean MOE value (mean MOE = 7 772 MPa) from Sawmill B, Month 1. The blue points represent the samples within the bundles. The green line is the target line at 7 800 MPa. 49

Figure 4-16: The variation observed within a bundle with a high mean MOE value (mean MOE = 9 636 MPa) from Sawmill B, Month 1. The blue points represent the samples within the bundles. The green line is the target line at 7 800 MPa. 50

Figure 4-17: Graded bundles from Month 1 Sawmill A. The yellow points represent the required mean to ensure a reliability index value of β = 1.5 for SLS. The grey points represent the required mean to ensure a reliability index value of β = 3 for ULS. The orange points represent the bundle mean MOE values. The green and blue vertical lines represent the bundles where the required mean exceeded the MOE for the bundle for serviceability limit state and ultimate limit state respectively. 55

Figure 4-18:Graded bundles from Month 1 Sawmill B. The yellow points represent the required mean to ensure a reliability index value of β = 1.5 for SLS. The grey points represent the required mean to ensure a reliability index value of β = 3 for ULS. The orange points represent the bundle mean MOE values. The green and blue vertical lines represent the bundles where the required mean exceeded the MOE for the bundle for serviceability limit state and ultimate limit state respectively. 55

Figure 4-19: The correlation between mean MOE and standard deviation of Month 1, Sawmill A bundle means. 57

Figure 4-20: The correlation between mean MOE and standard deviation of Month 1, Sawmill B bundle means. 58

Figure 4-21: Ungraded bundles from Month 1, Sawmill B. The green and blue vertical lines represent the areas where the required mean exceeded the MOE for the bundle for the serviceability limit state and ultimate limit state respectively. The areas with condensed vertical green and blue lines represent the "problem areas" in the month. 62

Figure 4-22: The quality control method proposed in SANS 1783-5-2 showing the moving average chart. The samples were sampled at **1 in a 1000** samples sampling intervals and the moving average averaged over 20 samples. The different target lines are also displayed on the graph. 62

Figure 4-23: The quality control method proposed in SANS 1783-5-2 showing the running total number of tests with a value less than 4 630 MPa. The orange target line provides a warning and the grey one a signal to stop production. 63

Figure 4-24: The quality control method proposed in SANS 1783-5-2 showing the moving average chart with a **1 in 750** sampling interval and the moving average averaged over 20 samples. The different target lines are also displayed on the graph. 65

Figure 4-25: The quality control method proposed in SANS 1783-5-2 showing the running total number of tests with a value less than 4 630 MPa with a **1 in 750** sampling interval. The target lines provide a warning and a signal to stop production........ 65

Figure 4-26: The quality control method proposed in SANS 1783-5-2 showing the moving average chart with a **1 in 500** sampling interval and the moving average averaged over 20 samples. The different target lines are also displayed on the graph. 66

Figure 4-27: The quality control method proposed in SANS 1783-5-2 showing the running total number of tests with a value less than 4 630 MPa with a **1 in 500** sampling interval. The target lines provide a warning and a signal to stop production........ 66

Figure 4-28: The quality control method proposed in SANS 1783-5-2 showing the moving average chart with a **1 in 250** sampling interval and the moving average averaged over 20 samples. The different target lines are also displayed on the graph. 67

Figure 4-29: The quality control method proposed in SANS 1783-5-2 showing the running total number of tests with a value less than 4 630 MPa with a **1 in 250** sampling interval. The target lines provide a warning and a signal to stop production........ 67

Figure 4-30: ARIMA model residuals plotted on a Shewhart chart. The chart shows the centreline (CL) as well as the upper and lower control limits marked by UCL and LCL, respectively. 69

Figure 4-31: CUSUM chart for Month 1, Sawmill B data when samples were taken at **1000** intervals. The positive and negative cumulative sum are shown on the y-axis. The summary statistics is displayed on the bottom of the chart. The chart shows the centreline (CL) as well as the upper and lower control limits marked by UCL and LCL respectively. The red points are for out-of-control samples. 71

Figure 4-32: CUSUM chart for Month 1, Sawmill B data when samples were taken at **750** intervals. The positive and negative cumulative sum are shown on the y-axis. The summary statistics is displayed on the bottom of the chart. The chart shows the centreline (CL) as well as the upper and lower control limits marked by UCL and LCL respectively. The red points are for out-of-control samples. 71

Figure 4-33: CUSUM chart for Month 1, Sawmill B data when samples were taken at **500** intervals. The positive and negative cumulative sum are shown on the y-axis. The summary statistics is displayed on the bottom of the chart. The chart shows the centreline (CL) as well as the upper and lower control limits marked by UCL and LCL respectively. The red points are for out-of-control samples. 72

Figure 4-34: CUSUM chart for Month 1, Sawmill B data when samples were taken at **250** intervals. The positive and negative cumulative sum are shown on the y-axis. The summary statistics is displayed on the bottom of the chart. The chart shows the centreline (CL) as well as the upper and lower control limits marked by UCL and LCL respectively. The red points are for out-of-control samples. 72

Figure 4-35: EWMA chart for Month 1, Sawmill B data when samples were taken at **1000** intervals. The MOE values are shown on the y-axis. The summary statistics is displayed on the bottom of the chart. The chart shows the centreline (CL) as well as the upper and lower control limits marked by UCL and LCL, respectively. The red points are for out-of-control samples. 74

Figure 4-36: EWMA chart for Month 1, Sawmill B data when samples were taken at **750** intervals. The MOE values are shown on the y-axis. The summary statistics is displayed on the bottom of the chart. The chart shows the centreline (CL) as well as the upper and lower control limits marked by UCL and LCL respectively. The red points are for out-of-control samples. 74

Figure 4-37: EWMA chart for Month 1, Sawmill B data when samples were taken at **500** intervals. The MOE values are shown on the y-axis. The summary statistics is displayed on the bottom of the chart. The chart shows the centreline (CL) as well as the upper and lower control limits marked by UCL and LCL, respectively. The red points are for out-of-control samples. 75

Figure 4-38: EWMA chart for Month 1, Sawmill B data when samples were taken at **250** intervals. The MOE values are shown on the y-axis. The summary statistic is displayed on the bottom of the chart. The chart shows the centreline (CL) as well as the upper and lower control limits marked by UCL and LCL, respectively. The red points are for out-of-control samples. 75

Figure 4-39: Figure showing the weightings used to compute the detection statistics of the moving average, EWMA and CUSUM charts. Adapted from Haque (2016). 77

Figure 4-40: The quality control method proposed in SANS 1783-5-2 showing the moving average chart. The samples were sampled at intervals of **1 in a 1000** and the moving average was averaged over 20 samples. The different target lines are also displayed on the graph. 78

Figure 4-41: EWMA chart for Month 1, Sawmill B data when samples were taken at **1000** intervals. The MOE values are shown on the y-axis. The summary statistics is displayed on the bottom of the chart. The chart shows the centreline (CL) as well as the upper and lower control limits marked by UCL and LCL, respectively. The red points are for out-of-control samples. 78

Figure 4-42: CUSUM chart for Month 1, Sawmill B data when samples were taken at **1000** intervals. The positive and negative cumulative sum are shown on the y-axis. The summary statistics is displayed on the bottom of the chart. The chart shows the centreline (CL) as well as the upper and lower control limits marked by UCL and LCL, respectively. The red points are the out-of-control samples. 79

List of tables

Table 3-1: Steps followed in plotting quality control charts. 33

Table 4-1: The MOE data for 38x114 mm S5 graded boards from the study sawmills. 38

Table 4-2: Summary of the numerical description of MOE variation between the 38x114 mm S5 graded bundles for the different months in both sawmills. 43

Table 4-3: summary of the variables used to calculate the required mean values to satisfy the ultimate and serviceability limit stated. 53

Table 4-4: The results show the number and percentage values of required mean values for serviceability and ultimate limit state above the mean MOE of the bundles. The table also showed the correlation (R^2) between mean MOE and the standard deviation of the bundles. 56

Table 4-5:ARIMA model output showing the model parameters, estimates, standard errors, and the AIC value for Month 1, Sawmill B. 68

Table 4-6: Calculated average run length (ARL) values for CUSUM AND EWMA charts. 76

List of abbreviations

Abbreviation	Definition
ACF	Auto correlation function
ADF	Augmented Dickey–Fuller
AIC	Akaike information criterion
AR	Autoregressive
ARIMA	Autoregressive integrated moving average
ARL	Average run length
CUSUM	Cumulative sum chart
DMAIC	Define measure improve control
EWMA	Exponentially weighted moving average
KPI	Key performance indicator
LCL	Lower control limit
MA	Moving average
MOE	Modulus of elasticity
$MOE_{5th\ perc}$	Fifth-percentile MOE
MOE_{dyn}	Dynamic MOE
MOE_{mean}	Mean MOE
OCAP	Out-of-control action plan
OQA	Ongoing quality assessment
SIPOC	Supplier input process output customer
SLS	Serviceability limit state
SPC	Statistical process control
UCL	Upper control limit
ULS	Ultimate limit state

List of symbols

Symbol	Definition
γ_i	Partial load factor
γ_m	Partial material factor
$(t - k)$	Period
$\bar{s}$	Average of the *m* standard deviations
$\bar{\bar{x}}$	Process average
$\bar{x}$	Average of subgroup
$z_{\alpha/2}$	Shift in mean
μ	Mean
μ_R	Required mean
A	Approximation factor used to calculate control limits
c	Constant dependent on sample size
C^-	One-sided lower CUSUM
C^+	One-sided upper CUSUM
D_n	Nominal permanent load effect
E_d	Design action effect
e_{t-k}	Forecast error
f	The frequency of the longitudinal vibration
f_k	Characteristic material strength
H	Decision interval
k	Reference value
l	The length of the lumber in mm
n	Sample of size
Q_{ni}	Effect of the nominal action or load
R_d	Design resistance
R_k	Characteristic mean value
s	Sample standard deviation
v	The velocity of the stress wave
V_R	Coefficient of variation.
w	Span
x_i	Individual measurements
α	Alpha
α_R	Sensitivity factor
β	Reliability index
δ	Delta
Θ_k	Moving average coefficient at lag k
λ	Lambda
σ	Standard deviation

ϕ_f	Resistance factor
Φk	Autoregressive coefficient at lag k
ψ_i	Load combination factor
i	Time period

Chapter 1 : Introduction

1.1 Background

In 2008, the South African industry body representing sawmillers, Sawmilling South Africa (SSA), sponsored a study at Stellenbosch University to investigate the mechanical properties of *Pinus patula* lumber from 16-20 year-old trees from the Mpumalanga escarpment (Dowse and Wessels 2013). The results indicated that the stiffness or modulus of elasticity (MOE) of the visually graded lumber was far below the required grade characteristic values as published in SANS 10163-1 (2003). For instance, the mean MOE value for visually graded S5 lumber was found to be 5 750 MPa compared to a required grade mean value of 7 800 MPa (Dowse and Wessels 2013). Additional studies were conducted on various tree resources including an investigation into the mechanical properties of graded lumber from six commercial sawmills using “mature” tree resources (Crafford and Wessels 2011) and a study on graded lumber from four “small log mills” (Wessels and Froneman 2012). The conclusion from these initial studies was that visual grading was not effective in controlling the MOE of lumber from young SA pine tree resources.

This was a significant problem for the sawmilling industry since it showed that there was a risk that some graded structural lumber resources did not conform to the published MOE requirements of the SANS 10163-1 design code. The sawmilling industry, through SSA, commissioned Mr. Peter Muller, an experienced wood technologist, to develop a quality control system for graded structural lumber to ensure that only compliant lumber enter the market. Mr. Muller developed a document which described (a) a test procedure to establish whether a grading system was effective in producing lumber, which conforms to the MOE and MOR requirements of a grade and (b) an on-going quality control system, which can be followed at a sawmill to ensure compliance to grade requirements.

A small SABS working committee was established to finalise the procedure and document and to get it published as part of the SANS 1783 standard for “Sawn softwood lumber”. The two parts of the quality control standard have, in the meantime, been circulated by the SABS as a draft document for public comment with the titles “SANS 1783-5-1 Stress-grade assessment” and “SANS 1783-5-2 Quality assurance of stress-grading” (see Appendix C). The broad aim of this MSc study was to evaluate the current draft standard for on-going quality control (SANS 1783- 5:2), using real sawmill data, and to evaluate other possible quality control methods using the same data.

The two common methods for controlling structural grading quality are machine control and output control (Lycken and Bengtsson, 2010; Sandomeer and Kohler, 2007; Kovryga et al., 2017). With machine control, the grading machine itself is certified and controlled, while with output control the product quality is measured and controlled (Lycken and Bengtsson, 2010). Sawmills define quality by meeting product quality specifications according to a national standard. For quality control in the South African sawmilling industry, the current proposed system (Appendix C) can be described as an output control system. Similarly, for this study only output control methods were considered as possible alternatives.

1.2 Objectives

The broad aim of this study was to propose a quality control system to South African sawmills, which will ensure the supply of structural lumber that is safe and reliable in its end-use application. The focus was on MOE, since previous studies showed that this was the property most at risk of non-compliance to current standards. The specific objectives of this investigation were:

- To quantify the amount of MOE variation within and between bundles of graded structural SA pine lumber from two sawmills;
- To attempt to define what is acceptable MOE variation for end-users of structural lumber in South Africa; and
- To evaluate the current proposed SANS 1783-5-2 quality assurance system and compare it with other possible systems in terms of its efficiency to ensure safe and reliable structural lumber in terms of lumber stiffness (MOE).

1.3 Key questions

Some key questions the research aims to answer are:

- What is the MOE variation in the lumber produced in a typical South African pine sawmill and how does it vary over time?

- Do the individual bundles produced at the sawmill have the required mean and 5th percentile characteristic MOE for structural lumber?

- How much MOE variation can roof truss plants and other structural lumber users handle in terms of MOE variation and still produce safe and reliable products?

- How do we best manage the variation of MOE in the structurally graded end products produced at sawmills?

- How efficient is the new proposed SANS 1783-5-2 quality assurance system in controlling the MOE of lumber?

- Are there alternative systems that are more efficient than the proposed SANS 1783-5-2 quality assurance system in controlling the MOE of lumber?

1.4 Research procedure and structure

This thesis consists of five chapters and three Appendices. The first chapter introduced the project and its objectives as well as the key questions that the project aimed to answer. The second chapter reviewed the literature concerning both wood characteristics and statistical quality control approaches. The third chapter explained the methods used in this research. The fourth chapter presents the findings of this investigation. The fifth chapter contains the conclusions and recommendations. Appendix A contains additional results not shown in the body, Appendix B contains extracts of the R statistical package program code used for data analysis and Appendix C contains the standard that was used as reference for this study (SANS 1783-5-2).

Chapter 2 : Literature review

2. Chapter overview

This chapter presents a literature review of the product (wood) and its characteristics in relation to its mechanical properties of interest, the processing thereof, as well as quality control practices. The first part addresses wood characteristics in terms of its provenance, its properties and variation. The second part explores wood as a structural material including its processing and design requirements for the final product. The third part explores quality assurance/control practices for industrial processes and ways to ensure the quality of the final product.

2.1 Wood characteristics

2.1.1 Wood properties

Wood has a wide range of physical and mechanical properties. It is therefore important for structural engineers, lumber researchers and sawmillers to understand the main principles and the limitations of the strength system (Ridley-Ellis et al., 2016). The key wood properties need to be assessed in the production of structural lumber; this is important in order to ensure the structural safety and economic use of the material. For structural purposes, the most important properties are often considered to be stiffness, bending strength and density (Kovryga A, 2017). Stiffness has been the focus of several investigations recently (Ivković et al., 2007; Jayawickrama, 2001; McLean et al., 2011; Wessels et al., 2014; Wessels et al., 2015 and Froneman and Wessels, 2018). In a study by Wessels and Petersen (2015), bending strength and stiffness were found to be the two most influential properties in the design of nail-plated roof trusses – the largest end-use application of structural lumber in South Africa.

The stiffness of wood refers to the ratio of applied load and deformation of a rigid body of wood. It can be estimated from the slope of the line that describes the relationship between load and deflection (Vikram et al., 2011). A study by Wessels et al. (2014), found that the edge modulus of elasticity of young *Pinus patula* lumber was lower than required for structural grade in South Africa. Large, carefully sampled datasets are necessary to properly measure important lumber properties. The main requirement in sampling is that the lumber tested is representative of the lumber to be graded in production. The aim is for the sampling to resemble this lumber population in terms of the mean and variance in the relationships between characteristics assessed during grading and the grade determining properties (Ridley-Ellis et al., 2016). Higher sampling rate allows more samples to be taken from each single period and thus, the probability to detect low quality lumber increases (Kovryga, 2017).

2.1.2 Wood property variation

Pine is one of the most important commercial tree species in the world; they are mostly planted in temperate and tropical regions in the southern hemisphere. Pine lumber is mostly used for furniture, wood panelling, flooring and roofing. There are many different species of pine trees in the world; the most commonly planted species in South Africa are *Pinus patula, Pinus elliottii, Pinus taeda, Pinus radiata* and *Pinus pinaster* (Geldenhuys, 1997). The wood properties of each species differ, which means that sawmills end up receiving logs from different pine species with different mechanical properties.

Several studies showed that the variation in wood and fibre properties is vast within a pile of logs that has been visually sorted for similar grade. This variation also applies to logs of the same age and from the same forest (Wang et al., 2007). The variation in wood, which is in part caused by genetic, environmental and silvicultural factors, includes the size and position of knots; the slope and spirality of the grain; the density of the wood; the microfibril angle, the ratio of earlywood to latewood; fissures; reaction wood; wane; rot and other damage (Ridley-Ellis et al., 2016).

The rotation age of sawlog rotation softwood (pine) is between 20-30 years in South Africa. The reduction in the harvesting age of pine increases the proportion of low quality, juvenile wood (Dickson et al., 2004). Juvenile wood is produced by the young cambium, and forms a cylinder of wood around the pith that extends through the length of the tree. The quicker a tree grows during its first few years of rotation, the larger the diameter of the juvenile core in the lower stem. The concern with the use of juvenile wood in structural lumber is that its physical and mechanical properties are inferior to those of mature wood, as juvenile wood is characterised by low density, short fibres and high microfibril angles, which reduce the strength and stiffness of the wood (Moyo, 2013). In South Africa, the mean age of plantation trees for sawlog production dropped from 14.1 years in 1983 to 11.3 years in 2003 (Crickmay and Associates, 2004). This suggests a mean harvesting age reduction from about 28.2 years in 1983 to about 22.6 years in 2003 for trees earmarked for sawlogs.

2.2 Structural lumber

2.2.1 Lumber grading

The lumber produced in sawmills is typically graded into different grades according to the intended use. Structural lumber is stress graded to ensure reliability (Divos and Tanaka, 1997). It is important for wood graders to understand what grades really mean with regard to properties of the lumber, in order to correctly analyse the results of testing, and to assign the right lumber for intended use (Ridley-Ellis et al., 2016). According to current South African specifications, sawn lumber has to conform to either visual or mechanical grading specification in order to qualify for structural purposes (Burdzik, 2004 and Wessels et al., 2014). A piece of lumber is assigned to a specific strength class based on boundary values or machine settings in the case of machine grading of certain grading properties during the grading process (kovryga, 2017).

The limits of the three grade determining properties (strength, density and stiffness) are defined by characteristic values that equate to the most useful description of the level and variation of a property for structural lumber. In Europe and South Africa, strength and density are defined by a lower fifth percentile value, while stiffness is defined by a mean (Ridley-Ellis et al., 2016; SANS 10163-1, 2003). The relationship used to correlate the modulus of elasticity and the density is usually simple or multiple linear regressions (Grazide et al., 2015).

2.2.2 Design with structural lumber

The structural design process is regulated by the relevant design codes, which are based on various principles, such as limit state design, reliability design or allowable stress design (Borgström, 2016; Holicky and Retief, 2005 and SABS 0160, 1989). The safety level prescribed in design codes should be able to fulfil the minimum socially acceptable level on the conditions that the basic requirements for structural integrity is achieved (Shiraishi et al., 1998 and Porteous and Kermani, 2013). Factors that are relevant to lumber structures according to Porteous and Kermani (2013) are the intended or foreseeable use of the structure; the required design criteria; the expected environmental conditions; the characteristics of the material and products; the choice of the structural system; the quality of the workmanship and the level of control and the intended maintenance during the design working life.

The form of structural lumber mainly used in South Africa is a roof truss. A roof truss is a framed structure with a system of members secured to each other such that the stresses transmitted from one member to another are mainly axial compression or tension (Parker and Ambrose, 1997). The designer of a truss must first account for the magnitude and character of the internal forces in each member (Parker and Ambrose, 1997 and SANS 10163-1, 2003) in order to minimise or prevent damage to the structure. Some of the causes of damage in lumber structures were identified as effects of moisture exposure (imposed strains, shrinkage); poor durability of the product; inadequate bracing of structural system; poor performance of material and products; insufficient accounting of the loads and failure of joints (Frühwald et al., 2007).

Structures designed following the limit-states design approach are designed so that they are serviceable during their useful life, and safe from collapse during their construction and during the useful life (SANS 10163-1, 2003; Code, 2005; and Porteous and Kermani, 2013, Ellingwood, 1980). The two types of limit states considered are the ultimate limit state and serviceability limit state

(Paikowsky, 2002). The ultimate limit state is concerned with the safety of the structure and includes exceeding of load-carrying capacity, fracture and fatigue. The serviceability limit state is concerned with the intended use and occupancy of the structure and includes excessive deflection and vibration, and permanent deformation (SANS 10163-1, 2003; Code, 2005 and Porteous and Kermani, 2013).

The ultimate and serviceability limit states can be obtained using the method below.

The formula for ultimate limit states is:

Factored resistance ≥ Factored load effects

The formula for serviceability limit states is:

Deformation ≤ Tolerable deformation to remain serviceable

2.2.3.1 Limit-states criterion of failure

The Limit-states criterion of failure is obtained from the equations below (SABS 0160, 1989). The requirements for limit state can be written as:

$$R_d > E_d$$

Equation 2-1

Where,

E_d =Design action effect

R_d = Design resistance

and

$$E_d = \sum (\psi_i \gamma_i Q_{ni})$$

$$R_d = \phi_f R (f_k/\gamma_m)$$

Where,

R() = a function defining the resistance of the structure for a particular limit state

f_k = the characteristic material strength.

γ_m = partial material factor which allows action for uncertainty in the material strength

ϕ_f = the resistance factor which allows for all other uncertainties for the limit state under consideration, and for brittle modes of failure

Q_{ni} = the effect of the nominal action or load defined in the loading code.

γ_i = the partial load factor which allows for variability in the action and an average uncertainty over all materials and limit states in the process of modelling the effect of the action.

ψ_i = the load combination factor applicable to action or load i which allows for the probability of simultaneous occurrence of different load types in a particular load combination.

2.2.3.2 The load and resistance factors

Load and resistance factor design represents a more rational approach by which load and material resistance can be incorporated quantitatively into the design process. This is done by multiplying the appropriate material partial factor with the characteristic value of the structural member (Lenner and Sykora, 2017; Smith and Foliente, 2002 and Nowak and Ritter, 1995). The advantage of this method is that the load and resistance factors can be determined based on the target performance levels determined by the users. Figure 2-1 illustrates the load and resistance factor diagram. The design load effect *Q* relating to the ultimate and serviceability limit states is obtained from the equations below (SABS 0160, 1989 and Goble, 1999):

$$\phi Q_n = \gamma_i D_n$$

Equation 2-2

$$Q = \gamma_i D_n + \gamma_i D_{nj} + \sum (\psi_i \gamma_i Q_{ni})$$

Equation 2-3

Where,

γ_i = the partial load factors

D_n = the nominal permanent load effect

Q_{nj} = the dominant imposed load effect for the load combinations and limit state under consideration

Q_{ni} = additional imposed load effects relevant and significant to the load combination and limit state under consideration

ψ_i = the load combination factors

ϕ = the resistance factor

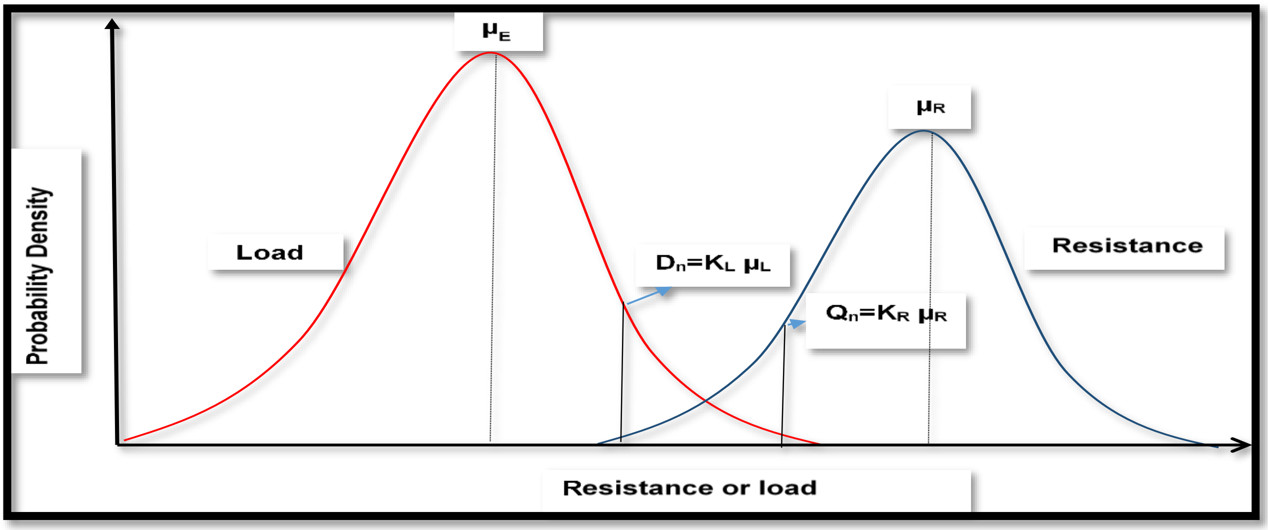

Figure 2-1: Load and resistance factor probability diagram. Adapted from Burdekin (2007).

2.3 Quality control and improvement

2.3.1 Quality definition

Quality management and improvement have become a central focus for many industries today, as they are recognizing that there is a close relationship between productivity and quality (Alwan, 1991). There are many ways in which the quality of a product and/or process is defined. Montgomery (2009) defines quality as fitness for use. It is also defined as one or more desirable characteristics that a product or service should have (Montgomery, 2009). A product which is fit for use is one produced in a stable process, which implies that the production process should be able to produce products with acceptable variability, and still be able to meet the desired quality as stated in the standard (Gejdoš, 2015).

It is however said that in any production process, regardless of how well it is designed or carefully maintained, a certain amount of natural variability will always be present in the process (Montgomery, 2009). There are many dimensions of quality of a product. These include performance (will the product do the intended job?); reliability (how often does the product fail?); durability (how long does the product last?); serviceability (how easy is it to repair the product?); aesthetics (what does the product look like?); features (what does the product do?); perceived quality (what is the reputation of the company or its product?); conformance to standards (is the product made exactly as the designer intended?) (Montgomery, 2009).

2.3.2 Customer satisfaction

The primary concern within quality orientated industries is the level to which they satisfy customers' needs and expectations. When the customer or end users' expectations are defined, it is essential for industries to quantify how they would be able to satisfy those expectations (Gejdoša, 2015). Most companies find it difficult and expensive to provide their customers with products that have the same quality traits that meet the customer's expectations. This is due to the fact that there is a certain amount of variability in each product as no two products are entirely the same (Montgomery, 2009).

2.3.3 Variation

Quality is said to be inversely proportional to variability (Montgomery, 2009). This implies that as the variability in the important characteristics of a product increases, the quality of the product decreases. Variation found in any process can be categorized as either common or assignable variation (Montgomery, 2009). Common causes of variation are usually chronic, associated with many minor variables, and thus difficult to diagnose and fix. Common variation is caused by factors such as poor design, working environment, equipment maintenance, and lack of information; and this might be common to all processes, all machines, all materials of a certain type, all work performed in a certain environment, or all work performed using a certain method. (Hoyle, 2009).

Adjusting a process on detection of a common cause will destabilize the process, as common cause variation is random. This means that the cause has to be removed instead of adjusting the process. Assignable causes are usually sporadic and often originate from a single variable, making it easier to detect (De Feo, 2014). Assignable cause variation causes variations in the location, spread and shape of a distribution, as the cause can be assigned to a specific or special condition that does not apply to other events. Elimination of assignable causes is part of quality control and many of these problems can be detected before they result in nonconforming products, through preliminary measures and routine checks. Once all the assignable causes of variation have been eliminated, the shape and spread of the distribution, and the location of the average become stable; the process is said to be under control and the results are predictable (Hoyle, 2009).

2.3.4 Cost of quality and financial impacts

In order to measure the cost of quality, i.e. cost of poor quality and cost of good quality, the activities that generate costs are accounted for in order to identify areas of improvement. The cost of quality and the financial impacts thereof at a production facility such as a sawmill can be explained in terms of the four categories of quality costs, which are internal failure costs; external failure costs; appraisal costs and prevention costs (De Feo, 2014 and Evans and Lindsay, 2013). Internal failure costs**,** which are costs of insufficiencies discovered before delivery of a product, can be in the form of re-inspection of lumber if the tests showed that the lumber in the bundles did not meet the required grade or satisfy the requirements for structural lumber. External failure costs are costs associated with insufficiencies found after the customer receives the product. Structural lumber with low stiffness tends to deform excessively under bending or buckle under compression, which can cause structural failure in service (Klohn and Hughes, 1964).

The financial impacts could be in the form of having to rebuild or repair a failed structure. Appraisal costs are costs incurred to determine the degree of conformance to quality requirements of a product. The lumber undergoes incoming inspection using visual or acoustic methods to try and process lumber of similar grades (Wang et al., 2007 and Farrell et al., 2012). The final lumber product may undergo final inspection to ensure that it meets the necessary requirements for intended use. All these processes have costs associated with implementing them. Prevention costs, which are costs associated with keeping failure and appraisal costs mentioned above at a minimum, are the costs associated with trying to keep all the costs of quality practices in the products down.

2.3.5 Quality control and improvement

Quality control and improvement involve the set of actions used to ensure that products produced and services rendered meet requirements and are improved on a continuous basis. The methods used in quality control include statistical process control, descriptive statistics and acceptance sampling (Evans and Lindsay, 2013). Quality improvement is the reduction of variability in processes and products (Montgomery, 2009). According to Alwan (1991), statistics provide a set of tools and a means for organized thinking that are necessary for process improvements. One of the methods used in structured problem solving procedures is the six sigma approach, see Figure 2-2. The six sigma approach includes 5 steps, which are define, measure, analyse, improve and control, and is known as the DMAIC model (De Feo, 2014). The DMAIC model encourages creative thinking about the problem and its solution within the definition of the original product, process, or service (Montgomery, 2009). Gejdoša (2015) cites that the use of the DMAIC model, as well as other statistical quality tools, is a way to achieve continuous quality improvement.

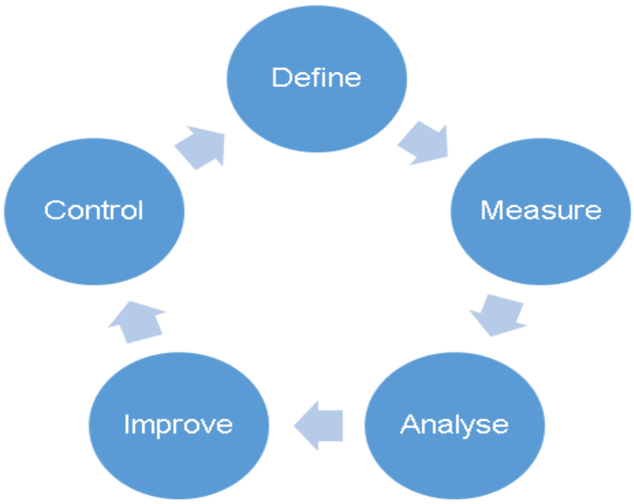

Figure 2-2: DMAIC model for continuous improvement. The different phases in an improvement process.

The DMAIC procedure according to (De Feo, 2014, Evans and Lindsay, 2013, Montgomery, 2009) is as follows:

- **Phase 1: Define**

In the definition phase, opportunities for improvement are identified and validated; the critical customer requirements are identified; a high level process map is documented in order to have an understanding of the process being analysed, the project charter is established and the project team is set up. Some of the tools used in this phase include cost of poor quality analysis.

The SIPOC (supplier-input-process-output-customer) diagram as a tool gives an overview of the process and helps to visualize elements in a process. These elements are: who are the suppliers of information or material; the input (information or materials that goes into the process); the process involved in carrying out the work; the output product, service, or information sent to the customer, and the customer (external or internal) who receives the output of the process.

The voice of the customer tool helps in gathering customer input in order to determine what the customer really wants, so that the company or industry can set priorities based on actual customer requirements. The voice of the customer data is usually obtained in the form of interviews, surveys, and analysis of customer satisfaction data, for the purpose of developing a set of critical to quality requirements for the product or service.

- **Phase 2: Measure**

The measurement phase focuses on evaluating and understanding the current 'as-is' state of the process. This can be achieved by defining the aspect(s) that is to be measured, i.e., key performance indicators (KPI) of a process, identifying the necessary data to be analysed, and establishing the data collection plan. Some of the tools used in this phase are graphs and charts, such as histograms, stem-and-leaf diagrams, run charts and Pareto charts. These charts are useful in explaining the distribution of the data in the case of histograms and stem-and-leaf diagrams, describing variability/variation over time using a run chart, and prioritizing projects using Pareto charts. The other tool that can be used is brainstorming, which can be used in generating ideas for plotting the cause-effect diagram, as well as generating solutions for improving the process. Process capability analysis is a tool that explains how the inherent variability in a process compares with the requirements of the product. One technique to measure process capability is to use control charts; alternatively, process capability ratios can be used.

- **Phase 3: Analyse**

The analysis phase, uses data collected in the measure phase to determine and understand the causes and effects of variability in the process. Possible theories are tested with data using hypothesis testing procedures with the purpose of proving or disproving them. The tools used in this phase include control charts, which are useful in differentiating causes of variation; statistical hypothesis testing, where a test of the validity of the claim is carried out by analysing a sample of the data and cause-effect-diagram, which provides information for identifying the input and output variables.

- **Phase 4: Improve**

The improvement phase involves coming up with solutions to the problem by conducting formal experiments, if needed, to determine process settings that improve product/process results. By carrying out the improvement phase, the best solution that achieves project goals is chosen for process improvement. Tools used in this phase include design of experiments, change management, project management, and mistake proofing. Design of experiments involves design of formal experiments that may be necessary to determine and analyse formal causes of poor quality, and design a solution for the problem. Change management deals with the process of continually renewing an organization’s direction, structure, and experiences, to serve the ever-changing needs of external and internal customers (Todnem By, 2005). Project management is concerned with the development of fundamental procedures for manufacturing/producing the concrete final project deliverable that is handed over to the customer. Mistake proofing may involve analysis of possible risks of implementing the solution, and establishing appropriate risk-management plans.

- **Phase 5: Control**

The steps followed in the control phase involve designing and documenting the improved process, where a feedback loop like the one in Figure 2-3 can be used; validating the measurement system, where the improved process is evaluated and made capable; determining the final process capability improvements and implementing and monitoring the process controls, which involves placing the improved process into operation, and the control steps described are used to monitor process conditions and product improvements. The tools used in this phase include a process control plan, which involves action to be taken when monitoring the process, 5s (sort-set in order- shine-standardize-sustain), statistical process control and change management.

2.3.6 Output control

2.3.5.1 Process monitoring and measurement

Monitoring is an on-going activity, and it is defined as the periodic or continual observation of processes to detect events before they occur, so that actions can be taken to prevent nonconformity of the outputs. Measurement involves setting of standards that can be used to assess performance against that particular standard (Hoyle, 2009). Visual observation (by a trained person) is the simplest form of monitoring variations and out-of-control signals in a process (Hoyle, 2009). An effective monitoring and measuring procedure should make use of a thorough method that is capable of detecting the variance from target, conveying the data, analysing the data and computing accurate results (Hoyle, 2009). In industrial processes, data may be recorded on control charts so that the observer can monitor the process in order to tell when the performance is deteriorating (Alwan, 1991; Cano et al., 2015 and Hoyle, 2009).

2.3.5.2 Process control

In quality management and improvement, it is important to differentiate between quality control and process control. Hoyle (2009) states that keeping the process under control is process control, whereas keeping the process within the limits of the customer specification is quality control. Statistical Process Control (SPC) is widely used in manufacturing industries to guide the adjustment of the process level and stop it from oscillating about a target value, as in the case where assignable variation is present (Park, 2013). SPC is a collection of problem-solving tools that are useful in achieving process stability and improving capability through the reduction of variability in the process (Montgomery, 2009; Gejdoša, 2015). The seven tools of SPC are histogram, check sheet, Pareto chart, cause-and-effect diagram, defect concentration diagram, scatter diagram and control chart. Alternatively, some literature lists include flow chart or run chart in the place of defect concentration diagram (Cano et al., 2015). The above mentioned tools play an important role in data collecting, analysing, visualizing and in decision making.

2.3.5.3 Control

A state of statistical control does not necessarily indicate that the process is producing satisfactory products (Alwan, 1991). According to Evans and Lindsay (2013), a controlled process that has too much variation can be detrimental in ensuring customer satisfaction. The term control refers to the act of ensuring conformance to the requirements and taking corrective action when necessary, to correct problems and maintain stable performance (Evans and Lindsay, 2013). According to De Feo (2014), the control process involves the steps shown in Figure 2-3.

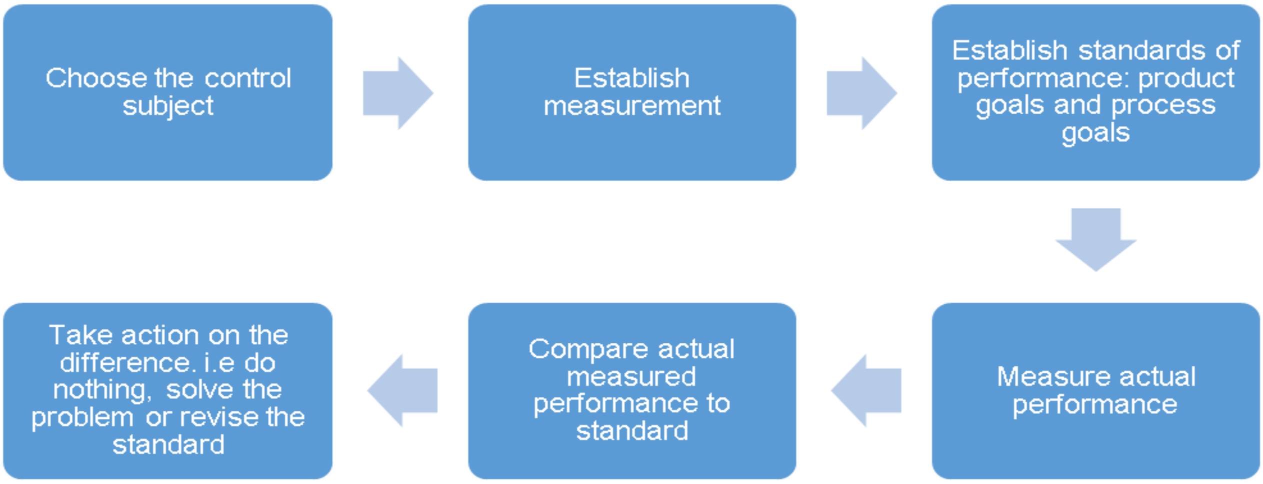

Figure 2-3: Steps followed in a control process.

2.3.5.4. Control charts

Companies can monitor their processes and produce quality products by using control charts (Lussier, 1990). Control charts are a powerful diagnostic tool that allows data to be plotted chronologically to show whether the variability from sample to sample is due to chance or due to assignable cause of variation (De Feo, 2014). When plotting control chats, it is important to know the nature of the data at hand first i.e. whether the data has autocorrelation or not, or whether the data is in the form of variables or attributes and the size of shifts observed (Montgomery, 2009). De Feo (2014) outlines the steps that are followed in plotting control charts as follows:

1. Choose the characteristic to be plotted.
2. Choose the type of control chart to use. See *Figure 2-4*.
3. Decide on the centre line to be used and the basis of calculating the control limits.
4. Choose the rational subgroup.

5. Provide a system for collecting the data.

6. Calculate the control limits and provide specific instructions for the interpretation of the results and actions that various production personnel are to take.

7. Plot the data and interpret the results.

8. Provide action plans for out-of-control results.

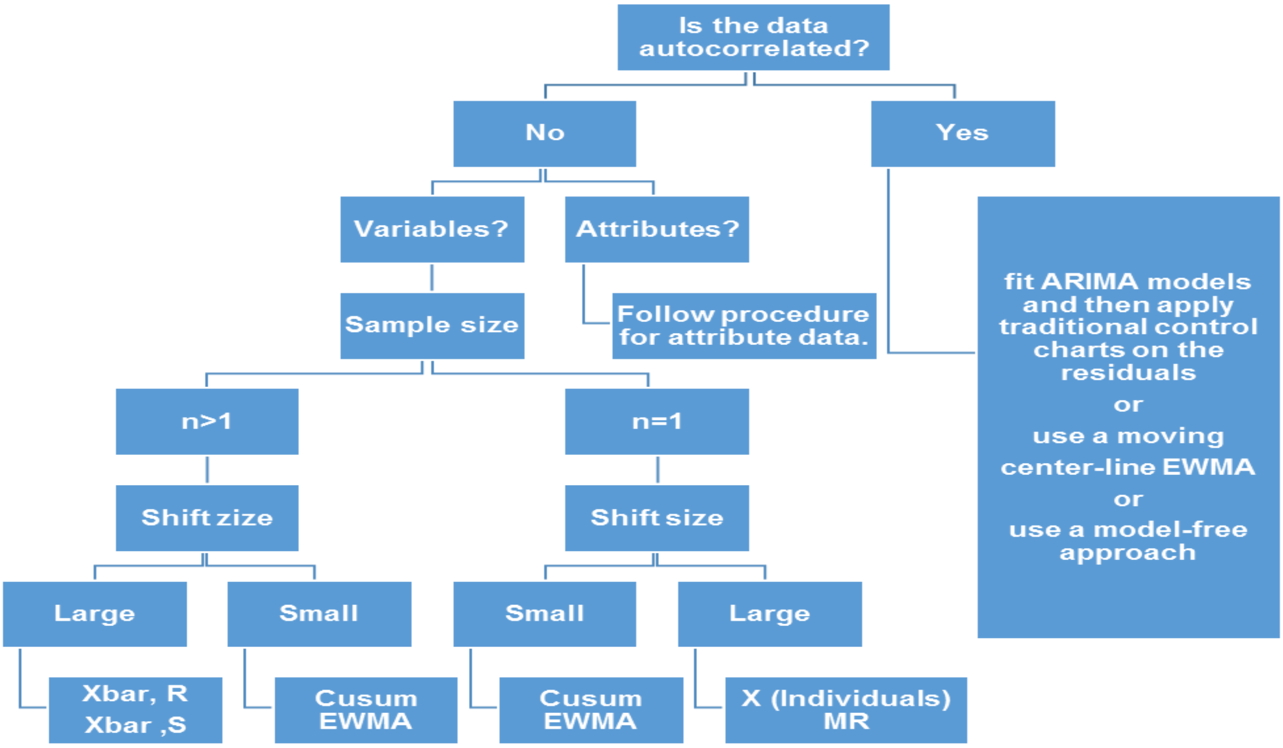

Figure 2-4: Diagram showing procedure on choosing the right control chart for your process. Adapted from Montgomery (2009).

- **Shewhart type charts**

One of the simplest control charts to construct, use and interpret is the Shewhart chart for variables (Alwan, 1991 and Montgomery, 2009). Shewhart charts are very useful in phase one implementation of SPC, where the process is likely to be out of control; they are useful in bringing the process into statistical control. One of the disadvantages of Shewhart control charts is that they only use the information about the process contained in the last plotted sample point and do not include information given by the whole sequence. These charts can be in the form of a means (Xbar) chart and ranges (R) chart, means (Xbar) chart and standard deviation (S) chart, and individuals chart (ImR or XmR) for variable data. There are also charts for attribute data such as the p-chart, np-chart, c-chart and u-chart. Some of the explanation for the charts used in this study is detailed below, according to Montgomery (2009).

The Xbar and S chart

The Xbar chart is used for averages when the number of observations is greater than 1. It is accompanied by an S chart for variability in the data. Suppose that a quality characteristic is normally distributed with mean μ and standard deviation σ, where both σ and s, are known. If $x_1, x_2, \ldots, x_n$ is a sample of size *n*, then the average of this sample can be calculated by equation 1:

$$\overline{x} = \frac{x_1 + x_2 + \cdots + x_n}{\mathrm{n}}$$

Equation 2-4

Where,

x_i are the individual measurements;

n is the number of samples;

$\overline{x}$ is the mean.

and $\bar{x}$ is normally distributed with mean μ and standard deviation $\sigma_{\overline{x}} = \frac{\sigma}{\sqrt{n}}$. Furthermore, the probability is 1- **α** that any sample mean will fall between

$$\mu + z_{\alpha/2}\sigma_{\overline{x}} = \mu + z_{\alpha/2}\frac{\sigma}{\sqrt{n}}$$

Equation 2-5

and

$$\mu - z_{\alpha/2}\sigma_{\overline{x}} = \mu - z_{\alpha/2}\frac{\sigma}{\sqrt{n}}$$

Equation 2-6

Therefore if μ and σ are known, equations 2 and 3 can be used to generate the upper and lower control limits on a control chart for sample means by replacing $z_{\alpha/2}$ with a value of sigma (Shift in mean). To get the center line of the Xbar chart, it is assumed that m samples are available, each containing n observations, then the best estimator of μ, the process average, is the grand total which is calculated according to equation 4.

$$\bar{\bar{x}} = \frac{\overline{x}_1 + \overline{x}_2 + \cdots + \overline{x}_n}{\mathrm{m}}$$

Equation 2-7

Thus, $\bar{\bar{x}}$ would be the centerline on the Xbar chart.

To set up the S charts, it is required that the sample average $\bar{x}$ and the sample standard deviation s be calculated for each sample. The limits (upper control limit (UCL) and lower control limit (LCL)) and center line for the S charts are calculated according to equation 5 and equation 6 respectively below.

$$\text{UCL} = \bar{x} + A_3\bar{s}$$

Equation 2-8

Center line $= \bar{\bar{x}}$

$$\text{LCL} = \bar{x} - A_3\bar{s}$$

Equation 2-9

Where

$$A_3 = \frac{3}{C_4\sqrt{n}}$$

Equation 2-10

Assuming that the sample standard deviation is defined according to equation 8

$$s = \sqrt{\frac{\sum_{i=1}^{n}(x_i - \bar{x})^2}{n-1}}$$

Equation 2-11

In phase two process monitoring, the cumulative sum (CUSUM) control chart, and the exponentially weighted moving average (EWMA) control chart are effective alternatives to the Shewhart control chart when small process shifts are of interest (Montgomery, 2009). The CUSUM and EWMA charts are time-weighted control charts. A study by Hawkins and Wu (2014) showed that the EWMA is more convenient for estimating where the process mean is following a signal while the CUSUM is better for estimating when a shift occurred.

- **CUSUM Chart**

The CUSUM chart uses all the information in the sequence of sample values by plotting the cumulative sums of the deviations of the sample values from a target value (Montgomery, 2009).The idea behind the CUSUM chart is that the sum of deviations from the target is zero if the process is in control (Abbas et al., 2013). There are two ways to represent the CUSUM chart; the tabular and the V-mask forms of the CUSUM (Montgomery, 2009). Tabular CUSUM charts may be constructed for both individual observations and for the averages of rational subgroups (Montgomery, 2009). The CUSUM procedure is effective when small shifts in the process have to be detected and measurements are expensive to collect (Xie et al., 2012). Some authors argue that the CUSUM chart is bounded by the three assumptions, which are normality, stationarity and independence of the data (Mertens et al., 2009), however some authors like Faltin et al. (1997) argue that CUSUM charts can be used when data does not meet all the assumptions.

Just as with any control chat, one should search for assignable cause and take corrective action, when an out-of-control signal is indicated by the CUSUM chart. The idea is to count backwards from the out-of-control signal to the time period when the CUSUM lifted above zero to find the first period following the process shift (Montgomery, 2009).

The formula for obtaining the tabular CUSUM chart is as follows:

$$C_i^+ = \max[(0, x_i - (\mu_0 + K) + C_{i-1}^+]$$

Equation 2-12

$$C_i^- = \max[(0, (\mu_0 - K) - x_i + C_{i-1}^-]$$

Equation 2-13

Where the starting values are C_0^+=C_0^-=0.

The statistics C^+ and C^- are called one-sided upper and lower CUSUMS respectively, and they are the limits of the CUSUM chart. *K* is usually called the reference value, and it is one-half the magnitude of the shift as outlined in Equation 2-14.

$$K = \frac{\delta}{2}\sigma = \frac{|\mu_1| - \mu_0}{2}$$

Equation 2-14

The statistics C_i^+ and C_i^- accumulate deviations from the target value μ_0 that are greater than *K*, with both quantities resetting to zero on becoming negative. If either C_i^+ and C_i^- exceeds the decision interval *H*, the process is considered to be out of control.

- **EWMA chart**

The EWMA chart, which is also referred to as a geometric moving average, was introduced by Roberts (1959), and it incorporates all the information in the sequence of sample points by assigning exponentially decreasing weights to the observations (Xie, et al., 2012; Khoo et al., 2010). The EWMA control chart is a good alternative to the Shewhart control chart when detecting small shifts in the process is of interest (Montgomery, 2009; Khoo et al., 2010). A properly designed EWMA control chart is very robust to the assumption of normality, and performs quite well for both heavy-tailed symmetric distributions and skewed distributions (Montgomery, 2009). This is because the EWMA can be viewed as a weighted average of all past and current observations, which makes it very insensitive to the normality assumption and is thus ideal to use with individual observations (Montgomery, 2009). The EWMA is defined by Equation 2-15.

$$z_i = \lambda x_i + (1-\lambda)z_{i-1}$$

Equation 2-15

where $0 < \lambda \leq 1$ is a constant, and the starting value is the process target, so that

$$z_0 = \mu_0$$

Equation 2-16

The control limits for the EWMA chart are

$$UCL = \mu_0 + L\sigma\sqrt{\frac{\lambda}{(2-\lambda)}[1-(1-\lambda)^{2i}]}$$

Equation 2-17

Center line = μ_0

$$LCL = \mu_0 - L\sigma\sqrt{\frac{\lambda}{(2-\lambda)}[1-(1-\lambda)^{2i}]}$$

Equation 2-18

- **Moving average chart**

The moving average chart is another type of time-weighted control chart based on a simple, unweighted moving average (Montgomery, 2009). The MA chart is more effective in detecting small process shifts than the Shewhart chart. However, it is not as effective against small shifts as either the CUSUM or the EWMA (Montgomery, 2009). The advantages of using a moving average chart are that it is considered by some to be simpler to implement than CUSUM and EWMA charts, they can be valuable in situations where data is less frequntly collected and expensive to collect, they showcase trends in the data, and they also use the central limit theorem to make data approximately normal.

The main disadvantage in using a moving average chart is that if the signal is averaged over a long period, the probability of Type II errors increases (Cambron et al., 2016). Another disadvantage of using moving average charts is that it is easy to overlook the fact that individual observations have more variability than do the averages when using similar charts, which may result in missed signals. The formula used to plot the MA chart is shown in equation 16.

The moving average of span w at time i is defined as

$$M_i = \frac{x_i + x_{i-1} + \cdots + x_{i-w+1}}{\mathrm{w}}$$

Equation 2-19

At time period i, the oldest observation in the moving average set is dropped and the newest one is added to the set.

- **ARIMA charts**

Autoregressive integrated moving average (ARIMA) models, which were introduced by Box and Jenkins (1976), represent a class of linear models which are part of stochastic model-based Box-Jenkins approach for time series (Jebb et al, 2015; Noskievičová, 2009 and Tasdemir, 2012,). Many authors have shown that the use of ARIMA models for statistical process control has proved to be useful in dealing with autocorrelated data; they are applied in some cases where data shows evidence of non-stationarity (Ham et al., 2017 and Geiger, 2018). The ARIMA control charts are created for a single numeric variable where the data has been collected either individually or in subgroups (Geiger, 2018).

The ARIMA model combines the autoregressive (AR) and moving average (MA) parameters with the differencing in the model. The AR part of ARIMA indicates that the variable of interest is regressed on its own lagged prior values, and the MA part indicates that each element in the series can also be affected by the previous error. The 'I' indicates that the data values have been replaced with the difference between them and the previous values (Tasdemir, 2012). Generally, ARIMA (p, d, q) models consist of three characteristic terms: a set of autoregressive terms (indicated by p), a set of moving average terms or non-seasonal differences (indicated by d), and a set of lagged forecast errors in the prediction equation (indicated by q) (Tasdemir, 2012).

The general form of the model is as follows:

$$\Delta_d X_t = \mu + \Phi_1 \Delta_d X_{t-1} + \Phi_2 \Delta_d X_{t-2} + \cdots + \Phi_p \Delta_d X_{t-p} + \varepsilon_t - \Theta_1 \varepsilon_{t-1} - \cdots - \Theta_q \varepsilon_{t-q},$$

Equation 2-20

Where,

μ is the constant

Φ_k is the autoregressive coefficient at lag k

Θ_k is the moving average coefficient at lag k

e_{t-k} is the forecast error that was made at period (t − k).

2.3.5.5 Data assumptions for control chart plotting

- **Normality**

The use of control charts to detect whether the process is under control may cause misinterpretations if standard data assumptions are violated (Yourstone and Zimmer, 1992). The standard assumption that is usually mentioned in justifying the use of statistical control charts is that the data generated by the process when it is in control is independent and identically distributed (Djauhari et al., 2014). The normality assumption is important, since control charts are based on statistical theory (Yazici and Yolacan, 2007). Many industrial quality characteristics do not follow the normality assumption, but they appear to have a lognormal or skewed distribution (Samanta and Bhattacherjee, 2004).

Montgomery (2009) stated that control charts (Shewhart) will still function reasonably well in circumstances where the normality assumption is slightly or moderately violated. One of the highly published approaches for dealing with the problem of normality is to increase the number of observations in a sample. The reason for doing so is based on Shewhart's theory that the distribution of many individual measurements is non-normal, however, the distribution of sample means of at least four samples will in many case follow the normal distribution as predicted by the central limit theorem (Montgomery, 2009).

- **Autocorrelation**

The other assumption which should be considered when using control charts is that of independence of the observations; which is due to the fact that some control charts do not work well if the monitored characteristic shows even low levels of correlation over time (Montgomery, 2009). Data obtained from many automated industrial processes is recorded periodically, and as a result, there exists some relationship between those successive values (Wheeler, 1995; Faltin et al., 1997; Tasdemir, 2012). Tasdemir (2012) stresses that autocorrelation should not be ignored when setting up control charts for process monitoring; there are several ways to deal with autocorrelated data. Montgomery (2009) and Chang and Wu (2011) suggested the use of residuals from a fitted time series model or original observations with adjusted control limits. Noskievicova (2009) suggests that when residuals from an ARIMA model do not satisfy all the assumptions, a different time series model must be fitted, such as a tar model, linear or non- linear volatility model and/or some non-parametric method may be applied.

Montgomery (2009) also suggested that less frequent sampling from the process data stream can break up the autocorrelation in process data. Some authors also proposed widening of control limits as it reduces false alarms, however, this slows down the rate of detection of out-of-control conditions (Faltin et al., 1997). Other documented methods include using a chart where the centreline and control limits are varying and not fixed (Alwan, 1991); applying traditional control charts, and making use of a chart of sub samples from the full data stream (Runger and Willemain, 1996); a method based on the number of consecutive values above or below a threshold level (Jones and Woodall, 1997) and according to Faltin et al. (1997), the EWMA and CUSUM charts may also be used directly with autocorrelated charts.

2.3.5.6 Alarms and action plans

The statistical design of the control charts should be aimed at minimizing the Out-of-Control average run length (Type II error minimized) given the In-Control average run length fixed at a certain value (Type I error fixed) (Park, 2013). Montgomery (2009) defines type I error as the probability of concluding that the process is out-of-control when it is really in-control, and type II error as the probability of concluding that the process is in-control when it is really out-of-control. Evans and Lindsay (2013) define Type I error as the error of giving a signal when no assignable cause has occurred, and Type II error as the error of not giving a signal when an assignable cause has occurred. The performance of control charts can be measured by average run length, which denotes the average number of observations until the SPC scheme signals a problem (Cox, 2010). When an alarm is given by the control chart, the assignable cause variation can be detected by following the Out-of-Control Action Plan (Park, 2013).

2.3.5.7 Output control of lumber products

A number of research outputs exists outside South Africa looking at methods to monitor and control the quality of lumber outputs from the sawmill. A study by Deublein et al., (2010) looked at different approaches for quality control and improvement by means of machine grading. Their findings showed that there should be an optimised combination of three elements, which are process monitoring, process calibration and process optimisation, as it may lead to improved benefit and reliability in the graded lumber material. A study by Sandomeer and Kohler (2007) gave an overview of the existing procedures for the control of grading machine settings according to the European standard EN14081. Their main focus was to look at the capability of the methods to incorporate statistical uncertainties, as well as model- related uncertainties into the grading process.

They indicated that the performance of the output control system by means of cumulative sum control charts is observed to be capable to detect deviations in the quality of the material supply. They also suggested a probabilistic approach that incorporates both machine and output control. Lycken and Bengtsson (2010) developed a simulation-evaluation program for introducing and using output control in the sawmilling industry. Kovryga et al., (2017) studied the quality control options of lumber for changing material quality under the prism of the different growth regions.

Chapter 3 : Materials and Methodology

3.1 Materials

Production data obtained from two anonymous sawmills (Sawmills A and B) in South Africa processing pine sawlogs were used for this study. The lumber production process followed by the two sawmills is outlined in Figure 3-1 and Figure 3-2. The data from Sawmill A contained records for individual lumber pieces of the nominal cross-sectional size 38 x 114 mm recorded every production day for a period of 1 year. The data obtained from Sawmill B was of the same dimensions and recorded for a period of 2 months. R statistical software (R version 3.4.1) and Excel 2013 were used for the analysis.

3.1.1 Production process

Figure 3-1 shows the supply chain of the lumber manufacturing process from the supplier to the customer – which is fairly typical for South African structural pine sawmills. The diagram includes visual representation of the process followed in the manufacturing process of lumber. The trees are grown in the plantation until they are ready to be cut. The logs are sent to the sawmill where they are processed into different sizes of lumber. The processed lumber is sorted according to their different sizes and grades, and packed into different bundles. The bundles are then sent to the customer to be used.

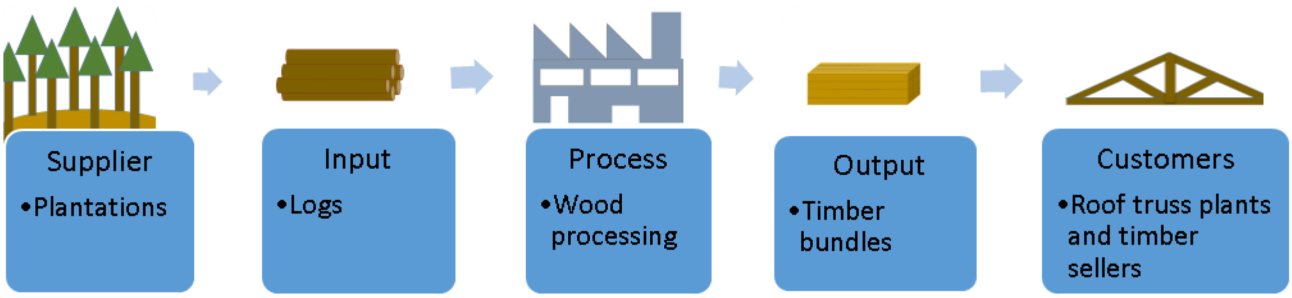

Figure 3-1: Supplier-input-process-output-customer (SIPOC) diagram showing the supply chain of the lumber manufacturing process.

Figure 3-2 shows the process diagram of the steps taken in the lumber production process. As is typical in South Africa, harvesting for both sawmills occurs in a small number of compartments at any given time. Once a compartment has been finished, the harvesting team will move on to the next compartment. The trees are cut and the logs are sent to the sawmill for processing. The logs are cut into different sizes lumber and stacked. Take note that at any given time in the production process, the same lumber dimensions could come from (a) different compartments, (b) different heights of a tree, and (c) different radial positions in a log. Normally one diameter class is processed at a time. The lumber is then transferred into kilns for drying, destacked and stress graded. The final lumber is stacked into bundles (of a single grade) and is ready to be shipped to the customer.

Stress grading of lumber was performed according to the rules of SANS 1783-2 (2005) for visual grading. All the rules regarding warp, density, dimensional tolerances, machining defects, wane, as well as the knot related rules were followed in the grading process. Boards were graded as either utility grade / XXX (non-conforming), or S5. All the higher grade boards were also graded as S5, which is a common practice in South Africa.

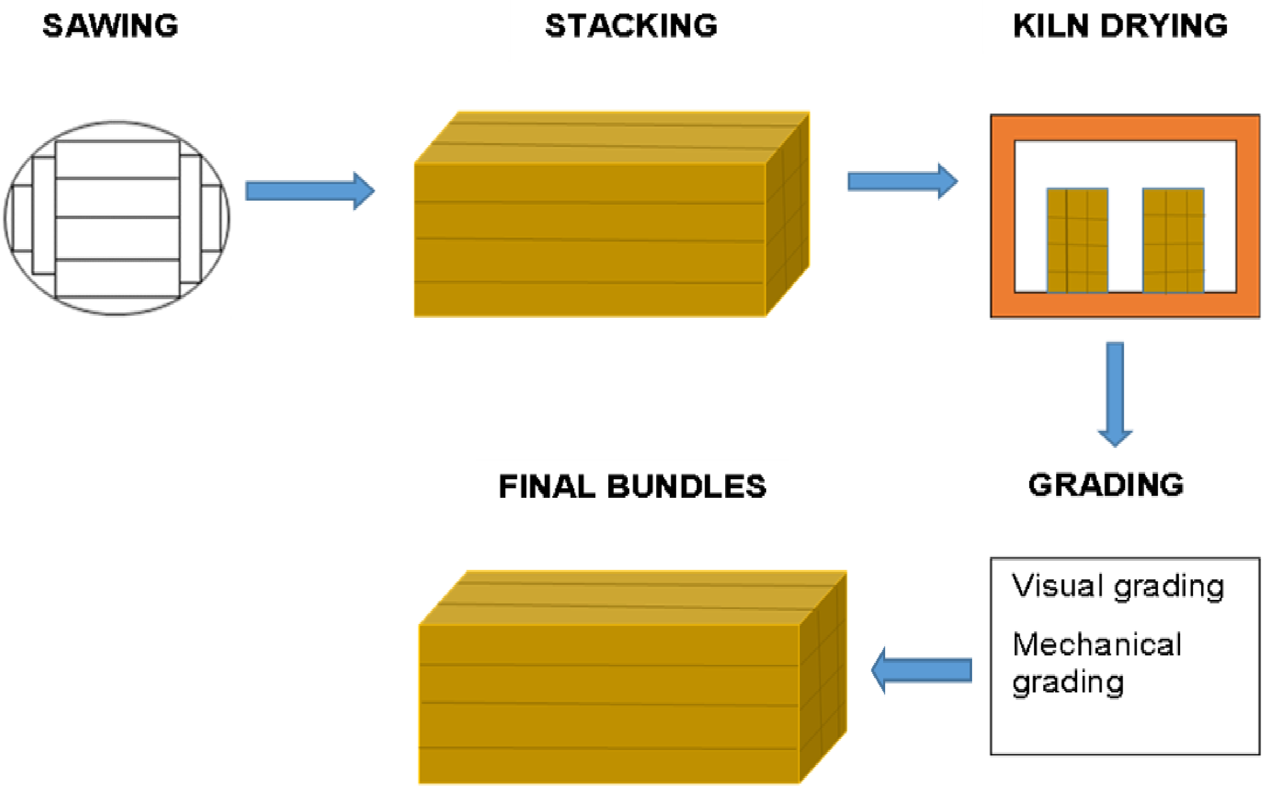

Figure 3-2: Schematic diagram showing Sawmills A and B lumber production system.

3.2 Methodology

3.2.1 MOE$_{dyn}$ measurement

The dynamic MOE (MOE$_{dyn}$) for each board was measured using a Microtec Viscan stress grading device. The dynamic MOE was measured on dry ungraded lumber. The lumber was graded in the sequence that it was destacked from the kiln trolleys. The Viscan measures the frequency of vibration with its built-in laser interferometer. The natural frequency of the board and the mean density are used to compute dynamic modulus of elasticity. An impact on the plank causes a vibration on the board and the natural frequency of vibration is measured by a non-contact laser interferometer

(Bacher, 2008; Barrett et al., 2008; Nocetti et al, 2013). Figure 3-3 shows an example diagram of Viscan machine used to measure the MOE_{dyn}. The length and density of the lumber are needed to determine the MOE_{dyn} (Wessels et al., 2014) according to the equation:

$$MOE_{dyn} = \rho \,.\, v^2 = \rho \,.\, (2.\ l.\ f)^2$$

Where ρ is the density of the lumber in kg/m^3;

v is the velocity of the stress wave;

l is the length of the lumber in mm;

f is the frequency of the longitudinal vibration in Hertz.

Due to the amount of data needed for the project, static MOE could not be measured on all the boards, hence the use of MOE_{dyn}. A study by Crafford and Wessels (2011) showed that the coefficient of determination (R^2) between MOE_{dyn}, as measured by the portable Viscan device, and static MOE was found to be 0.873. This relationship was deemed strong enough to use MOE_{dyn} as a substitute for static MOE, which is the actual property of interest. The absolute values was also close to each other, meaning that MOE_{dyn} values can be directly translated into $MOE_{stat.}$ As mentioned, the number of pieces that had to be measured and the time period of measurement made it impossible to measure static MOE – a labour intensive process, which can only be done at a facility with the necessary testing equipment.

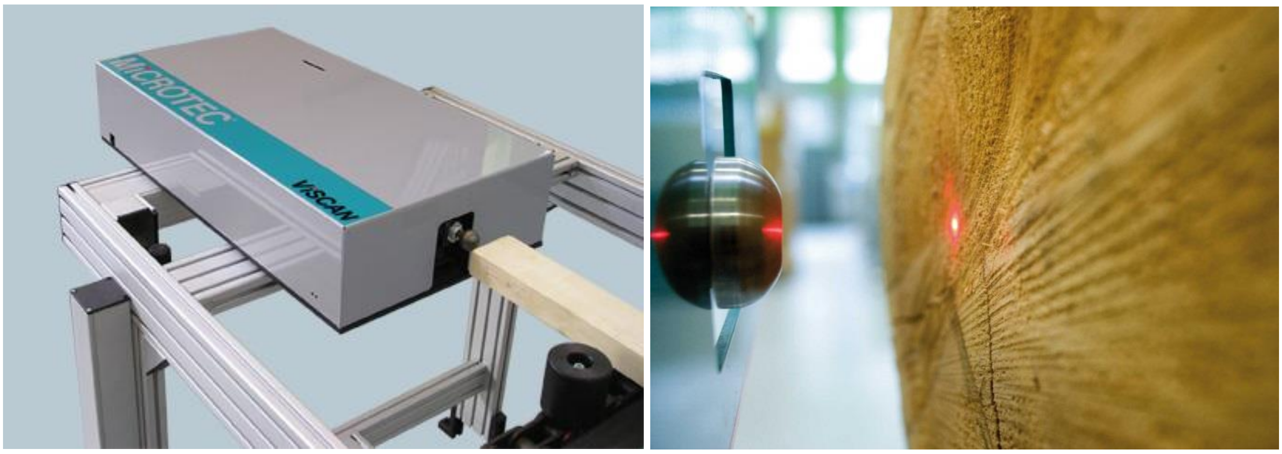

Figure 3-3: Pictures showing MOE_{dyn} measuring system using a Microtec Viscan stress grading machine. Retrieved from https://microtec.eu/.

3.2.2 Data preparation

The individual daily records of production data outputs were combined into files according to the month and order in which the lumber was processed in Microsoft Excel. The Excel files were then imported into R statistical software. The data was sorted according to board thickness, width and grade. The grades were either utility grade or S5. For further analysis, we focused the study on S5 and 38 x114 mm lumber sizes, since it is the main structural product in South Africa. In other words, all the utility grade boards that were not conforming to requirements for structural lumber were discarded in our analysis. Take note, as is common practice in SA sawmills, the S5 graded lumber will also include higher grades (S7 and S10) which usually are not removed and just form part of the S5 grade. Data was sorted into bundles using the intake bundle sizes (190 pieces per bundle). The production sequence of pieces were kept so that bundles contain the exact composition of pieces as it would have occurred in practice.

3.2.3 Data analysis

3.2.3.1 MOE variation of structural lumber

A code (function) was written in R to put data into bundles according to order of production. The bundle size used was 190 pieces of lumber per bundle, which was chosen to resemble the bundle sizes for the final product. The bundle MOE means and 5th percentile values were calculated for each bundle produced. A bundle of pieces was selected as the smallest group for statistical analysis. The reason is that sawmills normally sell their products in full bundles. Roof truss plants, the largest structural timber user sector in South Africa, will utilize a bundle to construct a set of trusses for a building. It will thus not be unusual that the pieces from a single bundle will end up in a single roof structure. The MOE 5th percentile and mean of the bundle will therefore be relevant for the members in a single roof structure or at least part of the roof structure.

- **Graphical description of variation.**

Tools to show graphical description of variation were used to display the data (Cano et al., 2015). Histograms were plotted in order to check the distribution of the bundle averages for the different months. Boxplots were plotted to show the variation within and between the bundle means for each month. Mean (Xbar) charts and standard deviation (S) charts were used to monitor averages and the process variability respectively in the bundle means (Alwan, 1991 and Montgomery, 2009). Scatterplots were plotted to show the variation within a bundle for selected bundles.

- **Numerical description of variation.**

Descriptive statistics were calculated for the data in each month (Cano et al., 2015). This was done to get the overall summary of the data for the two sawmills as well as that for the bundles.

- **Data assumptions**

The main data assumptions were tested on the mean values calculated (Tasdemir, 2012; Noskievicova, 2009; Yazici and Yolacan, 2007; Yourstone and Zimmer, 1992). The Anderson Darling Normality Test was performed, as well as plotting of the quantile-quantile plots to check if the points were normally distributed. Time series analysis was carried out for analysing the data (Jebb et al., 2015). The Augmented Dickey-Fuller test was performed to check whether the data was stationary. Time series plot, autocorrelation function and scatter plots of the data were plotted in order to test for autocorrelation in the data.

3.2.3.2 Acceptable MOE mean and variation

In this study it was necessary to determine whether a bundle of graded structural lumber had acceptable MOE properties (mean and 5th percentile) or not. This was a challenge since it is self-evident that for a property such as mean MOE, many of the bundles will have a lower mean MOE than the characteristic value listed in the design standard. The concept of reliability was used to calculate minimum acceptable values for mean MOE. The Load and Resistance Factor Design method, also referred to as the limit states design method, was used (Lenner and Sykora, 2017; Nowak and Ritter, 1995; SABS 0160, 1989 and Smith and Foliente, 2002). A limit state is a condition of a structure beyond, which it no longer fulfils the required design criteria. The ultimate limit state refers to the condition of the structure where it might collapse. The serviceability limit state refers to the condition where the deflection, cracking, or vibration in the structure is considered excessive. The design value (R_d) of a resistance of a structural member was determined based on the target performance levels required for structural lumber by multiplying the partial material factor with the characteristic value (stiffness) of the structural member. The safety level was measured using the reliability index (β).

The level of reliability used in the design process is different for ultimate and serviceability limit states (Porteous and Kermani, 2013). When β increases, the probability of failure or excessive deformation of structures decreases, meaning that the safety level becomes higher. It was assumed that the mean MOE was mostly applied to serviceability related design (i.e. bending deflection) whereas the 5th percentile MOE was related to ultimate limit states design (i.e. buckling). A β value of 1.5 was used for the required mean MOE calculations and a β value of 3 for 5th percentile MOE calculations.

The required mean values to satisfy the serviceability limit state and the ultimate limit state values were calculated for each of the bundle means in the bundles for each of the months.

The procedure for load factors can be summarized as follows:

- Determine the target performance level
- Determine the target reliability index
- Determine the statistic for each load
- Evaluate the load and resistance factors

The equation used to calculate the design value R_d of a resistance (load-carrying capacity) was obtained from Simpson (2000) and Gulvanessian and Holicky (2005). The equation used to calculate the required mean value for characteristic mean and required mean value for characteristic 5th percentile was obtained from Holický and Markova (2005). The equations are as follows:

$$R_d = \gamma_E R_k$$

Equation 3-1

Where,

R_d = design value of a resistance

R_k = the characteristic value of load-carrying capacity.

γ_E = partial material factor

$$R_d = \mu_R * exp\,(-\propto_R * \beta * V_R) = \mu_R * exp\left(-\propto_R * \beta * \frac{\sigma}{\mu_R}\right)$$

Equation 3-2

Where,

R_d = design value of a resistance

V_R = coefficient of variation

β = target reliability index

α_R = sensitivity factor

σ = standard deviation

μ_R = mean of R

Ultimate limit state.

The design value of a resistance, R_d (load-carrying capacity) was calculated by first multiplying the characteristic value, which is the 5th percentile value of 4 630 MPa as specified in the draft version of SANS 10163-1, with the material partial factor of 0.68 which resulted in R_d = 3 148 MPa according to Equation 3-1. The required mean value (μ_R)of each bundle was calculated using Equation 3-2 by substituting the values of R_d, the standard deviation for each of the bundles, the target reliability index of 3 and sensitivity factor α_R = 0.8.

Serviceability limit state.

The design value R_d of a resistance (load-carrying capacity) was calculated by first multiplying the characteristic value 7 800 MPa, which is the mean MOE for S5 lumber, with the material partial factor of 0.68 which resulted in R_d = 5 304 MPa according to Equation 3-1. The required mean value (μ_R) for each bundle was calculated using Equation 3-2 by substituting the values of R_d, the standard deviation for each of the bundles, the target reliability index of 1.5 and sensitivity factor α_R = 0.8 in Excel.

The calculated required mean values were compared with the actual mean to see if they satisfy the requirements according to the limit state approach. Scatter plots were used to show the relationship between the mean MOE and standard deviation.

3.2.3.3 Statistical quality control system for structural lumber.

For the evaluation of different statistical quality control systems, the data was sorted according to board thickness and width but not the grade. This was done in order to ensure that we still had poor pieces (utility grade) in the data in order to see how the quality control charts pick up the out-of-control conditions in the data. The key performance measures for control charts were identified.

Different control charting methods were tested and compared to see how effective they are in detecting out-of-conditions in the process output. Different sampling frequencies were also tested to see the effects of increased sampling in detecting out of control conditions. The methods used to plot the different control charts are outlined below.

The current proposed method (SANS 1783-5-2 procedure)

The proposed quality assurance procedure in the SANS 1783-5-2 is described below. For a detailed explanation of the proposed procedures refer to a copy of the standard draft attached in Appendix C. The sampling approach proposed was that samples shall be drawn in a random manner from the production process outputs for each combination of grade or dimension (or both) and spread over the duration of the production of that combination. The responsible employee shall sample one sample board per 1 000 boards produced and accumulate them for testing. These boards shall be marked to identify them uniquely by grade, size, date and time of sampling and production line, if there is more than one. They shall be stored in a safe, clean place protected from weather and damage until they are tested.

Steps followed in plotting the quality control charts.

1. The raw grading data from the 2 study sawmills was tabled in sequence in columns 1 to 4 and charted as shown;
2. The running mean E of the 20 latest mean E's was calculated in column 5 and charted (Table 3-1);
3. Boolean equation was used in column 6 to identify all mean E's less than $E_{0.05,k}$;
4. The running total number of tests with a value less than $E_{0.05,k}$ and the percentage of these out of 50 were determined respectively in columns 7 & 8 and the latter charted in the second chart;
5. Columns 9 to 12 were used to create the end points for the four horizontal lines that provide assessing criteria;
6. In the absence of an actual standard deviation for E_m, it was assumed to have a value of 0.25 x $E_{m,k}$.

Table 3-1: Steps followed in plotting quality control charts.

Presumed results from OQA proof-load tests											
Date	Time	Broard number	M of E	Running avg. Em,k	Value if < *E0.05,k*	Run. Total < *E0.05,k*	Run. % (50) < *E0.05,k*	Targets			
								$E_{m,k}$	$E_{m,k}$ - SD	$E_{0.05,k}$	0.75 $E_{0.05,k}$
1	2	3	4	5	6	7	8	9	10	11	12
50/01/15	08h12	1	10524.6		5000.0	0		7800	5850	4630	3514.17
"	09h53	2	7382.9		5000.0	0					
"	11h37	3	7831.6		5000.0	0					
"	12h48	4	14550.6		5000.0	0					
"	14h05	5	10555.0		5000.0	0					
"	15h00	6	10986.3		5000.0	0					
"	15h58	7	9890.0		5000.0	0					
"	16h33	8	6531.2		5000.0	0					
50/01/16	13h58	9	7337.6		5000.0	0					
"	15h32	10	8579.7		5000.0	0					
"	16h12	11	8002.9		5000.0	0					
"	16h57	12	7048.8		5000.0	0					
50/01/17	07h24	13	7205.6		5000.0	0					
"	09h43	14	7971.0		5000.0	0					
"	11h13	15	9311.3		5000.0	0					
"	12h41	16	10585.1		5000.0	0					
"	14h15	17	7384.1		5000.0	0					
"	14h43	18	5550.5		5000.0	0					
"	15h36	19	10986.3		5000.0	0					
"	16h49	20	11346.2	8978.1	5000.0	0					
50/01/20	08h05	21	8738.8	8888.8	5000.0	0					

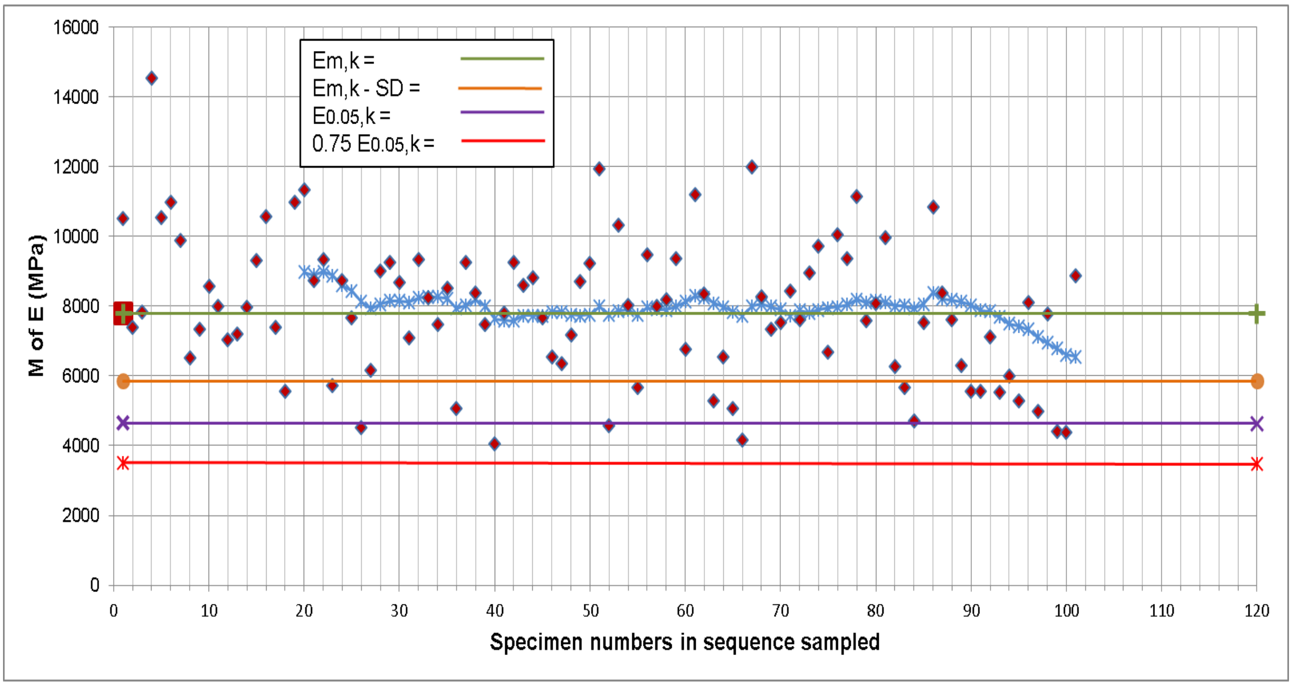

Figure 3-4: The quality control method proposed in SANS 1783-5-2 showing the moving average chart. The samples were sampled at 1 in a 1000 samples sampling intervals and the moving average averaged over 20 samples. The different target lines are also displayed on the graph.

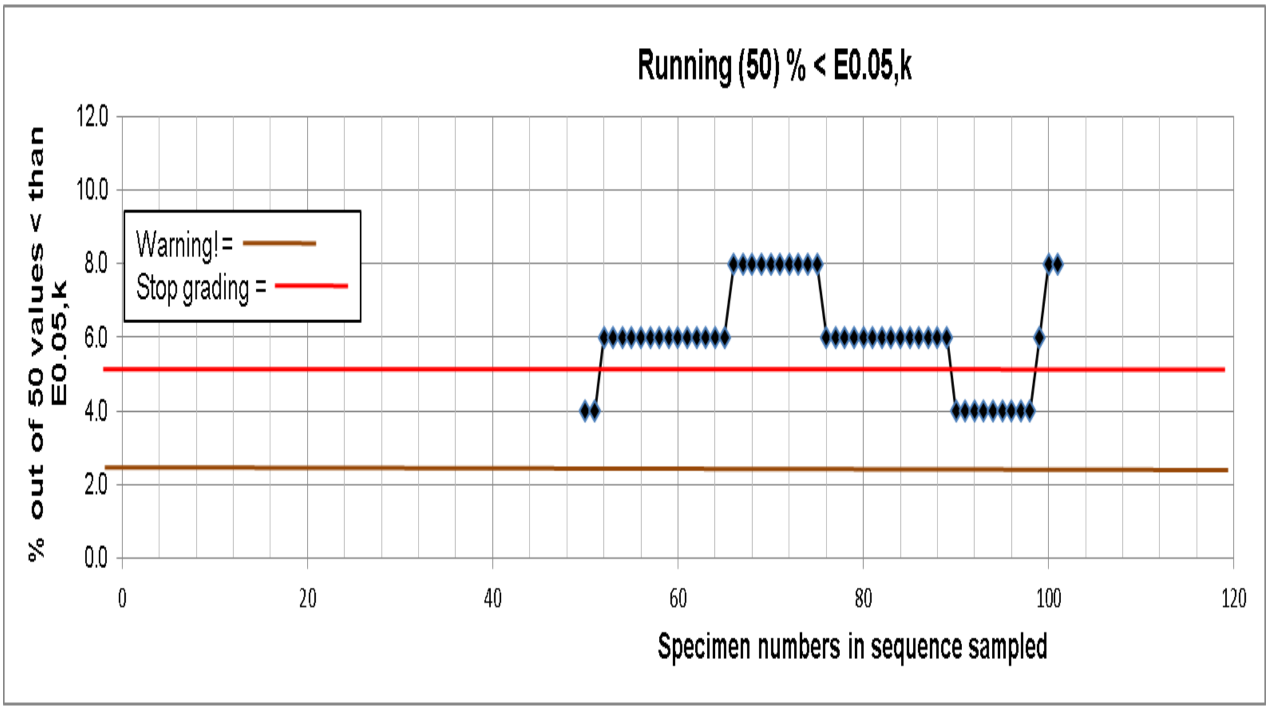

Figure 3-5: The quality control method proposed in SANS 1783-5-2 showing the running total number of tests with a value less than 4 630 MPa. The target lines provide a warning and a signal to stop production.

Action signals.

From the charts, two criteria provided warnings. The first is the trend of the running average E (blue line in Figure 3-4). The second is when the percentage of sub-standard test results out of the most recent 50 exceeds 5 % (that is the brown warning line in Figure 3-5). At either of these two warning signals corrective action shall be initiated to preclude the next step. Either of two further criteria can produce a signal for the grader to stop the stress-grading process until the cause or causes have been identified and shown to be corrected. The one is when the running average E drops below the $E_{m,k}$ – SD line (Figure 3-4) and the other when the percentage of sub-standard test results out of the last 50 exceeds 10 % (that is the stop grading line in Figure 3-5).

ARIMA charts procedure.

The method of applying ARIMA charts was used to plot residual control charts (Jebb et al., 2015, Noskievičová, 2009 and Tasdemir, 2012). Time series, autocorrelation function and scatter plots of the data were plotted to confirm the presence of autocorrelation in the data. The series was checked to see if it was stationary by conducting an Augmented Dickey-Fuller test. A regression model was also fitted to the data. Model residuals diagnostic checks were performed by examining a plot of the model residuals which should appear as random white noise. A Ljung–Box test was conducted to assess if the autocorrelation observed was different than expected from a white noise series. The Akaike's Information Criteria (AIC) was used to evaluate the fit of the model. The AIC was calculated from the equation:

$$AIC = 2\ln(RSME) + \frac{2c}{n},$$

Equation 3-3

where RSME is the root mean squared error during the estimation period, c the number of estimated coefficients in the fitted model, and n is the sample size used to fit the model. The model residuals were plotted.

The CUSUM and EWMA charts procedure.

The CUSUM and EWMA charts were designed using the built-in functions in R (Cano et al., 2015; Montgomery, 2009). The choice of limits for the CUSUM chart where decision interval (h) = 5 and se-shift (k) = 0.5. The choice of limits for the EWMA chart where lambda (λ) = 0.1 and nsigmas (σ) = 1. This was chosen based on work by Montgomery (2009) to result in an in-control average run length of around 500 and an out-of-control average run length of 10.3 for detecting a shift of one standard deviation in the mean. The centre line was chosen as the target value of 7 800 MPa for both charts.

Testing the effectiveness of the sampling strategy

Samples were pulled from each month using the proposed sampling of 1 per 1000 according to SANS 1783-5-2. For the purpose of this study, the kind of sampling approach used was Systematic Sampling (Cano et al., 2015). The samples were pulled using intervals of a 1000 each, thereafter sampling interval was reduced to sampling every 750, 500 and 250th sample to see if there was an improvement in the detection of out-of-control conditions when more samples were pulled from the population (month). The selection of the subsequent (750, 500 and 250) sampling intervals was judgement based. The samples were used in plotting the charts discussed above.

Chapter 4 : RESULTS AND DISCUSSION

4. Chapter overview

The results were addressed in three parts. Section 4.1 addressed objective 1 (To quantify the amount of MOE variation within and between bundles of graded structural SA pine lumber from two sawmills), section 4.2 addressed objective 2 (To attempt to define what is acceptable MOE variation for end-users of structural lumber in South Africa) and section 4.3 addressed objective 3 (To evaluate the current proposed SANS 1783-5-2 quality assurance system and compare it with other possible systems in terms of its efficiency to ensure safe and reliable structural lumber in terms of lumber stiffness (MOE). It should be noted that where graphs were involved, results were presented only for Month 1 from Sawmill A and Month 1 from Sawmill B. The lower control limit is of interest, where control charts were involved. It should be emphasised that only boards graded as S5 (including higher grades) were analysed in this study. Some of the graphs from some of the remaining months are presented in Appendix A.

4.1 MOE variation of structural lumber.

4.1.1 Overall MOE variation in the boards for the 2 sawmills

The mean MOE of all the 38x114 mm S5 boards from both sawmills that were analysed was 8 470 MPa and the 5th percentile value of the full population was 5 609 MPa (see Table 4-1). A histogram showing the distribution of all the data from both sawmills can be seen in Figure 4-1.

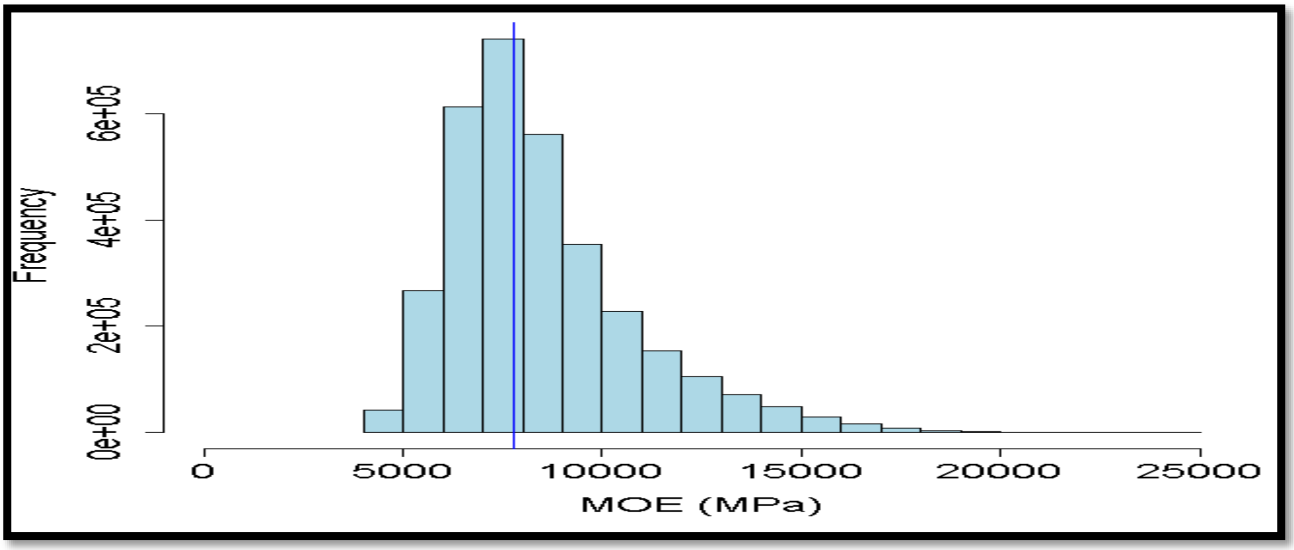

Figure 4-1: Histogram of individual board MOE for 38x114 mm S5 graded boards from both sawmills. The blue vertical line represents the target mean MOE (7 800 MPa).

Table 4-1: The MOE data for 38x114 mm S5 graded boards from the study sawmills.

	n	MOE (MPa)			
		Mean	5th percentile	Minimum	Maximum
Sawmill A	1672768	8573	5538	4600	25000
Sawmill B	427256	7855	5878	5500	19055
Sawmills A & B	2100024	8470	5609	4600	25000

4.1.2 MOE variation between the individual boards.

Results of graphical display of variation tools are shown below. First the variation of the individual planks is shown followed by the variation in the mean MOE of bundles. Figure 4-2 and Figure 4-3 show the distribution in the data for individual planks. The graphs showed that the data was skewed to the right since the graph tails off for the 2 months represented below.

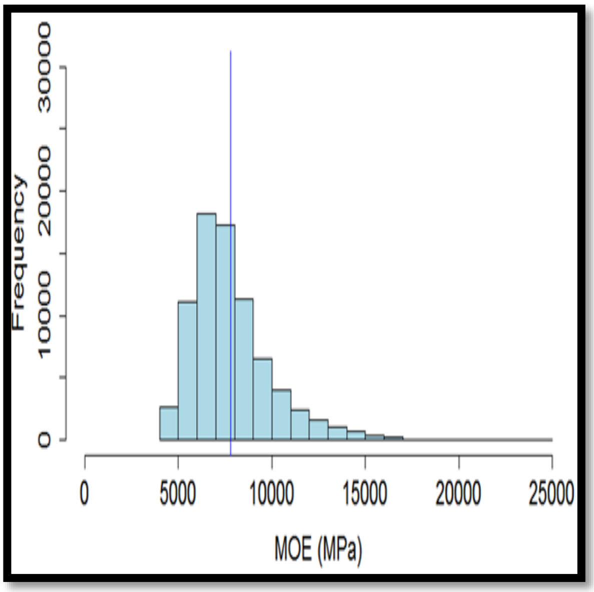

Figure 4-2: Histogram of individual board MOE for Month 1, Sawmill A. The blue vertical line represents the target mean MOE (7 800 MPa).

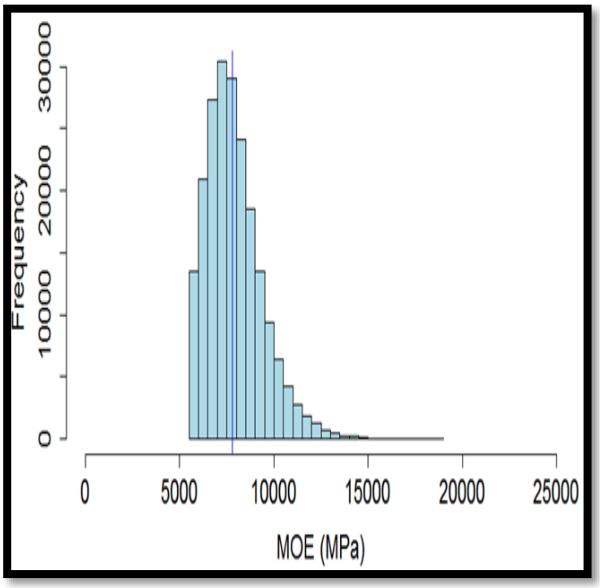

Figure 4-3 : Histogram of individual board MOE for Month 1, Sawmill B. The blue vertical line represents the target mean MOE (7 800 MPa).

The variation within and between the MOE of S5 graded boards in the different months is shown below. In Figure 4-4, the median value for 6 of the months is higher than the mean target value. The median value for 1 of the months was lower than the mean target value. The median value for 5 of the months was approximately on the mean target value. The graphs showed that there was some variation between the lumber produced each month. The median value for 1 of the months was around the mean target value while the median value for the other month was lower than the mean target value.

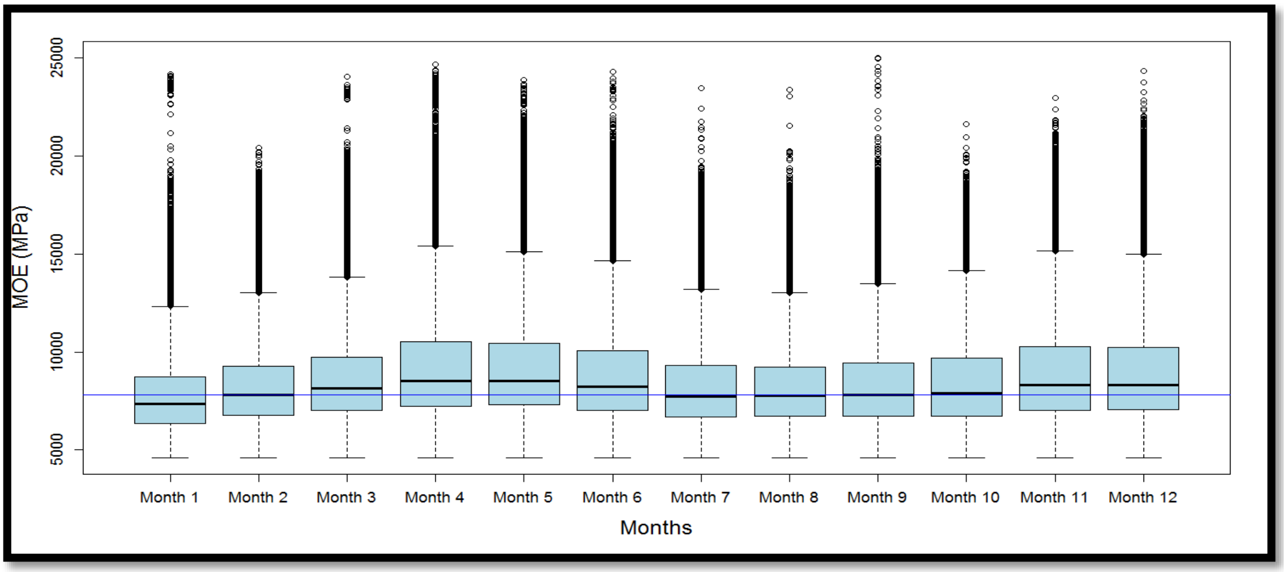

Figure 4-4: Boxplots of mean MOE of the individual S5 graded boards for Sawmill A over 12 months showing the median, upper quantile and lower quantile values. The blue horizontal line shows the target mean for the bundles at 7 800 MPa and the circular data points are outliers.

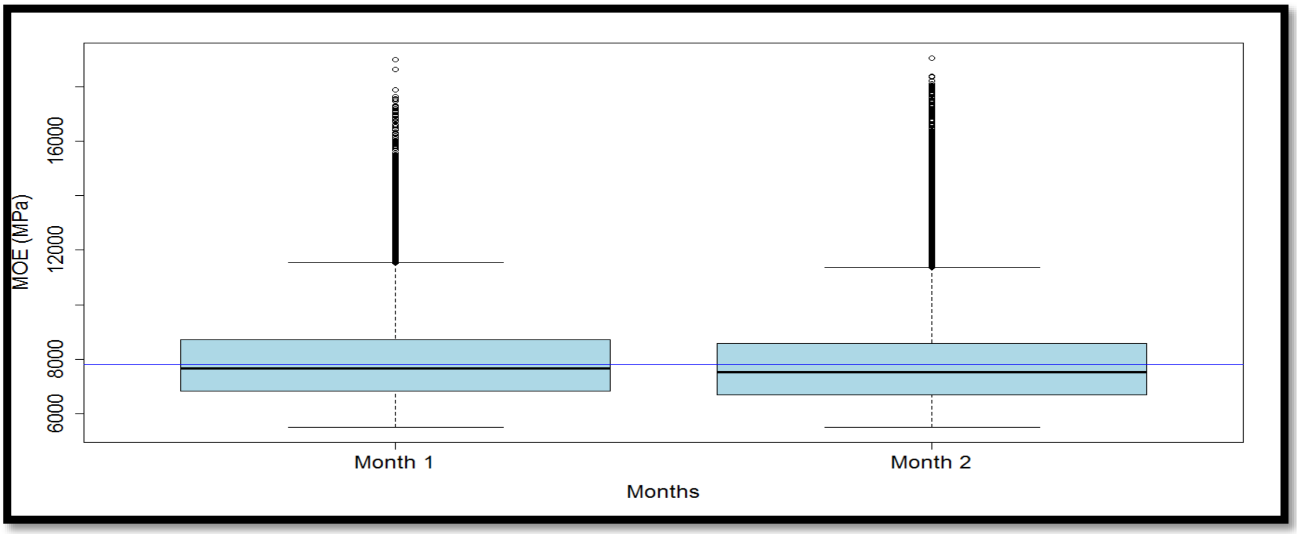

Figure 4-5: Boxplots of mean MOE of the individual S5 graded boards for Sawmill B over 2 months showing the median, upper quantile and lower quantile values. The blue horizontal line shows the target mean for the bundles at 7 800 MPa and the circular data points are outliers.

4.1.3 The variation in MOE within and between the bundles

The distribution of the mean MOE of bundles was evaluated using histograms. Each bundle consisted of 190 pieces of 38x114 mm S5 graded boards. The histograms in Figure 4-6 and Figure 4-7, show the mean MOE distribution in the bundles for the different first months of the two sawmills. The graph for Sawmill A showed that the data is skewed to the right since the graph tails off to the right similar to the graph for MOE of individual pieces Figure 4-2. The distribution for the bundle means is bimodal for data for Month 1, Sawmill B bundle (Figure 4-7). It was interesting to see that the histogram for Month 1, Sawmill B is bimodal, which is different from the observed right skewed distribution for the one on the individual boards. Although it will be difficult to determine with certainty the reason for this distribution, we hypothesize that one possibility might be that the bimodal distribution is a result of the sawmill sourcing logs from two tree resources with very different mean MOE characteristics. Sawmill B sources logs from their own plantations as well as two other large suppliers where the genetics, growing sites, and management regimes can be very different.

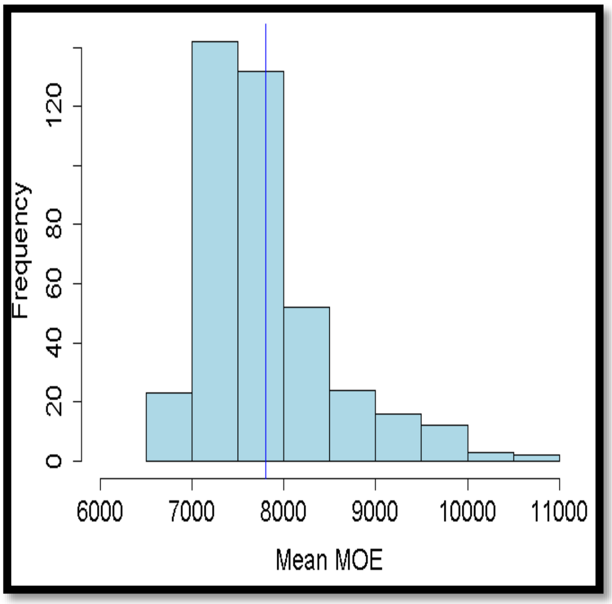

Figure 4-6: Histogram showing mean MOE for bundles for Month 1, Sawmill A. The blue vertical line represents the target mean MOE (7 800 MPa).

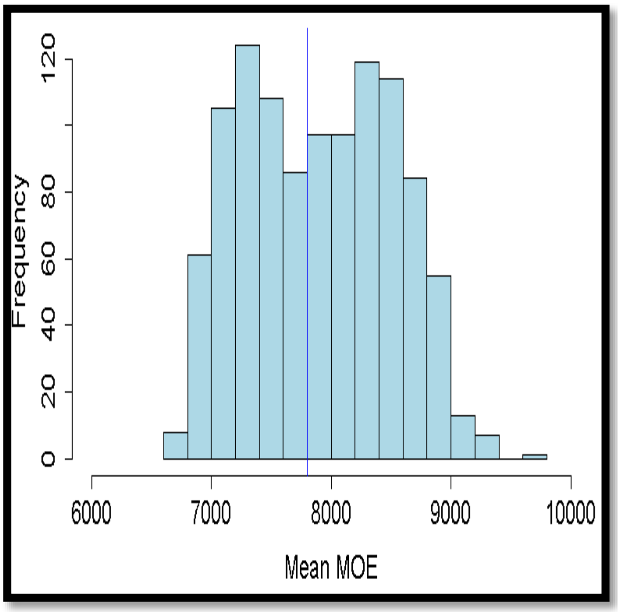

Figure 4-7: Histogram showing mean MOE for bundles for Month 1, Sawmill B. The blue vertical line represents the target mean MOE (7 800 MPa).

The variation in MOE within and between the bundles for the different months is shown in Figure 4-8 and Figure 4-9. Boxplots showing the minimum, lower quartile, median, upper quartile and maximum values, as well as the outliers within each month are shown below. The blue line on the boxplots shows the target mean for the bundles at 7 800 MPa. The median value for all but 1 month is higher than the mean target value for the bundle averages. The graphs showed that there were significant variation within and between the mean MOE of bundles produced each month.

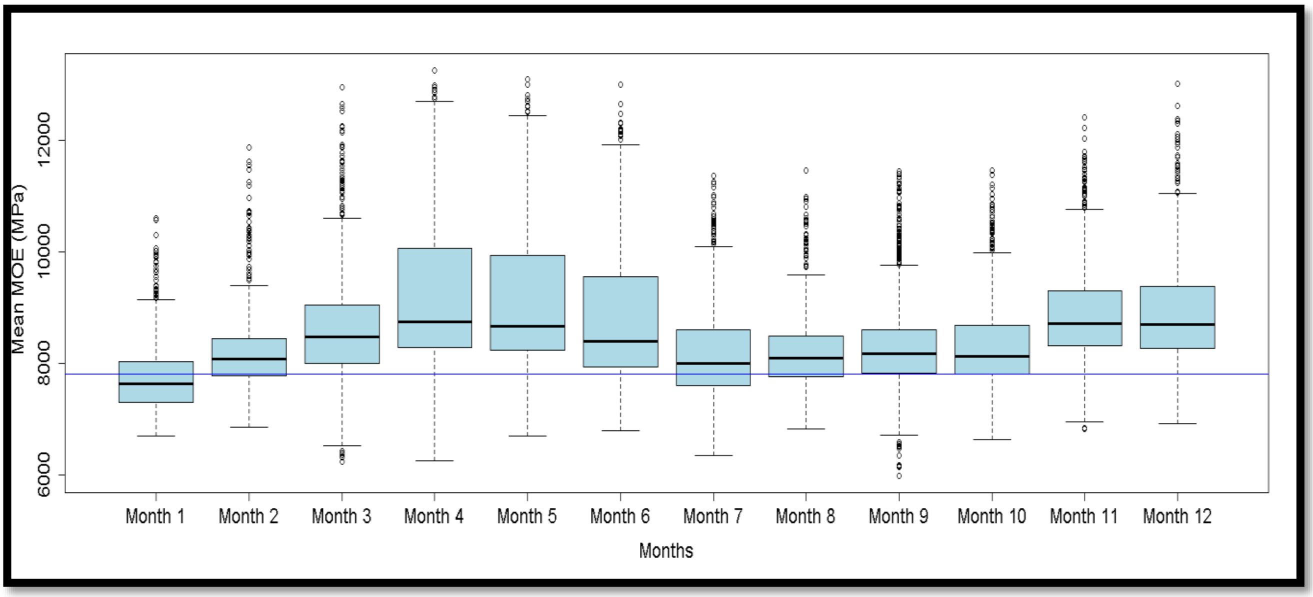

Figure 4-8: Boxplots of bundle MOE characteristics of Sawmill A over 12 months showing the median, upper quantile and lower quantile values. The blue horizontal line shows the target mean for the bundles at 7 800 MPa and the circular data points are outliers.

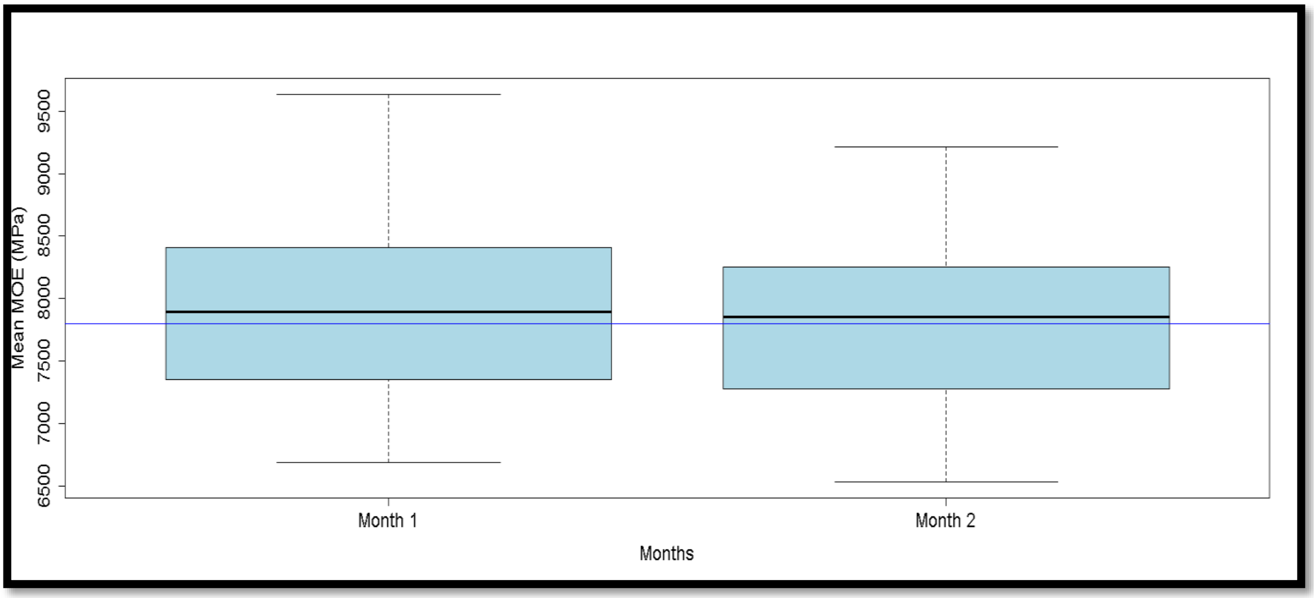

Figure 4-9: Boxplots of bundle MOE characteristics of Sawmill B over 2 months showing the median, upper quantile and lower quantile values. The blue line shows the target mean for the bundles at 7 800 MPa.

The numerical description of variation for the data in the bundles is summarized in Table 4-2. The calculated values were the mean, the standard deviation, the coefficient of variation, the minimum, the median, the maximum, the range, the skewness, the kurtosis and the standard error. The monthly mean in the bundles was always higher than the target mean of 7 800 MPa for all the months and both sawmills. The standard deviation for the bundle means was higher for most of the months from Sawmill A data. The standard deviation for the bundle means was slightly lower for the Sawmill B data. The bundles mean for Month 9 was the lowest and Month 4 had the highest maximum bundle mean.

The data from all the months showed a positive skewness. The implications of the results in terms of the skewness was that the data was not symmetrical, which would suggest that the data is not normally distributed (kurtosis refers to the sharpness of a peak of a frequency curve). The kurtosis of a normal distribution is equal to three (DeCarlo, 1997). The kurtosis was less than 3 for all the months. The implications of the results in terms of the kurtosis was that the data was not normally distributed.

The difference between the bundle MOE characteristics of the two sawmills was quite striking (Table 4-2). In general, Sawmill A had higher mean bundle MOEs than Sawmill B. Sawmill B on the other hand had much lower variation in MOE and a much smaller range in bundle mean MOE values. On the low end of the mean bundle MOEs the sawmills were fairly similar (minimum and 5th percentile values) but on the high end (maximum) Sawmill A had much higher values than Sawmill B. Observe for instance the large number of bundles considered as outliers with high mean MOEs of Sawmill A compared to none for Sawmill B (Figure 4-8 and Figure 4-9).

Table 4-2: Summary of the numerical description of MOE variation between the 38x114 mm S5 graded bundles for the different months in both sawmills.

Sawmill	Month	Number of bundles	Mean	Standard Deviation	5th percentile	Coefficient of variation	Median	Min	Max	Range	Skewness	Kurtosis	Standard error
Sawmill A	Month 1	406	7796	1953	5281	0.25	7441	4696	15207	10512	1.07	1.61	97.15
	Month 2	360	8298	1993	5662	0.24	7962	4806	15640	10834	1.00	1.44	105.23
	Month 3	899	8647	2076	5921	0.24	8284	4919	16057	11138	0.96	1.28	69.37
	Month 4	648	91637	2308	6157	0.25	8796	5027	17716	12689	1.05	2.16	90.81
	Month 5	1027	9148	2194	6211	0.24	8816	5058	16927	11868	0.90	1.24	68.58
	Month 6	875	8829	2145	5959	0.24	8500	4917	16498	11581	0.92	1.30	72.64
	Month 7	415	8243	1932	5696	0.23	7920	4869	15373	10504	0.98	1.48	95.02
	Month 8	639	8218	1979	5668	0.24	7845	4840	15397	10557	1.02	1.34	78.44
	Month 9	1220	8326	2082	5615	0.25	7943	4782	15771	10989	0.99	1.25	59.73
	Month 10	358	8429	2164	5589	0.26	8044	4789	16225	11436	1.00	1.32	114.59
	Month 11	781	8900	2434	5774	0.27	8436	4843	17466	12624	0.99	1.13	87.22
	Month 12	1170	8918	2372	5902	0.27	8458	4916	17434	12518	1.04	1.31	69.46
Sawmill B	Month 1	1079	7896	1326	6053	0.17	7731	5386	12716	7330	0.80	1.08	40.49
	Month 2	1169	7788	1345	5978	0.17	7592	5432	12721	7289	0.86	1.13	39.45

Data assumptions

It was noted in chapter 2 that data assumptions should be tested before applying control charts to avoid misinterpretation of results. Statistical inference was performed to make a judgment regarding the properties of the population. Statistical data assumptions were tested on the mean MOE of bundles to formally see whether the data was normally distributed and/or correlated. The results of the normality tests showed that the P values for the data for each month were found to be less than 0.05, therefore the null hypothesis that the data was normally distributed was rejected. The conclusion was that the data was not normally distributed.

Time series analysis was performed to test for data stationarity and autocorrelation. The results obtained from the Augmented Dickey-Fuller test showed that the P values for the mean MOE of bundles for all the months in Sawmill A, except for Month 10, were 0.01. The P value for the mean MOE of bundles for Month 10, Sawmill A, was found to equal 0.03698. The P value for the mean MOE of bundles for Month 1, Sawmill B was equal to 0.0167 and the P value for Month 2, Sawmill B was found to equal 0.01. The P values were less than 0.05, therefore the null hypothesis was rejected. It was concluded that the series is stationary – therefore the statistical properties of the data can be considered as constant over time within the months of production in the two sawmills.

The results of the autocorrelation test for the mean MOE of the bundles are displayed in the graphs in Appendix A. The autocorrelation function (ACF) and correlation plots for all the months from Sawmill A showed that there was moderate autocorrelation in the mean MOE of the bundles. The lag-1 autocorrelation on the autocorrelation function plots was between 0.3 and 0.5 for all the months in Sawmill A. The autocorrelation function and correlation plots for Month 1, Sawmill B and Month 2, Sawmill B showed a significantly high presence of autocorrelation in the mean MOE of the bundles. The lag-1 autocorrelation on the autocorrelation function plots was around 0.8 for both months in Sawmill B. Autocorrelation can informally be described as the similarity between observations as a function of the time lag between them. In this case it implies that there was similarity of MOE means of bundles within a month as a function of the time lag between production units.

Variation in bundle MOE means (Xbar) and standard deviation (S) within a month

The mean (Xbar) and standard deviation (S) chart pairs are shown below in Figure 4-10 to Figure 4-13 for the different months. The Xbar chart was used to monitor the process mean and the S chart was used to monitor the process standard deviation. Although the data normality tests above proved that the mean MOE for the bundles was not normally distributed, the charts were plotted under the assumption of normality. This is following the central limit theorem, which states that the sum of n random variables (regardless of its mean, variance, and distribution) approximates a normal distribution as n increases (Cano et al., 2015 and Oakland, 2007). The red points on the graphs represent the points that are out-of-control, i.e. outside the set limits. The black points represent points that are in control, i.e. within the set limits. The control limits were set at a distance of 3 standard deviations above and below the centre line for both the Xbar and S charts as is customary according to Montgomery (2009).

The S chart was evaluated first for each month to see the amount of variation in the mean standard deviation in the bundles. The points that are of main concern are the points below the LCL (lower control limit). The S chart for Month 1, Sawmill A had a couple of points above and below the control limits. This explains why there was a lot of variation in the groups. The Xbar chart did not signal any out-of-control signal, meaning that there was less variation in the means. In the S chart for Month 1, Sawmill B shows only 2 points above the upper and 2 points below the lower control limits. This explains why there was a lot of variation in the group's standard deviations. The Xbar chart did not signal any out-of-control conditions, meaning that there was less variation in the means.

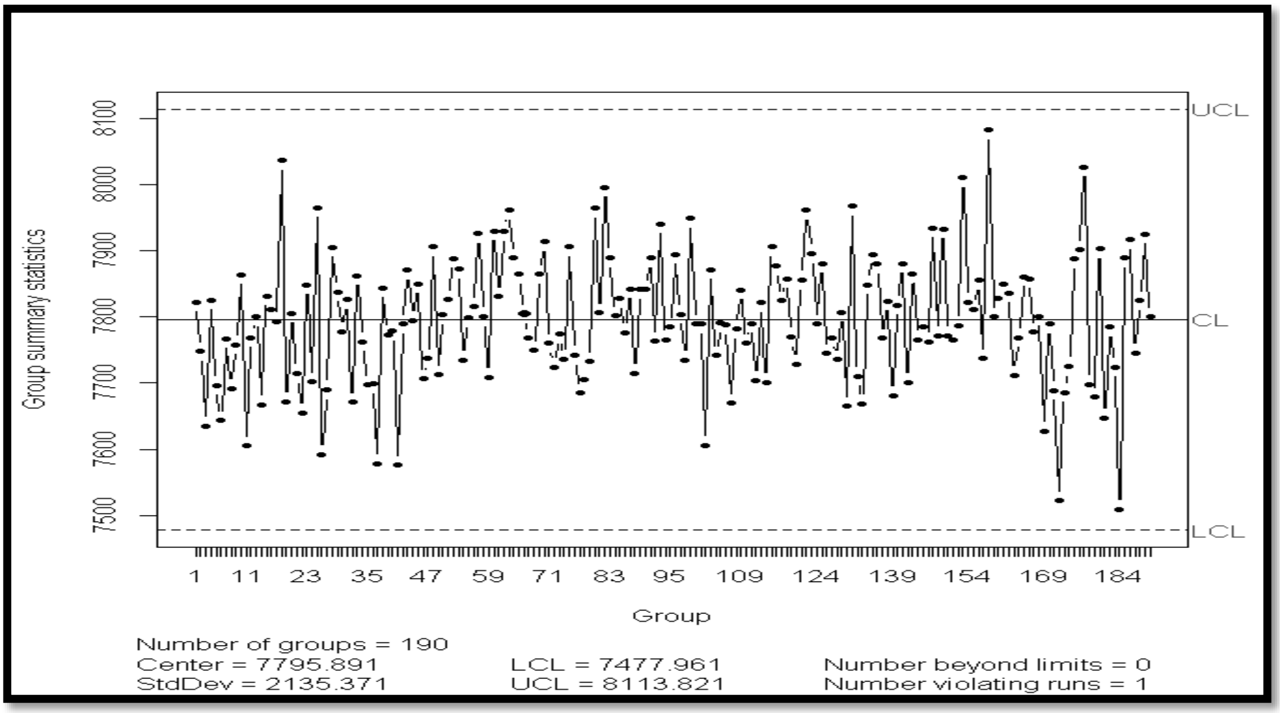

Figure 4-10: Xbar chart to monitor the mean MOEs of bundles for Month 1, Sawmill A. The MOE values in MPa are plotted on the y-axis and the summary of the data is shown on the graph. The chart shows the centreline (CL) as well as the upper and lower control limits marked by UCL and LCL, respectively.

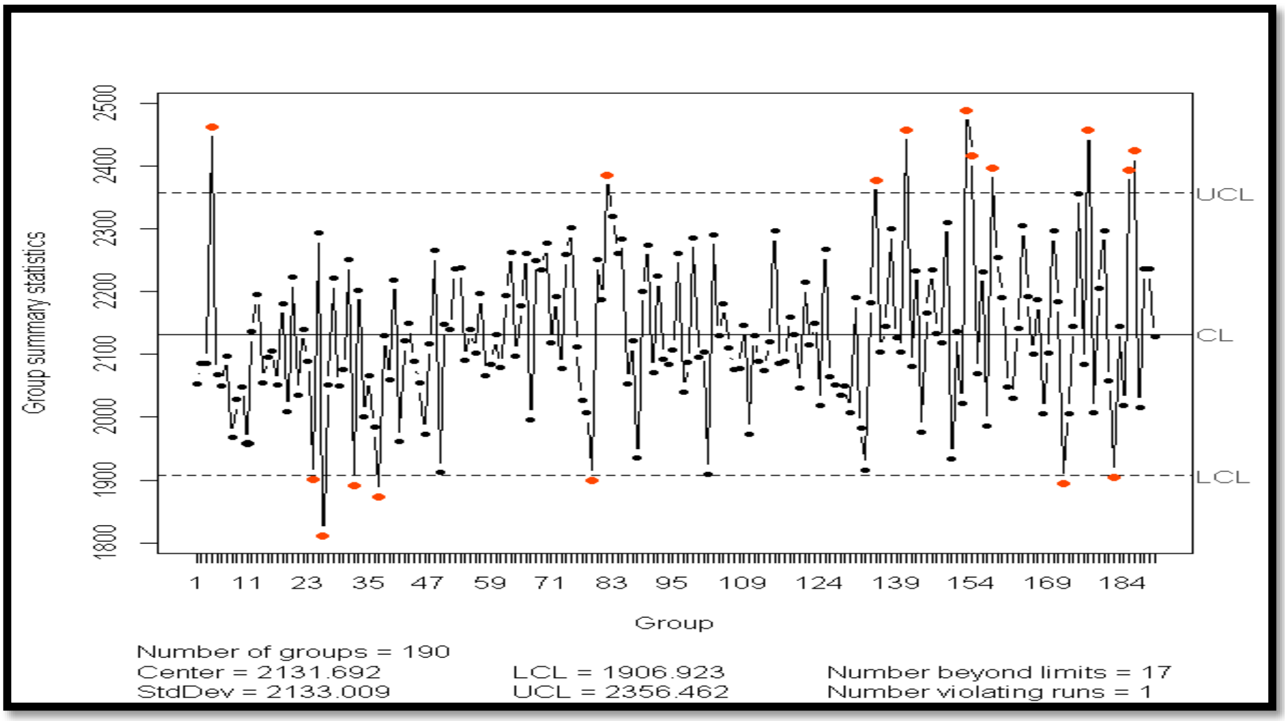

Figure 4-11: S chart to monitor the standard deviation of MOE within bundles for Month 1, Sawmill A. The MOE values in MPa are plotted on the y-axis and the summary of the data is shown on the graph. The chart shows the centreline (CL) as well as the upper and lower control limits marked by UCL and LCL, respectively.

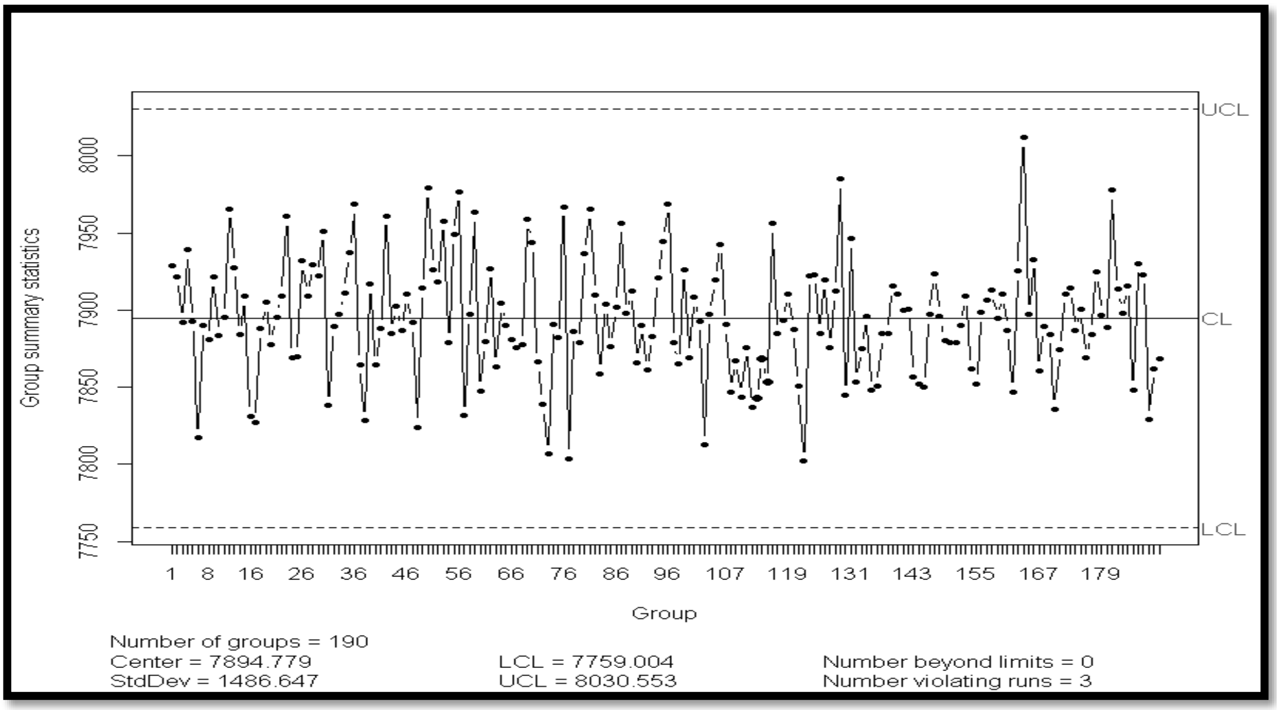

Figure 4-12: Xbar chart to monitor the MOE means of bundles for Month 1, Sawmill B. The MOE values in MPa are plotted on the y-axis and the summary of the data is shown on the graph. The chart shows the centreline (CL) as well as the upper and lower control limits marked by UCL and LCL, respectively.

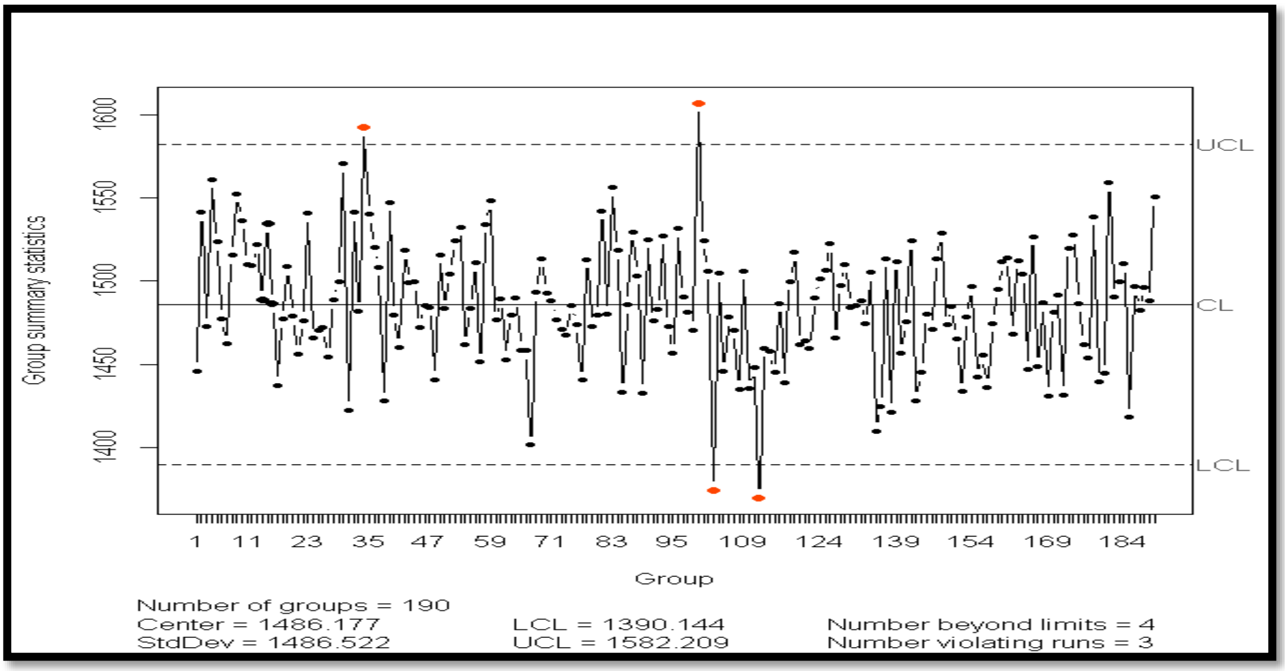

Figure 4-13: S chart to monitor the standard deviation of MOE within bundles for Month 1, Sawmill B. The MOE values in MPa are plotted on the y-axis and the summary of the data is shown on the graph. The chart shows the centreline (CL) as well as the upper and lower control limits marked by UCL and LCL, respectively.

Variation within selected bundles

Three bundles were selected from Month 1, Sawmill B in order to see the variation within bundles where these bundles, had very different mean MOE values. A bundle with a low mean MOE value (mean MOE = 6 688 MPa), an average mean MOE (mean MOE = 7 772 MPa) and a high mean MOE (mean MOE = 9 636 MPa) was selected. The idea was to see whether the within bundle variation is different for bundles having different MOE means. The results are shown in Figure 4-14 to Figure 4-16. The blue points represents the individual board MOEs within the bundles. The green line is the mean MOE target line at 7 800 MPa.

Figure 4-14 showed that the bundle with the lowest mean value had only a few samples above the 7 800 MPa target line and a majority of samples below 7 000 MPa. Figure 4-15 shows that the bundle with a mean value around 7 800 MPa had most of the samples below 7 800 MPa, but several samples with very high MOE values. The four samples with MOE values around 11 000 MPa might have contributed in pushing the mean value higher to be around 7 800 MPa since most of the samples were below 7 800. Figure 4-16 shows that the bundle with the highest mean value out of all the bundles for that month had a couple of samples below the 7 800 MPa target line and a majority of samples above 7 000 MPa.

Interestingly, the minimum board MOE values in all three bundles were close to 5 500 MPa. It is just the frequency of these very low board MOEs that increase with the lower mean MOE bundle. The maximum board MOEs between the three bundles were, however, very different with the high MOE bundle having a maximum between 16 000 and 18 000 MPa whereas the low MOE bundle had a maximum of about 10 000 MPa. It seems that the difference in minimum MOE values of boards in a bundle is not excessive between high and low MOE bundles. It is rather on the higher end of board MOEs where differences are pronounced.

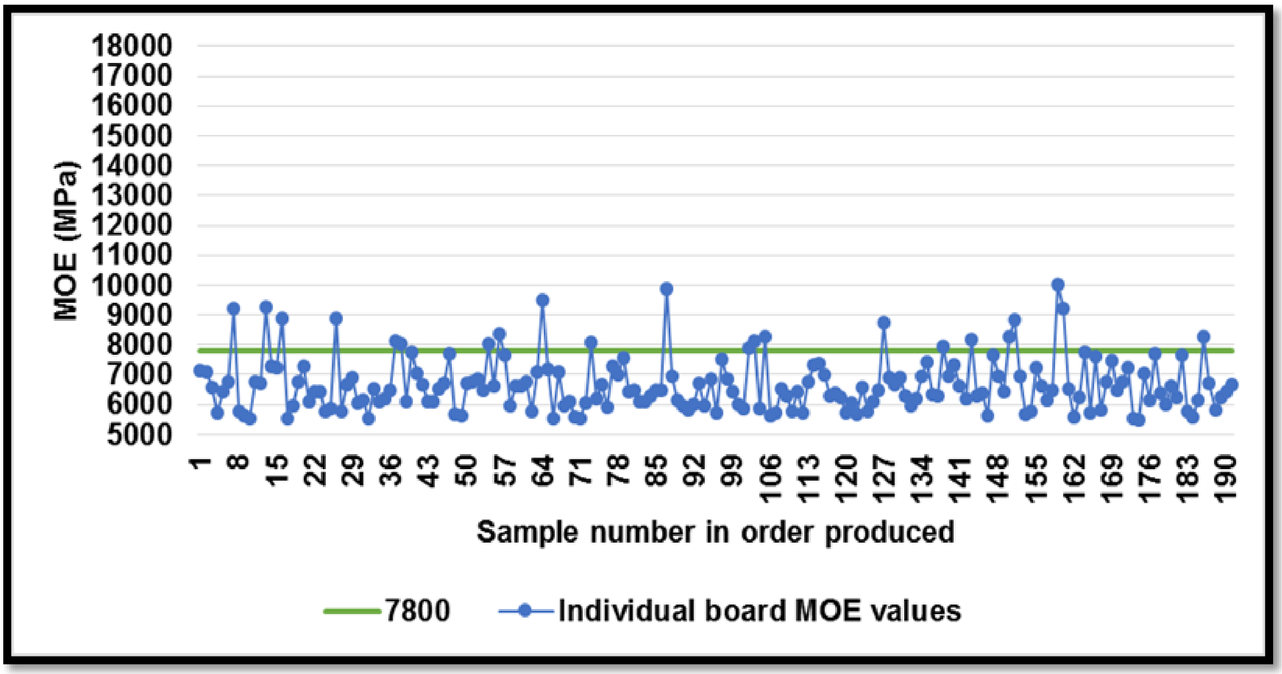

Figure 4-14: The variation observed within a bundle with a low mean MOE value (mean MOE = 6 688 MPa) from Sawmill B, Month 1. The blue points represent the samples within the bundles. The green line is the target line at 7 800 MPa.

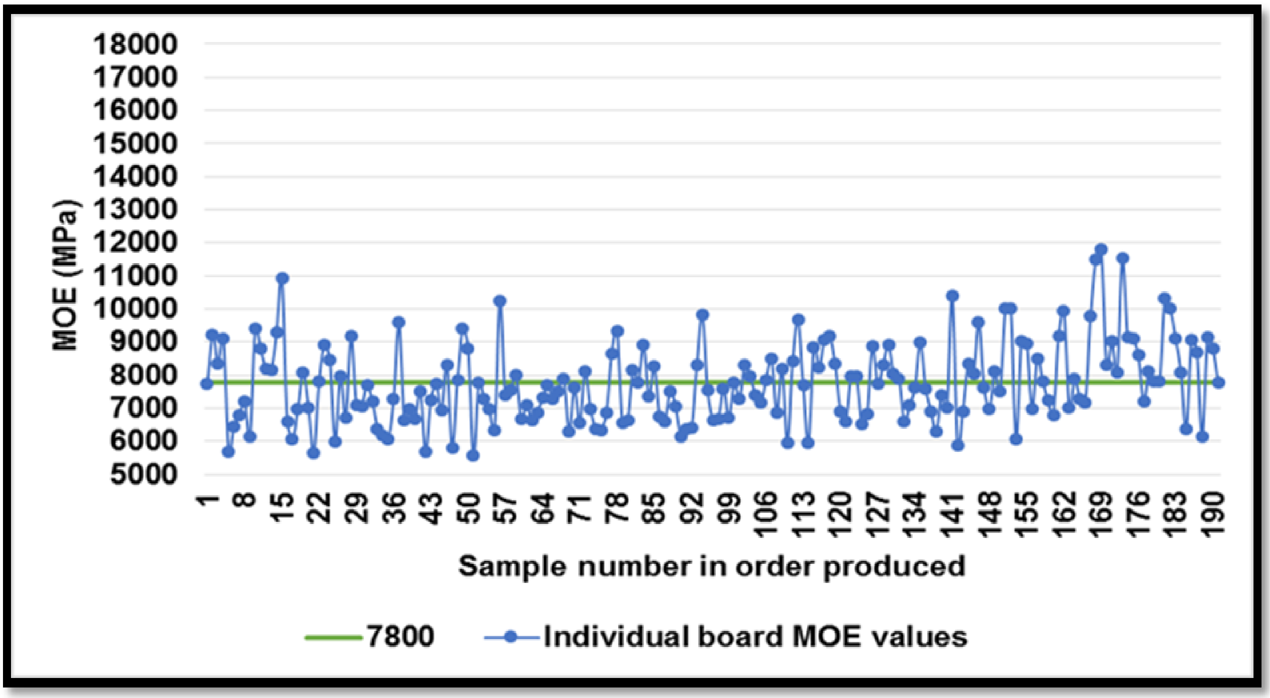

Figure 4-15: The variation observed within a bundle with an average mean MOE value (mean MOE = 7 772 MPa) from Sawmill B, Month 1. The blue points represent the samples within the bundles. The green line is the target line at 7 800 MPa.

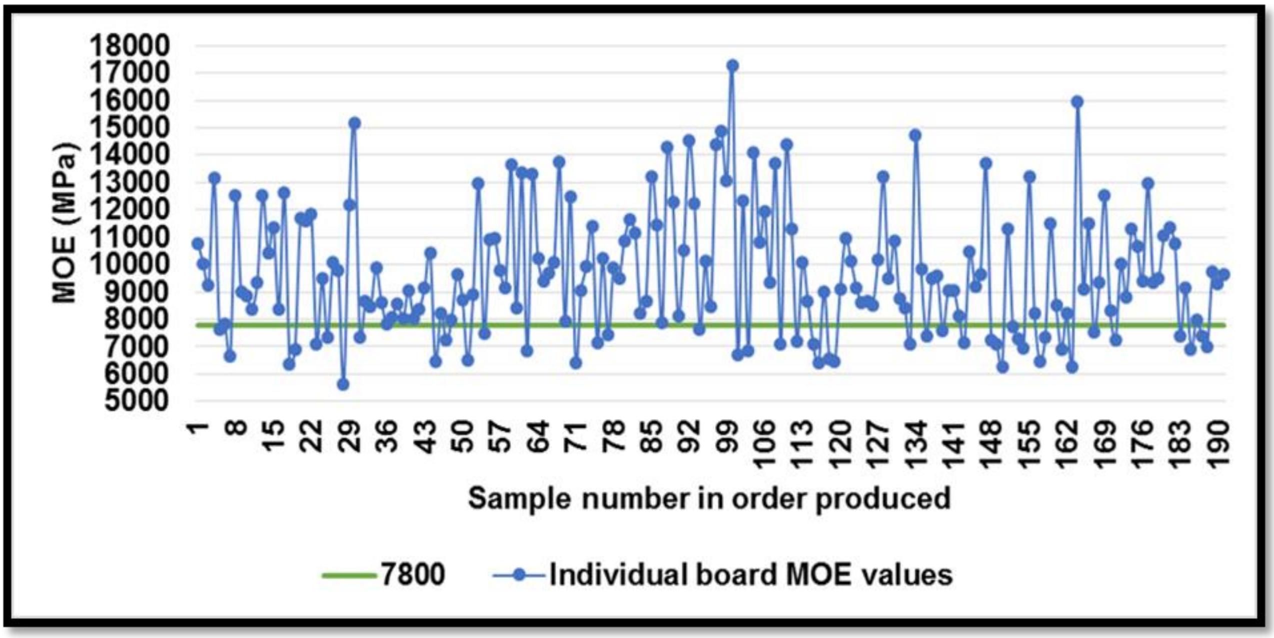

Figure 4-16: The variation observed within a bundle with a high mean MOE value (mean MOE = 9 636 MPa) from Sawmill B, Month 1. The blue points represent the samples within the bundles. The green line is the target line at 7 800 MPa.

4.1.4 General discussion on MOE variability

Variation in the individual boards

The combined boards from both sawmills had MOE values between 4 600 to 25 000 MPa (Figure 4-1 and Table 4-1). The distribution of the board MOEs was skewed with a short tail towards the 4 600 MPa lower limit and a long tail towards the high MOE values. This was the same when the histograms were evaluated individually for the two months (Figure 4-2 and Figure 4-3). The overall mean MOE of all the boards was 8 470 MPa and the 5th percentile was 5 609 MPa (Table 4-1) - which were well above the required values according to SANS 10163-1 (2003). The mean and 5th percentile MOE for the individual sawmills were also above the required values (Table 4-1).

The range between the median and lower quantile was always fairly small for both sawmills in all months whereas the range between the median and upper quantiles was always large with many outliers above the upper quantile (Figure 4-4 and Figure 4-5). There were many boards with an MOE in the bracket between 20 000 – 25 000 MPa (Figure 4-4), especially for Sawmill A. It is clear that the complete population of tested boards (when treated as a single group), as well as the two individual sawmills, comply with MOE requirements for the S5 grade. However, it is clearly inappropriate from this analysis to conclude that the lumber produced at the two sawmills, in the period considered, comply with requirements since there might be time periods and sub-groups of boards produced during the study where bundles did not comply with MOE requirements.

Variation between bundles

One of the difficulties of strength and stiffness assessment of lumber is that it is not done on an individual board level but statistical properties (mean, 5th percentile) of a group is considered for evaluation. A central question then, is the size of a group to be assessed. Twelve months of production or even two months of production of a sawmill is clearly too large a group since that lumber will go into thousands of roofs. Essentially, one would like to be sure that the group of boards going into a single structure, such as a roof, comply as a group with the requirements since load sharing will occur within that group of lumber members. It is for that reason that bundles of lumber are considered in this study as the smallest group that should be evaluated for compliance. From a practical perspective it is the most sensible grouping since lumber is sold in bundles to large users such as roof truss manufacturers.

It is clear from the results (Figure 4-8, Figure 4-9 and Table 4-2) that the mean bundles MOEs and 5th percentile bundle MOEs behaved differently for the two sawmills, as well as over time. The range between the median and lower quantile was always fairly small for all the months in Sawmill A whereas the range between the median and upper quantiles were always large with many outliers way above the upper quantile. Interestingly, there were 3 months with a few outliers below the lower quantile, when the data was displayed in bundles (Figure 4-8). The range between the median and both the lower and upper quantiles was fairly equal, with no outliers for both months in Sawmill B (Figure 4-9).

The overall conclusion in terms of testing data assumptions was that the bundle means were not normally distributed as was shown by the normality tests and the values of the kurtosis, which was not equal to three (Table 4-2). The autocorrelation test shows that there was moderate autocorrelation in the bundle means for Sawmill A and high autocorrelation in the 2 months from Sawmill B. The implication is that we expect to have bundles with similar qualities closer to each other especially in Sawmill B. This would suggest that a poor bundle is most likely followed by a poor bundle and a good bundle by a good bundle until such a point in time when there is a shift in the process mean and/or process variation. Inspection of the mean (Xbar) and standard deviation (S) chart pairs (Figure 4-10 to Figure 4-13) shows that there was less variation in the process mean and more variation in the process standard deviation as indicated by the out-of-control signals (Figure 4-11 and Figure 4-13).

Variation within bundles

The within-bundle variation was not investigated in much depth but three bundles from Sawmill B were selected to represent bundles with (a) a low mean MOE, (b) an average mean MOE around 7 800 MPa, and (c) a high mean MOE (Figure 4-14 to Figure 4-16). Once again it was clear that boards from the lower level of individual board MOEs (around 5 500 MPa) were present in all three bundles. The big difference between the board MOEs between bundles was the relative high number of boards at the upper MOE levels for the average and high mean MOE bundles.

4.2 Acceptable MOE mean and variation

A challenge of this study was to determine when the mean MOE of a bundle was unacceptable. The concept of "reliability" used in the limit states design methods, was used to determine these threshold values. It was noted that the lumber was graded as either S5 or utility grade, meaning that grade S5 was not capped at the top (no S7 or S10 removed), which is why the MOE histograms were generally skewed to the right (Figure 4-2 and Figure 4-3). It was expected that there would be some variation in the bundles, however, the questions were how much MOE variation can roof truss plants and other structural lumber users handle in terms of reliability of structures and how do we best manage the variation of MOE in the structurally graded end-products produced at sawmills?

The method used to define acceptable MOE characteristics of structural lumber was the load and resistance factor design method by calculating the requirements for serviceability limit state and the ultimate limit state for the lumber. These values are linked to the acceptable reliability of structures. The generally acceptable target reliability index, β = 1.5 for serviceability limit state and β = 3 for ultimate limit state conditions were used with the mean taken as a characteristic value for serviceability limit state and 5th percentile value taken as characteristic for ultimate state limit (SABS 0160, 1989 and SANS 10163-1, 2003). The partial factor γ_m = 0.68 and sensitivity factor α_R = 0.8 were used (Holicky and Retief, 2005; SABS 0160, 1989 and SANS 10163-1, 2003). The design value R_d of a resistance for ultimate limit state was found to be 3 148 MPa and for serviceability limit state it was found to be 5 304 MPa. The variables are summarized in Table 4-3.

The standard deviation values for each bundle were used with the appropriate values for each limit state to get the required mean value to satisfy serviceability limit state (SLS) requirements and the required mean value to satisfy the ultimate limit state (ULS) requirements according to the standard deviation of that particular bundle.

Table 4-3: summary of the variables used to calculate the required mean values to satisfy the ultimate and serviceability limit stated.

Parameters	Definition	Required MOE_{mean} for serviceability limit states	Required MOE_{mean} for ultimate limit states
R_k	Characteristic value	7 800 MPa	4 630 MPa
β	Reliability index	1.5	3
α_R	Sensitivity factor	0.8	0.8
γ_m	Partial factor	0.68	0.68
R_d	Design value of resistance	5 304	3 148

Figure 4-17 and Figure 4-18 show the results for two of the months, that is Month 1 Sawmill A and Month 1 Sawmill B for some of the results summarized in Table 4-4. The required mean value to satisfy serviceability limit state (SLS) requirements (required mean (SLS)) and the required mean value to satisfy the ultimate limit state (ULS) requirements (required mean (ULS)) were compared with the mean MOE values for each bundle. For each bundle, four values were calculated to determine whether the bundle was acceptable in terms of the reliability of a possible structure from that lumber. The yellow points in Figure 4-17 and Figure 4-18 represent the required mean MOE to ensure a reliability index value of $\beta = 1.5$ – related to the serviceability limit state. The grey points represent the required mean MOE to ensure a reliability index value of $\beta = 3$ – related to the ultimate limit state. The orange points represent the mean MOE of the individual bundles. The green and blue vertical lines represent the areas where the required mean exceeded the mean MOE for the bundle for both serviceability limit state and ultimate limit state respectively.

At Sawmill A, Month 1 (Figure 4-17) one can see that the required mean (SLS) (yellow dots) are sometimes higher than the actual mean MOE (orange dots). This is represented by the green vertical lines plotted on a secondary scale to show the non-compliant bundles. For the bundles where this occurred it means that the reliability index for those bundles will be lower than 1.5, which is viewed as unacceptable. For Sawmill A, Month 1 a total of 8.62% of the bundles had required mean (SLS) values above mean MOE value, that is higher than what was acceptable from a reliability perspective (Table 4-4). It is also clear from Figure 4-17 and Table 4-4 that 2 of the bundles had required mean (ULS) higher than the mean MOE of bundle.

For Sawmill B, Month 1, it can be seen that none of the required mean (SLS) values were above the mean MOE of the bundle as reflected by the yellow and orange points in Figure 4-18 and in Table 4-4. There were two bundles where the required mean (ULS) values were above the mean MOE of the bundles. The two periods are represented by the 2 vertical lines (Figure 4-18). Month 1, Sawmill A was the worst month for this sawmill as all other months had less than 4% of the bundles with unacceptable mean MOEs.

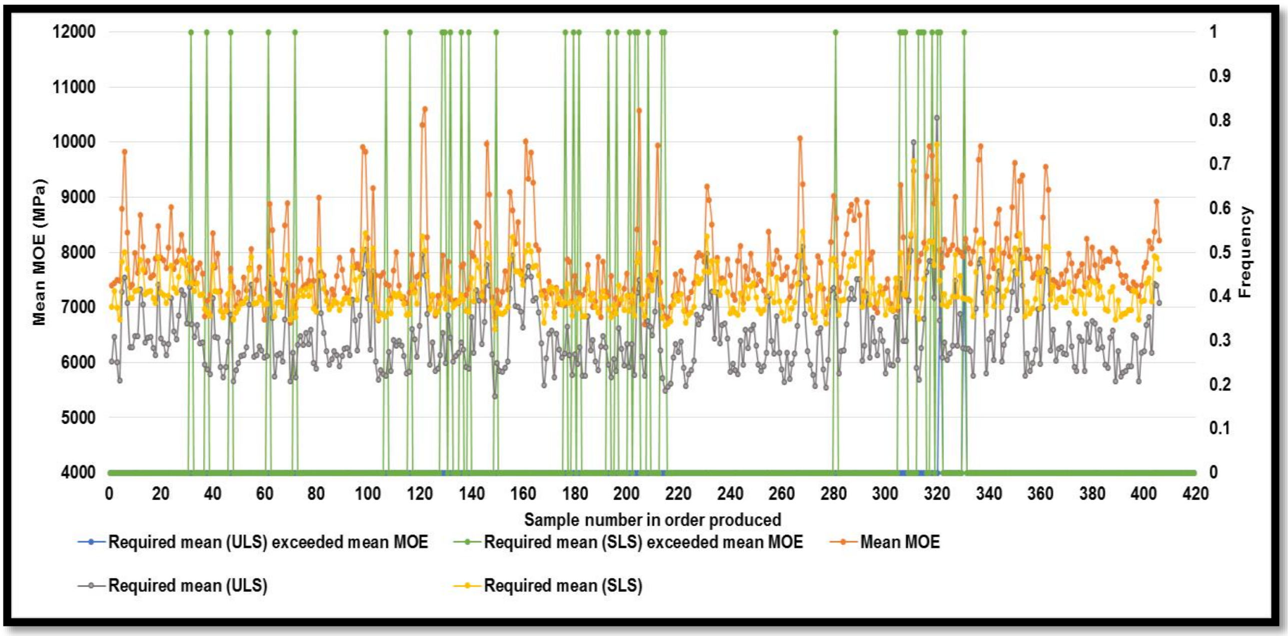

Figure 4-17: Graded bundles from Month 1 Sawmill A. The yellow points represent the required mean to ensure a reliability index value of β = 1.5 for SLS. The grey points represent the required mean to ensure a reliability index value of β = 3 for ULS. The orange points represent the bundle mean MOE values. The green and blue vertical lines represent the bundles where the required mean exceeded the MOE for the bundle for serviceability limit state and ultimate limit state respectively.

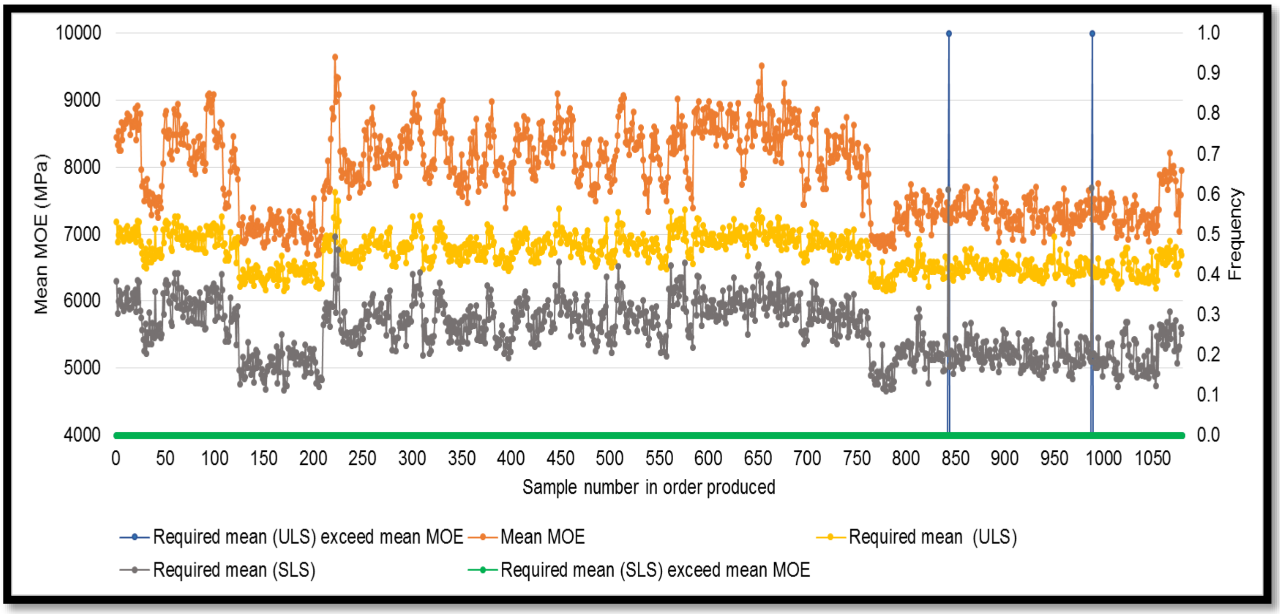

Figure 4-18:Graded bundles from Month 1 Sawmill B. The yellow points represent the required mean to ensure a reliability index value of β = 1.5 for SLS. The grey points represent the required mean to ensure a reliability index value of β = 3 for ULS. The orange points represent the bundle mean MOE values. The green and blue vertical lines represent the bundles where the required mean exceeded the MOE for the bundle for serviceability limit state and ultimate limit state respectively.

Table 4-4: The results show the number and percentage values of the mean MOE of the bundles below required mean values for serviceability and ultimate limit state. The table also *shows* the correlation (R^2) between mean MOE and the standard deviation of the bundles.

Sawmill	**Month**	**Number of bundles**	**Number of bundles with mean MOE value below the required mean(SLS)**	**% values of mean MOE value below required mean (SLS) value**	**Number of bundles with mean MOE value below the required mean (ULS)**	**% values of mean MOE value below required mean (ULS) value**	**The correlation (R^2) between MOE mean and the MOE standard deviation.**
Sawmill A	Month 1	406	35	8.62	2	0.49	0.65
	Month 2	360	0	0.00	0	0.00	0.60
	Month 3	899	20	2.22	0	0.00	0.54
	Month 4	648	25	3.86	4	0.62	0.47
	Month 5	1027	3	0.29	0	0.00	0.59
	Month 6	875	6	0.69	0	0.00	0.63
	Month 7	415	11	2.65	0	0.00	0.58
	Month 8	639	8	1.25	0	0.00	0.46
	Month 9	1220	23	1.89	0	0.00	0.53
	Month 10	358	10	2.79	0	0.00	0.46
	Month 11	781	8	1.02	0	0.00	0.41
	Month 12	1170	3	0.26	0	0.00	0.56
Sawmill B	Month 1	1079	0	0.00	2	0.002	0.76
	Month 2	1169	0	0.00	0	0.00	0.78
TOTAL	-	11046	152	1.38	8	0.07	-

It can be noted that the required mean MOE value of a bundle to comply with the reliability requirements (Equation 3-2) are largely based on the standard deviation (input variable) and mean MOE (for comparison) of the individual bundles. A high standard deviation and a low mean MOE of a bundle will therefore result in poor reliability. Sawmill A generally had more bundles with high mean MOEs but the variability in bundles was much higher than Sawmill B's lumber (see Table 4-2). The relationship between the standard deviation and the mean MOE of the bundles were therefore investigated - Figure 4-19 and Figure 4-20 show the correlation between the mean MOE and the standard deviation. The values for the coefficient of determination in Month 1, Sawmill A (Figure 4-19) and Month 1, Sawmill B (Figure 4-20) were 0.65 and 0.76 respectively. This shows that there was a moderately strong correlation between the standard deviation and the mean MOE of the bundles.

One can therefore see that a high mean MOE of a bundle is often offset by high variability in board MOEs. Additionally, despite Sawmill A having more high mean MOE bundles than Sawmill B (Figure 4-8 and Figure 4-9), it was clear that the lowest mean MOE bundles of the two sawmills were at a similar level. The result was that a much higher percentage of Sawmill A's bundles were unacceptable in terms of reliability than that of Sawmill B (Table 4-4). The standard deviation within bundles, therefore, seems to have a larger effect in terms of acceptable reliability of bundles than the mean MOE.

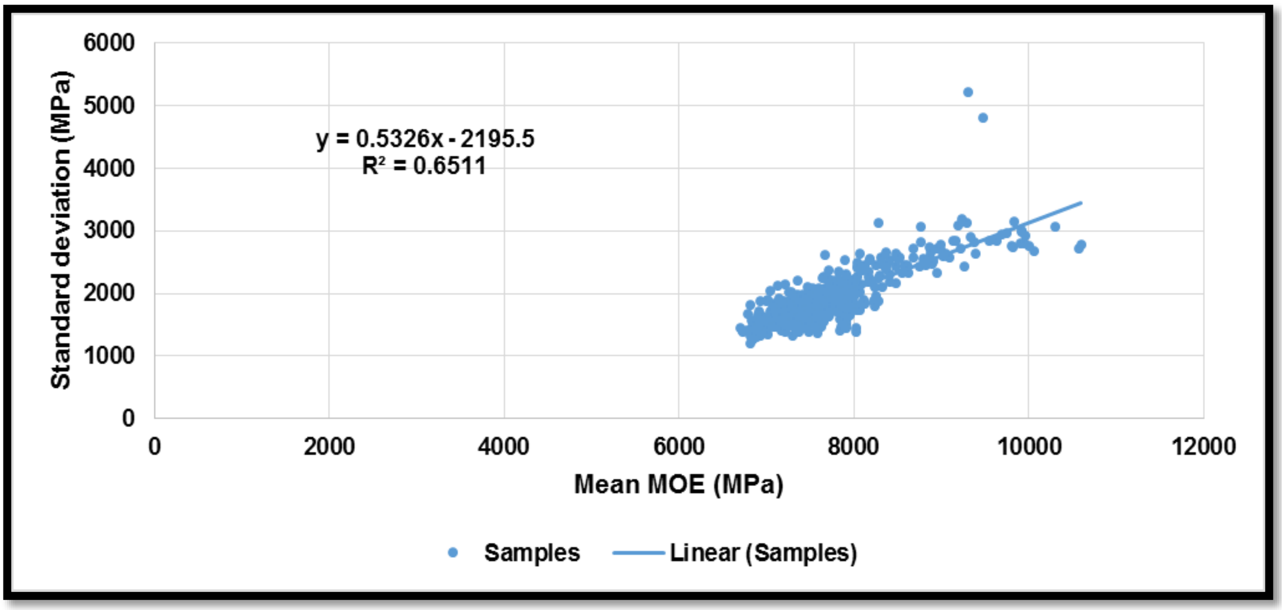

Figure 4-19: The correlation between mean MOE and standard deviation of Month 1, Sawmill A bundle means.

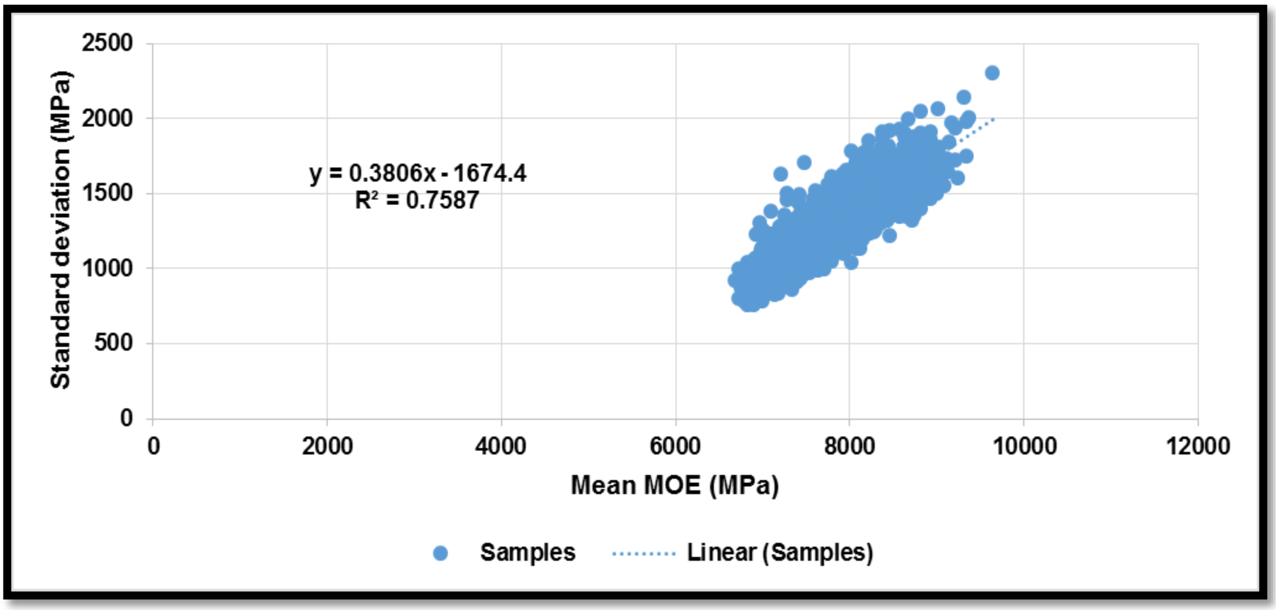

Figure 4-20: The correlation between mean MOE and standard deviation of Month 1, Sawmill B bundle means.

There were a small percentage of sub-standard bundles for 11 out of the 12 months for Sawmill A where the required mean (SLS) was higher than the mean MOE of the bundle. The implication of this is that if the bundles were to be used for structural purpose, the structure would be deemed unfit for use from a serviceability perspective. None of the bundles from the two months from Sawmill B had a bundle where the required mean (SLS) was higher than the mean MOE (Table 4-4). Only 2 months from Sawmill A and 1 month from Sawmill B had bundles where the required mean (ULS) was higher than the mean MOE of the bundles. In total 1.38 % of all the bundles did not comply with the reliability level in terms of serviceability and less than 0.1% did not comply with the required reliability level in terms of the ultimate limit state. From a safety perspective one can conclude that there were only 8 bundles from a total of 11 046 bundles produced by the two sawmills that did not comply with the ultimate limit state reliability requirement. The serviceability limit state will be related to the deflection levels of members in a structure, and here a total of 152 bundles did not comply with the reliability requirement.

Although the results in Table 4-4 showed that some of the bundles did not satisfy the requirements for the serviceability limit state (SLS) and the ultimate limit state (ULS), it was noted that some bundles with really high mean MOE values were rendered unfit. Recall that the bundles from Sawmill B had an average standard deviation of around 1 300 MPa and a mean of around 7 800 MPa. The bundles from Sawmill A had an average standard deviation from 1 900 and up 2 434 MPa and a mean ranging from 7 800 MPa to 9 000 MPa (Table 4-2). The test to see the correlation between the standard deviation and the mean showed that the mean MOE increased with the standard deviation (Figure 4-19 and Figure 4-20). The results in Table 4-4 showed that for all the months, the mean MOE and the standard deviation were correlated with an R^2 value above 0.4 for all the data, with Sawmill B having the highest values of R^2 at around 0.7.

The lack of normality in the mean MOE of the bundles data, especially in sawmill 1 data (Figure 4-6 and Figure 4-7 and appendix A) resulted in very high standard deviation values. Less variation in the bundles resulted in fewer bundles being rejected. This would suggest that the variation in the output should be controlled as the presence of high variation would render even the bundles with really high MOE values as unsafe.

4.3 Statistical quality control system for structural lumber

The third objective was to evaluate the current proposed SANS 1783-5-2 quality assurance system and compare it with other possible systems in terms of its efficiency to ensure safe and reliable structural lumber in terms of lumber stiffness (MOE). The analysis of the mean MOE of the bundles revealed that there was significant MOE variation within and between the bundles. Calculation to determine acceptable bundle mean MOE and variation for end users revealed that some of the bundles had mean MOEs below both the target MOE for structural lumber and the required values that will ensure acceptable reliability of products. The goal of this study was to ensure that the statistical quality control method used was able to detect out-of-control conditions in the process output data and that the sampling strategy was able to capture the variation that was observed in the bundles. This is important because the customer / industry expectation is that the lumber used in structures has the required stiffness to prevent it from buckling under pressure or showed excessive deflection.

4.3.1 Key performance measures

The key performance measures for the statistical control charting methods for quality control were identified as:

- The sampling frequency should be such that the samples are a good representation of the population from which they were taken.
- The control chart used is able to detect out-of-control conditions timely.
- The control chart is easy to setup and interpret.

4.3.2 Measuring the performance of the quality control method in SANS 1783-5-2 using data collected.

The collected data was used to check the effectiveness of the sampling strategy, as well as the proposed quality control method in SANS 1783-5-2. The process was evaluated in Figure 4-21 to Figure 4-23. The first figure is a graph of **ungraded** samples that were formed into bundles together with the identified problem areas based on the limit state method (take note that this also includes downgraded pieces of utility grade lumber). From the graph, one is able to see the areas that were identified as not meeting the requirements for structural timber. The second and the third graphs demonstrate the proposed quality control methods in SANS 1783-5-2. The graph of ungraded samples (Figure 4-21) was used as a reference graph in order to see if the sampling graphs picked up the problems that the bundle mean graph signaled. Ungraded samples were used simply because the graded samples did not provide enough “problem” areas.

The orange points represent the MOE values of the samples. The yellow points represent the required mean (SLS), or, in other words, the required mean MOE to ensure a reliability index value of β = 1.5. The grey points represent the required mean (ULS), i.e. the required mean MOE to ensure a reliability index value of β = 3. The green and blue vertical lines represent the areas where the required mean exceeded the MOE for the bundle for both serviceability limit state and ultimate limit state respectively. The bundle mean graph for Month 1, Sawmill B showed certain areas where the mean MOE values were below the required mean (SLS) values (green vertical lines), meaning that those bundles did not satisfy the requirements for structural lumber in terms of reliability.

In order to evaluate the chart performance of the proposed methods, the results were compared with that of the mean bundle MOE chart. The y-axis on the chart in Figure 4-22 shows the mean MOE values and the x-axis shows the sampled values. The grey line represents the 7 800 MPa target line. The MOE moving average of the last 20 sampled pieces is shown in orange and the sampled values are the points in blue. The red line represents the mean (7 800 MPa) minus 1 standard deviation target line to signal for the stress grading process to be stopped if the moving average line drops below it. The yellow line represents the 5 850 MPa target line, which is to be used in the absence of actual data standard deviation, to signal for the stress grading process to be stopped if the moving average line drops below it. The blue line is the 5th percentile line (4 360 MPa). The green line is the 3 473 MPa target line which was described as 0.75 times the 5th percentile value in the SANS 1783-5-2 procedure. The y-axis on the chart in Figure 4-23 shows the running total number of tests with a value less than $E_{0.05,k}$ (4 630 MPa) and the percentage of these points out of 50. The blue points represent the running total number of tests with a value less than 4 630 MPa. The orange and grey target lines provide a warning and signal to stop production, respectively.

The moving average in Figure 4-22 signaled a warning multiples times when the trend of the moving average showed a downward trend below the 7 800 MPa target line. The sampled values can be seen below all the target lines, although most of them are concentrated around the areas that were flagged as being below the required mean (SLS) values. The moving average never went below the 6 023 or 5 850 MPa target lines to signal for the stress grading process to be stopped in order to search for assignable causes of variation, i.e. out-of-control conditions in the process output. The chart in Figure 4-23 that accompanies the chart in Figure 4-22 gave both a warning and a signal to stop and search for out-of-control conditions in the process output when the points representing the running total number of tests with a value less than 4 630 MPa crossed both of the target lines.

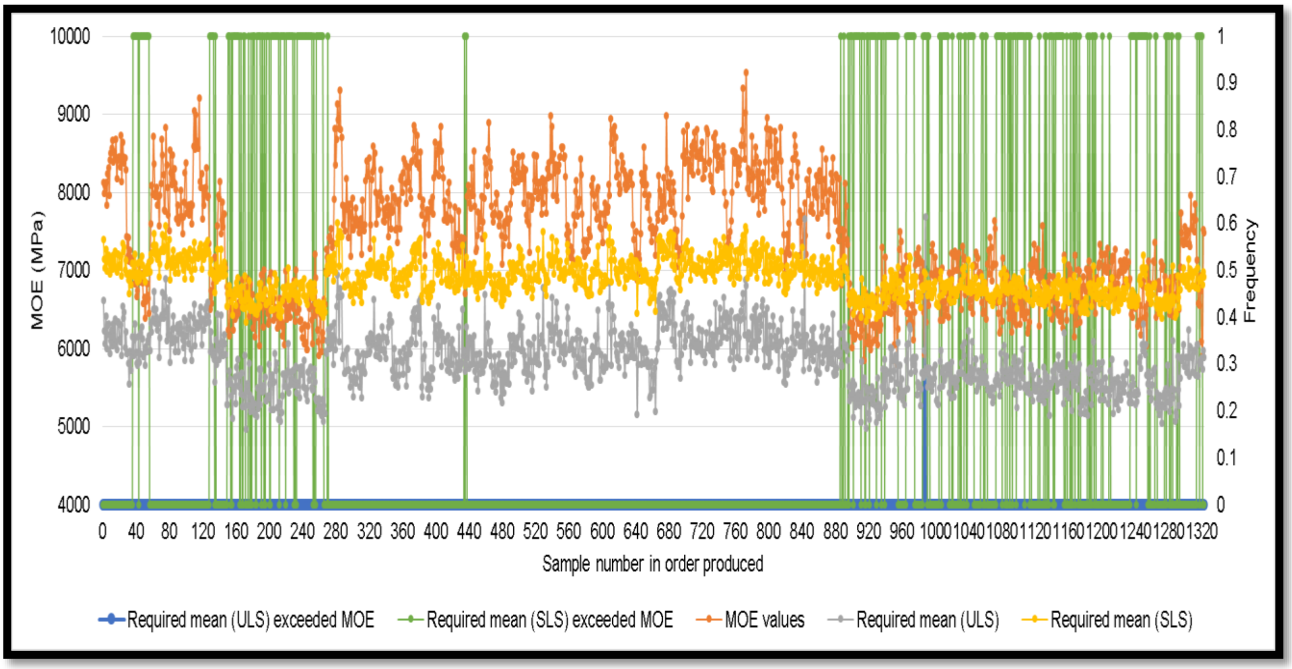

Figure 4-21: Ungraded bundles from Month 1, Sawmill B. The green and blue vertical lines represent the areas where the required mean exceeded the MOE for the bundle for the serviceability limit state and ultimate limit state respectively. The areas with condensed vertical green and blue lines represent the "problem areas" in the month.

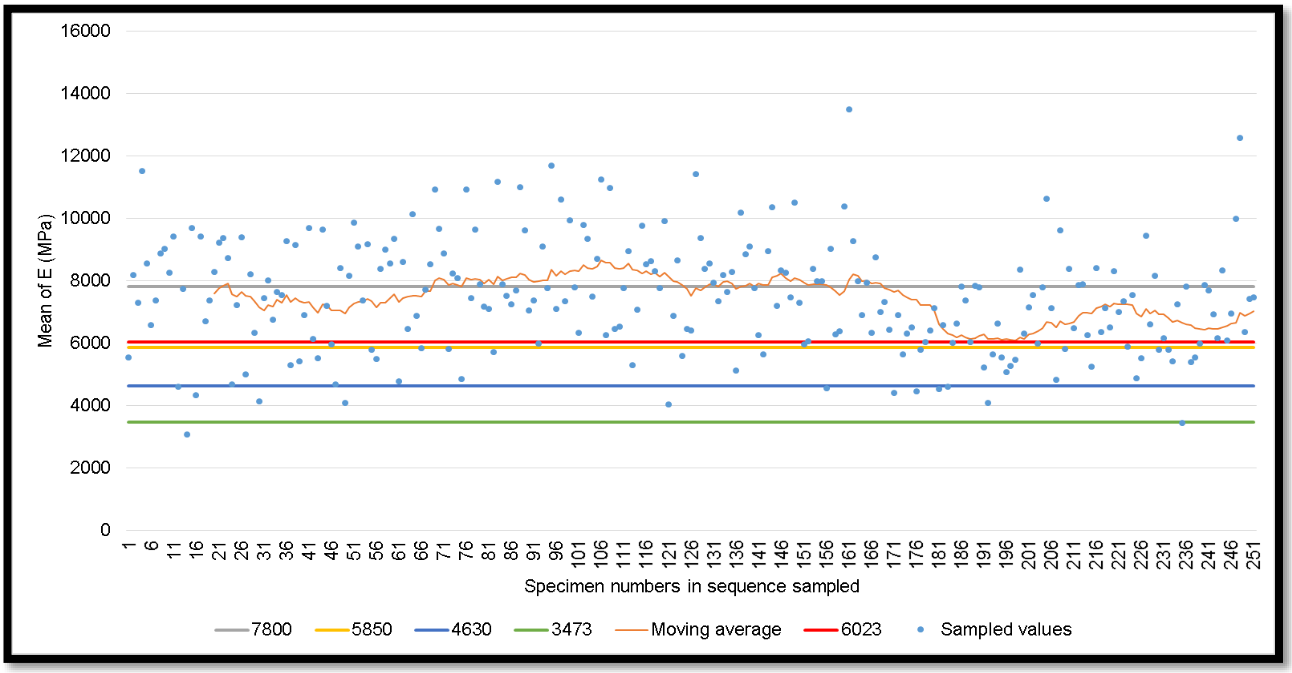

Figure 4-22: The quality control method proposed in SANS 1783-5-2 showing the moving average chart. The samples were sampled at **1 in a 1000** samples sampling intervals and the moving average averaged over 20 samples. The different target lines are also displayed on the graph.

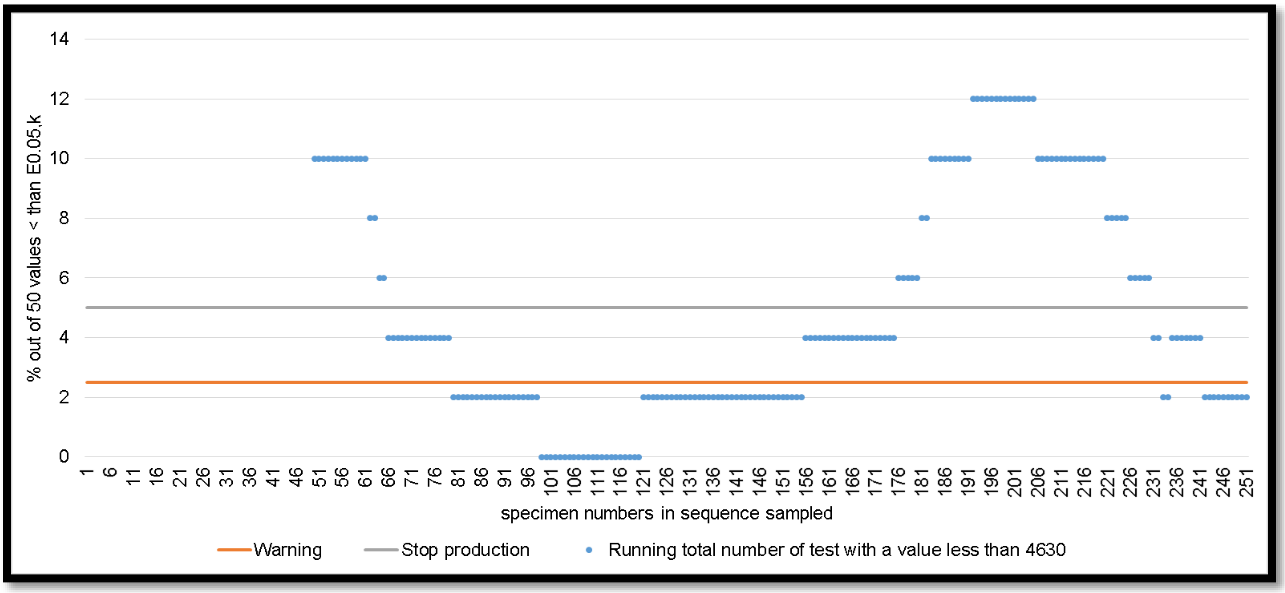

Figure 4-23: The quality control method proposed in SANS 1783-5-2 showing the running total number of tests with a value less than 4 630 MPa. The orange target line provides a warning and the grey one a signal to stop production.

Looking at the performance of the chart discussed above (Figure 4-22), it was observed that the moving average signaled a warning but did not give a signal to stop and search for out-of-control conditions. The sampled values in blue were able to highlight the areas where the boards were below the target lines. A possible disadvantage with a low sampling frequency (1 in a thousand) and averaging over a long period (20 samples) is that a signal, if present, may be indicated long after the out-of-control condition occurred and it might be difficult to trace back to see where the problem occurred.

The chart in Figure 4-23 shows the areas where the MOE values were less than the required 5th percentile MOE value required for structural timbers. The areas where the chart gives a warning and a signal to stop production corresponded with the areas that were highlighted by the chart in Figure 4-21. Taking into account the key performance measures for the statistical control charting indicated above in 4.3.1, it is possible that the sampling frequency was not a good representation of the population from which the samples were taken, therefore the sampling frequency was increased to see how the above control charting method detects out-of-control conditions. This was done to also see if the other types of charts and sampling frequencies would be able to detect out-of-control conditions timely compared to what was observed in Figure 4-22 and to see if the other control charts are easier to setup and interpret.

4.3.3 Testing different control charts and sampling strategies.

Different quality control techniques were evaluated to find the methods that work best in assuring the quality of the final product. The proposed sampling frequency was tested on the quality control charting methods. The sampling frequency was also varied to see the effect of increased sampling frequency on the detection of out-of-control occurrences on the control charts. The proposed method in SANS 1783-5-2 with increased sampling frequency, ARIMA chart, CUSUM chart and EWMA chart are presented below.

4.3.3.1 The proposed method in SANS 1783-5-2 with increased sampling frequency.

The sampling frequency was increased in order to see the effects of increased sampling frequencies in the detection of out-of-control conditions. The samples were tested at intervals of 750, 500 and 250. The results are shown in Figure 4-24 to Figure 4-29. The moving average signaled a warning multiples times when the trend of the moving average showed a downward trend below the 7 800 MPa target line in all 3 graphs (Figure 4-24, Figure 4-26 and Figure 4-28). The chart obtained for samples taken at intervals of 750 was not too different from the chart obtained when sampling every 1 in 1 000 samples as shown in Figure 4-24 and Figure 4-22 in that the moving average never went below the 5 967 or 5 850 MPa target lines to signal for the stress grading process to be stopped in order to search for out-of-control conditions in the process output.

The moving average of the chart where the samples were taken every 500 sampling intervals (Figure 4-26) went below the 6 119 MPa (but not the 5 850 MPa as stated in the standard) target line around point 315 to signal for the stress grading process to be stopped in order to search for out-of-control conditions in the process output. The moving average of the chart where the samples were taken every 250 sampling intervals (Figure 4-28) went below the 6 157 MPa (not the 5 850 MPa) target line around points 155 and 841 to signal for the stress grading process to be stopped in order to search for out-of-control conditions in the process output.

The sampled values for all the charts went below all the target lines and just like when samples were taken every 1000 sampling intervals, most of them are concentrated around the areas that were flagged as being below the required mean (SLS) values. Figure 4-25, Figure 4-27 and Figure 4-29 gave both a warning and a signal to stop and search for out-of-control conditions in the process output when the points representing the running total number of tests with a value less than 4 630 MPa crossed both of the target lines. From these results it seems as if there are no compelling reasons to increase the sampling frequency above a 1 in 1000 sampling interval.

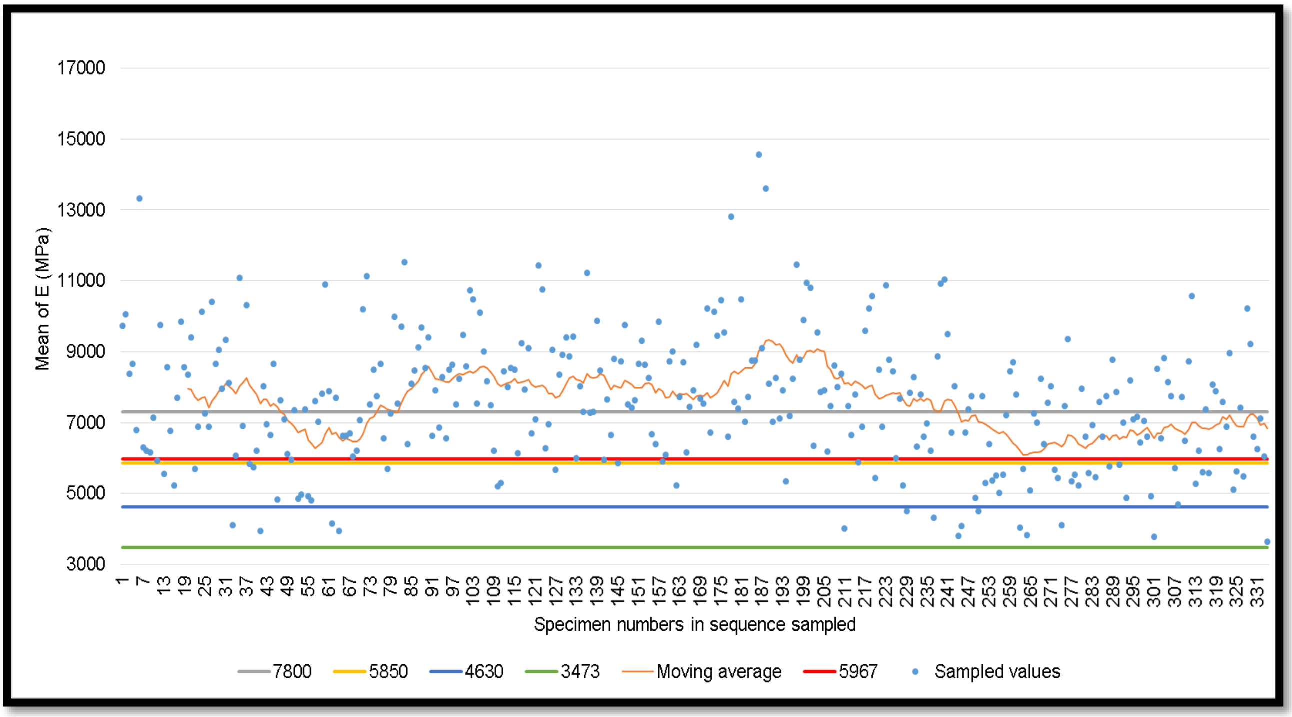

Figure 4-24: The quality control method proposed in SANS 1783-5-2 showing the moving average chart with a **1 in 750** sampling interval and the moving average averaged over 20 samples. The different target lines are also displayed on the graph.

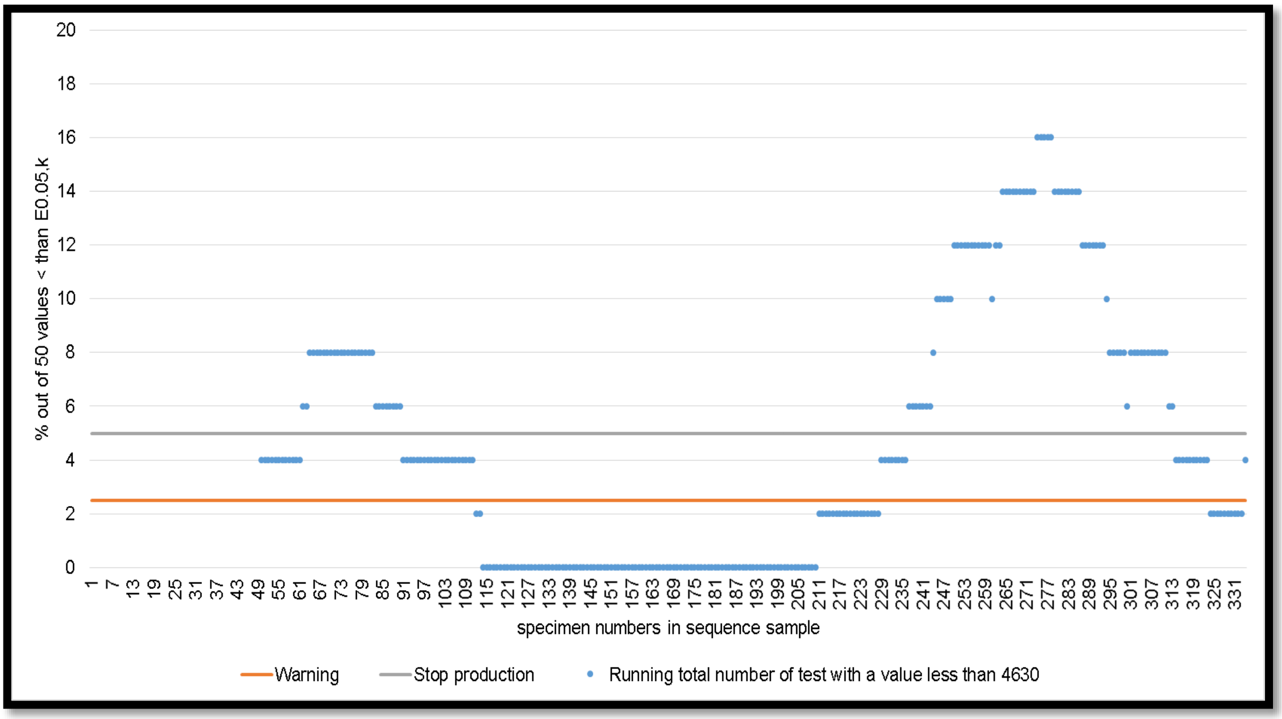

Figure 4-25: The quality control method proposed in SANS 1783-5-2 showing the running total number of tests with a value less than 4 630 MPa with a **1 in 750** sampling interval. The target lines provide a warning and a signal to stop production.

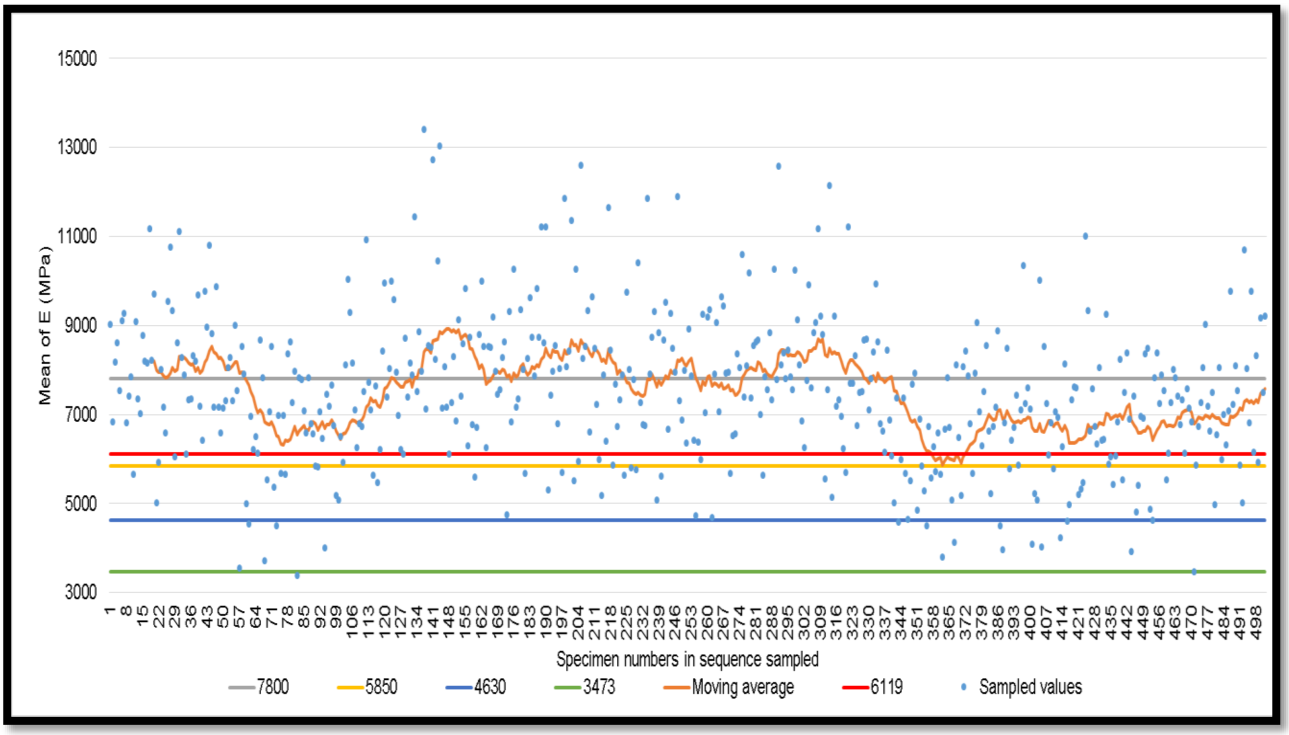

Figure 4-26: The quality control method proposed in SANS 1783-5-2 showing the moving average chart with a **1 in 500** sampling interval and the moving average averaged over 20 samples. The different target lines are also displayed on the graph.

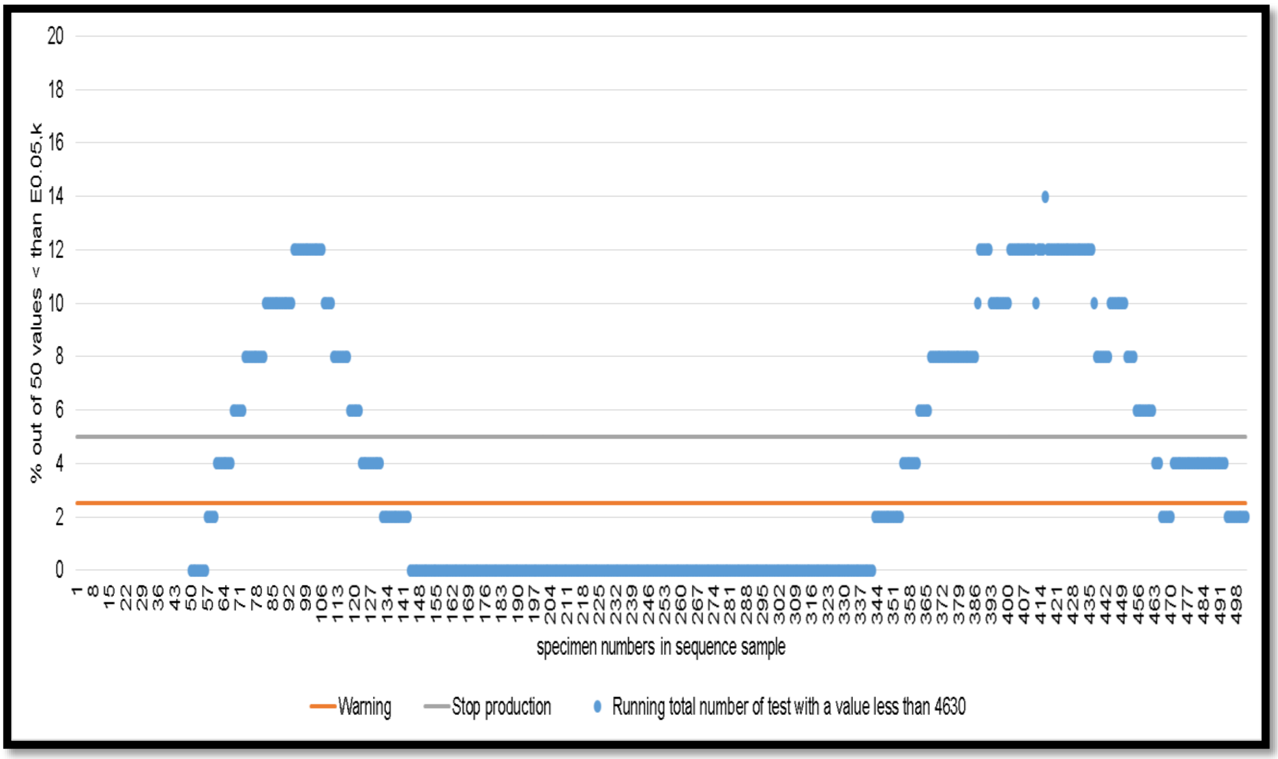

Figure 4-27: The quality control method proposed in SANS 1783-5-2 showing the running total number of tests with a value less than 4 630 MPa with a **1 in 500** sampling interval. The target lines provide a warning and a signal to stop production.

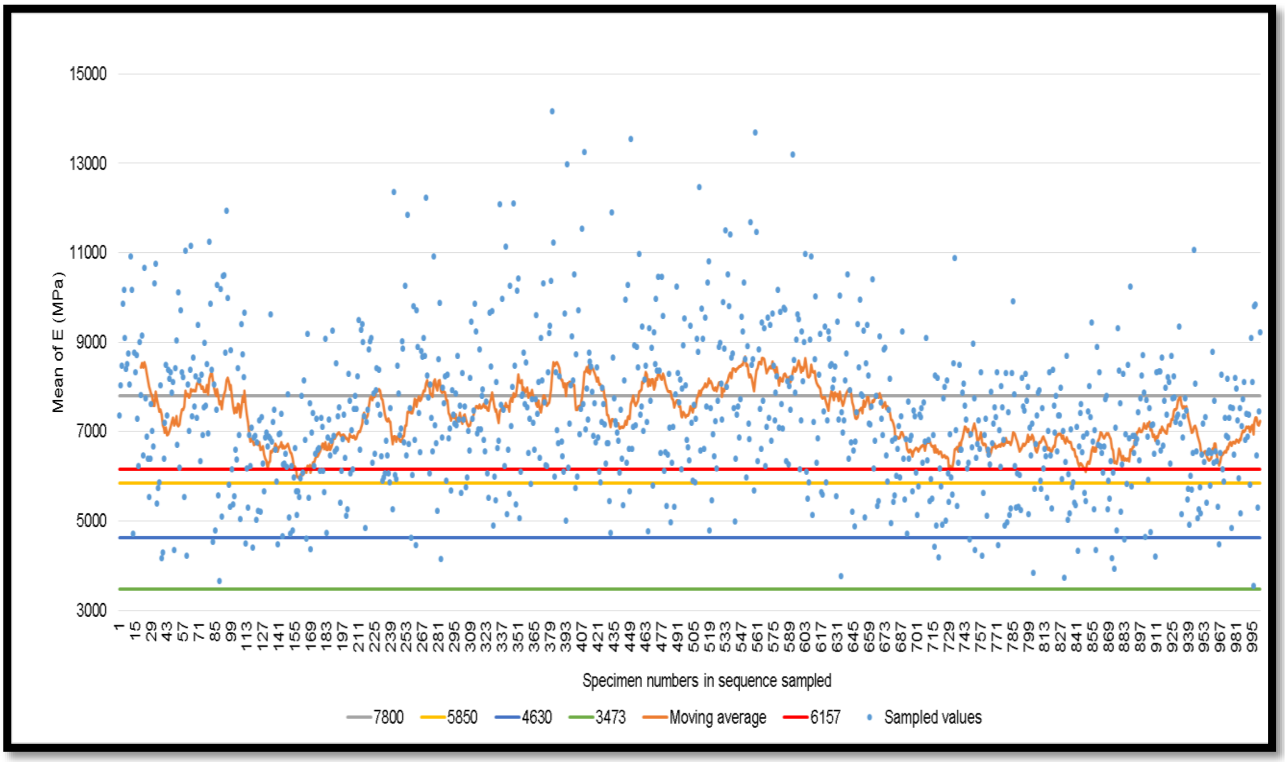

Figure 4-28: The quality control method proposed in SANS 1783-5-2 showing the moving average chart with a **1 in 250** sampling interval and the moving average averaged over 20 samples. The different target lines are also displayed on the graph.

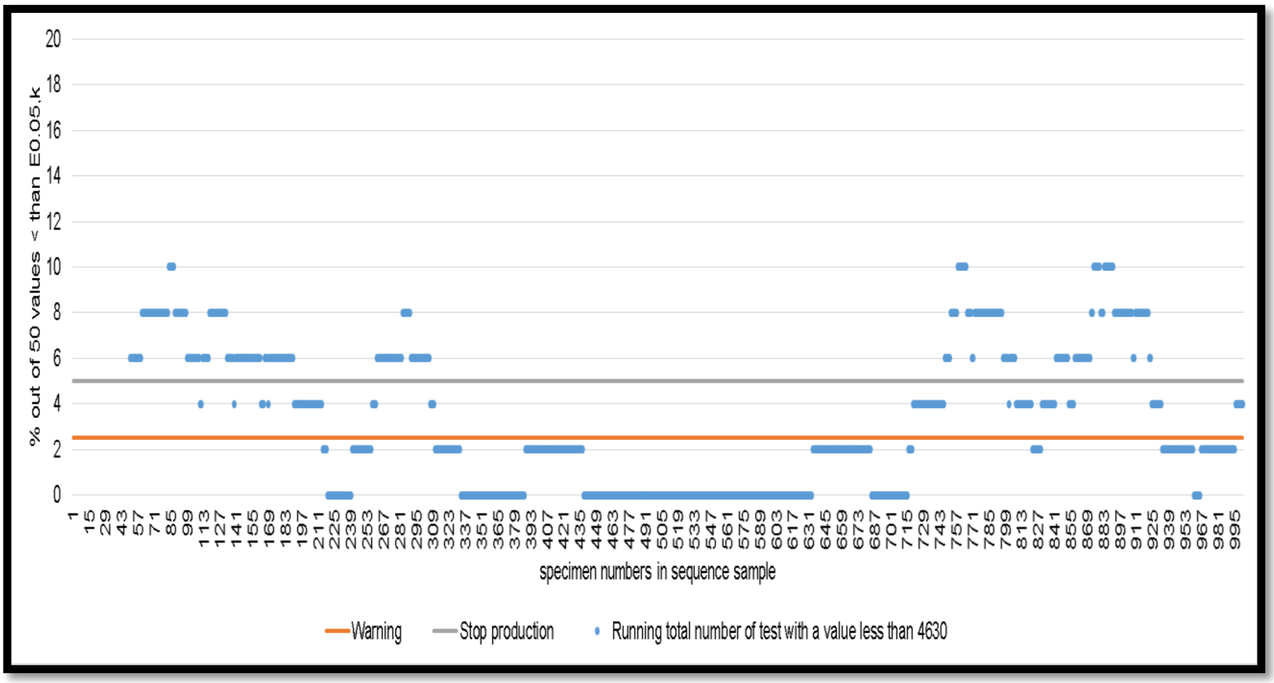

Figure 4-29: The quality control method proposed in SANS 1783-5-2 showing the running total number of tests with a value less than 4 630 MPa with a **1 in 250** sampling interval. The target lines provide a warning and a signal to stop production.

4.3.3.2 ARIMA control charts

The second method tested was that of using the ARIMA chart, which is highly recommended to use when the data shows presence of autocorrelation. The ARIMA method was tested to see if ARIMA charts would be a better fit for quality control than the current proposed method described in SANS 1783-5-2. The best fitting model was chosen using the Akaike Information Criterion (AIC) method. The model with the lowest value of the AIC was chosen. The model estimation procedure was performed using the auto.arima () function in R. The model output is summarised in Table 4-5. The ARIMA model with the lowest value of AIC was found to be ARIMA (2, 1, 3) for Month 1, Sawmill B data. The model estimates in Table 4-5 were used to formulate the model equations shown below.

The ARIMA (2, 1, 3) means that the model has a second-order autoregressive term (AR), the data was differenced (I) once and has a third-order moving (MA) term.

The obtained model was in the form:

$X_t = 0.090_{t-1} + 0.478_{t-2} - \varepsilon_t - 0.997\varepsilon_{t-1} - 0.417\varepsilon_{t-2} + 0.421\varepsilon_{t-3}$ with the AIC of 4401912

Table 4-5:ARIMA model output showing the model parameters, estimates, standard errors, and the AIC value for Month 1, Sawmill B.

Month	**Model**	**Parameters**	**Estimate**	**Standard error**	**AIC**
Month 1, Sawmill B	ARIMA(2,1,3)	AR(1)	0.090	0.098	4401912
		AR(2)	0.478	0.078	
		MA(1)	-0.997	0.099	
		MA(2)	-0.417	0.167	
		MA(3)	0.421	0.070	

Diagnostics check for the model was performed to see if the model produced residuals that were uncorrelated. The tests performed were the Ljung-Box test, to identify if the model was successful in removing the autocorrelation in the data and the normality test to see if the data was normally distributed.

The null hypothesis tested for the Ljung-Box test was:

H_0: The errors are uncorrelated

H_1: The errors are correlated

The p-value from the Ljung –Box test was found to be 0.773 for Month 1, Sawmill B data. The null hypothesis could not be rejected. It can be concluded that the model residuals were not correlated. The ARIMA models were successful at removing the autocorrelation, which meant that there was no autocorrelation between the residual values.

The residuals obtained from the fitted models were plotted on a Shewhart chart with 3 sigma control limits, that is, within +/- 3 standard deviations from the centre in Figure 4-30. The residuals are from the whole dataset for Month 1, Sawmill B. The black points represent the data points within the UCL and LCL, while the red points represent the points that fell outside the limits. The residual graphs showed that there were a lot of out-of-control points above the UCL and below the LCL. It was interesting to observe that the areas with a lot of variability were the areas where most of the samples were above the target value of 7 800 MPa as shown in Figure 4-21. This is maybe to be expected from a forestry perspective. When harvesting in areas with older material, you will have the strong butt logs as well as weaker tops, compared to younger trees where the differences are less pronounced. If this type of chart was to be used to check out-of-control conditions, one would assume that the areas with the red dots below the LCL were out-of-control, when in fact most of those areas had most values above the target mean MOE of 7 800 MPa as represented in Figure 4-21 above.

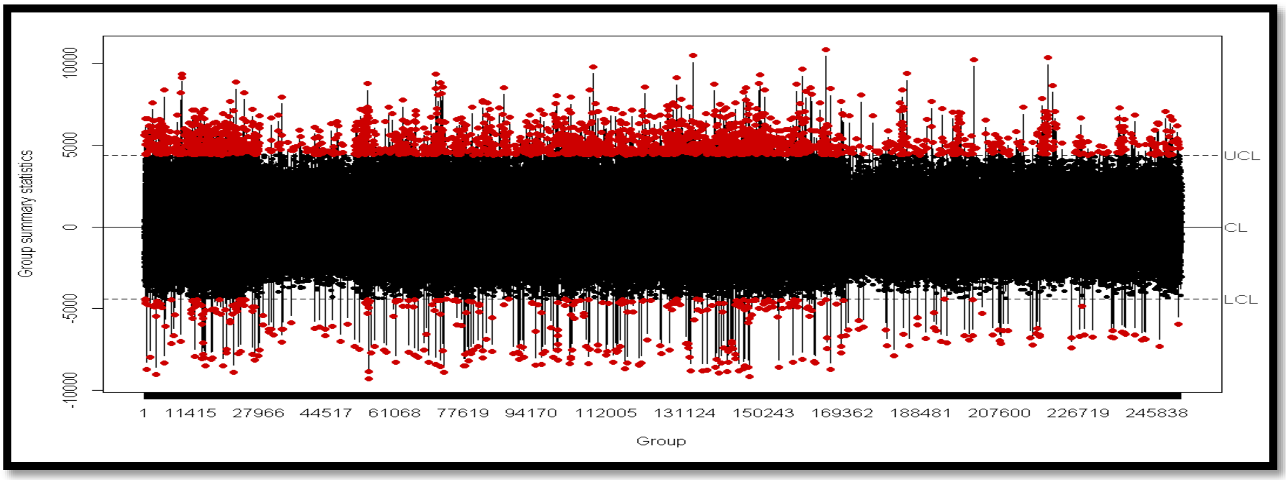

Figure 4-30: ARIMA model residuals plotted on a Shewhart chart. The chart shows the centreline (CL) as well as the upper and lower control limits marked by UCL and LCL, respectively.

Looking at Figure 4-30, it can be noted that this type of quality control graph is not suitable to analyse the quality control measures in the sawmill, as the residuals show the variation in the data and not necessarily the areas that were observed to have been out-of-control as noted in Figure 4-21. Since the concern for this study was less about the distribution of variation and more about detecting out-of-control conditions where low and varying MOE cause reduced reliability of structures, the ARIMA chart methodology does not seem to produce the desired results. For this reason, we did not test the effectiveness of the different sampling frequencies, as we would have had to sample from the plotted residuals.

4.3.3.3 Cumulative sum (CUSUM) and exponentially weighted moving average (EWMA) charts

The CUSUM and EWMA charts in Figure 4-31 to Figure 4-38 were plotted using the same sampled data used in 4.3.2. The intervals tested were sampled every 1000, 750, 500 and 250 boards. The limits for the two types of charts were set at 1 standard deviation from the mean (7 800 MPa) just as with the evaluation of the method proposed in SANS 1783-5-2.

CUSUM charts

The CUSUM charts for Month 1, Sawmill B are shown in Figure 4-31 to Figure 4-34. The x-axis shows the group count (sampled values in order produced), while the y-axis shows the cumulative sum. The black points represent the accumulated positive and negative deviations from the target value (7 800 MPa). The centre line, although shown on the graph as 0, was placed at 7 800 MPa to resemble the top target line (grey target line) in the charts showing the quality control method proposed in SANS 1783-5-2 in Figure 4-22 above. The line labelled LCL (lower control limit) resembles the red target line in the chart in Figure 4-22 above, as it is placed 1 standard deviation below the centre line. The red points represent the out-of-control points. The red points below the LCL are the signals we were interested in for the CUSUM design. The red points above the UCL (upper control limit) indicate the lumber with really high MOE, which is not a concern in this instance. The summary statistic of the samples is also shown at the bottom of the graph. This shows the total number of samples used; the value where the centreline is placed; the standard deviation; decision interval and shift detection which are used to set the LCL and UCL and lastly the number of points beyond the LCL and UCL.

The CUSUM chart in Figure 4-31, where samples were sampled at 1000 sampling intervals showed a warning by showing all the points below the target line. The chart also gave two signals to stop and search for out-of-control conditions around points 47 and 173. Figure 4-32, where samples were sampled at 750 sampling intervals, showed a warning since there are points below the target line. The chart also gave three signals to stop and search for out-of-control conditions around points 44 and 239. Similarly, there are points below the target line for a sampling interval of 500 (Figure 4-33) which indicates a warning. The chart also gave two signals to stop and search for out-of-control conditions around points 53 and 340. Figure 4-33, where samples were sampled at 250, sampling intervals showed a warning by showing all the points below the target line. The chart also gave four signals to stop and search for out-of-control conditions around points 23, 100, 468 and 666.

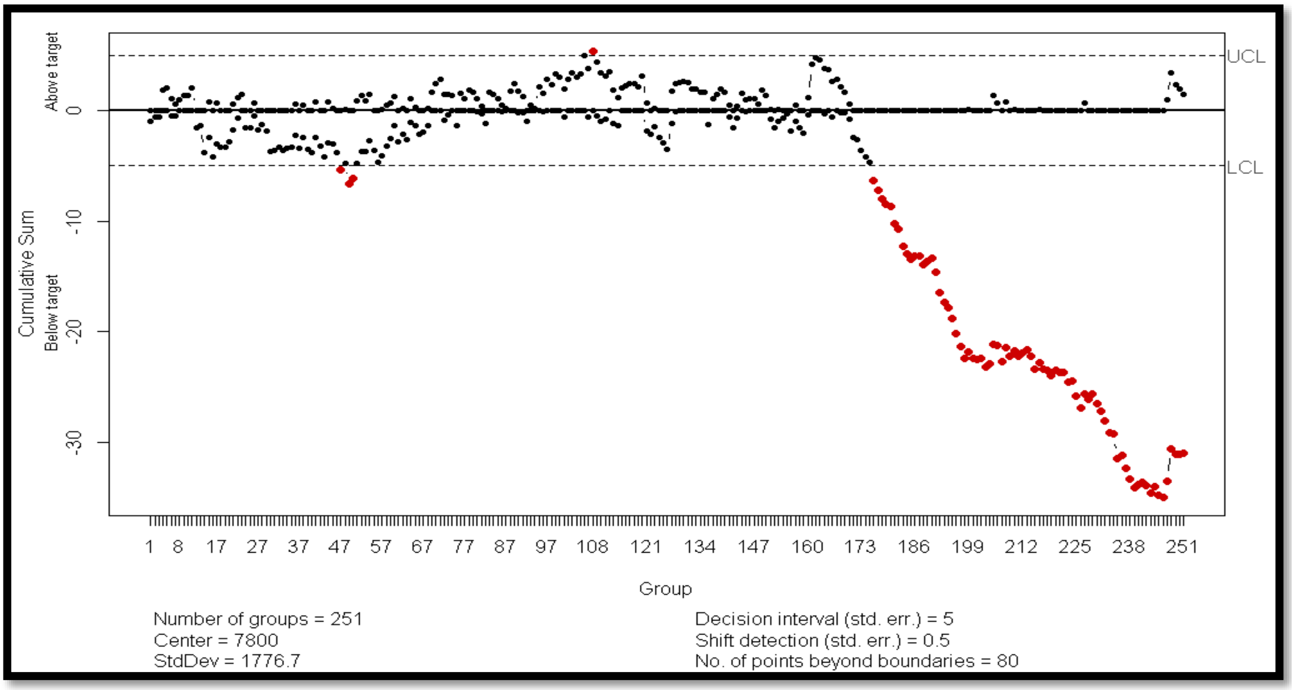

Figure 4-31: CUSUM chart for Month 1, Sawmill B data when samples were taken at **1000** intervals. The positive and negative cumulative sum are shown on the y-axis. The summary statistics is displayed on the bottom of the chart. The chart shows the centreline (CL) as well as the upper and lower control limits marked by UCL and LCL respectively. The red points are for out-of-control samples.

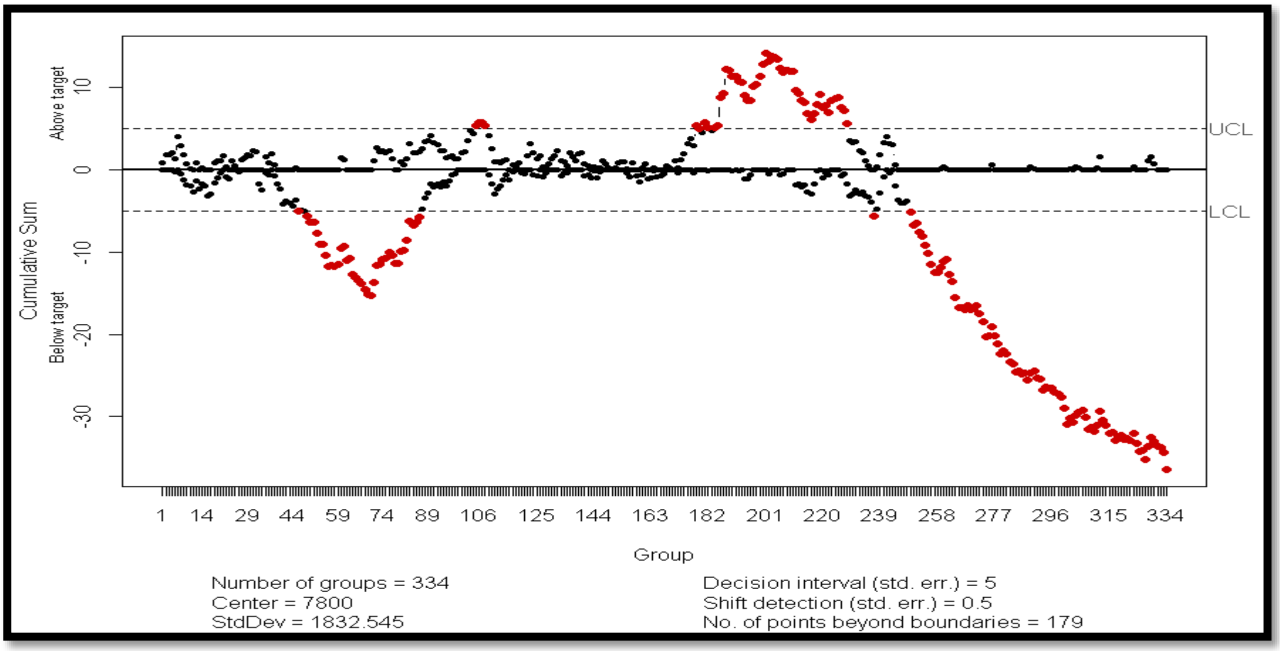

Figure 4-32: CUSUM chart for Month 1, Sawmill B data when samples were taken at **750** intervals. The positive and negative cumulative sum are shown on the y-axis. The summary statistics is displayed on the bottom of the chart. The chart shows the centreline (CL) as well as the upper and lower control limits marked by UCL and LCL respectively. The red points are for out-of-control samples.

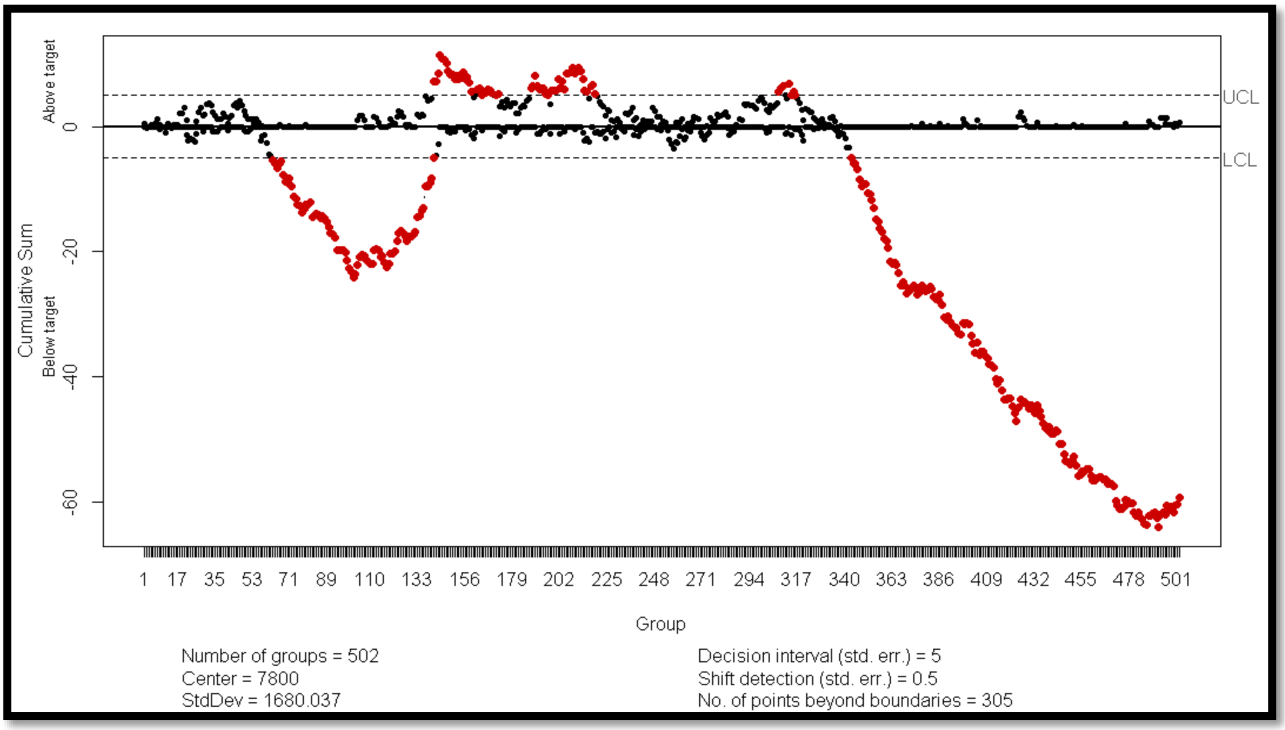

Figure 4-33: CUSUM chart for Month 1, Sawmill B data when samples were taken at **500** intervals. The positive and negative cumulative sum are shown on the y-axis. The summary statistics is displayed on the bottom of the chart. The chart shows the centreline (CL) as well as the upper and lower control limits marked by UCL and LCL respectively. The red points are for out-of-control samples.

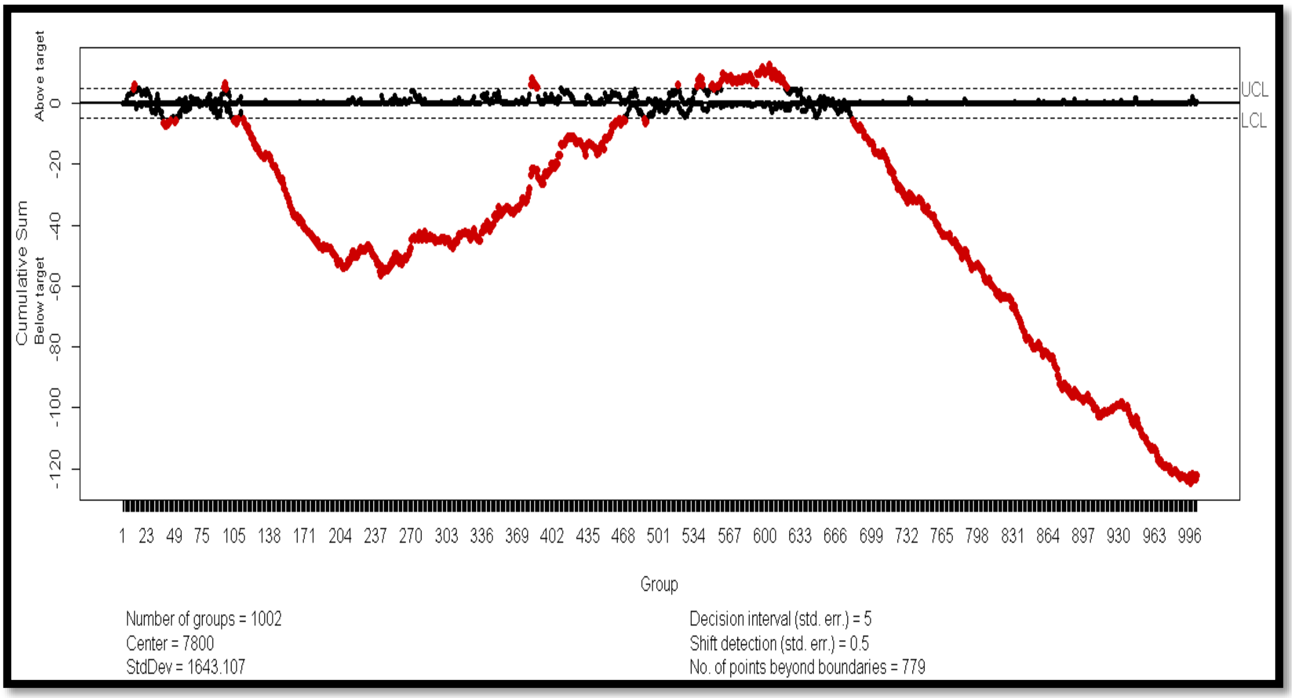

Figure 4-34: CUSUM chart for Month 1, Sawmill B data when samples were taken at **250** intervals. The positive and negative cumulative sum are shown on the y-axis. The summary statistics is displayed on the bottom of the chart. The chart shows the centreline (CL) as well as the upper and lower control limits marked by UCL and LCL respectively. The red points are for out-of-control samples.

EWMA charts

The EWMA charts for Month 1, Sawmill B are shown in Figure 4-35 to Figure 4-38. The x-axis shows the group count (sampled values in order produced), while the y-axis shows the MOE of the samples. The centre line was placed at 7 800 MPa as was done with the graphs discussed before. The line labelled LCL (lower control limit) was placed at 1 standard deviation below the centre line. The '+' sign on the chart represents the sampled values, while the black and red points are the EWMA values that were above and below the target value of 7 800 MPa. The red points are the points above and below the UCL and LCL respectively. The respective black and red points are the warning and signal we were interested in for the EWMA design. The red points above the UCL indicate the lumber with really high MOE, which is not a concern in our study.

The EWMA charts in Figure 4-35 to Figure 4-38 all gave warnings when samples were taken at intervals of 1 000, 750, 500 and 250, as we saw samples that were below 7 800 MPa. The actual sampled values marked with '+' showed different MOE values, from the lowest values to the highest for all four graphs and how most of the values are concentrated around the areas that were flagged as being below the required mean (SLS) values. Figure 4-35, where samples were sampled at an interval of 1 000, gave four signals to stop and search for out-of-control conditions around points 1, 17, 27 and 173. As shown in Figure 4-36, three signals to stop and search for out-of-control conditions around points 36 and 238 were obtained when sampling at an interval of 750. In Figure 4-37, where the sampling interval was 500, three signals to stop and search for out-of-control conditions are observed around points 53, 247 and 339. Figure 4-38 gave a lot of signal on multiple points, which showed that increased sampling frequency, increases the chances of detection of out-of-control conditions.

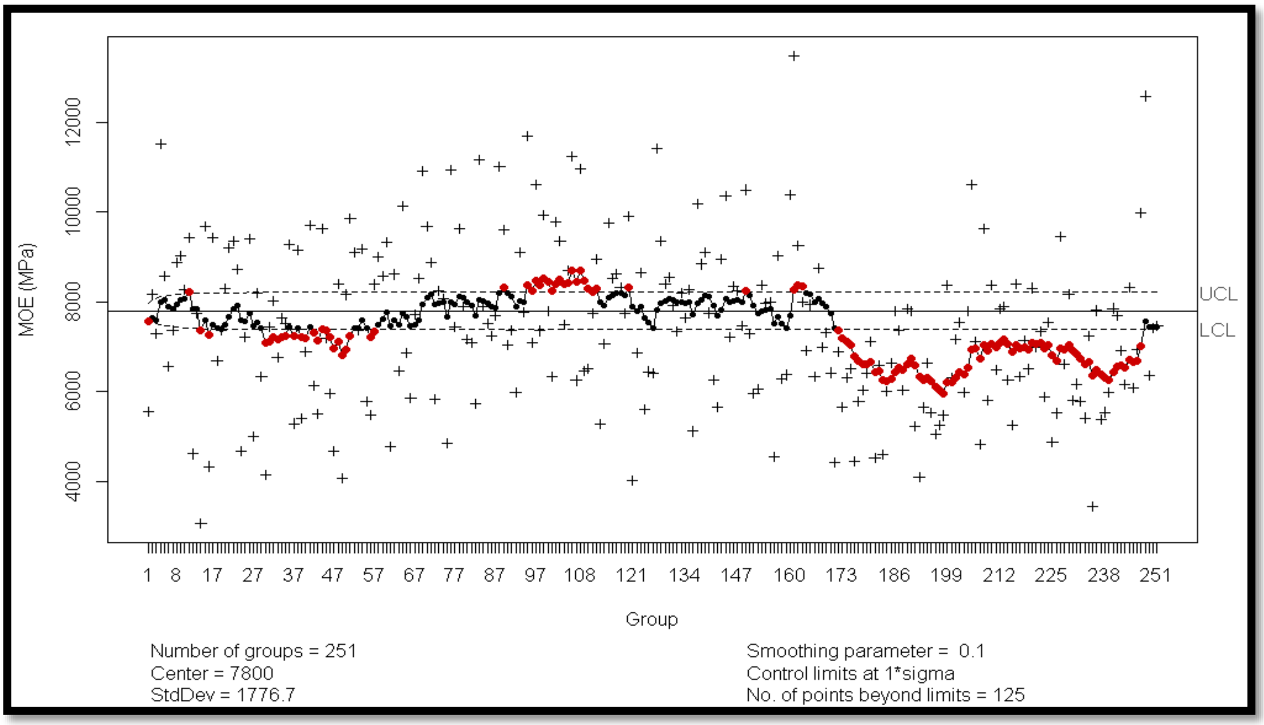

Figure 4-35: EWMA chart for Month 1, Sawmill B data when samples were taken at **1000** intervals. The MOE values are shown on the y-axis. The summary statistics is displayed on the bottom of the chart. The chart shows the centreline (CL) as well as the upper and lower control limits marked by UCL and LCL, respectively. The red points are for out-of-control samples.

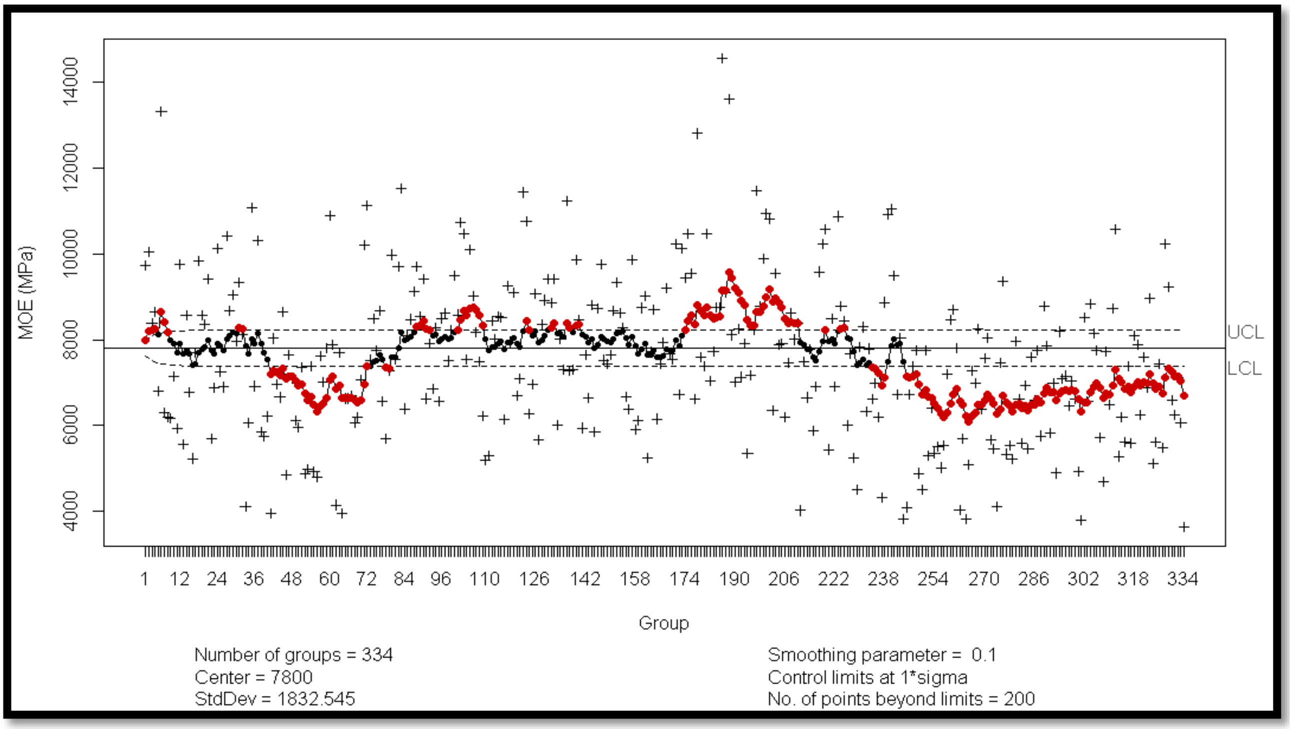

Figure 4-36: EWMA chart for Month 1, Sawmill B data when samples were taken at **750** intervals. The MOE values are shown on the y-axis. The summary statistics is displayed on the bottom of the chart. The chart shows the centreline (CL) as well as the upper and lower control limits marked by UCL and LCL respectively. The red points are for out-of-control samples.

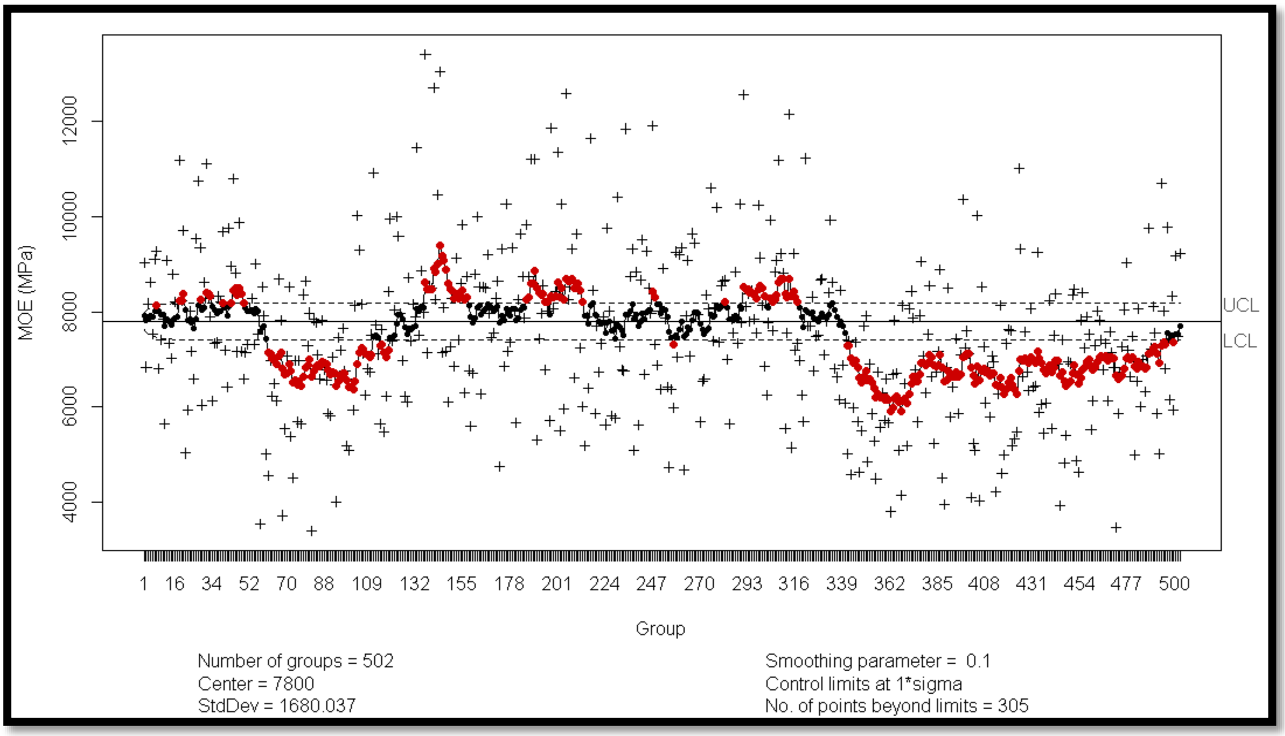

Figure 4-37: EWMA chart for Month 1, Sawmill B data when samples were taken at **500** intervals. The MOE values are shown on the y-axis. The summary statistics is displayed on the bottom of the chart. The chart shows the centreline (CL) as well as the upper and lower control limits marked by UCL and LCL, respectively. The red points are for out-of-control samples.

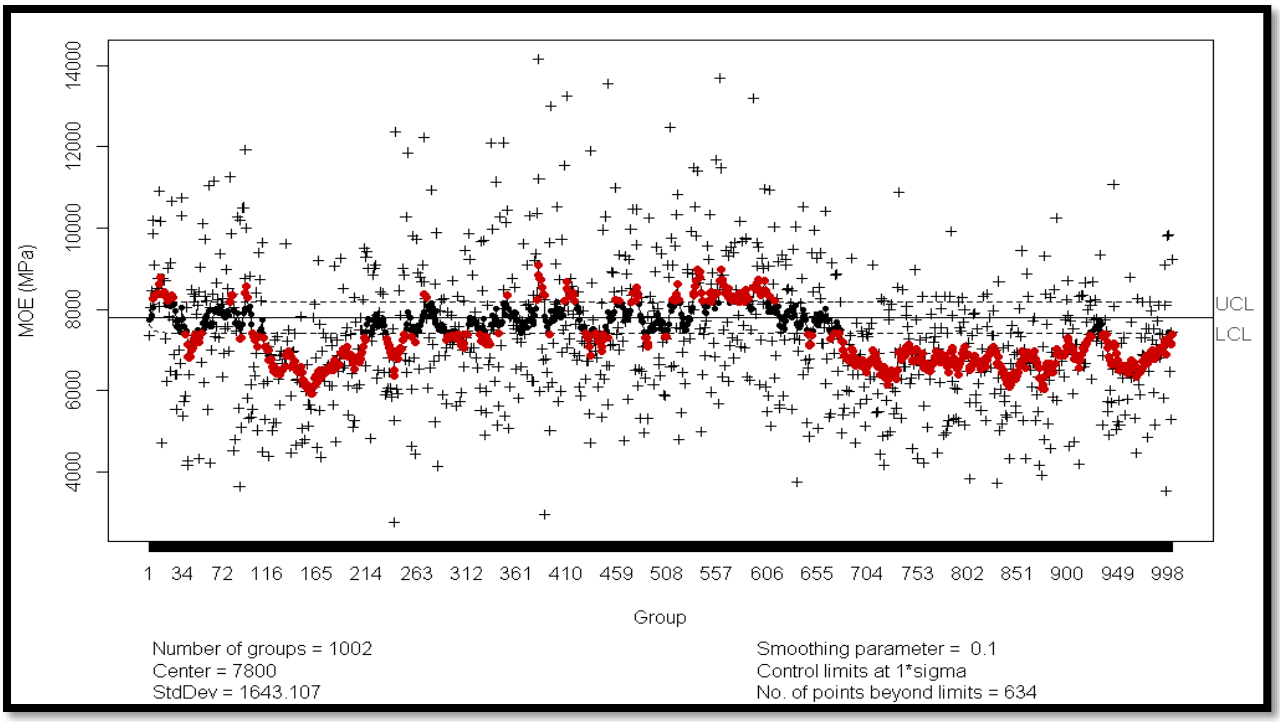

Figure 4-38: EWMA chart for Month 1, Sawmill B data when samples were taken at **250** intervals. The MOE values are shown on the y-axis. The summary statistic is displayed on the bottom of the chart. The chart shows the centreline (CL) as well as the upper and lower control limits marked by UCL and LCL, respectively. The red points are for out-of-control samples.

4.3.4 Control chart comparison

4.3.5.1 CUSUM AND EWMA performance comparison according to average run length

In literature the average run length is typically used to measure the performance of control charts. Table 4-6 shows the calculated values for the in-control and out-of-control average run length for CUSUM AND EWMA charts. The in-control average run length for the CUSUM chart was found to equal 465.44, which implied that if the process was in control, it was expected that a signal will be given every 465 samples on average. The out-of-control average run length was found to equal 10.38 (for mean shift of 1 sigma), which implied that if the process mean had shifted, it was expected that a signal will be given every 10 samples on average. The in-control average run length for the EWMA chart was found to equal 500, which implies that if the process is in control, it is expected that a signal would be given every 500 samples on average. The out-of-control average run length was found to equal 10.33 (for mean shift of 1 sigma), which implies that if the process mean shifted, it is expected that a signal would be given every 10 samples on average.

These results seem satisfactory, because for a good performing chart, the in-control average run length should be high and the out-of-control average run length should be low in order to detect out-of-control conditions sooner. It can be noted that the EWMA chart will detect a shift sooner than CUSUM chart when the shift is less than or equal to 1 sigma (+/- 1 standard deviation from the centre line). For shifts larger than 1 sigma, a CUSUM chart will detect the shift sooner. Although the performance of the two charts does not differ much for shifts greater or equal to 1 sigma, a study by Hawkins and Wu (2014) showed that the EWMA chart is more convenient for estimating where the process mean is following a signal, while the CUSUM chart is better for estimating when the shift occurred. Therefore, the CUSUM chart may be favourable for quality control as we want to see when out-of-control conditions in the output occur.

Table 4-6: Calculated average run length (ARL) values for CUSUM AND EWMA charts.

Average run length (ARL)	Shift in mean (multiple of σ)	ARL CUSUM	ARL EWMA
In-control average run length	0	465.44	500.00
Out-of-control average run length	0.25	139.49	106.37
	0.5	38.00	31.31
	0.75	17.05	15.85
	1	10.38	10.33
	1.5	5.75	6.08
	2	4.01	4.36
	2.5	3.11	3.44
	3	2.57	2.87

4.3.5.2 Chart comparison

Control charts showing results and comparison of the performance of the different control charts are shown in Figure 4-40 to Figure 4-42. The three charts were plotted using the same samples and under the same conditions as explained in section 4.3.3 above. The moving average, EWMA and CUSUM charts are memory charts, meaning that they account for information from the previous samples as noted in chapter 2. The memory capacity of each chart is shown in Figure 4-39. The moving average chart and EWMA work in a similar manner besides that the moving average gives the same weight to all the samples used in the averaging and the EWMA gives more weight to the most recent sample in the process. The CUSUM chart takes into consideration all the samples provided. This will affect the rate of detection of out-of-control shifts in the process output.

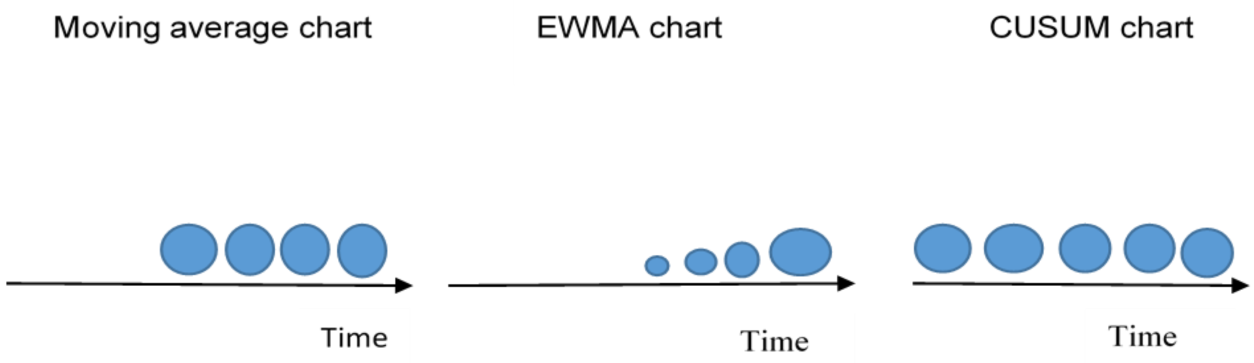

Figure 4-39: Figure showing the weightings used to compute the detection statistics of the moving average, EWMA and CUSUM charts. Adapted from Haque (2016).

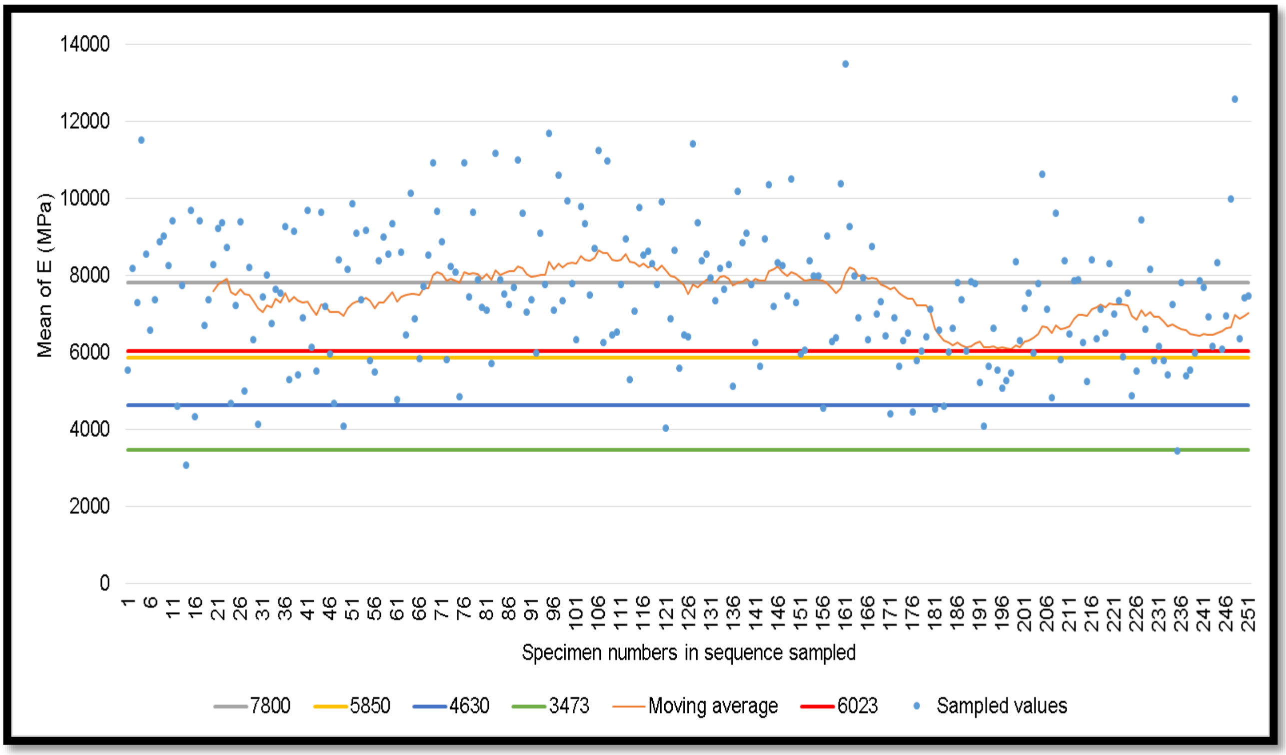

Figure 4-40: The quality control method proposed in SANS 1783-5-2 showing the moving average chart. The samples were sampled at intervals of **1 in a 1000** and the moving average was averaged over 20 samples. The different target lines are also displayed on the graph.

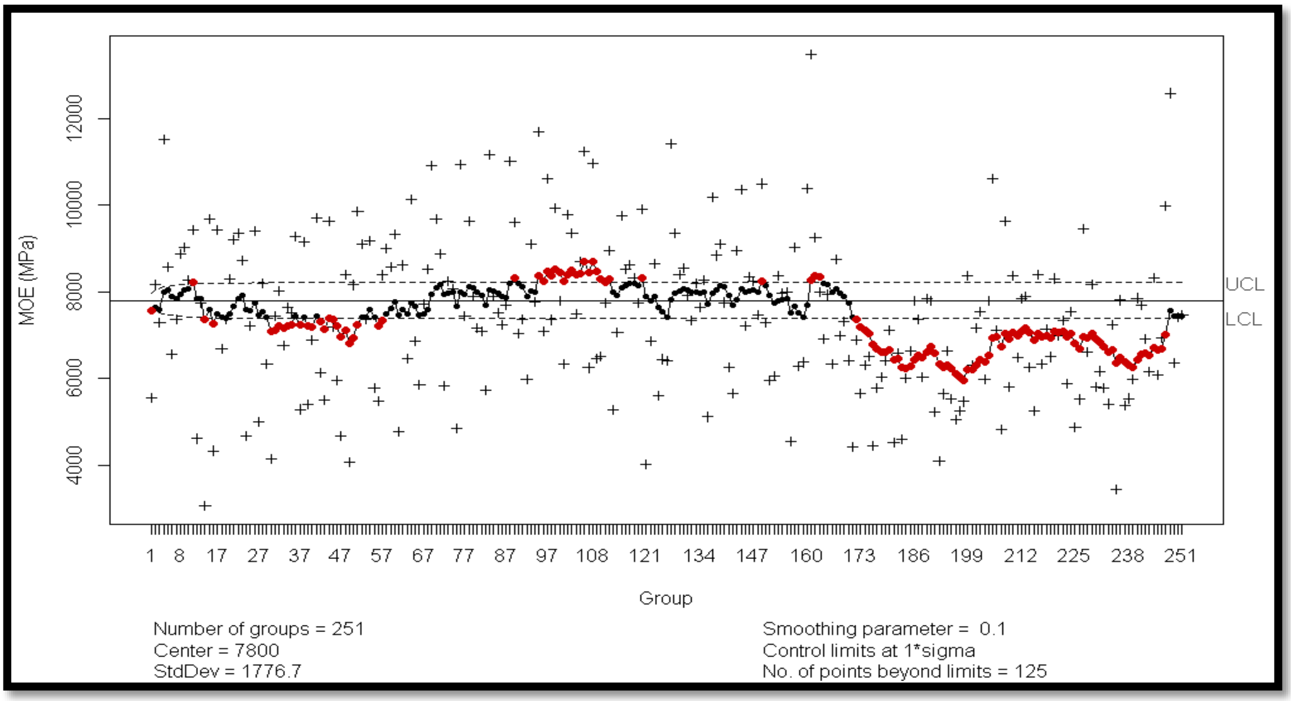

Figure 4-41: EWMA chart for Month 1, Sawmill B data when samples were taken at **1000** intervals. The MOE values are shown on the y-axis. The summary statistics is displayed on the bottom of the chart. The chart shows the centreline (CL) as well as the upper and lower control limits marked by UCL and LCL, respectively. The red points are for out-of-control samples.

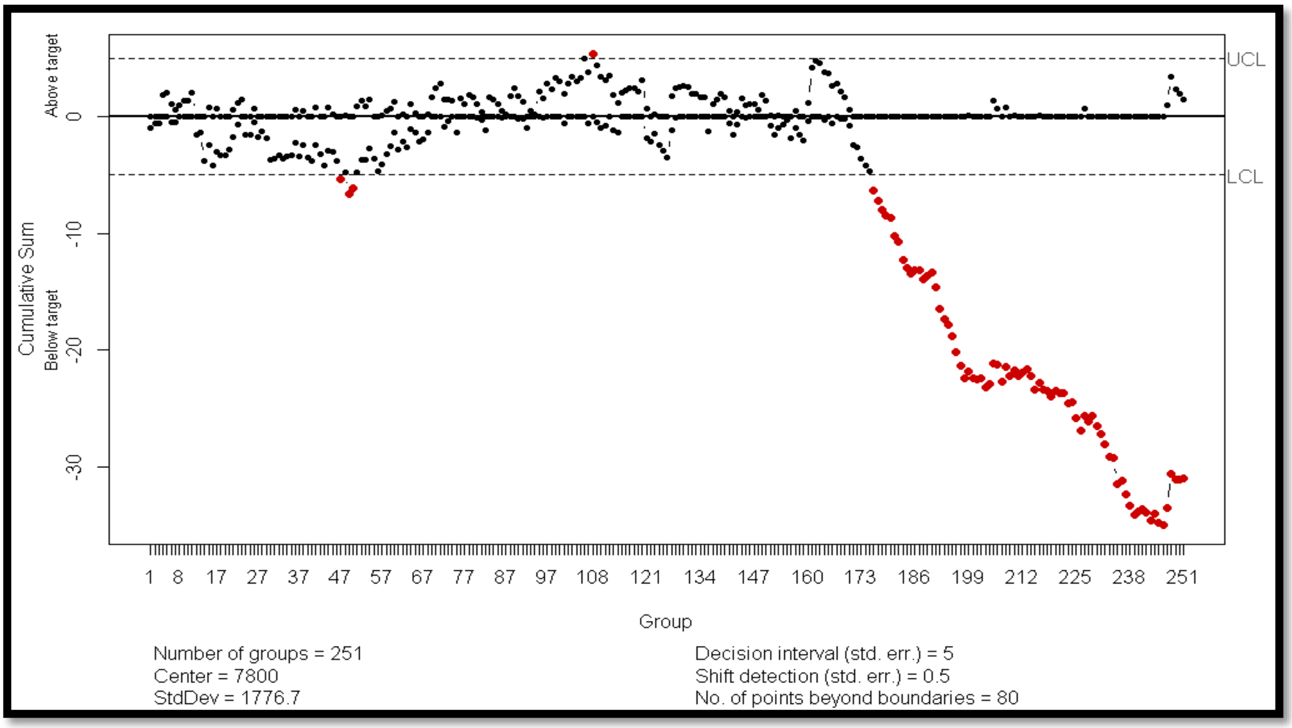

Figure 4-42: CUSUM chart for Month 1, Sawmill B data when samples were taken at **1000** intervals. The positive and negative cumulative sum are shown on the y-axis. The summary statistics is displayed on the bottom of the chart. The chart shows the centreline (CL) as well as the upper and lower control limits marked by UCL and LCL, respectively. The red points are the out-of-control samples.

The moving average, EWMA and CUSUM charts above (Figure 4-40, Figure 4-41 and Figure 4-42) demonstrated how each type of chart works. From an appearance standpoint, the moving average and EWMA charts look rather similar in that they both show the sampled values as well as the trend. The two charts looked rather congested because both the actual data and the moving average / exponential weighted moving average are displayed on the chart. The CUSUM chart appears less congested because it only shows the deviations from the set target. A person interpreting the chart would have to understand that the centre line, which is marked 0, is the set target value in the case of CUSUM charts, whereas in the moving average and EWMA charts the centreline is set on the actual target. All the charts were able to demonstrate that with more frequent sampling, the out-of-control conditions reflected in Figure 4-21 could be detected, although not all the charts showed big enough improvements to merit a change in the sampling frequency.

Since there won't be a chart like the one in Figure 4-21 as reference in reality, assessment of performance will strictly depend on the chart chosen, therefore whichever chart is used should be able to indicate problems without giving a lot of false alarms. The out-of-control action plan will be to look at the samples below the target line (0 or 7 800 MPa), which represents the target value of 7 800 MPa. If there are multiple samples clustered below the target line, one can check how far below target the points are. The points above target can be observed to see if the bundles will have enough good lumber and that there isn't a lot of variability in the samples as it was observed from section

4.2 that variation in the output should be controlled as the presence of high variation would render even the bundles with really high MOE values as unsafe. When the sampled values fall below the lower control limit, action should be taken to look for assignable causes and downgrade the lumber from the higher grade to lower, e.g. downgrading from S5 to utility grade if needed.

Taking into consideration that the three graphs were on the same scale, the EWMA and CUSUM charts detected shifts in the process right from the beginning. Under the above conditions, the EWMA chart seems to better pick up the observed problem areas in Sawmill B with a sampling frequency of 1 000, but it was also shown in Table 4-6 that for higher shifts, the CUSUM chart would detect shifts sooner. Based on the graphs, the detection of out-of-control conditions was sooner and clearer for less frequent sampling. Regarding which chart was better, the EWMA chart, which is similar to the moving average, can be used with the running total chart proposed in SANS 1783-5-2 as it detected shifts sooner than the moving average chart but also showed the samples on the chart. On the other hand, a study by Hawkins and Wu (2014) showed that the EWMA is more convenient for estimating where the process mean is following a signal while the CUSUM is better for estimating when a shift occurred, so in order to detect and be able to search for out-of-control conditions in order to take corrective action, a CUSUM chart might be more appropriate.

Since the current proposed procedure (moving average), EWMA and CUSUM all produced relatively acceptable results in terms of detecting out-of-control MOE, it might be best to simply keep the proposed method. However, since this method seemed to have a rather high threshold for stopping production, it will be best if the "stop production" signal is moved to 0.8*(MOE standard deviation) instead of the current1*(MOE standard deviation). It is a rather arbitrary decision at what specific point the number of bundles with a sub-standard reliability can be considered to be unacceptable and when production should be stopped. In our case we used visual evaluation (Figure 4-21) where it can be clearly seen that a relatively high proportion of bundles, at specific time periods, were sub-standard. However, it must be acknowledged that the specific point of "stop production" could possibly be researched further to see whether a better quantifiable method is possible.

Chapter 5 : Conclusions and recommendations

5.1 Conclusions

The observed data from the two sawmills were not normally distributed as was expected. The data also showed the presence of autocorrelation as is often the case with data from automated industrial processes. The following conclusions can be drawn from this study:

- The mean MOE and 5^{th} percentile MOE values of the full population of S5 graded 38x114 mm pieces were above the required SANS levels for both Sawmill A and Sawmill B; Over time and between bundles, however, there were fairly large changes in the MOE means and 5^{th} percentile values;
- The variation in lumber MOE between the two sawmills were very different. In general, Sawmill A had higher mean bundle MOEs than Sawmill B. Sawmill B on the other hand had much lower variation in MOE and a much smaller range in bundle mean MOE values. On the low end of the bundle mean MOEs, the sawmills were fairly similar (minimum and 5^{th} percentile values) but on the high end Sawmill A had much higher MOE values than Sawmill B;
- In terms of reliability, it was found that overall for all the bundles produced in Sawmill A and B in the respective sampling periods, 1.38% of the bundles did not conform to the required reliability index for the serviceability limit state (152 bundles from a total of 11 046 bundles produced); Less than 0.1% of the bundles did not conform to the required reliability index for the ultimate limit state (8 bundles from a total of 11 046 bundles produced);
- It was observed that the variability of MOE played a larger role in determining acceptable reliability than the mean MOE. Sawmill A, with bundles with generally higher mean MOE than Sawmill B, had bigger variation in MOE values, and also a larger percentage of bundles not conforming to the reliability requirements. Sawmill B had lower variation in MOE within bundles;
- The current proposed quality control system (SANS 1783-5-2), as well as the EWMA and CUSUM methods seem to be able to effectively detect production periods where a large percentage of bundles do not conform to reliability requirements. However, the stop-production signal threshold in the current proposed quality control system (SANS 1783-5-2) may need to be changed;
- The ARIMA method was not able to detect production periods where a large percentage of bundles do not conform to reliability requirements; and
- Although increased sampling frequency enable quicker detection of out-of-control MOE, the current proposed sampling frequency of 1 out of 1 000 pieces seem to give acceptable results.

5.2 Recommendations

The following recommendations can be made:

- Based on the results, the quality control method recommended to use in the standard is to replace the moving average chart with the EWMA and use it in conjunction with the running total chart showing the running total number of tests with a value less than 4 630 MPa in Figure 4-23;
- Alternatively, the use of the moving average method recommended in SANS 1783-5-2 can be used, but the stop-production limit to signal for the stress grading process to be stopped should be reduced to the mean MOE minus 0.8*(MOE standard deviation);
- The current proposed sampling frequency of 1 out of 1 000 pieces can be retained;
- Additional research is recommended including a pilot study at several sawmills evaluating the lumber quality control procedure recommended from this study. In this case the static MOE values need to be measured instead of dynamic MOE or possibly larger calibration sets where MOE_{stat} and MOE_{dyn} values are related to each other. This is because one of the limitations of this study was that the number of pieces that had to be measured and the time period of measurement made it impossible to measure static MOE as it is a labour intensive process which can only be done at a facility with the necessary testing equipment. This could possibly also involve more research on adequate sampling numbers.

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Appendix A

Additional results

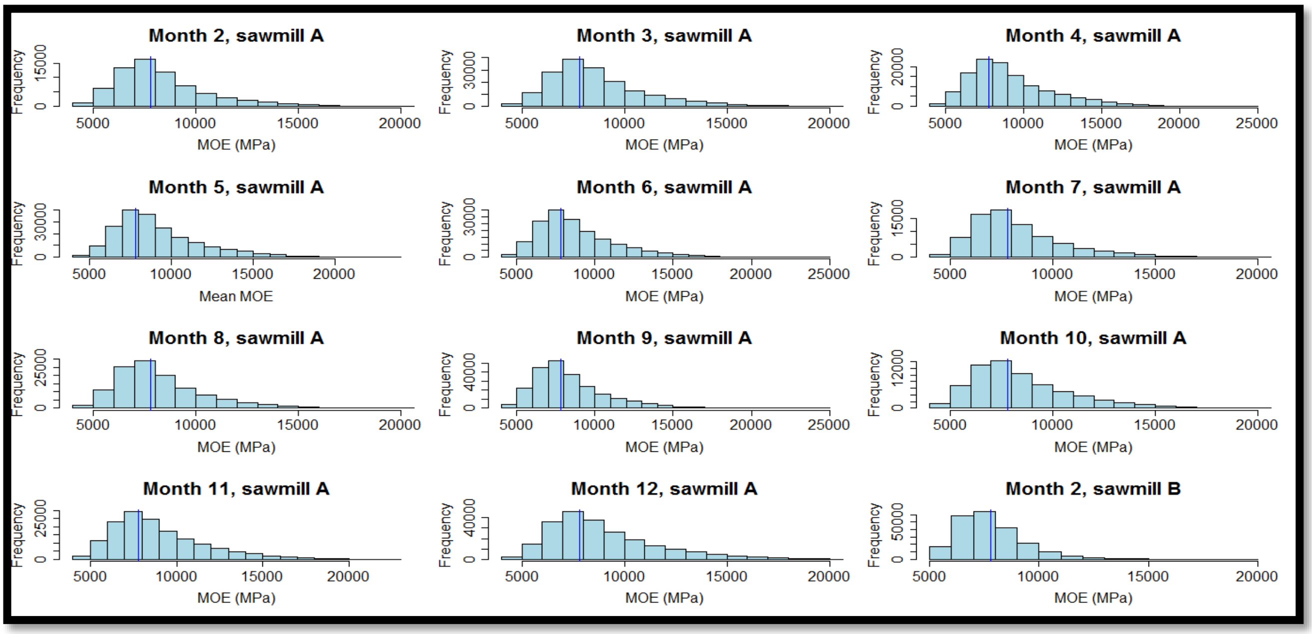

FIGURE A1: Histogram of individual board MOE for both sawmills. The blue vertical line represents the target mean MOE (7 800 MPa).

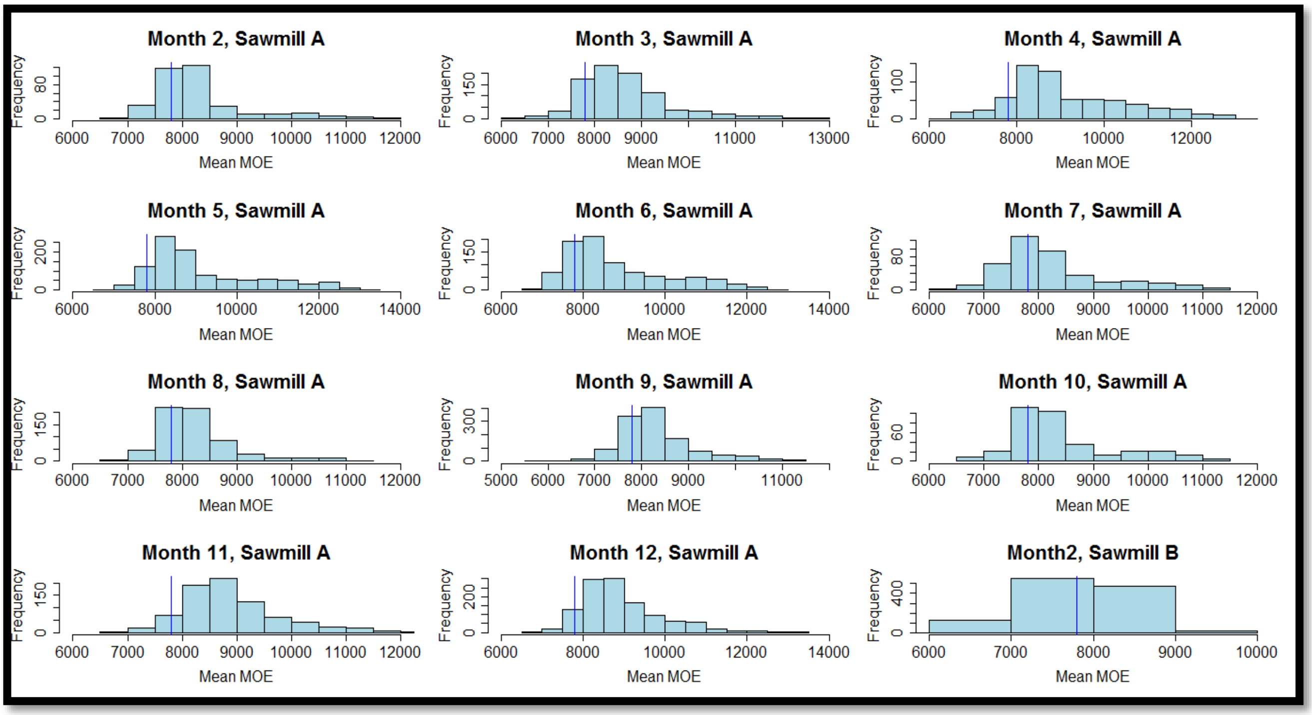

FIGURE A2: Histogram of bundle mean MOE for both sawmills. The blue vertical line represents the target mean MOE (7 800 MPa).

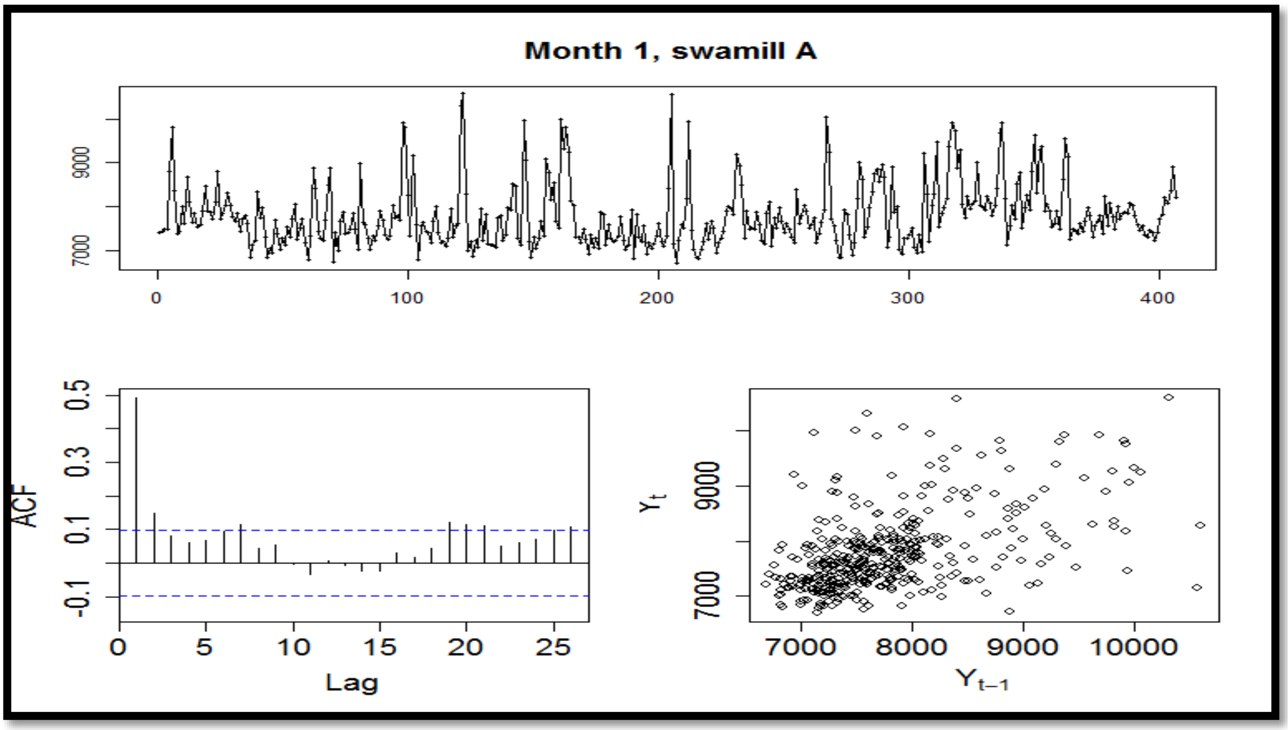

Figure A3: Run chart, autocorrelation function (ACF) and scatter plot of Month 1, sawmill A bundle means. The ACF shows autocorrelation of around 0.5 in the data.

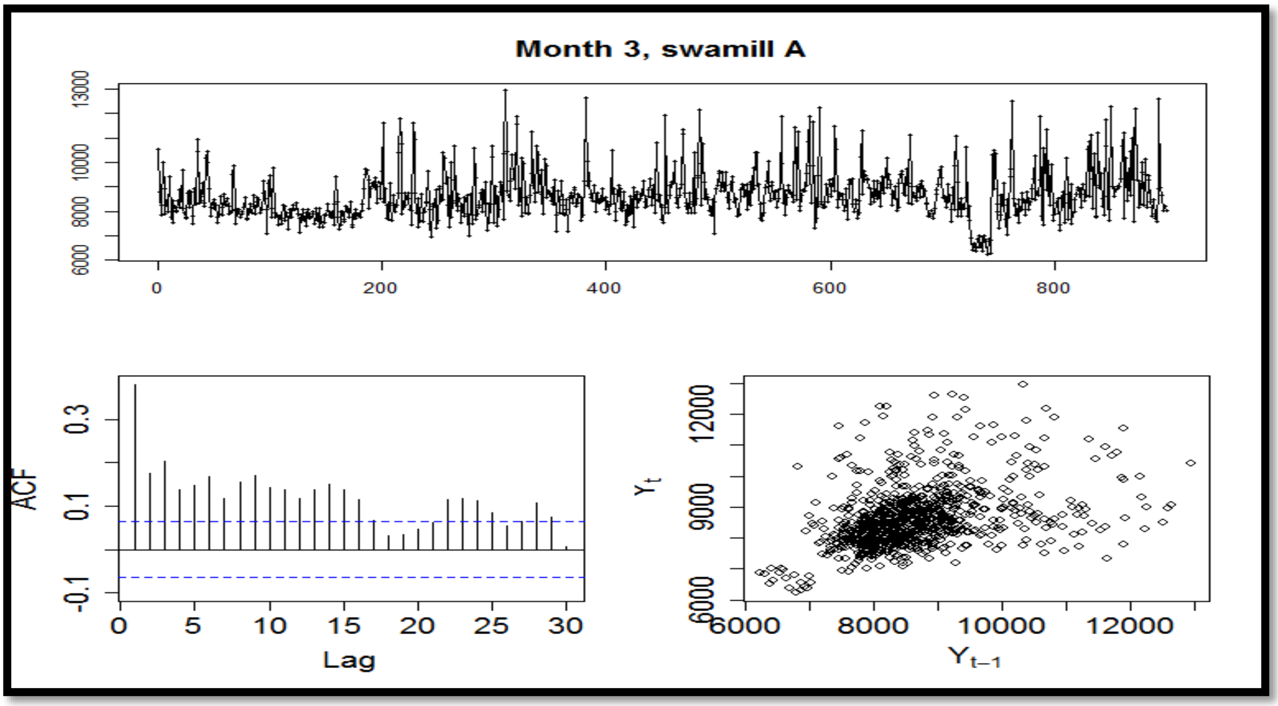

Figure A4: Run chart, autocorrelation function (ACF) and scatter plot of Month 3, sawmill A bundle means. The ACF shows autocorrelation of around 0.4 in the data.

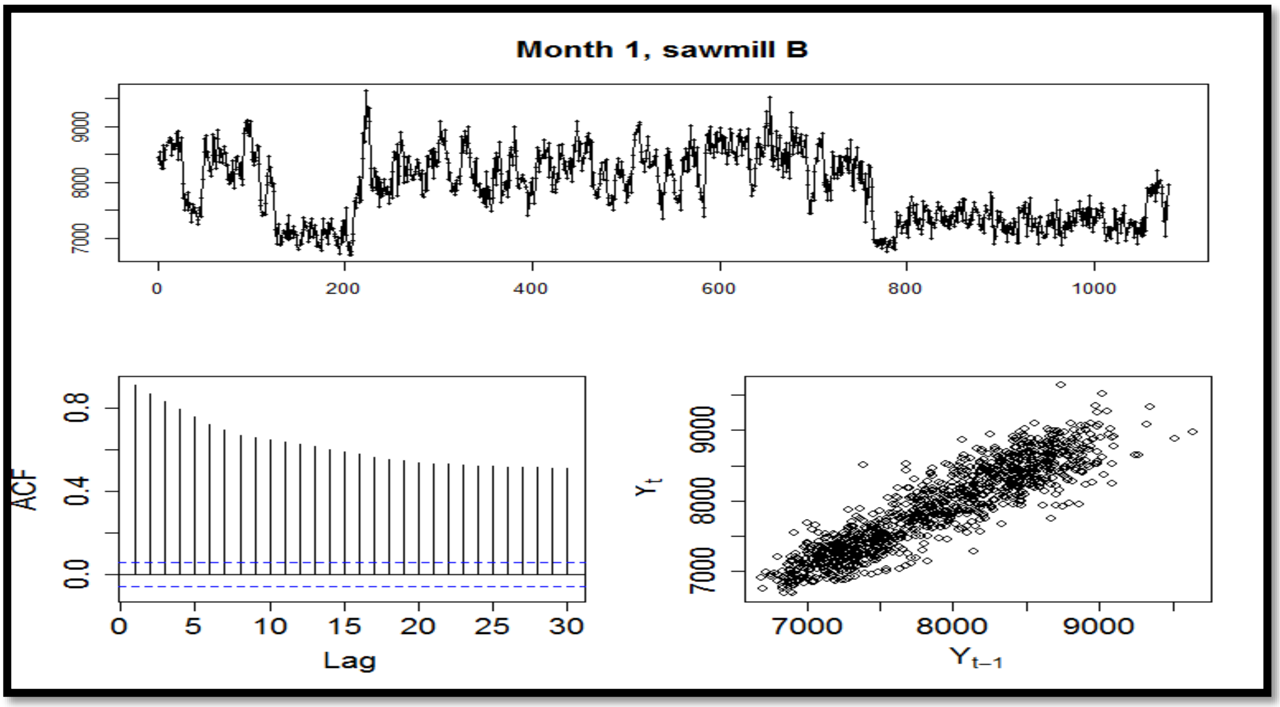

Figure A5: Run chart, autocorrelation function (ACF) and scatter plot of Month 1, sawmill A bundle means. The ACF shows autocorrelation of around 0.8 in the data.

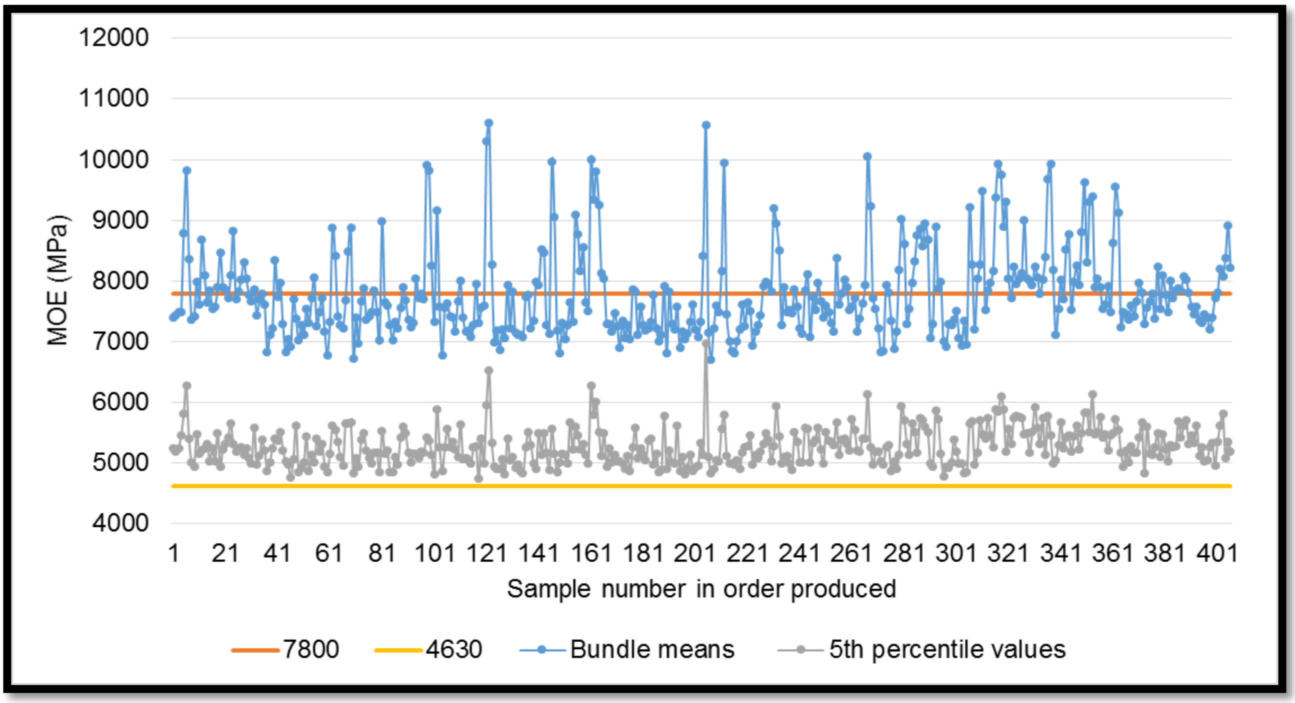

Figure A6: Mean MOE and 5th percentile values Month 1, Sawmill A bundles. The target lines represent the characteristic mean and 5th percentile values as specified in SANS 10163-1 at 7 800 MPa and 4 630 MPa, respectively.

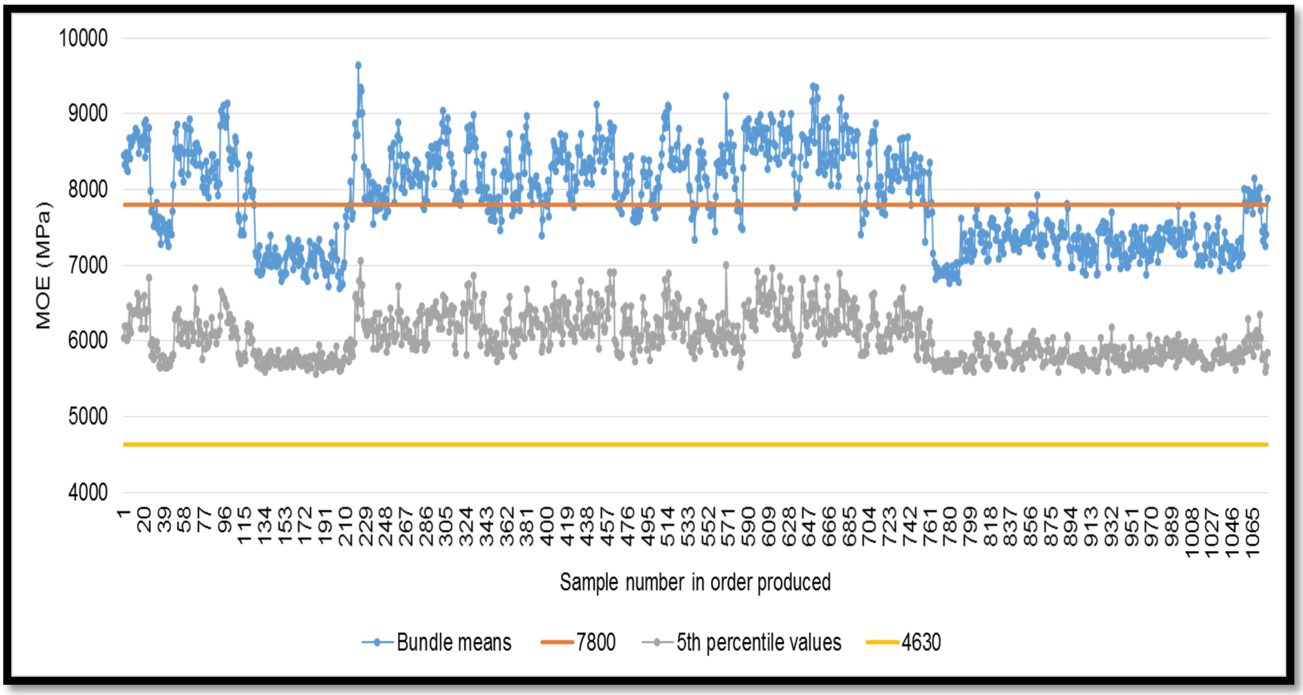

Figure A7: Mean MOE and 5th percentile values Month 1, Sawmill B bundles. The target lines represent the characteristic mean and 5th percentile values as specified in SANS 10163-1 at 7 800 MPa and 4 630 MPa, respectively.

Appendix B

Table: data analysis methods in R statistical software

Method / tools	Usage	R built in function
Column averages	Bundle means	*colmeans()*
The Anderson Darling Normality Test	Test for data normality	*ad.test()*
Quantile-quantile plot	Verify normality	*qqnorm()*
The Augmented Dickey-Fuller	Test for data stationarity	*adf.test()*
Time series analysis	Time series, ACF and scatter plots	*tsdisplay()*
Histogram	Check data distribution	*hist()*
Descriptive statistics	Descriptive statistics summary	*describe()*
ARIMA model	Select best fitting ARIMA model	*auto.arima()*
The Ljung-box test	Inspect model residuals	*Box.test()*
Subset	Sub-setting the data	*Subset ()*
Box plots	Checking variation within and between bundles.	*boxplot()*
Control chart	Plotting Xbar and S chart	*qcc()*
Control chart	Plotting CUSUM charts	*cusum()*
Control chart	Plotting EWMA charts	*ewma()*
ARL	Computation of the (zero-state) Average Run Length (ARL) for different types of CUSUM control charts monitoring normal mean.	*xcusum.arl()*
ARL	Computation of the (zero-state) Average Run Length (ARL) for different types of EWMA control charts monitoring normal mean.	*xewma.arl()*

Appendix C

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SANS 1783-5-2:20XX
Edition 1

SOUTH AFRICAN NATIONAL STANDARD

Structural timber

Part 5-2: Quality assurance of stress-grading

WARNING
This standard references other documents normatively.

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SANS 1783-5-2:20XX

Edition 1

Table of changes

Change No.	Date	Scope

Acknowledgement

The SABS Standards Division wishes to acknowledge the valuable assistance of Sawmilling SA and PHM Wood Technology CC.

Foreword

This South African standard was approved by National Committee SABS/TC 1008, *Wood and associated products*, in accordance with procedures of the SABS Standards Division, in compliance with annex 3 of the WTO/TBT agreement.

This document was published in xxxx.

SANS 1783 consists of the following parts, under the general title *Sawn softwood timber*:

Part 1: General requirements.

Part 2: Stress-graded structural timber and timber for frame wall construction.

Part 3: Industrial timber.

Part 4: Brandering and battens.

Part 5-1: Structural timber – stress-grade assessment.

Part 5-2: Quality assurance of stress-grading

Introduction

Stress-grading has been practiced in South Africa since the late 1950s, first only by visual grading. Mechanical stress-grading followed in the 1960s and more recently other methods have been introduced. The timber resource has changed over this period from a mix of thinnings and up to 45 year old rotation ages to rotation ages in the range of 20 years to 28 years at present. Tree breeding has also had its effect on the nature of the structural properties of the timber resource by increasing the size of the juvenile core and because of inadequate attention to wood properties in some cases. Furthermore, structural timber is being imported from other countries in some of which similar trends have occurred, and of other species. Recent research has shown that the stress-graded timber does not always meet the structural properties of the grades while much of it has properties well in excess of grade strength values.

SANS 1783 Parts 5.1 and 5.2 has been developed in response to these changes to ensure that all stress graded timber marketed in South Africa will meet the structural grade requirements as published in SANS 10163-1.

Contents

Page

Foreword

Introduction 1

1 Scope 3

2 Normative references 3

3 Terms and definitions ....

4 Symbols ....

5 General

6 Initiation of the system ....

7 Sampling procedure

8 OQA tests

9 OQA evaluation and assessment

9.1 General
9.2 Modulus of elasticity – stress-grades
9.3 Structural strength properties – stress grades
9.4 Reliability of finger joints in structural timber

Addendum

Bibliography ....

1 Scope

1.1 This part of SANS 1783 specifies procedures for stress-grading timber by both standard and non-standard methods.

1.2 A variation of these procedures for finger-jointed structural timber is included.

1.3 This part of SANS 1783 is applicable to all sawn timber species of rectangular cross sections. Its continuous evaluation procedure is specifically intended to be used for quality assurance purposes to ensure that timber so graded by suppliers complies with structural timber grade requirements.

1.4 This part of SANS 1783 is implemented by the grader under the supervision of the grader's Accredited Product Certification Body.

1.5 Hence the purpose of SANS 1783-5 is twofold; to provide a method of ensuring that stress-graded softwood and hardwood timber from all sources meets the structural requirements of the grades and to provide means whereby a wider range of grading methods may be developed and used to utilize the available resource as efficiently as possible.

1.6 SANS 1783-5 consists of two parts as follows:

a) SANS 1783-5-1 is a qualification testing (QT) procedure and provides requirements for sampling, testing and assessing characteristic values of structural properties for specific grades and sizes of sawn softwood and hardwood timber, and also finger-jointed structural timber, to meet the stress-grade requirements of selected grades as given in SANS 10163-1. It is concerned with the measurement of properties similar to those that occur under service conditions in accordance with the requirements of performance-based international standards.

b) This part of SANS 1783 is concerned with ongoing quality assessment (OQA) and provides procedures that should be followed when stress-grading timber. It has the purpose of ensuring that the timber so graded meets the requirements of the selected stress-grades at all times. One or more indicator properties (IPs) may be identified that will provide a sufficient assessment of the effectiveness of the stress-grading method. The procedure encompasses a continuous sampling and testing programme of such IPs against set targets in a prescribed manner.

   The method of grading to be used by the grader may be developed through the grader's own efforts, by a commercial supplier of grading equipment, by any suitably qualified research and development entity or consultant or by any other capable entity. This part of SANS 1783 is to be implemented by the grader under the supervision of the grader's Accredited Product Certification Body.

2 Normative references

The following referenced documents are indispensable for the application of this document. For dated references, only the edition cited applies. For undated references, the latest edition of the referenced document (including any amendments) applies. Information on currently valid national and international standards can be obtained from the SABS Standards Division.

SANS 1783-5-1, *Structural timber—stress-grade assessment*

SANS 6122, Structural timber — Characteristic values of strength-graded timber — Sampling, full-size testing and evaluation.

3 Terms and definitions

For the purposes of this document, the terms and definitions given in SANS 1783-5-1 and the following apply.

Accredited Product Certification Body

APCB
A person or organization that has been accredited by the SANAS to certify that products meet the requirements of a SANS standard and may be marked and sold as such.

responsible employee
RE
employee of the grader who has been assigned the task and responsibility for the sampling and testing of boards stress-graded by the method used by the grader

4 Symbols

For the purposes of this document, the symbols given in SANS 1783-5-1 apply.

5 General

The procedures in this part of SANS 1783 shall be implemented by the grader to ensure that the stress-graded and structural finger-jointed timber he/she produces meets the structural requirements of the grades. It is implemented after a successful conclusion of the work dealt with in SANS 1783-5-1.

This part of SANS 1783 consists of an ongoing programme of tests of random samples of stress-graded or finger-jointed timber taken during every production shift and tested within 24 h. The results of the tests are by the grader under the supervision of his Accredited Product Certification Body (APCB). The system consists of the following two stages:

a) The first stage is of one or more warning signals to which the operational staff should react promptly to avoid any further deterioration in the quality of the products.

b) The second stage is the identification of critical faults in the standard of the products produced and this leads to a stoppage of that production process until the cause is identified and shown to be eliminated before production operations may continue normally. Should it be found that the tests indicate that either the grading system or the finger joints are out of control, it may require that the process be subjected to a repetition of the relevant parts of SANS 1783 (SANS 1783-5-1 and this part of SANS 1783-5-2).

6 Initiation of the system

The grader shall identify a responsible employee (RE), who shall be responsible for the sampling of boards from the grading or finger-joint production lines and the testing of these boards. The RE shall preferably not be a member of the operational or supervisory staff of either operation. The APCB shall satisfy itself that the RE knows how to do the work and will do so in an unbiased manner.

NOTE It will be advantageous if this RE is identified before Part 1 of SANS 1783-5 is started so that he can assist the APCB with that work and be trained in random sampling and testing of boards and be familiar with the factors that may influence the results in a biased manner.

7 Sampling procedure

An OQA shall be applied to all the stress grades and finger-jointed structural timber produced by the grader. The APCB shall identify at least one size of each product produced for OQA. In doing so the grader shall be informed of the results of the evaluation of the characteristic values as set out in 6.7 of SANS 1783-5-1 and the knowledge he/she has gained from the implementation of SANS 1783-5-1 in respect of the reference resource, the timber processing methods and the grading method used.

If a wide range of dimensions are stress-graded, he/she shall select two dimensions for OQA per grade. Samples shall be drawn in a random manner from the production process outputs for each combination of grade or finger-jointed size (or both) and spread over the duration of the production of that combination.
The APCB and RE shall determine the frequency of sampling during a production shift such that one sample board per 1 000 boards of a grade or finger-joints made are accumulated for each test that is to be done.[1)] These boards shall be marked to identify them uniquely by grade, size, date and time of sampling and production line if there is more than one. They shall be stored in a safe, clean place protected from weather and damage until they are tested. They shall be tested within 24h of having been produced, or as per the discretion of the APCB.

NOTE It is to the grader's advantage to test sampled boards and obtain the feedback of the analyses of the results as quickly as possible since the despatch of structural timber of a type of product will be stopped by the APCB in the event that it finds that the production process is out of control.

8 OQA tests

In general a proof-load bending test will be done on all the sampled boards to determine their E_{app} and f_b. The E_{app} shall be determined for all stress grades evaluated. Only the f_b (or the equivalent proof load) is determined for finger-jointed timber[2]. The APCB may decide, on the same basis on which it decided on the sizes to be used for the OQA, to have tension tests done on stress grades in addition to bending tests.

The tests shall be done with proof-loading in accordance with the appropriate procedure set out in clause 6 of SANS 6122 with the exception that for the bending, tension and compression (if the latter is used) tests, the proof-load shall only be increased by 10 % and also be adjusted in the case of specimen sizes other than 36 mm × 111 mm for size effects by the factors given in annex A of SANS 6122.

The sample boards need not be cross-cut to specimen lengths if this can be avoided so that

unbroken boards may be returned to stock in due course. The *MC* of all sample boards shall be measured and recorded.

Density tests can be done on full size specimens.

The RE is advised to analyse the test results as soon as possible to enable the grader to react promptly to any indications of material not meeting the required grade. The APCB shall arrange the frequency, format, nature and method for the RE to send the raw test data and the RE's analyses of it if done by him to the APCB for analysis or confirmation.

Once the tests have been completed, all the boards shall be retained until the results have been analysed for possible re-examination in the event of sub-standard results. The APCB shall inform the grader when they can be returned to stock or be disposed of.

9 OQA evaluation and general assessment

9.1 General

The method of evaluating the OQA test results recommended in this part of SANS 1783 is based on the use of variations of Shewhart charts. These are relatively easy to use and provide information on trends and also out-of-control results that can be used to anticipate sub-standard results and therefore enable the APCB and the mill operational staff to attempt to advance corrective action. Odd but consistent sub-standard test results and detailed inspection of the test specimens involved can be used to identify their cause or causes and a

---

1) It may be in the interest of the grader to take more samples if production rates are low so that he/she obtains earlier warnings of sub-standard quality.
2) It is known that well-made finger-joints generally either increase or maintain the stiffness of the wood to either side of the joint while the strength is reduced to a small extent.
3) This has been done at a sawmill in South Africa to great effect. Persistent low-strength specimens were examined in detail and a simple override rule added to the grading process that eliminated the problem boards with no more than a minor reduction in yields. An ill-considered stiffening of the general grading limits to achieve the same effect would have proven far more costly in yield reduction.

modification of the stress-grading method to improve its effectiveness[3)].

The test data are best recorded and regularly updated in spreadsheets in which the charts can be set-up and similarly maintained.

9.2 Modulus of elasticity – Stress grades

Two criteria provide warnings. The first is the trend of the running average *E*. The second is when the percentage of sub-standard test results out of the most recent 50 exceeds 5 %. At either of these two warning signals corrective action shall be initiated to preclude the next step.

Either of two further criteria can produce a signal for the RE or APCB to stop the stress-grading process until the cause or causes have been identified and shown to be corrected. The one is when the running average *E* drops below the $E_{m,k}$ – *SD* line and the other when the percentage of sub-standard test results out of the last 50 exceeds 10 %. If such events are repeated a number of times within 30 days, the APCB may insist on a repeat of compliance with SANS 1783-5-1.

9.3 Structural strength properties – Stress grades

The first warning signal is produced by a persistent drift of the test results towards the line representing the characteristic value and by numbers of test results with a value below it. The second is when the percentage of results out of the last 50 tests below the characteristic value increases above 5 %. In either event the operational staff shall attempt to identify the causes and correct them.

The critical point at which the grading operation shall be stopped occurs when the percentage of results out of the last 50 tests below the characteristic value increases above 10 %. In this event the grading operation shall be stopped until the cause has been found and the problem has been shown to be corrected. If such events are repeated a number of times within 30 days, the APCB may insist on a repeat of compliance with SANS 1783-5-1.

9.4 Reliability of finger joints in structural timber

A warning signal is produced when the failure loads of numbers of tested joints falls below the equivalent load of the characteristic value. Corrective action should immediately be taken. Particular attention should be given to the nature of the failures, low percentage or no wood failures in the joints being of particular concern as these are indicative of adhesive bonding problems.

The structural finger-jointing operation shall be stopped as soon as the second failure load of the last 20 tests drops below 75 % of the load equivalent to the characteristic value. The cause shall be found and shown to be eliminated before production can proceed. If such an event is repeated within any 30 production shifts, the APCB must ask for the procedures below to be followed.

9.4.1 Proof-load tests of finger-jointed timber

Visual inspection and production control alone cannot reliably ensure the strength of finger-joints to comply with the requirements of stress grades in timber. Hence there is a need for specific strength tests for this purpose. (Finger-joints either do not affect or increase the stiffness of timber in the vicinity of the joints.)

Either tension tests on full sized specimens or bending test on the flat may be used for this purpose.

If the flat bending test is used, the test specimen length shall be 6t plus 1 000 mm, 1 200 mm and 1 800 mm for 36 mm, 48 mm and 73 mm thick boards respectively, with a joint located at mid-length. (The test spans are 1 000 mm, 1 200 mm and 1 800 mm respectively.)

This has been done at a sawmill in South Africa to great effect. Persistent low-strength specimens were examined in detail and a simple override rule added to the grading process that eliminated the problem boards with no more than a minor reduction in yields. An ill-considered stiffening of the general grading limits to achieve the same effect would have proven far more costly in yield reduction.

NOTE The testing of visually rejected finger-joints specimens in addition to the required number of graded ones may prove highly informative.

Use the bending test set-up for finger-joint strength assessment is shown in figure 1 with the specimen loaded on the wide face and the joint located centrally below the loading head. Load the specimens at a steady rate to failure or a proof load within about 1 min.

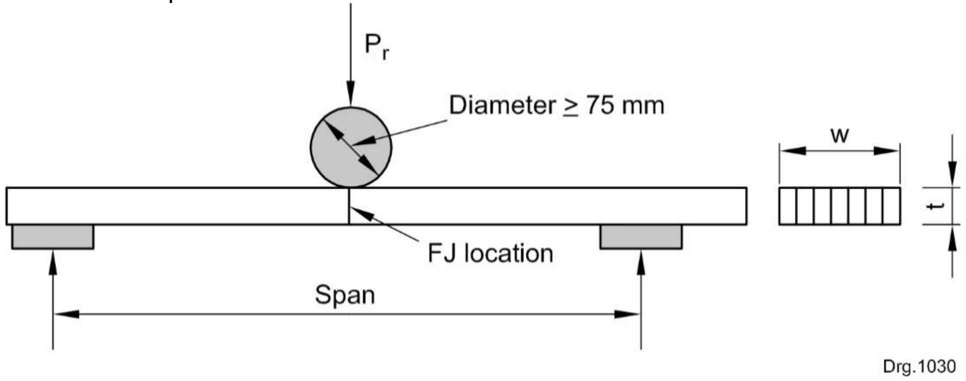

Figure 1 – Configuration for testing finger jointed timber

Calculate the proof load using the following equation:

$$P_r = \frac{1{,}15 \times k_{lc} \times k_{se} \times f_b \times w \times t^2}{1{,}5L}$$

where

P_r is the proof load, in newtons;

k_{se} is the adjustment factor for the size (span) effect;

k_{lc} is the adjustment factor for the effect of load configuration;

f_b is the characteristic bending strength (modulus of rupture);

w is the width of the test specimen, in millimetres;

t is the thickness of the test specimen, in millimetres;

L is the test span in millimetres.

NOTE The thickness is the beam depth.

The constant of 1,15 is to ensure that at least 15 % of the sample boards fail so that the 5th percentile can be calculated by the preferred method in annex A of SANS 6122.

The adjustment factor k_{lc} is to cater for the differences in the loading configuration and k_{se} for test span and dimensions[4)] used with this test as compared to the preferred standard test method on the reference size of 36 mm × 111 mm for the determination of characteristic values as given in SANS 6122. These adjustment factors are given in table 1.

NOTE It is useful to record the nature of any failures in the report so that corrective action can be taken as required.

[4)] For further information on these effects, see Madsen, B. 1992. *Structural behaviour of timber*. Timber Engineering Ltd, North Vancouver, Canada.

Table 1 — Adjustment factors k_{lc} and k_{se} for the calculation of finger-joint proof loads

1	2	3	1	2	3	1	2	3
Size mm	k_{lc}	k_{se}	**Size** mm	k_{lc}	k_{se}	**Size** mm	k_{lc}	k_{se}
36 ×73	0,95	0,92	48 × 73	0,88	0,92	-	-	-
36 × 111	1,12	1,00	48 × 111	1,04	1,00	73 × 111	0,87	1,00
36 × 149	1,26	1,06	48 × 149	1,11	1,06	73 × 149	1,00	1,06
36 × 187	1,38	1,11	48 × 187	1,28	1,11	73 × 187	1,04	1,11
36 × 225	1,43	1,15	48 × 225	1,38	1,15	73 × 225	1,18	1,15

Should the specimen not fail, turn it around and test it in the same manner in the opposite direction. Record the lowest actual load attained.

Calculate the bending strength (modulus of rupture) of each specimen using the following equation:

$$f_{bu} = \frac{1{,}5 \times P_f \times L}{w \times t^2} \quad \text{or} \quad f_{bu} = \frac{1{,}5 \times \mathrm{P_r} \times L}{w \times t^2} \qquad (2)$$

where

f_{bu} is the bending strength (modulus of rupture), in megapascals;

P_f is the load at failure, in newtons;

L is the test span, in millimetres;

w is the width of the test specimen, in millimetres;

t is the thickness of the test specimen, in millimetres;

P_r is the proof load, in newtons.

Calculate the 5th percentile and characteristic bending strength by the second method given in annex A of SANS 6122. Since the load configuration and size effects will have been built into the proof-loads these test results on finger-jointed timber are directly comparable to the standard characteristic values as given in SANS 10163-1.

In addition to attaining the standard characteristic bending strength of the grade in question no more than 1 % of the specimens tested shall have failed at a bending stress less than 50 % of this characteristic value. Failure to meet these criteria means that the finger-jointed timber is not accepted.
where is note 4)?

Annex A

(normative)?

OQA data processing and evaluation

A.1 General

The test results for each product and property are recorded on separate pages of a spreadsheet.

With this data control charts should be produced in order to determine whether the process is still within the control limits.

A.2 Modulus of elasticity, *E*, of stress grades

A.2.1 4
In the case of the OQA of *E*, the E_{app} of each test specimen and a running mean of the latest 20 specimens are compared against horizontal target lines on the control charts.

A.2.2 The first check on performance is done by comparing the individual and especially the running mean *E* results against the line representing the characteristic mean *E*, $E_{m,k}$. The running mean *E* should stabilize very quickly after the initiation of the OQA process and may not digress too far below the $E_{m,k}$ line. The APCB shall use his judgement to a large extent to determine when corrective action is required. This will typically be done in two stages, the first being a warning when the running mean *E* shows a persistent downward trend as is evident in the example from about specimen number 92 onwards. The second occurs if this trend persists and drops below one

standard deviation less than $E_{m,k}$ when an instruction to stop the grading operation is given until the cause is identified and shown to be corrected. (In the absence of an actual value for the standard deviation of E_m, a standard deviation equal to 25 per cent of $E_{m,k}$ is assumed and used).

The second check on performance in respect of *E* is done by comparing the running percentage of actual *E* test values that are less than the characteristic 5th percentile *E*, $E_{0.05,k}$ out of the last 50 test results. When this percentage exceeds 5 %, corrective action is required and if it exceeds 10 % an instruction is given to stop the grading operation until the cause is identified and shown to be corrected.

A.3 Other structural properties of stress-grades

The process of evaluating the performance of all other structural properties is similar to that for *E* other than that the test results are only assessed against the relevant 5th percentile based characteristic value. Two charts are required as for *E*. The first will only have two horizontal criteria
lines, namely f_b, f_t or f_c and 0,75 × f_b, f_t or f_c lines. Warnings are provided by any values of f_b that fall below the f_b line and the running percentage out of the last 50 tests that are below the f_b, f_t or f_c value, as plotted in a second chart (see example or equation). Should the running percentage of values less than the f_b, f_t or f_c value exceed 10%, an instruction is to be given to stop production until the cause of sub-standard performance is identified and shown to be eliminated.

A.4 Finger-jointed timber

A.4.1 The OQA of finger-jointed timber differs from that of stress-graded timber as regards the test method as well as the nature of the data analysis and chart used.

A.4.2 The appropriate proof load is calculated with a 10 % increase above that equivalent to the fb value of the grade concerned. The lowest of the two load values obtained from the reverse bending tests is recorded, the other being discarded. It is not necessary to calculate the bending stress as the proof or failure load can be used for the OQA evaluation and in the control charts. A warning is provided by any failure loads that fall below the proof load equivalent to the fb value of the grade concerned or 0,75 times that value, at which times corrective action should be initiated. Should more than one failure load fall below 0,75 times the proof load equivalent to the fb value within 15 finger-jointing production shifts, the operation is to be stopped, the cause identified and corrected before production may resume. Should more than one such stoppage occur within 30 production shifts the structural finger-jointing operation, the operation shall be subjected to a re-appraisal in terms of Part 1, Section 6.6.7 of this standard.

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change to the Harvard Method in part 5-1 as well.