Accurately Estimating and Minimizing Costs for the Cellulosic Biomass Supply Chain with Statistical Process Control and the Taguchi Loss Function

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This research focuses on the statistical evaluation of the feedstock attributes of the biomass supply chain and the estimation of attribute costs as a function of the feedstock variability. Challenges of using cellulosic feedstocks include the variability of feedstock quality (*e.g.*, ash content and moisture content), which impacts the final cost of the manufactured product. Statistical Process Control (SPC), Taguchi Loss Function, and components of variance techniques were illustrated for quantifying cumulative variance in the biomass supply chain. Costs in the presence of cumulative variance were estimated for switchgrass (*Panicum virgatum* L.) and loblolly pine residues (*Pinus taeda* L.). Findings of the study indicated that additional costs from ash content variability in switchgrass increased the net cost by $19.15 per dry tonne. Additional costs from densification due to particle size variation increased net cost by $11.59 per dry tonne. Moisture content variation increased costs by $14.86 per dry tonne. This would represent a 50 to 100% increase in costs due to variation based on a $60 to $70 per dry tonne manufactured product cost. This study illustrates that total costs may be considerably underestimated if the influence of variance for key factors in the supply chain and associated costs are not estimated.

Keywords: Statistical process control; Taguchi loss function; Variance; Cost; Biomass feedstocks

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INTRODUCTION

Biomass is well documented as an important feedstock for a multitude of manufactured products that have valuable attributes for the end users, and it is also beneficial to society as a sustainable and renewable supply source (Singha and Thakur 2008, 2009; Thakur and Singha 2011; Thakur *et al.* 2012). A significant issue with biomass feedstocks is the high variability in the quality attributes associated with the feedstocks (Kenney *et al.* 2013b). Variability in input feedstocks for any manufactured product increase costs of the final product (Taguchi *et al.* 2004; Deming 1986, 1993). This study advances the research of estimating the variability and associated costs for biomass feedstocks in the context of statistical process control (SPC) and the Taguchi Loss Function (TLF) with the application of '*components of variance*' for the logistical stages of the biomass supply chain.

Biomass supply consists of a multicomponent supply network that faces challenges of providing low cost feedstock with small variation (Langholtz *et al.* 2016). In a general context, this network is a construct of five stages: feedstock production, feedstock logistics, biomass processing, biomass product distribution, and the biomass final product (Parish *et al*. 2012). The logistic stages include all necessary procedures to transport feedstock from harvest site to a production facility's gate (Sooduck and Farrey 2010). For example, Rentizelas *et al.* (2009) describes this system for a power station as six steps: harvesting and collection, in-field and forest handling, storage, loading and unloading, transportation, and processing. A challenge of supplying loblolly pine (*Pinus taeda* L.) and switchgrass (*Panicum virigatum* L.) is the high cost of transportation and handling (Lu *et al*. 2015).

A key problem for biofuels is the large variance associated with feedstock quality and the ability of the manufacturing system to process this variability to produce a low-cost output that meets customer specifications. For biofuel and associated products, this '*large variance*' feedstock problem directly influences the processing operational targets for solvents, batch time, and temperature, which all negatively impact yield and the final costs of manufactured product. High costs influence competitiveness in the marketplace.

The research study attempts to model the 'advanced uniform-format' feedstock supply chain system as described by Hess *et al*. (2009) by estimating the variances and costs from variance for individual systems' components (Platzer 2016). Estimating costs from the influence of variance is the contribution of this research, which has not been documented for biomass feedstocks.

The '*supply chain concept*' aims to generate standardized commodity feedstocks through the integration of an intermediate preprocessing stage, located immediately after feedstock harvest and collection, defined hereafter as the '*bio-depot*' (Fig. 1). The bio-depot is a concept focused on a centralized processing system that receives woody biomass from multiple supply lines such as loblolly pine residuals and switchgrass. The biomass sources are then blended and converted into feedstocks with more uniformity in ash content, moisture content, and particle size to improve conformance to specifications for a biorefinery (Jacobson *et al*. 2014). Quantifying the cumulative variance of the feedstocks in the supply chain and identifying those components that have the largest variance and associated high costs will facilitate reduction in variance and lower costs. As Taguchi *et al*. (2004) noted in the '*Taguchi Loss Function*' (TLF), costs increase at a non-linear rate as a function of the variance. The TLF is a well-accepted method for estimating costs in the automotive industry and other significant sectors.

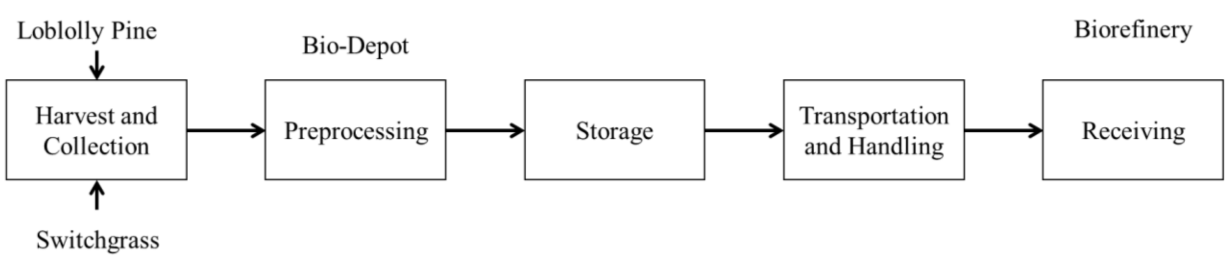


Fig. 1. Advanced uniform-format feedstock supply chain with intermediate preprocessing stage (Metzner 2018)

EXPERIMENTAL

Key Biomass Feedstock Attributes

Ash content

Ash content is inorganic matter that consists of a wide range of elements (James *et al*. 2012) and negatively influences the production of bio-based products by loss of yield, *e.g.*, cellulosic biomass to biofuel conversion (DOE 2014). Ash in biomass feedstock originates from either the natural physiology of the plant or through contamination with soil or rocks (Lacey *et al*. 2016). Natural ash in plants is either associated with structural ash in cell walls or vascular in cell extracts (Kenney *et al*. 2013b). Supply management and harvesting methods have a direct influence on the quality of biomass (Obernberger *et al.* 1997). Ash content varies across biomass types, for example, woody biomass compared to herbaceous plants, or roundwood compared to woody residues (Tao *et al*. 2012). The ash content in woody biomass such as loblolly pine residues, depending on the origin, ranges from 0.5 to three percent of dry weight. However, ash content can be as high as ten percent, if the limbs, branches, leaves or needles, and bark are taken into account (Sjoding *et al*. 2013). This is a key challenge for implementing the bio-depot concept.

Particle size

Particle size influences the '*flowability*' and bulk density of cellulosic feedstocks. This crucially affects the efficiency of the biomass supply chain and the attainable biofuel yield from the conversion process (Bitra *et al*. 2009; Miao *et al*. 2011). Particle size of the raw material is a key metric due to its effect on overall feedstock quality (Paulitsch and Barbu 2015). Comminution, which means particle size reduction, is vital to increase both '*flowability*' and bulk density of cellulosic raw material that effects costs (Hess *et al*. 2009; Miao *et al*. 2011). The location of the comminution process in the supply chain is important in early stages (Meunier-Goddik *et al.* 1999). Particle size and distribution depends on the milling equipment, which are typically either hammer mills or knife ring flakers. Particles produced from hammer mills tend to be finer than particles produced from knife ring flakers (Kenney *et al*. 2013). Specifications of particle size reduction are typically set by the end-users (Igathinathane *et al*. 2008).

Moisture content

Biomass moisture content is an important cost driver for biofuel production. Excessive moisture variation negatively affects storing, transporting, handling, and feeding. Biomass handling and feeding becomes tedious with increased levels of moisture content, due to an increase of the cohesive strength of the material, increasing the likelihood of plugging of feeders (Dai *et al*. 2012). Emery and Mosier (2012) showed that, with increasing moisture content, dry matter loss increased for aerobic stored biomass. Furthermore, high moisture content levels in biomass lowers transportation efficiency and increase costs, especially in the case of truck transport (Eggink *et al*. 2018). Biomass moisture content affects not only biofuel conversion performance, it also affects grinding energy and execution (Tumuluru *et al*. 2014), which also indirectly impacts the conversion performance (Williams *et al*. 2016), *i.e.*, deviations from target that results in low, or high moistures influence the conversion process given that the conversion process is set to operate at the target. The specification limits for the moisture content for woody residues (Keefe *et al*. 2014) and herbaceous biomass depend on the final conversion technology. Moisture content of roundwood after logging is estimated at 50% (Lu *et al*. 2015), whereas for Switchgrass moisture content ranges from 15% to 30%, depending on the season (Mitchell and Schmer 2012).

Simulation of key feedstock attributes

Nonparametric bootstrap simulations (N = 10,000) were made from an actual data set for the ash content in Switchgrass (n = 137). Nonparametric bootstrap simulations are a statistical method of resampling from the original data to build a simulated probability density function for a large N that may be unique in its functional form. See Efron and Tibshirani (1993) and Davison and Hinkley (1997) for detailed descriptions of the bootstrap methodology. The other data sets for particle size, and moisture content (n = 100) were obtained from the literature and mimics receiving biomass from multiple suppliers (Antony 1997; Tumuluru *et al*. 2011; Rector *et al*. 2013; Jacobson *et al*. 2014; Thompson *et al*. 2014; Williams *et al*. 2016). The average and variances from the nonparametric bootstrap simulations were used to estimate costs using the TLF. An outcome of the research was the development of a Microsoft Excel template for practitioners (www.spc4lean.com), which included nonparametric bootstrap simulations, TLF, and statistical process control (SPC) capabilities for the three feedstock attributes studied.

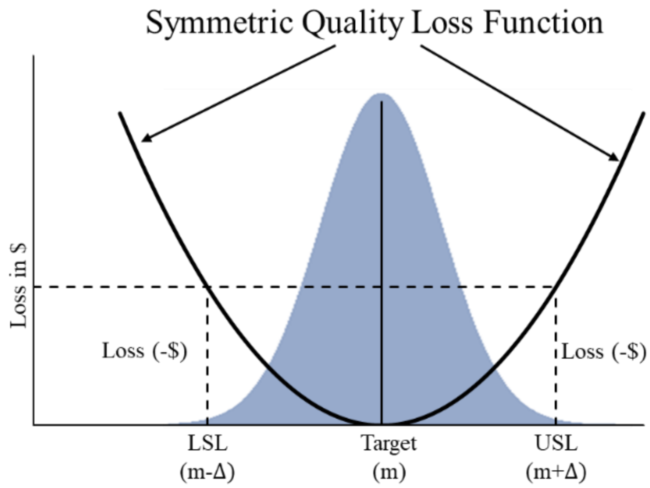
Statistical Process Control

Statistical process control (SPC) procedures are well established for quantifying the natural (common-cause) and special-cause (event) variations of the process and are used by a vast number of industries for facilitating variation reduction (Shewhart 1931). SPC is a well-established method for improving industrial processes, and there is a plethora of literature documenting SPC applications in automotive, aerospace, electronics, and other industries (not cited in this paper for the sake of brevity). SPC is not well documented in the public domain literature for biomass applications; Silva *et al.* (2014) illustrates the use of SPC for evaluation of effluent treatment in an agro industrial plant; Gomes *et al.* (2018) documents the use of SPC for improving bioreactor products. There is no literature reported in the public domain for applications of SPC for improvement of the biomass supply chain. Given the lack of reported literature on SPC applications for biomass, a review of key concepts is presented.

The well-recognized Deming (1986, 1993) successfully implemented SPC for many global industries (most notably in Japan) as a statistical-based method for improving processes by enhancing a company's focus on variation reduction to lower costs while at the same time improving processes and product quality. SPC is fundamental to initiating root-cause analyses and documenting variation improvements (Grant *et al.* 1994). Large variability in the biomass-using industries is unavoidable, but it can be reduced and controlled (Young and Winistorfer 1999; Young *et al*. 2007). In this study, the control chart accentuated changes in the data and highlighted the stability of the process simulation.

Taguchi Loss Function (TLF)

Young *et al.* (2014) documents the use of the TLF for accurately costing variation in formaldehyde (CH_2O) emissions from wood composites applications. A review of the public domain literature did not identify any studies documenting the use of the TLF for biomass applications or biomass supply logistics. The TLF quantifies the economic loss or cost due to variation in the process or product. In this study, the economic loss was a function of the variation in feedstock quality attributes deviating from the operational target.



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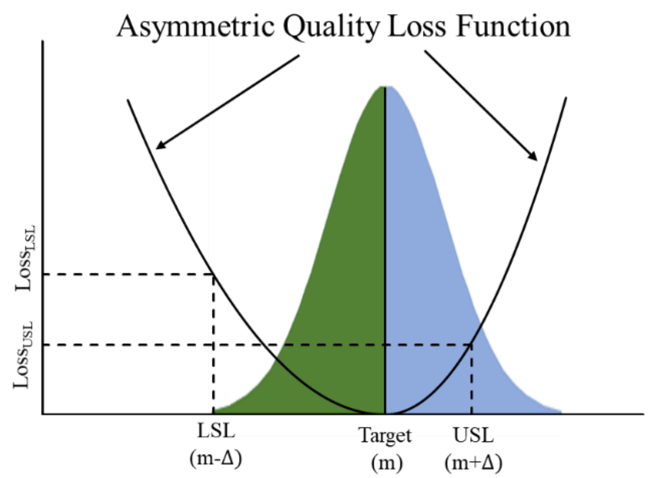

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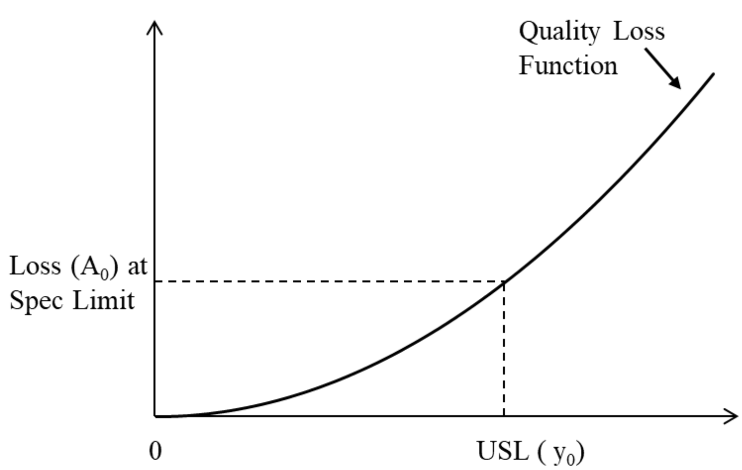

c)

Fig. 2. Illustrations of Taguchi's quality loss functions a) symmetric nominal-the-best, b) asymmetric nominal-the-best, and c) smaller-the-better (Metzner 2018)

Taguchi *et al.* (2004) emphasized that economic loss is reduced if a company minimizes variation around the target. Taguchi *et al.* (2004) developed a two-sided loss function '*nominal-the-best*' (*i.e.*, target centered within specifications) which estimates economic loss for a quality attribute that has both lower and upper specifications, *e.g.*, moisture content (Fig. 2a). For some production settings or quality characteristics, the two-sided loss function may be asymmetric (Fig. 2b), *i.e.*, target is set closer to either upper or lower specification limit, *e.g*., particle size. Taguchi *et al.* (2004) also developed a one-sided loss function where '*smaller-is-better*' with only one lower or upper specification (*e.g.,* the desired value of the quality characteristic should be as small as possible, ideally zero, as would be the case for ash content) (Fig. 2c). Taguchi provided equations for each type of loss function. Taguchi *et al.* (2004) argued that operational targets are established as a function of the variation in the process, *i.e.*, operational targets are equal to the sample average which is three standard deviations within the specification limits, also known as the '*Natural Tolerance*' (NT). Operational targets can only be reduced (or increased) for one-sided specification limits if the variance of the process is first reduced. Most operations run the smallest possible target, but they must also avoid producing product outside of specification, and they are therefore constrained from lowering the target due to the variation of the quality attribute.

Taguchi's '*nominal-the-best*' loss function for one unit is defined as follows,

$$L = k(y_0 - m)^2 \tag{1}$$

where L is the economic loss, k is the cost constant, $k = \frac{A_0}{(SL-m)^2}$, y_0 is the value of the quality characteristic at the upper or lower specification limit, m is the operational target value of the quality characteristic (*e.g.*, moisture content, particle size, *etc.*), SL is the lower (or upper) specification limit, and A_0 is the cost at attaining the specification limit. Taguchi's symmetric '*nominal-the-best*' loss function for more than one unit of production, accounts for the variance of the feedstock characteristics, and is defined as follows,

$$L = k[\sigma^2 + (\bar{y}_0 - m)^2] \tag{2}$$

where σ^2 is the quality characteristics' variance, and $\bar{y}_0$ is the average value of the quality characteristic.

The asymmetric '*nominal-the-best*' loss function is adjusted to account for the variance and average for the data above and below the target independently, thus is defined for the upper side as follows,

$$L_{USL} = k_{USL}\left[\sigma_{USL}^2 + \left(\bar{y}_{0,USL} - m\right)^2\right] \tag{3}$$

where σ_{USL}^2 is the quality characteristics' variance, $\bar{y}_{0,USL}$ is the average value of the quality characteristic for the data below the target, and $k_{USL} = \frac{A_{0,USL}}{(USL-m)^2}$. The lower side is defined as,

$$L_{LSL} = k_{LSL}\left[\sigma_{LSL}^2 + \left(\bar{y}_{0,LSL} - m\right)^2\right] \tag{4}$$

where σ_{LSL}^2 is the quality characteristics' variance, $\bar{y}_{0,LSL}$ is the average value of the quality characteristic for the data below the target, and $k_{LSL} = \frac{A_{0,LSL}}{(LSL-m)^2}$. Taguchi's '*smaller-the-better*' loss function for one unit is defined as follows,

$$L = k \cdot y_0^2, \quad where\ k = \frac{A_0}{y_0^2}, \tag{5}$$

and for more than one unit is,

$$L = k\left(\sigma^2 + \bar{y}_0{}^2\right) \tag{6}$$

Theory of 'Components of Variance'

Sir Francis Galton's early writings on the study of variability of systems was the genesis for the '*components of variance'* concept (Stigler 2010). Galton hypothesized that in any component system, variance accumulates throughout the system, so that the total variance is the sum of all the components variances. In this study for example, increased moisture content of harvested biomass can have an impact on the dry matter loss, which influences the storage operation. Depending on the storage type, additional moisture can be introduced by environmental influences, which increases the moisture content and the overall variance of the system, *e.g.*, biomass supply chain (Montgomery 2012). For a '*series system*', the components are dependent and may have a positive or negative influence on each other depending on the co-variability of the components. For equal variances the equation is defined as,

$$Var(\sum_{i=1}^{n} X_i) = \sum_{i=1}^{n} Var(X_i) \pm 2(\sum_{1 \leq i<j \leq n} Cov(X_i, X_j)), \tag{7}$$

where $Var(\sum_{i=1}^{n} X_i)$ is the total system variance for all *i to n*, $\sum_{i=1}^{n} Var(X_i)$ is the sum of variances for each the component i, and $\sum_{1 \leq i<j \leq n} Cov(X_i, X_j)$ is the sum of the covariance between all components *i, j to n*. For unequal variances for each component of the series the equation is defined as,

$$Var(\sum_{i=1}^{n} a_i X_i) = \sum_{i=1}^{n} a_i^2 Var(X_i) \pm 2(\sum_{1 \leq i<j \leq n} a_i a_j Cov(X_i, X_j)) \tag{8}$$

where variables a_i and a_j define the proportion or weight of the variance for each component in the system. Equations 7 and 8 are used in this study to estimate system variance and calculate economic losses using the TLF.

RESULTS AND DISCUSSION

Economic Loss for Ash Content

The '*smaller-the-better*' loss function was most applicable for ash content variability (Fig. 4). Even though Jacobson *et al.* (2014) defined an upper specification limit (USL) of four percent, the Taguchi Loss Function (TLF) illustrated that economic loss increased the greater the distance from zero percent ash content, and it increased at an increasing rate. Taguchi *et al.* (2004) argued that economic loss did not average itself around the mean, *i.e.*, loss is not uniform around the mean. The cost of producing a final product from 4% ash content was much greater than that with 1% ash content, including additional cost factors such as more chemical treatment, longer dwell times, higher temperature, and lower yields. If the final product had to be remanufactured or abandoned above the USL of 4%, the costs of rescheduling a new order, delays to on-time shipment, inventory carrying costs, and work-in-process (WIP) costs, are much greater than producing a final product at the target, or below target. As illustrated in Fig. 3, simply shifting the operational target to the left below 3.5% was not feasible because the entire distribution would shift to the left, and this implied a baseless negative ash content for feedstocks.

A numerical example of estimating loss was presented using Eq. 6. A nonparametric bootstrap simulation of the original data displayed in Fig. 3 resulted in an $\bar{x}$ = 3.35% and σ^2 = 2.68%². The average loss per unit (*i.e.*, average loss per dry tonne) based on Taguchi's smaller-the-better loss function with a hypothetical cost constant k = \$2.25 (%²)$^{-1}$ is \$34.48 per dry tonne.

A sensitivity analysis was conducted to analyze patterns of the average loss per unit for the smaller-the-better quality loss function based on changes in constant k, the variance, and the mean (Table 1). The mean and variance were increased or decreased by 0.1, and the cost constant k by \$0.1 (%²)$^{-1}$ from the original loss per unit of \$34.48 per dry tonne. The sensitivity analysis for scenario A (Table 1) with a reduction in cost constant k, and no change in the mean and variance resulted in a reduced cost of 16% from \$37.55 to \$31.42 per dry tonne.

The sensitivity analysis for scenario B (Table 1) indicated that if the variance is reduced from 2.88% to 2.48% with no change in the cost constant k, the loss per unit is reduced by three percent from \$34.98 to \$33.98 per dry tonne. However, as illustrated in the sensitivity analysis for scenario C, if the operating target is by 0.4% due to a reduction in variance, cost is reduced by 20% from \$38.40 to \$30.76 per dry tonne.

A real world scenario may have an average ash content as high as 6% per dry tonne (*e.g.*, Switchgrass) with σ^2 = 2.68%², and a cost constant k = \$2.25 (%²)$^{-1}$ (Kenney *et al.* 2013a). For an industrial-scale facility using 250,000 dry tonnes per year of biomass, the cost when accounting for variability is approximately \$89.29 per dry tonne. One dry tonne yields roughly 87 gallons of cellulosic ethanol (Mitchell *et al*. 2012). If new preprocessing technologies reduced the average ash content to 3% per dry tonne, a savings of \$22.12 per dry tonne would occur assuming the TLF.

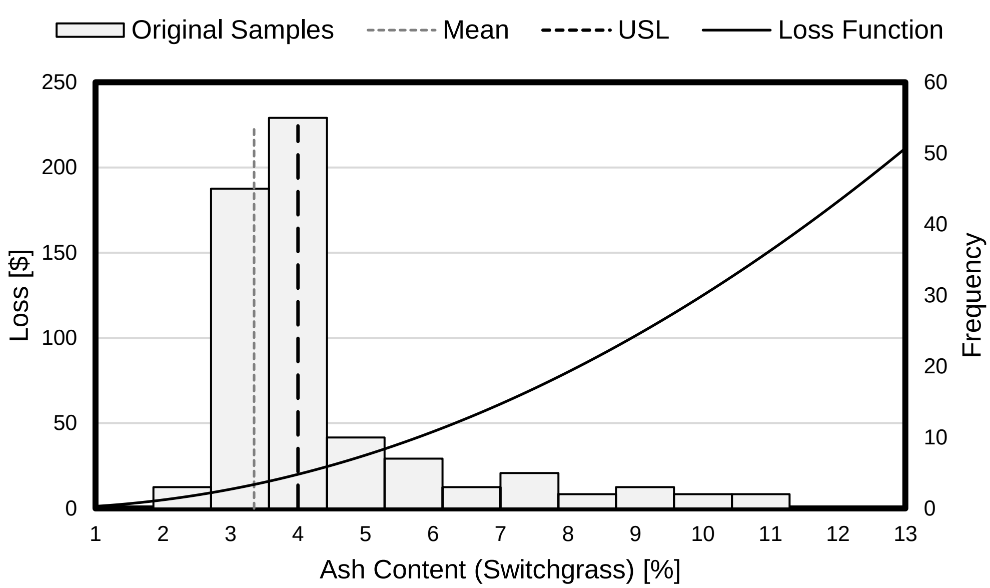

Fig. 3. Smaller-the-better loss function for the ash content of switchgrass using k = \$1.25 (%²)$^{-1}$ (Metzner 2018)

Table 1. Sensitivity Analysis of the Economic Loss Per Unit for the Ash Content with the Smaller-the-better Loss Function (Metzner 2018)

Sensitivity Analysis	USL (%)	*k*	Mean (%)	Variance (%²)	CV	Average Loss per Unit ($)	Reduction in Average Loss
A	4.0	2.45	3.35	2.68	80%	37.55	
		2.35				36.01	
		2.25				34.48	
		2.15				32.95	
		2.05				31.42	-16.3%
B	4.0	2.25	3.35	2.88	86%	34.98	
				2.78	83%	34.73	
				2.68	80%	34.48	
				2.58	77%	34.23	
				2.48	74%	33.98	-2.9%
C	4.0	2.25	3.55	2.88	81%	38.40	
			3.45	2.78	81%	36.42	
			3.35	2.68	80%	34.48	
			3.25	2.58	79%	32.60	
			3.15	2.48	79%	30.76	-19.9%

Economic Loss for Particle Size during Densification

The '*nominal-the-best*' asymmetric loss function for a densification operation using a '*cuber*' is illustrated in Fig. 4. Cubes are in the form of a square cross sections of chopped biomass with sizes ranging from 12.7 to 38.1 mm in the cross section, where the length of a cube is usually equal to or longer than the dimensions of the cross section typically from 25 to 100 mm. Cubes are less dense than pellets, with a bulk density ranging from 450 to 550 kg/m^3 depending upon the cube size (Sokhansanj and Turhollow 2014).

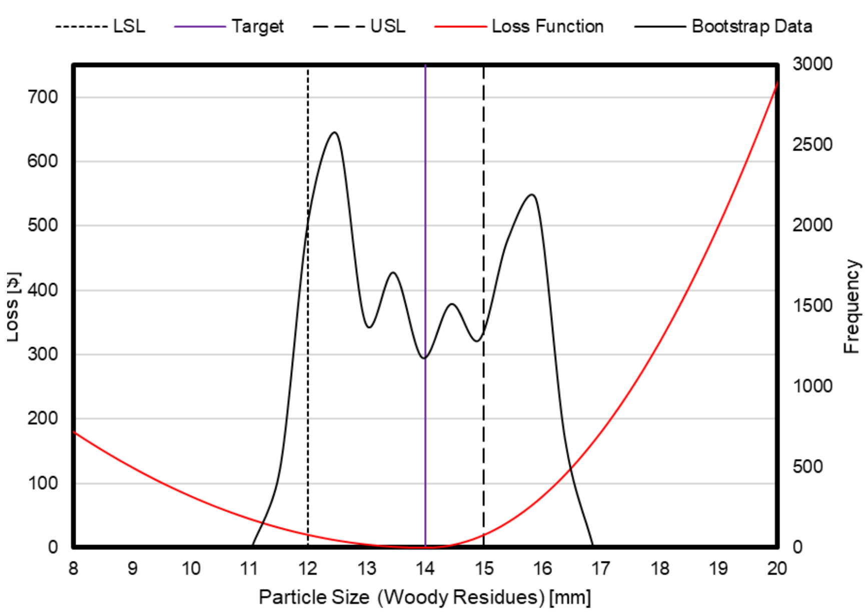

Fig. 4. Nominal-the-best asymmetric loss function for the particle size of biomass

Sensitivity analyses were conducted assuming a lower specification limit (LSL) of 12 mm, upper specification limit (USL) of 15 mm, and an operational target of 14 mm (Tumuluru *et al*. 2011). The nonparametric bootstrap simulation had an $\bar{x}$ = 15.27 mm and σ^2 = 0.43 mm². Most of the data from the simulation are within specification limits. The average losses per dry tonne are determined with different hypothetical cost constants *k* (*i.e.*, equations 3 and 4) due to asymmetric specification settings, *i.e.*, the distances from the target to the respective specification limit are different. The average loss per dry tonne is $45.04 using a cost constant *k* of $20.00 $(mm^2)^{-1}$. For data below the target, the nonparametric bootstrap simulation had an $\bar{x}$ = 12.71 mm and σ^2 = 0.43 mm². The average loss per dry tonne for this asymmetric nominal-the-best (includes both non-equidistant sides) was $11.54 using a cost constant *k* of $5.00 $(mm^2)^{-1}$. Hypothetically, for a 250,000 dry tonnes per year biorefinery, the accumulated loss due to variation in particle size would equate to $7.6 million dollars (*i.e.*, $1.2 million for the biomass below target and $6.4 million dollars above the target). If the variance in particle size could be reduced by one millimeter, the loss due to variability from particle size would be reduced to $1.5 million dollars annually.

Economic Loss for Moisture Content

The symmetric '*nominal-the-best*' loss function was most applicable for moisture content variability. This TLF illustrates that economic loss increases the more the biomasses moisture content value deviates from the operational target of the respective biomass supply chain operation, and it will increase at an increasing rate. For enterprises integrated in biomass supply chain it will be important for moisture content to be within specification limits. For example, chipped wood particles with great moisture content variability, possible with particles ranging outside specification limits are more cost intensive to dry than chipped wood particles with low moisture variability. Thus, it is important for operators to maintain a process mean moisture content near the target.

The computed statistics from nonparametric bootstrap simulations and associated economic losses for three different cases for each component of a hypothetical supply chain are presented in Table 2. The cost constants (*k*) for the components harvest/collection and transport were derived from the dockage fees for moisture content for switchgrass (U.S. Department of Energy, 2016). For the components drying and densification the cost constants are derived in dollars per dry tonne (Kenney *et al*. 2013a). Three simulation scenarios were analyzed:

- Scenario 1): Series system with independent components, recall Eq. 2;
- Scenario 2): Series system with dependent components with equal variances (recall Eq. 2 for the loss and Eq. 7 for the total variance);
- Scenario 3): Series system with dependent components with unequal variances (recall Eq. 2 for the loss and Eq. 8 for the total variance). The weights were derived from the coefficients of a simulated multiple linear regression model.

Scenario 1: Series system with independent components

The coefficient of variation (CV) ranged from 4.76% for harvest/collection process to 7.42% for the densification process (Table 2). The highest average loss per unit (*i.e.*, average loss per dry ton) based on Taguchi's nominal-the-best loss function was $13.45 per dry tonne (*k* = $3.36 $(\%^2)^{-1}$) in the harvest/collection process. Densification had the smallest loss with $4.30 per dry tonne, given the smallest σ^2 = 2.12 %² and *k* = $1.47 $(\%^2)^{-1}$.

Table 2. Taguchi's Nominal, the-Best Symmetric Loss Function for Simulated Moisture Content for Series System with Various Independent Components (Metzner 2018)

Component	Harvest/ Collection[1]	Transport[2]	Drying[3]	Densification[4]
CV [%]	4.76	5.69	5.65	7.38
$\bar{x}$ [%]	40.02	30.12	29.82	19.73
σ^2 [%²]	3.63	2.95	2.84	2.12
k in [$/%²]	3.36	3.36	1.87	1.47
L in [$/dry tonne]	13.45	10.94	5.92	4.30
[1] Target = 40% (Jacobson *et al*. 2014)				
[2] Target = 30% (Jacobson *et al*. 2014)				
[3] Target = 30% (Jacobson *et al*. 2014)				
[4] Target = 19% (Jacobson *et al*. 2014)				

Scenario 2: Series system with dependent components and equal variances

The CVs ranged from 4.76% for the harvest/collection process to 17.21% for the densification process (Table 3). The harvest/collection process was the first component of the system and had the same CV and variance as Scenario 1. The variances for the transport component (σ^2 = 5.42 %²), drying (σ^2 = 8.08 %²), and densification (σ^2 = 9.02 %²) increased to 8.51% to 17.21% due the cumulative effect. In this scenario the doubled sums of the covariances for each component were negative, thus decreasing the variance for each component. The loss for harvest/collection was $13.45, densification was $15.48, drying was $16.72, and transport was $20.13 per dry tonne. For 250,000 dry tonnes of production, a total annual economic loss of $16.4 million dollars occurred due to moisture variability in the supply chain. Given the average cost estimates of $63.84 to $86.19 per tonne documented by Amundson (2016) in the study of high moisture content biomass feedstocks, variation in moisture content using the symmetric '*nominal-the-best*' TLF may increase costs by an additional 19% to 26%. Given the average estimates by Sokhansanj and Turhollow (2014) of $21.60/tonne and $23.60/tonne for harvesting and collection equipment, the additional increase in costs due to variability using the TLF would be from 57% to 62%.

Table 3. Taguchi's Nominal-the-best Symmetric Loss Function for Moisture Content in Series System with Dependent Equal Variance Components (Metzner 2018)

Component	Harvest/ Collection	Transport	Drying	Densification
CV [%]	4.76	8.51	10.29	17.21
$\bar{x}$ [%]	40.02	30.12	29.82	19.73
σ^2 [%²]	3.63	5.42	8.08	9.02
$\sum \sigma^2$ [%^{2}]	3.63	6.57	9.41	11.53
$\sum 2 \times COV$ [%^{2}]	-	-1.15	-1.33	-2.51
k in [$/%²]	3.36	3.36	1.87	1.47
L in [$/dry tonne]	13.45	20.13	16.72	15.48

Scenario 3: Series system with dependent components and unequal variances

Scenario 3 presented a hypothetical biomass supply chain in which the moisture content variability of each component has a weighted impact on the subsequent operation. The CVs ranged from 4.76% for harvest/collection to 7.85% for densification (Table 4). Given the dependent components in the supply chain, the variances for the components transport (σ^2 = 0.11 %²) and drying (σ^2 = 0.31 %²) decreased in a series system, resulting in much smaller CVs compared with scenario 1 and 2 with 1.03% and 1.77%. The CV for densification (σ^2 = 3.05 %²) slightly increased to 7.85%. The weights in Table 4 were generated from a multiple linear regression model (MLR). Densification was set to be the response variable in the MLR, since actual data for a response variable such as biofuel yield at the biomass conversion were not available at the time of the experiment. Due to the weights, the highest loss was experienced at the harvest/collection process with $13.45 per dry tonne. The losses for transport and drying, of $0.46 per dry tonne and $0.70 per dry tonne, respectively, are much lower, similar to scenarios 1 and 2. For densification, the average loss of $5.80 per dry tonne was slightly higher as in the scenario with independent components. For 250,000 dry tonnes of production, a total annual economic loss from variability is estimated to be $5.1 million dollars. The costs were much smaller relative to Scenario 2 because the weights (Table 4) are relatively small and impact the components 2, 3, and 4 of the supply chain.

Table 4. Taguchi's Nominal-the-best Symmetric Loss function for Moisture Content in Series System with Dependent Unequal Variances Components (Metzner 2018)

Component	Harvest/ Collection[1]	Transport[2]	Drying[3]	Densification[4]
CV [%]	4.76	1.03	1.77	7.85
$\bar{x}$ [%]	40.02	30.12	29.82	19.73
σ^2 [%²]	3.63	0.11	0.31	3.05
$\sum \sigma^2$ [%²]	3.63	0.10	0.28	2.40
$2 \times \sum COV$ [%²]	-	0.01	0.03	0.65
Weights	-0.08	0.16	-0.25	1
k in [$/%²]	3.36	3.36	1.87	1.47
L in [$/dry tonne]	13.45	0.46	0.70	5.80

CONCLUSIONS

1. The contribution of this research is to advance the understanding and improve the estimates of costs associated with key factors in the biomass logistic supply chain. Use of cumulative variance with the Taguchi Loss Function to estimates has not been previously studied for biomass feedstocks.
2. The use of Taguchi's quality loss function (*i.e.*, nominal-the-best and smaller-the-better) in the context of Galton's theory of cumulative variance allows for a more accurate quantification of the economic impact of variation in cellulosic feedstock supplies. An improved quantification of costs of feedstock supplies reduces risk for businesses using biomass feedstocks.
3. The simulation Excel tool allows decision makers to quantify the economic loss induced by variation of the key quality characteristics and focus resources on the components in the system with the greatest variance which induce the greatest cost.

4. Future research should be conducted between the biomass industry and academic researchers to estimate the costs associated with cumulative effect of variance for key attributes of biomass (*e.g.*, ash content, moisture, etc.) using the Taguchi Loss Function in the presence of the *'scale-up effect'* from the laboratory to pilot-scale; from pilot-scale to industry scale production.

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REFERENCES CITED

Amundson, M. J. (2016). *An Economic Comparison of High Moisture Feedstock Biofuel Production*, Graduate Theses and Dissertations 15125, Iowa State University, Ames, IA.

Antony, J. (1997). "Experiments in quality," *Manufacturing Engineer* 76(6), 272-275. DOI: 10.1049/me:19970609

Bitra, V. S. P, Womac, A. R., Chevanan, N., Miu, P. I., Igathinathane, C., Sokhansanj, S., and Smith, D. R. (2009). "Direct mechanical energy measures of hammer mill comminution of switchgrass, wheat straw, and corn stover and analysis of their particle size distributions," *Powder Technology* 193(1), 32-45. DOI: 10.1016/j.powtec.2009.02.010

Dai, J., Cui, H., and Grace, J. R. (2012). "Biomass feeding for thermochemical reactors," *Progress in Energy and Combustion Science* 38(5), 716-736. DOI: 10.1016/j.pecs2012.04.002

Davison, A. C., and Hinkley, D. V. (1997). *Bootstrap Methods and their Applications,* Cambridge University Press, Cambridge, England.

Deming, W. E. (1986). *Out of the Crisis*, Massachusetts Institute of Technology, Center for Advanced Engineering Study, Cambridge, MA, USA.

Deming, W. E. (1993). *The New Economics*, Massachusetts Institute of Technology, Center for Advanced Engineering Study, Cambridge, MA, USA.

Efron, B., and Tibshirani R. J. (1993). *An Introduction to the Bootstrap,* Chapman and Hall, New York, NY.

Eggink, A., Palmer, K., Severy, M., Carter, D., and Jacobson, A. (2018). "Utilization of wet forest biomass as both the feedstock and electricity source for an integrated biochar production system," *Applied Engineering in Agriculture* 34(1), 125-134. DOI: 10.13031/aea.12404

Emery, I. R., and Mosier, N. S. (2012). "The impact of dry matter loss during herbaceous biomass storage on net greenhouse gas emissions from biofuels production," *Biomass and Bioenergy* 39, 237-246. DOI: 10.1016/j.biombioe.2012.01.004

Gomes, J., Chopda, V., and Anurag, R. (2018). "Monitoring and control of bioreactor: basic concepts and recent advances," in: *Bioprocessing Technology for Production of*

Biopharmaceuticals and Bioproducts, John Wiley & Sons, Inc. DOI: 10.1002/9781119378341.ch6

Grant, R. M., Shani, R., and Krishnan, R. (1994). "TQM's challenge to management theory and practice," *Sloan Management Review* 35(2), 25-35.

Hess, J. R., Wright, C. T., Kenney, K. L., and Searcy, E. M. (2009). *Uniform-Format Solid Feedstock Supply System: A Commodity-Scale Design to Produce an Infrastructure-Compatible Bulk Solid from Lignocellulosic Biomass-Executive Summary* (INL/EXT-09-15423), Idaho National Laboratory, Idaho Falls, USA.

Igathinathane, C., Womac, A. R., Sokhansanj, S., and Narayan, S. (2008). "Knife grid size reduction to pre-process packed beds of high- and low-moisture switchgrass," *Bioresource Technology* 99(7), 2254-2264. DOI: 10.1016/j.biortech.2007.05.046

Jacobson, J. J., Roni, M. S., Cafferty, K. G., Kenney, K., Searcy, E., and Hansen, J. (2014). *Feedstock Supply System Design and Analysis* (INL/EXT-14- 33227), Idaho National Laboratory, Idaho Falls, USA, (https://inldigitallibrary.inl.gov/sites/sti/sti/6359707.pdf).

James, A., Thring, R., Helle, S., and Ghuman, H. (2012). "Ash management review-Applications of biomass bottom ash," *Energies* 5(10), 3856-3873. DOI: 10.3390/en5103856

Keefe, R., Anderson, N., Hogland, J., and Muhlenfeld, K. (2014). "Woody biomass logistics," in: *Cellulosic Energy Cropping Systems,* D. L. Karlen (ed.), John Wiley & Sons, Ltd, Oxford, UK. DOI: 10.1002/9781118676332.ch14

Kenney, K., Cafferty, K. G., Jacobson, J. J., Bonner, I. J., Gresham, G. L., Hess, J. R., Ovard, L. P., Thompson, D. N., Thompson, V. S., Smith, W. A., Tumuluru, J. S., *et al.* (2013a). *Feedstock Supply System Design and Economics for Conversion of Lignocellulosic Biomass to Hydrocarbon Fuels* (INL/EXT-13-30342), Idaho National Laboratory, Idaho Falls, USA, (https://inldigitallibrary.inl.gov/sites/sti/sti/6013245.pdf).

Kenney, K. L., Smith, W. A., Gresham, G. L., and Westover, T. L. (2013b). "Understanding biomass feedstock variability," *Biofuels* 4(1), 111-127. DOI: 10.4155/bfs.12.83

Lacey, J. A., Emerson, R. M., Westover, T. L., and Thompson, D. N. (2016). *Ash Reduction Strategies in Corn Stover Facilitated by Anatomical and Size Fractionation* (INL/JOU-14-32946), Idaho National Laboratory, Idaho Falls, USA, (https://www.osti.gov/servlets/purl/1251419).

Langholtz, M. H., Stokes, B. J., and Eaton, L. M. (2016). *2016 Billion-ton Report: Advancing Domestic Resources for a Thriving Bioeconomy, Volume 1: Economic Availability of Feedstocks* (ORNL/TM-2016/160), U.S. Department of Energy, Oak Ridge National Laboratory, Oak Ridge, TN.

Lu, X., Withers, M. R., Seifkar, N., Field, R. P., Barrett, S. R., and Herzog, H. J. (2015). "Biomass logistics analysis for large scale biofuel production: case study of loblolly pine and switchgrass," *Bioresource Technology* 183, 1-9. DOI: 10.1016/j.biortech.2015.02.032

Metzner, C. (2018). *Strategies for Continuous Improvement and Improved Competitiveness for the Sustainable Bio-based Industries,* Master's Thesis, The University of Tennessee, Knoxville, TN, USA.

Meunier-Goddik, L., Bothwell, M., Sangseethong, K., Piyachomkwan, K., Chung, Y. C., Thammasouk, K., Tanjo, D., and Penner, M. H. (1999). "Physicochemical properties of pretreated poplar feedstocks during simultaneous saccharification and fermentation," *Enzyme and Microbial Technology* 24(10), 667-674. DOI: 10.1016/S0141-0229(99)00003-4

Miao, Z., Grift, T. E., Hansen, A. C., and Ting, K. C. (2011). "Energy requirement for comminution of biomass in relation to particle physical properties," *Industrial Crops and*

Products 33(2), 504-513. DOI: 10.1016/j.indcrop.2010.12.016
Mitchell, R., and Schmer, M. (2012). "Switchgrass harvest and storage," in: *Switchgrass, Green Energy and Technology*, A. Monti (ed.), Springer-Verlag, London. DOI: 10.1007/978-1-4471-2903-5_5
Mitchell, R., Vogel, K. P., and Uden, D. R. (2012). "The feasibility of switchgrass for biofuel production," *Biofuels* 3(1), 47-59. DOI: 10.4155/bfs.11.153
Montgomery, D. C. (2012). *Design and Analysis of Experiments* (8th Ed.), John Wiley and Sons, New York, USA.
Obernberger, I., Biedermann, F., Widmann, W., and Riedl, R. (1997). "Biomass quality for power production concentrations for inorganic elements in biomass fuels and recovery in the different ash fractions," *Biomass and Bioenergy* 12(3), 211-224. DOI: 10.1016/S0961-9534(96)00051-7
Parish, E. S., Hilliard, M. R., Baskaran, L. M., Dale, V. H., Griffiths, N. A., Mulholland, P. J., Sorokine, A., Thomas, N. A., Downing, M. E., and Middleton, R. S. (2012). "Multimetric spatial optimization of switchgrass plantings across a watershed," *Biofuels, Bioproducts and Biorefining* 6(1), 58-72. DOI: 10.1002/bbb.342
Paulitsch, M., and Barbu, M. C. (2015). *Holzwerkstoffe der Moderne,* DRW-Verlag, Leinfelden-Echterdingen.
Platzer, M. (2016). *A Simulation Model of the Bio-depot Concept in the Context of Components of Variance and the Taguchi Loss Function*, Master's Thesis, The University of Tennessee, Knoxville, TN, USA.
Rector, L. R., Allen. G., Prof. Hopke, P. K., Chandrasekaran, S. R., and Lin, L. (2013). *Elemental analysis of wood fuels,* New York State Energy Research and Development Authority, NYSERDA Report 13-13
Rentizelas, A. A., Tolis, A. J., and Tatsiopoulos, I. P. (2009). "Logistics issues of biomass: The storage problem and the multi-biomass supply chain," *Renewable and Sustainable Energy Reviews* 13(4), 887-894. DOI:10.1016/j.rser.2008.01.003
Shewhart, W. A. (1931). *Economic Control of Quality of Manufactured Product,* D. Van Nostrand Company, New York, NY.
Silva, T. A. L., da Silva, H. A., Santos, D. Q., and Rodrigues, E. C. (2014). "The use of Statistical Process Control (SPC) in the evaluation of effluent treatment in an agroindustrial plant," *Revista Virtual de Quimica* 6(2), 310-322. DOI:10.5935/1984-6835.20140022
Singha, A. S. and Thakur, V. K. (2008). "Synthesis and characterization of pine needles reinforced RF matrix based biocomposites," *E-Journal of Chemistry* 5(S1), 1055-1062. DOI: 10.1155/2008/395827
Singha, A. S. and Thakur, V. K. (2009). "Study of mechanical properties of urea-formaldehyde thermosets reinforced by pine needle power," *BioResources* 4(1), 292-308. DOI:10.1177/0021998311401102
Sjoding, D., Kanoa, E., and Jensen, P. (2013). *Developing a Wood Pellet/Densified Biomass Industry in Washington State: Opportunities and Challenges,* Washington State University, (http://www.energy.wsu.edu/portals/0/documents/Densified BiomassReport-Dec28.pdf).
Sokhansanj, S., and Turhollow, A. F. (2014). "Biomass densification-cubing operations and costs for corn stover," *Applied Engineering in Agriculture* 20(4), 495-499. DOI: 10.13031/2013.16480
Sooduck, C., and Farrey, M. (2010). *Biofuel Supply Chain Challenges and Analysis*, Master's

Thesis, Massachusetts Institute of Technology, Boston, MA.
Stigler, S. M. (2010). "Darwin, Galton and the statistical enlightenment," *Journal of the Royal Statistical Society* Series A 173(3), 469-482. DOI: 10.1111/j.1467-985X.2010.00643.x
Taguchi, G., Chowdhury, S., and Wu, Y. (2004). *Taguchi's Quality Engineering*, S. Taguchi, and H. Yano (eds.), John Wiley and Sons, Inc., Hoboken, NJ, USA.
Tao, G., Lestander, T. A., Geladi, P., and Xiong, S. (2012). "Biomass properties in association with plant species and assortments I: A synthesis based on literature data of energy properties," *Renewable and Sustainable Energy Reviews* 16(5), 3481-3506. DOI: 10.1016/j.rser.2012.02.039
Thakur, V. K. and Singha, A. S. (2011). "Physicochemical and mechanical behavior of cellulosic pine needle-based biocomposites," *International Journal of Polymer Analysis and Characterization* 16(6), 390-398. DOI: 10.1155/2009/176072
Thakur, V. K., Singha, A. S., and Thakur, M. K. (2012). "Rapid synthesis of MMA grafted pine needles using microwave radiation," *Polymer-Plastics Technology and Engineering* 51(15), 1598-1604. DOI: 10.1080/03602559.2012.721443
Thompson, D. N., Campbell, T., Bals, B., Runge, T., Teymouri, F., and Ovard, L. P. (2014). "Chemical preconversion: Application of low-severity pretreatment chemistries for commoditization of lignocellulosic feedstock," *Biofuels* 4(3), 323-340. DOI: 10.4155/bfs.13.15
Tumuluru, J. S., Tabil, L. G., Song, Y., Iroba, K. L., and Meda, V. (2014). "Grinding energy and physical properties of chopped and hammer-milled barley, wheat, oat, and canola straws," *Biomass and Bioenergy* 60, 58-67. DOI: 10.1016/j.biombioe.2013.10.011
Tumuluru, J. S., Wright, C. T., Hess, J. R., and Kenney, K. L. (2011). "A review of biomass densification systems to develop uniform feedstock commodities for bioenergy application," *Biofuels, Bioproducts and Biorefining* 5(6), 683-707. DOI: 10.1002/bbb.324
U.S. Department of Energy (DOE) (2014). *Multi-year Program Plan,* Bioenergy Technologies Office, (https://www.energy.gov/sites/prod/files/2015/01/f19/mypp_beto_november_2014_0.pdf).
Williams, C. L, Westover, T. L., Emerson, R. M., Tumuluru, J. S., and Li, C. (2016). "Sources of biomass feedstock variability and the potential impact on biofuels production," *BioEnergy Research* 9(1), 1-14. DOI: 10.1007/s12155-015-9694-y
Young, T. M., and Winistorfer, P. M. (1999). "SPC: Statistical Process Control and the forest products industry," *Forest Products Journal* 49(3), 10-16.
Young, T. M., André, N., and Otjen, J. (2014). "Quantifying the natural variation of formaldehyde emissions for wood composite panels," *Proceedings of the 3rd International Conference on Processing Technologies for the Forest and Bio-based Products Industries (PTF BPI 2014),* Kuchl/Salzburg, Austria, pp 84-85.
Young, T. M., Bond, B. H., and Wiedenbeck, J. (2007). "Implementation of a real-time statistical process control system in hardwood sawmills," *Forest Products Journal* 57(9), 54-62.

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