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Biomass Size Reduction Energy - Multiple and Generalized Regression Models Development

Igathinathane C* and Yu M

Department of Agricultural and Biosystems Engineering North Dakota State University 1231 Albrecht Boulevard Fargo ND 58102 USA

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*Corresponding author: Igathinathane C, Department of Agricultural and Biosystems Engineering North Dakota State University, Fargo ND, USA

Abstract

Developing models for biomass size reduction energy (SRE) requires an understanding of how various parameters influence the size reduction process. Moisture content, grinder parameters, mechanical properties of biomass, and particle size distribution (PSD) of the ground product are some of the parameters that are involved in the size reduction process and are expected to influence the SRE. Grinding experiments using laboratory grinders and specific SRE measurements using a clamp-on power meter were conducted on selected big bluestem, corn stover, and switchgrass, samples at different moistures using a knife mill and a hammer mill. Shear stress and the PSD of the ground biomass were measured (machine vision method). Correlation analysis was performed with various parameters and specific SRE to select the most influential parameters for SRE modeling. Using the most influential parameters ($r > 0.5$), such as moisture content (MC), screen size (SS), shear stress (ST), and uniformity index (UI), grinder-specific generalized regression models using categorical variables (4- and 3-term), as well as the most generalized model applicable both for the biomass feedstocks and grinding devices selected, were developed. All the models were compared statistically, and the best-simplified 4-parameters SRE direct regression model (R2 = 0.92) is recommended for specific SRE prediction. Among the generalized models, the grinder-specific followed by the most generalized is recommended. The outlined SRE model development methodology can be extended to more feedstocks and grinding equipment, and this finds application in process simulation and processing equipment design.

Keywords: Biomass; Categorical variables; Grinding; Pre-processing, Physical Properties, Mechanical Properties, Regression Models; Renewable Energy; Size Reduction

Abbreviations: GSTDTR: Geometric STD of Total Region; GSTDLR: Geometric STD of Lower Region; HM: Hammer Mill; KM: Knife Mill; MC: Moisture Content; PSD: Particle Size Distribution; SRE: Size Reduction Energy; SRVC: Size Range Variation Coefficient; SS: Screen Size; ST: Shear Stress; UI: Uniformity Index

Introduction

Biomass size reduction is a significant step for biomass to bioenergy conversion, which can affect the economics of the whole bioprocessing process. Corn stover (*Zea mays L.*), switchgrass (*Panicum virgatum L.*), and big bluestem (*Andropogon gerardii* Vitman) are some of the potential biomass feedstocks with the most abundant cultivated fields in the US [1]. The size reduction of biomass feedstocks employing various grinding devices was used for the production of both liquids (e.g., cellulosic ethanol) and solid biofuels as well as densified products (e.g., pellets and briquettes). The particle size and particle size distribution (PSD) influence size reduction energy (SRE). It was observed that with the increase in particle size in grinding, the SRE decreased for wheat (*Triticum aestivum L.*) straw, corn stover, and rice (*Oriza sativa L.*) straw [2]. The mono-sugar yields have increased with the decrease in particle size because small particle sizes enhance enzymatic hydrolysis. The smaller particle size of the feedstocks benefits further processing stages for the production of liquid and solid fuels, as size reduction increases the newly formed reactive surfaces [3,4]. Smaller particle size achieved by size reduction was also beneficial to biomass densification for producing pellets [5-10].

The process of size reduction consumes high energy [11], and is important to evaluate and reduce the energy involved in this pre-processing operation. To increase the SRE efficiency, the specific SRE consumption for various feedstocks by different grinders and other devices has been widely investigated. The various technologies applied to biomass size reduction have been reviewed [12]. Several researchers have studied the SRE consumption of various biomass feedstocks with different grinders. Some of these studies dealing with the grinding of biomass feedstocks and biomass pellets include: energy consumption by using a knife mill for poplar (*Populus L.*) and wood chips [13], switchgrass, wheat straw, and corn stover [14] and biomass pellets [15] and using hammer mill for alfalfa *(Medicago sativa L.)* [16] Miscanthus (Miscanthus giganteus), switchgrass, willow *(Salix babylonica L.)*, energy cane *(Saccharum spp. L.)* [17], pine wood chips [18], and biomass pellets [19].

Size reduction theories, based on the semi-empirical equations, such as Kick, Rittinger, and Bond were available to estimate the SRE [20]. These models determine the SRE requirement using parameters that were a function of the known input and output particle sizes.) Most of SRE models developed were based on only the particle size as the independent variable [21]. Different types of SRE regression models including linear, exponential, and polynomial were developed successfully [5,18,22]. Second-order polynomial models were developed to describe the SRE using grinder speed (rpm) for switchgrass, wheat straw, and corn stover in a knife mill and hammer mill [14,23-25], and to evaluate several PSD parameters from the knife mill screen size for switchgrass ground in a knife mill. The specific SRE with respect to the ratio of the initial to the final size of the screen was found to fit well in a linear model [16]. Mathematical models for PSD in grinding based on the population balance method were developed [22,26].

When the material is ground based on a particular screen size opening, the ground particle produced will have an array of sizes and the screen size will serve as only a rough indication of the actual particle size. The size reduction process produces a clear distribution of particle sizes and the parameters that represent this distribution may serve as a good factor in modelling the specific SRE consumption. The effect of the initial size of biomass, moisture content, and screen opening size on corn stover to SRE consumption was studied [27]. Energy consumed in grinding raw biomass materials is related to the toughness of the feedstock, which is one of the basic mechanical properties, as well as the other mechanical properties, such as cohesion and friction, are expected to influence the SRE [16]. Information on the mechanical stress related to SRE consumption was not reported. As to the several mechanisms involved in size reduction, shearing is the dominant action and efficient mode of operation [28-30], therefore, shear stress is an important mechanical property in the grinding process, and which is needed to be studied. In addition, biomass moisture contents are often cited as a factor influencing grinding energy consumption [5,17]. Exposure of biomass in the field or the condition in storage raises more concern about the moisture content of the feedstock and its influence on bioenergy utilization aspects [31].

Therefore, moisture content should also be included as one of the factors in modelling the SRE requirement.

No studies have reported a comprehensive selection of crop, grinder, mechanical properties, and PSD parameters and subsequent modelling for SRE. Therefore, it will be useful to develop a family of SRE models, using the most influential parameters, from that involving the most number of parameters to the most simplified involving only a few parameters, and study their performance statistically. As several biomass feedstocks and grinding devices are involved, the number of specific SRE models will increase based on the combination. It is possible to develop generalized SRE models applicable to a set of biomass feedstocks specific to a grinding device and the most generalized SRE model applicable to both biomass and grinder. For the development of generalized SRE models, categorical regression methodology can be followed, and such generalized models, applicable to SRE evaluation, have not been reported so far.

The specific objectives of this study were to (i) determine specific SRE for selected biomass (big bluestem, corn stover, and switchgrass) using two different grinders (knife mill and hammer mill) at different screen sizes (ii) determine the mechanical shear stress of biomass stems and PSD parameters of the ground biomass, (iii) develop a family of SRE regression models from the most influential parameters (most parameters to simplified with less number of parameters), (iv) develop a family of generalized models using with categorical variables (grinder specific and most general), and (v) statistically analyze the models and make recommendations for SRE prediction model selection.

Materials and Methods

Test materials collection

Big bluestem ('Bonilla' cv; seeded May 2000), corn stover (YS8002GT cv; planted May 2012, and switchgrass ('Sunburst' cv; seeded May 2008) samples were collected in mid-October from the Northern Great Plains Research Laboratory (NGPRL) USDA-ARS, Mandan, ND research field plots. Samples were harvested with a mechanical mower for big bluestem and switchgrass, but the whole corn plants were cut with a lopper from the base internode for the corn stover samples. Collected samples were made as bunches and were transported without baling and stored indoors until the experiment.

Moisture conditioning

Moisture is an important factor that influences the mechanical, handling, and size reduction properties of biomass. Thus, it is necessary to determine its effect on the size reduction. The test materials' initial moisture contents were estimated based on ASABE Standards S358.3 [32], wherein the samples were oven-dried at 103°C for 24 h, and results were expressed in dry basis. Three sub-samples of each biomass feedstock (big bluestem, corn stover, and switchgrass) were used. Starting from a uniform moisture reference material, samples of different moistures were produced by artificial conditioning by moisture addition. Although the conditioned material is technically different from the material in the green state (different growth stages), the conditioned material represents a practical feedstock used in processing. Moisture conditioning of the biomass to the required moisture content was performed by applying a calculated amount of water evenly over the materials and equilibrating them in airtight bags. Several researchers follow a similar procedure of moisture conditioning [17,33]. Starting from a dry material, the amount of water required for moisture conditioning was calculated and applied to samples. The conditioned material was kept in a sealed plastic bag at room temperature at 22 to 25°C for 72 h for moisture equilibration before size reduction [5,17]. The exact moisture after equilibration was again determined [32] and was used in the analysis.

Sample preparation for experiments

For the mechanical characteristics measurements, the leaves were removed from the biomass samples and were cut into lengths of about 127 to 152 mm (5 to 6 in). Five samples were used for the shear test. Sample preparation was similar to that followed by researchers [28,34,35]. For the size reduction experiments, the whole harvested plants with leaves were used and the biomass samples were manually chopped to the length of about 38 mm (1.5 in) for better feeding and flow through the grinders. Three samples were used for size reduction energy measurement, and each grinder used three different sieves during grinding experiments. The ground samples were collected and kept in sealed plastic bags before the PSD measurements. A well-mixed portion of the ground material was taken, from which a representative sample (a few mg) suitable for the machine-vision based PSD measurement was derived using a "cone-and-quartering" technique [36]. Three samples were used for the PSD measurement for each combination of grinder and biomass feedstock.

Size reduction performance

Overall size reduction energy modeling study experimental plan is presented in the form of a flowchart (Figure 1). The plan consists of three experiments, namely, (1) size reduction energy measurement using two different grinders, (2) mechanical characteristics (shear energy) measurement on a single stem of selected biomass, and (3) ground material PSD measurement. The results of these experiments were combined to determine the correlation of various parameters to the specific SRE and regression models were developed based on the most influential and meaningful parameters.

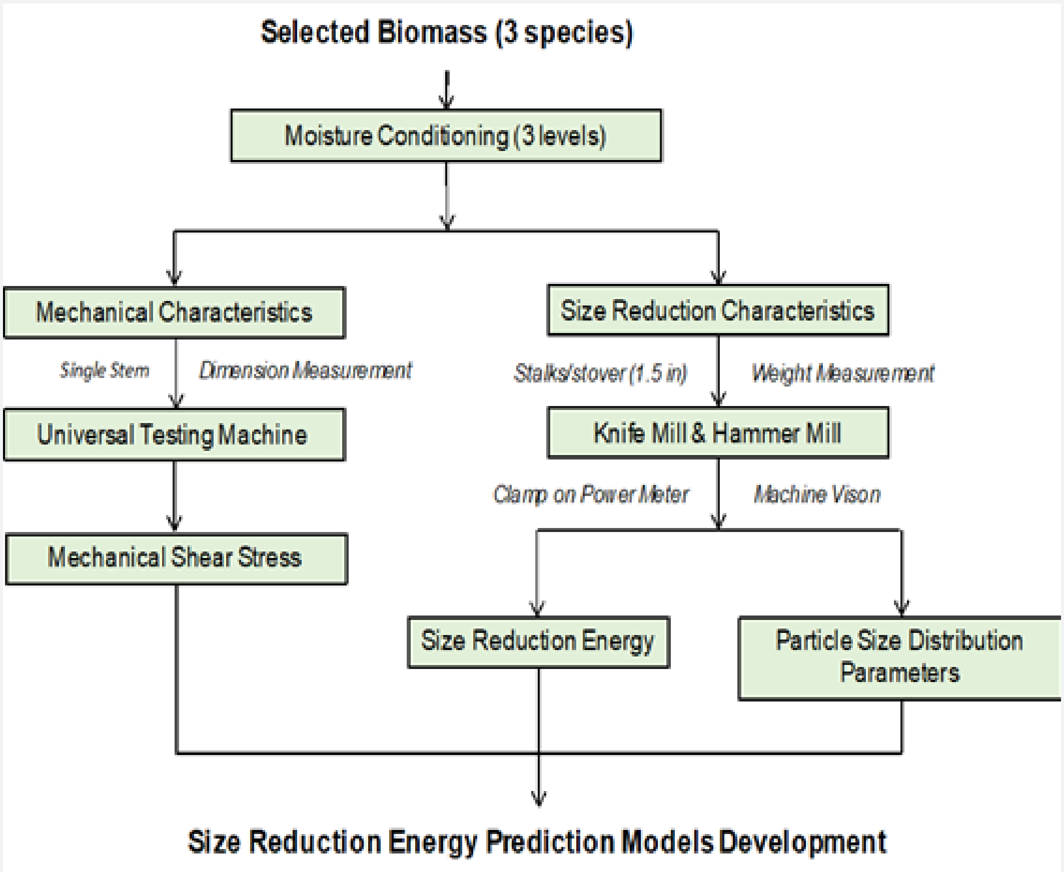

Figure 1: Flowchart of size reduction energy study experiments.

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Size reduction equipment

Knife mill (KM) and hammer mill (HM) are the commonly used size reduction equipment in the industry, and the laboratory models of these grinders were used in the experiments. A laboratory Wiley knife mill (Model 4, with a single-phase induction motor, 1 hp, 115 V, 50/60 HZ, 800 rpm, Thermo Scientific, Swedesboro, NJ, USA) fitted with the screens of 1, 3, and 6 mm was used in the study (Figure 2a). Weighed samples were fed into the grinder hopper. The amount of opening of the feed gate controlled the feeding rate of the sample. The ground sample was received in a collector attached at the bottom of the mill. The mass of the input and ground material was measured using a digital weighing scale (Model: KS-1, KTRON Arizona, Inc.) with an accuracy of 0.1 g. This knife mill allowed more residence time for the material while grinding, and the grinding was dust-free as all the components of the equipment were well sealed during operation.

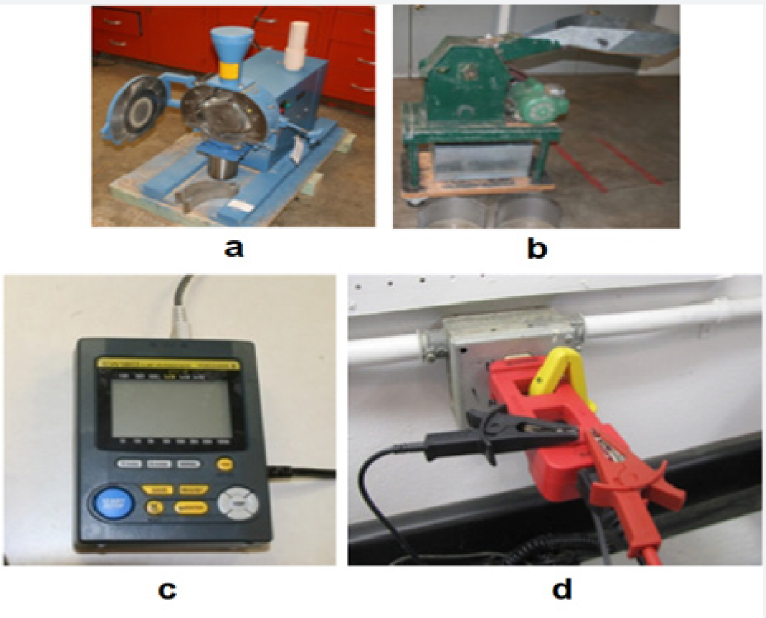
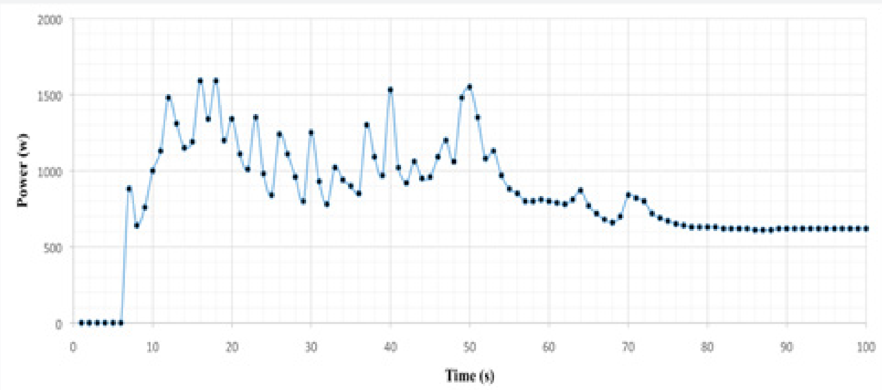


Figure 2: Equipment used in size reduction study (a) Knife mill, (b) hammer mill, (c) clamp-on power meter digital display unit, and (d) power outlet wall connection showing line splitter for electrical power measurements during size reduction experiments.



OUTPUT DATE	OUTPUT TIME	INTEG START DATE	INTEG START TIME	ELAPSED TIME	V1	V2	I1	I2	P	Q	PF	F	Wh(+)	Wh(-)
5/14/14	11:31:23	5/14/14	11:30:22	0:01:01	1.20E+02	3.98E+01	0.00E+00	5.40E+01	8.50E+02	1.97E+03	3.96E-01	6.00E+01	3.69E+01	0.00E+00
5/14/14	11:31:24	5/14/14	11:30:22	0:01:02	1.20E+02	3.99E+01	0.00E+00	5.37E+01	8.00E+02	1.98E+03	3.75E-01	6.00E+01	3.71E+01	0.00E+00
5/14/14	11:31:25	5/14/14	11:30:22	0:01:03	1.20E+02	3.99E+01	0.00E+00	5.35E+01	8.00E+02	1.98E+03	3.73E-01	6.00E+01	3.73E+01	0.00E+00
5/14/14	11:31:26	5/14/14	11:30:22	0:01:04	1.20E+02	3.98E+01	0.00E+00	5.36E+01	8.10E+02	1.98E+03	3.80E-01	6.00E+01	3.75E+01	0.00E+00
5/14/14	11:31:27	5/14/14	11:30:22	0:01:05	1.20E+02	3.99E+01	0.00E+00	5.36E+01	8.00E+02	1.98E+03	3.74E-01	6.00E+01	3.77E+01	0.00E+00

Figure 3: A typical measured electrical power showing the power variation during grinding and idle run and a sample of the collected data.

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A laboratory hammer mill (Model G, 15”, Montgomery Ward, USA, with a single-phase induction motor 1 hp, 0.75 kW, 60 Hz, 1750 rpm) fitted with 1.5875, 3.175, and 6.252 mm sieves was also used in the study (Figure 2b). Biomass samples were fed into the mill at a constant rate manually. About 2.27 kg (5 lb) of each selected biomass was fed to the mill at a fixed rate matching the grinding rate of the hammer mill. The ground biomass samples with different screen sizes were collected and weighed. Unlike the knife mill, the hammer mill grinder presented relatively less residence time for the material in the grinding chamber, which allowed for partially ground biomass also to fall through the screen.

Size reduction energy measurement

A clamp-on power meter (Model: CW120, YOKOGWA, Melrose, MA, USA) was used to measure the continuous stream of power consumed by the grinder indirectly measuring the flow of electrical energy (Figure 2c). The instantaneous grinding power was measured through the electric energy (watt-hour, Wh) data derived from voltage and amperage. A line splitter (Fluke ELS2A Outlet Line Splitter; 120 Volt, 15 Amp, Wilmington, NC, USA) was attached to the single-phase electrical power outlet, and the power card of the grinder was attached to the line splitter (Figure 2d). The digital display unit of the clamp-on power meter was separately powered. The yellow clamp attached to the line splitter measured the current flow (ampere) and black and red alligator clips measured voltage shown in a digital display unit. The wiring was carried out according to the single “three-phase” connections shown in the power meter.

On the digital meter, settings for wiring method (1ø2W – read as a single-phase two-wire, 1ø3W, 3ø3W, 3ø4W) voltage range (150V, 300V, and 450V) and current ranges (5A, 10A, 20A, 50A, 100A, 200A, 500A and 1000A) were appropriately selected (1ø2W; 150V; 20A) to avoid overloading. Measurements were made with grinder running without any material to determine the “no-load” characteristics. Regular size reduction experiments with samples were then performed at the desired feed rate and power measurements were made for all the grinder and biomass combinations. Power measurement data were saved at 1s intervals on a memory PC card. The data was later transferred from the memory card to the computer for data analysis. A typical sample measurement output plot of power (W) with respect to time (s) along with raw textual data during grinding from the power meter is shown in Figure 3.

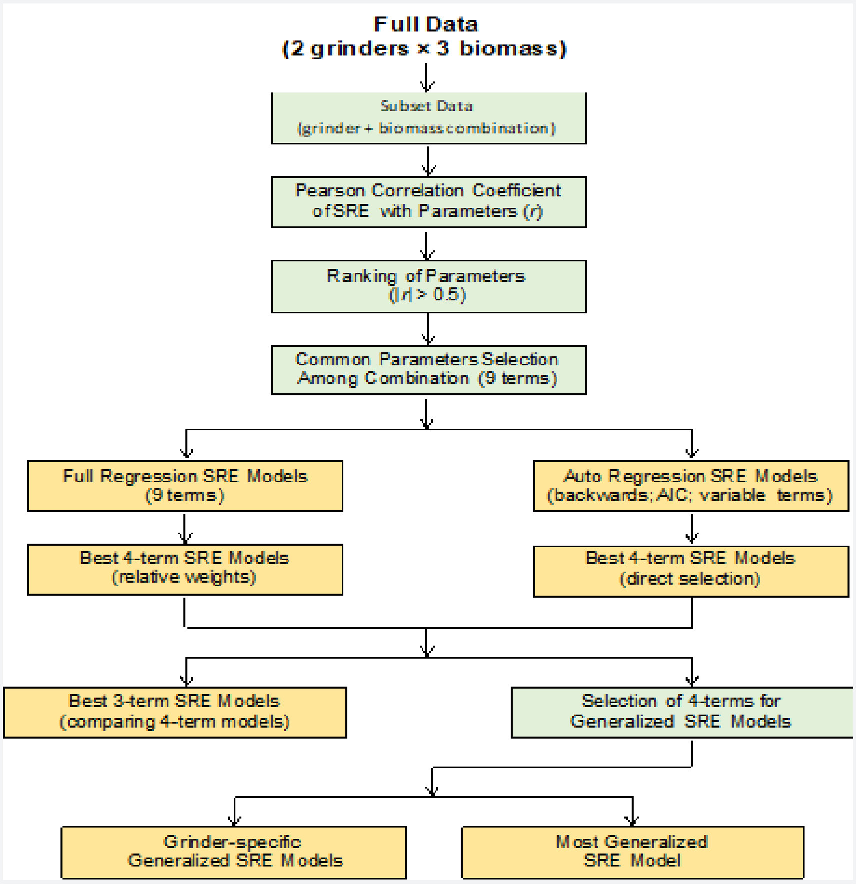

Figure 4: Flowchart of various specific size families of reduction energy (SRE) models development.

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The area under this power-time curve gives the energy consumed during grinding, which is also obtained from the sum of all power data (P derived from V2 and I2) multiplied by the total elapsed time of interest (Figure 3). The idle run (no-load) power was represented by the relatively flat variation around 600 W. The collected energy data will be in watts-hour (Wh) and the specific energy is calculated by dividing this by the amount of ground product (g) collected as Wh g^{-1}. The size reduction energy thus measured is expressed as the energy consumed per unit mass of the ground material with standard units of kJ kg^{-1}, for further calculations and reporting. The effective specific size reduction energy was obtained as a difference between the total power with load and no-load power measurements and this procedure was followed by several researchers [23,25,37,38].

Biomass mechanical characteristics and ground biomass PSD

Shear stress is a mechanical property that is characteristic of the biomass, hence considered an influential biomass property for modelling the SRE. The shear stress experiments were performed using the same method with the universal testing system (UTM) as outlined elsewhere [39]. The shear stress for corn stalks were based on the whole cross-section area, whereas for big bluestem or switchgrass the cross-section was hollow. The PSD of the selected biomass feedstocks generated by the knife mill and the hammer mill were determined through an image processing technique. The representative ground samples PSD were studied utilizing ΣVolume machine vision approach through a developed ImageJ plugin [36]. In this method, a regular document scanner (CanoScan 8800F, Canon, Melville, NY), at a high-resolution section of 1270 DPI, was used for capturing color digital images of the samples. An alternative user-friendly method for the PSD determination is using the ASABE Standard [40]. Particle sizes and PSD produced depended on the type of biomass, grinder, and other operating conditions. The plugin produced several particle size and PSD parameters, which are used in the correlation analysis and regression model development. A brief definition and description of the various PSD parameters are found elsewhere [41].

Methodology of SRE models development

The specific SRE models were developed following the methodology shown in Figure 4. Overall, the correlation of SRE with various biomass, grinder, mechanical characteristics, and PSD of ground material parameters were studied, the influential parameters were extracted, and various family of models was developed using linear regression. For the statistical analysis, R programs [42] were developed and utilized. As the number of variables considered in the regression, the most correlated variables to SRE (starting with 9 terms) were selected and progressively simpler regression models were developed.

In the methodology (Figure 4), one family of models called "Full Regression SRE Models" use the highly correlated 9 terms and develops the regression models (R function: lm), involving only the first order terms without interaction (6 models) using and their performances were reported as R^2 and adjusted R^2. To derive simplified models with the most influential 9 variables, a relative weights analysis [43,44] was performed. The relative weights ranked all 9 predictor variables based on their contribution to the model's R^2 (R function: relweights), and the most common high-ranking variables were selected for the simpler 4-term regression models. The second family of models called "Auto-Regression SRE Models" uses the 9 terms and determines the best significant model, with the least number of terms, using a backward stepwise linear regression (R function: step with lm) based on Akaike information criterion (AIC). A model with the lower AIC value was considered the best model among the set of models tested. These auto models will result in a variable number of terms, based on the significance of the terms, and linear regression was again run to estimate the coefficients and model performance.

Generalized grinder-specific and most generalized SRE model development

A model capable of predicting the SRE for the selected biomass, using the biomass as an independent variable, will be compact and useful. Such a generalized model was developed using linear regression with categorical variables. Considering a categorical variable (sometimes referred as dummy variable), say DC, for the three selected biomass, where DC equals 0, 1, and 2 represents big bluestem, corn stalks, and switchgrass, respectively. Along with the selected independent variables (V1 through V4), the crop-based categorical variable DC will make the generalized model specific to a grinder as follows:

SRE = f (V1, V2, ...Vn, DC) (1)

Simple linear regression procedure (R function: lm) was again used for this generalized model development after suitably categorizing the biomass variable names (DC) with numerical values and sub setting the data. Extending the analogy, the most generalized model that used biomass and grinders as categorical variables will be in the most compact form. Such most generalized model will represent six (3 biomass x 2 grinders) of the specific SRE models. Considering a categorical variable to represent the grinder, say DM, where DM = 0 represents hammer mill and DM = 1 represents knife mill. With the selected dependent variables (V1 through V4), and the DC (crop-based) and DM (grinder-based) categorical variables the most generalized SRE model suitable for any biomass or grinder, again derived from linear regression is given as:

SRE = f (V1, V2, ...Vn, DC, DM) (2)

Models comparison statistical analysis

Performance of the various groups of models (e.g., 9-term, 4-term, 3-term, and generalized categorical) was compared using their performance measures, such as R^2 and adjusted R^2 (penalizing more variables), subjecting to Duncan's new multiple-range test

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[45] from the R package agricolae. Each group of models except the generalized models will have six models representing their grinder and biomass combination. For generalized models, which will be a single model representing a particular grinder or the most general for both grinders, the replications were simulated from the observed performance of the respective models and an assumed average standard deviation derived from the other models. The mean separation test with α = 0.05, will help select the best model based on statistically significant difference among them.

Results and Discussion

Specific SRE of biomass ground in knife mill and hammer mill

Measured specific SRE was inversely proportional to the size of both knife mill screens (1, 3, and 6 mm) and the hammer mill screens (1.5875, 3.175, and 6.252 mm) for the selected biomass at the studied range of moistures (Figure 5). Overall, with the knife mill, the SRE was the highest for switchgrass followed by corn stover and big bluestem, while with the hammer mill the trend was opposite and the curves intersect around the 3 mm. Knife mill-specific SRE is lower than hammer mill SRE. The lower SRE of the knife mill may be attributed to the efficient size reduction mechanism of shear in the knife mill as opposed to the impact in the hammer mill. The specific SRE for both grinders increased as moisture content increased. A similar trend of increase in specific SRE with moisture content was also observed by others for bermudagrass *(Cynodon dactylon L.)* [46], for wheat, barley *(Hordeum vulgare L.)*, corn stover, and switchgrass [5], and canola stem [47]. However, an opposite trend was observed for sugarcane [48].

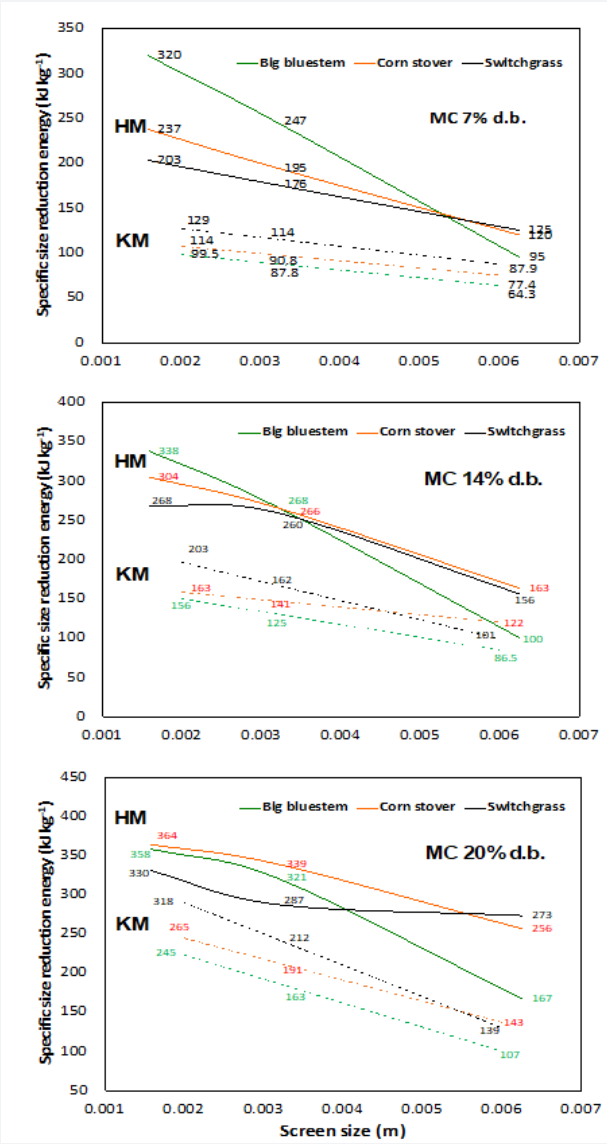

Figure 5: Specific SRE at different screen size for knife mill (KM) and hammer mill (HM) with different biomass and moisture contents.

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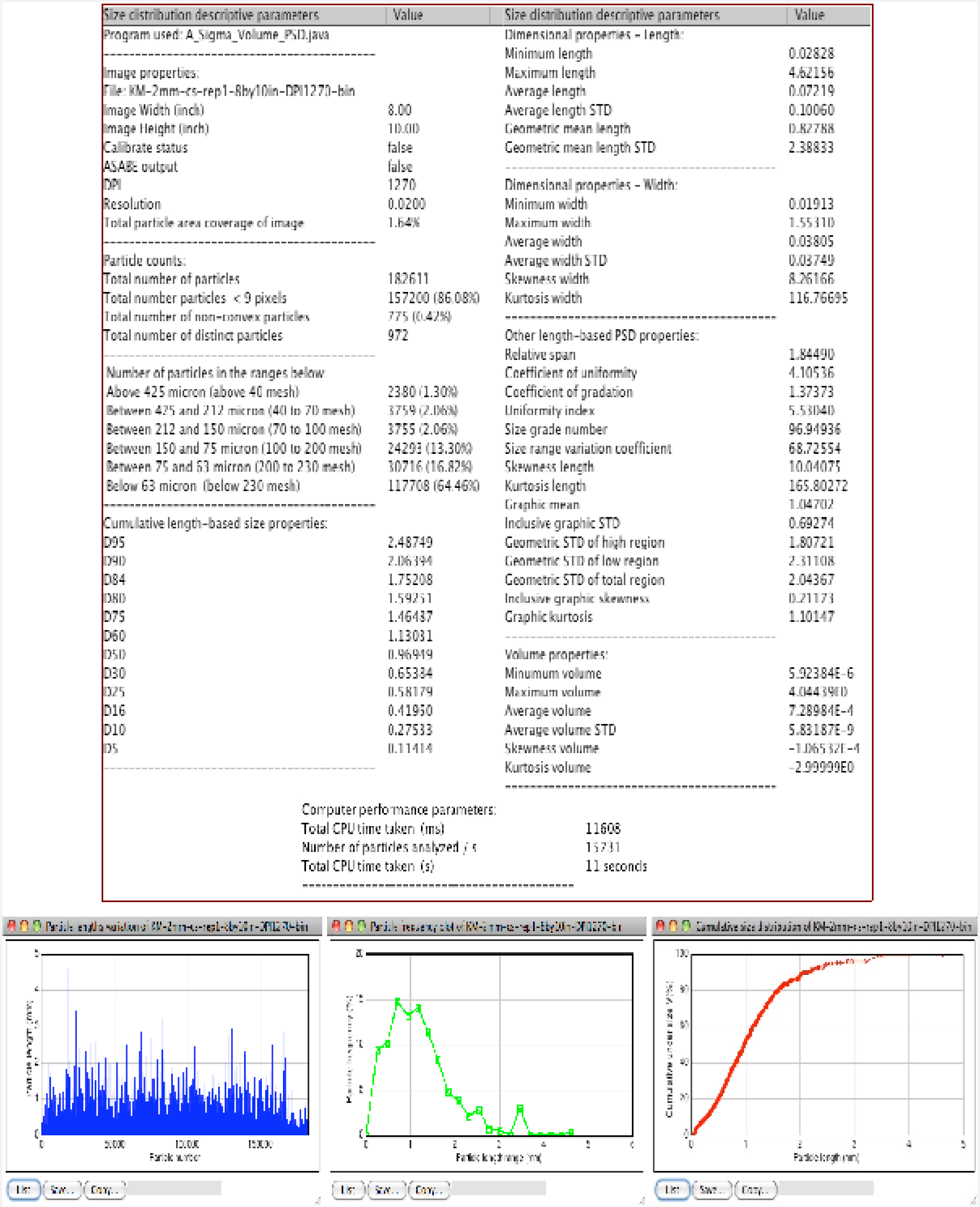
Ground biomass machine-vision of PSD outputs

The scanned images had a 0.02 mm measurement accuracy (1270 DPI). The PSD plugin analysed over 15000 particles per second and the total CPU time taken is about 11 s and outputs the results in textual and graphical forms (Figure 6). The PSD results in combination with the other grinder, biomass, and mechanical properties formed the full data.



Size distribution descriptive parameters	Value	Size distribution descriptive parameters	Value
Program used: A_Sigma_Volume_PSD.java		Dimensional properties - Length:	
---		Minimum length	0.02828
Image properties:		Maximum length	4.62156
File: KM-2mm-cs-rep1-8by10in-DPI1270-bin		Average length	0.07219
Image Width (inch)	8.00	Average length STD	0.10060
Image Height (inch)	10.00	Geometric mean length	0.82788
Calibrate status	false	Geometric mean length STD	2.38833
ASABE output	false	---	
DPI	1270	Dimensional properties - Width:	
Resolution	0.0200	Minimum width	0.01913
Total particle area coverage of image	1.64%	Maximum width	1.55310
---		Average width	0.03805
Particle counts:		Average width STD	0.03749
Total number of particles	182611	Skewness width	8.26166
Total number particles < 9 pixels	157200 (86.08%)	Kurtosis width	116.76695
Total number of non-convex particles	775 (0.42%)	---	
Total number of distinct particles	972	Other length-based PSD properties:	
---		Relative span	1.84490
Number of particles in the ranges below		Coefficient of uniformity	4.10536
Above 425 micron (above 40 mesh)	2380 (1.30%)	Coefficient of gradation	1.37373
Between 425 and 212 micron (40 to 70 mesh)	3759 (2.06%)	Uniformity index	5.53040
Between 212 and 150 micron (70 to 100 mesh)	3755 (2.06%)	Size grade number	96.94936
Between 150 and 75 micron (100 to 200 mesh)	24293 (13.30%)	Size range variation coefficient	68.72554
Between 75 and 63 micron (200 to 230 mesh)	30716 (16.82%)	Skewness length	10.04075
Below 63 micron (below 230 mesh)	117708 (64.46%)	Kurtosis length	165.80272
---		Graphic mean	1.04702
Cumulative length-based size properties:		Inclusive graphic STD	0.69274
D95	2.48749	Geometric STD of high region	1.80721
D90	2.06394	Geometric STD of low region	2.31108
D84	1.75208	Geometric STD of total region	2.04367
D80	1.59251	Inclusive graphic skewness	0.21173
D75	1.46437	Graphic kurtosis	1.10147
D60	1.13031	---	
D50	0.96949	Volume properties:	
D30	0.65334	Minumum volume	5.92384E-6
D25	0.58179	Maximum volume	4.04439E0
D16	0.41950	Average volume	7.28984E-4
D10	0.27533	Average volume STD	5.83187E-9
D5	0.11414	Skewness volume	-1.06532E-4
---		Kurtosis volume	-2.99999E0

Computer performance parameters:	
Total CPU time taken (ms)	11608
Number of particles analyzed / s	15731
Total CPU time taken (s)	11 seconds

Figure 6: Sample textual and graphical outputs generated by the PSD plugin showing various results (mm or mm3) of analysis and performance parameters for corn stalks process in knife mill (2 mm screen).

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Correlation of specific SRE with other parameters

The actual Pearson's correlation coefficients of the specific SRE with other moisture, mechanical, and PSD parameters of grinder and biomass combinations are presented in Table 1. In general, the moisture content, mechanical shear stress, and uniformity index are positively correlated to specific SRE, while the particle size-based parameters were negatively correlated. Thus, predominantly the parameters were negatively correlated with specific SRE with variation depending on the type of parameters.

Table 1: Pearson's correlation coefficients of the specific SRE with other size reduction experimental parameters.

Parameter	Big bluestem	Knife mill Corn stover	Switchgrass	Big bluestem	Hammer mill Corn stover	Switchgrass
SRE	1	1	1	1	1	1
MC	0.687	0.802	0.674	0.257	0.796	0.807
SS	-0.608	-0.471	-0.625	-0.955	-0.459	-0.534
ST	0.611	-0.556	0.673	0.207	-0.513	0.806
GM	-0.371	-0.107	-0.416	-0.906	-0.005	-0.354
UI	0.732	0.71	0.617	-0.552	0.281	-0.441
D95	-0.498	-0.257	-0.545	-0.814	-0.034	-0.079
D90	-0.463	-0.262	-0.511	-0.867	-0.038	-0.246
D84	-0.518	-0.262	-0.499	-0.866	-0.063	-0.276
D80	-0.5	-0.247	-0.486	-0.877	-0.097	-0.258
D75	-0.488	-0.228	-0.467	-0.896	-0.116	-0.229
D60	-0.443	-0.181	-0.435	-0.91	-0.086	-0.296
D50	-0.413	-0.145	-0.422	-0.91	-0.018	-0.415
D30	-0.337	-0.065	-0.379	-0.915	0.058	-0.402
D25	-0.305	-0.033	-0.361	-0.908	0.054	-0.421
D16	-0.232	0.019	-0.31	-0.893	0.095	-0.441
D10	-0.133	0.079	-0.242	-0.883	0.141	-0.446
D5	-0.01	0.15	-0.147	-0.768	0.146	-0.41
MaxL	-0.524	-0.238	-0.526	-0.779	-0.192	-0.164
AvgL	0.54	0.723	0.049	0.391	-0.126	0.053
AvgLstd	0.115	0.554	-0.189	-0.78	-0.207	-0.361
GMLstd	-0.646	-0.72	-0.481	0.503	-0.278	0.397
AvgW	0.662	0.715	0.211	0.277	-0.022	0.319
AvgWstd	0.447	0.68	0.256	0.183	-0.149	0.13
SkewW	-0.696	-0.451	-0.384	-0.84	0.275	-0.37
KurtW	-0.63	-0.386	-0.432	-0.851	0.311	-0.329
RS	-0.66	-0.57	-0.587	0.585	0.061	0.382
CU	-0.577	-0.623	-0.454	0.589	-0.517	0.266
CG	-0.345	-0.355	-0.247	-0.249	-0.125	0.021
SGN	-0.413	-0.145	-0.423	-0.91	-0.018	-0.415
SRVC	-0.763	-0.677	-0.539	0.654	-0.053	0.32
SkewL	-0.528	-0.453	-0.396	-0.834	0.078	-0.299
KurtL	-0.295	-0.31	-0.27	-0.767	0.097	-0.116
GraMean	-0.453	-0.181	-0.459	-0.893	-0.03	-0.345
Igstd	-0.559	-0.34	-0.557	-0.847	-0.076	-0.139
GstdHR	-0.713	-0.634	-0.509	0.621	0.028	0.277

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GstdLR	-0.642	-0.632	-0.45	0.629	-0.506	0.244
GstdTR	-0.741	-0.676	-0.525	0.713	-0.367	0.36
IGS	-0.489	-0.367	-0.501	0.653	0.082	0.362
Gkurt	-0.143	0.002	-0.383	0.269	0.214	0.255
MaxV	-0.43	-0.188	-0.527	-0.805	-0.09	-0.13

Note: For definitions and formulas of the listed PSD parameters Igathinathane et al. [41] may be referred. Data indicate the means of three moisture contents studied.

Selection of parameters for specific SRE model development

The overall selection of influential parameters based on correlation coefficients will be easily accomplished through absolute values and ranking, rather directly from the actual values (Table 1). Increase values of r, either positive or negative correlation, are important in influencing the SRE, which can be easily collected by absolute values (|r|). Therefore, the absolute and ranked correlation coefficients of specific SRE with other parameters with $r > 0.5$ clearly depicted by gray shading of parameters with $r < 0.5$ for easy selection are presented in Table 2. From the results, it can be observed that several parameters with $r > 0.5$ indicate that the specific SRE is well correlated with these parameters. It can be seen that the list and ranking of the parameters for the six combinations of grinder and biomass were different. However, some of the parameters were common among the combinations.

Table 2: Ranked absolute Pearson's correlation coefficients of size reduction energy with other parameters (r < 0.5 in gray).

Knife mill						Hammer mill					
Big bluestem		Corn stover		Switchgrass		Big bluestem		Corn stover		Switchgrass	
Parameter	|r|	Parameter	|r|	Parameter	|r|	Parameter	|r|	Parameter	|r|	Parameter	|r|
SRVC	0.763	MC	0.802	MC	0.674	SS	0.955	MC	0.796	MC	0.807
GstdTR	0.741	AvgL	0.723	ST	0.673	D30	0.915	CU	0.517	ST	0.806
UI	0.732	GMLstd	0.72	SS	0.625	SGN	0.91	ST	0.513	SS	0.534
GstdHR	0.713	AvgW	0.715	UI	0.617	D50	0.91	GstdLR	0.506	D10	0.446
SkewW	0.696	UI	0.71	RS	0.587	D60	0.91	SS	0.459	D16	0.441
MC	0.687	AvgWstd	0.68	Igstd	0.557	D25	0.908	GstdTR	0.367	UI	0.441
AvgW	0.662	SRVC	0.677	D95	0.545	GM	0.906	KurtW	0.311	D25	0.421
RS	0.66	GstdTR	0.676	SRVC	0.539	D75	0.896	UI	0.281	D50	0.415
GMLstd	0.646	GstdHR	0.634	MaxV	0.527	GraMean	0.893	GMLstd	0.278	SGN	0.415
GstdLR	0.642	GstdLR	0.632	MaxL	0.526	D16	0.893	SkewW	0.275	D5	0.41
KurtW	0.63	CU	0.623	GstdTR	0.525	D10	0.883	Gkurt	0.214	D30	0.402
ST	0.611	RS	0.57	D90	0.511	D80	0.877	AvgLstd	0.207	GMLstd	0.397
SS	0.608	ST	0.556	GstdHR	0.509	D90	0.867	MaxL	0.192	RS	0.382
CU	0.577	AvgLstd	0.554	IGS	0.501	D84	0.866	AvgWstd	0.149	SkewW	0.37
Igstd	0.559	SS	0.471	D84	0.499	KurtW	0.851	D5	0.146	IGS	0.362
AvgL	0.54	SkewL	0.453	D80	0.486	Igstd	0.847	D10	0.141	AvgLstd	0.361
SkewL	0.528	SkewW	0.451	GMLstd	0.481	SkewW	0.84	AvgL	0.126	GstdTR	0.36
MaxL	0.524	KurtW	0.386	D75	0.467	SkewL	0.834	CG	0.125	GM	0.354
D84	0.518	IGS	0.367	GraMean	0.459	D95	0.814	D75	0.116	GraMean	0.345
D80	0.5	CG	0.355	CU	0.454	MaxV	0.805	KurtL	0.097	KurtW	0.329
D95	0.498	Igstd	0.34	GstdLR	0.45	AvgLstd	0.78	D80	0.097	SRVC	0.32
IGS	0.489	KurtL	0.31	D60	0.435	MaxL	0.779	D16	0.095	AvgW	0.319
D75	0.488	D84	0.262	KurtW	0.432	D5	0.768	MaxV	0.09	SkewL	0.299
D90	0.463	D90	0.262	SGN	0.423	KurtL	0.767	D60	0.086	D60	0.296
GraMean	0.453	D95	0.257	D50	0.422	GstdTR	0.713	IGS	0.082	GstdHR	0.277

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AvgWstd	0.447	D80	0.247	GM	0.416	SRVC	0.654	SkewL	0.078	D84	0.276
D60	0.443	MaxL	0.238	SkewL	0.396	IGS	0.653	Igstd	0.076	CU	0.266
MaxV	0.43	D75	0.228	SkewW	0.384	GstdLR	0.629	D84	0.063	D80	0.258
D50	0.413	MaxV	0.188	Gkurt	0.383	GstdHR	0.621	RS	0.061	Gkurt	0.255
SGN	0.413	GraMean	0.181	D30	0.379	CU	0.589	D30	0.058	D90	0.246
GM	0.371	D60	0.181	D25	0.361	RS	0.585	D25	0.054	GstdLR	0.244
CG	0.345	D5	0.15	D16	0.31	UI	0.552	SRVC	0.053	D75	0.229
D30	0.337	D50	0.145	KurtL	0.27	GMLstd	0.503	D90	0.038	MaxL	0.164
D25	0.305	SGN	0.145	AvgWstd	0.256	AvgL	0.391	D95	0.034	Igstd	0.139
KurtL	0.295	GM	0.107	CG	0.247	AvgW	0.277	GraMean	0.03	MaxV	0.13
D16	0.232	D10	0.079	D10	0.242	Gkurt	0.269	GstdHR	0.028	AvgWstd	0.13
Gkurt	0.143	D30	0.065	AvgW	0.211	MC	0.257	AvgW	0.022	KurtL	0.116
D10	0.133	D25	0.033	AvgLstd	0.189	CG	0.249	SGN	0.018	D95	0.079
AvgLstd	0.115	D16	0.019	D5	0.147	ST	0.207	D50	0.018	AvgL	0.053
D5	0.01	Gkurt	0.002	AvgL	0.049	AvgWstd	0.183	GM	0.005	CG	0.021

Note: Frequency of $r > 0.5$: MC(5), ST(5), SS (4),UI(4), RS(4), CU(4), SRVC(4), GstdTR(4), GstdLR(4), GMLstd(3), GstdHR(3), Igstd(3) - The first 9 (out of 12) were used in the models development. Data indicate the means of three moisture contents studied.

Even though the highly correlated parameters for individual combinations were different, it will be useful to identify the common variables and develop SRE models based on them. A simple frequency of the most common parameters among the six combinations was obtained (Table 2 footnote). It is interesting to note that the moisture content (MC), ranked first in 4 out of 6 combinations, and the shear stress mechanical (ST) property of the biomass had the highest frequency of 5 out of 6 combinations. The next group of 7 parameters that had a frequency of 4 out of 6 are screen size (SS), uniformity index (UI), relative span (RS), coefficient of uniformity (CU), size range variation coefficient (SRVC), geometric STD of total region (GSTDTR), and geometric STD of low region (GSTDLR). Considering only $r > 0.5$, the average $|r|$ of the two high-frequency parameters (MC, ST) was 0.693, for the next group of 7 parameters (SS, UI, RS, CU, SRVC, GSTDTR, and GSTDLR) was 0.634, and overall these 9 parameters (MC, ST, SS, UI, RS, CU, SRVC, GSTDTR, and GSTDLR) were 0.649, which shows their strength of correlation with SRE. The less frequent terms (≤ 3) were not considered in the model development. Thus, these total 9 parameters were used in the full and auto-regression model development.

The 9-term specific SRE models used all the terms in the regression. The auto-regression specific SRE models, developed to eliminate the insignificant terms based on AIC, made the models as compact as possible without compromising the performance. In each combination, the auto-regression models had a variable number of terms (3 to 7) after elimination and on average had 5 terms, which is an elimination of 4 parameters. However, the auto-regression models also had good predictions similar to the full model with R^2 in the range between 0.87 and 0.99. In addition, the adjusted R^2 showed an improvement with values ranging from 0.8 to 0.99, and this improvement in performance is expected as the adjusted R^2 penalizes models with an increased number of terms and overfitting. Overall, based on the mean R^2 value of the combination of 6 models (not shown), the auto-regression models had 0.931±0.043 comparable to 0.934±0.043 of the full 9-term models, but the adjusted R^2 had 0.913 which is a little improvement over 0.899 of the full models. Hence, in general, when possible, it can be recommended that the auto-regression models, which use fewer and the most significant parameters, is recommended for SRE predictions when the values of the necessary parameters are available. This set of models will help in selecting the best parameters for the simpler models.

Simplified 4-term specific SRE model development

Simplified specific SRE models using only 4 parameters were selected from each group of models (full and auto-regression) following the methodology outlined in the flowchart (Figure 4). Different strategies were followed to obtain the most significant 4 terms from each group of models. A simple frequency analysis from the group of full (9-term) specific SRE models was not possible as this group features all the 9 parameters. Thus, a relative weight analysis [43,44] determining the relative importance of the SRE predictor variables was performed (Figure 7). The ranking among the selected 9 parameters and the parameter's relative contribution to the total R^2 in the six grinders and biomass combination can be easily visualized from the relative analysis plot. It can also be observed that a few top-ranking (e.g., SS, MC, ST) parameters contribute more than the others, in other words, about 6 out of 9 parameters have < 10% contributions individually to the total R^2 (Figure 7).

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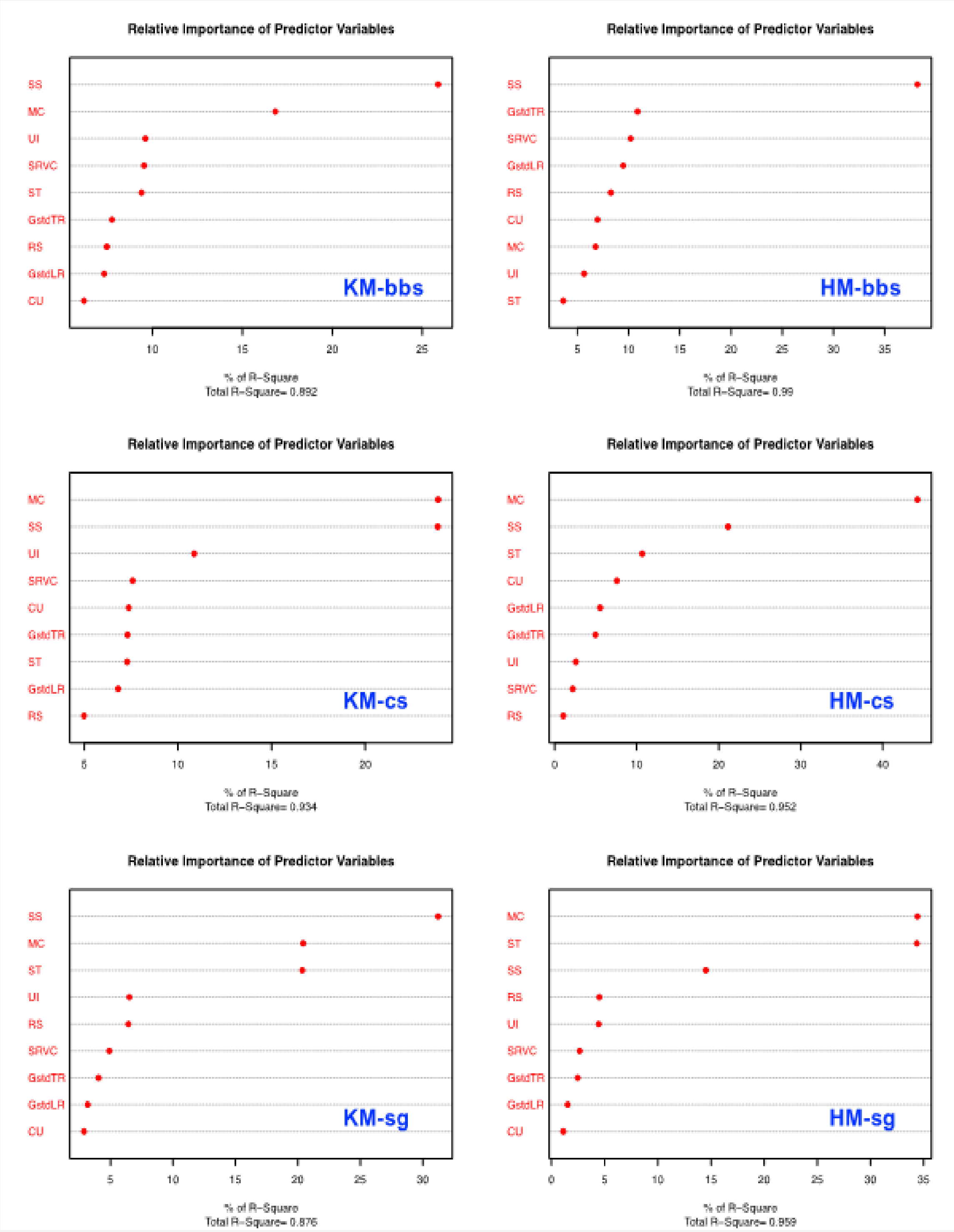

Figure 7: Correlation plot of selected parameters for specific SRE modeling showing the variation among types of grinder and biomass tested. KM – knife mill, HM – hammer mill, bbs – big bluestem, cs – corn stover, and sg – switchgrass.

To select the best 4 parameters, the frequency of parameters based on the three top-ranked relative weights in the grinder and biomass combination was considered (Table 3). The frequencies of these three top-ranked parameters (shown in parenthesis) were: SS (6), MC (5), ST (3), UI (2), GSTDTR (1), and SRVC (1). The best 4 parameters selected for the simplified models from the full model category, based on their increased frequency, were: MC, SS, ST, and UI. The simplified (4-term) specific SRE models,

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from the group of full models, based on the selected parameters using relative weights are presented in Table 4. These simplified (4-term) models gave good SRE predictions with R^2 in the range between 0.87 and 0.99 (Adj. R^2: 0.84 to 0.98), considering fewer of parameters. Among the 4 parameters, the contribution of UI was the least, as the absolute value of its coefficient < 6.5 compared to the next SS > 14.8 (Table 4). Overall, the mean R^2 of all the combinations of 6 models was 0.917±0.049, and the mean adjusted R^2 was 0.901±0.057, which substantiates the good performance of the simplified models.

Table 3: Ranked relative weights (% or R^2) of the 9-terms based on full model for simplified 4-term model SRE selection (rank > 3 in gray).

Knife Mill						Hammer Mill					
Big Bluestem		Corn Stover		Switchgrass		Big Bluestem		Corn Stover		Switchgrass	
SS	25.886	MC	23.891	SS	31.23	SS	38.201	MC	44.229	MC	34.413
MC	16.836	SS	23.872	MC	20.423	GstdTR	10.867	SS	21.132	ST	34.357
UI	9.609	UI	10.875	ST	20.358	SRVC	10.2	ST	10.673	SS	14.52
SRVC	9.535	SRVC	7.585	UI	6.519	GstdLR	9.46	CU	7.586	RS	4.502
ST	9.394	CU	7.375	RS	6.444	RS	8.265	GstdLR	5.541	UI	4.436
GstdTR	7.753	GstdTR	7.307	SRVC	4.91	CU	6.953	GstdTR	4.977	SRVC	2.655
RS	7.468	ST	7.293	GstdTR	4.049	MC	6.775	UI	2.587	GstdTR	2.472
GstdLR	7.317	GstdLR	6.812	GstdLR	3.174	UI	5.651	SRVC	2.208	GstdLR	1.525
CU	6.202	RS	4.991	CU	2.893	ST	3.628	RS	1.067	CU	1.121

Note: Frequency of 3 top-ranked relative weights: SS - screen size (6), MC - moisture content (5), ST - shear stress (3), UI - uniformity index (2), GstdTR - geometric STD of total region (1), and SRVC - size range variation coefficient (1). Data indicate the means of three moisture contents studied.

Table 4: Developed simplified size reduction energy models using selected parameters (4-term) from full and automatic backward regression family of models.

Type	Grinder	Crop	Model	R^2	AdjR^2R2
Simplified 4-term models from relative weights of the full model parameters	Knife Mill	Big blue-stem	SRE = 308.019 + 865.292 MC - 16.445 SS - 40.537 ST + 1.915 UI	0.865	0.84
		Corn stover	SRE = -63.6618 + 688.5365 MC -14.874 SS + 48.0305 ST + 2.6880 UI	0.903	0.885
		Switchgrass	SRE = 16123.621 + 209.411 MC - 27.652SS - 377.423 ST - 1.902 UI	0.864	0.839
	Hammer Mill	Big blue-stem	SRE = 573.4361+873.9211 MC - 47.6839SS - 41.1975 ST + 0.4083 UI	0.987	0.984
		Corn stover	SRE= -1474.415 +2006.703 MC - 22.221 SS + 547.183 ST + 6.538 UI	0.935	0.923
		Switchgrass	SRE = 6466.764 + 8890.914 MC - 15.137SS - 543.984 ST - 1.847 UI	0.946	0.937
Mean				0.917	0.901
(STD)				-0.049	-0.057
Simplified 4-term models from auto-regression model parameters (r > 0.5)	Knife Mill	Big blue-stem	SRE = 351.975 + 873.558 MC - 17.720 SS -33.832 ST - 28.863 GstdLR	0.859	0.833
		Corn stover	SRE = -96.627 + 802.485 MC - 15.110 SS + 96.827 ST - 39.261 GstdLR	0.89	0.87
		Switchgrass	SRE = 15266.889 + 199.425 MC - 26.535 SS -1310.690 ST + 28.569 GstdLR	0.863	0.838
	Hammer Mill	Big blue-stem	SRE = 555.943 + 907.154 MC - 46.015 SS - 43.167 ST + 7.699 GstdLR	0.988	0.985
		Corn stover	SRE = -897.732 + 1922.930 MC - 20.815 SS + 346.243 ST + 7.033 GstdLR	0.913	0.897
		Switchgrass	SRE = 8137.780 + 10982.426 MC - 17.975SS -687.924 ST - 1.898 GstdLR	0.941	0.931
Mean				0.909	0.892
(STD)				-0.05	-0.058

Note: SRE - size reduction energy, MC - moisture content, SS - screen size, ST - shear stress, UI - uniformity index, and GstdTR - geometric STD of lower region (auto-regression introduced).

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A simple frequency analysis from the group of auto-regression (average 5-term) specific SRE models was possible to select the simplified (4-term) models. The simple frequency analysis of the auto-regression model parameters (Table 2) gave the following frequency (shown in parenthesis) for the parameters: MC (6), SS (6), ST (5), GSTDLR (4), GSTDTR (3), SRVC (2), UI (2), RS (1), and CU (1). Thus, the high-frequency 4 parameters selected for the simpler (4-term) model in the auto-regression group were: MC, SS, ST, and GSTDLR. It can be seen that the UI of the full model group was replaced by GSTDLR in the auto-regression group, while the other three parameters (MC, SS, and ST) remained the same underlying their importance in modelling the specific SRE.

The simplified (4-term) specific SRE models, from the auto-regression group of models, based on the selected parameters using simple frequency are presented in Table 4. These simplified models also gave SRE predictions with R^2 ranging between 0.86 and 0.99 (Adj. R^2: 0.83 - 0.99) similar to simplified models of the full model group (R^2: 0.87 - 0.99; Adj. R2: 0.84 - 0.98). Among the 4 parameters, the contribution of SS and GSTDLR parameters in SRE prediction was less, as their coefficient absolute values were between 1.8 and 46.0. The mean R^2 of all the combinations of six models was 0.909±0.050, and the mean adjusted R^2 was 0.892±0.058, although comparable with the full model group but slightly reduced performance (Table 4). Therefore, the simplified (4-term) models, derived from the relative weights analysis can be recommended based on their performance and the selected parameters (MC, SS, ST, and UI) can be used for developing the generalized models.

Specific SRE model development - simplest 3-term models

The simplest specific SRE models (3-term) by selecting the best three parameters were also developed to study their performance. From the group of 4-term models (full and auto-regression; Figure 4, Table 4), the most common parameters such as MC, SS, and ST were selected, and the developed prediction models are presented in Table 5. These simplest (3-term) specific SRE model predictions had R^2 ranging between 0.85 and 0.99 (Adj. R^2: 0.83 to 0.91), the mean R^2 was 0.903±0.055, and the adjusted R^2 was 0.877±0.043. The performance was slightly less than the 4 and 9 parameters models, but it was comparable to them (4-term Table 4; and 9-term models - not shown) with their mean R^2 between 0.90 and 0.93 (Adj. R^2: 0.89 and 0.91).

Table 5: Developed most simplified specific SRE models (3-term) based the most influential and common parameters.

Type	Grinder	Crop	Model	R^2	AdjR^2
Best 3- term models from #3+#4 r>0.5	Knife Mill	Big bluestem	SRE = 205.736 + 205.736 MC - 18.583 SS - 19.610 ST	0.847	0.827
		Corn stover	SRE = -89.211 + 900.660 MC - 14.856 SS + 60.451 ST	0.871	0.854
		Switchgrass	SRE = 12103.324 + 158.514 MC - 25.273 SS -1032.650 ST	0.857	0.838
	Hammer Mill	Big bluestem	SRE = 576.316 + 881.991 MC - 47.369 SS - 41.685 ST	0.987	0.909
		Corn stover	SRE = -956.709 + 1908.333 MC - 20.325 SS +375.000 ST	0.912	0.9
		Switchgrass	SRE = 7936.244 + 10736.657 MC - 17.689 SS -671.047 ST	0.941	0.933
Mean				0.903	0.877
(STD)				-0.055	-0.043

Note: SRE - size reduction energy, MC - moisture content, SS - screen size, and ST - shear stress.

Generalized specific SRE models using categorical variables for each grinder

The generalized specific SRE models were developed based on the selected 4 influential parameters, such as MC, SS, ST, and UI, derived from the full and auto-regression model with 9 parameters. It is also possible to have more parameters and derive the generalized equations, but using only the most significant parameters will lead to compact as generalized models add new parameters (categorical variables) to represent biomass and grinders (Eqs. 1 and 2). The correlation of these parameters with SRE, as well as the inter-correlation among themselves for the grinder and biomass combinations are presented in Figure. 7. The first row of the correlation diagram shows the correlation (r) of the selected 4 parameters with SRE visually in the form of a coloured dot of various sizes, and the actual values are shown along the first column. Any gaps in the correlation diagram mean non-significant correlation (e.g., MC vs SS), and no gaps in the first row showed a definite correlation of SRE with the selected variables. The generalized specific SRE models developed for each grinder, based on categorical variables representing the biomass tested, with model performance parameters as generated by the R program are presented in Table 6. The performance of these knife mill and hammer mill-specific generalized models in terms of R^2 were 0.74 and 0.77 (Adj. R^2: 0.73 and 0.77), respectively. The derived generalized SRE model applicable individually for knife mill and hammer mill (4 + 1 term) are as follows:

Specific $SRE_{knife\text{-}mill}$ = 160.560+ 7.623×MC - 7.8098×ST - 15.7606 ×SS + 4.8413×UI - 4.9953×Crop(R^2=0.744; Adj-R^2=0.727) (3)

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$$\text{Specific SRE}_{\text{hammer-mill}} = 242.0621 + 929.2551\times MC - 2.9642\times ST - 28.8756\times SS + 0.4223\times UI + 2.1832\times Crop$$

$$(R^2=0.786;\ Adj\text{-}R^2=0.772) \quad (4)$$

Where, the variable "Crop" takes numerical values of 0 = big bluestem, 1 = corn stalks, and 2 = switchgrass, respectively. Refer to Table 6 for the symbols and units.

Table 6: Generalized specific SRE model for knife mill and hammer mill.

Knife mill			Hammer mill		
Parameter	Estimate	P-value	Parameter	Estimate	P-value
Intercept	160.56	1.67e-13 ***	Intercept	242.0621	< 2e-16***
MC	7.623	2.75e-07 ***	MC	929.2551	< 2e-16***
SS	-15.7606	1.75e-10 ***	SS	-28.8756	< 2e-16***
ST	-7.8098	1.31e-05 ***	ST	-2.9642	0.0243*
UI	4.8413	3.84e-11 ***	UI	0.4223	0.8108
Crop	-4.9953	0.491	Crop	2.1832	0.7683
R^2	0.744		R^2	0.786	
AdjR^2	0.727		AdjR^2	0.772	
F	43.62		F	55.14	
P	<2.2e-16		P	<2.2e-16	
AIC	559.85		AIC	579.26	
Note: Model: SRE ~ MC + SS + ST + Crop (with appropriate parameter estimates)					
Specific SRE - specific size reduction energy (kJ kg-1), MC - moisture content (% d.b.),					
SS - screen size (mm), ST - shear stress (MPa), UI - uniformity coefficient (decimal),					
Crop - categorical variable: 0 - big bluestem, 1 - corn stalks, and 2 - switchgrass,					
AIC - Akaike Information Criteria.					

Note: Model: SRE ~ MC + SS + ST + Crop (with appropriate parameter estimates).

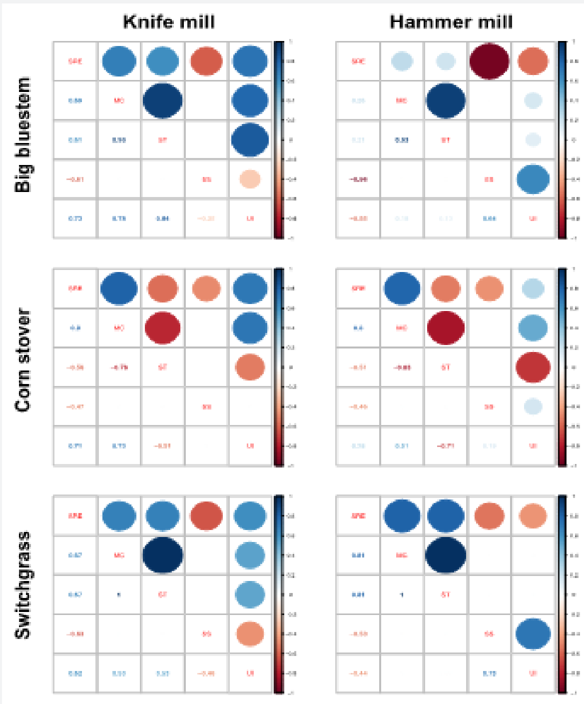

Figure 7: Correlation plot of selected parameters for specific SRE modelling showing the variation among types of grinder and biomass tested.

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Prediction performance of the specific generalized models of knife mill (Eq. 3) and hammer mill (Eq. 4) with the observed values are plotted in Figure 8. The observed and predicted SRE were well correlated both for knife mill (r = 0.863) and the hammer mill (r = 0.887).

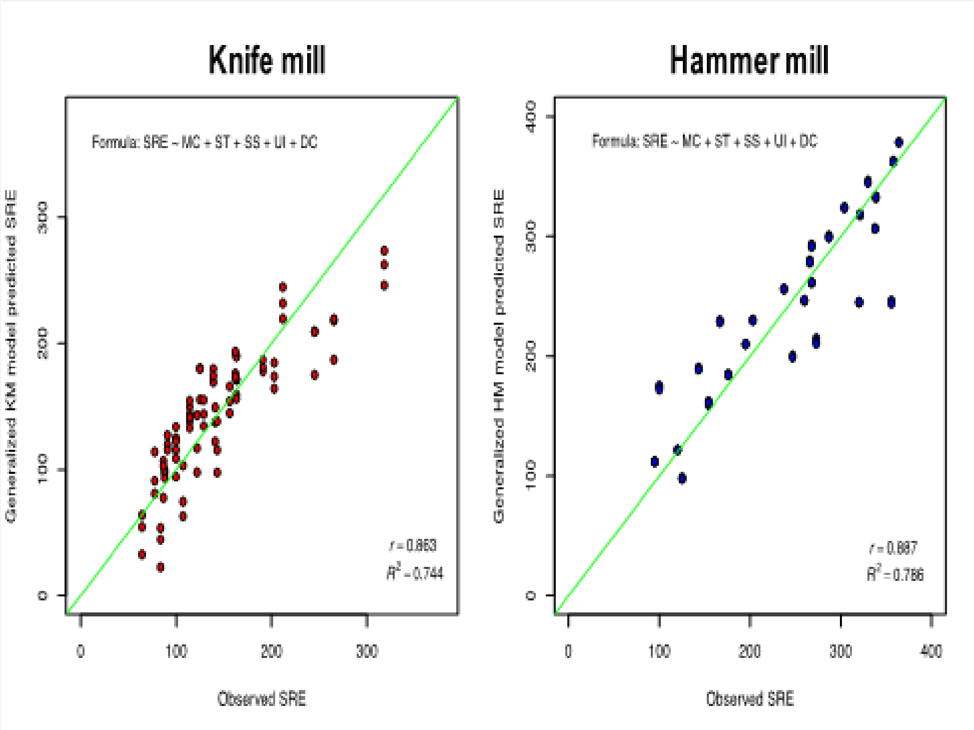

Figure 8: Observed and predicted SRE based on generalized grinder-specific SRE models with categorical variables.

Following the previous methodology (3-term), the most simplified generalized model with fewer parameters developed by selecting the most influential parameters (MC, SS and ST) are:

Specific $SRE_{knife\text{-}mill}$ = 252.848+ 9.440×MC -8.286×ST-19.571×SS -17.047×Crop

(R^2 = 0.540: Adj-R^2 = 0.516) (5)

Specific $SRE_{hammer\text{-}mill}$ = 242.172+ 934.644×MC-2.991×ST -28.529 ×SS +2.694×Crop

(R^2 = 0.786; Adj-R^2 = 0.775) (6)

Comparing to the above 4 parameters (4+1-term; Eqs. 3 and 4) and 3 parameter (3+1-term; Eqs. 5 and 6) models for knife mill and hammer mill, in general, the 4 parameter models (R^2: 0.74 - 0.77) were better than the 3 parameter (R^2: 0.54 – 0.79). Hence, the simplified generalized (4+1-term) models will be useful and the most simplified (3+1-term) models cannot be used for better predictions. These generalized models have the advantage of being simple and valid for different biomass types. It is evident that a direct regression model can be more accurate than the generalized model. However, the generalized model offers the convenience of being compact and gives a wide range of applications for approximate estimation, provided the data supports such modeling.

Generalized specific SRE model applicable to both grinders and biomass

The most generalized model applicable to both grinders and the three biomass species tested was developed using two categorical variables (Mill = 0-HM, 1-KM; and Crop = 0-bbs, 1-cs, 2-sg). The model (4+2-term) is highly significant (p < 2×10-16) and its performance was lower than the grinder-specific (4+1-term) models (R^2 > 0.74). Results also revealed that 'Crop' variable was not significant (p = 0.756), while the 'Mill' variable was highly significant (p < 2×10-16) along with other variables. The developed most generalized model (4+2-term) and its simplified version (3+2-terms) are presented in Eqs. 7 and 8, respectively.

Specific SRE = 338.632 + 4.775×MC – 2.947×ST – 25.106×SS + 3.918×UI – 2.088×Crop – 157.143×Mill

(R^2 = 0.668; Adj-R^2 = 0.655) (7)

Specific SRE = 357.382 + 5.020×MC – 2.604×ST – 24.631×SS – 2.737×Crop – 123.230×Mill

(R^2 = 0.624; Adj-R^2 = 0.612) (8)

As observed before with the grinder-specific models, the 4 parameters (4+2-term; Eq. 7) had a better performance (R^2 = 0.67) than the 3 parameters (3+2-term; Eq. 8) model (R^2 = 0.62). Based on this result, it was observed that the grinder-specific models

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tend to be better than the most general models; however, the most general (combined crop and grinder) model performance was not far behind given its compactness. The SRE prediction performance of the most generalized model (Eq. 7), with the observed values (whole data) plotted (Figure 9), were well correlated (r = 0.82). The results showed that it is possible to have a good prediction based on the most generalized model commonly applicable to grinding devices as well as biomass processed using categorical variables. The procedure outlined can be applied to develop better models with more devices and crops that will be compact and find application in the simulation and design of processing equipment.

Figure 9: Observed and predicted SRE based on the most generalized SRE model with categorical variables.

Comparison of all models

A comparison of the performance (R^2) of all regular regression models, such as full with 9 parameters model (Full9), auto-regression with 9 parameters model (Auto9), simplified full model of 4 parameters using relative weights (SimF4), simplified auto-regression model of 4 parameters using simple frequency (SimA4), and the most simplified model of 3 parameters (Sim3) was made to study their distribution for all the 6 combinations of grinder and biomass studied (Figure 10). These results (Tables 4 and 5) show the usual ranking of the models from more to fewer parameters, which was evident from the relatively similar heights of the bars. However, the loss of performance (R^2) with a reduced number of parameters was not too low. The simplified full model of 4 parameters (SimF4), having a comparable performance of the 9 parameter models, forms the middle ranking. The compactness (4-term) and good performance make SimF4 a practical model for the prediction of specific SRE.

The statistical analysis results of Duncan new multiple-range tests of all models (including generalized total 11) showed how these models compared statistically (Figure 11). The generalized models also included in the analysis are: generalized specific knife mill with 4+1 parameters (GKM4), generalized specific hammer mill with 4+1 parameters (GHM4), simplified generalized specific knife mill with 3+1 parameters (GKM3), simplified generalized specific hammer mill with 3+1 parameters (GHM3), the most generalized model with 4+2 parameters (MG4), and the simplified most generalized model with 4+2 parameters (MG4).

It can be seen from the results that the adjusted R^2, in general, is lower than the R^2 but was not significantly different, however when it was higher a significant difference was observed as in the cases of GKM4 and MG4 (Figure 11). Overall, the regular model group (Full9 through Sim3) were not significantly different among themselves, but they were significantly different from the generalized model group (GKM4 through MG3). As there was

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no significant difference among the regular group of models, the best-performing yet simplified model of SimF4 was selected and recommended for specific SRE prediction. All the models of the generalized group are also significantly different from one another. Among the generalized models, the first choice should be the specific models and the next will be the most generalized models. Between the most generalized models, based on adjusted R^2 it is better to select the MG4 rather than the most simplified MG3.

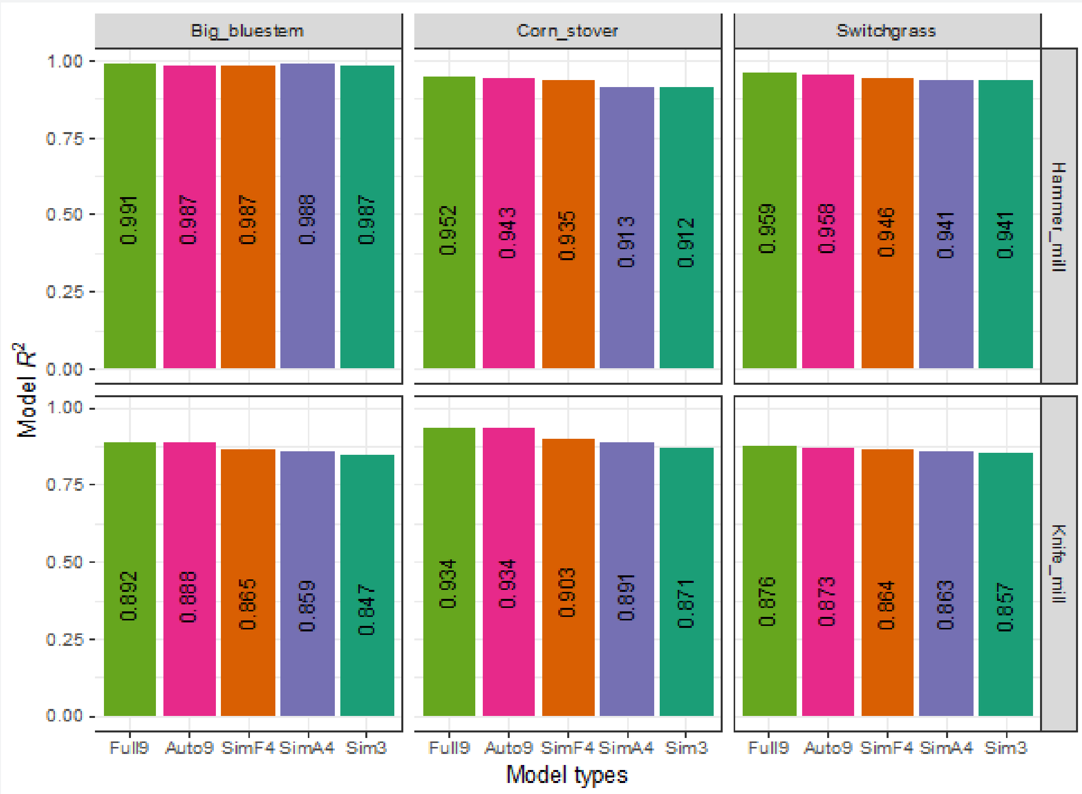

Figure 10: Performance of the family of regular SRE models of the combination of biomasses and grinders.

Conclusion

This research showed that different specific SRE models developed based on crop, mechanical properties, grinder, and particle size distribution parameters to predict the specific SRE that can be useful to various applications. The 9 most influential parameters for specific SRE were found as moisture content (MC), shear stress (ST), grinder screen size (SS), uniformity index (UI), relative span (RS), coefficient of uniformity (CU), size range variation coefficient (SRVC), geometric STD of total region (GSTDTR), and geometric STD of low region (GSTDLR) were used to develop a family of full, simplified, and generalized models. All direct regression models, with all 9 parameters (Full9; mean R^2 = 0.934±0.043), auto-regression with 9 parameters (Auto9; mean R^2 = 0.931±0.043), simplified full models of 4 parameters using relative weights (SimF4; mean R^2 = 0.917±0.049), simplified auto-regression models of 4 parameters using simple frequency (SimA4; mean R^2 = 0.909±0.050), and the most simplified models of three parameters (Sim3; mean R^2 = 0.903±0.055) were not significantly different among themselves. However, these models were significantly different from the generalized model with 4 parameters (GKM4, GHM4; $0.744 \le R^2 \le 0.786$), three parameters (GKM3, GHM3; $0.516 \le R^2 \le 0.775$), and the most generalized model with 4 parameters (MG4; R^2 = 0.668), and three parameters (MG3; R^2 = 0.624).

All the models of the generalized group are significantly different from one another ($p < 0.05$). The best-performing simplified model (SimF4) with 4 parameters, namely MC, SS, ST, and UI were selected and recommended for specific SRE prediction. When predicting the specific SRE through the generalized models using categorical regression, the specific models should be the first choice and the next will be the most generalized. The procedure outlined in the study for developing the generalized models can be extended to other feedstocks and grinding equipment easily. Both regular models and generalized models will find application in process simulation and processing equipment design.

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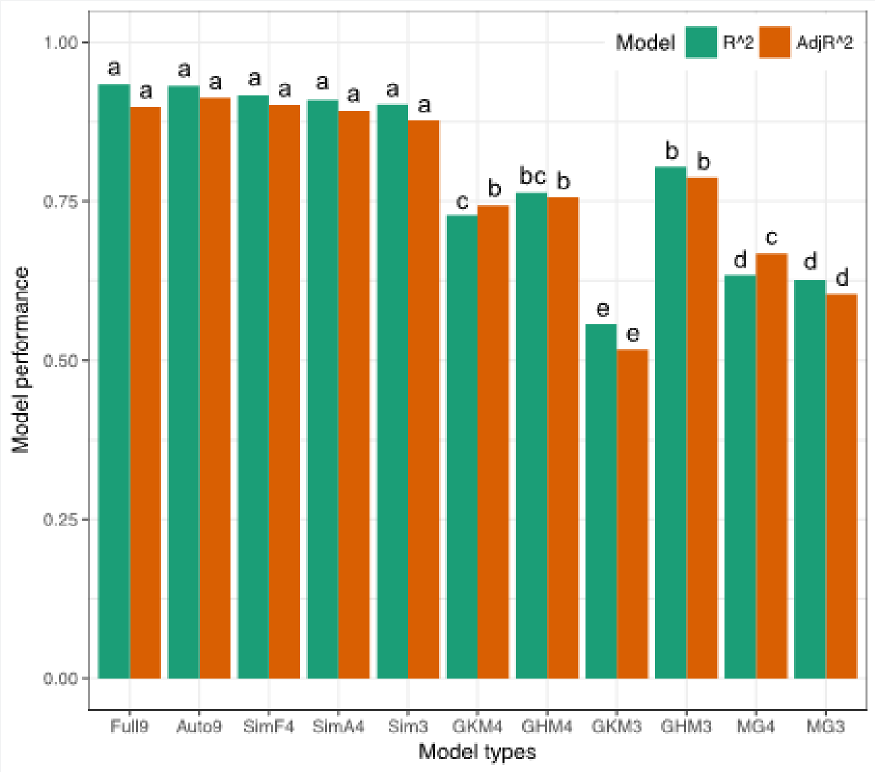

Figure 11: Comparison of performance of the developed SRE models and statistical significance.

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