SENSING MISCANTHUS STEM BENDING FORCE FOR MAXIMIZING THROUGHPUT RATE IN A DISK MOWER-CONDITIONER

S. K. Mathanker, A. C. Hansen, T. E. Grift, K. C. Ting

ABSTRACT. One of the reasons for relatively high biomass harvesting cost is challenges in adjusting the ground speed of harvesting machines with respect to the yield level within a field. A real-time biomass yield sensor that can predict the yield in front of a machine could be a useful tool to control ground speed. It was hypothesized that the force required to bend Miscanthus stems is a reliable predictor of biomass yield. Based on this novel concept, a stem bending force-sensing system was developed and field tested with a disk mower-conditioner. A bale-specific method, segmenting the field area from which a bale was formed, was developed to correlate sensed bending force and Miscanthus yield. The measured bending force showed a logarithmic relationship ($R^2 = 0.80$) with Miscanthus yield. The average error in predicting bale-specific yield was 10.3% for training data and 12.9% for validation data. The average error in predicting plot yield was 3.4% for training plots and 10.0% for validation plots. Using the developed logarithmic correlation model, yield maps were also generated. For the specific case analyzed, a proper control strategy to maximize throughput rate (mass per unit time) would be to either operate the mower-conditioner at the maximum feasible ground speed (9 km h$^{-1}$) or at the maximum achievable throughput rate (60 Mg h$^{-1}$). The yield-sensor controlled machine would result in 44.2% higher field capacity, 41.3% higher throughput rate, and 31.2% lower mowing-conditioning cost for the specific case analyzed compared to the operator-controlled machine. Studies are needed to extend the stem bending force-sensing concept to other thick-stemmed crop harvesting machines, such as sugarcane harvesters and coppice harvesters.

Keywords. Bioenergy, Biomass, Cost, Harvesting, Miscanthus, Mowing, Throughput rate, Yield map, Yield sensor.

Reducing biomass harvesting cost is one of the ways to make biofuels economically viable. Khanna et al. (2008) reported that harvesting machinery cost was one of the most sensitive factors in biomass delivery cost. A ±25% variation can change biomass delivery cost from $50.8 Mg$^{-1}$ to $67.7 Mg$^{-1}$. In this study, Miscanthus was chosen as a candidate crop because of its high productivity and low input requirements (Heaton et al., 2008). However, similar to any other crop, Miscanthus yield varies widely depending on success of crop establishment, environmental growth conditions, water availability, soil nutrient availability, and age of the crop (Heaton et al., 2010). Heaton et al. (2008) reported that Miscanthus yield was 20.9 ±2.4 Mg ha$^{-1}$ in northern Illinois, 33.4 ±2.8 Mg ha$^{-1}$ in central Illinois, and 34.6 ±2.6 Mg ha$^{-1}$ in southern Illinois. However, the above plot-scale yield levels differed significantly from the field-scale harvested yield level of 14.5 Mg ha$^{-1}$ recorded in this study. The yield levels are reported on a dry matter basis. Typical Miscanthus harvesting consists of mowing-conditioning followed by baling. Disk mower-conditioners, which employ a push bar to bend Miscanthus stems before cutting by the disk cutterbar, have been found suitable for Miscanthus (Johnson, 2012). In-field variability of a high-yielding crop such as Miscanthus creates challenges in configuring machine settings that are optimal for the whole field. Knowledge of the anticipated yield at specific locations in the field would be of value for real-time adjustment of variables such as ground speed so as to maximize crop throughput in the machine.

There are few studies that examine the influence of ground speed on machine performance parameters. Shinnors et al. (2009) reported that increasing ground speed of the corn ear snapper head from 4.5 to 7.2 km h$^{-1}$ increased the throughput rate from 30.7 to 49.2 Mg h$^{-1}$. Isaac et al. (2006) optimized ground speed of a combine harvester to maximize net income. These studies indicate that throughput rate and profitability can be maximized by adjusting ground speed. However, the maximum throughput rate would be limited by plugging of the machine. Most operators can adjust in-field ground speed of a mower-conditioner depending on yield level to maximize the throughput rate. However, it is a challenging task, and a biomass yield sensor that can predict the biomass yield in front of a machine can relieve an operator from the drudgery of making these decisions.
Many yield sensing approaches have been studied to measure biomass yield. Mass flow rate in forage machinery was correlated with force on the conditioning roll springs, displacement of the top conditioning roll, and impact force on the swath shield (Shinners et al., 2000). A patent on yield monitor apparatus and methods was granted to Shinners et al. (2002) in which the yield monitor measured yield by measuring impingement force, forage volume, and drive load. Five sensors were mounted on a forage harvester, and sensed data were correlated with timothy grass yield (Savoie et al., 2002). Load cells were used to measure bale weight for estimating mass flow rate through a large square baler (Shinners et al., 2003). Biomass feed rate was studied under laboratory conditions by employing a torque sensor and an impact plate (Kunhála and Prösek, 2003). Torque and hydraulic pressure drop were recorded to measure grass mass flow (Wild et al., 2005). The influence of conveyor belt parameters on grass mass flow was also investigated (Wild and Ruhland, 2007). Conditioner power measured with a torque sensor was correlated (R² = 0.73) with alfalfa yield (Kunhála et al., 2007). A weighing plate predicted sugarcane yield with an accuracy of 89% on a billet-type sugarcane harvester (Mailander et al., 2010).

Leaf area index at harvest showed a close correlation (R² = 0.86) with opium yield (Kun et al., 2011). An ultrasonic sensor that measured grass height predicted biomass yield with an accuracy of 78.6% (Fricke et al., 2011). Zhang and Grift (2012a) developed a laser beam and camera system to measure Miscanthus stem diameter. Zhang and Grift (2012b) also developed a light detection and ranging (LIDAR) sensor that measured Miscanthus stem height to predict Miscanthus stem weight. No reliable and field-robust biomass yield sensors that could predict Miscanthus yield in front of a mower-conditioner were identified in the literature.

Various options for Miscanthus yield sensing were explored, and it was proposed that Miscanthus stem bending force could be a reliable predictor of Miscanthus yield. Additionally, bending of stems using a push bar (fig. 1) is one of the functional processes in mowing-conditioning because it facilitates stem cutting and crop flow. As the push bar, mounted approximately 1.5 m in front of a disk cuttermower-conditioner, moves forward, the stems are bent because of the force applied by the push bar. To counteract the bending force, the bent stems offer a measurable bending resistance. The bending resistance depends on the Miscanthus stem diameter, stem strength (Liu et al., 2012), and stem density. Overall, it was hypothesized that a Miscanthus stem bending force sensor could be a good predictor of Miscanthus yield while mowing.

This study aimed to develop a stem bending force-sensing system to predict Miscanthus yield in front of a disk mower-conditioner. The specific objectives of this study were to: (1) develop a Miscanthus stem bending force-sensing system, (2) determine the correlation between Miscanthus stem bending force and Miscanthus yield, (3) calculate the yield prediction accuracy and generate yield maps, and (4) propose a strategy to control the ground speed of a mower-conditioner with the aim of maximizing its throughput rate.

**MATERIALS AND METHODS**

Fourth-year Miscanthus crop was harvested at the Bioenergy Farm (40.0685° N, 88.2000° W) and SoyFace Farm (40.0420° N, 88.2245° W) of the University of Illinois at Urbana-Champaign. The data from the Bioenergy Farm (plots C1, C2, C3, and C4) were used for training and validation, and the data from the SoyFace Farm (plots V1, V2, and V3) were used for validation. These two field locations are about 3 km apart. A self-propelled disk cutterbar mower-conditioner (New Holland model H8080, 750 HD Specialty Head with 4.7 m cutting width, New Holland, Pa.) was used for cutting and conditioning the Miscanthus crop at all the training and validation plots. After the mowing operation, a square baler (New Holland model BB9080, New Holland, Pa.) collected the biomass windrowed by the mower-conditioner. The baler was equipped with an on-the-go bale weighing and moisture content sensing system. It was also equipped to record GPS coordinates of the location where a bale was tied and released. Both of these features were part of a commercial yield monitor (Harvest Tec model 479, Hudson, Wisc.) fitted to the square baler.

![Figure 1. Location of GPS and load cells mounted on a second push bar ahead of the original push bar on a mower-conditioner head, attached to a self-propelled unit operating in a field of Miscanthus.](image-url)
Three S-type load cells with a maximum load rating of 445 N (Transducer Techniques, Temecula, Cal.) were fitted between the mower-conditioner push bar and another metal pipe of similar diameter (fig. 1) to measure the Miscanthus stem bending force. Load cell outputs were combined and filtered through a 160 Hz signal conditioner (model O-2-160, Transducer Techniques, Temecula, Cal.). The combined and filtered output of the developed bending force-sensing system was calibrated by applying known weights to the push bar. A high correlation ($R^2 = 0.99$) was found between the weights applied and the output voltage of the sensing system. The sensing system output was sampled at 300 Hz and averaged at 1 s intervals when the mower-conditioner was operating in the field. The averaged output of the sensing system was used in this study. These 1 s interval GPS locations are hereafter referred to as bending force data points or sensed-point locations. To determine the sensing system offset due to vibrations attributable to operating mechanisms of the mower-conditioner, the sensing system output was recorded when the cutting disks were running while the disk mower-conditioner was stationary. The offset of approximately -0.35 V was added to all the sensed-points. An RTK GPS (real-time kinematic global positioning system) receiver was used to record the latitude and longitude of the disk mower-conditioner when the bending force-sensing system output was averaged. Experimental data were recorded using a program written in LabVIEW (National Instruments, Austin, Tex.).

A bale-specific method to correlate a machine or crop parameter with the Miscanthus yield was developed. This method consisted of selecting a bale if it was formed in a single row or pass. Then, the field area from which that bale was formed was segmented using GPS locations. In that segmented area, corresponding machine and crop parameters were determined. Since this method segments the field area corresponding to the formation of a bale, it is hereafter referred to as the bale-specific method. The term “bale-specific” refers to a parameter observed in forming a bale, and it is usually representative of 150 to 500 m$^2$ field area depending on the Miscanthus yield. The bale selection and parameter determination are described for the bale numbered 489 (fig. 2, top row). The distance between bale 488 and 489 multiplied by the effective cutting width of the disk mower-conditioner gave the field area from which bale 489 was formed. The weight of bale 489 divided by the field area gave the average Miscanthus yield of the field area from which bale 489 was formed. To determine the sensed bending force corresponding to the formation of bale 489, the averaged bending force values, recorded at 1 s intervals, at the 55 sensed-points (small dots) were added. This accumulated bending force value was then divided by the field area from which bale 489 was formed. This procedure was also used to determine ground speed, field capacity or work rate, throughput rate, and mowing-conditioning cost.

The field capacity or work rate (ha h$^{-1}$) of the disk mower-conditioner was calculated with an average effective width of cut of 4.5 m, resulting from a 0.2 m overlap between passes generally observed in this study, and 80% field efficiency (ASABE Standards, 2011). The bale-specific throughput rate (Mg h$^{-1}$) was calculated by multiplying bale-specific work rate and bale-specific Miscanthus yield (Mg ha$^{-1}$). Similarly, the bale-specific mowing-conditioning cost ($ Mg^{-1}$) was calculated by dividing cost of use per hour ($ h^{-1}$) by bale-specific throughput rate. The cost of use per hour was calculated assuming a used mower-conditioner price of $125,000 with 250 h of annual use and repair and maintenance cost over the life-span of the mower-conditioner as 55% of list price while following the procedure described in ASABE Standards EP496.3 and D497.7 (ASABE Standards, 2006, 2011). The calculated cost of use per hour was $139.6. A total of 60 bales from the training plots (C1, C2, C3, and C4) were selected, and corresponding machine parameters and bale-specific yields were determined.

To verify the accuracy of the bale-specific-yield predic-

![Figure 2. GPS locations of the recorded data points for training plot C2: small dots = bending force data points recorded at 1 s intervals, squares = bales used in correlation study, and circles = bales not used in correlation study. The numbers are bale numbers.](image-url)
tion, half of the 60 selected bales were used to train a logarithmic correlation model between bending force and Miscanthus yield, and the other half were used to validate the model. A logarithmic model was selected because it represented the stem bending phenomenon better when the stem density becomes higher, which also translates into higher yield. As the stem density becomes higher, all the stems cannot contact the push bar directly, thereby reducing their cumulative impact on the bending force experienced. This may be described as a cushioning effect, and a logarithmic model represented it better. In the first study, the 60 selected bales were arranged in ascending order of sensed bending force, and alternate bales were assigned to the training and validation data sets, each consisting of 30 bales. In the second study, the testing and validation data points were randomly selected, and 20 such random runs were made similar to the study by Mathanker et al. (2011) or as done in a typical cross-validation study. A typical run consisted of training the model with 30 bales and validating the trained model using the remaining 30 bales. Average error and root mean square error were calculated for each random run. Error was calculated as: \( \frac{\text{predicted yield} - \text{observed yield}}{\text{observed yield}} \times 100. \)

To predict plot yield and generate yield maps, a comprehensive logarithmic correlation model between bending force and yield was trained using all 60 selected bales. The sensed bending force per unit field area recorded at 1 s interval sensed-points (small dot locations in fig. 2) was entered into the trained logarithmic correlation model equation to predict the sensed-point-specific yield. The term “sensed-point-specific” refers to a parameter observed while mowing a field in 1 s, and it usually corresponded to about 5 to 10 m² of field area. Predicted yield levels were divided into three categories to create a yield map: low yield (<15 Mg ha⁻¹), medium yield (15 to 20 Mg ha⁻¹), and high yield (>20 Mg ha⁻¹). The predicted yield was multiplied by the corresponding field area to calculate the sensed-point-specific biomass weight. All sensed-point-specific biomass weights in a plot were added to predict the plot yield. In this study, the yield levels are reported on a dry matter basis and were corrected using the moisture content data recorded by the commercial yield monitor (Harvest Tec model 479, Hudson, Wisc.) that was fitted to the baler.

**RESULTS AND DISCUSSION**

The stem bending force-sensing system was field-tested while mowing Miscanthus. Sensed bending force and observed yield, corresponding to the formation of a bale, were calculated to establish the relationship between them. The accuracy of the sensing system was evaluated in terms of predicting bale-specific yield and plot yield. The impact of the sensing system for maximizing throughput rate by controlling ground speed based on yield level was quantified.

**BALE-SPECIFIC YIELD PREDICTION**

To determine the bale-specific yield prediction accuracy, the 60 selected bales from the Bioenergy Farm (40.0685° N, 88.2000° W) were used in the following two studies. In the first study, the selected bales were arranged in ascending order of sensed bending force, and alternate bales were assigned to the training and validation data set. The trained logarithmic correlation model (fig. 3) was used to predict bale-specific yields (fig. 4). The average prediction error was 9.9% for the validation data and 12.1% for the training data.

The second study tested the influence of data variability on the predictive accuracy of the sensing system by randomly assigning data to training and validation sets (Mathanker et al., 2011). A logarithmic model, similar to figure 3, was fitted to the training data set for each run and was used to predict bale-specific yield. Figure 5 shows the average error and root mean square error for 20 random runs. The average training error was lower than the average validation error for most of the random runs. The average error was about 10.3% for the training data and 12.9% for the validation data (fig. 5). The average root mean square error was 2.2 Mg ha⁻¹ for the training data and 2.6 Mg ha⁻¹ for the validation data. It is expected that the prediction accuracy could be further improved with a more accurate sensing system and more data points.

![Figure 3. Logarithmic correlation model trained for bale-specific yield prediction. The 60 selected bales from the Bioenergy Farm were alternatively assigned to the training and validation sets by arranging the bales in ascending order of sensed bending force.](image)

![Figure 4. Bale-specific yield predicted by the logarithmic model in figure 3. The 60 selected bales from the Bioenergy Farm were alternatively assigned to the training and validation sets by arranging the bales in ascending order of sensed bending force.](image)
Figure 5. Average error (AE) and root mean square error (RMSE) in predicting bale-specific yield. The 60 selected bales from the Bioenergy Farm were divided randomly into training and validation sets for each random run.

Figure 6. Correlation between Miscanthus stem bending force and Miscanthus yield trained using all 60 selected bales from the Bioenergy Farm (plots C1, C2, C3, and C4).

**Correlation of Sensed Stem Bending Force and Miscanthus Yield**

To develop a comprehensive correlation model between stem bending force and yield, all 60 selected bales from the Bioenergy Farm were used. Accumulated bending force (sum of averaged bending force values at all the sensed-points corresponding to a bale), bale formation area, and bale weight were determined for each bale. About 1% to 2% of the bending force data points or sensed-points could not be recorded correctly because of a poor GPS signal and were replaced by interpolated data. The relationship between sensed bending force and Miscanthus yield (fig. 6) could best be described as logarithmic ($R^2 = 0.80$, solid line) rather than linear ($R^2 = 0.74$, dashed line). The coefficient of determination found in this study was comparable to the coefficient of determination ($R^2 = 0.73$) found by Kumhála et al. (2007), indicating a degree of yield prediction accuracy achievable under field conditions. Sensed stem bending force increased as Miscanthus yield increased. However, the rate of increase decreased as Miscanthus yield increased. Furthermore, it was observed that some of the stems were not able to contact the push bar due to stem overcrowding at higher yield levels.

**Biomass Yield Prediction and Mapping**

The logarithmic model in figure 6 was used to predict plot yield for two locations: Bioenergy Farm (40.0685° N, 88.2000° W; plots C1, C2, C3, and C4) and SoyFace Farm (40.0420° N, 88.2245° W; plots V1, V2, and V3). The 60 selected bales used to train the model represented about 40% of the bales formed in the four training plots (C1, C2, C3, and C4). The average bending force per unit area recorded at 1 s intervals (i.e., the sensed-points) was entered into the logarithmic model in figure 6 to predict the sensed-point-specific yield. This predicted yield was multiplied by the corresponding field area to calculate the sensed-point-specific biomass weight. The biomass weights thus calculated for all the sensed-points in a plot (e.g., 4400 sensed-points for plot C2, as shown in figure 2) were added to predict plot biomass.

The predicted plot biomass weight and harvested plot biomass weight are shown in table 1. The prediction error for the training plots varied from -3.6% to 7.6%. For training plot C4, the higher prediction error (7.6%) may be attributed to the presence of experimental equipment within the field, creating an obstacle and requiring the disk mower-conditioner to take a curved path (e.g., the bottom rows of fig. 7c). The average prediction error in predicting harvested biomass weight was 3.4% for the training plots and 10.0% for the validation plots. Importantly, the validation plots (SoyFace Farm: 40.0420° N, 88.2245° W) were about 3 km away from the training plots (Bioenergy Farm: 40.0685° N, 88.2000° W), and this indicates the robustness of the developed sensing system. The average prediction accuracy obtained in this study is comparable to the 89% sugarcane yield prediction accuracy reported by Mailander et al. (2010). The prediction accuracy could be further improved if a real-time biomass weighing system were employed in developing the correlation model.

Yield maps were generated using the logarithmic correlation model in figure 6. Predicted yield levels were plotted at the sensed-point GPS locations (fig. 7), and the GPS locations of the bales (squares) were superimposed. Plot C2 mostly had low-yield points (fig. 7a), plot C3 mostly had medium-yield points (fig. 7b), and plot C4 mostly had high-yield points (fig. 7c). The top three rows of training plot C2 (figs. 2 and 7a) produced two bales per row, which was reflected in the medium-yield and low yield points. In contrast, the second row from the bottom in training plot C2 produced three bales, which resulted in more medium-yield and high-yield points (figs. 2 and fig. 7a).

**Table 1. Predicted and harvested plot biomass for training (Bioenergy Farm plots C1 to C4) and validation (SoyFace Farm plots V1 to V3).**

<table>
<thead>
<tr>
<th>Plot</th>
<th>Harvested Plot Yield (Mg ha⁻¹)</th>
<th>Predicted Plot Yield (Mg ha⁻¹)</th>
<th>Prediction Error (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>C1</td>
<td>15.64</td>
<td>15.09</td>
<td>-3.53</td>
</tr>
<tr>
<td>C2</td>
<td>12.31</td>
<td>12.41</td>
<td>0.84</td>
</tr>
<tr>
<td>C3</td>
<td>17.16</td>
<td>17.46</td>
<td>1.72</td>
</tr>
<tr>
<td>C4</td>
<td>15.58</td>
<td>16.77</td>
<td>7.63</td>
</tr>
<tr>
<td>V1</td>
<td>10.99</td>
<td>11.35</td>
<td>3.26</td>
</tr>
<tr>
<td>V2</td>
<td>17.32</td>
<td>19.66</td>
<td>13.52</td>
</tr>
<tr>
<td>V3</td>
<td>12.65</td>
<td>14.28</td>
<td>12.94</td>
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</tbody>
</table>
Development of Sensing System to Maximize Throughput Rate

The main purpose for developing the bending force-sensing system was to predict the yield in front of a mower-conditioner and use the predicted yield to maximize the throughput rate. The results in the previous section demonstrated the successful operation of the biomass yield sensing system. The following analysis quantifies the impact of deploying the sensing system for mowing a 4 ha Miscanthus area in the training plots at the Bioenergy Farm (40.0685° N, 88.2000° W). Figure 8 shows the operator-controlled ground speed (solid line) relative to Miscanthus yield. The operator-controlled ground speed resulted in varied throughput rate: 20 to 60 Mg h⁻¹ (solid line in fig. 9). It also resulted in varied mowing-conditioning cost: $2.3 to $7.1 Mg⁻¹ (solid line in fig. 10). This finding is in agreement with Khanna et al. (2008), who concluded that harvesting cost is one of the most sensitive factors in delivered biomass cost. It appears that the operator-controlled ground speed was one of the reasons for the variable mowing-conditioning cost (figs. 8 and 10).

This situation can be remedied to a great extent by employing the developed bending force-sensing system. It can be a useful tool to remove operator bias and to solve the challenging task of yield prediction based on human visual perception. It may not be feasible to operate a mower-conditioner at a very high ground speed because of field conditions and power limitations. In addition, potential plugging of the conditioning rolls would determine the maximum achievable throughput rate. It appears that the maximum feasible field speed and maximum achievable

Figure 7. Yield maps for the training plots at Bioenergy Farm (40.0685° N, 88.2000° W): (a) C2, (b) C3, and (c) C4.

Figure 8. Observed and targeted ground speeds of disk mower-conditioner as affected by bale-specific Miscanthus yield in 4 ha area.
The projected throughput rate is that which would be expected if the target ground speed in figure 8 were used.

Based on these two main limitations, a logical control strategy would be to either operate a disk mower-conditioner at the maximum feasible ground speed or at the maximum achievable throughput rate. To quantify the impact of this control strategy, the maximum ground speed was assumed to be 9 km h\(^{-1}\) (ASABE Standards, 2011), and the maximum throughput rate was assumed to be 60 Mg h\(^{-1}\). While 9 km h\(^{-1}\) may be slower than commonly used ground speeds for harvesting hay crops, we believe that 9 km h\(^{-1}\) is an appropriate maximum feasible speed for mowing Miscanthus yielding 20 to 25 Mg ha\(^{-1}\) harvestable biomass yield with available commercial equipment. Note that in this study no plugging of the conditioning rolls was observed for throughput rates up to 60 Mg h\(^{-1}\). With these assumptions, the mower-conditioner would be operated at 9 km h\(^{-1}\) field speed unless the throughput rate exceeded 60 Mg ha\(^{-1}\). If the throughput rate exceeded 60 Mg h\(^{-1}\), then the ground speed would be reduced to maintain a constant throughput rate of 60 Mg h\(^{-1}\). The dashed line in figure 8 shows the target ground speed if the proposed control strategy is implemented. The dashed line in figure 9 shows the corresponding projected throughput rate. It is evident that the projected throughput rate is less than 60 Mg h\(^{-1}\) for Miscanthus yields up to 18.3 Mg ha\(^{-1}\). However, the maximum throughput rate could be achieved in field sections with yield higher than 18.3 Mg h\(^{-1}\). The estimate for the specific case studied indicated that by adopting the proposed yield-sensor controlled strategy about 44.2% higher field capacity (fig. 8), 41.3% higher throughput rate (fig. 9), and 31.2% lower mowing-conditioning cost (fig. 10) could be achieved compared to operator-controlled strategy. The reduction in Miscanthus harvesting cost could be critical in improving the economic viability of the resulting biofuels. It is expected that integration of the developed bending force-sensing system with existing mower-conditioners would stabilize their throughput rate under variable yield conditions and reduce harvesting cost.

However, adjusting ground speed can change the sensed bending force because the bending force could be a function of the ground speed. In this study, the operator adjusted ground speed in the range from 3.6 to 6.9 km h\(^{-1}\), and despite these ground speed adjustments, a close correlation (\(R^2 = 0.80\)) was found between the sensed bending force and Miscanthus yield. Crop lodging presents another limitation, but it is typically less of an issue for Miscanthus, energy cane, and short-rotation woody crops than for sugarcane or sweet sorghum. The ability of critical machine components, such as the conditioning mechanism, to respond to sudden changes in yield fluctuations may present another limitation. Operator input would also be required to account for changes in biomass material properties brought on by moisture, dew, and other factors. In conclusion, further studies to overcome limitations for field implementation of the proposed control strategy are needed. Similarly, there is a need to adapt the bending force sensing approach to other thick-stemmed bioenergy crop harvesting machines, such as sugarcane harvesters and coppice harvesters.

**CONCLUSIONS**

A novel Miscanthus stem bending force-sensing system was developed and field tested. Sensed Miscanthus stem bending force showed a logarithmic relationship (\(R^2 = 0.80\)) with Miscanthus yield. The average error in predicting bale-specific yield was 10.3% for the training data and 12.9% for the validation data. The average error in predicting plot yield was 3.4% for the training plots and 10.0% for the validation plots. Based on the analysis, a logical control strategy to maximize throughput rate would be to either operate a mower-conditioner at its maximum feasible ground speed (9 km h\(^{-1}\)) or at its maximum achievable throughput rate (60 Mg h\(^{-1}\)). However, further studies to overcome limitations and field implementation of the proposed control strategy are needed. The concept of stem bending force as a biomass yield predictor can also be extended to other thick-stemmed crops, such as energy cane, willow, and short-rotation woody crops.

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