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An online visible and near-infrared spectroscopic technique for the real-time evaluation of the soluble solids content of sugarcane billets on an elevator conveyor

Kittisak Phetpan, Vasu Udompetaikul*, Panmanas Sirisomboon

Department of Agricultural Engineering, Faculty of Engineering, King Mongkut's Institute of Technology Ladkrabang, 1 Chalongkrung Road, Ladkrabang, Bangkok 10520, Thailand

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ABSTRACT

The aim of this research study is to propose a prototype online detection system based on the visible and near-infrared spectroscopic (vis/SW-NIR) technique for the real-time evaluation of the soluble solids content (SSC) of sugarcane billets on an elevator conveyor. The system consisted of two main parts, a cane billet elevator and a spectral acquisition device. An elevator speed of 2 m/s was used for the transfer of sugarcane billets. Spectra acquisition was performed using four 50 W tungsten halogen lamps as a light source in conjunction with vis/SW-NIR spectrometer in reflectance mode. Partial least squares regression (PLSR) was subsequently used to correlate the spectra with the experimentally determined SSC values. The model performance was then assessed using an independent prediction set. The model was found to display a coefficient of determination of prediction (R^2) of 0.785, a root mean square error of prediction (RMSEP) of 0.30 and a residual predictive deviation (RPD) of 2.16. The result on the prediction set confirm that the proposed system is suitable for the online SSC measurement of the sugarcane billets on an elevator conveyor.

1. Introduction

Sugarcane is one of the principal raw materials used in sugar production worldwide. It is an economically important crops, with a global export value of around 27 billion USD in 2017 (http://www.trademap.org/Country_SelProduct.aspx?nvpm=1|||||1701|||4|1|1|2|1||2|1|1). Brazil is the world's largest sugarcane producer and sugar exporter, followed by Thailand and France. Brazil has been a pioneer in the use of sugarcane to produce alternative fuels in the form of ethanol. It produces more than 20bn liters of ethanol a year from sugar and is expected to reach 50bn liters a year by 2020 (Cookson, 2012).

Demand for cane sugar derived ethanol fuels have been consistently growing in other parts of the world. This has prompted efforts to achieve improvements in agricultural productivity in terms of crop yield and quality without necessarily increasing the amount of farmland being employed. The primary industrial sugarcane quality index is defined by the commercial cane sugar (CCS) parameter which is the percent of recoverable sucrose from fresh cane. This measure of sugar content is used for pricing and trading between growers and sugar mills (Dixon and Johnson, 1988). Variation in the sugarcane CCS parameter is dependent on numerous factors including; cultivar, age, moisture, nutrient and temperature (Naderi-Boldaji et al., 2016). Lawes et al. (2000) studied the spatial variability in CCS, finding that it was up to 9 units in an individual field. They noted that site-specific management of the field input and activities could help minimize the CCS variation by maximizing the yield and/or quality of the production in the less productive areas.

Precision agriculture (PA) are all-encompassing tools or technologies to improve the management of agricultural production processes through the recognition of limiting production factors, soil fertility as well as the variation in yield and quality across a given field. It is one of the means for crop management strategies (Bramley, 2009). Nevertheless, its application requires the generation of a spatial variability map to perform the necessary site-specific management of industrial farms. The key issue is developing an efficient, cost effective ways of determining PA in such situations.

Bramley (2009) reviewed PA applications in the sugarcane industry and found that to monitor the sugarcane yield and to construct variability maps was not necessarily an arduous process. However, the monitoring of crop quality during harvesting, and the production of the subsequent map was still going on the research and still based on the laboratory scale. This prompted the development of several field based

* Corresponding author.
E-mail address: vasu.ud@kmitl.ac.th (V. Udompetaikul).

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techniques for rapid sugar cane quality measurement including; electronic refractometers (Mccarthy and Billingsley, 2002), microwaves (Nelson, 1987; Klute, 2007; Shah and Joshi, 2010) and spectroscopic techniques (Nawi et al., 2013a, 2013b). The refractometer based method required a mechanism for squeezing cane juice prior to measurement, while the non-destructive microwave and spectroscopic methods proved to be useful in the laboratory but were unproved in field use. This prompted Nawi et al. (2014) to propose that a spectroscopic method had real potential for field use if installed on the elevator conveyor used during sugarcane harvesting. This would allow for the direct measurement of the soluble solids content (SSC, °Brix) of sugarcane, without the requiring the direct analysis of the sugarcane juice.

The spectroscopic technique of Nawi et al. (2013a) utilizes an area of the electromagnetic spectrum that covers the wavelength range from around 350–2500 nm. Visible and shortwave near-infrared spectroscopy (vis/SW-NIR), 350–1100 nm, appear to be promising bands as these are typically ascribed to the third and fourth overtones of O-H and C-H stretching modes (Walsh et al., 2000) that are present in sugar molecules. In addition, the method has been used to determine the value of SSC for the sugarcane stalk (Nawi et al., 2013b) and it has been claimed that it has the potential to be developed into a sensor for monitoring sugarcane quality during harvesting (Nawi et al., 2014).

In an effort to develop an online sugarcane quality measurement, a prototype system for SSC prediction was developed and tested. The goals of this work are twofold (1) to propose an online detection system of the sugarcane billets based on the vis/SW-NIR technique and could be installed on the elevator conveyor of the sugarcane harvester; (2) to evaluate the performance of the system for online SSC measurement of the sugarcane billets on the elevator conveyor.

2. Material and methods

2.1. Sample preparation

Fifty clumps of sugarcane were collected from fields in Suphan Buri, Thailand, in February 2017. Each clump is comprised of approximately 20 stalks which were cut into billets with approximately length of 20 cm. The cane variety was Khonkaen 3, one of the most common commercial varieties in Thailand. The sugarcane were collected at approximately 11 and 12 months after planting in order to cover the different maturity stages in commercial harvesting period of this sugarcane variety.

2.2. On-line detection system and spectral acquisition

An online measurement system (Fig. 1) had been developed in this study for monitoring the value of SSC in sugarcane billets. The system consisted of two main parts – a cane billet elevator and a spectral acquisition system. The elevator used in the study was built with the same dimensions as those of a common sugarcane harvester (John Deere 3520). It was set at an angle of 32° from the ground. The elevator was divided into three distinct regions for controlling the velocity speed. The starting and ending regions, each being one meter in length, were used for ramping up and down the speed to and from the stationary state. The middle region, which was two meters in length, was set to deliver the sugar cane at a constant conveying speed. Two slats were mounted to the conveyor chain. The upper one was used to trigger the acquisition switch and the lower one was used for moving the billets along the elevator. The sample movement was set according to the velocity profile as shown in Fig. 1a. The acquisition system was used to collect the spectral data of the billet group as it moved along the elevator. A chamber was built around the acquisition device to allow for the installation of a constant light source and to protect interference from environment light. Four halogen lamps (Aluline Halogen 12 V R111, Royal Philips, Holland) were mounted at a distance of 60 cm and at 45° away from the elevator floor. A vis/NIR spectrometer (AvaSpec-2048-USB2, Avantes BV, Netherlands) was installed, operating in the spectral range of 350–1100 nm with the spectral resolution of 2.4 nm. The amount of light reflected from the samples was collected using a 25° field-of-view (FOV) of the optic fiber that was fitted to the spectrometer and was fixed at 9 cm over the top edge of the slat on the elevator. At that distance, the scanning area covered a circle of approximately 4 cm diameter (Fig. 1b). The spectrometer was set to scan the spectra using an external trigger.

An appropriate integration time must be specified to achieve the optimum system sensitivity. Based on our chamber environment, the integration time was set to 14 ms, yielding approximately 90% full-scale Analog-to-Digital Converter (ADC) of the reference material reflectance. Each triggering of the device led to the collection of 19 spectral scans (one set of scans), with the integration time set to cover the spectral measurement between 2 slats (a distance of 52 cm) with a conveying speed of 2 m/s (typical speed of the elevator of the sugarcane harvester and the speed used in this study).

In order to obtain four representative optical spectral sets of each clump, two replications with two repeated measurements were obtained. One set of scans was performed for each repeated measurement. After finishing the first measurement, the slat and chain were retracted to the starting position before proceeding with the second measurement. This was performed without reshuffling the cane billets. To date, two sets of spectra (19 spectra each) were obtained for first replication. The cane billets were then collected for °Brix (SSC) determination (detailed in the next section). With the first replication, two spectral sets and a corresponding SSC value were acquired. After the first replication, the remaining billets were removed from the elevator and reshuffled before reloading to the elevator for the second replication (using the same procedure). Therefore, four sets of spectra (2×19 spectra for the 1st replication + 2×19 spectra for the 2nd replication) and two SSC values (for the 1st and 2nd replications) were obtained for each billet clump. Two hundred spectral sets, along with 100 SSC values were obtained in total.

2.3. Soluble solids (°Brix) determination

Reference SSC values for the sugarcane billets those lied on the scanning path (Fig. 1b) were obtained by squeezing the billet in a small hydraulic press. The juice from each billet was stirred, screened with filter paper, and immediately poured onto a digital refractometer (Pocket PAL-1, ATAGO, Japan) to enable °Brix measurement. The SSC values obtained from each replication were averaged.

2.4. Spectral filtration

Spectral bands outside the range of 450–900 nm were first removed due to excessive noise. This is because during the continuous online measurement, many spectra from various sources are scanned and recorded necessitating a spectral screening process to filter out non-sugarcane related spectra. All 200 spectral sets obtained from the previously described experiments were performed using this process. Each of the spectral sets contained spectra from 3 different sources - cane, slats and floor – as showed in Fig. 2. Undesirable spectra from the slats and floor must be removed before further analysis. Slat spectra could be easily filtered out if the difference in percent reflection value at the wavelength of 550 and 620 nm was higher than 0.6. For floor spectra, the reflection value at 800 nm was used as the marking point to eliminate this group of spectra from the set. The eliminated spectra were those with the reflection at the marking point less than 20%. In addition, spectra from partial scans of sugarcane with weak signal were also eliminated.

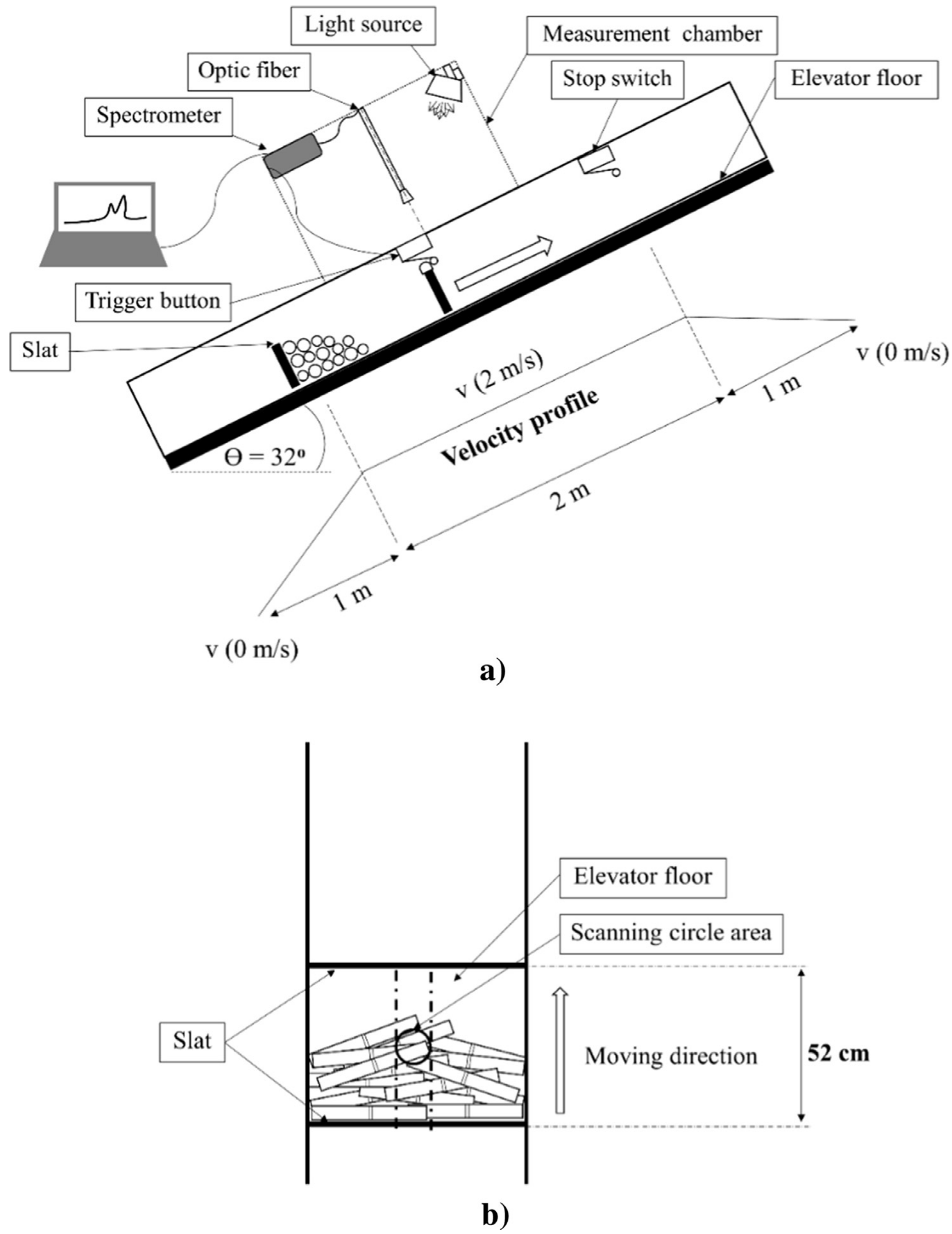

Fig. 1. Scheme of an online measurement system, (a) side view and (b) top view.

2.5. NIR modeling

After the filtration step above, 150 sets of spectra remained for modeling against their SSC values. Note that 50 sets of spectra were eliminated. Partial least square (PLS) regression is regarded as one of the most popular linear statistical methods for modeling the linear relationships between the variable matrix X or the spectra and the variable matrix Y or the properties of interest (Jie et al., 2014). It was applied in order to obtain the linear model correlating the online spectra of sugarcane billets on the elevator with their SSC. In this study, the software used for multivariate analysis (Unscrambler X 10.3, Camo, Norway) was used in both spectral pretreatment and model development.

To obtain the model with more reliable performance, this necessitated the formation of two independent datasets, which were obtained by randomly splitting the 100 sets of spectra with their corresponding SSC from 150 sets mentioned above to be calibration set. The other set (50 sets) was used for external testing set. However, from observation, signal noises and offset were spectral characteristics that have a negative impact on model development. Spectral pretreatment is a key step to improve the model accuracy. Several techniques including smoothing, multiplicative scatter correction (MSC), standard normal variate (SNV) scaling, mean normalization and baseline offset were applied in the calibration and the external testing sets separately to overcome these characteristics. In this paper, moving average (MA) smoothing with segment size of 21 points was first applied to minimize spectral noises and then the others were individually applied to diminish the offset effect in spectra. After the pretreatments, each spectral set in both datasets were averaged. Thus, 100 samples and 50 samples with matching averaged spectra and their SSC were obtained and ready for PLS modeling and the external testing, respectively.

To initially seek an optimum model based on the data obtained from different pretreatments, the PLS models were developed and validated using the leave-one-out cross-validation. The optimum one was selected based on high coefficient of determination (R^2) and low root mean square error of cross-validation (RMSECV). Then, this selected model was used to test its true performance by predicting the external testing set. This procedure is a more realistic measure of model performance as

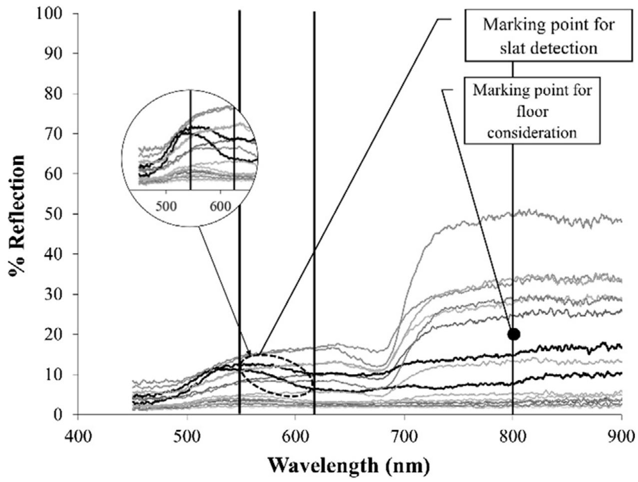

Fig. 2. An example of NIR spectra obtained from a group of the sugarcane billets on the elevator.

the samples used in the analysis were not used to develop the initial model. The model performance is assessed statistically using the coefficient of determination (R^2) of prediction, root mean square error of prediction (RMSEP) and residual predictive deviation (the standard deviation to standard error of prediction, RPD).

3. Results

3.1. Spectral description

Four different spectral pre-processing methods were considered in this study including moving average (MA) + baseline offset, MA + mean normalization, MA + MSC and MA + SNV. Fig. 3 shows the spectra after the filtration process, while Fig. 4 shows the spectra in the calibration dataset after the pre-processing operations. The normalized descriptors were used for modeling against the average SSC values. The effect of noise in the original spectra was minimized by utilizing the smoothing technique (MA). The baseline offset, one of mathematical techniques well known in the correction of offset existing in group of spectra, was applied in this study to diminish some effects that occur during the spectral detection. There is still a scattering effect in the spectra, which is tolerable if eliminated by the other pretreatments, particularly the MSC and SNV operations.

The absorption region at around 670–680 nm, which could be seen clearly in all pretreated spectra, appears to be related to the chlorophyll content at the peel (Guo et al., 2003) of cane billets. The prominent peak does not appear in the region around 700–900 nm, instead, this region is the location of the bands typically related to the third or fourth

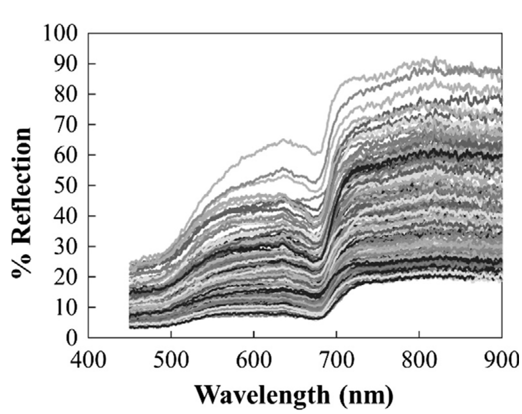

Fig. 3. The sugarcane spectra remained from the filtration of all sample groups.

overtone C-H and O-H stretching of both sugar and water groups (Ecarnot et al., 2013; Guo et al., 2003; Osborne et al., 1993; Golic, et al., 2003).

3.2. Near-infrared spectroscopy models for SSC prediction

Fig. 5 shows the distribution of the SSC values used for PLS modeling and external testing. A summary of their statistical characteristics for the two sets are shown in Table 1. The 100 average spectra after pretreatments were used for modeling against the average SSC values and evaluated with full cross-validation to initially seek an optimum model. The regression and validation results for SSC prediction with different pretreatments are shown in Table 2 and corresponding regression coefficient plots are displayed in Fig. 6. The models constructed from the spectra pretreated by the smoothing (MA) and combined with SNV, MSC and normalization show good performances. They provide R^2 values approximately 0.7–0.8 and RMSECV values of around 0.3 °Brix. Among the best models, the optimum one was that obtained using MA + SNV, displaying an R^2 and RMSECV of 0.807 and 0.33 °Brix, respectively. On the other hand, using the spectra obtained from the MA + Baseline offset operation provides the lowest R^2 and highest RMSECV values of 0.656 and 0.45 °Brix, respectively. For the regression coefficient plots, their spectral patterns look similar. The two dominant peaks at 755 and 890 nm stand out.

To confirm the independent prediction performance of the PLS model from MA + SNV operation, the external validation was performed. This selected model presents the performance for predicting a series of 50 samples not used during model generation by explaining the 78.5% of the variation existing in this dataset. RMSEP and RPD values of 0.30 °Brix and 2.16 were obtained, respectively. The corresponding scatter plots are displayed in Fig. 7.

4. Discussion

Based on the results of the spectral pre-processing methods applied in this study, we found that they improve the linear relationship obtained between the spectral signals and the SSC values which were obtained from the sugarcane billets moving on the elevator. Good predictability was obtained using three pre-processing techniques after spectral smoothing including mean normalization, MSC and SNV. They are not different because these techniques have the same concept for solving the scattering effect existing in the spectra. Among the three spectral treatment methods, the MSC and SNV techniques provided the best results (R^2 and RMSECV). The SNV technique is more suitable for practical application, especially for our proposed system, due to there is no need for a reference spectrum. Self-correction is achieved by using only the standard deviation and mean of the scan in question.

To build robust PLS models, it is important to have a large sample size with good sample variability. Low variability in the SSC values used for modeling in this study was caused by collecting only one sugarcane variety with a narrow range of maturity stages. Although expanding the variability could be done by starting the sampling before 11 months after cane planting, it is not necessarily useful for real world application since it is not desirable to harvest such immature sugarcane. Given the emphasis on the primary evaluation, the proposed system for online SSC measurement of the sugarcane, it is adequate for this study. However, to obtain more robust models samples of several cane cultivars with different ranges of maturity (°Brix) could be added in the future application.

With the spectral range of 450–900 nm used for the PLS modeling, the coefficient plots show that the models contained two sugar related peaks at 755 nm (the 4th overtone of C-H stretching of sugar at 762 nm (Osborne et al., 1993) or the 3rd overtone of O-H stretching of sucrose in water at 740 nm (Golic et al., 2003)) and 890 nm (the 3rd overtone of C-H stretching of sucrose in water at 910 nm (Golic et al., 2003)). Based on those, the absorption bands relating sugar are mainly weighted

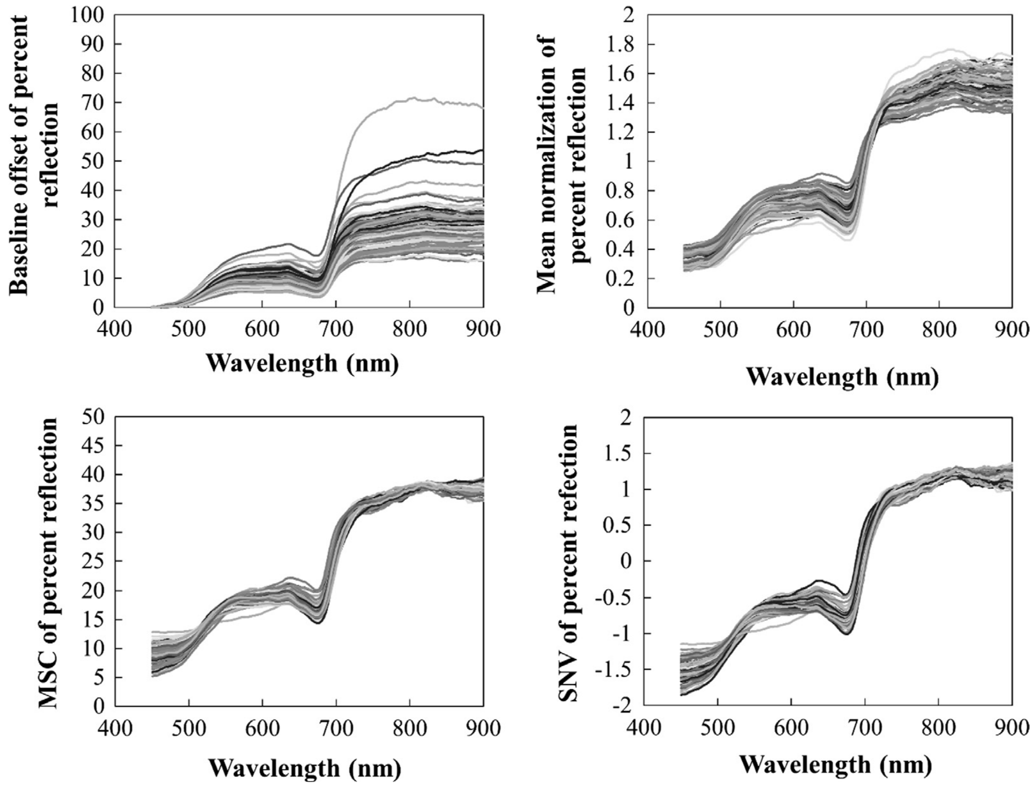

Fig. 4. Average NIR spectra pretreated by different pretreatments, MA + baseline offset (Top left), MA + mean normalization (Top right), MA + MSC (Bottom left) and MA + SNV (Bottom right).

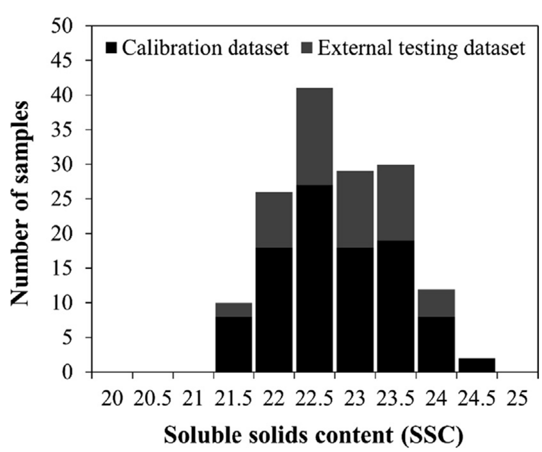

Fig. 5. Frequency histograms of the soluble solids content values used for PLS model development (100 samples) and external testing (50 samples).

Table 1
Statistical SSC values of sugarcane billets used in developing and testing the PLS model.

Dataset	N	Max	Min	Mean	SD
Calibration set	100	24.5	21.2	22.6	0.76
External testing set	50	23.9	21.4	22.6	0.66

N is the number of samples. Max is maximum. Min is minimum. SD is standard deviation.

when predicting a particular SSC value of sugarcane billets moving on the elevator.

Typically, a few latent variables (LVs) are required to describe most of the data variance, however, the first LV accounts for the greatest amount of variance (Nawi et al., 2013b). Additionally, it is desirable to use only a limited number of LVs in the model to avoid the inclusion of signal noise (Xiaobo et al., 2007). In this study only 4 LVs were used to explain the data variance in the SSC values.

Table 2
Regression and validation results for SSC prediction with different pretreatments.

Pre-Processing	Calibration			Validation	
	LVs	R^2	RMSEC	R^2	RMSECV
MA + Baseline offset	4	0.695	0.42	0.656	0.45
MA + Mean Normalization	4	0.821	0.32	0.767	0.37
MA + MSC	4	0.844	0.30	0.805	0.34
MA + SNV	4	0.846	0.30	0.807	0.33

Note: LVs is Latent variables, MA is moving average method, MSC is Multiplicative scatter correction, SNV is Standard normal variate.

This laboratory scale analysis is an important first step in the development of an on-the-go sensing system for the assessment of cane yield and quality during harvesting. The results presented here show the potential of online vis/SW-NIR spectroscopic techniques for the determination of soluble solids content in sugarcane billets moving on an elevator. From the findings present here, it should be possible to adapt this technique as an all-encompassing tool for PA already had the ability in yield assessment. This combination would allow the production of spatial variability maps describing the yield and quality within sugarcane farmlands. This variability map could help farmers reach their yields and quality responses, customize crop input and maximize farm profits. This could also allow the establishment of a fairer payment system for growers and allow mills to optimize their production processes.

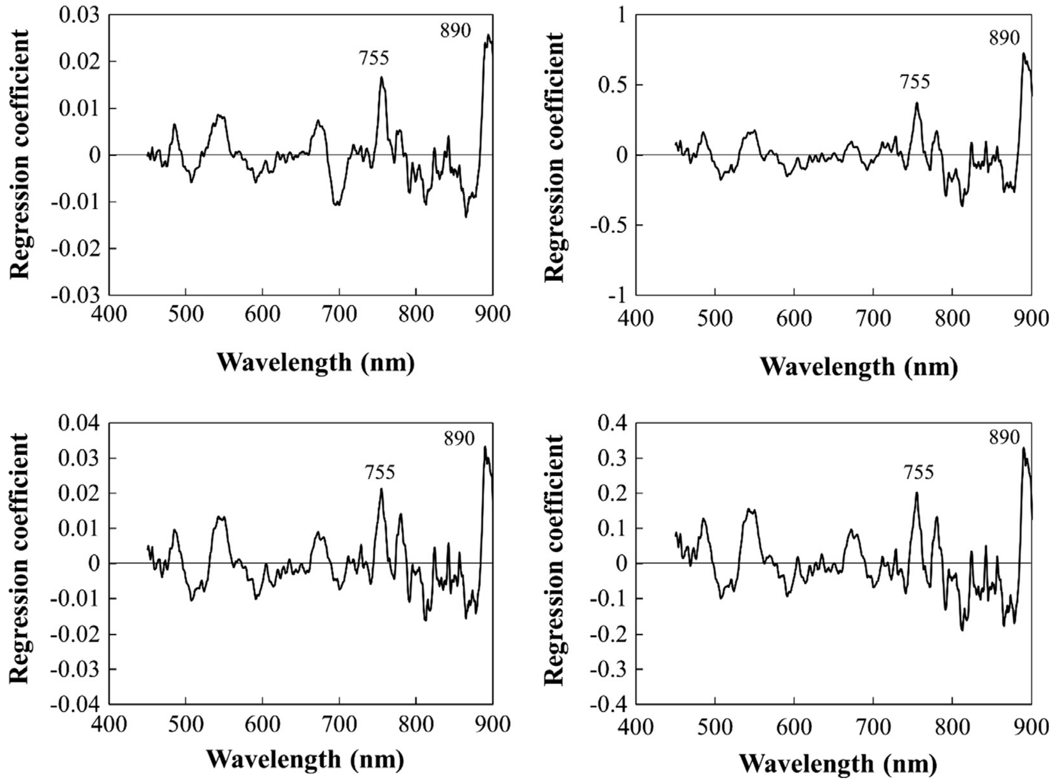

Fig. 6. Regression coefficient plots of the models constructed from the different pretreated spectra, MA + Baseline offset (Top left), MA + Mean normalization (Top right), MA + MSC (Bottom left) and MA + SNV (Bottom right).

5. Conclusion

In this work a lab-scale prototype of an online detection system has been designed and developed for the real-time SSC assessment of the sugarcane billets on an elevator conveyor. The system detects the spectra of the cane billets which are conveyed at the speed of 2 m/s (typical speed of a sugarcane harvester elevator) using an integration time of 14 ms. PLS modeling was used to correlate the obtained spectra with the SSC values. The results showed that the system is certainly feasible for the online SSC measurement of the sugarcane billets on the elevator, with an R^2, RMSEP, and RPD values of 78.5%, 0.30 °Brix and 2.16 for the prediction set, respectively. Nevertheless, it is acknowledged that modeling with a dataset consisting of a greater number of sugarcane cultivars is necessary for a production of on-the-go SSC sensing system. This additional validation would help to improve the robustness of method for online SSC measurements in real world sugarcane fields.

This on-the-go sensing system would benefit agriculturists in that it would minimize yield and quality variations across sugarcane farmland. A further side effect would be the establishment of a fairer payment system for the growers reflecting the quality of their product and optimized production processes within mills.

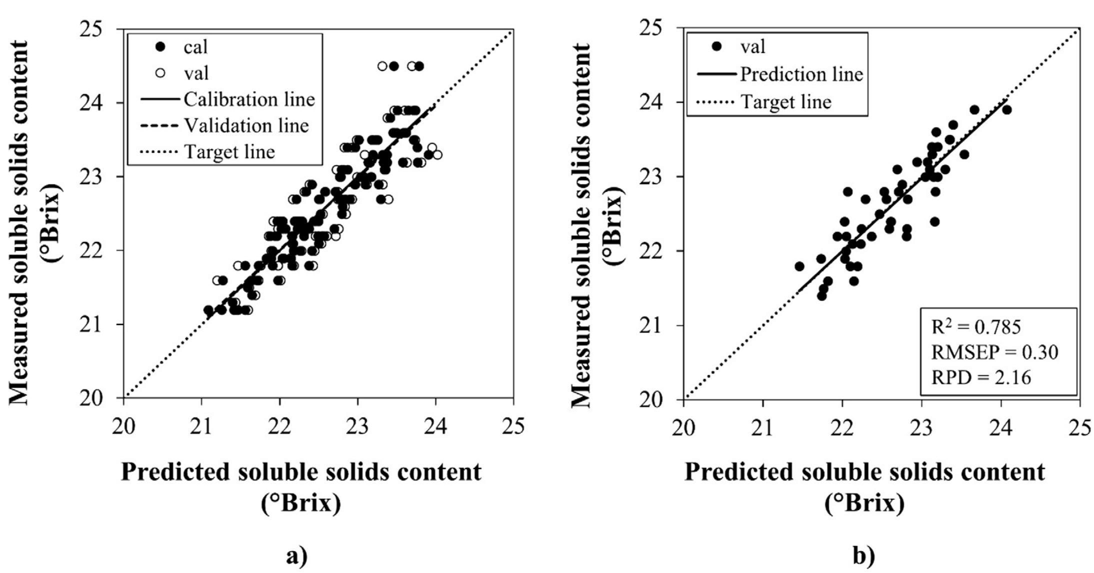

Fig. 7. PLS model with external validation constructed from the spectra pretreated with MA combined with SNV, comparison of SSC predicted by PLS model and measured by the standard reference for (a) the calibration set and (b) the external testing set.

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