Bioelectrical measurement for sugar recovery of sugarcane prediction using artificial neural network

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***Abstract*— One of the problems in the sugar industry is lack of low cost, simple and accurate measurement techniques for sugar recovery of sugarcane in the field or laboratory. This study investigated the potential using of bioelectrical properties as a non-destructive technique for this purpose. A parallel plate capacitor was developed to measure the bioelectric properties of sugarcane in a lateral and longitudinal position of the samples. Eighteen internode samples from 3 sugarcane varieties were measured within 0.1-10 kHz frequency range of LCR meter and then was analyzed sugar recovery in the laboratory. The result showed that in the lateral position are more capacitive and resistive than the longitudinal position. Artificial neural network (ANN) was developed for prediction of sugar recovery as a function of bioelectrical properties. The best ANN model produces a high accuracy in the lateral bioelectrical measurement position with a correlation coefficient (R) > 0.90 and mean square error (MSE) < 0.05. It showed that the ANN model based on bioelectrical properties had the potential to be developed as a simple technique to predict the sugar recovery of sugarcane.**

Keywords—ANN, Bioelectrical measurement, Sugar recovery, Sugarcane

I. INTRODUCTION

Sugarcane is an important raw material to produce several types of sweetener through a long process in the sugarcane industries. One of the limitations in the sugarcane industry is the lack of reliable and low cost technique to measure the sucrose content from standing sugarcane in the field or stalk sample in the laboratory. This technique would be a useful for the breeding program during sugarcane growth in field, evaluation of the input sugarcane for a fair payment to the farmers in the sugar factory and precision agriculture of sugarcane quality.

In standard practice, the quality of sugarcane was determined using sugar recovery. In Indonesia, sugar recovery measured based on °Brix (soluble solids content of sugarcane is determined from the refraction index of the light passed through the stalk sample) and %Pol (the percent sucrose is determined from rotated polarized light when is passed along the sample) which are measured in laboratory through sugarcane juice samples. Therefore, the measurement of sugar recovery in the laboratory is take a long time and not applicable in field, because it need a preparation of sugarcane juice.

Mat Nawi [1] reviewed the potential method for measuring sugarcane quality in the field such as refractometry, polarimetry, chromatography, biosensor, wet chemical, and spectroscopy. All the methods mentioned above other than spectroscopy was need sugarcane juice, and therefore are not appropriate for in field measurement. Spectroscopy method using NIR revealed the accurate prediction, however need a high skilled operators and may not be a proper technology.

Bioelectrical properties of the agricultural products has been proven as a reliable, simple and non-destructive sensing technique [2, 3]. This method based on the electrical properties of the material and describes the electric field or material interaction [2, 4]. Naderi-Boldaji [5] revealed that the bioelectrical properties can be used as parameter for the non-destructive measurement of sugar concentration in sugarcane. They used dielectric power of sugarcane to predict sugar concentration by mean of multiple linear correlation. In addition, the bioelectrical properties are applied in prediction moisture content of sugarcane using a simple quadratic function [6].

Initial research have been standardized the bioelectrical properties measurement at frequency below 1 kHz to measure sugar recovery of sugarcane [7]. However, there is not yet a robust model to predict sugar recovery of sugarcane. Therefore, to build a robust predictive model, artificial neural network (ANN) was used. ANN theory, generally accepted as a useful tool for the recognition of various patterns [8]. ANN modelling has been proven as reliable predictive formulation in a various studies such as predicting water content of Sunagoke moss [9], water status of plants [10] and sugar yields during hydrolysis of lignocelluloses biomass [11].

This research aimed to develop a low cost, reliable and non-destructive system for sugar recovery of sugarcane based on the bioelectrical properties measurement and also to develop predictive models of sugar recovery using bioelectrical properties.

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II. MATERIALS AND METHODS

A. Sample Preparation

Sugarcane sample were taken from 3 commercial varieties of BL, PS 864, PS 862 at Indonesian Sugar Research Institute Pasuruan, East Java, Indonesia. These samples were selected according to their variety of sucrose content (low, mid and high) with early and late maturity to capture a wide range of variation. In addition, the samples were randomly taken from the different zone of the field with 3 stems were taken from each variety without time delay and transferred to the laboratory for bioelectric properties and sugar recovery measurements.

Sugar content usually decreases along the stem heigh [1], hence the stem samples were cut for three internodes (bottom, mid and top). On the other hand, there are early and late maturing sample. Therefore in total, 18 internode were measured from 3 varieties. For each internodes was re-cut into two paired-samples using a cutter, one was used for bioelectrical measurement and the other one for sugar recovery measurement in laboratory.

B. Instrumentation Setup and Measurement Principle

The bioelectrical properties were measured at 100 Hz, 120 Hz, 1 kHz and 10 kHz using LCR Meter (BK Precision 879b) connected with a pair of parallel plate. In this study, a parallel plate was constructed by printed circuit board with diameter of 3 cm and the gap between parallel plates was diameter of sample. A sample was placed between parallel plate in lateral position and maintained at 30°C during measurement using thermometric cooler (WAECO). The capacitor is formed by a combination of sample and air as the dielectric. The conductive plates selected from copper material due to its consistency which would not be easily ionized as a factor that will maintain the measurement using capacitive properties. The measurement of bioelectrical properties including inductance (L), resistance (R) and capacitance (C) was repeated six times for each frequency. Therefore, for each sample was obtained 24 dataset and in total there are 432 dataset.

The primary point in measuring bioelectrical properties is the capacitance of the sample. The capacitance of the sample measure was described by Equation 1.

$$C=\varepsilon A/d \tag{1}$$

Where C is capacitance (F), A is the area of plates (m^2), d is the gap between parallel plates (m), and ε (F/m) is the complex relative permittivity of the substance between parallel plates. When a sample is placed between a pair of parallel plate, capacitance of probe will be changed. In addition thickness of sample will affect the bioelectrical properties.

C. Laboratory Measurement of Sugar Recovery of the Sugarcane Samples

The laboratory measurement for °Brix and %Pol measurement was conducted according to [5]. Each one of the pair internodes samples were milled and crushed by a small mill (A11 analytical basic mill, IKA®-Werke GmbH & Co. KG, Germany) and then squeezed and centrifuged for extraction of juice. For refractometer (°Brix) test, the juice sample was clarified through a Whatman filter paper. For polarimetry (%Pol) test, lead acetate was added to the juice sample with 0.02 g ml^{-1} concentration and the mixture was clarified by a filter paper. °Brix and optical rotation were analyzed by a digital refractometer (model HI 96801, Hanna instruments, USA) with a range of 0-85° and an accuracy of 0.2 °Brix and a high speed polarimeter (model P8000, Kruss optronic Co., Germany) with a range of ±90° optical rotation, an accuracy of ±0.003° and a tube volume of 5 ml, respectively. %Pol was calculated from °Brix and the degree of optical rotation (OR). The sugar recovery (SR) of sugarcane was calculated using Equation 2.

$$SR=0.78\ (\%pol-0.4(°brix-\%pol)) \tag{2}$$

D. Artificial Neural Networks Modelling

ANN have been shown to be successful as predictive tools in a variety of ways such as predicting the level of some event outcome [12]. Comparative studies made by researchers suggest that ANN compare favorably with conventional statistical pattern recognition methods [8]. A three layers of ANN structure has been developed for predicting sugar recovery of sugarcane, namely input layer, hidden layer(s) and output layer.

The number of neurons in the input layer was determined by the number of input features obtained from bioelectrical properties. Prior to develop ANN model, selecting feature that are suitable for an application is one of the most critical parts to improve the accuracy and speed of prediction system. There are three category of feature selection, namely filter methods, wrapper methods, and embed methods. In this study, the simplest filter methods namely linear regression was carried out to select the features that is suitable for sugar recovery prediction. The selected features was then applied to the input layer of ANN model, there are capacitance and resistance. Learning rate and momentum were chosen at 0.1 and 0.9, respectively based on the results of preliminary runs. Five models of hidden nodes architecture were developed, i.e. 10, 20, 30 and 40 within one and two hidden layers. The output layer consisted of single neuron namely sugar recovery corresponding to the input features. The activation function namely *logsig*, *tansig* and *purelin* were used to optimize the prediction accuracy. Mean square error (MSE) and correlation coefficient (R) were used to determine training and testing performance of ANN models.

III. RESULT AND DISCUSSION

A. Characteristic Sugar Recovery of Sugarcane

Laboratory result of sugar recovery measurement (Fig. 1) revealed that the lower internode has a higher sugar recovery than the upper one. This is due to the lower internode (older) contain more sugar than the younger one [13]. According to Indonesian Sugar Research Institute, PS 862 has a higher sugar content than the other varieties.

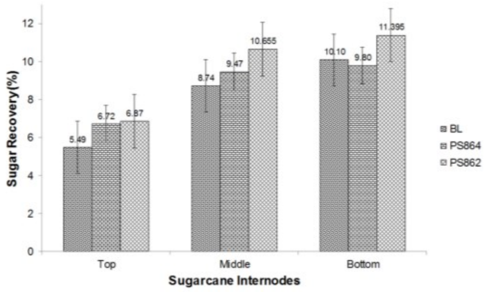
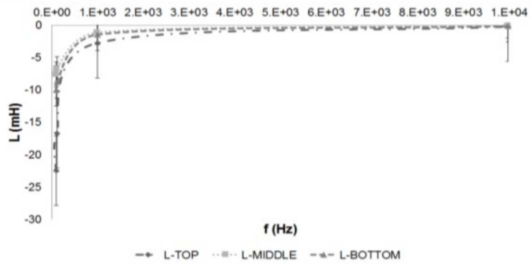


Fig. 1. Sugar recovery distribution in various internodes within three varieties.

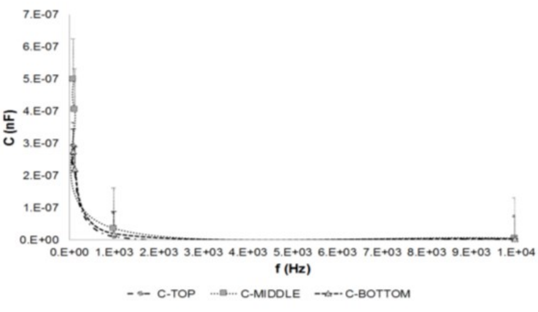
B. Bioelectrical Characteristic of Sugarcane

Bioelectrical properties of sugarcane were measured within various frequency. Frequency changes in the dielectric material affect the molecular condition [3]. According to Faraday's law, inductance defined as an electromotive force (EMF) generated to counter a given change in the negative electrode, hence in the Fig. 2A shown a decreased of EMF.

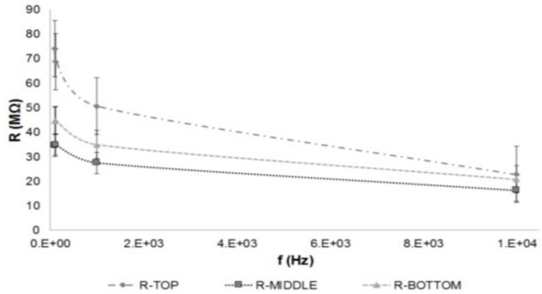
High frequency caused a short time of polarization, hence the polarization does not occur completely without sufficient times [14]. Therefore, the increasing frequency will lead to the decrease in the total polarization. This is produce a low capacitive phenomena in the sample (Fig. 2B). On the other hand, the change of frequency also affect to the condition of ion the sample. Therefore, produced a rapid mobility of dipole due to electrode polarization within high free water state also produce a low resistance (Fig. 2C). The electrical circuit model of sugarcane was constructed in a resistor-capacitor relation suitable with Zhang model.



(A)



(B)



(C)

Fig. 2. The bioelectrical properties of the samples: (A) inductance (B) capacitance and (C) resistance within frequency range of 0.1-10 kHz..

C. Artificial Neural Network Prediction Model

The normalized dataset was used to determine an optimal proportion of data training and data validation. Data training of 66.67% was obtained the higher correlation coefficient (R). According to [15], the optimal training process can use different data groups by changing the percentage of data and evaluate with the highest regression. A sensitivity analysis performed to determine the best ANN model. In this stage, the sensitivity analysis was carried out using twenty combinations of node in the hidden layer. The sensitivity analysis of ANN was depicted in Table I.

TABLE I. ANN SENSITIVITY ANALYSIS

Topology	MSE Validation	R Validation
2-40-40-1	0.1476	0.7543
2-30-40-1	**0.04**	**0.9175**
2-20-40-1	0.2452	0.7136
2-10-40-1	0.2117	0.6586
2-40-1	0.1068	0.7372

The best ANN model is 2-30-40-1 (2 input nodes, 30 nodes in hidden layer 1, 40 nodes in hidden layer 2 and 1 output node) (Fig. 3) with MSE and correlation coefficient (R) are 0.04 and 0.9175 respectively. According to [16], sometimes ANN with more hidden layer can generalize better than simple ANN with low hidden layers. Increase number of hidden layer can inhibit the rate of convergence. Following is the phase of convergence on the best topology with 5000 iterations.

The best ANN model was yet convergence (Fig. 4). This showed the complexity of dataset, so the convergence was slow, even though the target has been achieved. One of the factors that affect the convergence is determination of momentum constant (μ) and learning rate. Learning rate is inversely proportional to the changes of weight and MSE, hence it is takes a longer time. Appropriate momentum constant can be used to offset the learning rate, and avoid a fluctuation of weight changes [8, 9]. The best combination of results obtained from the parameters of 0.1 learning rate and 0.9 momentum constant (μ). The best ANN model can be applied to predict sugar recovery of sugarcane in an interactive application.

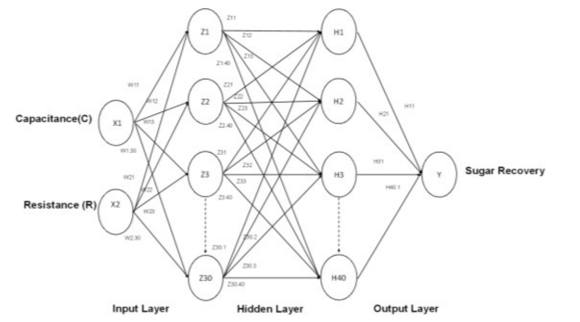


Fig. 3. Selected ANN model

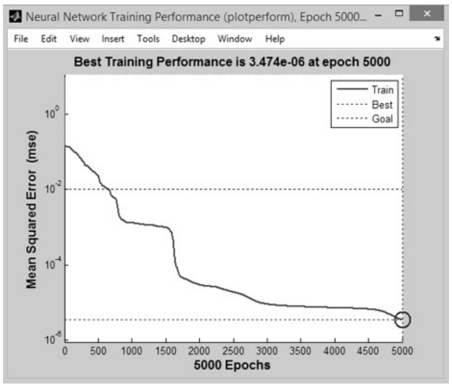


Fig. 4. Generated error in selected ANN model

D. Comparison of Lateral and Longitudinal Bioelectric Measurement

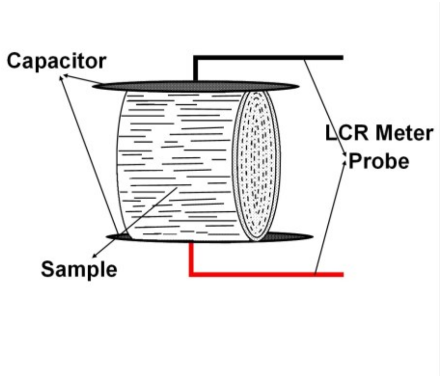


Fig. 5. Lateral position of the sample

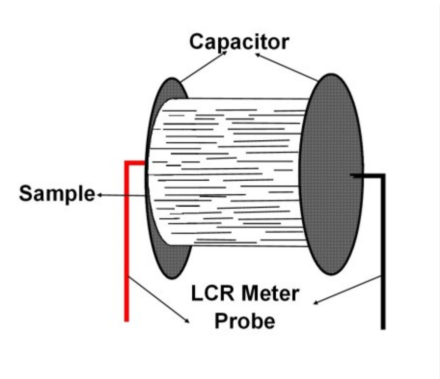


Fig. 6. Longitudinal position of the sample

Initial research bioelectrical properties has been measured in the longitudinal position within the direction of fibre (Fig. 5). On the other hand, in this research, bioelectrical properties was measured in the lateral position (Fig. 6). Therefore, the resistance of will be slightly higher, caused by resistance of the fibre. According to [2], structure as well as the geometry of material as well as the placement of sample will affect the bioelectrical properties.

TABLE II. BIOELECTRICAL PROPERTIES OF SUGARCANE IN LATERAL POSITION

Node	Frequency (kHz)	Capacitance (nF)	Resistance (kΩ)
Top	0.1	0.0000002922	74079.30
	1	0.0000000099	50605.75
	10	0.0000000012	22731.08
Middle	0.1	0.0000004987	34528.48
	1	0.0000000342	27454.41
	10	0.0000000031	16174.33
Bottom	0.1	0.0000002750	44628.68
	1	0.0000000184	34899.83
	10	0.0000000021	20730.83

TABLE III. BIOELECTRICAL PROPERTIES OF SUGARCANE IN LONGITUDINAL POSITION

Node	Frequency (kHz)	Capacitance (nF)	Resistance (kΩ)
Top	0.1	0.000002367	3112.44
	1	0.000000220	1891.98
	10	0.000000043	1007.19
Middle	0.1	0.000001847	3827.80
	1	0.000000181	2360.46
	10	0.000000036	1250.52
Bottom	0.1	0.000001707	4449.65
	1	0.000000175	2779.80
	10	0.000000033	1415.23

Table II shows the values of bioelectrical properties of lateral measurement tend to be larger than the longitudinal measurement (Table III). Longitudinal measurement result such as capacitance (C), there is the same higher at a frequency of 1 kHz, 10 kHz respectively and another frequency have capacitance gap between $1x10^{-9}$ to $1x10^{-6}$ nF. The resistance of lateral measurement is greater longitudinal ones by approx. 1 kΩ. Those results show some tissue layer on stem of sugarcane acts as a capacitor and resistor, so the electric current in the form of a wave has disruption in wax layer of the flow paths, as well as some membrane resistance at intracellular and extracellular of the stems [2, 17]. The cell wall of each layer in stem of sugarcane is very influential on the resistance at lateral position, because on each layer of sugarcane is perpendicular to direction of electric current, so it has high resistance. On the other hand, at longitudinal position sugarcane stems was placed in a parallel position to the electric current, hence there is a little resistance to the electric current flowing through the tissue. The results of measurements bioelectrical properties certainly affect the prediction of sugar recovery of sugarcane. Prediction sugar recovery of sugarcane using ANN in longitudinal model produce the best topology at 3-30-40-1 MSE and R are 0.0104 and 0.97733 respectively. On the other hand, the best results were obtained on the lateral measurement topology at 2-30-40-1 with MSE and R were 0.04 and 0.9175 respectively. Although in terms of topology ANN lateral measurement results are simpler with 2 inputs, but the complexity of the data inputs affect the results of prediction.

IV. CONCLUSION

Bioelectrical properties using a parallel plate capacitor were assessed for rapid and simple measurement of sugar recovery of sugarcane. Sugar recovery was affected the bioelectrical properties, hence the bioelectric model of sugarcane become a resistor-capacitor (R-C) series. There are two model of measurement procedure, which are lateral and longitudinal position of the samples. The first one shown that there is more capacitance and resistance produced by the samples than the last one, which affect the prediction model. ANN model was used to predict sugar recovery based on the bioelectrical properties of the samples. The best ANN structure is 2 input, 30 nodes in first hidden layer and 40 nodes in second hidden layers, also 1 prediction network output (sugar recovery of sugarcane). The sugar recovery of sugarcane was strongly predicted by bioelectrical properties data (MSE of 0.04). Finally, ANN models based on the bioelectrical properties has been proposed to develop an accurate, simple and reliable technique for sugar recovery of sugarcane measurement.

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