Miscellaneous

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Mass-balance based soft sensor for monitoring ash content at two-ply paperboard manufacturing

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Abstract: Continuous and robust measurements are needed for the high end-product quality and efficient and eco-friendly process in paperboard manufacturing. As the online measurements enable the optimization of the manufacturing process making it more cost effective and environmentally friendly, these measurements must be validated carefully and continuously. This paper presents the development of a mass-balance based soft sensor for online estimation of a two-ply paperboard ash content. The developed soft sensor considers the basis weight, moisture and fiber measurements to derive the ash content of the paperboard at the reel. The development of the soft sensor was success (Mean Absolute Percentage Error was 11.80) and during the long-term simulation with measured data, this robust online estimator showed the level and changes in ash content accurately, enabling also the continuous validation of the hardware sensor.

Keywords: measurement uncertainty; online estimator; reliability assessment; virtual sensor.

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Introduction

In the paper and paperboard manufacturing, the demands for the end-product quality and the process efficiency are high, but also the goals for more sustainable production process with reduced energy consumption and wastes are tightening. Low or varying quality causes excessive costs in a form of downgraded or discarded product batches. The optimization of the manufacturing process and maintaining the high and less varying quality of the end-product require continuous and robust process monitoring. The traditional laboratory analyses of manually taken samples include several disadvantages (Viitamäki and Ritala 2018); The procedure is time-consuming and there is a long delay before receiving the results. In other words, the results of infrequent laboratory analyses always present the past information from the manufacturing process, limiting its usability in online applications. In addition, the analyses may be based on too few samples from the statistical point of view, and there can be challenges with linking the laboratory data to dynamic process information (Karlström et al. 2019). The online quality measurements, on the other hand, eliminate these disadvantages by increasing the measurement frequency enabling almost continuous measuring, minimizing the delays for receiving the results, and giving a more representative overview of the quality within an entire machine reel. Online quality monitoring enables quicker reaction in case anomalies are detected and therefore unnecessary downgrading or discarding the entire batches of the products can be avoided.

In a modern industrial process, hundreds or thousands of sensors are routinely measuring and automatically recording the data with a frequency of minutes or even seconds. Hence, a great volume of data is collected in a relatively short period of time for process monitoring, evaluation, and control. This has initiated a great interest in academy and industry to transform the data into information to business and operation decision-making (Chiang et al. 2017). Indeed, advanced data analysis has also been studied in several application within the pulp and paper industries; some of the examples comprise a mill-wide root-case analysis of paperboard indents (Fu and Hart 2016), identifying energy savings (Harding 2020), fault detection in pulping (Karlsson 2020), and modeling grade changes in a paperboard machine (Skoglund et al. 2018).

Although the online measurements may enable the optimization of the manufacturing process making it more cost effective and environmentally friendly, the online measurements must be carefully validated. Some of the technical challenges related to data analytics are related to selecting meaningful data (variables and time-resolution) and efficiently coupling that with domain knowledge (Chiang et al. 2017). The previous research has highlighted the need for validated, accurate measurements; for example, Avelin et al. (2009) discusses how only the small portion of 254 sensors along the fiber line and the paper machine were reliable enough for online applications of statistical models. Hence, different means to validate the sensory data and replace uncertain measurements are needed. For example, data reconciliation and gross error detection are applied together to improve accuracy of measured data (Narasimhan and Jordache 2000). Data reconciliation in pulp and paper applications has been discussed, for example in papers by Avelin et al. (2009) and Wilson (2008).

Soft sensors (virtual sensors) can be used redundantly for monitoring the functionality of the hardware sensors or for estimating the process variables that are difficult, unsafe, costly, or impossible to measure reliably with the hardware sensors, utilizing the easy-to-measure variables as the inputs of the model (Souza et al. 2016). Therefore, when applied as an additional redundant measurement, soft sensors can offer one option to assess also the validity of data. In the case related to paperboard manufacturing, developing many single-grade models or one model for every paperboard grade is an important soft sensor design decision because intergrade quality variations tend to be easier to model but intragrade variations are more relevant to practical quality management (Viitamäki and Ritala 2018). Examples of soft sensors developed for paper properties include strength properties prediction (Raffaele and Ondruch 2020, Alonso et al. 2009), ash content prediction for web break situations (Nobakhti and Wang 2010), and moisture estimation (Viitamäki and Ritala 2018, Dijkstra 2011). Nobakhti and Wang (2010) developed a soft sensor estimating base sheet ash content for improved web break situation awareness and control. The model was based on four variables (headbox total consistency, headbox ash, whitewater total consistency and whitewater ash) and Least absolute value regression. In this case, a mass-balance approach was deemed to be impossible as the whitewater flow, and therefore the amount of drained pulp away from the wire, was not measured.

In this paper, a development of a mass-balance based soft sensor for online estimation of the ash content at a reeling stage of a paperboard manufacturing process is presented. A single soft sensor for multiple paperboard grades is presented that applies existing paperboard quality measurements in a novel way together with the utilization of known physical dependencies between the measured variables. The main goal of the research work is to inspect the functionality and to compare the similarity of the developed online estimator with the available data measured with a hardware sensor. Additionally, it is also explored by simulations if it would be possible to replace the hardware ash measurement with the developed soft sensor and hence avoid usage of a measurement technique based on radioactive emission.

The paper is structured as follows: In Materials and methods section and its subsections, a general description of the online quality measurements to acquire the data is given, the acquired data set is described, and the development steps of the soft sensor are presented. In Results and discussion section, the training and testing data are depicted, the soft sensor performance in the training set and in the testing set are presented, together with a discussion of practical considerations and future perspective. Finally, Conclusions section concludes the research presented.

Materials and methods

Quality measurements in paperboard manufacturing

Sensors measuring the paperboard quality online are attached to measurement platforms that move across the paperboard web and continuously scan and measure the product characteristics from edge to edge. The primary measurements are the basis weight, moisture content and ash percentage, which are validated via internal protocols of production plants (comparison between online and offline measuring system). This research work utilizes the basis weight, moisture content and ash content online measurements at the reeling stage of paperboard machine. In addition, the online fiber amount measurement at the same position is considered.

The ash content of the paperboard consists of for instance filling, coating, pigmenting and other added materials. The online ash measurement is based on the energy selective absorption of x-rays. The sensor measures the absorption of the x-rays in the web, and the sensor data is automatically transformed into ash measurement and standardized. (Holik 2006) Typically the online ash measurement accuracy is in the range of 0.5 to 1 % (Hu et al. 2020).

Basis weight is the most important quality variable measured at the paper or paperboard manufacturing. The basis weight is the mass of one square meter of paperboard in grams (g^{m-2}). The basis weight consists of dry weight and the water weight of the paperboard. Dry weight is the mass of one square meter of paperboard in grams (g^{m-2}) after drying. The water weight is defined as the difference of masses of paperboard measured before and after drying or calculated based on the moisture content measurement. The online non-contact basis weight measurement is commonly based on the absorption of beta radiation or infrared (IR) absorption measurement. (Holik 2006)

Moisture content, another important quality variable, can be calculated indirectly by dividing the water weight with the basis weight value obtained. That is, the moisture of paperboard is given as a percentage of original mass. The most common online moisture measurement principle at paperboard manufacturing is based on IR technique. The principle of the IR measurement is based on the specific absorption of water molecules at the near infrared (NIR) range. The IR method can be used for paperboards at basis weight range of 10–500 g^{m-2}. Frequent automatic internal calibration is required in order to remove the sensor-related errors (dirt etc.). (Holik 2006)

Spectroscopic measurement can also be used for determining the amount of fiber in the paper web (Mäntylä 2017). The method utilizes a fiber-specific absorption band and several baseline wavelengths which are chosen for their response to water and fiber (organic dry matter). The measurement technique utilized in this research was based on the NIR spectroscopic method. Here, the sensor that measured the water weight (moisture content), also measured the amount of fibers of the paperboard. However, this feature of the NIR measurements was not under internal use and was therefore without continuous validation and calibration at the mill. Therefore, the fiber measurement was deemed to carry the highest uncertainty within the studied measurements.

Dataset

The data used in this research was collected using measurements at a two-ply kraft paperboard machine with product basis weight ranging from circa 125 to 240 g^{m-2} during two separate collection campaigns between January and August 2020. The data was acquired at five seconds interval and saved to the automation system of the mill. For training data of the soft sensor, the shortest possible subset of data where all paperboard grades were present was selected. Hence, for the testing, a vast amount data was left available for exploring the robustness of the developed soft sensor. The both, training and testing, subsets of data included the produced paperboards in range of measured dry weight between circa 115 and 220 g^{m-2} and ash content between 0 % and 7 %. The training data set omitted production breaks and it was almost free from severe measurement errors. Therefore, the data was deemed to be suitable for identifying the soft sensor. The length of the training set was circa 5 days (80 001 data points) and the length of the dataset for testing the soft sensor was circa 25 days.

Theoretical framework of the soft sensor

The development of the soft sensor for online monitoring of ash content was carried out following the steps and equations presented below and utilizing the selected training data described in the previous section. The proposed concept for the soft sensor is illustrated in Figure 1 with the model identification stage presented as dashed lines and the soft sensor testing presented as solid lines. Figure 1 also shows the data flow in case of training and testing stages. In Figure 1, the white background illustrates the measurements, the light grey background illustrates the training stage, and the dark grey background illustrates the testing stage of the identified model. The subscript *m* denotes the weight (g^{m-2}), whereas the subscript *c* refers to content (w-%). The measurements utilized in the soft sensor development were from the same measurement platform at the reeling stage of the paperboard machine, and thus there is similar lag between the measurements.

The development of the ash soft sensor includes two steps, namely the fiber measurement calibration and the ash content estimation, and it bases on the mass balance of instantaneous values of the four properties with their dependencies written as in Equation (1).

$$Basisweight = Fiber + Water + Ash. \quad (1)$$

The ash content and moisture are typically expressed as percentages (%) so they need to be converted into masses (g^{m-2}) by multiplication of basis weight and moisture content, and basis weight and ash content, respectively. The $Waterweight_m$ is the weight of water in paper-

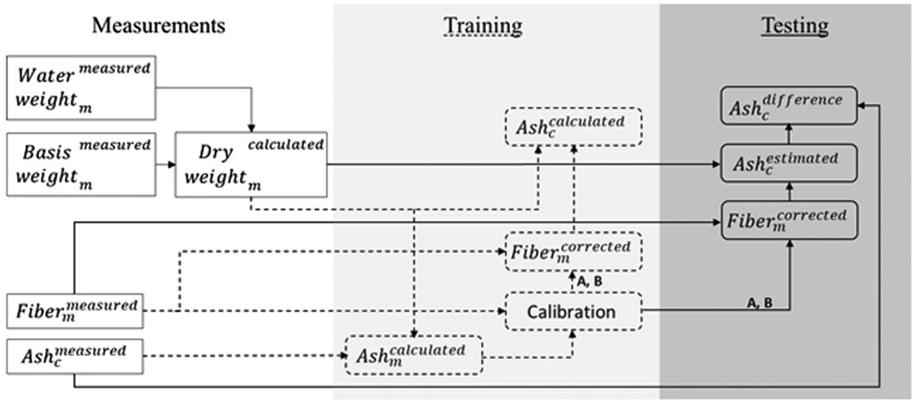

Figure 1: The framework of the real-time soft sensor for monitoring the ash content.

board based on the measured moisture content at the reeling stage as determined in Equation (2):

$$Waterweight_m^{measured} = Moisture_c^{measured} \times Basisweight_m^{measured}/100, \quad (2)$$

where $Moisture_c$ is the measured moisture content (%) and the $Basisweight_m$ is the total weight of the paperboard (g^{m-2}) measured at the reeling stage. The dry weight (g^{m-2}) of the paperboard is determined by subtracting the measured water weight from the basis weight (g^{m-2}) as in Equation (3).

$$Dryweight_m^{calculated} = Basisweight_m^{measured} - Waterweight_m^{measured}, \quad (3)$$

where $Basisweight_m$ is the total weight of the paperboard (g^{m-2}) measured at the reeling stage and the $Waterweight_m$ is the weight of water determined with Equation (2).

The absolute amount of Ash (g^{m-2}) is calculated as in Equation (4).

$$Ash_m^{calculated} = Dryweight_m^{calculated} \times Ash_c^{measured}/100, \quad (4)$$

where $Dryweight_m$ is the dry weight (g^{m-2}) of the paperboard calculated in Equation (3) and the Ash_c is the ash content (%) measured at the reeling stage.

In the first phase, the uncertainties in fiber measurement are solved. The errors can be seen by comparing the calculated fiber from the mass balance and the measured fiber from the reel. Hence, the fiber measurement requires calibration. Here, the online data from the training dataset is utilized. However, calibration can also be based on laboratory data from the basis weight, water weight (moisture) and ash aligned with the online fiber measurement data. The calibration of fiber measurement is performed with the following equations.

The amount of fiber (g^{m-2}) is calculated as in Equation (5) and compared with the amount of fiber (g^{m-2}) measured at the reeling stage. The difference (g^{m-2}) between the calculated and measured fiber amount is calculated as in Equation (6).

$$Fiber_m^{calculated} = Dryweight_m^{calculated} - Ash_m^{calculated}, \quad (5)$$

where $Dryweight_m$ is the dry weight (g^{m-2}) of the paperboard at the reeling stage and Ash_m is the absolute amount of ash (g^{m-2}) calculated in Equation (4).

$$Fiber_m^{difference\_m-c} = Fiber_m^{measured} - Fiber_m^{calculated} \quad (6)$$

A linear fitting with the measured and calculated amount of fibers is carried out to determine the coefficients A and B for calculating the corrected fiber (g^{m-2}) values as in Equation (7). As there are one dependent variable (corrected amount of fiber) and only one independent variable (measured amount of fiber), the procedure is a simple linear regression.

$$Fiber_m^{corrected} = A \times Fiber_m^{measured} + B, \quad (7)$$

where A is the slope of the fitting line, $Fiber_m$ (measured) is the amount of measured fiber (g^{m-2}), and B is the y-intercept of the fitting line. Hence, the corrected fiber values were determined and compared with the calculated fiber values as in Equation (8).

$$Fiber_m^{difference\_c-c} = Fiber_m^{calculated} - Fiber_m^{corrected}. \quad (8)$$

The second step uses the mass balance (Equation (1)), but with the corrected fiber measurement (i. e. the linear model coefficients and measured fiber) and the online measurements from the basis weight and water weight (moisture). The calculated and estimated ash content (%)

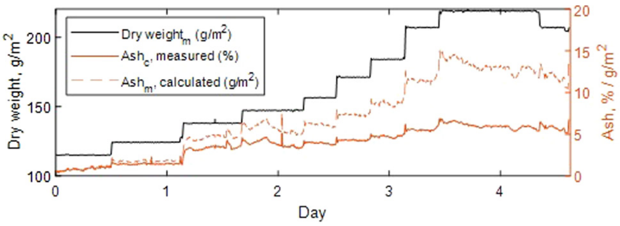

Figure 2: The measured ash content (%) at the reel and the amount of calculated ash (g^{m-2}) (right axis) with the range of paperboard dry weight (g^{m-2}) (left axis) during the circa 5 day training period.

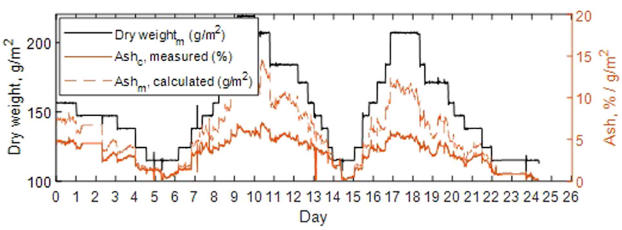

Figure 3: The measured ash content (%) at the reel and the amount of calculated ash (g^{m-2}) (right axis) with the range of paperboard dry weight (g^{m-2}) (left axis) during the circa 25 day testing period.

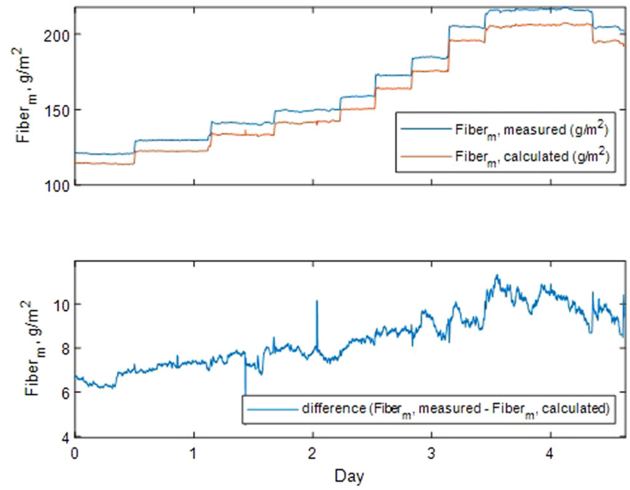

Figure 4: The measured amount of fiber (g^{m-2}), the calculated amount of fiber (g^{m-2}), and their difference (g^{m-2}).

is determined using the corrected amount of fiber (g^{m-2}) from Equation (7) and dry weight (g^{m-2}) from Equation (3) as shown in Equation (9).

$$Ash_c^{estimated} = ((Dryweight_m^{calculated} - Fiber_m^{corrected}) / Dryweight_m^{calculated}) \times 100, \quad (9)$$

where $Dryweight_m$ is the dry weight (g^{m-2}) of the paperboard determined in Equation (3) and $Fiber_m$ is the corrected amount of fiber calculated in Equation (7). The calculated and estimated ash content (%) are compared with the ash content (%) measured at the reel as in Equation (10).

$$Ash_c^{difference} = Ash_c^{estimated} - Ash_c^{measured}. \quad (10)$$

Results and discussion

Data

The range of paperboard dry weight (g^{m-2}) during the training stage is presented in Figure 2 with the calculated amount of ash (g^{m-2}) and the ash content (%) measured at the reel. It can be observed that the selected training data included paperboard grades with a dry weight range from circa 115 g^{m-2} to 218 g^{m-2}. No cleaning or smoothing of the data was performed and hence at day 2 there is a spike in the measured dry weight and at day 3 a notable spike is shown in the measured ash content. These and other spikes shown last generally only a few minutes and may be resulted from an error of hardware measurements or measurement internal standardization. The spikes are also shown in corrected fiber and calculated ash content figures presented in Soft sensor training section. The ash content measured at the reel and the amount of calculated ash (g^{m-2}) during the testing period are presented in Figure 3 with the range of paperboard dry weight (g^{m-2}).

Soft sensor training

The soft sensor development for the redundant online ash measurement was carried out following the steps described above. The calculated fiber, the measured fiber and their difference are presented in Figure 4. As seen, there is a notable difference between the measured and calculated fiber, indicating poor calibration of the IR-based fiber measurement. As mentioned in Quality measurements in paperboard manufacturing section, this additional feature of IR measurement was utilized at the mill for the first time, and thus lacking routine calibration. Therefore, a linear fitting with the measured and calculated fiber was carried out to determine the coefficients for calculating the corrected fiber values (Figure 5). The coefficients A = 0.965 and B = –2.56 g^{m-2} were achieved based on the linear fitting and new corrected fiber values were determined as described earlier. The comparison of the corrected fiber and calculated fiber is presented in Figure 6. The difference after the

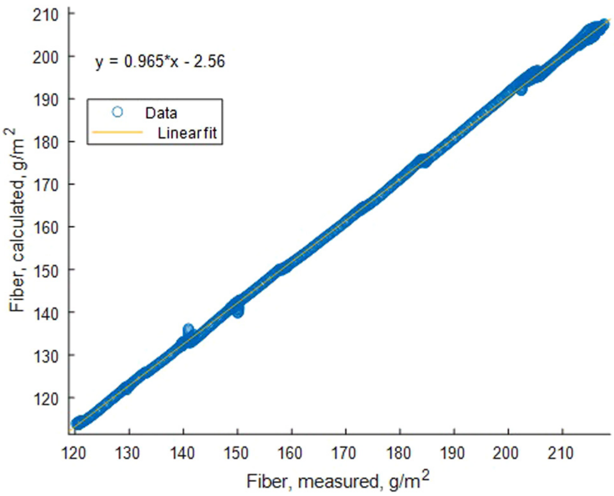

Figure 5: The linear fitting of the calculated and the measured fiber.

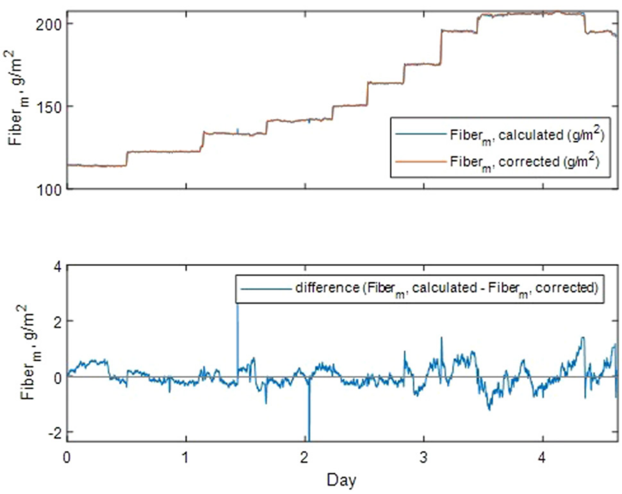

Figure 6: The calculated amount of fiber (g^{m-2}) and the corrected amount of fiber (g^{m-2}), and their difference (g^{m-2}).

Table 1: The calculated values of the differences presented in Figures 4, 6, 7, 9, 10 and 11.

	Training			Testing		
	Mean	Median	2σ	Mean	Median	2σ
Calculated fiber (Figures 4 & 9)	8.387	8.224	2.546	7.843	7.749	2.964
Corrected fiber (Figures 6 & 10)	0.015	−0.048	0.758	0.145	0.148	1.930
Calculated and estimated ash (Figures 7 & 11)	0.010	−0.028	0.444	0.118	0.099	1.292

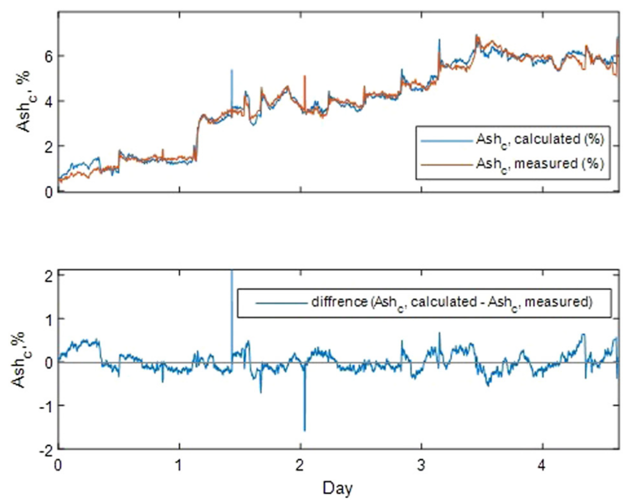

Figure 7: The calculated and the measured ash content (%) and their difference during the training period.

calibration is small, in average 0.015 g^{m-2} during the training period (Table 1).

The calculated ash content was determined as in Equation (9) and compared with the measured ash content (see Figure 7). As seen, the difference is small, on average only 0.01 percentage points (standard deviation 0.2) with training data (Table 1). The calculated Mean Absolute Percentage Error (MAPE) during the training period was 0.078. Therefore, the accuracy of the developed soft sensor is within the appointed target value +-0.5 percentage points in the training data, namely exhibiting the same scale of accuracy as a hardware sensor (see Hu et al. 2020). However, there are short periods when the difference is larger, due to some unknown process conditions or stock properties that cause abrupt spikes or changes to the measured values. It should be also noted that the calculations related to the training procedure utilize the measured online ash content information. The ash content information would also be available through regular laboratory ash analyses as an alternative reference measurement.

In Figure 8, the Normal Probability Plot (NPP) of the developed soft sensor error values (shown in Figure 7) during the training period is presented. The NPP is a graphical technique for assessing the normality assumption of a data set (NIST 2021). There, data with a normally distribution appears approximately along the reference line and departures from abnormal distribution introduces curvature in the plot. Quantiles of the data are matched here to the quantiles of the normal distribution. The data is sorted and plotted on the x-axis and the y-axis represents the quantiles of the normal distribution converted into probability values. As seen in the Figure 8, the modelling error NPP of the developed soft sensor with training data indicates that residuals are reasonably normally distributed,

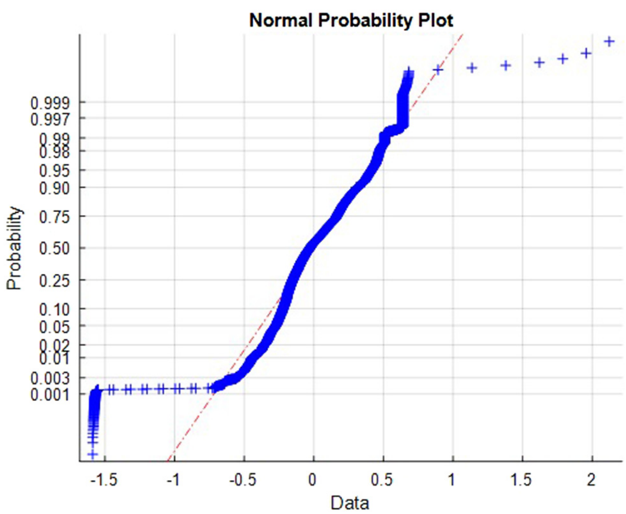

Figure 8: The Normal Probability Plot of the training error.

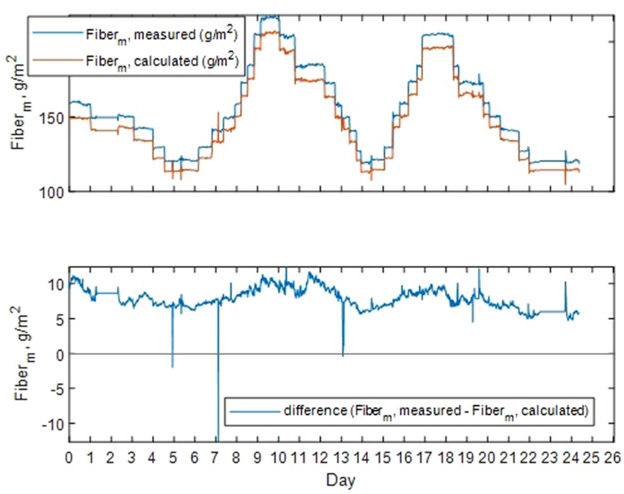

Figure 9: The measured fiber (g^{m-2}), the calculated fiber (g^{m-2}), and their difference (g^{m-2}) during the testing period.

excluding the few data point considered as outliers resulting left-skewed tails to the plot. Furthermore, the estimates are almost unbiased (Table 1).

Soft sensor testing

The performance of the developed soft sensor was evaluated by determining the estimated ash content and comparing it with the measured ash content using the test data described in Dataset section. Again, the calculated fiber was determined as described earlier and is presented with the measured fiber in Figure 9. As seen in the difference trend, there is a notable and varying difference between the measured and the calculated fiber. No refitting was performed, instead the corrected fiber values (Figure 10) for the testing data were calculated using the predetermined coefficients A and B, and thereafter the average difference between the calculated fiber is only 0.145 g^{m-2} (Table 1). Although this error is ten times higher than in the absolute error with training data (0.015), the relative error between the corrected and measured fiber is small considering the length of the testing data (circa 25 days) and the variations in the process conditions (basis weight ranging between 125 and 240 g^{m-2}).

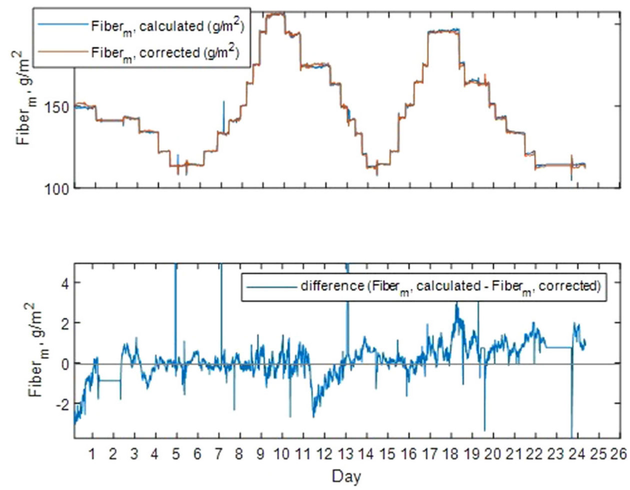

Figure 10: The corrected fiber (g^{m-2}), the calculated fiber (g^{m-2}), and their difference (g^{m-2}) during the testing period.

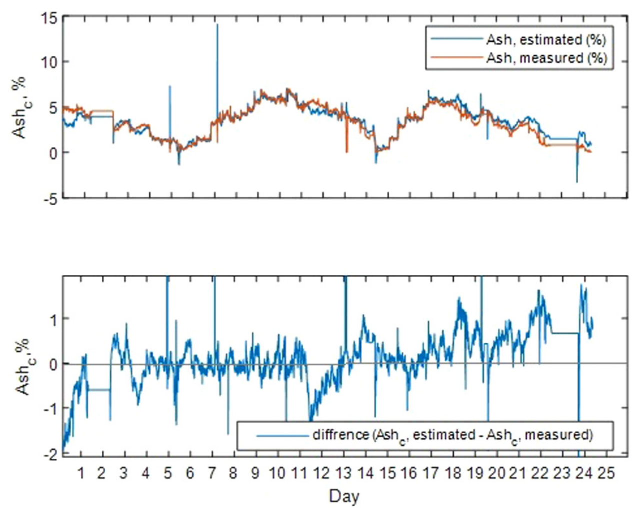

Figure 11: The estimated and the measured ash content (%) and their difference during the testing period.

The difference between estimated and measured ash content is presented in Figure 11. During the testing with measured data, the determined mean difference was only 0.12 percentage points (Table 1) with standard deviation

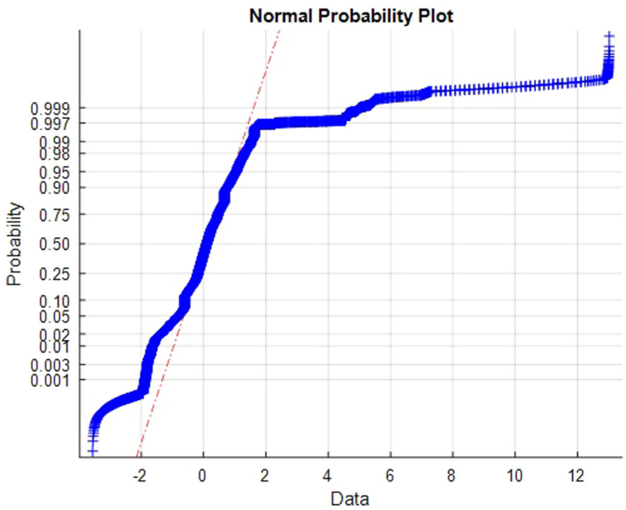

Figure 12: The Normal Probability Plot of the testing error.

0.65. The calculated MAPE was 11.80. It should be noted that the large spikes and some unexplainable disturbances have increased the calculated error values. The drift seen in Figure 11 in estimated values is probably due to a fouling of the IR fiber sensor which data was utilized in the calculations. One interesting event takes place just before day 12; the dry weight is constant, but there is a significant change (increment) in the measured ash content. This is propagated into calculated fiber as a decreased value as well as to the predicted ash content. Another remarkable occurrence of the error is after day 18 where the calculated ash content starts to drift (overestimation of the ash content). However, the further root cause analyses for the observed errors was excluded from this research. The observed examples above give indication to the possible utilization of the developed ash measurement validation framework together with fault detection and diagnostics methods such as (Weidl and Dahlquist 2002) and (Karlsson 2020).

In Figure 12, the Normal Probability Plot of the ash content error values (shown in Figure 11) with test data is presented. Here, the NPP reveals reasonably normally distributed modeling error within the center line but includes also a right-skewed tail. Skewed tails to the plot are here due to the few outliers seen in Figure 11, which are caused by the errors in measurement used in the calculations described above. However, based on the NPP, the proposed model structure seems to be feasible choice for the task.

Practical implications

The earlier studies with statistical models have shown that the paper properties can be predicted with good reliability. However, with prolonged periods of operation, their performance was significantly reduced (Avelin et al. 2009). In the approach presented in this paper, the known physical dependencies between the measured variables are utilized to build the mass-balance based robust soft sensor capable of describing the intragrade variations in paperboard ash content. The approach also includes a new way to utilize the existing measurement hardware at the paperboard machine allowing online determination of amount of fiber. In general, the achieved result of the single soft sensor for multiple grades can be considered very good as the independent test data involved a long time period with a large variation of paperboard grades and process conditions. The measured data was utilized without preprocessing that potentially reduces the manual work needed for implementation and maintenance the soft sensor. In addition, no recalibration of the soft sensor was made before or during the simulation with measured test data comprising approximately one month. The routine laboratory analyses and measurement quality protocols in paperboard machines consider shorter intervals, meaning that also updates to the model coefficients could take place within the studied test data. Alternatively, automated update methods or alarms for manual calibration (Lu and Chiang 2018) could also be considered to improve the soft sensor performance and robustness further.

The developed soft sensor seems to be suitable for estimating the ash content of the paperboard robustly. Thus, it potentially can also indicate the abnormal behavior of the hardware sensor, therefore having possible use in data reconciliation and fault detection. According to the results, the accuracy of the soft sensor is occasionally high enough to replace the hardware sensor during normal process situations. In abnormal process situations, such as recovering from sheet breaks, the ash content could be alternatively estimated utilizing headbox and whitewater measurements (Nobakhti and Wang 2010). Utilizing the developed mass-balance based soft sensor together with another soft sensor based on independent measurements, an ensemble model could be then built, allowing these several redundant estimators simultaneously to further reduce estimation uncertainty, thus bringing new tools to improve the process performance. As this soft sensor is intended to operate mainly without manual labor opposite to laboratory analyses, it is therefore usable in large scale autonomous processes. Validated measurement also gives more opportunities to advanced data analytics and real-time quality control.

Conclusions

In this paper, the development of a soft sensor for estimating the ash content at the reel of a two-ply paperboard manufacturing process was described. The developed soft sensor is based on mass balances utilizing typical online quality measurements and novel fiber measurement at the reel as inputs and their known dependencies. The training of the soft sensor was success and the functionality during the long testing period was very good, especially considering the fact that a single soft sensor for multiple paperboard grades was used and no recalibration was performed before or during the testing period. Even though the online ash measurement was utilized in the development of the soft sensor, it should be noted that the calibration of the soft sensor is independent on it. The calibration can be carried out also with the regularly performed laboratory analysis of the paperboard ash percentage. The developed framework can be applied in the paperboard machines to reveal the abnormal behavior of the hardware sensor or after some improvements to replace the hardware sensor for ash measurement. Utilizing the developed soft sensor, the measurement reliability is increased and hence it enables the improved process performance.

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References

Alonso, A., Negro, C., Blanco, A., San Pío, I. (2009) Application of advanced data treatment to predict paper properties. Math. Comput. Model. Dyn. Syst. 15(5):453–462. 10.1080/13873950903375445.

Avelin, A., Jansson, J., Dotzauer, E., Dahlquist, E. (2009) Use of combined physical and statistical models for online applications in the pulp and paper industry. Math. Comput. Model. Dyn. Syst. 15(5):425–434. 10.1080/13873950903375403.

Chiang, L., Lu, B., Castillo, I. (2017) Big Data Analytics in Chemical Engineering. Annu. Rev. Chem. Biomol. Eng. 8:63–85. 10.1146/annurev-chembioeng-060816-101555.

Dijkstra, B.K. (2011) Development of a predictive model for the moisture content in a paper mill. Master Thesis, University of Groningen. 89 p. Available: https://fse.studenttheses.ub.rug.nl/9771/1/Development_of_a_predictive_mo_1.pdf.

Fu, J., Hart, P. (2016) Leveraging mill-wide big data sets for process and quality improvement in paperboard production. Tappi J. 15(5):309–319.

Harding, G. (2020) Big data opportunities in pulp and paper: A case study of what can be achieved from a recent energy audit. Appita J. 1:44–46.

Holik, H. Handbook of Paper and Board. Wiley-VCH Verlag GmbH & Co. KGaA, 2006. 10.1002/3527608257.

Hu, L., Lu, X., Ma, J. (2020) Research review on devices and methods for rapid measurement of paper ash. BioResources 15(1):2096–2110. 10.15376/biores.15.1.2096-2110.

Karlsson, E. (2020) Evaluation of sodium salt scaling in black liquor evaporators using existing process data. Nord. Pulp Pap. Res. J. 35(4):516–532. 10.1515/npprj-2020-0038.

Karlström, A., Johansson, L., Hill, J. (2019) On the modeling of tensile index from larger data sets. Nord. Pulp Pap. Res. J. 34(3):289–303. 10.1515/npprj-2018-0019.

Lu, B., Chiang, L. (2018) Semi-supervised online soft sensor maintenance experiences in the chemical industry. J. Process Control 67:23–34. 10.1016/j.jprocont.2017.03.013.

Mäntylä, M. (2017) Sheet measurement, US9574994B2, Feb. 21, 2017. Available: https://patents.google.com/patent/US9574994B2/en?inventor=mantyla+markku&scholar&oq=mantyla+markku&sort=new. Accessed: November 2021.

Narasimhan, S., Jordache, C. Data reconciliation & gross error detection – An intelligent use of process data. Gulf Publishing Company, Houston Texas, 2000. 405 p.

NIST/SEMATECH e-Handbook of Statistical Methods. Available: http://www.itl.nist.gov/div898/handbook/. Accessed: October 2021.

Nobakhti, A., Wang, H. (2010) Minimization of Wet End disturbances during web breaks using online LAV estimation. Control Eng. Pract. 18(4):433–447. 10.1016/j.conengprac.2010.01.003.

Raffaele, D., Ondruch, T. (2020) Data-driven soft sensor for continuous production monitoring: an application to paper strength. In: 25th IEEE International Conference on Emerging Technologies and Factory Automation (ETFA), 2020. IEEE. pp. 1335–1338. 10.1109/ETFA46521.2020.9212113.

Skoglund, A., Brundin, A., Mandenius, C. (2018) A multivariate process model for grade change in a paperboard machine. Nord. Pulp Pap. Res. J. 15(3):183–188. 10.3183/npprj-2000-15-03-p183-188.

Souza, F., Araujo, R., Mendes, J. (2016) Review of Soft Sensor Methods for Regression Applications. Chemom. Intell. Lab. Syst. 152:69–79.

Viitamäki, M., Ritala, R. (2018) Soft sensor for compression and burst strength: identification and uncertainty analysis. J. Sci. Technol. For. Prod. Process. 7(1):38–47.

Weidl, G., Dahlquist, E. (2002) Root cause analysis for pulp and paper applications. In: Proc. of 10th Control Systems Conference, June 3–5, 2002, Stockholm, Sweden. pp. 343–347.

Wilson, D. (2008) Applying data reconciliation and the diagnostic model processor to a paper machine. In: Proc. of the 27th IASTED International Conference on Modelling, Identification and Control (MIC'08), February 11–13, 2008, Innsbruck, Austria. pp. 376–380.