

Data-Driven decision making in Paper Machines using Virtual Measurements



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Abstract:

In today's paper manufacturing industry, efficient and precise decision-making is critical for maintaining a competitive edge. Virtual measurements, driven by advanced modeling and data analytics, provide real-time insights into critical production parameters that were previously difficult or impossible to measure directly. The solution, suitable for all grades of papers, works by leveraging machine-learning generated models blended with domain expertise to produce online calculations for properties such as Conditioned Weight and Sheet Strength (RCT, SCT, Tensile, etc.) at a frequency needed to meet machine-specific requirements. Frequent measurements, with an accuracy that approaches lab results, help operators to proactively maintain quality properties closer to their specification limits, reducing raw material usage, increasing machine speed and enabling faster start-ups and grade changes.

The article also examines case studies that highlight the practical applications and benefits of virtual measurements, emphasizing their potential to drive sustainable and efficient paper production. By integrating these virtual measurements into existing systems, manufacturers can enhance operational decisions, predict performance outcomes, optimize processes, improve efficiency and reduce operational costs.

Keywords: Virtual Measurements, Paper Strength, Machine Learning, Optimal Decision Making, Quality Control System

Introduction

The pulp and paper industry is a critical sector that provides essential products for packaging, communication, and hygiene applications. However, the production process is complex, involving numerous chemical, physical, and mechanical operations that must be carefully monitored and controlled to ensure efficiency, quality, and sustainability. Traditional measurement techniques, often based on physical sensors, have long been used to track critical process parameters. However, these sensors come with limitations, such as high costs, maintenance requirements, and difficulties in measuring certain variables in real-time. This is where virtual measurements play a transformative role.

Virtual measurements are computational tools that use mathematical models and data-driven algorithms to estimate process parameters that are challenging to measure directly [1]. By leveraging data from physical sensors, process models, and machine learning techniques, virtual measurements can infer key variables like freeness, conditioned weight, caliper, and strength (e.g. RCT, SCT, Tensile, Burst, etc.) in real time. Their ability to provide continuous, reliable, and cost-effective monitoring makes them indispensable in modern pulp and paper manufacturing.

One of the primary advantages of virtual measurements is their ability to enhance process optimization and efficiency. Real-time estimation of key parameters allows for precise control over production processes, reducing raw material and energy consumption while maintaining product quality. For instance, virtual measurements can predict deviations in critical variables and enable timely corrective actions, minimizing downtime and preventing rejects.

Moreover, virtual measurements contribute significantly to sustainability in the pulp and paper industry. The sector faces growing pressure to reduce its environmental footprint, and accurate process monitoring is essential for achieving this goal. Virtual measurements enable more efficient use of raw materials, chemicals, and energy, reducing waste and emissions. They also support the integration of advanced control systems, such as model predictive control (MPC), which further improves process efficiency. In addition, the flexibility and scalability of virtual measurements make them well-suited for modern industrial environments. Unlike physical sensors, which may degrade or fail under harsh conditions, virtual measurements rely on robust data analytics and modeling. They can also be updated and refined as process conditions evolve, ensuring long-term reliability and adaptability.

Virtual measurements are a vital innovation in the pulp and paper industry, addressing the limitations of traditional measurement methods while unlocking new opportunities for efficiency, quality, and sustainability. As the industry continues to embrace digital transformation, the adoption of virtual measurement technology will be a cornerstone of achieving smarter, more sustainable production processes.

Virtual Measurements

Virtual measurements, estimate difficult-to-measure process parameters by using mathematical models (first principles) and machine learning techniques [2]. These tools rely on data from physical sensors, historical databases, and process knowledge to generate accurate, real-time predictions (Fig. 1). Among the various machine learning approaches to virtual measurement development, multilinear regression (MLR) and artificial neural networks (ANNs) stand out as widely used techniques, each suited to different levels of complexity and data availability. This section outlines the methodology for developing virtual measurements and highlights the roles of MLR and ANN in this context.

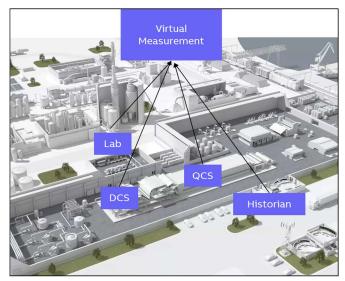


Figure 1: Typical Data Sources for Virtual Measurements

Methodology for Virtual Measurement Implementation

The process of developing robust data-based virtual measurements involves several structured steps [3] and the general workflow is shown in Fig. 2:

- 1. Define Objectives
 - Identify the parameter(s) to be estimated, the required frequency, the required accuracy, and operational constraints.
- 2. Data Collection
 - Gather data from physical sensors/scanners, laboratory tests, and process logs (DCS, QCS, etc.).
- 3. Data Preprocessing
 - Preprocess the data by normalizing variables, removing outliers, and handling missing values.
 - Merging and aligning data in from different sources to ensure time synchronization.
 - Incorporating domain expertise to verify correlations between inputs and outputs as well as identifying the time lags between input changes and the consequent effect on the target variable(s).
- 4. Model Selection and Development
 - Choose an appropriate modeling approach, such as multilinear regression for simple relationships or artificial neural networks for complex, nonlinear systems.
- 5. Integration and Testing
 - Implement the virtual measurement in a real-time system, validate its performance, and refine the model based on pilot tests.
- 6. Deployment and Maintenance
 - Continuously monitor the sensor's performance, update it with new data, and retrain the model as needed.

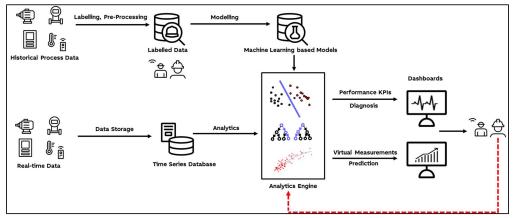


Figure 2: Virtual Measurement Implementation Pipeline

Multilinear Regression (MLR) as a Virtual measurement

Multilinear regression is a statistical technique [4] used to model the linear relationship between a dependent variable (the target) and multiple independent variables (inputs). MLR is one of the simplest and most interpretable methods for building virtual measurements, making it suitable for processes where the relationships are primarily linear.

Steps in MLR-Based Virtual Measurement Development

- 1. Feature Selection: Identify key input variables that influence the target parameter. For example, in the paper industry, inputs like stock consistency and flow, furnish blend ratios, ash content, etc. might be useful inputs to predict paper conditioned weight.
- 2. Model Equation: Construct a linear equation of the form:

 $Y{=}\beta_0{+}\beta_1 \; X_1{+}\beta_2 \; X_2{+}...{+}\beta_N \; X_N{+}\varepsilon$

where,

Y is the target variable to be estimated,

X1~XN are input variables,

 β_0 is an offset variable,

 $\beta_1 \sim \beta_N$ are linear coefficients for the input variables,

 ϵ is the error or noise term.

- 3. Parameter Estimation: Use historical data to calculate the coefficients using techniques like least squares estimation.
- 4. Validation: Test the model on unseen data to ensure its reliability.

Advantages of MLR

- Easy to implement and interpret. The magnitude of the coefficient signifies the importance or contribution of the input variable.
- Suitable for systems with well-understood linear relationships.
- Requires relatively small datasets.

Limitations

- Ineffective for highly nonlinear processes.
- Sensitive to multicollinearity among input variables.

Artificial Neural Networks (ANN) as a Virtual Measurement

Artificial neural networks are advanced machine learning models

inspired by the human brain [5]. ANNs consist of interconnected layers of nodes (neurons) that process data and learn complex relationships between inputs and outputs (Fig. 3). They are particularly effective for nonlinear, dynamic, and high-dimensional systems.

Steps in ANN-Based Virtual measurement Development

- 1. Network Design:
 - Input Layer: Includes nodes for each input variable. For instance, stock consistency and freeness, fiber morphology, furnish blend ratios, chemical dosages could serve as inputs to predict paper strength.
 - Hidden Layers: One or more layers of interconnected neurons perform nonlinear transformations.
 - Output Layer: Produces the estimated target variable (e.g., paper strength).
- 2. Training the Model:
 - Use historical data to adjust the weights of connections between neurons.
 - Apply backpropagation, an algorithm that minimizes error by iteratively updating weights based on the gradient descent method.
 - Activation Functions: Introduce nonlinearities using functions like ReLU (Rectified Linear Unit) or sigmoid, enabling the ANN to capture complex relationships.
 - Validation and Optimization: Test the model on unseen validation data and optimize its architecture (e.g., number of layers, neurons, and learning rate).

Advantages of ANN

- Capable of modeling highly nonlinear and dynamic processes.
- Adapts well to high-dimensional data with complex interactions.
- Self-learning and improvement through retraining.

Limitations

- Requires large datasets for effective training.
- Computationally intensive and challenging to interpret the influence of inputs.
- Risk of overfitting without proper regularization (e.g., dropout, early stopping).

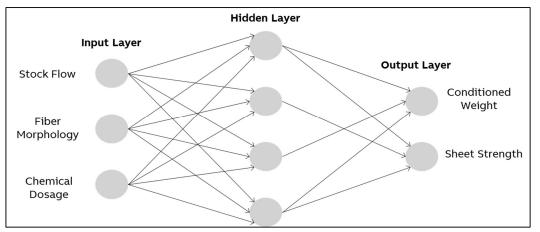


Figure 3: Artificial Neural Network for Paper Machine Virtual Measurement

Aspect	Multilinear Regression (MLR)	Artificial Neural Network (ANN)
Complexity	Simple linear relationships	Handles nonlinear, complex relationships
Data Requirements	Requires smaller datasets	Needs large amounts of training data
Interpretability	Highly interpretable	Acts as a "black box"; less intuitive
Computation	Low computational requirements	High computational effort during training
Flexibility	Limited to linear models	Adaptable to dynamic, nonlinear systems

Table 1: Comparison of MLR and ANN in Virtual measurements

The choice between multilinear regression and artificial neural networks in virtual measurement development depends on the complexity of the process and the availability of data. While MLR offers simplicity and interpretability, ANNs provide unparalleled accuracy for nonlinear systems. By following a structured methodology and leveraging these techniques, virtual measurements can improve decision-making in the pulp and paper processes, improving efficiency and reducing operational costs.

Case Study 1: Conditioned Weight Virtual Measurement

The ABB Ability[™] Conditioned Weight Virtual Measurement provides auto-correlating calculations for online conditioned weight measurement to enable mills to reduce quality losses by getting on-spec faster during sheet breaks and production startup.

Many papermakers are losing profit to due to weight variability [6] and the key challenges are:

- Off-spec paper after sheet breaks
- Excessive time to re-thread machine after sheet breaks due to weight changes Long start-up times
- No online weight measurement if scanner is off-sheet or if QCS weight sensor fails
- Off-target weight or increase in weight variability due to long paper machine transport delays

If the QCS is offline for maintenance or during a sheet break, operators are blind to the moving web's weight measurement. The Conditioned Weight Virtual Measurement helps operators get (and maintain) weight properties within their target limits while the paper machine is starting up or recovering from a sheet break decreasing downtimes as seen in Fig. 4.

This is accomplished through a three-step process that helps maintain target weight while the paper machine is starting up.

- First, an initial static conditioned weight model is created using historical machine data to establish an initial expectation of the accuracy of the calculated conditioned weight.
- Once the accuracy of an initial model is confirmed, an online calculated weight measurement is implemented by leveraging the ABB Ability[™] platform.
- The third step is continuous performance monitoring and optimization tasks to maintain and improve the conditioned weight calculation by compensating for any machine changes or implementing continuous solution improvement updates.

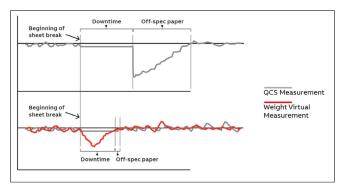


Figure 4: Weight Virtual Measurement helping Reduce Downtime and Off-spec Paper

Typically, MLR models are used for developing weight virtual measurements using key process parameters such as wire speed, thick stock flow rate, thick stock consistency, fiber retention and furnish blends.

The benefits of the Conditioned Weight Virtual Measurement are:

- Decreases sheet break recovery time
- · Reduces off-spec paper after sheet break and when experiencing long transport delays
- Decreases downtime due to sheet breaks
- Improves runnability
- Enables faster grade changes
- Increases mill profitability

The ABB AbilityTM Conditioned Weight Virtual Measurement was implemented at a paper mill in North America to help them improve their operations during machine startups and sheetbreaks. Through intuitive dashboards, the operators were able to continuously track the Key Performance Indicators (KPIs) of the weight virtual measurement, visualize the weight measurement during sheet breaks and proactive make changes to the process operational parameters to ensure weight was on target as soon as possible. Using this solution, the mill was able to improve sheet break recovery and startups by over 75% as seen in Fig. 5.

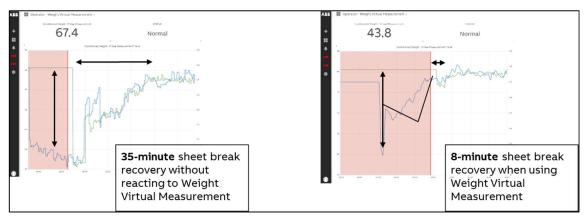


Figure 5: 77% Reduced Sheetbreak Recovery Time using Weight Virtual Measurement

Case Study 2: Sheet Strength Virtual Measurement

Lab measurements are valuable in understanding the strength of paper, but these are performed periodically only after a reel is produced. The lack of frequent measurements could be affecting your process optimization [7] opportunities and your profitability due to:

- High amount of rejects
- High cost of increased strength characteristics
- Not enough machine throughput

ABB Ability[™] Strength Virtual Measurement enables operators to keep strength properties within their target limits, creating on-spec paper at less cost. By using machine learning-generated models to predict one or more strength properties for accurate, online measurements, mills can reduce raw material usage and increase machine speed (Fig. 6).

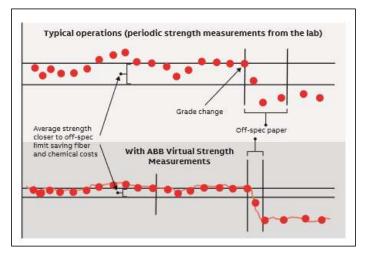


Figure 6: Strength Virtual Measurement helping reduce product variability

Typically, ANN models are used for developing strength virtual measurements using key process parameters such as wire speed, chemical dosages, fiber morphology, draw information, furnish blends, vacuums and consistencies as well as QCS scanner measurements such as weight, moisture and caliper. Commonly modelled strength properties are Short-Span Compression Test (SCT), Ring Crush Test (RCT), Concora Corrugating Medium Test (CMT), etc.

The benefits of the Strength Weight Virtual Measurement are:

- Lowers fiber and/or chemical costs
- Enables more consistent quality
- Improves runnability
- Enables faster grade changes
- Increases paper machine speed
- Increases mill profitability

The ABB Ability[™] Strength Virtual Measurement has been implemented at multiple paper mills in Europe and North America to provide continuous intra-reel strength measurements helping them optimize their production, diagnose issues and identify improvement opportunities.

In the example shown in Fig 7, the paper mill increased strength at no cost by changing the rush drag to optimize the fiber orientation in the paper. The operators where able to monitor the strength property as they made changes to various parameters in the paper machine. Hence, a precise sheet fiber orientation square point was achieved, keeping the strength well above target while simultaneously enabling the weight target to be reduced.

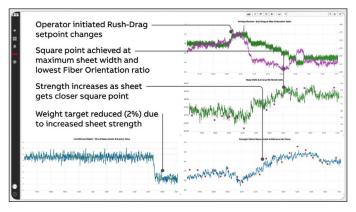


Figure 7: Maintaining On-Spec Strength at Lower Operating Costs

Another use case of the strength virtual measurement was to diagnose the root cause of sheetbreaks. The operators were able to track sheetbreaks (red vertical shaded region in the Fig. 8) and correlate the sheetbreak with abnormal behavior of the strength virtual measurement. By identifying abnormal patterns in the strength virtual measurement, the operators can further drill down and identify the input measurements used in the model that caused the strength disturbance. Once the root cause is identified, preventive actions can be taken to prevent these abnormal situations from repeating in the future.

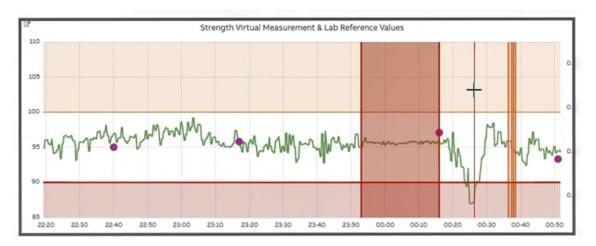


Figure 8: Strength Virtual Measured used for Sheetbreak Diagnostics

Furthermore, the strength virtual measurement was used to identify out-of-spec production much before the reel was produced, enabling the operators to take corrective action, avoiding significant losses in terms of rejected reels.

Through the improved decision making using the Strength Virtual Measurement, a North American container board mill was able to reduce reject by 3.5%, increase machine speed by 6.5% and decrease weight by 1.5% leading to significant financial savings.

Conclusion

The ABB AbilityTM Virtual Measurement solutions offer immense potential benefits, contingent on the implementation of a robust data strategy, as outlined earlier. Virtual measurement solutions play a pivotal role in predicting infrequent or previously unmeasured variables, enabling optimization of operational performance. As the advantages of these technologies become more widely recognized across the industry, their adoption is expected to grow, with paper mills increasingly relying on virtual measurements to infer multiple paper properties.

However, like all digital tools, virtual measurement solutions are only as effective as the expertise behind their application. Maximizing the value of these solutions requires not only cuttingedge technology but also a deep understanding of the papermaking process and domain-specific expertise. ABB Ability[™] Virtual Measurement, supported by industry expertise and a proven datadriven approach, delivers enduring value.

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