Final Outcomes Report

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Project Title: Application of Artificial Intelligence at Pulp Refiners to Optimize Energy Usage and Product Quality

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Lead Institution: Millar Western Forest Products Ltd
Project Partners: Innotech Alberta

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TRL at Project Start: TRL 2-3
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Project Description: The proposed project will look at the value and feasibility of using a Pulp Expert System (PES) driven by artificial intelligence (AI) developed by Innotech Alberta (ITA) at the refining stage of the pulping process to reduce energy consumption and improve product quality. An estimated energy reduction of up to 120 kwhr/ADMT may be realized with the implementation of the AI enabled refiner control in combination with the installation of hydraulic plate positioners. The expected energy reduction represents an annual savings of up to 23,000 tonnes of CO2e. Enhanced quality will support the production of higher-value added products and expand market opportunities.

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1.0 Executive Summary

The AI-Based Pulp Refining Expert System aims to transform pulp refining processes through advanced artificial intelligence and machine learning technologies. The focus of this project is on optimizing the refining process to enhance efficiency, resource utilization, and waste reduction.

Technology Implementation

The project has developed an AI system that leverages sophisticated data analysis and predictive modeling to enhance pulp refining operations. This system integrates with upgraded refiner plate positioners to further optimize the refining process and improve pulp quality. Key components include:

- ***Backend and Frontend Development***: The system includes a robust backend server for data processing, model serving and frontend webserver for web-browser based user interfaces access.
- ***Process Optimization***: The PES dashboards are tailored to identify inefficiencies and suggest improvements in refining processes using developed AI models.

Although the system is not yet fully integrated with process control systems, it is poised to significantly enhance process optimization through its advanced analytical capabilities.

Project Status and Potential Outcomes

While trials and data collection to demonstrate specific outcomes have not yet begun, the AI-Based Pulp Refining Expert System shows considerable potential:

- ***Efficiency Gains***: The system is expected to improve refining efficiency by identifying and addressing operational inefficiencies.
- ***Cost Savings***: Enhanced process optimization could lead to substantial cost reductions by maximizing resource use and minimizing waste.
- ***Job Creation***: The development phase has already contributed to job creation, supporting regional economic growth.

Environmental Benefits

The anticipated environmental benefits of the project include:

- ***Resource Optimization***: Improved process efficiency is likely to reduce the consumption of raw materials and energy.
- ***Waste Reduction***: By optimizing processes, the system aims to decrease waste production.

- ***Sustainability***: The project supports sustainable practices in the pulp refining industry, aligning with broader environmental conservation goals.

In summary, the AI-Based Pulp Refining Expert System is set to make a significant impact on process optimization within the mechanical pulping industry. As the project advances towards integration and trial phases, it holds promise for enhancing operational efficiency, reducing costs, and contributing to environmental sustainability.

2.0 Project Description

2.1 Introduction

Alberta-based Millar Western Forest Products Ltd. (Millar Western) operates a bleached chemi-thermo-mechanical pulp (BCTMP) mill in Whitecourt, Alberta, with two production lines and a capacity of 345,000 air-dried metric tonnes (ADMT) per year. BCTMP is used primarily in applications such as fine printing and writing papers, paperboard, specialty papers and, to a lesser extent, tissue and toweling. Millar Western's Whitecourt mill produces more than 20 grades of hardwood and softwood pulps to meet the end-use requirements of customers around the work.

The BCTMP manufacturing process is distinguished from the kraft process by its reliance on mechanical action over chemicals to convert wood chips to pulp. While the BCTMP process is high yielding, producing more pulp per m3 of wood that its chemical counterpart, it is also more energy intensive. In 2019, the mill consumed 1,424 kWhr per ADMT on production of 345,513 ADMT. In a conventional BCTMP manufacturing process, the pulp refiner process accounts for over 60% of the mill's total electricity consumption, which is why energy reduction initiatives tend to focus on this part of the process. The mill sees opportunities to significantly enhance quality by improving refiner control through the integration of an advanced online, AI Pulp Expert System (PES) developed by InnoTech Alberta (ITA).

2.2 Background of the Project

Millar Western has been a long-time partner of ITA, serving as a test facility for many new online measurement and control systems, including several independent modules: e.g., advisory control, predictive simulation, diagnosis, and adaptive control for the pulp mill's effluent treatment system. Other examples include a joint "Intelligent Bleaching Systems" project that sought to improve pulp bleaching efficiency by using an online Raman peroxide residual analyzer and an online pulp brightness analyzer on the pulp finishing line. A pulp tensile and bulk prediction analysis system using Millar Western Whitecourt's pulp slab press data and process variables as inputs was also developed. The analysis mode adopted the artificial neural network (ANN) as the backbone of the pulp tensile and build prediction method.

Each of these collaborative projects has strengthened the ITA-Millar Western working relationships, which is based on a shared interest in jointly assessing new and, at times, unproven technologies that have the potential to improve products, optimize processes, reduce costs, and enhance environmental performance. When ITA began developing an advanced PES using machine-learning (ML) and AI technologies for real-time pulp quality prediction and BCTMP production quality control, they approached Millar Western about its interest in testing these technologies, initially in an offline trial but migrating to an online trial.

While new to the pulp and paper sector at the time, AI systems were already revolutionizing other industries due to their ability to rapidly analyze historical and real-time data to aid in better, faster decision making. With Alberta's pulp producers facing increased competition from low-cost, low regulation jurisdictions such as South America, it was imperative that this opportunity was seized to try to improve efficiency.

2.3 Project objectives

This project will serve as a demonstration facility for the advancement of innovative technology employing machine learning (AI). The project is focused on two key aspects concerning the refining area of the pulping process; 1) the reduction of energy consumption and the associated Green House Gases and 2) an improvement in process stability and pulp quality. The project will help to showcase the potential of AI in the forestry industry and support the diversification of the Alberta economy.

The project aims to employ AI in conjunction with new upgraded refiner plate positioners to improve overall pulp quality and reduce energy variability and usage at the refining stage of the pulp manufacturing process. The resulting energy reduction will translate into decreased annual Green House Gas emissions (GHG) of up to 23,000 tCO2. Further benefits include the strengthening of Alberta's expertise in innovation through a demonstrated application of AI in the forestry sector.

2.4 Performance/success metrics identified in the Contribution agreement

Success Metric	**Commercialization Target**	**Project Target**	**Achievements to Date**
ROI	> 10%	5-10%	
% Quality Improvement- On Grade Efficiency	5-10%	5%	N/A (PES prototype has just been installed. It has potential to lower product quality variation by more than 10%, but needs to confirm with future mill trials and operations)
GHG reduction:CO2e tonnes/yr (BCTMP mills in Canada)	200,000, by 2050	23,000	3,183
Specific Energy reduction kWh/ADMT	100	120	30

2.5 Discussion on any changes in the Project during the lifecycle of the ERA funded Project scope

Millar Western Forest Products sold its sawmill assets to another company in 2022. In 2024, Millar Western Forest Products has bought two additional BCTMP mills. These transactions are not anticipated to have an impact on the project.

One team member, Regan Baer, resigned from the company in June 2022. Colleen Mireau, an engineer from the Technical group, has joined the project team. Colleen is a senior process engineer with over 10 years' experience in the Pulp and Paper industry.

Gerard Orlowski, the project lead, resigned from the company in Sept 2022. Colleen Mireau took over as the project lead.

2.6 Technology Risks

Technology Risks and Evolution

- ***Integration Complexity***: One of the primary risks identified at the start of the project was the complexity of integrating the AI system with existing pulp mill infrastructure. Initially, there was uncertainty about how well the new technology would align with existing processes. As the project progressed, this risk materialized, leading to additional adjustments and modifications. The mitigation strategy involved iterative testing and collaboration with industry experts, which helped address integration issues, though it extended the project timeline.
- ***Data Quality and Availability:*** Another risk was related to data quality and availability. The effectiveness of the AI system depends heavily on high-quality, reliable data. Early in the project, there were concerns about the consistency and completeness of data from the mill. This risk became apparent as data related issues were encountered during development. Mitigation efforts included additional data cleaning and preparation, which partially resolved the issues but also highlighted the need for improved data management practices.
- ***Regulatory Uncertainty:*** The evolving and unclear regulatory landscape for AI technologies was a significant risk. At the outset, the lack of established guidelines for AI applications posed uncertainty regarding compliance. This risk persisted throughout the project and required ongoing engagement with regulatory bodies to navigate the changing requirements. Mitigation strategies included proactive consultations and adaptive compliance measures, which helped manage the risk but did not entirely eliminate the regulatory uncertainties.

Unidentified Challenges

- ***Resource Allocation***: A challenge that was not initially identified as a risk was the delay in acquiring specialized talent. This issue impacted the project timeline more than anticipated. Although resource planning was part of the initial strategy, the actual demand for specific expertise exceeded expectations, leading to unexpected delays. Mitigation involved adjusting project schedules and increasing efforts to recruit necessary talent.
- ***Technical Scalability***: Another unanticipated challenge was the scalability of the AI system. While scalability was considered a factor, the extent to which the technology would need to be adapted for different scales of operation was not fully anticipated. This challenge required additional development work and adjustments to ensure the system could perform effectively at various scales.

Throughout the project, several technology risks were identified and addressed, including integration complexity, data quality issues, and regulatory uncertainty. While mitigation strategies were largely effective, some challenges, such as resource allocation delays and unexpected scalability issues, emerged as the project progressed. These experiences underscore the importance of ongoing risk assessment and adaptive management strategies in technology development projects.

3.0 Project Work Scope

This project, *Application of Artificial Intelligence at Pulp Refiners to Optimize Energy Usage and Product Quality*, looks at the value and feasibility of using a Pulp Expert System (PES) driven by artificial intelligence (AI) at the refining stage of the pulping process, to reduce energy consumption and improve product quality. This AI-based Pulp Expert System consists of three main subsystems: the PES Machine Learning System, the PES Optimization Guide System, and the Deployment Package.

- **PES Machine Learning System**: This subsystem employs a machine learning framework to assess raw process data, lab quality data, and online analyzer data, creating a pulp-quality prediction knowledge database or machine learning models.
- **PES Optimization Guide System**: This subsystem provides recommendations for process conditions using input conditions and machine learning models.
    - Interactive optimization maps for key operating parameters are generated based on these machine learning models and the input operating conditions. These maps assist engineers and operators in adjusting key parameters to achieve the target pulp quality at pulp refiners.
    - It can also provide optimal decision-making for grade transition planning based on historical data using pre-defined optimization algorithms.
- **Deployment Package**: This integrates data flow, AI models, optimization algorithms, and the front-end dashboard/user interface. It is essential for transitioning the AI models from a development environment to a production environment where they can be used reliably and efficiently for optimizing processes.

3.1 Development Methodology

The **methodology** of developing this online AI-based Pulp Expert System involves a systematic approach to collecting data, developing models, deploying solutions, and continuously improving the system. Here's a detailed outline of the methodology:

Goal Setting with KPIs

- ***Energy Optimization***
    - reduce energy consumption by an additional 5% on top of the saving from new plate positioner installation.
- ***Product Quality Optimization***
    - Identify anomalies of the online pulp freeness measurement
    - Achieve standard deviation of pulp freeness at pulp refiner to ±15 or a RMSE of 15 comparing to standard lab test results;

Data Flow and Management

- ***Data Collection***
    - <u>Sources</u>: Identify and connect to data sources, including raw process data, lab quality data, online analyzer data and databases from historical production data.
    - <u>Real-time Data Acquisition</u>: Implement mechanisms to continuously collect real-time data through OPC interface.
- ***Data Integrations***
    - <u>Data Server</u>: Extract, transform, and load data from various sources into a unified storage system using SQL server.
- ***Data Processing and Cleaning***
    - <u>Data Quality Assurance</u>: Clean the data to remove errors, duplicates, and inconsistencies.
    - <u>Feature Engineering</u>: Create new features or transform existing features to improve model performance.

Model Development and Improvement

- ***Data Analysis***

    - Exploratory Data Analysis (EDA): Analyze the data to understand patterns, trends, and relationships.
    - Visualization: Use visual tools to identify insights and anomalies in the data.
- ***Model Selection***
    - Algorithm Choice: Select appropriate machine learning algorithms based on the problem and data characteristics (e.g., XGBoost, Artificial Neural Network (ANN), First Principle (FP) Model, etc.).
    - Model Training: Train models using historical data, employing techniques like cross-validation to ensure robustness.
- ***Model Evaluation***
    - Performance Metrics:
        - Evaluate models using metrics RMSE.
        - Validate models using domain knowledge for explainability, which is critical for process optimization.
    - Hyperparameter Tuning: Optimize model parameters to enhance performance.
    - Model Refinement: Adjust the model architecture or training process to address identified weaknesses.

Deployment Package

- ***Model Deployment***:
    - Containerization: Package models into containers (Docker) for consistent deployment across environments.
    - Serving Frameworks: Deploy models using frameworks TensorFlow Serving.
- ***Backend Server***:
    - Data Interface: OPC Interface with DCS real time OPC data server.
    - Data Server: SQL data server deployment.
- ***Frontend Server:***
    - Webserver: Frontend web-browser based user dashboard.
- ***Security***
    - Access Control: Implement role-based access control (RBAC) and user authentication mechanisms.

Continuous Improvement

- ***Feedback Loops***
    - User Feedback: Collect feedback from users to identify areas for improvement.
    - Model Retraining: Continuously retrain models with new data to improve accuracy and adapt to changes.
- ***Performance Analysis***
    - Periodic Reviews: Regularly review system performance and KPIs to assess the impact of optimizations.
    - A/B Testing: Experiment with different model versions or optimization strategies to determine the best approach.
- ***System Updates***
    - Software Updates: Keep the underlying software and libraries up to date.
    - Model Updates: Update models and algorithms to incorporate the latest advancements in AI and machine learning.

By following this methodology, an AI-based online process optimization system can effectively harness data to improve processes, adapt to changing conditions, and continuously enhance performance.

3.2 Technology development, installation and commissioning description

As described in the development methodology, there are several stages for building this online AI-based PES: Goal Setting, Data Flow, Model Development, and Deployment Package. Each stage builds on the previous one to ensure a robust, efficient, and scalable solution. Given the nature of software development, an agile approach is applied, emphasizing iterative progress, collaboration, and adaptability, aligning with best practices for software development. Therefore, as we describe the installation and commissioning at different milestones, these development stages will be interwoven, with versions continuously improving throughout the entire project execution. Here's a detailed outline of technology milestones including installation of plate positioning systems by Millar Western:

Phase 1, **Offline model development** (July 2021 to June 2022)

- ***Goal Setting***
- ***Data flow and management***
    - Offline Dataset Preparation
        - Identifying key input features, collecting process and mill lab quality historical datasets, preprocessing data and conducting data analysis.
        - Feature engineering to transform the existing features to improve model performance
        - This is an on-going task throughout the project execution.
- ***Model Development/improvement***
    - <u>XGBoost Model Version 1.0 (January 2022)</u>
        - Machine learning model selection, model training and testing
    - <u>XGBoost Model Version 2.0 (June 2022)</u>
        - Enhancing model performance with Feature Engineering Version 2.0
- ***Deployment Package***
    - <u>Online Data Server Version 1.0 (June 2022)</u>
    - <u>PES System Design Version 1.0 (June 2022)</u>
        - Defined the framework of AI-based expert system
    - <u>Software Architecture (June 2022)</u>
        - Defined software architecture

Phase 2, **Online system development and testing** (July 2022 to June 2023)

- ***Data flow***
    - <u>OPC Interface (January 2023)</u>
- ***Model Development/Improvement***
    - <u>ANN Model Version 1.0 (June 2023);</u>
    - <u>FP Model Version 1.0 (June 2023);</u>
        - Enhancing the accuracy of the model prediction
- ***Deployment Package***
    - <u>PES Data Server (January 2023)</u>
    - <u>Data Manager Version 1.0 (January 2023)</u>

    - Model Server Version 1.0 (June 2023)
        - Refiner pulp quality AI model server (line #1 and line #2) was configured and optimized through the trial.
    - SQL Server Database (February 2023)
        - Optimized system runnability performance of AI server SQL database, OPC interface and OPC data interface & SQL server performance for online deployment.
    - Dashboard Version 1.0 (June 2023)
        - The 1st version browser-based online dashboard

Phase 3, Installation of plate positioning system on Production Line 1 (Q3 2022, by Millar Western).

Phase 4, **Optimization algorithm development for pulp refining guidance** (April 2023 to February 2024)

- ***Data flow***
    - Continued expanding the production data to updating the model training
    - Optimizing the performance of the data server
- ***Model Development/Improvement***
    - ANN Model Version 2.0 (January 2024)
    - XGBoost Model Version 3.0 (January 2024)
    - First Principle Model Version 2.0 (January 2024)
        - Improved explainability of AI models for process optimization
- ***Deployment Package***
    - Dashboard Version 2.0 (January 2024)
        - A major runnability issue that prevented the software from continuously operating was resolved by shifting to a more robust platform.
        - The deployment method has been modified to make it available to business network users.
        - The refiner specific energy optimization AI tool was designed, developed and integrated into the dashboard.
        - Dashboard Manual Version 1.0 was prepared (January 2024)

Phase 5, Installation of plate positioning system on Production Line 2 (Q2 2023 by Millar Western)

Phase 6, **Integration of new plate positioning devices and AI model** (October 2023 to June 2024)

- ***Data flow***
    - Expanded dataset to include new production data after installation of new plate positioning devices
- ***Model Development***
    - First Principle Model Version 3.0 (May 2024)
        - Improved the representation of chemical dosages
    - ANN Model Version 3.0 (May 2024)
        - Updated AI model with new plate positioning data optimizing Refiner AI Models, validating optimization functions with chemicals dosage
- ***Deployment Package***
    - Dashboard Version 3.0 (June 2024)

- Integrated the updated AI model into PES AI system and its Dashboard with new features based on Millar's inputs.

3.3 Overall Project achievements relative to stated objectives and performance metrics

The objective of this project, "Application of Artificial Intelligence at Pulp Refiners to Optimize Energy Usage and Product Quality," was to evaluate the value and feasibility of using a Pulp Expert System (PES) driven by artificial intelligence (AI) at the refining stage of the pulping process. The goal was to reduce energy consumption and improve product quality.

By the end of the project, the first prototype of the AI-based PES system, which includes three subsystems: the PES Machine Learning System, the PES Optimization Guide System, and the Deployment Package, has been installed online. The performance of this system is summarized as follows:

Performance of Machine Learning Approach

- ***Pulp Freeness Prediction*****:** The current version of machine learning models predicts pulp freeness at the pulp refiner with a Root Mean Square Error (RMSE) of 45.7 when validated against manual lab test results. Compared to the RMSE of 62.4 for online pulp freeness measurements validated with manual test results, the trained machine learning models perform better than the online measurements for the production scenarios on which they were developed.
- ***Frequency of Measurement***: It generates pulp freeness values as frequently as needed (current frequency is one prediction every one minute by AI model), compared to one measurement every 50 minutes with the existing online PulpEye system.
- ***Anomaly Detection***: It is capable of identifying anomalies in online pulp freeness measurements.

Performance of Optimization System with the Digital Solution

- ***Optimization Maps***: Interactive optimization maps can be generated for key operating parameters based on machine learning models and input operating conditions. These maps assist engineers and operators in adjusting key parameters to achieve target pulp quality at pulp refiners.
- ***Grade Transition Planning***: This optimization system provides optimal decision-making for grade transition planning based on historical data using pre-defined optimization algorithms.
- ***Energy and Quality Optimization***: When integrated with pulp quality data at the finishing line and historical production data, this digital platform can quickly provide optimal recommendations for optimizing energy usage and product quality.
- ***Auto Adaptation Function*****:** When process changes cause a shift, this system can update the optimization function with the latest production data, ensuring it accurately reflects the current state of the production process.

Deployment Package

- ***Data Server Integration***: A data server system was integrated with the DCS control system to access real-time process data.
- ***Real-time AI Model Serving***: Real-time AI model serving modules were developed to extract insights from historical and real-time process data for refining process optimization.
- ***User Interface***: A web-browser-based dashboard provides operators with a user-friendly, secure access interface. Multiple user authentication has been implemented in the new dashboard.

Upon the completion of the first prototype of this AI-based process optimization system using the latest deployment technology, the project successfully demonstrated the concept of implementing an online AI system tailored to customer needs. This system integrates seamlessly with the production line, providing real-time recommendations for optimizing the decision-making process, enhancing energy efficiency, and improving product quality.

3.4 Results of System Development

Results of this PES system development are summarized into AI Model Performance and Process Optimization Approach.

3.4.1 AI/Machine Learning Model Performance

For pulp freeness at the pulp refiner, which is the quality metric we aim to predict, existing PulpEye online measurements are taken approximately once every 50 minutes. Additionally, manual lab tests are conducted once every few days to validate the accuracy of the PulpEye online readings. When developing the machine learning models, we used the online PulpEye measurement readings as target values because there are significantly more online PulpEye data points than manual lab tests. However, online PulpEye system can malfunction due to various reasons, such as pump plugging or mechanical failure. Incorrect readings can go unnoticed until a manual lab test is conducted.

To evaluate the performance of machine learning models, we compared the model predictions with ground truth values, for this case, online PulpEye measurements results and manual lab test results. The comparison results are plotted in Figure 01 over the production period from July 2023 to July 2024, with the black dots representing online PulpEye measurements, the blue dots representing AI model prediction results, and the red dots representing manual lab results. Root Mean Square Error (RMSE), a common performance metric, was also calculated for cross comparisons.

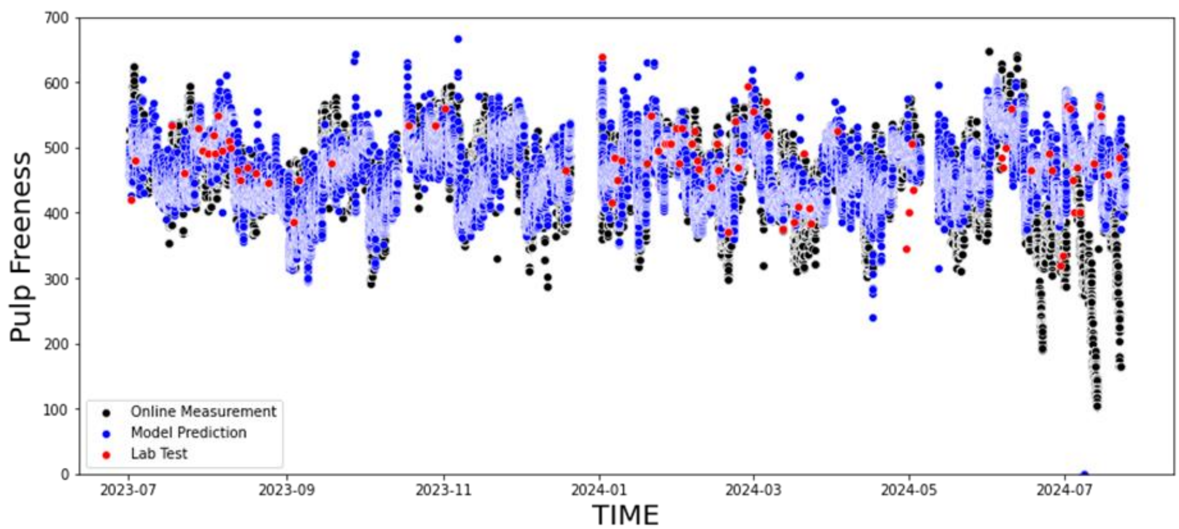

Figure 1 Comparison of pulp freeness values at the pulp refiner: online PulpEye measurement (black), AI model prediction (blue) and manual lab test results (red)

It can be observed that:

- Overall, AI model predictions (blue dots) capture the trend of pulp freeness similar to online PulpEye measurement (black dots). While there are times that AI model predictions can be under or overestimated when compared with online PulpEye measurements.
- When model performance is validated with manual lab test results,
  - AI Model predictions agree with manual lab test results better than online PulpEye measurements, indicating stable performance.
  - Online PulpEye measurements can deviate significantly from lab results (red dots) while AI model predictions are still on track, especially for data from June 2024 and later. A close-up of this period is shown in Figure 02. That indicates that online PulpEye system was malfunctioning and required maintenance. **<u>AI model can be used for anomaly detection for online PulpEye freeness measurement</u>**.

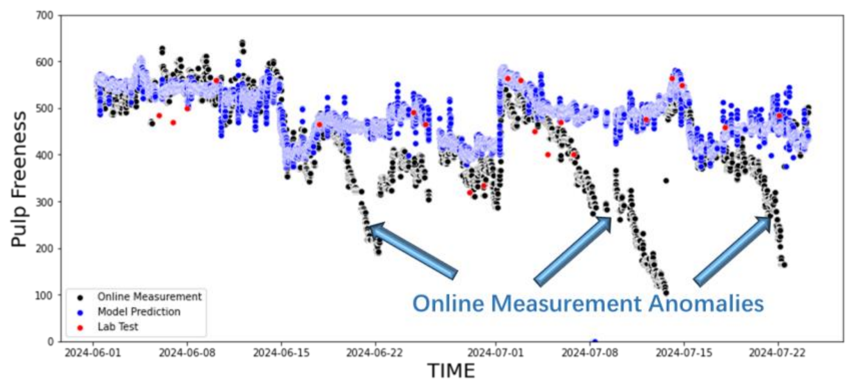

Figure 2 Anomaly detection capability of ai model for online measurement devices

  - There are times that AI model predictions are in good agreement with online PulpEye measurements, while manual test results (red dots) are a bit off. This indicates that neither online PulpEye measurement nor manual lab test is absolutely correct. When it comes to evaluate AI model performance, cross validation is the recommended approach.
  - RMSE results for performance evaluation are calculated and listed in the following table:

Comparison of Performance Evaluation	**RMSE**	**RMSE/Average Lab Value**
AI Model Predictions vs. *Manual Lab Test*	45.7	9.56%
Online PulpEye Measurements vs. *Manual Lab Test*	62.4	13.07%

This confirms our findings that **<u>the AI model performs with an RMSE of 45.7, outperforming the online PulpEye measurements, which have an RMSE of 62.4.</u>** This represents a reduction in variation of more than 20%. The improvement is largely attributed to data cleaning and model training approaches.

Since online measurements are used as ground truth target, the accuracy of the machine learning model performance is limited by the quality of the ground truth data when only production data is used, for example:

- Less frequent (PulpEye or lab) measurements may not capture the dynamics of the process between measurements, which can mislead the AI model when it tries to learn the insights of the process.
- Errors in ground truth data can provide incorrect information for training the machine learning models. While data cleaning can help to some extent, it cannot completely solve these problems.

The current version of the machine learning models is not able to achieve the goal of predicting pulp freeness at the pulp refiners with a ±15 deviation or an RMSE of 15 against lab test results due to limitations in the ground truth data quality (i.e., online PulpEye measurements). To improve the accuracy of the model performance, mill trials to collect more online PulpEye measurements specifically designed for model training are essential.

3.4.2 Process Optimization

PES Optimization Guide System is a holistic digital solution for optimizing energy consumption and product quality. It utilizes resources from historical datasets, data analytics, and machine learning models, along with interactive optimizer maps, to assist engineers and operators in making decisions for optimal operating conditions. Next, we will use an example to illustrate how this system achieves further energy efficiency on top of the energy savings from the new plate positioning devices installed during the execution of this project by Millar Western.

In this study, pulp freeness at pulp refiners is the target pulp quality. Generally, if other operating conditions remain the same, higher specific refining energy results in lower pulp freeness. To meet product specifications, engineers and operators need to ensure that the specific refining energy is sufficient to achieve the target pulp freeness. At the same time, they want to avoid applying more energy than necessary to reduce pulp freeness beyond the required level. This necessitates a careful decision-making process.

Typically, at the planning stage, the last successful production period for the same pulp grade is intended to be used as a reference or starting point for the next run. Given the hundreds of operating variables involved, any changes without solid evidence of benefit can be risky, making this approach a safe practice.

During the project execution, Millar Western installed new plate positioning devices, which have been proven to be more energy efficient. Before more solid evidence is collected, mill engineers continue to follow their safe practice and operate in a similar manner as before the installation.

Effectiveness of New Plate Positioning Device

Figure 03 shows the specific refining energy distribution (left) and the pulp freeness difference between the actual and target values (right) before and after the installation of the plate positioning device for Grade A. It can be observed that:

- The specific energy values remain consistent around 600 kWh/Ton before and after the installation of the plate positioning device.
- The pulp freeness difference between the actual and target values at the central value of the distribution shifted from about +5 to -12 before and after the installation. A value of ‘0’ indicates hitting the target, demonstrating that the actual pulp freeness has decreased with the same energy input. This confirms that the new plate positioning device is indeed more energy efficient, providing an opportunity to save energy while producing pulp with similar freeness using less energy.

- However, due to the lack of a holistic approach to confirm this effectiveness, engineers are reluctant to reduce the specific refining energy to avoid the risk of producing off-grade pulp. Therefore, this potential energy saving has not been fully realized.

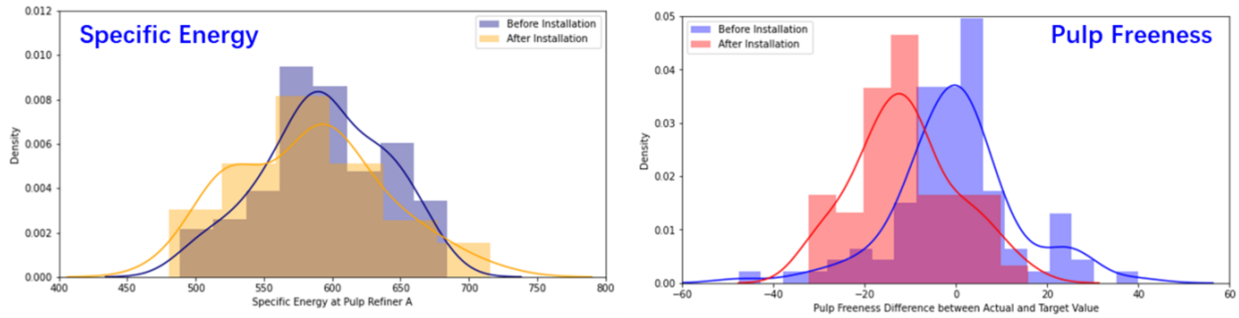

Figure 3 Distribution of specific energy (left) and pulp freeness difference between actual and target value (right) before and after installation of new plate positioning devices

PES Guide for Optimizing Energy Consumption and Product Quality

With the machine learning models developed, pulp freeness at the pulp refiner can be derived as a function of specific energy specifically for the production lines at Millar Western. The plot on the left in Figure 04 is a simplified version of this function for various pulp grade categories, while the plot on the right is a 3D interactive optimizer map generated by our PES Optimization subsystem. This map provides guidance on how to adjust specific energy to achieve a predefined shift in pulp freeness. For example, to increase pulp freeness by 12 units, specific energy can be reduced by about 50 units for Grade A.

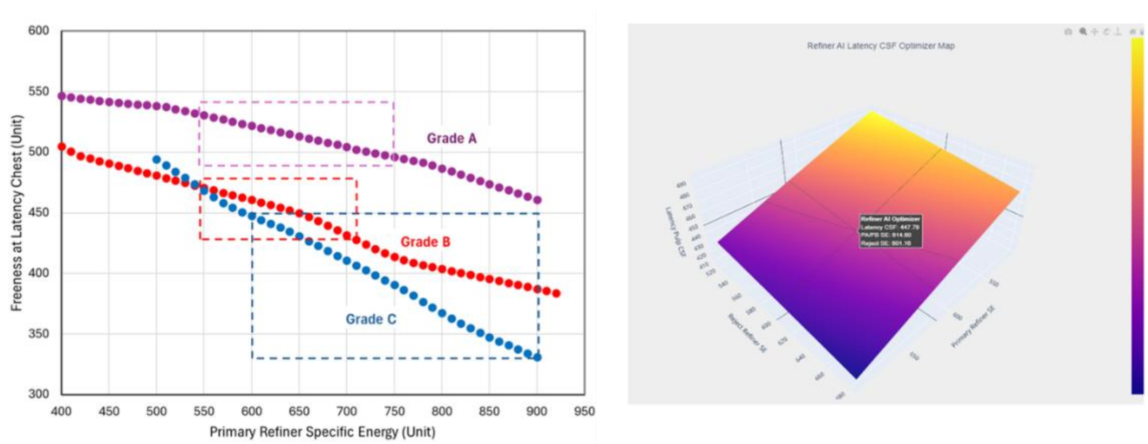

Figure 4 Pulp freeness at the pulp refiner as a function of refining specific energy based on machine learn Model: simplified version (left) and 3D interactive optimizer map (right)

Through this **process optimization**,

- **Production Quality:** Pulp freeness can be adjusted much closer to the target value, indicated by the pulp freeness difference at the central value of the distribution shifting closer to zero, as shown in the right plot in Figure 05.

- **Energy Saving and GHG Reduction:** As shown in the left plot in Figure 05, specific refining energy is reduced by 50 kWh/ADMT for this grade category, which is equivalent to approximately 5,300 tCO_2e GHG emissions annually. This improvement in energy efficiency is primarily due to the new plate positioning device. With the holistic digital solution provided by the PES Optimization Guide System, engineers and operators can achieve these savings more effectively by making optimal decisions rather than following previous safe practices. This alone can account for at least a 5% energy saving on top of the installation of the new positioning devices.

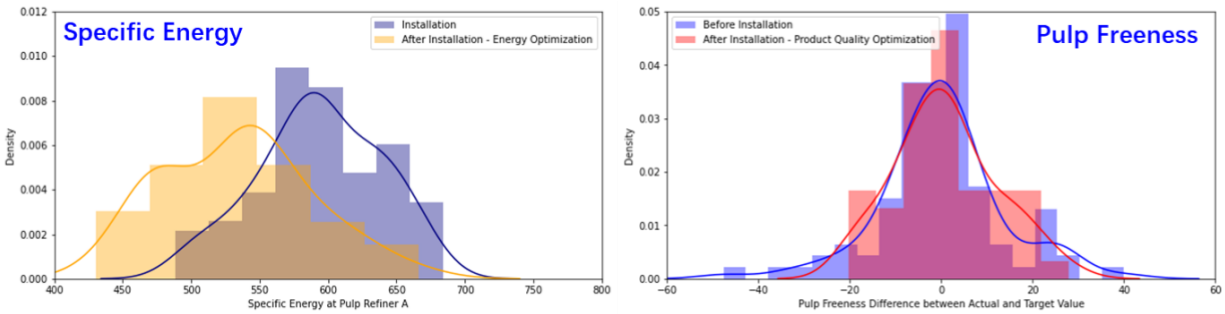

Figure 5 Shifts in distribution of specific energy (left) and pulp freeness difference between actual and target value (right) as a result in process optimization

By using the interactive optimization maps, engineers and operators can determine different combinations of operating conditions when multiple pulp refiners are used on the production lines. Since these interactive maps are generated based on the developed machine learning models, they can be updated to reflect the current conditions of the production line due to the machine learning models' auto-adaptation capability. This SMART approach accommodates shifts in the production system, which are common in reality, especially when the mill is trying different methods to improve process efficiency.

4.0 Commercialization

4.1 Advancements Toward Commercialization

The AI-Based Pulp Refining Expert System has made notable strides toward commercialization, although the full deployment and market adoption are ongoing. Key advancements include:

- ***Technology Development***: Significant progress has been made in developing the AI system, including enhancements in backend and frontend architecture and the optimization algorithms used for process improvement. These advancements are designed to address the specific needs of the pulp refining industry and improve operational efficiency.
- ***Partnerships***: The ongoing collaboration between Millar Western and InnoTech Alberta has been instrumental in advancing the technology. These partnerships are crucial for validating the system's effectiveness and facilitating its transition to commercial deployment.
- ***Market Preparation***: Efforts are underway to prepare for market entry, including developing strategies for customer engagement, identifying potential early adopters, and planning for pilot programs to demonstrate the system’s capabilities.

4.2 Technology Advancement

Throughout the project, the AI system has undergone significant technological advancements:

- ***Algorithm Development:*** The project has refined the AI algorithms to enhance their accuracy and reliability in process optimization.
- ***System Integration:*** The system's integration with existing mill operations has been improved to ensure compatibility and ease of deployment.
- ***Performance Metrics:*** Preliminary evaluations indicate that the technology has the potential to meet or exceed the performance metrics outlined in the Contribution Agreement, such as improved process efficiency and cost savings. Final validation will be based on upcoming mill trials.

4.3 Technology Readiness Level (TRL) Advancement

At the outset of the project, the AI-Based Pulp Refining Expert System was at an early TRL, focused on proof of concept and initial development. Since then, the technology has advanced through several stages:

- ***TRL Progression***: The system has moved from initial research and development (TRL 2-3) towards a more advanced stage of technology readiness (TRL 5-6). This progression reflects successful development and initial testing, with further validation and refinement planned as the project progresses.
- ***Milestone Achievement***: Key milestones in technology advancement have been achieved, including the development of a functional prototype and initial validation of the technology's effectiveness. The next steps involve comprehensive trials and market readiness assessments.

In summary, the AI-Based Pulp Refining Expert System has made significant progress toward commercialization, with advancements in technology development and preparation for market deployment. Continued efforts will focus on validating the technology's performance, furthering its readiness for commercial use, and engaging with potential market adopters.

5.0 Lessons Learned

5.1 Challenges, Delays, and Obstacles

- ***Technical Integration***: Integrating the AI system with existing pulp mill infrastructure posed significant challenges. As the project focused on process optimization rather than direct process control, aligning the new technology with traditional systems required additional time and adjustments.
- ***Resource Allocation***: Delays in acquiring specialized talent for backend, frontend, and process control development affected the project timeline. Effective resource planning and management became crucial to address these delays.
- ***Regulatory Uncertainty***: The evolving and often unclear regulatory framework for AI applications created challenges. Navigating this uncertainty extended the project timeline and complicated compliance efforts.
- ***Data Quality and Availability***: Ensuring high-quality and reliable data for the AI system was an obstacle. Inconsistent or incomplete data required additional efforts for cleaning and preparation.

5.2 Important Lessons Learned

- **Business and Commercialization**

- *Early Market Engagement*: Engaging with potential customers and partners, including industry players and research institutions, early in the development process provides valuable insights and helps tailor the technology to meet market needs.
- *Flexible Planning*: Adapting project plans and timelines in response to unforeseen challenges, such as delays and regulatory issues, is essential for maintaining progress and achieving successful outcomes.

- **Government Policy and Regulation**
  - ***Proactive Regulatory Compliance***: The unclear regulatory landscape for AI applications emphasizes the importance of proactive engagement with regulatory bodies. Understanding and addressing regulatory requirements from the beginning can help mitigate delays and facilitate smoother implementation.
  - ***Policy Adaptation***: Staying informed about and adapting to evolving government policies and regulations is crucial for managing uncertainties and ensuring compliance.

- **Technology Development**
  - ***Data Quality***: High-quality data is critical for effective AI system performance. Investing in thorough data acquisition, cleaning, and validation processes improves technology outcomes and reliability.
  - ***Integration Considerations***: When developing technology for integration with existing systems, it is important to anticipate compatibility issues and plan for technical challenges. Early testing and iterative development are key to addressing these issues.

- **Partnerships and Collaboration**
  - ***Effective Collaboration***: The partnership between Millar Western and InnoTech Alberta has been instrumental in advancing the technology. Effective collaboration between industry and research institutions can enhance technology development, provide valuable insights, and facilitate successful implementation.
  - ***Leveraging Expertise***: Leveraging the combined expertise of industry and academic partners can address challenges more effectively and drive innovation. This partnership model can serve as a valuable framework for future projects.

- **Project Management**
  - ***Resource Planning***: Careful planning and management of resources, including acquiring specialized talent, are critical for project success. Anticipating needs and addressing them proactively helps mitigate delays and keep the project on track.
  - ***Communication and Coordination***: Regular communication and coordination among team members, stakeholders, and partners are vital for overcoming obstacles and ensuring alignment throughout the project lifecycle.

In summary, the project highlighted the complexities of developing and commercializing advanced technology, particularly within an evolving regulatory environment. Lessons learned from this experience can inform future projects, improving efficiency, collaboration, and overall success.

6.0 Environmental Benefits

6.1 Emissions Reduction impact

The refining stage of the BCTMP process accounts for over 60% of a mill's electricity consumption, making it a key target for GHG emissions optimization. The introduction of the new hydraulic plate positioning device and the AI-driven PES (Process Expert System) each provide distinct opportunities to reduce energy use and related GHG emissions.

Hydraulic Plate Positioning Device:

The new hydraulic refiner-plate positioning device significantly reduces refiner load (megawatt) variability compared to the historically used electromagnetic plate positioning system. Since the installation of the hydraulic plate positioners, energy savings of 30 kWh/ADMT have been achieved, resulting in a reduction of approximately 3,183 tCO2e annually per mill, independent of additional control systems or lower-energy plates.

However, the installation of hydraulic plate positioners has not yet enabled the mill to use more aggressive refiner plates. Plate trials have occurred, but a plate pattern that provides reliable operation and energy reduction has not been found, particularly in controlling low-debris grades.

- **2030 Forecast (Positioning Device):** By 2030, the expected annual GHG reduction from the widespread adoption of the hydraulic plate positioning device across Alberta's mills is approximately 3,183 tCO2e per mill. These savings are attributed solely to the reduction in refining load variability enabled by the new device.
- **2050 Forecast (Positioning Device):** By 2050, the cumulative annual GHG reduction is expected to remain at 3,183 tCO2e per mill or slightly increase if further refinements in plate design and operational efficiency are achieved.

AI-Driven PES System:

The AI-driven PES system has the potential to further optimize energy consumption by providing real-time predictive adjustments to pulp quality, reducing refiner variability, and enhancing energy efficiency. Although the PES has been installed, full implementation has been delayed due to operational issues following the installation of the hydraulic plate positioners. Once fully operational, the PES system is expected to deliver an additional energy savings of up to 20 kWh/ADMT, resulting in an additional reduction of approximately 2,122 tCO2e annually per mill.

- **2030 Forecast (PES System):** By 2030, the PES system is expected to contribute an additional GHG reduction of approximately 2,122 tCO2e annually per mill. When combined with the hydraulic plate positioner, total emissions reductions from both technologies could reach approximately 5,300 tCO2e per mill annually.
- **2050 Forecast (PES System):** By 2050, with continued optimization and widespread deployment, the PES system could sustain or exceed its 2,122 tCO2e annual reduction per mill. In combination with the positioning device, total GHG reductions could surpass 5,300 tCO2e per mill annually, supporting Alberta's long-term emissions reduction targets.

Combined Forecast:

- **2030 Total Reduction** (Positioning Device + PES System): ~5,300 tCO2e per mill annually
- **2050 Total Reduction** (Positioning Device + PES System): >5,300 tCO2e per mill annually

The PES system plays a key role in enabling further emissions reductions by optimizing the performance of the new hydraulic positioning devices. The combination of both technologies represents a powerful solution for energy efficiency and GHG emissions reduction in Alberta's pulp and paper industry.

6.2 Other Environmental Impacts

The use of ITA's innovation PES coupled with the installation of hydraulic plate positioner and new low-energy refining plates provides several **immediate environmental benefits**:

- ***Reduced Air Contaminants***: By improving process efficiency, the system can lower emissions of harmful air pollutants like particulate matter, sulfur dioxide, and nitrogen oxides.
- ***Resource Efficiency***: Optimizing the pulp refining process reduces the use of raw materials and energy, decreasing the environmental impact of resource extraction and processing.
- ***Waste Reduction***: Better product quality optimization leads to less waste, which helps minimize landfill use and the environmental effects of waste management.

Potential Future Benefits

As the technology advances and becomes more widely used, it is expected to offer further environmental improvements:

- ***Less Land Use***: More efficient refining processes could reduce the need for additional land for production, helping to protect natural habitats.
- ***Conservation of Soil and Water***: Improved efficiency may lower water consumption and better manage waste, benefiting soil and water resources.
- ***Sustainability***: Overall, the technology supports more sustainable industrial practices, contributing to a lower environmental footprint in the long run.

7.0 Economic and Social Impacts

Industrial AI application for optimizing energy consumption and product quality is poised to bring significant economic and social benefits to Alberta.

Economically, the project is expected to enhance revenues through increased pulp production efficiency and cost savings by optimizing resource use and reducing waste. This efficiency boost will likely create jobs within the mill and its supply chain, attract investment in cutting-edge technology, and diversify the local economy. Additionally, increased production and profitability will contribute to higher tax revenues.

Socially, the project is fostering innovation by hiring highly skilled personnel with expertise in backend, frontend, and process control, and facilitating partnerships with research organizations. This initiative also supports the growth of startup companies specializing in AI and industrial optimization. Furthermore, the project emphasizes inclusivity by engaging local and underserved communities ensuring they benefit from job creation and economic opportunities. Through these efforts, the project promotes equity, diversity, and inclusion, making a lasting positive impact on Alberta's socio-economic landscape

8.0 Scientific Achievements

As of this stage in the project, no patents, published books, journal articles, or conference presentations have been produced. The primary reason for this is the current lack of mill trial data, which is essential for validating and demonstrating the effectiveness of the AI-Based Pulp Refining Expert System.

Planned Intellectual Property and Publications

- **Copyright**: We are considering copyright protection for the deployment package of the AI-Based Pulp Refining Expert System. This will safeguard the unique aspects of the software and its deployment process.

- **Journal Articles**: Future journal articles are planned to detail the methodology, technology development, and preliminary findings once mill trial data becomes available.
- **Conference Presentations**: We anticipate presenting our findings and technological advancements at relevant industry conferences upon completion of trials and data analysis.

In summary, while no formal publications or patents have been completed at this stage, significant efforts are underway to secure intellectual property and prepare for future dissemination of research findings. These activities will be pursued as the project progresses and mill trial data becomes available.

9.0 Overall Conclusions

The AI-Based Pulp Refining Expert System represents a significant advancement in optimizing pulp refining processes through the application of cutting-edge artificial intelligence. The project, developed in collaboration between Millar Wester and InnoTech Alberta, has achieved noteworthy outcomes, aligning with its goals of improving operational efficiency and environmental performance.

Project Outcomes

The implementation of the AI system has successfully enhanced the efficiency of pulp refining processes. Key outcomes include:

- ***Increased Operational Efficiency***: The technology has demonstrated potential for significantly improving the efficiency of pulp refining operations, leading to optimized resource use and reduced operational costs.
- ***Cost Savings***: Anticipated improvements in process optimization are expected to result in substantial cost savings for the industry, contributing to economic benefits.

Greenhouse Gas (GHG) Emissions Reductions

While specific trial data to quantify GHG emissions reductions is still forthcoming, the project holds promise for substantial environmental benefits:

- ***Resource Optimization***: By enhancing process efficiency, the AI system is expected to reduce the consumption of raw materials and energy. This optimization directly contributes to lower GHG emissions associated with resource use.
- ***Sustainability Impact***: The project supports broader sustainability goals by advancing technology that contributes to lower environmental impacts, both in Alberta and potentially on a global scale as the technology is adopted more widely.

In summary, the AI-Based Pulp Refining Expert System has demonstrated substantial potential for improving both operational efficiency and environmental performance. The project's focus on process optimization aligns with significant reductions in GHG emissions, contributing to the broader goals of sustainability and environmental stewardship. As the technology progresses towards trials and broader implementation, it is expected to deliver substantial benefits both economically and environmentally.

10.0 Next Steps

The next steps for the AI-Based Pulp Refining Expert System focus on further refining the technology and exploring additional applications within the mechanical pulping industry. We plan to initiate follow-up projects that will:

- Enhance the AI algorithms for broader process optimization applications.
- Integrate advanced data analytics to improve predictive maintenance and operational efficiency.

- Test and validate the system in various pulp mill environments to ensure robustness and adaptability.
- Long-Term Commercialization Plan

Our long-term plan for commercialization involves several key stages:

- ***Market Analysis and Strategy Development:*** Conducting detailed market research to identify target customers and develop a tailored commercialization strategy.
- ***Pilot Programs***: Implementing pilot programs in collaboration with industry partners to demonstrate the system's benefits and build a strong case for adoption.
- ***Product Development and Scaling***: Refining the technology based on pilot feedback and scaling up production to meet market demand.

Actions Within Two Years of Project Completion

Within two years of project completion, we will undertake the following commercialization-related actions:

- ***Intellectual Property Protection***: Securing copyrights to protect our innovations.
- ***Marketing and Outreach:*** Launching a marketing campaign to raise awareness and attract early adopters.
- ***Sales and Distribution Channels***: Establishing sales and distribution channels to ensure effective market penetration.
- ***Customer Support and Training***: Developing comprehensive customer support and training programs to facilitate smooth adoption and usage.

Potential Partnerships

We are actively developing partnerships with various stakeholders, including:

- ***Technology Integrators***: Collaborating with technology integrators to incorporate our system into broader industrial solutions.
- ***Industry Adopters***: Engaging with leading pulp and paper companies to pilot and adopt the technology.
- ***Research Institutions:*** Partnering with academic and research institutions to further enhance the technology and explore new applications.
- ***Government and Funding Agencies***: Seeking support from government programs and funding agencies to accelerate commercialization and deployment.

These steps will ensure the successful transition of our project from development to widespread industry adoption, driving long-term benefits for the mechanical pulping sector and beyond.

11.0 Communication Plan

During the development of this technology, we will keep our key audience informed and engaged, including industry partners, academic institutions, research organizations, local communities, and government agencies. Key activities include:

- ***Workshops and Webinars***: Regular sessions to share progress and technological advancements with professionals and students.
- ***Reports and Publications***: Detailed reports and academic papers will be shared with the industry and academic communities.
- ***Conferences***: Presentations at industry conferences to reach a broader audience.

- ***Community Sessions***: Informational sessions for local and underserved communities, including Indigenous groups.
- ***Internal Meetings***: Regular updates to keep the team aligned and informed.

Communicating with Third Parties

To share information about the project, its findings, and technology with others, we will use the following tools and strategies:

- ***Website and Social Media***: A project website and social media updates to provide ongoing information and interactive content.
- ***Newsletters***: Regular updates sent to industry partners, academics, and interested public members.
- ***Press Releases***: Announcements of significant achievements sent to media outlets.
- ***Academic Partnerships***: Collaborations with universities and colleges for lectures, student projects, and joint research.
- ***Publications:*** Articles and case studies published in industry journals and magazines.
- ***Stakeholder Meetings***: Regular meetings with investors, government representatives, and community leaders to ensure transparent communication and collaboration.

These strategies will help us effectively share our progress, findings, and innovations with a wide audience, ensuring broad engagement and support.

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