ISSN: 0379-5462
IPPTA: Quarterly Journal of Indian Pulp and Paper Technical Association
Vol. 32, E3, 2020, pp. 29-37

Advanced Analytics for Optimization of stage-wise ISO Brightness gain in Kraft Pulp Bleaching

Abstract: *Through the application of Advanced Analytics at ITC Bhadrachalam Kraft Pulp mill, the top control variables which effect the ISO brightness gain, and in turn, bleaching chemicals' dosage were identified and optimized to prevent lag in dosage changes as a response to changes in incoming pulp properties. This was done by defining logics to automate the dosage of bleaching chemicals as a function of such top control variables.*

In addition to this, a critical dosage limit for each bleaching stage was identified, beyond which there is little to no brightness gain, irrespective of increase in dosage. Trials were conducted to demonstrate the above observations and the results were implemented after further fine tuning. As a result, the responsiveness to the changes in incoming pulp properties increased, and there was a significant reduction in bleaching chemicals dosage.

Key Words: *Kraft Pulp Bleaching, ISO Brightness, Advanced Analytics, Bleaching Chemicals Dosage, Random Forest, Cluster Analysis, Multivariate Regression.*

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Introduction

Kraft pulping process involves conversion of wood to usable pulp through a series of treatments such as chipping, impregnation, cooking, screening, washing and bleaching. The process has a two-fold objective; separation of lignin from cellulose and hemicellulose fibres, and improvement of pulp ISO brightness. Kraft pulp bleaching predominantly operates for fulfilment of the latter, simultaneously handling traces of residual lignin. To the effect, various bleaching and extraction chemicals are used in a stage-wise manner in Kraft pulp bleaching with each stage operating at predefined condition. These predefined conditions are set such as to optimize the rate of bleaching reaction for desired pulp ISO brightness, strength properties, etc.

More often than not, there are numerous other variables in a plant scale that govern the brightness gain at a given stage. Though such variables may not be directly linked to the operation of such a bleaching stage, the consequential changes that trigger due to them could have a profound impact on parameter control and optimization. A modern pulp mill has various sources such as Distributive Control System (DCS), Digital Logbooks, etc. that hold volumes of data corresponding to thousands of such control parameters. However, it is not a straightforward procedure to identify such definitive parameters and control them in order to optimize brightness gain. Fortunately, Advanced Analytics offers methodologies to integrate, clean, filter, analyse, and offer insights from such data.

Methodology

At ITC PSPD, all data-driven improvements are carried out using the DMAIC philosophy, which stands for Define-Measure-Analyse-Improve-Control. Overall, the same methodology was used, with some slight tweaks to suit the data size.

Define Problem

The problem statement was to optimize stage-wise ISO Brightness gain in Kraft Pulp Bleaching to reduce the bleaching chemicals consumption. The scope was Kraft pulp bleaching, with process boundaries being brown stock washing and final bleaching stage.

In advanced analytics, a target function is a parameter identified to best represent the impact on the objective/ problem statement. In the present context, the main target function is overall chemical consumption in Kg/T of Bleached Pulp. For better understanding, the main target function was broken down into sub-target functions; which were specific chemicals consumptions, in Kg/T of Bleached Pulp, at each bleaching stage and stage-wise pulp ISO brightness gains.

After the target function identification, data corresponding to bleaching chemicals consumption, stage-wise pulp ISO brightness, and Bleaching Pulp production was collected and formatted to identify the baseline, i.e., the bleaching chemicals consumption in Kg/T of Bleached Pulp, before improvement.

Capturing & Structuring Data

For any data-driven improvement, the most important step is capturing and structuring of data. For pulp ISO brightness optimization, data corresponding to all parameters was captured from each process stage. The usual data sources are Data Loggers of Distributive Control Systems (DCSs), Digital Logbooks, ERP Software, etc. In addition, several synthetic variables not captured at the above data sources, which are thought out to be important by process experts were generated from the above datasets. As a norm, it was ensured that the available data encompasses almost all possible process variations. This completeness check was necessary to avoid ineffectiveness of implementations due to previously uncaptured process variations.

The data obtained from different sources was at different time frequencies. In order to integrate such data, the time stamp format was corrected to match between different sources and data was rolled up to equalize the time behaviour. Given the size of data, this kind of processing cannot be done on traditional applications and was done using R programming languages in a software interface called R-Studio.

R-Studio is an open-source software interface offering solutions for data cleaning, data mutation, data analysis, data modelling, and data visualization. It is a library based interface wherein libraries containing functions capable of performing specific tasks are invoked. These functions then work on the dataset to generate the required results. Alternatively, Python based and Java based software environments are also available to carry out the tasks required for advanced analytics.

Cleaning Data

Sometimes, data collected from various digital sources might contain practically impossible values appearing due to disturbances in plant and/or zero errors. In order to eliminate such outliers; minimum, maximum, mean, 5th percentile, 10th percentile, 25th percentile, etc. were identified for each of the control parameters. They were then filtered out to remove values deemed infeasible for normal operational conditions by process experts (Figure1). Multicollinearity is a condition where two or more control parameters are highly correlating to each other. Such multicollinear variables lead to redundancies and can effect modelling, and hence, one or more of each such variable pairs needs to be filtered out (Figure - 2). After removing such inconsistencies, the data was verified for continuity and correctness, by comparing it with the data sources and measured values of control parameters.

mean	std	min	1%	5%	25%	50%	75%	95%	99%	max
22.2	3.5	1.8	3.1	17.9	21.4	23.3	24.0	25.0	25.5	25.9
21.7	2.8	2.0	7.4	17.8	21.4	23.0	23.0	23.2	23.3	23.3
23.0	2.9	3.0	8.4	18.9	22.7	24.0	24.4	24.6	24.9	24.9
18.9	2.4	3.6	10.5	15.2	18.1	19.4	20.3	21.6	22.3	22.5
7.2	0.8	1.5	2.2	6.4	7.3	7.4	7.4	7.4	7.5	7.5
2.9	0.4	0.5	0.6	2.5	2.9	3.0	3.0	3.0	3.0	3.1
87.9	1.1	81.1	83.1	86.1	87.8	88.1	88.4	88.9	89.9	90.1
90.9	1.0	85.7	86.3	89.4	90.9	91.0	91.2	91.6	92.1	92.4
103.0	1.5	96.4	96.9	99.8	102.5	103.2	103.9	104.7	105.7	106.6
100.4	1.6	92.5	94.3	97.8	99.9	100.6	101.3	102.1	103.5	104.9
10.2	0.5	8.1	8.2	9.7	10.0	10.0	10.5	10.9	11.0	11.2
67.1	1.6	58.6	62.3	64.5	66.3	67.3	68.1	69.2	70.3	70.7
54.9	0.3	52.9	52.9	54.7	55.0	55.0	55.0	55.0	55.1	55.3
51.4	1.2	41.7	47.4	49.9	50.8	51.6	52.0	52.8	53.0	53.1
49.5	1.6	40.3	45.3	46.8	48.5	49.7	50.7	51.5	52.1	52.5
66.0	2.4	55.1	57.5	61.5	64.5	66.8	67.7	68.6	69.0	69.3
19.1	1.0	17.0	17.2	17.5	18.5	19.1	19.5	20.7	22.5	23.5
73.7	2.3	65.4	66.5	68.7	72.6	74.3	75.3	76.4	76.9	77.2
10.5	0.1	10.4	10.4	10.4	10.5	10.5	10.5	10.6	10.6	10.7
80.1	2.6	68.0	73.4	75.3	79.0	80.4	81.7	84.0	84.2	84.6
0.8	1.5	-	-	-	-	-	0.6	4.2	5.2	7.7
21.4	1.9	-	19.5	20.1	20.8	21.8	22.0	22.7	23.2	24.0
24.7	2.5	2.2	19.6	21.0	24.0	24.3	25.9	27.3	28.4	30.5

Figure1. Outlier Treatment. Values marked in red were practically infeasible and all values below/above them were filtered out.

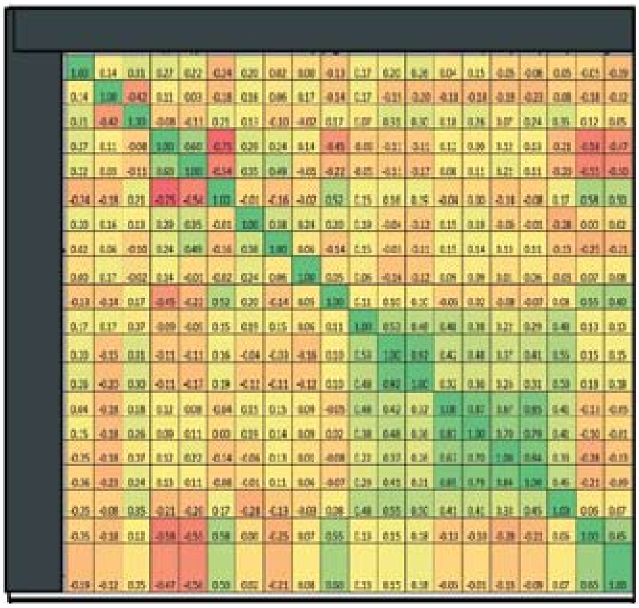


Figure2. Multicollinearity matrix. Darker the cell colour, higher the correlation.

Initial Analytics

For every process, certain control parameters are in general thought to be more important than others, by virtue of theoretical relationship with the target functions, or established relationship from previous data analyses. In initial analytics, testing and visualization of such hypotheses, formed from extensive literature review corresponding to bleaching chemical reactions, was carried out. For pulp ISO brightness optimization, data visualization of target functions for each stage with incoming Kappa number, incoming pulp ISO brightness, temperature, pressure, etc. was done to understand their relationship (Figures- 3,4,5&6). Basically, bleaching is a chemical reaction and each parameter needs to be maintained at a certain level to achieve the desired effect and any disturbance might lead to loss of efficiency. This fact was reinforced by the observations made from data visualization. These exercises showed that each bleaching stage is unique and needs to be modelled separately, and at the same time, incoming pulp properties play a major role in governing the chemical dosage and pulp ISO brightness gain at any bleaching stage.

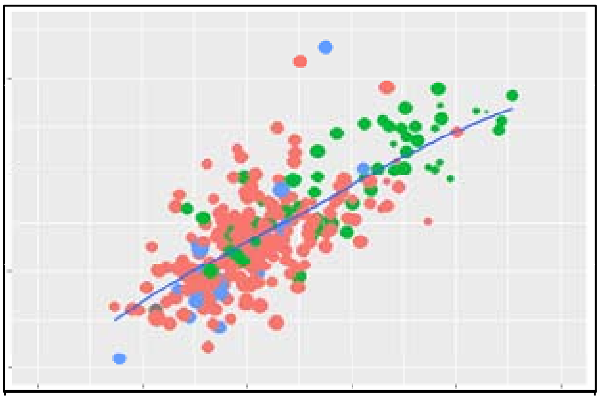


Figure3. Output pulp ISO brightness vs. Input ISO brightness in a bleaching stage.The dot size corresponds to incoming pulp Kappa number.

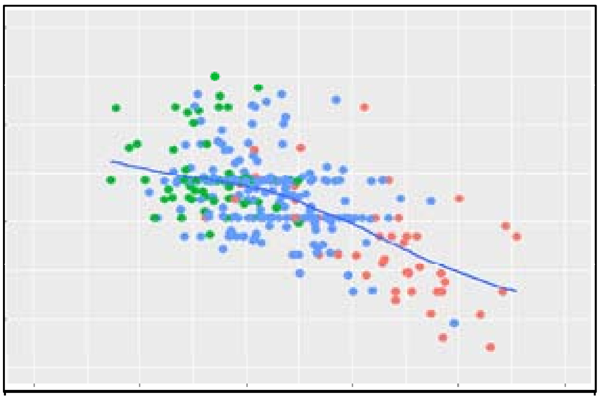


Figure4. Bleaching Chemical Dosage in Kg/T vs. Input ISO brightness.Strong inverse relationship is observed.

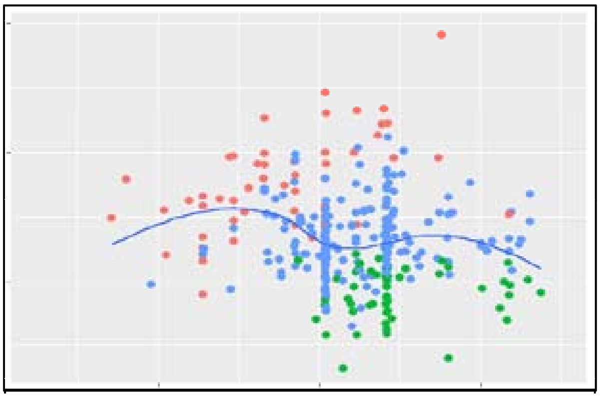


Figure5. Pulp ISO Brightness Gain vs. Bleaching Chemical Dosage in Kg/T.It is observed that ISO Brightness gain peaks at a certain dosage.

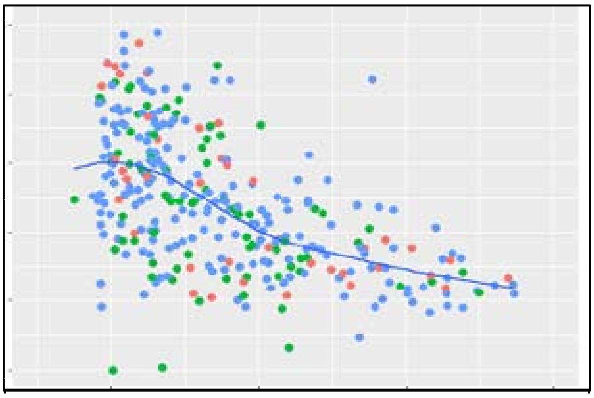


Figure6. Bleaching chemical efficiency (ISO Brightness gain per Kg/T) vs. Bleaching Chemical Dosage in Kg/T. Bleaching chemical efficiency is defined as ISO Brightness gain per unit dosage of that Bleaching chemical.

Process Modelling

After analysing the relationship of target functions with theoretically important parameters, the next step was identifying other parameters which, as per the data, have a significant effect on target functions but whose relationship is non-intuitive. Different methods like Random Forest Algorithm, Gradient Boosting Method, Cluster Analysis, and Multivariate Regression were used to identify such control parameters out of 3000+ parameters' data and build a model of the target function in terms of such important control parameters.

For applying these algorithms, the dataset was to be imported to R-Studio.

Random Forest Algorithm

Decision trees are algorithms used to identify the threshold values and importance levels of control parameters against a desired target function value (Figure7). On one side of such threshold values, the chance of attaining the desired target function value would be higher. In a Random Forest, many such decision trees are generated and each decision tree takes a random subset of control parameters and determines their importance level and threshold value level for obtaining a desired target function value (Figure8). The ensemble of all such decision trees yields the importance levels and threshold values of all control parameters.

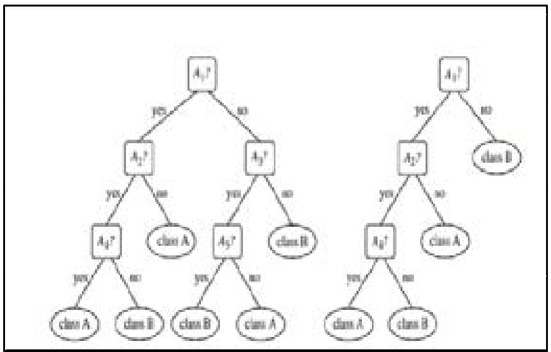


Figure7. Graphical Representation of a decision tree

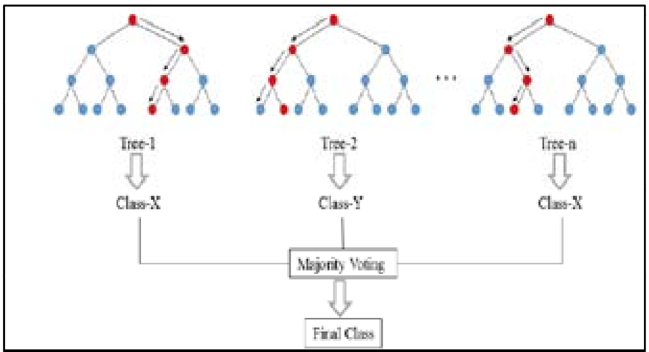


Figure8. Graphical Representation of a Random Forest Algorithm

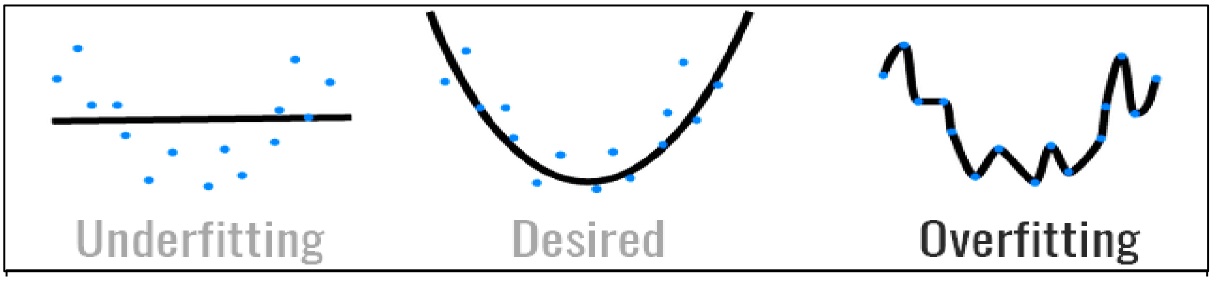


Figure9. Graphical Representation of model fit

This way, it is ensured that no observation is left behind and the results are reasonably uniform across different segments of the dataset. Based on dataset and desired model accuracy, the number of decision trees in a random forest needs to be fixed. Too many decision trees can prolong modelling and may lead to overfitting, which is loss of simplicity of model due to increased model adherence to the sample dataset (Figure 9).

For each bleaching stage, all the upstream control parameters were considered for generating a Random Forest model (Figure10). The results of Random Forest Modelling showed that top control variables were mostly the ones considered for initial analytics.

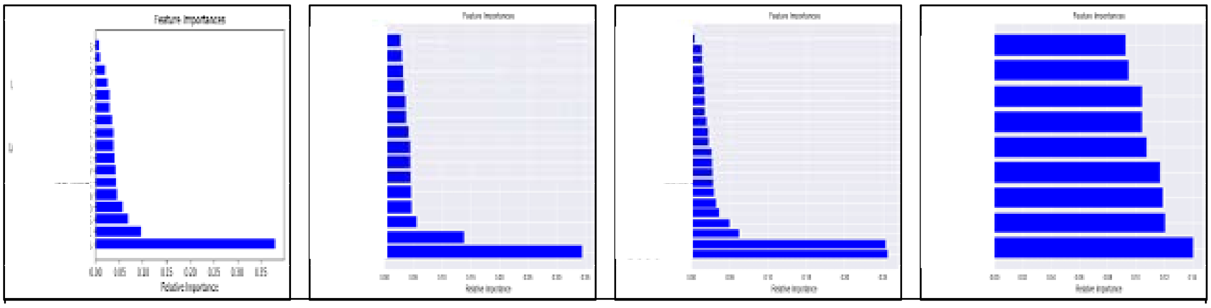


Figure10. Results of Random Forest for all bleaching stages, showing the top 20 important control parameters. The parameters with highest relative importance are mostly the ones which were theoretically known to have significant relationship with the target function, pulp ISO brightness gain in this case.

Gradient Boosting Method

Gradient Boosting method is also a decision tree based algorithm, where new models are developed for decision trees with poor classification in an iterative manner. This way, the convergence to final ensemble is faster, but at the same time, small changes can cause big variations in the overall model. This method was mainly used to verify the results of Random Forest Algorithm. For the data size considered, there is little to no variation between stage-wise results from Gradient Boosting method and Random Forest Algorithm.

Cluster Analysis

From Random Forest Algorithm, it was evident that the variation of most of control parameters, other than variables identified by process experts for Initial Analytics, does not have a significant effect on bleaching reaction at each stage. Next step was to identify optimization opportunity within the process, as a function of control parameter variation. This was carried out using K-Means Clustering.

K-Means clustering is a method of classification of data into k clusters. It starts out with K random data points, takes the nearest data point for each such point and marks the mean for the two points, and iteratively continues till all the points of the dataset are covered (Figure11). The optimal K value for each dataset is determined by calculating average within-cluster sum of squares for each K and finding out the point of inflection for the same (Figure12).

For the present context, clustering was done for each bleaching stage based on top variables identified in Random Forest Algorithm for respective bleaching stage. For example; Chemical dosing in Kg/T, incoming and output pulp ISO brightness, and Chemical Efficiency were considered to be clustering variables for a bleaching stage. The bleachability of pulp was represented by the incoming pulp ISO brightness and it was observed that higher the incoming brightness, lower bleaching chemical consumption for attaining desired output brightness. It was observed that in one of the clusters, dosage was not adjusted to the changes in incoming pulp ISO brightness. This resulted in higher dosage than requirement (Figure13). Bleaching being a chemical reaction, the proportion of inputs to attain chemical equilibrium remains unaltered and all the overdosing was found to be of little use.

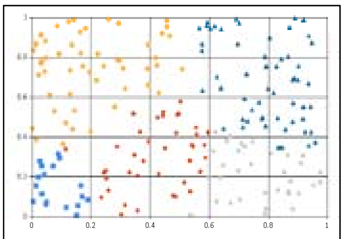
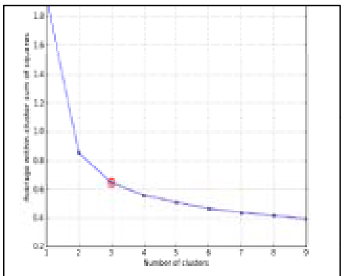


Figure11. Graphical Representation of *K-Means Clustering*



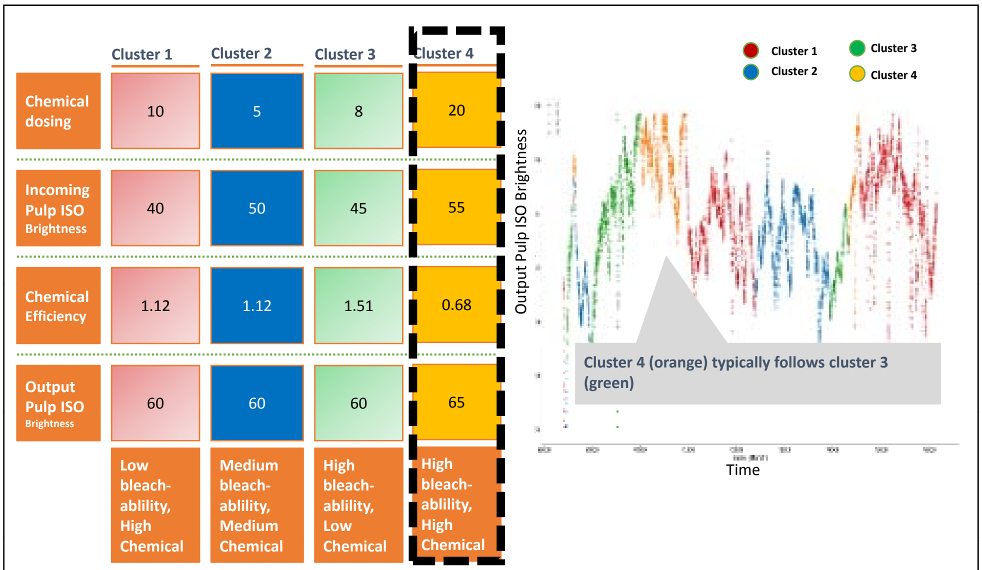


Figure12. Point of inflection for average within-cluster sum of squares determines K

Figure13. K-means Clustering revealed 4 clusters out of which one cluster was over-dosing due to slow responsiveness to the changes in incoming pulp properties. This cluster can be eliminated by automating the dosage based on multivariate regression of Clusters1,2&3.

Due to manual control of bleaching chemical dosage, the rate of response was low compared to the rate of change in incoming pulp ISO brightness from Cluster3 to Cluster4 of Figure14. It was thought out that by modelling the data from Clusters1,2&3 and automating the dosage, the overdosing in Cluster4 can be eliminated in most cases.

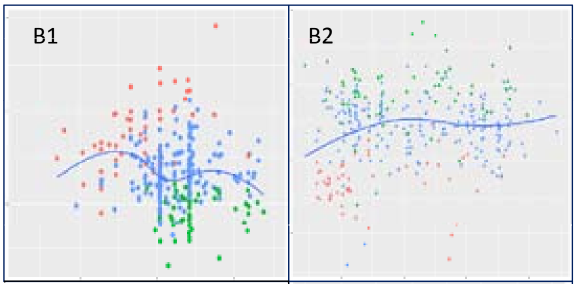
Defining Optimization Logic

Based on the insights from literature review, Random Forest Algorithm, and K-Means Clustering, Multivariate regression was performed to obtain bleaching chemicals dosage at each stage as a function of the important control parameters identified in that stage. Clusters where overdosing was evident were removed from the dataset used for Multivariate regression.

Feature Engineering is considering a function of a control parameter, like a square root, exponential, logarithm, etc. instead of the control parameter itself, for a better correlation. Extensive Feature Engineering was performed to arrive at the optimal function for the control parameter, by comparing the correlation improvement across different feature engineered functions. Auto-dosage logics were developed at each bleaching stage and were integrated into the DCS (Figure14). However, during Initial analytics, it was observed that dosage beyond a certain value resulted in little to no Brightness gain (Figure15). So, maximum dosage at each stage was limited to that particular value.

Line	Stage	Chemical	Equation
NFL1	B1	C1	C1= CON1*(K1)+CON2
NFL1	B1	C2	C2=CON3*LOG(CON4*B1 pH)+CON5
NFL1	B2	C3	C3=CON6+(CON7*K2)-(CON8*B1 Brightness)
NFL1	B3	C4	C4=CON9*LOG(CON10*B3_pH)-CON11
NFL1	B3	C5	C5=CON12+CON13(CON14-B22)-(CON15*B2 Brightness)
NFL1	B4	C6	C6=CON16-(CON17*B3 Brightness)
NFL2	B1	C1	C1=CON18*(K3)+CON19
NFL2	B1	C2	C2=CON20*LOG(CON21*B1 pH)-CON22
NFL2	B2	C3	C3=(CON23*K4)+CON24-(CON25*B1 Brightness)
NFL2	B3	C4	C4=CON26*exp(CON27*B3_pH)-CON28
NFL2	B4	C5	C5=CON29*LOGNATURAL(CON30*B3 Brightness)+CON31*(CON32-B23)
NFL2	B5	C6	C6=CON33*exp(CON34*B3 Brightness_lagged)+CON35*exp(CON36*B4 Brightness)-CON37
NFL2	B5	C7	C7=(CON37*C6)

Figure14. Multivariate Regression for Bleaching chemicals in Kg/T of Bleached Pulp



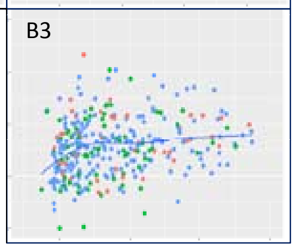


Figure15. Pulp ISO Brightness Gain vs. Chemical Dosage in Kg/T for consecutive bleaching stages. It was observed that dosage beyond a certain value does little to improve the brightness gain. The dots' colour represents the input pulp ISO Brightness range. The chance of overdosing in B3 is higher because of relative mix-up across different input Brightness ranges.

Piloting, Validation & Operationalization

Pilot trials at each bleaching stage were conducted after the implementation of auto-dosage logics. In case of any deviation from auto-dosage, the reason was duly noted and taken care of after analysis and subsequent changes to the logics. Several exceptions and modifications were formulated within the equations in an iterative manner to rationalize auto-dosage (Figure16).

Target Function was tracked at a day-wise, and month-wise frequency to check for chemical consumption and adherence of Final Brightness as per SLAs with downstream.

After it was established that there was a positive impact after optimization, the sustenance was tracked as a function of adherence% to auto-dosage, and in terms of Bleaching Chemicals Consumption Reduction (Figures17&18).

NFL#1		NFL#2	
Dosing Switch	Compliance %	Dosing Switch	Compliance %
C1	100	C1	100
C2	82	C2	84
C3	87	C3	93
C4	88	C4	100
C5	97	C5	97
C6	89	C6	85
C7	81	C7	100

Figure16. Month-wise tracking of adherence% to auto-dosage.

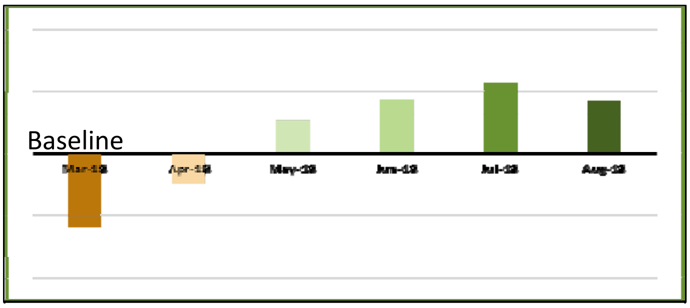


Figure17. Month-wise tracking of Chemical Consumption reduction against Baseline.

Results & Conclusion

The following results were achieved by auto-dosage of Bleaching Chemicals:

- Overall reduction in Bleaching Chemicals' Specific Consumption in Kg/T by 4%.
- Reduction in cases of overdosing by 75%.
- Reduction in standard deviation of final pulp ISO Brightness by 8%.
- Reduction in cases of final pulp ISO Brightness lower than LSL by 39%.
- Increase in cases of final pulp ISO Brightness above USL by 23%.
- Potential to increase the pulp production rate by 1.3%.

Increase of cases of Final Brightness greater than USL suggests that there is further potential to reduce the bleaching chemicals consumption. The same methodology is being redeployed to solve this situation by addressing overdosing clusters and important control parameters in final bleaching stage.

The objective of this technical paper was to device a scientific way to optimize stage-wise pulp ISO Brightness gain in Kraft Pulp Bleaching. It starts out with basic bleaching chemistry and builds models for auto-dosage of bleaching chemicals through deployment of advanced analytics for data structuring, analysis and insights. At the crux of it all, it is a study to understand a chemical reaction and control it in a better way, through the eyes of data. For sustenance of results, continual modelling at a defined frequency needs to be carried out for maintaining the achieved optimization.

At the end of the project, it was observed that given a suitable database infrastructure, pulp & paper turns out to be a good case for application of Advanced Analytics and deliverance of results. Usage of a naturally occurring raw material triggers significant enough variation in the system which is difficult to observe and predict, thereby demanding an alternative approach to carry out operations; one which involves continuous data capture, real-time process control, and end-to-end integration to adapt and counter the changes in input parameters. After the learnings and insights were implemented in system, efforts are underway to facilitate continuous background modelling which automates the generation of dosing logics in real time, leading to a smart pulp mill DCS.

Acknowledgment

We would like to express our special thanks of Gratitude to the following people, for their able guidance and support extended for implementation:

1) Mr. Sanjay Singh, Divisional Chief Executive, ITC PSPD Division
2) Mr. Vadiraj Kulkarni, Chief Operating Officer, ITC PSPD Division
3) Mr. B Makarand, Unit Head, ITC Bhadrachalam

4) Mr. KD Sharma, General Manager, Pulp and Recovery, ITC Bhadrachalam
5) Mr. Shailender Singh, Business Excellence Cell Head, ITC PSPD Division
6) The McKinsey team guiding this effort, especially Suyog, Kartik, Praveen, and Chitraketh.

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