Stochastic Modelling of Biomass Fuel Mix Cost for Boilers in Tea Processing

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Abstract**—** Wood fuel is the main supply of heat energy for withering and drying of tea. With the diminishing trends of wood fuel caused by reducing land mass due to increased population and government ban on logging of wood fuel from the forest, tea factories are looking for alternative biomass fuels to supplement the wood fuel. However, most biomass are faced with uncertainties such as availability and calorific value which is affected by moisture content. This work presents a stochastic modelling approach for a reliable biomass fuel mix strategy of wood and macadamia nutshells taking into account the stochastic nature of the availability and calorific value of the biomass. These variables determine the quantity of biomass consumed to produce the required 400 kg of steam per hour at pressure of 10 bar and temperature of 180°C. The variables also determine the cost of energy per kg of processed tea which affects the profits and competitive advantage of tea factories. The model generated randomly 40 values of moisture content between 12% and 50% and 40 values of wood availability between 60% and 100%. The moisture content and wood availability were used to calculate the energy content and mass of wood fuel used. The model subsequently calculated the mass of macadamia nutshells required to supply the deficit energy. In addition, the model calculated the total cost of the fuel mix. The model was iterated 20 times to generate more data sets to check the consistency of the model. Sensitivity analysis was also carried out to test the validity of the model. This model will be beneficial to the factory management and the Kenya Tea Development Agency in developing policy and strategies for biomass fuel acquisition.

Keywords**—** biomass fuel , calorific value, fuel mix, moisture content, stochastic model

I. Introduction

TEA (*Camellia sinensis*) is the most widely consumed beverage throughout the world and is served in several different ways. It's production in Kenya has played an important role in the Kenyan social economic development since its introduction in 1903 [14]However according to [1] the tea industry is facing several adverse forces that threaten the industry among them the high cost of fuel. Tea processing is a moisture removal process through withering, rolling and drying from a moisture content of 80% to 3% [2],[3]. Over 90% of the tea factory energy requirement is used as thermal energy for the withering and drying of tea. The thermal energy is provided by wood fuel [4]. Wood fuel calorific value and availability hold a significant share of the fuel cost. Therefore, wood fuel quality, supply security, sustainability and price are great concern to the KTDA management [5]. There is high demand for wood fuel by rural community and various industries for thermal energy supply which has led to deforestation and competition of the scarce resource [6]. Tea industries have also been hit hardest by the ban of the procurement of wood fuel from the forest by the Kenyan government since 2018. Due to the ban, the wood fuel has become scarce and therefore sold at exorbitant prices leading to decline in profits [7]. Various studies have exploited to provide alternative energy source for tea processing among them wind energy, solar energy drying technologies, and wood fuel substitution using husks and tea waste [8]- [11]. Briquettes from rice husks and tea waste are favorable for the thermal energy providence in the tea industry, however further evaluation needs to be carried out to determine its optimum combustion properties [11]. Other sources of bioenergy to provide thermal energy in the tea industry have been attempted including the use of macadamia nut shells [12]. There exists bioenergy substitution opportunities in the tea processing sector. However, the main challenge to the substitution is the economic aspect [13].Against this uncertainty background, this research aims to stochastically model the effect of calorific value and availability in determining an optimum cost effective fuel mix strategy of wood and macadamia nut shells.

II. Materials and Methods

A. Problem Formulation

Consider a biomass boiler required to produce 400 kg of saturated steam at a dryness fraction x per hour at a pressure of 10 bar and temperature of 180°c. The steam is required for withering and drying of tea in the amounts of 30- 40 % and 60-70% respectively. The minimum energy required in one hour is 18,675,240 kJ. There are various types of biomass available supplied by different suppliers. Biomass availability and quality impact the cost of production of tea and the conversion efficiency of the boiler. The quality of biomass is affected by the calorific value and moisture content of a particular biomass

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in wet basis. This research used macadamia nut shells as the available biomass source. It is assumed that there is no variation of moisture content of macadamia nutshells from measurements taken hence a constant calorific value of 21,296.56 kJ/kg from a proximate analysis undertaken. Wood calorific value is affected by moisture content as shown in equation 1[15]

$$NCV_{MC} = \frac{19\times(1-MC)-2.44\times MC}{1} \qquad (1)$$

Where *NCV* is the net calorific value and *MC* is moisture content. The unit purchasing cost of biomass is *c* and the amount of biomass available is *i*. ξ represents the probability parameter of the chosen biomass. The cost of the biomass will depend on the availability and quality of biomass. The objective function is to maximize energy and minimize the cost of purchasing cost as shown in equation 2 and 3 respectively[16].

$$Max \sum_{i=1}^{2} i \sum_{NCV=1}^{2} NCV \sum_{\xi}^{N} p_\xi P_{i,\xi} P_{NCV,\xi} \qquad (2)$$

Where *N* is the total number of scenarios generated. ξ is the scenario representation for the stochastic variable, p_ξ is probability of the scenario of each stochastic variable, $P_{i,\xi}$ is the stochastic biomass quantity from source *i* based on scenario ξ $P_{NCV,\xi}$ is the stochastic low heat value of the biomass source with relation to moisture content based on scenario ξ.

$$Min \sum_{ci=1}^{2} ci \sum_{\xi}^{N} p_\xi P_{ci,}\, \xi \qquad (3)$$

Where *N* is the total number of scenarios generated. ξ is the scenario representation for the stochastic variable, p_ξ is probability of the scenario of each stochastic variable, $P_{ci,\xi}$ is the stochastic biomass cost from source *i* based on scenario ξ .

III. SOLUTION APPROACH

A. Generating of Stochastic Variables in MATLAB

Monte Carlo approach was utilized in the generation of the stochastic variables of moisture content and availability of wood. 40 sets of moisture content between 0.12 and 0.5 and 40 sets of wood availability between 50 and 100% were generated The iterations were done 20 times to generate 20 data set. The energy supplied by wood and macadamia was also calculated using equation1. Further the quantities of wood and macadamia and their costs were calculated. The total energy costs for all the data sets was also calculated. A sample generated data sets are shown in table 1.

TABLE 1:SAMPLE SIMULATION DATA

Moisture content of wood(%)	Calorific value of wood(kJ/kg)	wood availability (%)	Energy in wood (kJ)	Energy macadamia(kJ)	Mass of wood kg	cost of wood (KSH)	Mass of macadamia(kg)	cost of macadamia (KSH)	Total cost of energy mix (KSH)
0.1321	16490	0.719	13434000	5240800	814.7	4073.6	246.09	3691.3	7764.9
0.1331	16471	0.691	12900000	5774800	783.2	3916.1	271.16	4067.4	7983.5
0.1336	16462	0.883	16486000	2189500	1001.5	5007.3	102.81	1542.2	6549.5
0.1375	16386	0.898	16763000	1912300	1023	5114.9	89.80	1346.9	6461.8
0.1569	16018	0.593	11083000	7592700	691.9	3459.3	356.52	5347.8	8807.1
0.2258	14709	0.840	15684000	2990800	1066.3	5331.7	140.44	2106.5	7438.2
0.2803	13674	0.560	10449000	8226500	764.1	3820.6	386.28	5794.2	9614.8
0.3044	13215	0.749	13991000	4684100	1058.7	5293.7	219.95	3299.2	8592.9
0.3278	12771	0.980	18299000	375900	1432.9	7164.6	17.65	264.8	7429.4
0.3603	12153	0.670	12516000	6159200	1029.8	5149.1	289.21	4338.2	9487.3
0.4079	11248	0.946	17657000	1018700	1569.7	7848.7	47.83	717.5	8566.2

B. Design of Experiment

Response surface Methodology (RSM) was used in this study to optimize the variables of moisture content and wood availability in order to generate an optimum energy cost of the mix. Design expert version 13 was used to run randomized 800 runs of data .The factors and the responses are as shown in table 2 and 3

TABLE 2: FACTORS

Factor	Name	Units	Type	Subtype	Minimum	Maximum	Coded Low	Coded High	Mean	Std. Dev.
A	Moisture Content	%	Numeric	Continuous	0.1217	0.4997	-1 ↔ 0.12	+1 ↔ 0.50	0.3085	0.1108
B	wood availability	%	Numeric	Continuous	0.5000	1.0000	-1 ↔ 0.50	+1 ↔ 1.00	0.7478	0.1375

Table 3: Responses

Response	Name	Units	Observations	Minimum	Maximum	Mean	Std. Dev.	Ratio
R1	Cost of energy Mix	KSH	800.00	5755.11	11385	8761.57	1265.23	1.98

IV. RESULTS

A. Graphical Summary

The data was clustered in 28 bins as shown in fig.1. From the histogram, majority of the energy mix cost lied between 8972.19 Kenya shillings and 9173.26 Kenya shilling clustering 54 out of 800 values of data and equivalent to 6.75%.

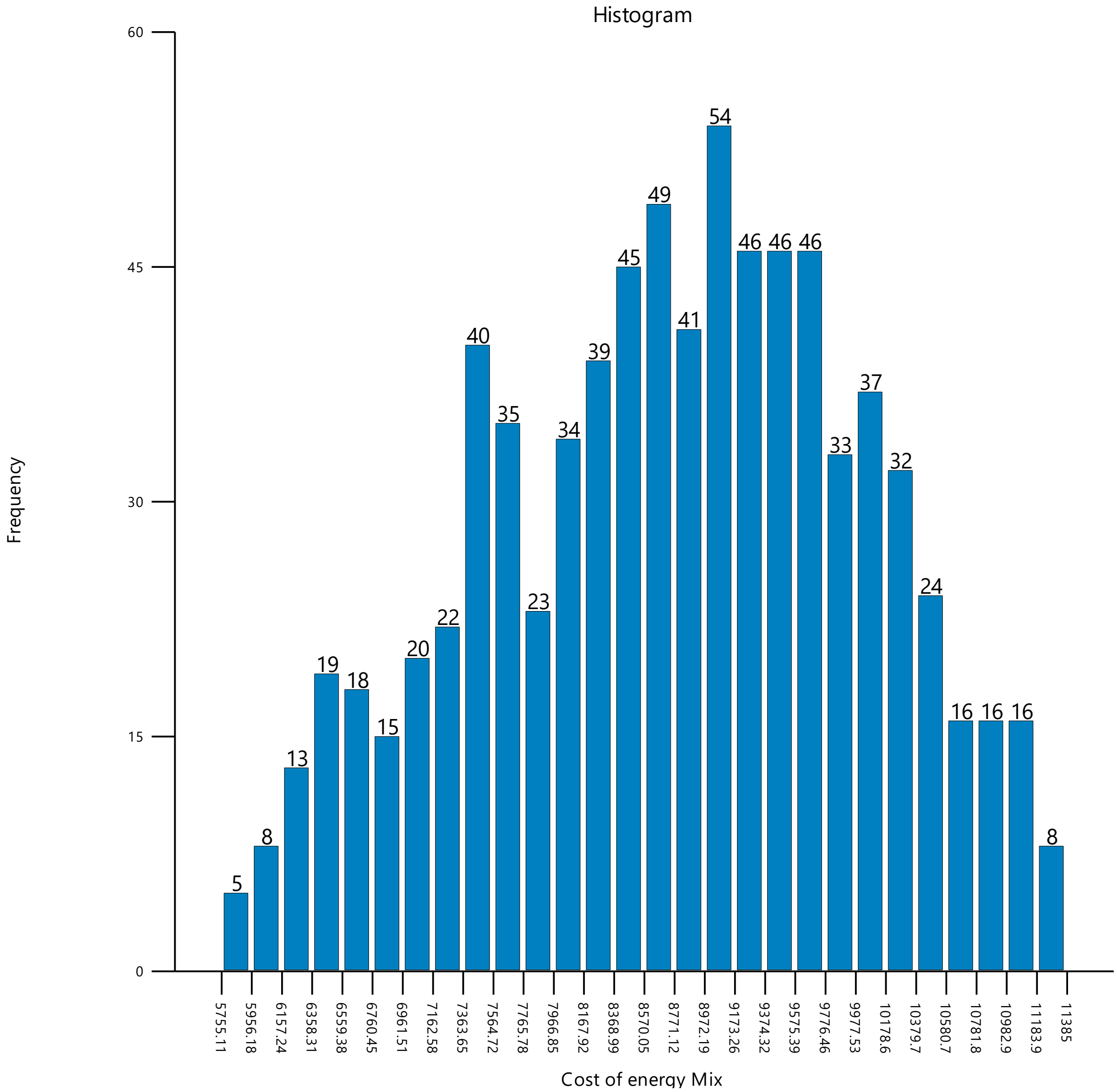

Fig 1. Clustering of the energy mix data

V. MODEL FIT SUMMARY

The model fit summary is as shown in table 4. From the analysis of data, a fifth order polynomial model was suggested. This is because of a low p-value of <0.0001 indicating 99.99% significance of the model, low f-value of 3.80 indicating a low variation between the sample means relative to the variation within the samples and low prediction error sum of squares(PRESS) value indicating a better model predictive ability. The model was also maximizing the **Adjusted R^2** and the **Predicted R^2**.

TABLE 4 FIT SUMMARY FOR COST OF ENERGY MIX

Source	p-value	F-value	df	Std. Dev.	R^2	Adjusted R^2	Predicted R^2	PRESS	
Linear	< 0.0001	15280.81	1	201.96	0.9746	0.9745	0.9743	3.287E+07	
2FI	< 0.0001	1088.02	2	131.36	0.9893	0.9892	0.9891	1.392E+07	
Quadratic	< 0.0001	7672.30	3	29.17	0.9995	0.9995	0.9995	6.947E+05	
Cubic	< 0.0001	5012.94	4	5.69	1.0000	1.0000	1.0000	26802.95	
Quartic	< 0.0001	186.23	5	3.86	1.0000	1.0000	1.0000	12296.06	
Fifth	**< 0.0001**	**5.73**	**6**	**3.80**	**1.0000**	**1.0000**	**1.0000**	**12001.36**	**Suggested**
Sixth	0.3548	1.11	7	3.79	1.0000	1.0000	1.0000	12198.59	

The equation for predicting cost of energy mix was computed as shown in equation 4

$$Cost\ of\ energy\ Mix = 8636.01 + 1465.70A - 1505.19B + 487.79AB + 399.73A^2 + 127.58A^2B + 112.29A^3 + 39.87A^3B + 35.39A^4 + 17.77A^4B + 7.40A^5 \quad (4)$$

The equation in terms of coded factors can be used to make predictions about the response for given levels of each factor. The coefficients of the coded factors are tabulated in table 4

TABLE 5: COEFFICIENTS IN TERMS OF CODED FACTORS

Factor	Coefficient Estimate	df	Standard Error	95% CI Low	95% CI High	VIF
Intercept	8636.01	1	0.2526	8635.51	8636.50	
A-Moisture Content	1465.70	1	1.03	1463.69	1467.72	20.26
B-wood availability	-1505.19	1	0.4755	-1506.12	-1504.26	3.82
AB	487.79	1	1.06	485.72	489.87	6.62
A^2	399.73	1	1.60	396.60	402.87	12.91
A^2B	127.58	1	2.91	121.87	133.28	30.68
A^3	112.29	1	4.01	104.42	120.17	133.06
A^3B	39.87	1	1.61	36.71	43.02	6.70
A^4	35.39	1	1.81	31.83	38.95	12.94
A^4B	17.77	1	3.22	11.45	24.10	21.17
A^5	7.40	1	3.55	0.4321	14.38	64.67

The coefficient estimate represented the expected change in response per unit change in factor value when all remaining factors were held constant. variance inflation factors (VIFs)greater than 1 indicated a multi-collinearity, the higher the VIF the more severe the correlation of factors.

VI. Analysis of Variance

Table 6 indicate the ANOVA for Fifth model

TABLE 6 ANOVA OF COST OF ENERGY MIX

Source	Sum of Squares	df	Mean Square	F-value	p-value	
Model	1.279E+09	10	1.279E+08	8.926E+06	< 0.0001	significant
A-Moisture Content	2.911E+07	1	2.911E+07	2.032E+06	< 0.0001	
B-wood availability	1.436E+08	1	1.436E+08	1.002E+07	< 0.0001	
AB	3.041E+06	1	3.041E+06	2.122E+05	< 0.0001	
A^2	8.965E+05	1	8.965E+05	62565.22	< 0.0001	
A^2B	27590.42	1	27590.42	1925.54	< 0.0001	
A^3	11233.65	1	11233.65	784.00	< 0.0001	
A^3B	8810.01	1	8810.01	614.85	< 0.0001	
A^4	5458.25	1	5458.25	380.93	< 0.0001	
A^4B	436.02	1	436.02	30.43	< 0.0001	
A^5	62.27	1	62.27	4.35	0.0374	
Residual	11305.34	789	14.33			
Cor Total	1.279E+09	799				

From the analysis of variance of the **Model, F-value** of 8,926,328.68 implied the model was significant. There was only a 0.01% chance that an F-value this large could occur due to noise. **P-values** less than 0.0500 indicated that model terms were significant too. In this case A, B, AB, A^2, A^2B, A^3, A^3B, A^4, A^4B, A^5 were the significant model terms.

VII. Energy Cost Optimization

The objective function was to minimize the cost of energy and moisture content within the range wood availability. 13 solutions were found as shown in table 7

TABLE 7. OPTIMIZATION SOLUTIONS

Number	Moisture Content	wood availability	Cost of energy Mix	Desirability	
1	**0.122**	**0.983**	**5725.523**	**1.000**	**Selected**
2	0.122	0.986	5701.209	1.000	
3	0.122	0.997	5620.888	1.000	
4	0.122	0.980	5751.489	1.000	
5	0.122	0.994	5642.335	1.000	
6	0.122	1.000	5600.089	1.000	
7	0.122	0.989	5683.667	1.000	
8	0.122	0.991	5666.266	1.000	
9	0.122	0.982	5736.404	1.000	
10	0.124	1.000	5613.759	0.997	
11	0.122	0.964	5867.713	0.990	
12	0.122	0.950	5972.899	0.980	
13	0.122	0.906	6304.976	0.950	

From the optimization results solution 1 is selected which is of moisture content of 0.122%, wood availability of 98.3% a cost of kshs. 5,725.523 and a desirebility of 1. Figure 2 also indicate the graphical solution of desirability of and a prediction of the model of the selected model.

For optimal energy mix the wood availability should be greater than 80% and moisture content below 18%

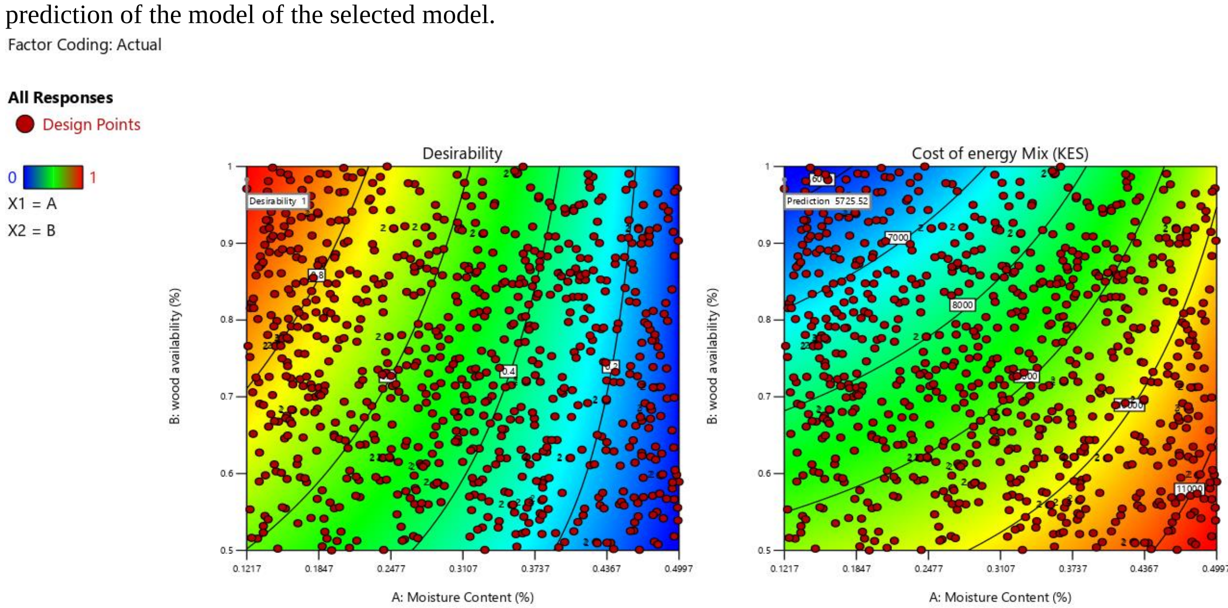

Fig 2 Desirability and prediction of the model

VIII. CONCLUSION

This study presents the stochastic modelling and optimization of the energy mix cost of wood and macadamia nutshells to identify the optimal moisture content and wood availability. The objective was to minimize the expected energy mix cost while meeting the thermal energy requirements. The model considered the effect of moisture content on the calorific value of wood . It also considered the effect of wood availability on the thermal energy requirement in order to substitute the deficit energy with macadamia nut shells. The model used a stochastic approach in order to generate randomly 800 samples of data which were used in the analysis. A fifth order polynomial model was suggested for the prediction of energy mix cost . The predicted optimum cost was ksh. 5725.523 at a moisture content of 0.122% and wood availability of 98.3%.

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