Maintenance Performance Classification using Machine Learning with multi-criteria – A Case of Dairy Industry

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***Abstract*— The purpose of this research is to implement classification of dairy industry based on their overall maintenance performance using multi-criteria ABC analysis and demonstrates the use of machine learning approach in dairy industry classification and finally, compares the results of two approaches. This work presents the application of machine learning approach (boosting tree) in classifying dairy industry into low, medium and high and comparing them with the results obtained from a multi-criteria (Analytic Hierarchy Process) decision-making process based on the example from the literature. MCDM method has classified total 18 dairy industries into 16.7% high, 55.6% medium and 27.8%, low segments respectively, while XGBoost has classified the same dairy industries equally into high and low segments. This empirical research help management to compare maintenance performance with a peer group to identify better maintenance policies.**

Keywords— Maintenance Performance, Dairy Industry, AHP, Machine Learning.

I. Introduction

The concept of maintenance management evolved to control and manage the activities of maintenance function and coordinate it with other business function to address the increased pressure of cost and availability of equipment due to automation [25]. Effective maintenance management helps in improving equipment availability, product quality and reduce rejection; operations cost leading to better service to the consumers and increased profitability to an organization [22]. Today, therefore effective maintenance management is very much essential to improve manufacturing performance and hence the organizational competitiveness. Maintenance management involves the decision of maintenance policy and deals with the identification of a problem and defining a process to solve the problem based on the importance [13, 20]. Maintenance management tries to align with the three levels (strategic, tactical, and operational) of the business.

Measuring performance is essential in any business, and it is the act of assigning numbers to properties or characteristics [31]. Performance measurement can be defined as the process of quantifying the action and performance measure can be defined as a metric used to quantify the efficiency and effectiveness of action where effectiveness refers to the extent to which customer requirements are met, while efficiency is a measure of how economically the firm's resources are utilized when providing a given level of customer satisfaction [21]. Kumar et al., (2013) [31] defined maintenance performance measurement (MPM) as the multidisciplinary process of measuring and justifying the value created by maintenance investments from the overall business perspective.

A large body of literature is available on maintenance performance management [9]. The purpose of this research is threefold. One, classification of dairy industry based on their overall maintenance performance using multi-criteria ABC analysis and second, demonstrates the use of machine learning approach in dairy industry classification and finally, compares the results of two approaches. Therefore, this study presents an idea of combining of the multi-criteria method with a machine learning algorithm in classifying the dairy industry based on the maintenance performance.

This work presents the application of machine learning approach (boosting tree) in classifying dairy industry into low, medium and high and comparing them with the results obtained from a multi-criteria (Analytic Hierarchy Process) decision-making process based on the example from the literature [10]. The literature review, methodology used and results obtained are briefly given next.

II. Literature Review

The main goal of maintenance is to increase the availability of equipment and facilities at a minimum cost and to reduce the adverse effects due to break down, if any, to improve the overall performance of an organization. Maintenance has been defined in the literature as below.

"*All activities aimed at keeping an item in or restoring it to, the physical state considered necessary for the fulfillment of its production function*" [11]. And "*The combination of all technical, administrative and managerial actions during the life cycle of an item intended to retain it in, or restore it to, a state in which it can perform the required function*" [19].

The important objectives of maintenance function are ([6], [5], [32])

- ✓ To establish the optimum frequency and extent of preventive maintenance to be performed, to reduce the amount of supply support required,
- ✓ To improve and ensure maximum utilization of maintenance facilities.
- ✓ To reduce the amount and frequency of maintenance,
- ✓ To improve maintenance operations, to reduce the maintenance skills required.

- ✓ To maximize the equipment availability and operating conditions, desired output, and quality, cost-effective and confirms safety and environmental regulations.
- ✓ To improve the maintenance organization and reduce the effect of complexity.
- ✓ To ensure system function (availability, efficiency, and product quality), to ensure system life (asset management), and to ensure system safety with low energy consumption.
- ✓ To accomplish 'total asset lifecycle optimization' to achieve operational/business objectives.

Over last few decades maintenance has undergone many changes. It evolved from a "necessary evil" and simply a part of the production function that was mostly reactive to become an important business function linked to the manufacturing strategy with a proactive approach. Initially, maintenance has been largely considered as a support function [8], however, to achieve the higher performance more and more companies are replacing their reactive strategies (breakdown maintenance) with proactive strategies (preventive and predictive maintenance) to aggressive strategies (total productive maintenance) [29]. Today, with the increasing complexity, scope, and organizational role of operational advanced manufacturing technologies, the maintenance of these technologies is becoming very critical to the ability of the organization to compete [27]. Hence, the concept of maintenance management evolved to control and manages the activities of maintenance function and coordinates it with other business function to address the increased pressure of cost and availability of equipment due to automation. [25]. Maintenance can greatly influence the manufacturing performance as it has a direct link in controlling the cost of manpower, material, tools, and overhead [1]. In manufacturing organizations, maintenance related costs are estimated to be 25 percent of the overall cost ([4]; Komonen, 2002) and about 15-40 % of production cost (Kothamasu *et al.*, 2006) [15].

Maintenance performance needs to be measured to evaluate, control and improve the maintenance activities for ensuring the achievement of organizational goals and objectives. Swanson [29] measured maintenance performance regarding maintenance contribution for improvement in product quality, equipment availability, and reduction in production cost. Chalusake *et al.*, [3] measured maintenance performance in term of operational effectiveness and maintenance satisfaction. Pintelon and Van Puyvelde [23] argued that maintenance performance would depend on the perspective applied.

The recent review has reported important factors that need to be considered for the effective maintenance performance [27].

- ✓ Measuring value created by the maintenance
- ✓ Justifying investment and maximizing asset utilization
- ✓ Revising resource allocations
- ✓ Improving responsiveness
- ✓ Health, safety and environmental issues;
- ✓ Focus on knowledge management and developing core competencies;
- ✓ Adapting to new trends in operation and maintenance strategy; and
- ✓ Organizational structural changes.

The role of effective maintenance management in the manufacturing environment is gaining more importance as many organizations strive to become world-class [3]. Given this, firms increasingly realize the significance of effective maintenance management [22].

The review of 251 articles by Simões *et al.*, [27] from 1979 to 2009 indicates that importance of maintenance performance measurement has increased over the last few years. Measurement of maintenance performance is important as it helps identify the gaps between current and desired performance and provide insight into how the performance is aligned with the business [30]. Maintenance management and its impact on maintenance performance, including the use of performance measures at strategic, tactical and operational level have been extensively studied in the literature ([2]; [25]; [19]; [18];[16];[14]; [17]).

MCDM refers to analyzing and making decisions in the presence of multiple, usually conflicting, criteria for a given set of alternatives. Analytic Hierarchy Process (AHP), a multi-criteria decision-making method, is developed by Saaty that deals with complex, unstructured and multiple-attribute decisions [26]. The main steps of AHP include problem structuring, judgments and comparison, weight calculation and consistency testing. A wide range of AHP applications including the maintenance domain has been reported in the reviews indicating the versatility of AHP methodology in modelling the real-life problems. [28], [7].

This study presents an idea of combining of the multi-criteria method with a machine learning algorithm in classifying the dairy industry based on the maintenance performance. Dairy maintenance performance is classified into High, Medium and Low by using two methods, namely, AHP, a multi-criteria and machine learning methodology. Further, these results are then compared to draw a meaningful conclusion. A brief description of the methodology and results are presented next.

III. METHODOLOGY

The overall methodology (Figure 1) for comparing the dairy industry (18 dairies) maintenance performance consists of two parts. One, the use of AHP, a MCDM methodology for computing the maintenance performance and then by using the ABC methodology (also known as known Pareto principle) to classify dairy industry into three distinct groups, namely low, medium and high, according to their relative maintenance performance. The dairy maintenance performance computation is based on the methodology proposed by Gandhare and Akarte [10]. Important steps used in the AHP methodology are (1) Criteria Identification, (2) Structuring Decision Hierarchy (AHP Model), (3) Determining Relative Importance of Criteria and (4) Evaluating Maintenance Performance.

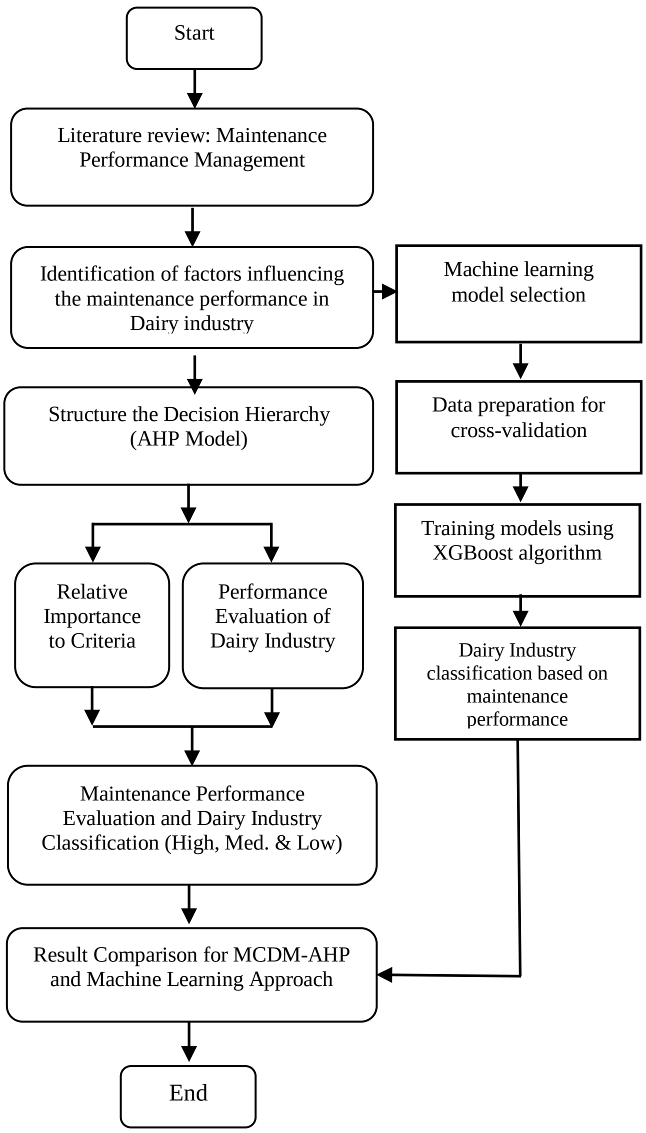

Figure 1: Overall Methodology

In the second part, boosting tree – a machine learning approach- has been used to classify the dairy industry into three distinct groups, namely low, medium and high, according to their relative maintenance performance. For this, the algorithm is trained for 100 dairy industry data, and the data for contextual perceptions of respondents about the maintenance performance is randomly generated between 1 to 5 (five-point Likert Scale, from 1-very less influence to 5-Very high influence). The maintenance performance obtained is then classified into three distinct groups (low, medium and high) using ABC methodology. The algorithm is trained on this data using XGBoost algorithm [33], and Multiclass logloss is used as an evaluation metric. The learning rate was set to 0.3 and max_depth was set to 2. The trained algorithm is then used to predict the specific class of 18 dairy industry. The idea of using a machine learning approach in classifying dairy industry into distinct groups using the ABC approach is taken from Hasan Kartal *et al.*, [12]. Finally, the results obtained by two methods are compared, and results are discussed. These are briefly summarized next. The classification of dairy industry shall help management to compare the maintenance performance with a peer group to identify better maintenance policies.

A. Multiclass Logloss

Logloss is a loss function which measures the performance of a classification model where predictions have probability values between 0 and 1. Log loss increases as the prediction diverge from the actual result. For example, predicting a probability of 0.05 for the actual value of 1 will result in high logloss. Logloss for binary classes is formulated as shown below.

$$logloss = -\frac{1}{N}\sum[y \log Pc + (1-y)\log(1-Pc)]$$

Where,

N = number of training examples,
y = actual value (0 or 1),
Pc = probability of observation equal to 1.

Generalizing above equation for more than two outcome classes, we get the following formula.

$$mlogloss = -\sum_{c=1}^{n} y * \log(Pc)$$

Where,

c = outcome class number,
y = 1 when observation *o* belongs to class *c*, else it is equal to 0,
Pc = probability of observation *o* belonging to class *c*.

IV. RESULTS

Based on the AHP methodology as discussed above, maintenance performance for 18 dairy industry has been calculated, and these are then classified into three distinct groups, namely low, medium and high using the ABC methodology. Table 1 shows the criteria (and sub-criteria) in the evaluation of dairy maintenance performance, the relative importance to the group and sub-criteria, contextual perceptions of respondents about the maintenance performance for the two sample dairy industry (Dairy1 and Dairy 2) and the overall performance for the two sample dairy industry. Figure 2 shows the overall maintenance performance for all the 18 dairy industry.

In this work, the XGBoost algorithm has been used to train the model after diving the training set into 70-30% training and validation data, where the *learning rate* was set at 0.3 and *max_depth* of trees was set to 6. '*early_stopping_rounds*' parameter was used to prevent overfitting and determine the number of iterations. The classification metric used for optimization is multiclass logloss (also referred to as mlogloss). The objective of this work is to minimize error across the segments which are computed by the XGBoost algorithm. Table 2 shows the training and validation error.

TABLE 1: CLASSIFICATION ERROR FOR THE DIFFERENT NUMBER OF ITERATION

Number of iterations	Training error	Validation error
5	0.6191	0.9175
10	0.4191	0.8519
15	0.3044	0.8415
20	0.2310	0.8276
25	0.1853	0.8092
30	0.1471	0.8157
35	0.1213	0.8485

As seen from Table 1, the validation error decreases till iteration 25 and then starts increases again. Hence, number of iterations was set 25. Table 4 shows the probability of dairy belonging to high, medium and low segments for test set. Table 3 shows the results for test set using MCDM method.

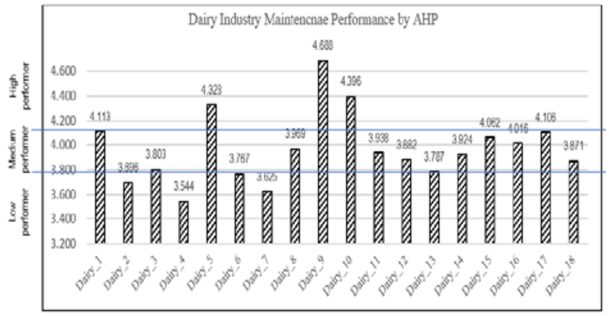

Figure 2: Overall Dairy Industry Performance

Table 3: DAIRY INDUSTRY CLASSIFICATION BY MCDM-ABC

Dairy No	Overall Maintenance Performance (descending order)	Contribution (%)	Cumulative (%)	Classification
Dairy_9	4.688	6.555	6.555	High
Dairy_10	4.396	6.147	12.702	High
Dairy_5	4.328	6.051	18.753	High
Dairy_1	4.113	5.752	24.505	Medium
Dairy_17	4.106	5.741	30.246	Medium
Dairy_15	4.062	5.680	35.926	Medium
Dairy_16	4.016	5.616	41.542	Medium
Dairy_8	3.969	5.550	47.092	Medium
Dairy_11	3.938	5.506	52.598	Medium
Dairy_14	3.924	5.487	58.085	Medium
Dairy_12	3.882	5.429	63.513	Medium
Dairy_18	3.871	5.413	68.927	Medium
Dairy_3	3.803	5.318	74.244	Medium
Dairy_13	3.787	5.295	79.539	Low
Dairy_6	3.767	5.267	84.806	Low
Dairy_2	3.696	5.169	89.975	Low
Dairy_7	3.625	5.069	95.044	Low
Dairy_4	3.544	4.956	100.00	Low

Table 4. PREDICTIONS OF TEST SET BY XBOOST
(Predicted class shown as bold)

	HIGH	LOW	MED
Dairy_1	0.024566	0.012299	**0.963134**
Dairy_2	**0.899135**	0.021079	0.079785
Dairy_3	0.386534	0.02449	**0.588976**
Dairy_4	0.32148	0.036945	**0.641575**
Dairy_5	**0.735813**	0.007794	0.256393
Dairy_6	0.118104	0.006328	**0.875568**
Dairy_7	0.122326	0.016025	**0.861649**
Dairy_8	0.300902	0.015838	**0.68326**
Dairy_9	0.433726	0.002132	**0.564143**
Dairy_10	**0.554332**	0.002121	0.443546
Dairy_11	0.156626	0.011019	**0.832355**
Dairy_12	0.174862	0.016922	**0.808217**
Dairy_13	0.047174	0.032149	**0.920677**
Dairy_14	0.013749	0.004975	**0.981276**
Dairy_15	0.395206	0.019234	**0.58556**
Dairy_16	0.180702	0.002037	**0.817261**
Dairy_17	0.092022	0.010838	**0.89714**
Dairy_18	0.016934	0.023113	**0.959953**

V. CONCLUSION

MCDM method has classified total 18 dairy industries into 16.7% high, 55.6% medium and 27.8%, low segments respectively, while XGBoost has classified the same dairy industries equally into high and medium segments. The classification using both the methods is similar for 12 dairy industries which include high and medium segments. The XGBoost algorithm was unable to classify the dairy industries into low segment may be due to high noise in training data. A larger training set may lead to better results. The classification of dairy industry shall help management to compare the maintenance performance with peer group to identify better maintenance policies.

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Table 2. Dairy Maintenance performance using AHP

Group Criteria	**Group Criteria Weight**	**Sub-criteria**	**Sub-Criteria Weight**	**Effective Weight**	**Average Score from Experts**		**Maintenance Performance**	
					Dairy_1	Dairy_2	Dairy_1	Dairy_2
Policy Development and Organization (PDAO)	0.100	TPM Involvement	0.318	0.032	4	2	0.128	0.064
		Directors involved	0.325	0.033	5	4	0.163	0.131
		Reviewing Policy	0.356	0.036	5	4	0.179	0.143
		Policy Development and Organization					0.470	0.338
Financial Aspects(FA)	0.166	Maintenance Budget	0.262	0.044	5	5	0.218	0.218
		Production Loss cost	0.244	0.040	4.9	5	0.198	0.202
		Financial Control	0.242	0.040	4.9	4	0.197	0.161
		Low cost with effective maintenance	0.252	0.042	4.27	4	0.179	0.168
		Financial Aspects					0.792	0.748
Task Planning and Scheduling (TPAS)	0.331	Focused approach	0.236	0.078	3	3	0.234	0.234
		Breakdown maintenance	0.257	0.085	4	5	0.340	0.425
		Task scheduling and completion	0.250	0.083	4.1	4	0.340	0.331
		Task Planning	0.257	0.085	3	4	0.255	0.341
		Task Planning and Scheduling					1.169	1.331
Human Resource Management (HRM)	0.118	Training	0.334	0.039	4.7	2.5	0.185	0.098
		Job Description	0.357	0.042	4.28	4	0.179	0.168
		Motivation	0.309	0.036	3.4	4	0.123	0.145
		Human Resource Management					0.488	0.411
Spare Part Management (SPM)	0.111	Spare recording	0.483	0.054	4.5	3	0.241	0.161
		Spare Controlling	0.517	0.057	5	5	0.286	0.286
		Spare Part Management					0.527	0.446
Maintenance Approach (MA)	0.174	Preventive maintenance	0.233	0.041	4.1	1.5	0.167	0.061
		Maintenance Policy & Prod. Strategy	0.268	0.047	3.1	4	0.145	0.187
		Continuous Improvement	0.274	0.048	4.1	2	0.196	0.095
		Efficient Workforce	0.225	0.039	4.1	2	0.161	0.078
		Preventive Maintenance Strategic					0.668	0.422
				Overall Performance			4.113	3.696

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