

CHAPTER-3

CHAPTER 3

METHODOLOGY FOR PERFORMANCE MEASUREMENT AND BENCHMARKING

3.1 PERFORMANCE MEASUREMENT

This chapter details the methodology for measuring the performance of dump trucks and various components of defined performance measure. As discussed in Chapter 2, the OEE defined by Nakajima considered only the internal losses while this research included internal as well as external losses for measuring the performance of dump trucks as given in Table 3.1.

Table 3.1 Comparison of various losses considered in measurement of performance

Losses by Nakajima (1988) in measurement of performance of Manufacturing industry	Losses considered in this research for measurement of performances of Mining dump truck
1- Downtime losses (a) Equipment failure (b) Setup and adjustment 2- Speed losses (a) Idling and minor stoppages (b) Reduced Speed 3- Defect losses (a) Defects in process (b) Reduced Yield	1- Time losses (a) Equipment failure (b) Setup and adjustment 2- Capacity losses i. Sticky materials in the dump truck ii. Loss of coal during transportation (spillage) iii. Quality Losses (Loaded materials other than coal, e.g., overburden, sandstone, shale) iv. Under loading of coal 3- Environmental losses (Internal losses and external losses)

3.1.1 Methodology to calculate the Overall Equipment Performance Indicator (OEPI)

The calculation of the proposed OEPI has been done by considering all the losses occurring in the system as well as beyond the system. A suitable methodology for the whole process of OEPI calculation has been given in Figure 3.1 with the help of a flowchart. The incorporation of a new parameter, i.e., environmental performance in the analysis of OEPI will consider the external losses. The proposed OEPI modifies the loss matrix and gives a more comprehensive view of various operational losses extending its applicability domain.

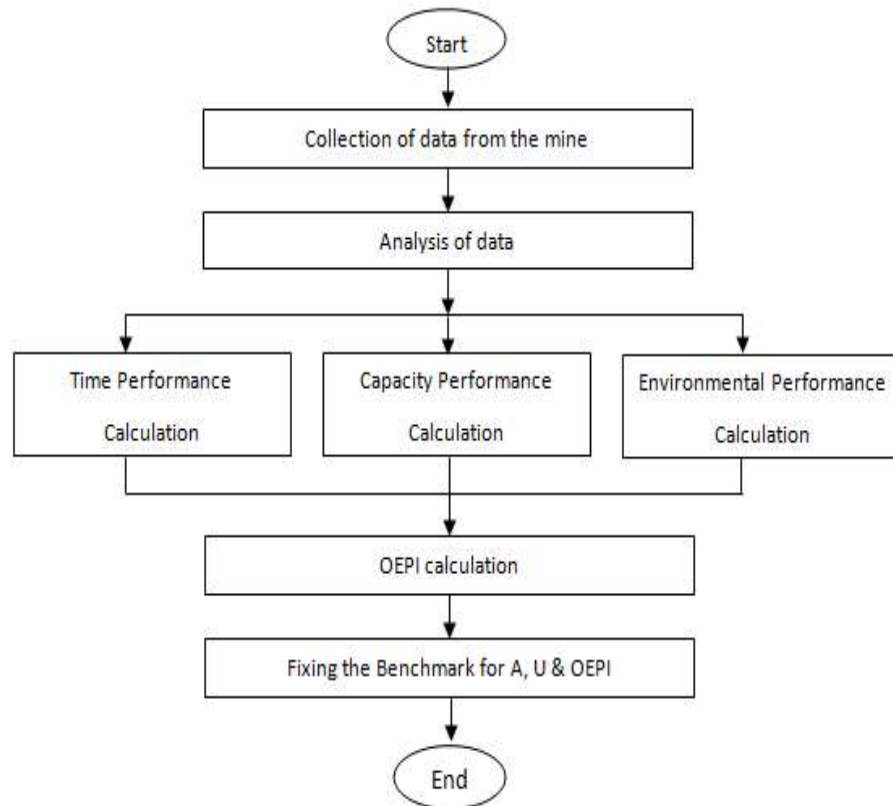


Figure 3.1 Methodology for computing the OEPI and fixing the Benchmark for A, U and OEPI

The Overall Equipment Performance Indicator (OEPI), as discussed above, categorizes the entire array of losses into three clusters, namely time losses, capacity

losses, and environmental losses. It is expressed as a product of three components as given below:

$$\text{Overall Equipment Performance Indicator (OEPI)} = \text{Time performance (T)} \times \text{Capacity performance (C)} \times \text{Environmental performance (E)} \quad \dots\dots (3.1)$$

The following section detailed the methodology for the calculation of different components of the proposed OEPI.

Several events of dump truck operations and various losses in the dump truck operations were identified through literature review, field observations, and interactions with field personnel. Various time losses identified in different operational events of dump truck operations were classified to calculate the time performance of dump truck. The suggested breakup of total calendar time into various time losses has been given and illustrated in Figure 3.2 which takes into account all the time components of a dump truck operation.

The unit of all the time components shown in Figure 3.2 is in hours. Different time components are: total calendar time (TT), planned operating time (POT), maintenance time (MNT), available time (AT), breakdown time (BDT), utilization time (UT), and idle time (IT) as defined below.

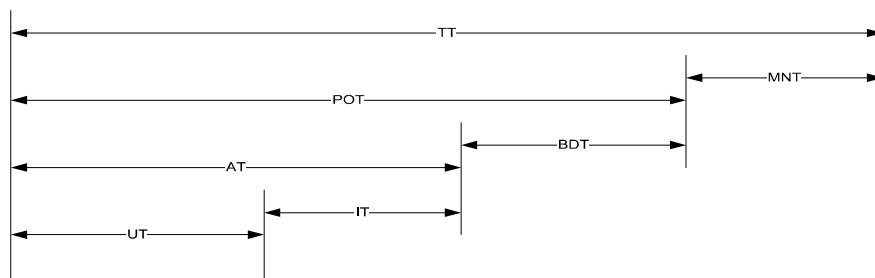


Figure 3.2 Breakup of total calendar time of dump truck under different time head

Breakdown Time (BDT) is the period when the equipment is non-operational due to breakdown maintenance. BDT includes repair time, shutdown activities such as delay time in repair.

Maintenance Time (MNT) is the time during which equipment is planned for not to operate but for maintenance and routine service.

Available Time (AT) represents the time available for operation of the equipment. AT can be calculated as

$$AT = TT - (MNT + BDT) \quad \dots (3.2)$$

Planned Operating Time (POT) is the time during which the machine is scheduled to operate. POT is calculated as the difference between TT and MNT. It includes Breakdown Time (BDT) and Available Time (AT).

Idle Time (IT) is the time losses by expected stoppages or unexpected events, which causes the equipment non-operating. It is generally the time, when, the equipment is available and ready to operate but not involved in the production process. These stoppages are extended tiffin time or extended shift change-over time, non-availability of blasted coal, serving shovel is not operating, non-availability of operator, etc.

Utilization Time (UT) is the time when the equipment is running and performing its designated function(s).

$$UT = AT - IT \quad \dots (3.3)$$

3.1.1.1 Methodology to compute the availability of the dump truck

A machine is considered available when it is fit for performing its duties. Availability does not take into account "lost time," which includes any event that stops

planned operation for an appreciable length of time due to maintenance, failures, and inspection of equipment. Then, availability is computed as follows:

$$\text{Availability} = \frac{\text{Available Time (AT)}}{\text{Total Time (TT)}} = \frac{TT - (MNT + BDT)}{TT} \dots (3.4)$$

3.1.1.2 Methodology to compute the utilization of dump truck

Utilization refers to the extent up to which a machine is being utilized for given available hours. The utilization of available hours can be expressed as the ratio of UT and AT (Lanke, 2014). Mathematically, it can be expressed as

$$U = \frac{UT}{AT} = \frac{TT - (MNT + BDT + IT)}{TT - (MNT + BDT)} \dots (3.5)$$

Time performance of a dump truck is calculated as the product of its availability and utilization.

$$\text{Time performance} = A \times U \dots (3.6)$$

3.1.1.3 Methodology to compute the capacity performance of a dump truck

The term “capacity” in the perspective of a dump truck can be defined as the amount of material it can transport from one place (loading point) to another place (dumping point) in case of a coal mine.

$$\text{Capacity Performance} = \frac{(\text{Designed capacity of dump truck} - \text{different capacity losses})}{\text{Designed capacity of dump truck}} \dots (3.7)$$

The four different capacity losses which generally occur during the operation of a dump truck in a mine are

- Sticky materials left in the dump truck
- Loss of coal during transportation (spillage)
- Quality Losses (Loaded materials other than coal, e.g., overburden, sandstone, shale)
- Under loading of coal

The framework for the different capacity losses has been given below in the Figure 3.3.

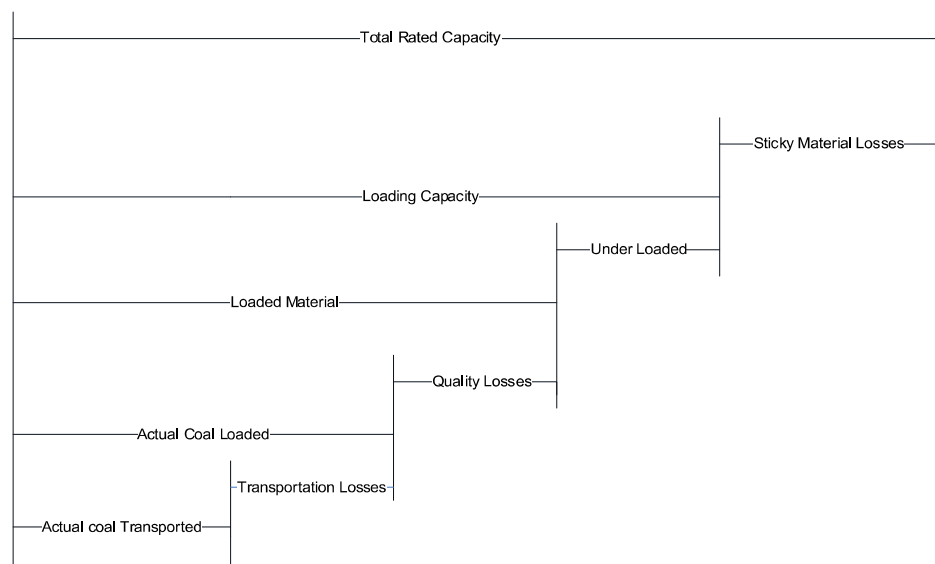


Figure 3.3 Capacity Loss Framework

Generally, the mining authority does not keep record of the capacity loss data. Therefore, capacity losses data was acquired through questionnaire survey. A questionnaire containing a set of multiple choice questions on the following heads of capacity losses was prepared and circulated to the field personnel to get their responses.

Sticky Material: Some times, there may leave some sticky materials inside the dump truck which may reduce the capacity of the dump truck.

Underloading: Many times, there may be capacity losses due to underloading in dump trucks.

Loss of Coal during Transportation: In coal mines, the haul roads are not well maintained and full of ditches and potholes. So, there are chances of spillage of material on transport and capacity losses occur during transportation.

Quality losses: Many times, materials other than coal, e.g., shale, overburden (OB), stones, soils, and sandstone may be loaded into a dump truck which will reduce the quality of coals.

3.1.1.4 Methodology to compute the environmental performance (E) of a dump truck

The environmental performance has been calculated from the measurement of CO₂ percentage in the dump truck engine exhaust. It indirectly measures the efficiency of the engine and the impact of its operation on the environment. It is expressed as

$$\text{Environmental Performance (E)} = \frac{\text{Percentage of CO}_2 \text{ in the engine exhaust}}{12}$$

$$\text{Environmental Performance (E)} = \frac{\%CO_2}{12} \quad \dots (3.8)$$

Percentage of CO₂ in the engine exhaust indirectly indicates the health of the engine and its efficiency. When an engine is in good condition, it will exhaust higher percentage of CO₂ due to better combustion of fuel. With increasing age (cumulative operating hours), the percentage of CO₂ in the engine exhaust will decrease and the percentage of other pollutants such as CO, unburnt fuel, NO_x, and hydrocarbons will increase in the exhaust.

The percentage of CO₂ in the exhaust is nearly 12% (Figure 3.4) in case of a diesel engine of the excellent condition [Khair et al., 2006]. If the engine is of excellent condition then the value of E will be near to 1.

CO emissions results where oxidation process does not occur completely. Basically, CO emissions occur more when loaded dump truck goes from mine to coal handling plant (CHP) because haul roads have lots of ups and downs for which it requires to take instantaneous acceleration where the rich mixtures (air-fuel ratio greater than 14.7:1) required. In the rich mixtures, due to air deficiency and reactant concentration, all the carbon cannot be converted to CO₂ and results an increase CO concentration in the exhaust.

Although, CO is produced during operation in a rich mixture, a small portion of CO is also emitted under lean conditions (air-fuel ratio less than 14.7:1) because of chemical kinetic effects (Faiz et al., 1996).

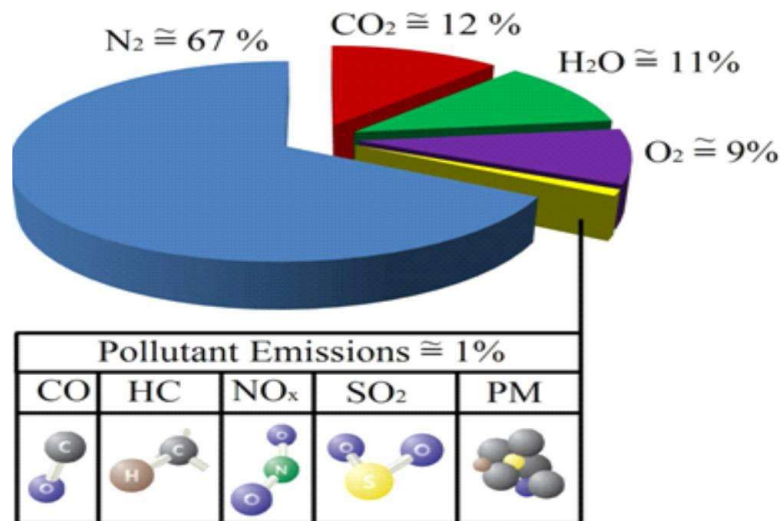


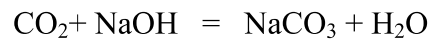
Figure 3.4 The composition of diesel exhausts gas

3.1.1.4 (a) *Experimental setup:* There are many situations where an accurate assessment of various gas concentrations is needed. Gas detector tubes are generally used in mines to obtain a direct reading of gas concentrations.



Figure 3.5 UNIPHOS gas detector tubes and pumps

The UNIPHOS gas detector tubes (Figure 3.5) and pumps are very useful for measuring the gas concentration. The detector consists of a small glass tube containing a chemical impregnated granular packing (reagents). As a standard volume of the specific gas is drawn through the tube, it reacts with chemical and produces a color change. There are different chemical detector tubes for detecting the target gas concentration. While measuring the carbon dioxide, the tube changes the color from blue to white [Sengupta, 1998]. The principle reaction which takes place during this measurement is:



The sampling time is 2.5 min per pump per stroke. The storage condition for the tubes and pump is below 10°C in the dark place.

3.2 BENCHMARKING

After measuring the performance of dump trucks, a comparison with the standard benchmarked values of performance helps the decision maker to devise suitable countermeasures for the improvement of dump trucks performances.

The following section gives a step by step methodology for fixing the benchmark for the availability, utilization and OEPI.

Step-1 Calculate month wise performance data of dump trucks

Step-2 Classify performance figures of a month into five clusters with the help of k-means clustering in SPSS.

Step-3 Draw the demarcation boundary between the two adjacent clusters using the SVM tool in MATLAB.

Step-4 Now, name each cluster from bottom to top as poor, marginal, average, moderate, and good performance levels.

Step-5 Calculate the Average of Good (AOG) performance of a month for fixing the performance benchmark for the respective month.

Step-6 Compute the average of the fixed twelve benchmarked values for fixing the overall benchmark value of the dump trucks.

The principal objective of clustering is to partition the data sets into a desired number of performance levels. The algorithm is given in Figure 3.6. This clustering algorithm assigns similar datapoints into same cluster while dissimilar dataset into another clusters. Present algorithm employs Euclidean distance for measuring the similarity between the two datapoints. Juanying et al. (2011); Yujun et al. (2012); and

Sujatha et al. (2013) have studied and explained that grouping of data is done by minimizing the sum of squared distances between the objects and their corresponding centroids in this process. Market research, data analysis, image processing, and pattern recognition are some fields where clustering analysis has generally got applications. For more accurate and precise result in this algorithm, the most essential thing is to choose the initial centre very cautiously. If the selection of initial centroid is poor, result may not be good and two or more clusters can combine into a single group or low and large-density clusters can appear into a piece. K- means clustering algorithm is an iterative algorithm. It considers the distance of each data points from the centroids of K-groups. This point will go to the closer centroid cluster and finally distributed accordingly. The algorithm of the k-means clustering is shown below in Figure 3.6. After getting different clusters by using K-means clustering, the next step is to draw hyperplanes and decision boundaries with the help of Support Vector Machine (SVM) in MATLAB.

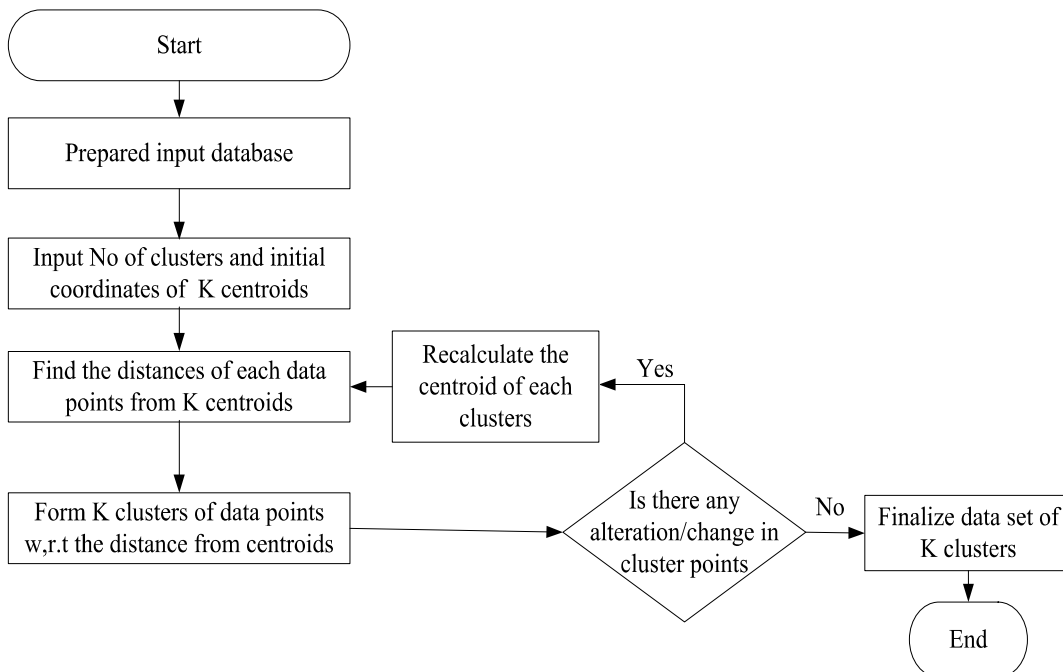


Figure 3.6 Algorithms for K-Mean Clustering

After getting different clusters by using K-means clustering, the next step is to draw hyperplanes and decision boundaries with the help of Support Vector Machine (SVM) and MATLAB (Kumar et al., 2016).

SVM is a supervised machine learning method which is generally used for classification and regression problems. It was initially developed by Boser et al. (1992), Cortes and Vapnik (1995), and Vapnik (1998). Over the last few years, various classification techniques were proposed in which some are linear supervised and others are non-linear supervised algorithms (Jing et al., 2013). The most important difference between other classifiers and SVM is that others focus at all the points equally while SVMs pay attention only on those points which are apart. In binary classification, the main focus of SVM is to locate an optimal hyperplane that separates the two clusters with a highest separating margin. Here, margin is the geometrical distance of the blank space between the two data clusters. For better generalization of SVM classifier, margin should be as maximum as possible (Vapnik, 1995). In this research, SVM has been used to construct the decision boundaries between the two adjacent data point clusters. The existence of decision boundary between two data type has been given with the help of Figure 3.7 (Kumar et al., 2016).

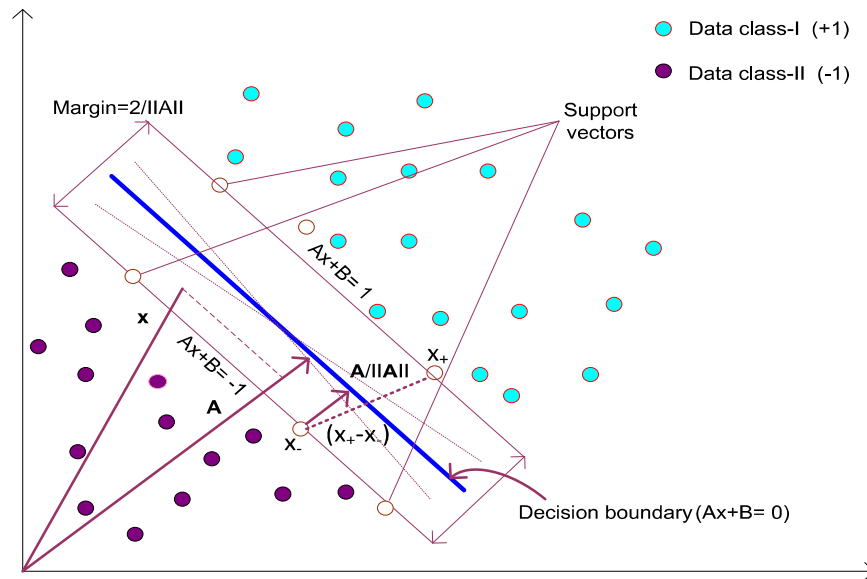


Figure 3.7 Existence of Decision boundary between two data type

The syntax which has been used in the MATLAB for drawing the demarcation boundaries have been detailed below.

3.2.1 MATLAB syntax for SVM

The SVM tool is used to construct decision boundaries between homogeneous clusters. Training data has been prepared first in an excel sheet, then data interpretation has been completed using MATLAB Software. To draw a decision line between poor and marginal-levels of OEPI, labeled data of poor group as L or -1 and of marginal group as U or +1 as per the output of SPSS homogeneous K-means clustering technique. Arrange the primary training data in excel spreadsheet format in to three columns in which second and third column contains coordinates for both poor group and marginal group clusters, first column contains respective attribute value e.g., 'L' or 'U' for Lower and Upper clusters of OEPI data points. The following steps given below in the Table 3.2 describes the method from preparing the excel data sheet to import data to MATLAB and then applying stepwise SVM tool syntax in MATLAB.

Table 3.2 Syntax used for support vector machine in MATLAB

Maintain groups (+1 (U) and -1 (L)) for training data
Import prepared training data from Excel sheet to MATLAB Editor prompt using syntax
<pre>data=xlsread('filename.xlsx',sheet no.);</pre>
Provide specific address with respect to Excel sheet rows and columns
<pre>A = data(1:end,1:2);</pre>
Provide address for respective attributes of above training data
<pre>B = textdata(1:end,1);</pre>
<pre>svmStruct = svmtrain(A,B,'showplot',true);</pre>

The above syntax was used to draw the linear boundary between poor and marginal groups of OEPI data. Similar process was used to draw a boundary between the adjacent groups of OEPI data such as between marginal and average, between average and moderate and between moderate and good.