

Use of Machine Learning Algorithm Models to Optimize the Fleet Management System in Opencast Mines

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Abstract—In surface mining operations, the dumper haulage system contributes the most in total operating cost of any mine. It is estimated that an average mining company spends around 50% to 60% in this truck haulage system only. So utmost priority should be given to keep up an effective haulage framework. So, to reduce the cost of operation the dumpers must be allocated and dispatched efficiently. The haulage systems should be designed in such a manner that the availability, performance and utilization of the dumper and shovel are maximized which ultimately yield in high production and reduction of operating cost. So, in this paper to enhance the productivity of truck haulage system an attempt is made to minimize the cycle time of dumpers and allocate an optimized number of dumpers to one shovel so that the idle time of dumpers can be minimized. In determining the cycle time of dumpers predicting the travelling time in different situation is given utmost importance. For this machine learning models are used which help in predicting the travelling time in different atmospheric situation of the mine. This approach of integrating the machine learning methods in minimizing the cycle time will provide a proper estimation of performance measure, truck scheduling and finally an optimized truck dispatch system.

Keywords—opencast mine, truck dispatch system, dumpers, shovels, cycle time, scheduling, overall equipment effectiveness, machine learning, optimization

I. INTRODUCTION

The Open pit mining industries are using extremely expensive machinery such as heavy dumpers, shovels, and loaders of high capacity to increase their production. So, there is a need of optimization of the utilization of such machines and at the same time operational cost should be reduced. This can be done by developing a sophisticated dumper haulage system which ultimately ensure an efficient utilization of equipment. So, in this paper the truck assignment approach has been implemented which uses the machine learning algorithm method. A general estimation shows that the surface mine alone contributes 70%-80% of total production of minerals in India. The open cast mining operation consists of loading of minerals at face, hauling and dumping operations. Shovel-dumper systems being the most flexible and efficient are mostly used in almost all surface mining activities. The mining industries always give importance to productivity and profitability. So, there is a need of automation in these systems.

The three important components of material handling in any surface mine are dumper, excavator, and loaders. The dumper hauls the materials from loading station to desired unloading station. One hauling cycle may consist of some

productive work as well as non-productive works. Productive work of dumper includes total travelling time of dumper, spotting time, loading/unloading time etc. Whereas ideal time, breakdown time may be included in the unproductive time. In this paper an approach is developed to reduce the non-productive work to increase utilization of available machinery.

The total travelling time of the dumper being loaded or empty take most of the portion of total cycle time. So, to minimize the hauling cycle time it is very crucial to predict the travelling time of dumper at different situation. This travelling time generally depends on the atmospheric conditions such as wind speed, dustiness of the atmosphere, precipitation, temperature etc. The dumper condition, driver experience and some other aspects also affect the travelling time but, in this paper, the atmospheric conditions are only used to predict the traveling time using machine learning models. This predicted travelling time further integrated with linear/integer programming methods for overall optimization the truck scheduling system.

Now-a-days with the development of GPS system many of the open pit mines are using the automated truck dispatch system (TDS) and fleet management system (FMS). In these systems real field data like truck location, its travelling time, total working hour etc. can be collected. The data can be used to train the machine learning model such that it predicts the traveling time with less error. In this work attempts are made to:

- Develop the machine learning model to predict total travelling time of dumper in different situations
- Develop an objective function for total cycle time of dumper
- Develop linear/integer programming method using Machine learning technique to minimize the total cycle time.
- Optimize the dumper scheduling assignment

Truck assignment/scheduling is one type of stochastic combinatorial problem. It is stochastic because it involves different activity duration in the mining field operation. Various researchers have tried to optimize the scheduling problem by incorporating different objective function. Travelling time prediction of dumpers in an open pit mine is very vital as it has a direct impact on total cycle time. Many researchers have tried to develop different mathematical approaches to predict the traveling time of vehicles being it in mining sector or in different fleet management systems.

Kresta et al. (2005) tried to develop an optimization technique which uses a two-stage stochastic approach. So, in this type of approach the stochastic model is first used to improve the initial truck scheduling problem then again reallocation of trucks can be done based on previously assigned mining operation.

Sun (1998) tried to build a relation between the travelling time and many other parameters which influence the following. It was observed that the travel time is dependent on different factors such as atmospheric conditions, condition of haulage road, type of truck used, loading, or unloading status of dumper. All these parameters make it difficult to build a particular relationship between the travel time and dependent factors accurately and efficiently.

Run-Bai (2005) tried to develop an artificial neural network (ANN) to predict the travel time of dumpers in opencast mines. The ANN model used various parameters such as atmospheric conditions, condition of haulage road, type of truck used, loading, or unloading status of dumper etc. A total of 336 data records were used in their ANN model. The results are comparatively good than those of statistical models.

Hauk (1979) presented an approach where an assignment problem is scheduled according to the developed integer equation. It considered the activity of each dumper at discrete time steps, and average travel and loading times. The system developed by Hauk was type of simulator that tried to give results in real-time to minimise shovel idle time and time spent with trucks travelling or waiting.

Temeng et al. (1997) developed a mathematical model that tried to optimise the total output production of a mine along the desired haulage road network. This Dispatch model gives a time scheduling which ultimately results in minimising the total waiting time at the same time it considers the shovel demand, based on how far behind schedule each shovel is.

Edwards and Griffiths (2013) have developed a model called ESTIVATE which can predict the travel time of the excavator in an open cast mine. ESTIVATE uses the MR equation to predict the time. Integration of ANN models increase the prediction efficiency of the model.

Ahangaran and Yasrebi (2012) have proposed a deterministic approach for the truck allocation algorithm. It uses integer programming which can estimate the time required for different activities. But the system seems to be relatively slow in proper mining condition which uses large numbers of equipment.

Rodrigo et al. (2013) have tried to optimize the truck allocation problem in which failure and maintenance of equipment also considered. It is a two-step method where the first step is optimization of truck allocation and in second step it estimates the failure and maintenance activity of equipment. Then these estimations are used as the feedback to the first step which results in a reallocation.

Bozo et al. (1993) have presented a solution to the truck allocation problem by defining different objective function. It is two stage stochastic approach. In the first stage the optimization of developed objective function was done by linear programming while in the second stage the fraction output for number of trucks is changed into an integer.

A. Indian surface mining status:

The mining industry plays a vital role in Indian Economy. Its contribution in India's GDP is around 2.5% but if we see the GDP of all industries mining industry alone contribute for more than 10%. As of 2019 India was 4th largest world producer of iron ore, 4th largest worldwide producer of chromium, 5th largest world producer of bauxite, 5th world largest producer of zinc, 7th largest producer of manganese. India is second only after China in production of coal. In all mineral production the share of surface mine is quite high. The share of surface mine in Indian coal mining giants Coal India Limited (CIL) and SCCL is around 80% and 54% respectively. So proper importance should be given in different scientific development of surface mining methodology.

B. Mines in abroad where the automation system is being used:

Many surface mines in abroad uses different automation systems such as TDS System, GPS system etc.

1. The Century Zinc Mine in Northern Queensland uses high end GPS. This system is installed in different machineries such as excavators, dumpers for effective management.
2. The Collinsville Coal Mine equipped with high precision guidance from GPS.
3. Arizona mine uses localised network which uses different high-end computer networking system. It tracks the movement of each truck and shovel and then decide when a shovel will need a truck to load, and which truck will be nearby. This system optimizes the waiting time for both the shovel and truck.
4. Borax's mine in California have developed a high-precision global positioning system (GPS) for machine counselling. This system is also used for mine safety in different hazardous conditions.

C. Mines in India where the automation system is being used:

1. The Northern Coalfields Ltd (NCL), Singrauli, Madhya Pradesh
2. Tata Steels Opencast Coal Mines West Bokaro, Jharkhand
3. Panchpatmali bauxite mines, Damonjodi, Odisha

II. CASE STUDY

This section presents the profile of a mine which uses the GPS based TDS system. The mine is one of the Asia's largest integrated aluminium complexes. The Panchpatmali bauxite mine is the largest single bauxite deposit in the world. Table 1 gives a brief introduction of the mine.

TABLE I. BRIEF INTRODUCTION OF THE MINE

| | |
|----------------------|------------------------------------|
| Name of the mine | Panchpatmali Bauxite mines |
| Location of the mine | Damanjodi, Odisha |
| Type of Mine | Open cast |
| Year of approval | 1985 |
| Original capacity | 24,00,000MT |
| Expanded capacity | 63,00,000MT |
| Mining methods | Drilling & blasting, Trench mining |
| Thickness of seam | 14.4m |

A. Important features of the mine:

The bauxite mine adopted the trench mining as mining method. It uses drilling and blasting method to excavate the mineral. It also uses ripper dozer combination to excavate the mineral as part of eco-friendly mining technology. For transportation of mineral, it uses 14.6 kms single flight multi curve cable belt conveyor from the mine to its refinery. ANFO is used to blast both overburden and bauxite ore. It is one of the highly mechanized mines which uses different automated system for its day-to-day operation. TDS system for the mine operation and pit optimization is there since 2005. GPS system is also used for this purpose.

B. Use of GPS system in mining:

GPS stands for global positioning system. It is a satellite-based tracking system that uses 24 satellites orbiting the earth twice every day in six different orbital planes at a height of 20,200 kms. Each satellite has an atomic clock which generates the signal with a precise time message. Similarly, the GPS receiver on the earth receive the signal and compare it with own time and difference among them is used to calculate the distance and positioning the specific equipment. Now-a-days GPS is extensively used in mining for the following applications:

- ✓ Automation of truck haulage system
- ✓ Truck Dispatch System
- ✓ Equipment tracking
- ✓ Quality control of minerals
- ✓ Slope stability/slope management
- ✓ Dump management

C. Use of TDS system in mine:

Truck Dispatch system is generally used in mines to automate the truck hauling unit as well as to monitor performances of other equipment. It consists of field computer systems (FCS), Colour Graphical console (CGC), wireless radio network system, GPS ground reference station and GPS location system. TDS system in a mine is used for the following purposes:

- ✓ Optimum utilization of HEMMs
- ✓ Health monitoring of HEMMs
- ✓ Reduction of idle time of equipment
- ✓ Mine safety
- ✓ Quality control
- ✓ Automatic optimization of truck haul assignment
- ✓ Auxiliary equipment tracking
- ✓ Maintenance tracking of equipment
- ✓ Automatic fuel assignment

D. Truck scheduling system:

The main objective of the truck scheduling systems is to improve the OEE while reducing the operational cost at the same time over a particular time (e.g., one shift). To achieve this aim objective functions with different constraints are developed to find truck schedule that uses the optimized number of trucks. An objective function to minimize the total cycle time is also constructed so that one can get maximum equipment utility. These objectives are suitable to the mining conditions as the shovels and loaders are expensive equipment. Pictorial problem of truck haulage cycling

system is shown in the Figure 1. In this approach we have considered the following:

Dumpers from different shovels can travel on and dump the material at same dumping site.

Truck of certain capacity cannot travel between the face and dumping site due to various constraints so in this problem we have considered same size for all the trucks.

Driver experience and condition of truck are not considered while developing the prediction model.

To solve the truck scheduling/assignment problem we must first develop an objective function which can be optimized according to various constraints. Let us consider total number of shovels available in the mine is S, total number of dumping site is D and maximum fleet size of the mine is F. The goals are considered while developing the objective function.

- Minimization of number of trucks so that the utilization of shovels is maximum i.e., above certain threshold limit.
- Minimization of cycle time of the dumpers.

Assuming $x(s, d, f)$ be the number of dumpers travelling from between shovel to dumper and vice versa the optimization problem can be mathematically expressed as:

$$\begin{aligned} \text{Minimize } Z &= \sum_{d=1}^D \sum_{s=1}^S \sum_{f=1}^F x(s, d, f) \\ \text{Subject to } U(S) &\geq C_s, s = 1, 2, \dots, S \\ \sum_{d=1}^D \sum_{s=1}^S x(s, d, f) &\leq N(f) \\ \forall(s, d, f) \quad x(s, d, f) &\geq 0 \\ \forall(s, d, f) \in R \quad x(s, d, f) &= 0 \end{aligned}$$

Here $U(S)$ = utilization of shovel s

C_s = Desired utilization of shovel for maximum productivity

$N(f)$ = Total number of trucks

R is a particular set of nonviable triplets (s, d, f) which signify constraints such as shovel matching problem, road constraints etc.

The utilization of shovel over the total cycle time can be defined as:

$$U(S) = 1 - \frac{Wt(S)}{T} \quad s = 1, 2, \dots, S$$

Where $Wt(s)$ is total waiting time of shovel during the period T . This shovel waiting time can be estimated according to the total cycle time of each fleet/dumper. Waiting time of shovels is developed as:

$$Wt(S) = T - \sum_{d=1}^D \sum_{f=1}^F \frac{T \cdot x(s, d, f)}{T_{\text{cycle}}(s, d, f)} T_{\text{loading}}(s, f)$$

The cycle time of the dumper consists of empty travel of the dumper, spotting of the dumper, loading, hauling the material to the dump site, and dumping as the productive work. There are also some unproductive activities like idle time, breakdown time and maintenance time of dumper. Thus, the actual cycle time of a dumper is estimated as:

$$T_{\text{cycle}}(s,d,f) = T_{\text{empty}}(s,d,f) + T_{\text{spotting}}(s,d,f) + T_{\text{loading}}(s,d,f) + T_{\text{haul}}(s,d,f) + T_{\text{unloading}}(s,d,f)$$

So, by combining the above two equations the constraint equation for utilization factor can be determined and used while solving the optimization problem. These phases of truck hauling system can be represented in a pictorial form shown in Figure 1.

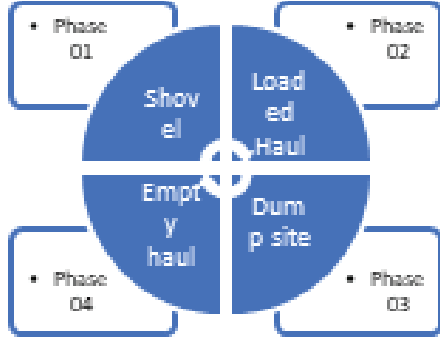


Fig. 1. Different phases of truck hauling system

The objective of minimizing total number of trucks at the loading point, number of trucks travelling on the road and number of trucks at dumping site can also be written as follows:

Minimize $Z = (\text{Number of trucks travelling on the road} \times \text{Travelling time of the truck in that path}) + (\text{Number of trucks at shovel} \times (\text{loading time} + \text{spotting time})) + (\text{Number of trucks at dump} \times (\text{unloading time} + \text{spotting time}))$

This can also be written as:

$$\begin{aligned} \text{Min } Z = & \sum_{d=1}^D \sum_{s=1}^S \sum_{f=1}^F x(s,d,f) \times (T_{\text{haul}}(s,d,f) \\ & + T_{\text{empty}}(s,d,f)) \\ & + \sum_{s=1}^S x(s) \times (T_{\text{spotting}}(s) + T_{\text{loading}}(s)) \\ & + \sum_{d=1}^D x(D) \times (T_{\text{spotting}}(d) + T_{\text{unloading}}(d)) \\ \text{Subject to } & U(s) \geq C_s, s = 1, 2, \dots, S \\ & \sum_{d=1}^D \sum_{s=1}^S x(s,d,f) \leq N(f) \\ & \forall (s,d,f) \ x(s,d,f) \geq 0 \\ & \forall (s,d,f) \in R \ x(s,d,f) = 0 \end{aligned}$$

Here $x(s,d,f)$ = Number of trucks travelling between the loading site to dump site

$x(s)$ = Number of trucks at the shovel/loading point

$x(D)$ = Number of trucks at the dump

T_{haul} = Time required to travel when the truck is loaded

T_{empty} = Time required to travel when the truck is empty

$T_{\text{spotting}}(s)$ = Spotting time of truck at shovel

$T_{\text{loading}}(s)$ = Time taken by shovel to load the truck

$T_{\text{spotting}}(d)$ = Spotting time of dumper at dump

$T_{\text{unloading}}(d)$ = Time required to unload the material at dump

Prediction of travelling time of dumper between face and dumping site:

The solution to the objective function that is developed is mostly dependent on the travelling time of dumper between the shovel and dump site. So, the optimization will be more efficient if we predict the travel time with least error. The travelling time of dumper generally depends on the driver condition, truck condition, route profile, atmospheric condition etc.

As many of the open pit mines uses the TDS or FMS system, we can easily get those historical data. Then machine learning algorithm is used to train these historical data so that we can predict travelling time with more accurate results.

So, these data which are Explanatory variables can be of two types such as categorical and continuous. Different types of data such as temperature, humidity, wind speed is different in different shifts. There are different models which uses different truck activities with different explanatory variables.

All models we have developed are in the form of:

$$Y_i = f(X_{Si}, X_i) + \epsilon_{si}$$

Here X_{Si} is an instance value of the big set X_s . X_s contains different variables that have certain relation with the travelling time. This relationship is defined by the variable X_i . Finally, the variable Y_i is the target value i.e., the travelling time. The set of these variable is defined below:

$X_s = \{\text{truck condition, driver experience, atmospheric condition, route profile}\}$

Each element can be further divided into subsets such as:

$\{\text{Truck condition}\} = \{\text{size of truck, efficiency of engine, etc.}\}$

$\{\text{Driver experience}\} = \{\text{age of driver, fatigue, visibility, etc.}\}$

$\{\text{Atmospheric condition}\} = \{\text{wind speed, humidity, temperature, precipitation, etc.}\}$

$\{\text{Route profile}\} = \{\text{starting node, end node, slope of the route, etc}\}$

So, the travelling time i.e., dependant on the above condition but for this project only the atmospheric conditions are taken into consideration.

III. MACHINE LEARNING

Over the last decades machine learning became a major part in the field of computer science and information technology. Gradually Machine learning is integrated with other fields such as mining engineering, civil engineering etc. as it can handle a large amount of data and process it at the same time. Machine Learning is an advanced version of computer science, which helps the computer to learn from its own feedback that does not need explicit programme. As shown in Figure 2 & 3 in machine learning it uses the data to learn their behaviour then it analyses these data to give the result. This whole process can be done with explicitly programming at every level.

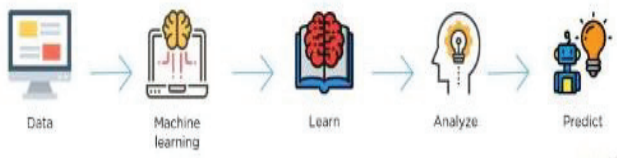


Fig. 2. Working process of ML

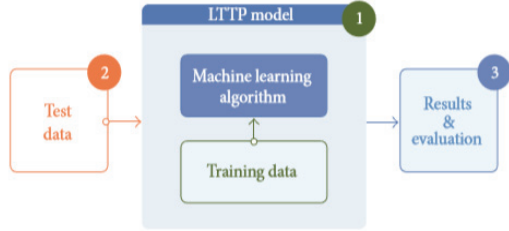


Fig. 3. Experimental flowchart of ML method

So, the Travel Time Prediction model uses these three steps to process all the available data and predict the travelling time. Training the datasets is the most vital steps because the efficiency and exactness of output depends on these trained data sets. This step consists of developing a ML algorithm and training of dataset. In this study the atmospheric data is collected from IMD, and the mining field data is collected from the TDS system of the mine. ML tasks are typically divided into four categories such as:

1. Supervised Learning
2. Unsupervised Learning
3. Semi Supervised Learning
4. Reinforcement Learning

Here in this study the prediction model is a type of supervised learning model as different labelled training data is available from the automated truck dispatch system. To solve these supervised learning different algorithm are used such as follows:

1. Artificial Neural Networking (ANN)
2. Bayesian Network (BN)
3. Support vector machine (SVM)
4. Random Forest (RF)
5. Logistic Regression (LR)
6. k -nearest neighbours (kNN)
7. Decision tree (DT)
8. Hidden Markov model (HM)

In this study three models i.e., SVM, K-nn and Random Forest are used to predict the travelling time and later the most suitable one with least error is chosen for further optimization. K-Nearest neighbours is the simplest supervised ML algorithm generally used in the classification problems. It tries to classify the data set based on the neighbour's classification. For example, suppose the square dataset are associated with the travelling time x and the circle one is for travelling time y . So, if we want to predict the travelling time for the triangle then in K-nn algorithm it will observe its neighbours and predict accordingly. Here there are two squares as compared to only one circle in its selected neighbouring region. So, it will predict travelling time in the given condition will be x i.e., as of the square.

A. Training Data Structure:

Training of dataset is most vital step in any Machine Learning Algorithm. This dataset generally consists of different features and their corresponding output value. In our study different features affect the output of the model. They can be classified broadly into the following categories: such as road features, dumper features, and atmospheric features.

The atmospheric conditions are considered in this study because these conditions have very huge impact on the friction coefficient of roads and the truck driver's vision.

The mining field data can be collected from the automated TDS system installed in the mine. The atmospheric data are collected from the *India Meteorological Department* (IMD). The different type of data is preprocessed, and these data sets are given in Table No. 2. Table 3 shows the description of the target and each feature used for the prediction in this study.

TABLE II. PREPROCESSED DATA FOR THE TRAINING THE PREDICTION MODEL

| Data | Value |
|----------------------------|----------|
| Truck ID | 503 |
| Truck type | BH – 60M |
| Truck status | Run |
| Load status | Yes |
| Starting Node | E |
| Arrival node | Dump |
| Wind speed (m/s) | 1.5 |
| Temperature($^{\circ}$ C) | 28 |
| Relative humidity (%) | 70 |
| Precipitation (mm) | 0 |
| Rain | No |
| Travel time(hr:min:sec) | 00:6:12 |

TABLE III. DESCRIPTION OF THE VARIABLES USED IN THE PREDICTION

| Variable | Type | Role | Description |
|-----------------------------|-------------|---------|--|
| Truck ID | Numeric | Feature | The serial number of trucks |
| Truck Type | Categorical | Feature | The type of truck |
| Truck Status | Categorical | Feature | Status of truck (waiting running, stop) |
| Load status | Categorical | Feature | Truck is empty or loaded |
| Starting node | Categorical | Feature | The node code of the starting position of the road |
| Arrival node | Categorical | Feature | The node code of the ending position of the road |
| Pressure (pa) | Numeric | Feature | A fundamental atmospheric quantity |
| Wind speed (m/s) | Numeric | Feature | A fundamental atmospheric quantity |
| Temperature ($^{\circ}$ C) | Numeric | Feature | A fundamental atmospheric quantity |
| Relative humidity (%) | Numeric | Feature | A fundamental atmospheric quantity |
| Precipitation (mm) | Numeric | Feature | A fundamental atmospheric quantity |
| Rain | Categorical | Feature | A fundamental atmospheric quantity |
| Travel time | Date time | Target | The travel time of each link |

IV. RESULTS AND DISCUSSIONS

Results of travelling time prediction model and error calculation of ML model was done to get the most suitable algorithm in accordance with the mining condition. Percentage of error are also calculated along with mean absolute deviation (MAD) and mean absolute percentage error (MAPE) which are presented and discussed in this section (Table 4).

TABLE IV. MAD & MAPE VALUE FOR SVM FOR THE PATH F – D

| Observed Travelling Time(sec) | Predicted Travelling Time | Absolute percentage error (%) |
|-------------------------------|---------------------------|-------------------------------|
| 362 | 346 | 4.419889503 |
| 365 | 346 | 5.205479452 |
| 400 | 362 | 9.5 |
| 346 | 346 | 0 |
| 378 | 346 | 8.465608466 |
| 365 | 362 | 0.821917808 |
| 340 | 368 | 8.235294118 |
| 352 | 346 | 1.704545455 |
| 378 | 346 | 8.465608466 |
| 352 | 346 | 1.704545455 |
| 340 | 368 | 8.235294118 |
| 370 | 370 | 0 |
| 480 | 480 | 0 |
| 358 | 362 | 1.117318436 |
| 390 | 362 | 7.179487179 |
| 480 | 370 | 22.91666667 |
| 362 | 362 | 0 |
| 520 | 370 | 28.84615385 |
| 354 | 362 | 2.259887006 |
| 358 | 362 | 1.117318436 |
| 342 | 368 | 7.602339181 |
| 358 | 358 | 0 |

Comparison between observed data & predicted data of SVM model is given in Figure 4.

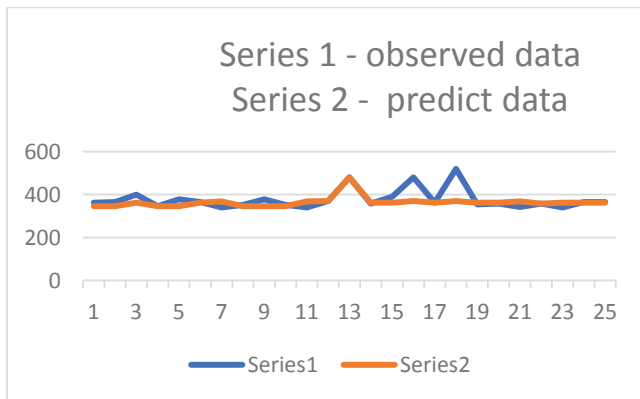


Fig. 4. comparison between observed data & predicted data

Comparison between observed data & predicted data for Knn model is given in Figure 5.

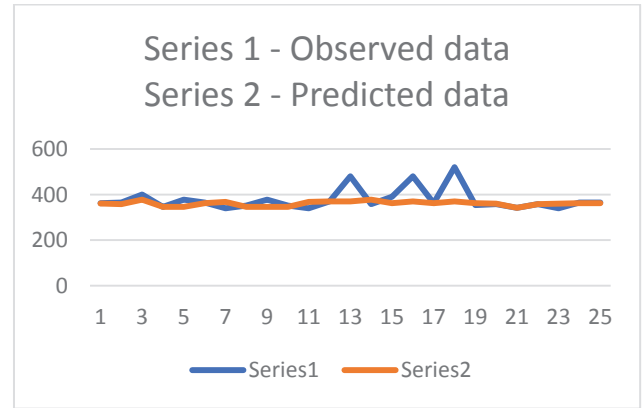


Fig. 5. Comparison between observed data & predicted data

Comparison between observed data & predicted data for RF is given in Figure 6.

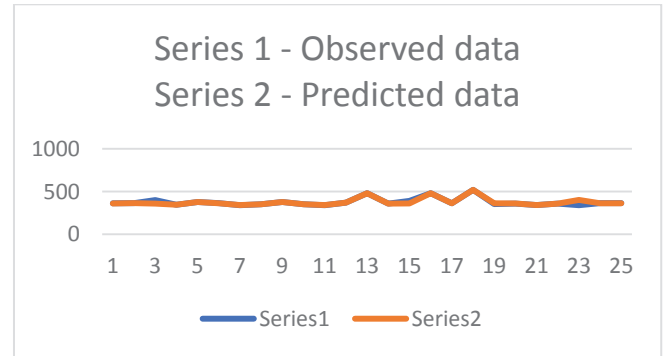


Fig. 6. Comparison between observed data & predicted data

A. Choosing the optimal model:

Different algorithm such as kNN, SVM, and RF is used to predict the travel time of dumpers in different atmospheric conditions. The mean absolute percentage error and mean absolute deviation are calculated for each of the developed model and optimal model is chosen which has the least error. The expected experimental results are of self-reflect, self-adaptive and self-feedback characteristics. It will help the mining industry to minimize the production cost and achieve the maximum production as well.

TABLE V. CHOOSING THE OPTIMAL ML MODELS

| Link road | Road type | Evolution | Models | VALUE (%) | Optimal |
|-----------|-----------|-----------|--------|-----------|---------|
| F-D | Fixed | MAD | SVM | 3.47 | RF |
| | | | Knn | 4.3 | |
| | | | RF | .06 | |

So, as we know random forest method has the least error while calculating the predicting time this model can be applied to predict the travel time between the other nodes.

TABLE VI. ERROR CALCULATION FOR DIFFERENT LINK ROAD IN RANDOM FOREST MODEL

| Observed Travelling Time(sec) | Predicted Travelling Time (sec) | % Error |
|-------------------------------|---------------------------------|---------|
| 442 | 440 | 0.9 |
| 450 | 445 | 1.1 |
| 430 | 436 | 1.37 |
| 460 | 556 | 0.86 |
| 444 | 442 | 0.45 |
| 448 | 442 | 1.33 |
| 462 | 454 | 1.73 |
| 440 | 444 | 0.90 |
| 456 | 450 | 1.31 |
| 458 | 450 | 1.74 |

Mean absolute deviation – 1.1%

Comparison between observed data & predicted data for RF is given in Figure 7.

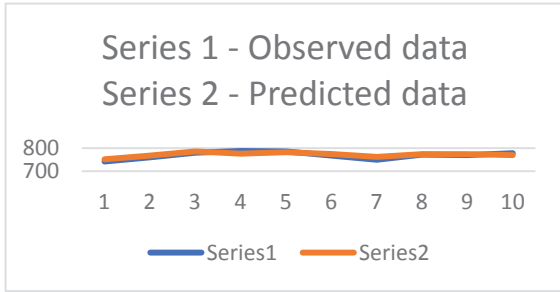


Fig. 7. comparison between observed data & predicted data

B. Developing the objective function:

The objective of minimizing total number of trucks at the loading point, number of trucks travelling on the road and number of trucks at dumping site can also be written as follows:

Minimize $Z = (\text{Number of truck travelling on the road} \times \text{Travelling time of the truck in that path}) + (\text{Number of truck at shovel} \times (\text{loading time} + \text{spotting time})) + (\text{Number of truck at dump} \times (\text{unloading time} + \text{spotting time}))$

This can also be written as

$$\begin{aligned}
 \text{Min } Z = & \sum_{d=1}^D \sum_{s=1}^S \sum_{f=1}^F x(s, d, f) \times (T_{\text{haul}}(s, d, f) \\
 & + T_{\text{empty}}(s, d, f)) \\
 & + \sum_{s=1}^S x(s) \times (T_{\text{spotting}}(s) + T_{\text{loading}}(s)) \\
 & + \sum_{d=1}^D x(D) \times (T_{\text{spotting}}(d) + T_{\text{unloading}}(d)) \\
 \text{Subject to } & U(s) \geq C_s, s = 1, 2, \dots, S \\
 & \sum_{d=1}^D \sum_{s=1}^S x(s, d, f) \leq N(f) \\
 & \forall (s, d, f) \quad x(s, d, f) \geq 0
 \end{aligned}$$

This can be further developed as follows:

$$\begin{aligned}
 \text{Minimize } Z = & X_{FD} \times (T_{FD} + T_{DF}) + X_{GD} \times (T_{GD} + T_{DG}) + X_{HD} \\
 & \times (T_{HD} + T_{DH}) + X_F \times (T_{\text{Loading}} + T_{\text{spotting}}) + X_G \times (T_{\text{Loading}} + \\
 & T_{\text{spotting}}) + X_H \times (T_{\text{Loading}} + T_{\text{spotting}}) + X_D \times (T_{\text{Loading}} + T_{\text{spotting}})
 \end{aligned}$$

Where,

$$\begin{aligned}
 \text{Subject to } & 1) X_{FD} + X_{GD} + X_{FD} + X_F + X_G + X_H + X_D = 10 \\
 & 2) 0.225X_F + 0.188X_G + 0.127X_H > 0.5 \\
 & 3) 0 < X_{FD}, X_{GD}, X_{FD}, X_F, X_G, X_H, X_D < 10
 \end{aligned}$$

C. Results for travelling time prediction:

The travelling time of dumpers from excavation sites to the dumping yard is calculated using three different ML model such as SVM, Knn & Random Forest. It is observed that the prediction of RF model is more accurate as the mean absolute deviation for this model is minimum (Table 7).

TABLE VII. SHOWS THE RESULT OBTAINED FROM MODELS

| Link road | Road type | Evolution | Models | Error value (%) | Optimal | Predicted travelling time(sec) |
|-----------|-----------|-----------|--------|-----------------|---------|--------------------------------|
| F-Dump | Fixed | MAD | SVM | 3.47 | RF | 376 |
| | | | Knn | 4.3 | | |
| | | | RF | .06 | | |
| G - Dump | Fixed | MAD | RF | 1.1 | RF | 456 |
| H-Dump | Fixed | MAD | RF | 0.95 | RF | 772 |

From the results we got from the optimization problem the following can be summarised:

Number of truck present at the loading site f is 01

Number of truck present at the loading site G is 01

Number of truck present at the loading site H is 02

Number of trucks traveling between F and dump is 01

Number of trucks traveling between G and dump is 01

Number of trucks traveling between F and dump is 01

Number of trucks at the dump is 03

V. CONCLUSIONS

Machine learning, Artificial Intelligence and various automation systems have a great potential in mining industry. It can reduce the operational cost and increase the productivity of the mine. Therefore, the mining system is slowly moving towards implementing these systems in various mines. In this paper an attempt is made to demonstrate an approach for the optimized truck scheduling system in a surface mine that uses the machine learning algorithm. This approach behaves stochastically in traveling time and queuing operation. The experimental results obtained in this study have shown the benefits of using machine learning in travelling time prediction which is ultimately used to optimize the truck allocation problem. This is achieved by using linear programming and different mining constraints. Finally, it is recommended that the application of machine learning along with operational research can make mines smarter and bring significant values to the mining industry.

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