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Prediction of fuel consumption of mining dump trucks: A neural networks approach

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HIGHLIGHTS

- A neural network model of fuel consumption in mining haul trucks was constructed and tested.
- Using the cyclic activities, the model was able to predict unseen (testing) data.
- Trucks idle times were identified as the most important unnecessary energy consuming portion of the network.
- Practical remedies, based on the nature of mining operations, were proposed to reduce the energy consumption.

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ABSTRACT

Fuel consumption of mining dump trucks accounts for about 30% of total energy use in surface mines. Moreover, a fleet of large dump trucks is the main source of greenhouse gas (GHG) generation. Modeling and prediction of fuel consumption per cycle is a valuable tool in assessing both energy costs and the resulting GHG generation. However, only a few studies have been published on fuel prediction in mining operations. In this paper, fuel consumption per cycle of operation was predicted using artificial neural networks (ANN) technique. Explanatory variables were: pay load, loading time, idled while loaded, loaded travel time, empty travel time, and idled while empty. The output variable was the amount of fuel consumed in one cycle. Mean absolute percentage error (MAPE) of 10% demonstrated applicability of ANN in prediction of the fuel consumption. The results demonstrated the considerable effect of mining trucks idle times in fuel consumption. A large portion of the unnecessary energy consumption and GHG generation, in this study, was solely due to avoidable idle times. This necessitates implementation of proper actions/remedies in form of both preventive and corrective actions.

1. Introduction

Dump trucks are the main haulage equipment in surface mining which account for a considerable amount of both capital and operational costs. Fuel consumption accounts for about 30% of total energy use in surface mines. Moreover, a fleet of large dump trucks is the main source of greenhouse gas (GHG) generation. Gibson [1] reported that elimination of the mining trucks idle time in a typical 20-truck surface mining operations results in saving 145,000 gal/year that would equate to 577,100 USD (at fuel price of 3.98 USD/gal). This is equal to 64.5 metric ton carbon reduction, and 722 engine hour reduction. The energy savings, carbon generation reduction, and maintenance cost reduction could be more considerable in case of larger mining operations (e.g., mines with haulage fleets of more than 100 large off-road trucks). Several researchers have studied fuel consumption in different ground moving vehicles. He et al. [2] studied the trend of fuel consumption of road transportation in China. Ahn et al. [3] studied fuel consumption of several light-duty vehicles via multiple regression methods. They assumed instantaneous speed and accelerations as the major independent variables for prediction of fuel consumption. Hellström et al. [4] predicted fuel consumption in a heavy diesel truck with an on board road slope database in combination with a GPS unit. Lutsey et al. [5] studied the effect of fuel cell auxiliary power units in fuel consumption reduction in idling heavy-duty trucks. Delgado et al. [6] tried to predict fuel consumption in heavy duty trucks based on driving cycle operations. Nguyen and Wilson [7] predicted fuel consumption during seven different daily activities of a garbage co-collection truck and a normal

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packer truck from the trucks global positioning system (GPS). Rahimi-Ajdadi and Abbaspour-Gilandeh [8] applied artificial neural network (ANN) and multiple regression techniques for prediction of fuel consumption of tractors. Kara Togun and Baysec [9] proposed ANN to predict torque and brake specific fuel consumption of a gasoline engine in terms of spark advance, throttle position and engine speed. Zamboni et al. [10] used Heavy Duty Emission Model (PHEM) to predict fuel consumption by experimental study of heavy vehicles in an urban area. Yap and Karri [11] employed artificial neural networks, as virtual sensors, in emissions prediction and control for a gasoline engine. Mohamed Ismail et al. [12] proposed an ANN model to predict nine different engine-out responses for a light-duty diesel engine. Numerical commercial simulators (e.g., EcoGest, CMEM and ADVISOR) are another approach to energy consumption and emission prediction [13–15]. Generally, these simulators apply physical laws to derive outputs (i.e., energy consumption and emissions) from inputs (i.e., vehicle characteristics, transmission type, engine characteristics, exhaust after-treatment, ambient temperature, road topography and vehicle occupancy). For instance, ADVISOR takes the required/desired speed as an input, and determines what drivetrain torques, speeds, and powers would be required to meet that vehicle speed. [13,14] demonstrate application of EcoGest, CMEM and ADVISOR in instantaneous fuel consumption prediction in urban trips. However, material haulage in surface mining operations has some major differences from that of other industries, like public or fridge transportation. Off-road mining roads are harsher with grades up to 16%. The payloads might be over three hundred metric ton and the amount of dust is usually higher than other industrial operations. Moreover, the operation is characterized with short cycles of material haulage. These specific conditions of mining haulage operations result in different trends in fuel consumption, which necessitates a customized study. Only few research studies have been published in the case of mining dump trucks. Kecojevic and Komljenovic [16] studied effects of power and engine load factors on fuel consumption of mining dump trucks. Sahoo et al. [17] proposed a generic model to benchmark energy consumption for dump trucks in surface mines. Awuah-Offei et al. [18] used multiple regression method and discrete event simulation for prediction of fuel consumption in mining trucks.

This paper tries to predict heavy mining dump trucks' fuel consumption per cycle based on cyclic haulage activities. The results will be used in cost estimation, fuel reduction, and GHG generation control in surface mining operations. The contribution of the study is to fill the gap in the knowledge of fuel consumption in the field of surface mining. The gap is in two folds as follow: (i) no robust mathematical technique has been developed/suggested for prediction of fuel consumption of mining dump trucks based on cyclic activities; and (ii) no comprehensive statistical analysis has been conducted on the effective parameters on fuel consumption, taking into account the inter-correlation of the independent variables. For instance, Awuah-Offei et al. [18] proposed a multiple linear regression solution for the problem. However, a multiple regression technique is linear and, hence, cannot consider the non-linearities. Moreover, there are some important statistical assumptions for application of multiple regressions such as the assumptions of linearity, normality, non-multi-collinearity, and homoscedasticity. In this case, neither of the assumptions was met, resulting in poor outputs from the multiple variable regressions.

In this study, the important effective parameters have been identified. These parameters are all based on material haulage cyclic activities and are easily available through the on-board data logging instruments such as Vital Information Management System (VIMS) from Caterpillar. In addition, to the best of our knowledge, this is the first time that a large-scale study, with over 5000 cyclic records, has been conducted on the specific problem of mining dump trucks. In a recent study, Sahoo et al. [17] proposed a deterministic approach to find a functional relationship between fuel consumption and a series of explanatory variable including: payload, material handling rate, vehicle speed, distance, mine gradient, and etc. They assumed mean values for the inputs (explanatory variables) such as distances, travel times, and speeds. However, all haulage cyclic activities are continuous stochastic variables that fall in different probability density functions [19–21]. To address this limitation, a neural network solution, based on historical data, is proposed in this study, taking into account the uncertainties in the input variables. Neural networks have been used successfully in several studies for modeling energy consumption and exhaust emissions [22].

Limitations of multiple regressions are addressed in this study. The novelty of this study is in, fuel prediction based on cyclic activities e.g. loading time, loaded haulage time, and so on. Moreover, a fleet of large mining dump trucks have been studied for a period of one year of continuous operation. Several practical preventive and corrective remedies for minimizing fuel consumptions are proposed in Section 3.2.

2. Methods and materials

Explanatory variables were: pay load (PL), loading time (LT), idled while loaded (LS), loaded travel time (LTR), empty travel time (ETR), and idled while empty (ES) and the output variable was the amount of fuel consumed in one cycle (F). Table 1 shows the descriptive statistics of all variables after elimination of outliers by the Grubs test.

Correlation coefficients of the variables are shown in Table 2. LTR, ETR, and ES show the highest positive correlation with fuel consumption per cycle (F).

2.1. Neural network overview

Artificial neural networks (ANNs) employ a massive interconnection of simple processing elements that incrementally learn from their environment to capture essential linear and nonlinear trends in complex data, so that it provides reliable predictions for new situations containing even noisy and partial information [23,24].

Neural networks are very powerful when fitting models to data. They can fit arbitrarily complex nonlinear models to

Table 1
Descriptive statistics of the variables.

Variable	Minimum	Maximum	Mean	Std. deviation
F (L/cycle)	4.700	59.600	13.844	3.362
PL (metric ton)	51.000	164.000	124.015	10.572
LT (s)	30.000	899.000	226.860	52.348
LS (s)	29.000	854.000	45.767	26.851
LTR (s)	21.000	687.000	162.152	36.082
ETR (s)	18.000	649.000	119.883	41.641
ES (s)	0.000	7200.000	137.132	328.694

Table 2
Correlation matrix.

Variables	PL	LT	LS	LTR	ETR	ES	F
PL	1.000	0.079	−0.004	0.259	0.107	0.015	0.203
LT	0.079	1.000	0.037	−0.066	0.007	0.084	0.050
LS	−0.004	0.037	1.000	0.020	0.047	0.141	0.150
LTR	0.259	−0.066	0.020	1.000	0.584	−0.007	0.663
ETR	0.107	0.007	0.047	0.584	1.000	0.326	0.668
ES	0.015	0.084	0.141	−0.007	0.326	1.000	0.538
F	0.203	0.050	0.150	0.663	0.668	0.538	1.000