Determining the environmental impact of material hauling with wheel loaders during earthmoving operations

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ABSTRACT
A method has been developed to estimate the environmental impact of wheel loaders used in earthmoving operations. The impact is evaluated in terms of energy use and emissions of air pollutants (CO₂, CO, NOₓ, CH₄, VOC, and PM) based on the fuel consumption per cubic meter of hauled material. In addition, the effects of selected operational factors on emissions during earthmoving activities were investigated to provide better guidance for practitioners during the early planning phase of construction projects. The relationships between six independent parameters relating to wheel loaders and jobsite conditions (namely loader utilization rates, loading time, bucket payload, horsepower, load factor, and server capacity) were analyzed using artificial neural networks, machine performance data from manufacturer’s handbooks, and discrete event simulations of selected earthmoving scenarios. A sensitivity analysis showed that the load factor is the largest contributor to air pollutant emissions, and that the best way to minimize environmental impact is to maximize the wheel loaders’ effective utilization rates. The new method will enable planners and contractors to accurately assess the environmental impact of wheel loaders and/or hauling activities during earthmoving operations in the early stages of construction projects.

Implications: There is an urgent need for effective ways of benchmarking and mitigating emissions due to construction operations, and particularly those due to construction equipment, during the pre-construction phase of construction projects. Artificial Neural Networks (ANN) are shown to be powerful tools for analyzing the complex relationships that determine the environmental impact of construction operations and for developing simple models that can be used in the early stages of project planning to select machine configurations and work plans that minimize emissions and energy consumption. Using such a model, it is shown that the fuel consumption and emissions of wheel loaders are primarily determined by their engine load, utilization rate, and bucket payload. Moreover, project planners can minimize the environmental impact of wheel loader operations by selecting work plans and equipment configurations that minimize wheel loaders’ idle time and avoid bucket payloads that exceed the upper limits specified by the equipment manufacturer.

Introduction

The construction sector’s energy consumption and environmental impact are increasing because the sector is rapidly expanding to meet demand stemming from the growth of the global population. Rising energy consumption and its environmental impact are serious problems because of their effects on global warming, human health, and project costs. To address these issues, governments around the world are introducing increasingly stringent regulations and recommendations on emissions and energy use. For example, the Swedish Transport Administration recommends that environmental plans should be drawn up during the early planning phase of construction projects (Toller 2018). Fossil fuel combustion is estimated to account for 76% of all emissions produced by the construction industry (Arocho et al. 2017), and construction machinery accounted for 71% of the fuel used in construction in Denmark in 2004 (Winther and Nielsen 2006). Moreover, despite stringent new emissions regulations (U.S. Environmental Protection Agency [EPA], 2007a) and improvements in the efficiency of construction equipment, the environmental impact of construction is increasing. This can be attributed to the existence of a large legacy fleet of non-road diesel-fueled construction machines that...
will remain in use for many years to come (EPA, 2007a), and the increasing operating hours of these machines (Notter and Schmied 2015). It is therefore important to find ways of accurately predicting the environmental impact of proposed operations during the early planning stages of a construction project, when it is still possible to modify plans to minimize the project’s overall environmental impact.

Diesel engines are major sources of air pollutants that have serious adverse effects on the environment and human health (Chow 2001), such as nitrogen oxides (NO\textsubscript{x}) and particulate matter (PM) (Bailey 2005). NO\textsubscript{x} and PM accounted for over 30% and 20%, respectively, of total emissions in the city of Stockholm in 1996 (Johansson et al. 1999), and the growth of these emissions was primarily attributed to construction and related sectors (International Energy Agency [IEA], 2015). To control and limit the emissions of the current legacy construction fleet, ways of accurately assessing its energy use and emissions are needed (U.S. Environmental Protection Agency 2007a).

Air pollution is a severe environmental burden, is harmful to human and animal health, and reduces crop yields and crop quality. Several studies have shown that mining and construction equipment is a particularly significant source of air pollutants and greenhouse gases, and thus has important effects on both climate change and air quality (Heidari and Marr 2015). For example, construction equipment accounts for 65% of all active industrial equipment in China (China Industrial Engineering Machinery Almanac [CIEMA], 2014), and has a commensurate environmental impact (Li et al. 2016). In Sweden in 2014, industry and the construction sector (excluding the non-metallic minerals, iron and steel, chemical, and pulp and paper industries) accounted for 34% of greenhouse gas emissions (Swedish Environmental Protection Agency [S. EPA], 2016). Furthermore, 18% of emissions originated from off-road vehicles and other machinery associated with just eight manufacturing and construction industry subsectors (S. EPA, 2016). The construction sector accounted for 3% of Sweden’s total greenhouse gas emissions in 2016; these emissions originated primarily from transport, machinery, and industrial vehicles (Statistics Sweden [SCB], 2017). In the United States in 2002, industrial sectors were responsible for 84% of all GHG emissions, and estimates based on historical emissions data for 14 industrial sectors indicated that construction accounted for 6% of these emissions (EPA, 2008). Construction machinery accounted for 34.7%, 10.3%, 9.8%, 32.9%, and 15.2%, respectively, of all CO\textsubscript{2}, CO, CH\textsubscript{4}, NO\textsubscript{x}, & PM emissions from non-road machinery in Switzerland in 2010 (Notter and Schmied 2015). During 2011, non-road vehicles and equipment accounted for approximately 15–20% of total NO\textsubscript{x} emissions, 25–40% of total PM2.5 emissions, 10% of total anthropogenic NO\textsubscript{x} emissions, and 4% of anthropogenic PM2.5 emissions in the USA and European Union (Dallmann and Menon 2016). Moreover, CO and VOC emissions from off-road machinery accounted for 7.3% and 10.9%, respectively, of total emissions of these substances in the USA, with the construction sector being responsible for 0.2–1.8% and 0.5–1.8% of the total for each pollutant (European Environment Agency [EEA], 2016). The contributions of non-CO\textsubscript{2} GHGs (such as CH\textsubscript{4} and NO\textsubscript{x}) to anthropogenic climate warming are commonly expressed in terms of CO\textsubscript{2} equivalents, or CO\textsubscript{2}-e (Yang et al. 2008). CO\textsubscript{2} is the dominant GHG, accounting for 60% of the global warming observed to date (Yamasaki 2003). Its relative contribution varies by country; CO\textsubscript{2} emissions account for 80% of Swedish GHG emissions, with 93% of these emissions being attributable to fossil fuel combustion (Johansson 2000). The corresponding figure for the USA is estimated to be 97% (U.S. Energy Information Administration [EIA], 2009). Since the early 1990s, the Scandinavian countries (Norway, Sweden, and Denmark) have introduced various taxes designed to limit industrial CO\textsubscript{2} emissions (Enevoldsen, Ryelund, and Andersen 2007). The Swedish Transport Administration (STA) recently declared that a major effort should be made to reduce the energy use and CO\textsubscript{2} emissions of infrastructure projects by minimizing the fuel consumption of non-road machinery (Trafikverket 2012). Efforts to characterize and reduce pollutant emissions from construction equipment, and particularly non-road machinery (Shao 2016), are thus needed to improve air quality at the national level (Arocho et al. 2017; Hong and Ma. 2017).

Earthmoving operations are unavoidable in road and infrastructure projects, and they have a significant environmental impact, primarily because earthmoving machines such as wheel loaders typically use Diesel engines that generate high emissions. A wheel loader is a machine designed to load haulers, move materials across specific/short distances, distribute dump materials, and perform other earth surface cutting activities. Wheel loaders are responsible for about 24% of the total energy consumption due to construction machinery (Notter and Schmied 2015), and accounted for 15% of all CO\textsubscript{2} emissions from the set of 26 distinct types of construction equipment included in the EPA National Emission Inventory (EPA, 2015). Moreover, wheel loaders were identified as the third biggest source of daily
NOx emissions in a study on construction equipment operating in the Dallas/Fort-Worth (DFW) area of the USA (EPA, 2007b). Similarly, a study conducted in Switzerland in 2010 found that wheel loaders accounted for about 22.3% and 25.9% of all NOx & PM emissions, respectively, from construction machinery (Notter and Schmied, 2015).

Several studies have been conducted to measure, analyze, assess, or mitigate the pollutant and GHG emissions of construction equipment: These studies can be divided into two groups, depending on the measurement techniques/tools used: the initial efforts and later efforts. The earliest studies in this area used steady-state engine dynamometers (Ainslie et al., 1999; Babbitt and Moskwa, 1999; LaClair and Truekker, 2005; Lindgren and Hansson, 2004; Matter, Siegmann, and Burtscher, 1999; Yanowitz, McCormick, and Graboski, 2000) to assess the emissions of heavy-duty diesel engines when operating at constant load and speed (Abolhasani et al., 2008; Rasdorf et al., 2010). Unfortunately, these measurements are not considered to accurately reflect real activity states of construction machinery because they cannot account for variation in operational modes (Armas et al., 2009). Later efforts used onboard portable emission measurement systems (PEMS) to measure the emissions of construction equipment during real-world operations (Abolhasani et al., 2008; Cao et al., 2016; Frey et al., 2010a; Frey, Rasdorf, and Lewis, 2010b; Frey, Zhang, and Rouphail, 2008; Fu et al., 2012; Lewis, Frey, and Rasdorf, 2009; Lewis et al., 2011; Rasdorf et al., 2010). This is an efficient approach whose results are generally more representative of actual machine activity (Frey et al., 2003). Despite the importance of PEMS-based studies for improving inventory emissions data for real-world machinery operations, there is much less emissions data for construction equipment than for on-road vehicles (Cao et al., 2016): Because emissions from construction machinery are highly variable, especially during earthmoving operations (where machines are used to perform very diverse tasks and in ways that depend on their characteristics and job-site considerations), there are still substantial uncertainties relating to emissions due to individual operations (Ahn et al., 2009; Lee, Skibniewski, and Jang, 2009; Wong et al., 2013). Consequently, there is a need for more comprehensive methodologies or frameworks for gathering emissions data relating to such operations.

Some models for estimating emissions from construction machinery have been proposed, and “a few have been put into regulatory use” (Heidari and Marr, 2015). For example, many environmental assessment studies have adapted the NONROAD model introduced by the U.S. Environmental Protection Agency to develop models or methods for assessing heavy-duty construction equipment emissions (Li and Lei, 2010; Rasdorf et al., 2012; Hajji and Lewis, 2013a and b; Arocho, Rasdorf, and Hummer, 2014; Hajji, Muladi, and Larasati, 2016). This model performs assessments based on the engine load factor, equipment age, and activity type. Additionally, the OFFROAD model, whose structure and methodology are closely related to those of the NONROAD model, has been used to account for the impact of regulations, technology types, and seasonal conditions when assessing emissions. However, the OFFROAD model is bespoken to the state of California and is not recommended for use in other areas (California Air Resources Board [CARB], 2010). Wang et al. (2018) and Melanta, Miller-Hooks, and Avetisyan (2013) reviewed studies on the construction sector that applied models and tools for predicting emissions at the level of individual non-road machinery/vehicles based on their fuel use and emissions rates. Their analysis revealed some of the limitations of these models and tools in project-level applications involving diverse types of equipment, processes, and fuels. MOVES2014a was developed to replace the EPA’s NONROAD2008 model for estimating the emissions of heavy-duty engines. It is designed to generate national inventories of air pollutants based on the EPA’s regulations and policies, taking into account national emission standards, vehicle populations and activity, local requirements and rules, fuel types, and meteorological conditions (EPA, 2017). While this model is regarded as a useful advance, it does not obviate the need for routine gathering of emissions data to produce inventories at the local, state, and national levels.

Although various studies have estimated emissions from construction machinery in order to evaluate the environmental impact of construction activities or improve environmental assessment models, there is still a need for more granular assessments of emissions during specific earthmoving operations (e.g., digging, loading, dumping, hauling, idling or utilizing) (Heidari and Marr, 2015; Muleski, Cowherd, and Kinsey, 2005). In addition, there is a lack of predictive methods that can be used during project planning (Melanta et al., 2013). Thus, to minimize the environmental impact of construction work, planners and estimators will need to consider the environmental impact of their machinery selections, although this is rarely done at present (Hajji, Muladi, and Larasati, 2016). A procedure to quantify and categorize the different pollutants emitted from each construction process is needed to improve emissions mitigation strategies (Marshall et al., 2012), especially given the global need for contractors to meet client requirements that include increasingly stringent environmental demands (Marshall et al., 2012). For
example, some local regulations state that only equipment of a certain tier may be used on projects in order to minimize emissions (Hampton 2005). Consequently, there is a need to understand the factors governing fuel efficiency in order to minimize the energy use and emissions of construction equipment (Frey, Rasdorf, and Lewis 2010b), and particularly to support emissions benchmarking for construction operations during the preconstruction stage (Heidari and Marr 2015). Suitable predictive methods can be developed using either artificial neural networks (ANN) or discrete event simulations (DES). While DES is regarded as the simulation protocol that best describes practical earthmoving activities, ANNs have the advantage of being able to generate and use very large quantities of data covering all common operating situations for construction machinery in construction projects. These data can subsequently be used to monitor and benchmark emissions during the construction phase.

This work presents two contributions relevant to practitioners (i.e. researchers, planners and contractors) working on projects involving earthmoving. The first is a predictive artificial neural network (ANN)-based model that estimates the fuel consumption per unit of hauled materials (and thus the energy use and air pollutant emissions) of wheel loaders based on the machines’ characteristics, the properties of the materials being hauled, and the earthmoving activities that are performed. By using this model to predict the per-unit emissions of earthmoving operations, planners will be able to minimize unit emissions or at least avoid unnecessary costs increases (Carmichael, Williams, and Kaboli 2012). The model also allows planners, estimators and contractors to estimate the emissions per cubic meter of material hauled by wheeled loaders without needing to conduct field emissions measurements, facilitating the creation of robust environmental plans during the pre-construction phase of projects. The resulting emissions datasets will provide theoretical support for life cycle impact assessments relating to construction machinery that, in turn, will help in developing future emissions strategies at different levels. The influence of different input parameters on the model’s output is also analyzed, revealing the parameters that are most important to consider when seeking to minimize the environmental impact due to construction equipment used in earthmoving operations. The second contribution is a comprehensive framework that can be applied in real-world operations to extract and generate emissions datasets based on PEMS measurements and to then develop a predictive model to investigate correlations between operations and/or develop predictive models for similar equipment.

**Methodology**

The study’s main objective was to develop an ANN model that can be used during the early planning stages of road and infrastructure projects to predict the fuel consumption per cubic meter of material hauled by wheel loaders, which can be used to estimate the machines’ energy use and the emissions of six air pollutants (CO$_2$, CO, CH$_4$, NO$_x$, VOC & PM). The loading of materials falling into three distinct loose density intervals between 640 and 2020 kg/m$^3$ was considered. The model was developed in three distinct stages (Figure 1) because the ANN method requires large amounts of data for training and testing to produce reliable models. The volume of data needed for model development was further increased by the need to consider the wide range of operating scenarios in which wheel loaders are used in practice.

The first stage of the framework focused on data extraction and analysis. Data were gathered for the 29 Caterpillar wheel loader models listed in editions 42 and 44 of the Caterpillar performance handbook (Caterpillar [Cat.], 2012; Cat., 2014). A database was extracted from these handbooks containing the range of cycle times (i.e. the minimum and maximum cycle times, $C_n$ in minutes) for each wheel loader model together with each model’s bucket capacity ($B_c$) in m$^3$, dump clearance at maximum raise ($HI$) in m, engine horsepower ($H_p$) in kW, hourly fuel consumption range (R) in L/h, and intervals of load factor relative to hourly fuel consumption ($H_f$), expressed as percentages for different earth types and work conditions. The wheel loaders’ cycle times for loading materials onto body haulers are specified in the performance handbooks for each model. In addition, haulage capacities ($HC$) in m$^3$ were extracted for different wheel loader models to compute their loading times ($Lt$) in minutes, which were needed to develop simulation scenarios for earth-moving operations. The bucket payload ($B_p$, m$^3$) is computed using data on the loose densities ($L_d$) in kg/m$^3$ for each earth type or material loaded by the wheel loader, together with a fill factor ($B_f$, decimal) (see Eq. 1) and the wheel loader’s load factor ($L_f$, decimal) (see Eq. 2). Therefore, a load factor range was estimated for each material type considered in the study using a second degree exponential expression (see Eq. 2).

$$B_p = B_c \cdot B_f$$

$$L_f = 0.1707e^{(0.0007649L_d)} - 2.074e^{(-0.004337L_d)}$$

Here, $B_p$ is the bucket payload in m$^3$, $B_c$ is the wheel loader’s bucket capacity in m$^3$, $B_f$ is the bucket fill factor (a decimal), $L_f$ is the load factor (a
decimal), and $L_d$ is the loose density of the loading material in kg/m$^3$.

The productivity rate ($P_r$) in m$^3$/h for each wheel loader model was estimated from the Caterpillar performance handbooks based on the previously established bucket payloads and cycle time ranges (i.e. min and max values); averaged values were used in the simulations. Different productivity values were thus estimated for each permitted combination of wheel loader, material type, and fill factor, generating a comprehensive productivity dataset for each studied wheel loader model. Loading times were calculated for each permitted combination of bucket payload and cycle time for each wheel loader model based on the expected work done with a specific hauler in each earthmoving scenario. At the end of this stage, four parameters were calculated for each wheel loader model under each of the studied hauling scenarios.

In the second stage of the framework, the wheel loader database, hauler database, outputs from the first stage, and jobsite conditions for the simulated earthmoving configurations were arranged in a separate Excel sheet, based on plans designed to reflect all of the circumstances that are likely to occur in real earthmoving operations. To this end, an earthmoving simulation model was established using an Ezstrobe template. The model incorporated timing information for all the quantities compiled in the previous stage relating to each component and entity involved in each earthmoving scenario. For example, to enable simulation, each earthmoving scenario had to specify a range of wheel loader loading times based on the capacity of the haulers used in the simulated scenario and the minimum and maximum cycle times of the wheel loader model under consideration. Similar estimated timings were required for all of the steps in the simulated earthmoving operations. Importantly, the simulations included some elements and components that are not directly related to the wheel loader’s work but nevertheless affect its efficiency. Examples include the trip time (calculated as half the quotient of the hauling distance and the hauler speed, to reflect the fact that the distance includes both the outbound and return journeys), the number of haulers (which must be accounted for to evaluate the effect of varying the wheel loaders’ utilization), and the dumping time (Figure 2).

Each simulation produced many outputs relating to the studied earthmoving configurations. The outputs relevant to wheel loader operation and the construction of the proposed ANN models were exported to an Excel sheet for the scenario under consideration. These outputs include actual productivity rates ($P_{ra}$), the average loading time for each hauler capacity ($L_{lat}$), and the

![Diagram](image-url)

Figure 1. Framework for the development of the predictive ANN-based model.
utilization rate ($L_{ur}$) of the wheel loader, which is a key parameter to consider when predicting the amount of fuel consumed per cubic meter of material loaded (and thus the wheel loaders’ energy use and pollutant emissions). In addition, the wheel loaders’ actual productivity was computed based on their utilization rates in each earthmoving scenario. Fuel consumption was estimated using Eqs. 3–5, which were developed by Jassim, Lu, and Olofsson (2018).

\[ F_{CL} = \left( \frac{SFC \cdot H_p \cdot L_f}{\rho_{fuel} \cdot P_{ra}} \right) \]  

(3)

\[ P_{ra} = P_r \cdot L_{ur} \]  

(4)

\[ L_{ur} = 1 - \left( \frac{L_{WAC}}{N_o \cdot L} \right) \]  

(5)

Here, $SFC$ is the specific fuel consumption, which was assumed to be 0.22 kg/kW.h – a value recommended for engines with power outputs between 28.8 and 370 kW (Klanfar, Korman, and Kujundžić 2016). $H_p$ is the maximum design horsepower of the machinery’s engine (kW). $\rho_{fuel}$ is the specific gravity of the diesel fuel to be consumed, which was taken to be 0.85 kg/L (Zhang et al. 2014) and may vary between 0.83 and 0.87 kg/L. $L_f$ is the engine load factor (decimal), which was estimated based on the loose density of the loaded material (kg/m$^3$) using Eq. 2. $P_{ra}$ is the actual productivity rate (m$^3$/h) of the wheel loader for the relevant level of utilization. $P_r$ is the productivity rate (m$^3$/h) of the wheel loader reported in the Caterpillar performance handbooks for the relevant cycle time range. $L_{ur}$ is the wheel loader’s utilization rate (decimal), and $N_o \cdot L$ is the number of wheel loaders used in the earthmoving scenario at hand. $F_{CL}$ is the fuel consumption (MJ/LCM) of the wheel loader in the simulated earthmoving scenario.

In the next stage, all specific wheel loader data from the first two stages relating to the input and output parameters needed to build the predictive ANN models were selected and imported into MATLAB as separate matrices. These data were then compiled into a single matrix to perform data quality processing (specifically, to remove duplicate rows) to avoid errors caused by the duplication of data in specific scenarios. The processed data matrix was then divided into two matrices, one (6*54,588) holding the input parameters ($L_{ur}$, $L_{WAC}$, $B_p$, $H_p$, $L_f$, $G_{T}$, $L_{T}$), and the other (1*54,588) holding the output ($F_{CL}$). The first step in creating an ANN model is to decide how many hidden layers should be used and how many nodes should be in each layer, both of which affect the final model’s accuracy. The input and output data sets were both divided into two subsets, one for training the neural network and one for testing. Previous studies have shown that for predictive purposes, a single hidden layer is sufficient to generate neural network models with good predictive performance. Therefore, several trials were conducted in which the proportions of the initial dataset allocated to the training and testing subsets were varied over the ranges 75–93% and 25–7%, respectively, to optimize the sizing of the training and testing subsets. Additional trials were conducted to identify the optimal number of hidden nodes for each dataset sizing. In all cases, the quality of the resulting model was evaluated based on the mean square error (MSE) of its predictions and the correlation coefficient (R). The numbers of hidden layers and nodes in the final model were thus selected.
by trial and error. The optimal sizing of the training and data subsets was found to be 89% and 11%; a model with 43 hidden nodes gave the best performance using these values (see Figure 3).

The neural network was trained using a sigmoid activation function in conjunction with the Perception Multilayer (PML) network approach, which is a supervised backward propagation learning method based on the Levenberg–Marquardt algorithm. There are three phases in the development of an ANN model. In the first phase, the training data subset is used to update the weights in the network layers using backward propagation. In the second phase, the testing subset is used to identify the designed neural network’s responses to the data, which are not part of the training data but do fall within the boundaries of the dataset as a whole. In the third phase, data not belonging to the training or testing sets are used to create a validation data set that is used to assess the model’s acceptability and validity. All the input and output values in the datasets were scaled inside the ANN such that they lay within the range (0.0, 1.0), which is the standard scaling used with sigmoid functions in backward propagation learning algorithms. In this work, the data were actually scaled to lie within the range (0.1, 0.9) to avoid the problem of slow learning rates at the boundaries of the dataset and to increase the quality of the training and testing data sets.

Sensitivity analysis for relative importance and effect parameters

A sensitivity analysis (SA) can provide a comprehensive overview of the influence of different input parameters on a model’s outputs (Alam et al. 2015). Two types of SA can be distinguished: local sensitivity analysis (LSA) and global sensitivity analysis (GSA) (O’Connor et al. 2017). LSA focuses on the local impact of parameters on model outputs (Saltelli, Chan, and Scott 2000), i.e. the impact when a single input parameter is varied while the rest are held constant. They are widely used to determine the effects of changing a given value of a specific input parameter. Conversely, a GSA examines the variation of all model input parameters simultaneously (Saltelli, Chan, and Scott 2000) to determine how variation over the entire input range can influence the model’s output (Pianosi, Sarrazin, and Wagener 2015). This is commonly done to assess the relative influence of different parameters on the model’s output. The model developed in this work was subjected to both global and local sensitivity analyses. A partitioning weights method (Garson 1991) implemented in MATLAB was also used to determine the relative influence of the various input parameters on the outputs (Goh 1995). To this end, the number of hidden layers in the ANN model was increased to five, and the number of nodes within each hidden layer was set to 15. This revealed that increasing the number of hidden layers increased the model’s accuracy by improving filtering during the forward and backward propagation processes.

Results and discussion

This section first discusses the factors influencing the selection of a load factor expression, then presents mathematical expressions based on matrix representations of the proposed ANN model together with arguments justifying their selection and data supporting the model’s validity. Finally, the results of the sensitivity analysis are presented, illustrating the relative importance of the model’s various inputs and parameters.

The load factor of construction equipment is a key variable in analyses of construction operations because it directly affects fuel consumption (and thus emissions). The logarithmic expression in Eq. 2 is one of this work’s key results because it allows the simple estimation of load factors for wheel loaders based on the properties of the hauled materials (i.e. their loose density). Figure 4 shows a plot of the load factor against the loose density of the loaded material together with the fitted curve used to derive Eq. 2. The mean and standard deviation of the loose density of the studied materials were 1504 and
372.4 kg/m³, respectively, and the curve’s goodness of fit is demonstrated by its SSE (0.01396), r-squared (0.9814), adjusted r-squared (0.9795), and RMSE (0.0190157) values. Figure 5 shows the loose densities of the materials considered in this work.

The data subset sizing that maximized the neural network’s performance was determined by trial and error optimization. The optimal number of hidden nodes in the hidden layer was assumed to be that which minimized the MSE during the training process. Similarly, the number of training cycles was varied to minimize the MSE and maximize R in order to maximize the model’s predictive accuracy. Many different combinations of data subset sizing and learning rate were evaluated; the six that yielded the best results are shown in Table 1, together with the corresponding MSE and R values.

The optimal number of nodes in the hidden layer was determined by trial and error: trials were performed using networks with between 5 and 43 hidden nodes, and the number that yielded the lowest MSE when comparing the predictions to the output training set was selected. The first three models listed in Table 1 (which all have a single hidden layer with 43 hidden nodes) all achieved R values close to 1 for both the training and testing datasets, demonstrating their predictive power (R values above 0.9 are considered to indicate good predictive performance) and potential to clarify the relationships between the studied inputs and the fuel consumption, energy use, and emissions of wheel loaders during earthmoving operations. The same criteria and indicators were used to choose the architecture of the sensitivity model. However, when evaluating sensitivity, models with multiple hidden layers were tested because adding hidden layers to ANN models can improve data filtration during backpropagation. The downside of adding hidden layers is an increase in the complexity of the model’s final mathematical expressions. The performance of the predictive and sensitivity models was evaluated based on their MSE (9.9983⋅10⁻⁶ & 8.4545⋅10⁻⁶, respectively) and R (0.99779 & 0.99812, respectively) values. In both cases, the training dataset comprised 89% of the total dataset, with the remaining 11% being allocated to the testing dataset. The neural network’s learning rate was set to 0.1 in accordance with published guidelines for selecting the

![Figure 4](image.png)  
*Figure 4. Fitting curve for load factor values.*

![Figure 5](image.png)  
*Figure 5. Loose densities of selected materials considered in this work.*
model best matching a chosen target function (Šibilija and Majstorović 2016). To facilitate model training and testing, the entire dataset was scaled during preprocessing. The expression used to scale the input parameters is given in Eq. 6:

$$X_i = \left(\frac{0.8}{\Delta_i}\right) x_i + \left(0.9 - \frac{0.8 x_{\text{max}}}{\Delta_i}\right)$$  \hspace{1cm} (6)

Here, “$X_i$” represents the scaled value of the input parameter, “$x_i$” represents its actual value, “$x_{\text{max}}$” represents the maximum value of the input parameter within the range of data used (Table 2), and “$\Delta_i$” represents the difference between the unscaled maximum and minimum values of the parameter within the dataset (Table 2). Matrices and equations (7–14) for predicting the fuel consumption per cubic of material hauled by wheel-loaders were derived from the ANN models; similarly, equations 15–21 were derived to estimate the wheel loaders’ energy use and air pollutant emissions per cubic meter of hauled material.

$$y_s = \left[1.0/(1 + \exp(-S))\right]$$  \hspace{1cm} (13)

$$F_{\text{CLLCM}} = \left(\frac{\delta_{\text{a}}}{0.8}\right) y_s - 0.9 \left(\frac{\Delta_{\text{a}}}{0.8}\right) + y_{\text{max}}$$  \hspace{1cm} (14)

$$E_{\text{RCCLCM}} = F_{\text{CLLCM}}, C_{\text{JE}}$$  \hspace{1cm} (15)

$$E_{\text{CCCLCM}} = F_{\text{CLLCM}}, C_{\text{FCO2}}$$  \hspace{1cm} (16)

$$E_{\text{CCCLCM}} = C_{\text{FCO}}$$  \hspace{1cm} (17)

$$E_{\text{CCCLCM}} = F_{\text{CLLCM}}, C_{\text{JCH4}}$$  \hspace{1cm} (18)

$$E_{\text{CCCLCM}} = C_{\text{Fnox}}$$  \hspace{1cm} (19)

$$E_{\text{CCCLCM}} = C_{\text{Fpm}}$$  \hspace{1cm} (20)

$$E_{\text{CCCLCM}} = C_{\text{FBPM}}$$  \hspace{1cm} (21)

Matrix $A$ is the weight connection matrix between the input and hidden layers ($1 \leq i \leq n, 1 \leq j \leq m$, $n = 43$, and $m = 6$) for the fuel consumption model (see matrix $A_1$), while matrix $B$ holds the scaled values of the input parameters; element $b_1$ is the wheel-loader utilization rate (decimal), $b_2$ is the loading time (min), $b_3$ is the wheel loader’s bucket payload (m$^3$), $b_4$ is the engine horsepower (kW), $b_5$ is the load factor (decimal), and $b_6$ is the hauler’s heaped capacity (m$^3$). Matrix $C$ holds the bias values (i.e., thresholds) of the nodes in the hidden layer (where $1 \leq c \leq p; p = 43$) for the fuel models (see matrix $A_2$), matrix $D$ is the resultant matrix (the product of matrices $A$ and $B$), $E$ is the sum of $D$ and $C$, and $H$ is the matrix of weight connection vectors linking the hidden layer to the output layer ($1 \leq h \leq O; O = 43$) for the fuel model (see matrix $A_3$). $F$ is the matrix obtained by applying a sigmoid activation function to each weight connection between

Table 1. Values of selected characteristic variables for ANN architectures tested while optimizing the predictive and sensitivity models developed in this work.

| Item                | $N^*$ | $L^*$ | $S_{\text{whole data}}$ | $S_{\text{training}}$ | $S_{\text{testing}}$ | MSE   | Epochs | $R_{\text{testing}}$ | $R_{\text{training}}$ |
|---------------------|-------|-------|--------------------------|------------------------|----------------------|-------|--------|-----------------------|-----------------------|
| Fuel Consumption Model | 6-43-1 | 0.1   | 54588                    | 48522                  | 6066                 | 9.9983*10^{-6} | 868    | 0.99768              | 0.99779               |
|                     | 6-43-1 | 0.1   | 54588                    | 48522                  | 6066                 | 9.9987*10^{-6} | 1198   | 0.99768              | 0.99777               |
|                     | 6-15-15-15-15-1 | 0.1 | 54588                    | 48522                  | 6066                 | 9.9977*10^{-6} | 762    | 0.99768              | 0.99773               |
|                     | 6-15-15-15-15-15-1 | 0.1 | 54588                    | 48522                  | 6066                 | 8.4545*10^{-6} | 171    | 0.99827              | 0.99812               |
|                     | 6-15-15-15-15-15-1 | 0.1 | 54588                    | 48522                  | 6066                 | 8.7792*10^{-6} | 112    | 0.99840              | 0.99795               |
|                     | 6-15-15-15-15-15-1 | 0.1 | 54588                    | 48522                  | 6066                 | 9.1970*10^{-6} | 208    | 0.99951              | 0.99940               |

Notes. $N^*$ = ANN architecture; $L^*$ = learning rate; $S_{\text{whole data}}$ = Size of whole data set; $S_{\text{training}}$ = Size of training data set; $S_{\text{testing}}$ = Size of testing data set; MSE = Mean square error for best training performance; Epochs = number of iterations needed to reach best output; $R_{\text{testing}}$ = Correlation coefficient for output training data subsets (output vs. target); $R_{\text{testing}}$ = Correlation coefficient for output testing data subsets (output vs. target).

Table 2. Scaling and bias values used in the predictive ANN models.

| Delta | $b_1$  | $b_2$  | $b_3$  | $b_4$  | $b_5$  | $b_6$  | $y_s$  | $\theta_y$ |
|-------|--------|--------|--------|--------|--------|--------|--------|-----------|
| Value | 93.16874 | 16.6915 | 17.64  | 11.35  | 0.64993549 | 45.2  | 3.272610164 | -5.9799203896523 |
| Maximum | $b_1$  | $b_2$  | $b_3$  | $b_4$  | $b_5$  | $b_6$  | $y_{\text{max}}$ | $\theta_{\text{max}}$ |
| Value | 93.2524 | 17.77917 | 18  | 1176 | 0.8 | 60.2 | 3.272825805 | |
the input and hidden layers, and contains forty-three elements (i.e. \( f_1, f_2, f_3, \ldots, f_{43} \)). \( K \) is the matrix obtained by element-wise multiplication of matrices \( F \) and \( H \) (i.e. the Hadamard product rather than the standard matrix multiplication product). \( S \) is a matrix with a single element whose value is equal to the sum of the elements of \( K \) plus the bias value of the output layer. \( \theta_y \) represents the bias value (i.e., threshold) of nodes in the output layer (Table 2). “\( y_s \)” represents the scaled prediction values for the wheel loader’s fuel consumption per cubic meter of hauled material (liter/LCM), which must be re-scaled using Eq. 14 to obtain a result in physically relevant units. “\( F_{CLLCM} \)” represents the final rescaled output (in physical units) of the ANN model, \( y_{imax} \) is the maximum output value for the ANN model, and \( Delta_o \) is the difference between the model’s maximum and minimum output values. Table 2 shows the values of \( Delta, y, \) and \( x \) used to scale and rescale the models’ inputs and outputs.

\[ En_{CLLCM} \] represents the energy consumption (MJ/LCM) of the wheel-loader, while \( Ec_{O2LLCM}, Ec_{CO2LLCM}, Ec_{CH4LLCM}, Ec_{NOxLLCM}, Ec_{VocLLCM}, \) and \( Ec_{PMLLCM} \) represent its emissions of CO\(_2\), CO, CH\(_4\), NO\(_x\), volatile organic compounds, and PM, respectively (all in kg/LCM). \( C_{fE}, C_{fCO2}, C_{fCO}, C_{fCH4}, C_{fnox}, C_{fvoc} \), and \( C_{fPM} \) are conversion factors used to estimate the loader’s energy consumption and emissions of CO\(_2\), CO, CH\(_4\), NO\(_x\), VOC, and PM per liter of diesel fuel that is consumed (Table 3).

To complement the evidence of the model’s goodness of fit (i.e. its favorable MSE and R values), it was validated against reference data. Figure 6 shows the agreement between the predicted and generated results for various earthmoving scenarios that cannot be satisfactorily modeled using more traditional methods. In addition, a randomly selected subset of the generated data (comprising 853 samples) was compared to reference hourly fuel consumption data supplied by Caterpillar for ranges of load factors specific to each individual wheel loader.

Table 3. Conversion factors for the predictive ANN model (International Council for Local Environmental Initiatives Europe [ICLEI], 2014; Ntzia chrístos and Samaras 2016).

| Item   | \( C_{fE} \) | \( C_{fCO2} \) | \( C_{fCO} \) | \( C_{fCH4} \) | \( C_{fnox} \) | \( C_{fvoc} \) | \( C_{fPM} \) |
|--------|--------------|----------------|--------------|----------------|--------------|--------------|--------------|
| Value  | 36 MJ/l      | 2.6569 kg/L    | 0.005806 kg/L| 0.000179 kg/L  | 0.027285 kg/L| 0.001326 kg/L| 0.00068 kg/L |

Figure 6. Validation of the model’s predictions against generated data for wheel loaders.

Figure 7. Validation of the model’s predictions against reference performance data for Caterpillar wheel loaders.
model included in the study (Figure 7). Once again, the model’s predictions were in good agreement with the reference data, as demonstrated by the high values of the correlation coefficient (0.9816) and coefficient of determination (0.9636), and the low root mean square error (0.1532) over a wide range of fuel consumption values (1.8–210 L/h). The developed model thus appears to be a generally applicable tool for estimating the environmental impact of wheel loader operations.

However, the uncertainty of actual working conditions may cause the model’s predictions to deviate from field measurements. To assess the practical usefulness of the developed model, its predictions were compared to the results of earlier field studies, as shown in Table 4.

There are some modest discrepancies between the predictions and measurements. These may be partly due to the use of different driving and operating modes during field measurements. It could also be because of the need to estimate what range of load factors should be considered in the model for each study, and to test different values within these ranges. A third possible reason is that the equipment utilization rates were not all estimated based on both idling and non-idling times. All these factors could lead to small variations in emission factors between the studies. The underpredicted values (i.e. the experimental values that exceeded the model’s predictions) in Table 4 demonstrate that the database used to assess equipment that is assumed to be used in a standard/typical operating mode (i.e. non-aggressive driving) should also be used to assess driving-mode emissions of construction machines in order to minimize overall emissions. However, it should be noted that after comparing their results to those of Frey, Rasdorf, and Lewis (2010b), Fu et al. (2012) concluded that the high emissions of certain wheel-loaders could be attributed to their operating modes and poor equipment maintenance. These results demonstrate the need for further research in this area to properly account for machine- and project-level variation and uncertainty. In this work, average hourly fuel consumption and emission rates for multiple wheel loader models were compared to those reported previously. In addition to validating the model, the results obtained demonstrate that the performance data provided in Caterpillar machine handbooks are reliable enough to be used when estimating environmental impacts due to construction operations such as earthmoving activities if a suitably rigorous analysis is performed. Other studies (Lucko and Vorster 2003; Han et al. 2005; Schexnayder, Knutson, and Fente 2005; Ok and Sinha 2006) have drawn similar conclusions about the performance data supplied by Caterpillar.

A sensitivity analysis using the weight proportion method (Figure 8) was conducted to determine the relative importance of the model’s input parameters. The engine load factor ($L_f$), which depends on the density of the loaded material and the level at which it is loaded onto body haulers, was the factor with the highest relative importance (56.75%) in the proposed ANN models. The second most important factor was the wheel loader’s utilization rate ($L_{ur}$, 18.21%), which depends on the wheel loader model and the fleet configuration. The remaining factors, ranked in order of decreasing importance, were the wheel loader bucket payload ($B_p$, 9.39%), engine horsepower ($H_p$, 8.49%), loading time ($L_{tav}$, 7.69%), and hauler capacity ($HC$, 1.47%). The sensitivity analysis also indicated that the fuel consumption per cubic meter could be reduced by 50–55% or 30–40% by increasing the wheel loader utilization rate from 40 to 70%. The model also indicates that fuel consumption per cubic meter can be minimized by using the maximum possible bucket payload given the jobsite conditions and the wheel loader’s operational characteristics. Finally, the sensitivity analysis demonstrated that multiple factors (i.e. load factor, horsepower, and loading time) correlate positively with

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Table 4. Average hourly emissions from wheel loaders in working mode determined in this work and previous studies.

| Wheel loader models | Studies | CO2 (kg/h) | CO (kg/h) | NOx (kg/h) | PM (kg/h) |
|---------------------|---------|------------|-----------|------------|-----------|
| 930G Wheel Loader and Caterpillar 924K | Frey, Rasdorf, and Lewis (2010b) | 12.339 | 0.033 | 0.148 | 0.001 |
| Caterpillar 980C Wheel Loader | Abolhasani and Frey (2013) | 17.569 | 0.038 | 0.180 | 0.0019 |
| Wheel loader SEM, SDLG, LONG GONG | Fu et al. (2012) | 15.012 | – | 0.1044 | – |
| WA470-6 Wheel loader and 928G Wheel Loader | Cao et al. (2016) | 12.517 | 0.038 | 0.180 | 0.001 |

Figure 8. Relative importance of the input parameters of the ANN-based model.
fuel consumption per cubic meter of material hauled by wheel loaders during earthmoving operations.

Figures 9–13 show how each input parameter is related to the fuel consumption according to the ANN model. In general, increasing the engine’s load factor, the engine’s horsepower, and the loading time all increase the fuel consumption per cubic meter (and thus the energy use and emissions). Conversely, increasing the wheel loader’s utilization rate reduces its fuel consumption per cubic meter hauled, and thus reduces energy consumption and emissions per cubic meter. These outcomes are discussed in the next section.

The 29 wheel loader models considered in this study were categorized into six groups based on their specifications – in particular, their engine size, loading capacity and body payload. The groups were numbered 1 to 6, with
higher group numbers corresponding to larger engines and higher loading capacities. The effects of varying the input parameters of the ANN model (between their maximum and minimum values) on the fuel consumption of wheel loaders during earthmoving investigations were investigated separately for each group, generating the results plotted in Figures 9–13.

The engine load factor is a particularly important input because of its high relative importance. The main functions of wheel loaders in earthmoving operations are to load materials from stockpiles at the construction site and the borrow pit, to distribute dumping materials during earthwork operations, and to cut or level surface layers (which usually consist of soft, loose and low density materials). Consequently, the engine’s load factor is very sensitive to the loose density of the hauled material and can be estimated based on this variable using Eq. 2. This approach is echoed in the Caterpillar performance handbooks, where bank densities and swelling factors are used to estimate load factors for excavators and haulers, respectively (Cat., 2012, 2014). A similar approach was also used in another study to estimate load factors for excavators, haulers, and loaders (Trani et al. 2016). The load factor of wheel loaders was estimated based on the loose density of the hauled material here because this variable was considered more relevant to the types of materials hauled by wheel loaders. This approach yielded an expression that represents the materials hauled by wheel loaders in practice. As shown in Figure 13, there was a positive relationship between fuel consumption per unit of hauled materials and load factor over all tested combinations of operational situation and wheel loader model. This finding is consistent with the results of Frey, Rasdorf, and Lewis (2010b) and Lewis (2009), who determined engine load based on manifold absolute pressure (MAP) measurements from PEMS datasets, along with engine speed and engine intake air temperature data. While the units used to measure fuel consumption and emissions in this work (where both variables were assessed per cubic meter of hauled materials) differ from the hourly and rate-based measures used previously, the results clearly demonstrate the need to reduce the engine load of heavy-duty equipment during operations.

As discussed above, Figures 9 and 11 show that according to the sensitivity analysis, the fuel consumption per cubic meter can be reduced in practice by increasing wheel loaders’ utilization rates during earthmoving activities and using their full bucket capacity (i.e. maximizing their payload). The utilization rate can be regarded as a measure of the overall operational efficiency of a construction machine fleet configuration; it is sensitive to the types, capacities, and numbers of machines that are selected to work alongside the wheel loaders, and the degree to which their hauling capacities complement those of the wheel loaders. Utilization can also be regarded as the opposite of idling; consequently, the first step towards improving the utilization rate is to minimize the idle time of equipment. Increasing the utilization rate of wheel loaders would significantly reduce their fuel consumption per cubic meter hauled if all other factors affecting operating efficiency remain constant. The third most important input parameter was the bucket payload. Optimizing the bucket payload also reduces fuel consumption per cubic meter hauled (if other productivity-affecting parameters such as cycle times are held constant) because it ensures that the maximum bucket capacity is not exceeded and the engine is not overloaded.

The engine horsepower and loading time were the fourth and fifth most important inputs; their effects on fuel consumption per cubic meter are shown in Figures 10 and 12. The same working conditions were assumed for all of the tested wheel loader models, and the same general behavior was consistently predicted: fuel consumption increased with engine size. However, the effect of increasing loading times can vary between wheel loader models: increasing the loading time by 10% (relative to the optimal time for the model in question) consistently increased fuel consumption, but the magnitude of the increase varied. Figure 10 also demonstrates the accuracy of the ANN-based model and its usefulness for selecting suitable machinery for specific tasks. The linearity and shallow gradient of the curves for groups 1 and 2 (i.e. the wheel loaders with the lowest engine power and loading capacity) indicate that increasing loading times had only a limited effect on fuel consumption in these cases. This was because the same working conditions were applied in all cases; as a result, the cycle times assumed in these studies were considerably longer than those that would normally be used with such small wheel loaders. The ANN model thus identified this issue and demonstrated the unsuitability of these smaller machines for the task considered here. This issue is also apparent in Figure 11: the bucket payloads assumed under the studied working conditions exceeded the design capacity of the smallest wheel loaders included in the study (i.e. those in groups 1 and 2). Consequently, the predicted fuel consumption per cubic meter hauled became negative for these two groups. For the same reason, the predicted fuel consumption for the intermediate-sized wheel loaders in groups 3 and 4 fell to almost zero at the highest bucket payloads. Hauler capacity was one of the least important inputs in terms of predicting wheel loader fuel consumption but could be important in terms of matching wheel loaders to haulers based on their operational characteristics.

The results of the sensitivity analysis are important both because they indicate the relative importance of
the different inputs and because they provide additional validation for the methodology used in this work and the model that was developed. In particular, the model exhibits good internal consistency and its output agrees well with the results of earlier studies.

The results presented here demonstrate that artificial neural networks are powerful tools for modeling the complex relationships that determine the environmental impact of construction operations in a way that lends itself to practical applications. It is important to be able to predict environmental impacts using information on equipment characteristics and site conditions, which is usually readily available during the pre-construction phase. By predicting emissions per unit of material hauled based on specific construction plans and project specifications, planners can satisfy client demands to minimize environmental impacts. The analysis of the model's inputs and outputs revealed that emissions reduction is most effectively achieved in practice by maximizing the utilization rate of construction machines. This result is consistent with the conclusions of Hajji and Lewis (2013a; 2013b), and indicates that increasing productivity (i.e. operational efficiency) can reduce fuel consumption and emissions as well as costs. The following section describes the practical use of the ANN model to select a suitable wheel loader configuration for a specific construction project.

Application of the ANN model in a case study

To assess the accuracy of the ANN-based model and its ability to help planners select machinery during the early planning stage of a construction project, it was tested in a case study based on earthwork operations data for a road construction project in southern Sweden known as the mullsjö project or väg 26/47. The construction company conducting the project considered multiple construction machinery configurations during the upstream stage of the project to reduce environmental impacts. The ANN model described above was used to study wheel-loading operations at three different cutting/loading stations along the main-line of the road construction project. At each station, wheel-loaders were used to load material excavated by excavators onto trucks. Three models of wheel loader were considered in the case study together with one excavator model and two truck models at each station. Therefore, there were six possible equipment configurations at each station, as shown in Table 5. The operating properties of the construction machines and the project characteristics are summarized in Tables 6 and 7; the load factors used to predict the wheel loaders' fuel consumption were computed using Eq. 2.

The results indicated that the wheel loaders' fuel consumption per cubic meter of material loaded (and hence the environmental impact due to their emissions) would be minimized by using the 924Hz wheel loader model in equipment configuration II at all three stations (Table 8 and Figure 14). The use of this wheel loader and configuration was predicted to considerably reduce the energy needed to perform the earthmoving operations at the three stations (by ~74681 MJ relative to those achieved with the 950H model), and to reduce overall emissions by ~47% relative to the same baseline (Figure 14). The case study's results also support the results of the sensitivity analysis: information compiled during the planning of the earthwork scenarios showed that the 924Hz wheel loader would be operating at ~84% of its maximum design capacity, giving it a higher utilization rate than the other two wheel loader models considered in the case study. Finally, the results obtained highlight the importance of selecting earthmoving configurations in which the individual machines have complementary characteristics (e.g. hauling and loading capacities), enabling synergistic performance gains. These findings are consistent with earlier analyses (Muleski, Cowherd, and Kinsey 2005).

Table 5. Equipment configurations considered in the case study.

| Configuration No. | Wheel loader model | Excavator model | Truck model |
|-------------------|--------------------|----------------|-------------|
| I                 | 924Hz (1)*         | 329D (1)*      | Cat.770 (5)* |
| II                | 924Hz (1)*         | 329D (1)*      | Cat.772 (5)* |
| III               | 930H (1)*          | 329D (1)*      | Cat.770 (5)* |
| IV                | 930H (1)*          | 329D (1)*      | Cat.772 (5)* |
| V                 | 950H (1)*          | 329D (1)*      | Cat.770 (5)* |
| VI                | 950H (1)*          | 329D (1)*      | Cat.772 (5)* |

Notes: *numbers in parentheses indicate the numbers of each machine used in the corresponding configuration.

Table 6. Characteristics of stations included in the case study.

| Station | Material quantity (m³) | Material density (kg/m³) | Load factor (decimal) |
|---------|------------------------|--------------------------|-----------------------|
| 6435 – 7325 | 17920                  | 1943                     | 0.750485982           |
| 12199.5 – 12950 | 5600                  | 1886.5                   | 0.722045647           |
| 12950 – 13958 | 8565                  | 1801.5                   | 0.676299198           |

Table 7. Characteristics of equipment used in case study.

| Equipment model | Bucket or body capacity (m³) | Cycle time (min) | Horsepower (kW) |
|-----------------|-------------------------------|------------------|-----------------|
| 924Hz           | 2.1                           | 0.45             | 55              |
| 930H            | 2.5                           | 0.50             | 113             |
| 329D            | 1.101                         | 0.25             | 152             |
| Cat.770         | 25                            | 3.15 – 12.98     | 381             |
| Cat.772         | 30                            | 3.15 – 12.98     | 446             |

Conclusion and suggestions for future work

The framework and methodology presented in this work provide a way to overcome problems caused by a lack of real-world data on the environmental impact of construction equipment, and could be used in future studies to
measure, assess, and monitor the environmental effects of construction operations. It would be desirable to benchmark the model’s performance by comparing its planning stage predictions to construction phase emissions data gathered using emissions measurement systems such as PEMS. Discrete event simulation was shown to be a powerful tool that can integrate equipment performance data and information on site conditions to accurately describe real situations encountered in construction operations and overcome the problem of lacking data on earthwork activities. Moreover, ANN-based modeling was shown to be an effective tool for solving complex nonlinear problems and clarifying the relationships between independent factors in construction operations. The ANN-based models developed in this work accurately predicted the environmental impact of hauling operations during earthworks in terms of the fuel consumption of wheel loaders. In future, they could be used to help practitioners identify environmentally optimal wheel loader operating configurations. A sensitivity analysis of the ANN-based model revealed the dominant factors affecting wheel loaders’ fuel consumption as well as factors with significant effects on inter-cycle variation in environmental impact. These findings provide important new insights into wheel loader duty-cycles that support the findings of Abolhasani et al. (2008) and will facilitate the development of improved models for assessing the environmental impact of earthmoving operations, which are a major source of emissions in the construction sector. The load factor equation presented here, which depends on the loose density of the hauled materials, can be used to estimate the engine state of wheel loaders under various loads and accurately reflects the impact of material type on wheel loaders’ fuel consumption. Importantly, the results obtained here show that the environmental impact of wheel loader operations can be controlled by selecting an equipment configuration in which the size of the wheel loaders is well-matched to the tasks at hand. The equipment utilization rate was shown to strongly affect wheel loaders’ energy use and emissions per cubic meter of material loaded, both of which are minimized by selecting a machinery configuration that minimizes idle times and ensures that the wheel loaders’ bucket payloads do not exceed the upper limit specified by the manufacturer. The case study demonstrated that the newly developed model can be used in practice to assess and minimize the environmental impact of earthmoving operations by helping practitioners make optimal equipment selections. This work could be extended by using

| Configuration No. | Energy MJ/m³ | CO₂ kg/m³ | CO kg/m³ | CH₄ kg/m³ | NOX kg/m³ | VOC kg/m³ | PM kg/m³ |
|------------------|--------------|-----------|----------|-----------|-----------|-----------|---------|
| I                | 2.35470      | 0.17378   | 3.80E-04 | 1.17E-05  | 0.00178   | 8.67E-05  | 4.45E-05 |
| II               | 2.27351      | 0.16779   | 3.67E-04 | 1.13E-05  | 0.00172   | 8.37E-05  | 4.29E-05 |
| III              | 2.15013      | 0.15869   | 3.47E-04 | 1.07E-05  | 0.00163   | 7.92E-05  | 4.06E-05 |
| IV               | 2.11601      | 0.15617   | 3.41E-04 | 1.05E-05  | 0.00160   | 7.79E-05  | 4.00E-05 |
| V                | 1.98969      | 0.14684   | 3.21E-04 | 9.89E-06  | 0.00151   | 7.33E-05  | 3.76E-05 |
| VI               | 3.47419      | 0.25640   | 5.60E-04 | 1.73E-05  | 0.00263   | 1.28E-04  | 6.56E-05 |
| VII              | 3.35043      | 0.24727   | 5.40E-04 | 1.67E-05  | 0.00254   | 1.23E-04  | 6.33E-05 |
| VIII             | 3.11835      | 0.23014   | 5.03E-04 | 1.55E-05  | 0.00236   | 1.15E-04  | 5.89E-05 |

**Figure 14.** Total CO₂ emissions from different wheel-loader models in the various configurations.
a questionnaire to gather data on practical earthwork operations that could be compared to the sensitivity analysis presented herein. In addition, it would be desirable to assess the potential environmental impact of factors that may affect the operational characteristics of construction machines such as operating modes and maintenance levels for wheel loaders.

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### Appendix

| \( A_1 \) | \( A_2 \) | \( A_3 \) |
|-----------------|-----------------|-----------------|
| \(-6.05894\)    | \(-0.3612\)     | \(-0.30838\)    |
| \(6.684201\)    | \(-0.21161\)    | \(0.259553\)    |
| \(-0.51651\)    | \(0.45483\)     | \(-1.25274\)    |
| \(5.226089\)    | \(-0.16015\)    | \(-1.09986\)    |
| \(1.753558\)    | \(0.382299\)    | \(0.144594\)    |
| \(3.950245\)    | \(3.743459\)    | \(0.487087\)    |
| \(10.74549\)    | \(0.931972\)    | \(0.63103\)     |
| \(4.025197\)    | \(-0.17333\)    | \(0.41323\)     |
| \(-6.678941\)   | \(-0.009\)      | \(0.292804\)    |
| \(-1.65496\)    | \(-0.00992\)    | \(-0.00076\)    |
| \(-1.06678\)    | \(1.425731\)    | \(-7.89663\)    |
| \(1.580957\)    | \(0.371349\)    | \(0.270061\)    |
| \(6.73741\)     | \(-0.89647\)    | \(-0.10765\)    |
| \(3.07498\)     | \(-0.05023\)    | \(0.215704\)    |
| \(-2.13549\)    | \(0.194086\)    | \(0.046308\)    |
| \(3.059644\)    | \(0.590008\)    | \(0.772081\)    |
| \(5.994224\)    | \(0.274972\)    | \(0.305367\)    |
| \(2.407837\)    | \(-0.06074\)    | \(-0.10656\)    |
| \(1.058356\)    | \(-0.32641\)    | \(0.39244\)     |
| \(-4.03712\)    | \(0.154734\)    | \(0.266894\)    |
| \(-8.11808\)    | \(-0.01614\)    | \(0.020565\)    |
| \(-4.63021\)    | \(0.360166\)    | \(-1.06236\)    |
| \(-7.47641\)    | \(0.301647\)    | \(-0.07184\)    |
| \(-0.59148\)    | \(0.439751\)    | \(0.098276\)    |
| \(6.59574\)     | \(0.302836\)    | \(0.264725\)    |
| \(13.60339\)    | \(0.877509\)    | \(1.20072\)     |
| \(3.043665\)    | \(-0.07636\)    | \(0.311272\)    |
| \(-6.2452\)     | \(-0.02318\)    | \(0.72423\)     |
| \(-8.08374\)    | \(0.030957\)    | \(-0.97781\)    |
| \(-5.70965\)    | \(0.841796\)    | \(-5.89534\)    |
| \(1.175696\)    | \(-1.57121\)    | \(-0.1615\)     |
| \(-5.30157\)    | \(0.293744\)    | \(0.284624\)    |
| \(-7.29716\)    | \(0.047749\)    | \(-0.01455\)    |
| \(3.542633\)    | \(-0.12778\)    | \(-0.31234\)    |
| \(-2.16297\)    | \(-0.83631\)    | \(0.284738\)    |
| \(6.678941\)    | \(-0.07967\)    | \(-0.34931\)    |
| \(-1.38267\)    | \(0.211989\)    | \(-0.53251\)    |
| \(-1.34293\)    | \(-0.43279\)    | \(0.00768\)     |
| \(-9.01868\)    | \(-0.40777\)    | \(0.120781\)    |
| \(-8.29046\)    | \(0.10529\)     | \(-0.53923\)    |
| \(-5.7153\)     | \(-0.68959\)    | \(0.083904\)    |