

A Comprehensive Simulation Model for Mining Operations: Development, Implementation, and Validation Using HaulSim

Yaa Serwaa Karikari¹ and Hooman Askari-Nasab²

^{1,2} School of Mining and Petroleum Engineering, University of Alberta, Edmonton, Canada

ABSTRACT

The present research investigates the design, implementation, and validation of a simulation model for optimizing mining operations with HaulSim, a specialized simulation software. The study starts with identifying the conceptual framework, system boundaries, and key performance criteria. Comprehensive data collection and preprocessing ensure the high-quality input parameters required for reliable simulations. HaulSim is used to simulate real-world mining operations, such as resource allocation, equipment utilizations, and process flow. To attain robustness, the simulation uses extensive initialization, iterative testing, and refining. The validation procedure systematically compares simulation results to actual operating data, utilizing statistical methods to determine accuracy and dependability. The findings highlight HaulSim's capacity to properly predict and improve mining operations, as well as its practical implications in strategic planning and decision-making. This study presents a verified framework that combines case-study data (CNRL) with simulation techniques to help optimize mining operations. By comparing simulation findings to real-world performance, the study emphasizes simulation models' potential for boosting operational effectiveness and creativity in the mining industry.

1. Introduction

1.1. Background and Motivation Discrete Event Simulation of Truck-Shovel Operations in Open Pit Mines

Mining operations involve a lot of cost and time to produce profits. Therefore, the mining industry must optimize processes to increase productivity and profit. Mining systems involve a lot of methods and systems, from exploration and extraction to transportation and processing. For this reason, there is an urgent need to optimize these processes and systems. Many ways and technologies have been developed to optimize processes. One of the most popular techniques - and our main focus and study here - is creating simulation models to predict behaviors and patterns in the processes before being implemented in real life under different scenarios [10]. Because of the stochastic nature of the truck-and-shovel systems that makes the studying of these systems difficult and time consuming, a simulation approach is chosen in this study to represent the truck-and-shovel operations in detail [15]. The simulation, in this regard, provides an alternate tool to analyze the impact of technological changes to the overall operations; and thus, help in decision making purposes [17]. HaulSim is a robust simulation software built primarily for the mining industry. HaulSim enables users to develop extensive models of mining operations, including haulage routes, equipment performance, and operational limitations. Mining operations can enhance efficiency by simulating various scenarios

and identifying bottlenecks [5]. However, the performance of these simulation models is greatly contingent upon their precision and validity. It is important to make sure that the models accurately represent real-world processes and can predict outcomes [6]. This paper aims to address this need by developing a thorough simulation model using HaulSim and evaluate its performance by comparing simulation results against real-world data from a mining operation [8]. The objective of this paper is to illustrate the potential of simulation models to improve decision-making in the mining business. This study will provide useful insights into HaulSim's strengths and limitations, as well as practical recommendations for its use in real-world mining settings.

1.2. Objectives of the Study

The primary goal of this research is to create and evaluate a comprehensive simulation model for mining operations with HaulSim. This objective is broken down into several distinct goals. To begin, the study's goal is to create a thorough simulation model of a mining operation using HaulSim, which will include all essential processes and variables such as haulage routes, equipment performance, operational limitations, and material handling. The model must accurately reflect the mining site's physical and operational characteristics [5]. Furthermore, the study aims to authenticate the simulation model by employing actual data obtained from the mine. The data gathered includes operational indicators such as equipment performance, production rates, transportation times, and operational expenses [10]. The simulation results will be compared to real-world data to determine the model's accuracy and reliability [6]. Moreover, the study intends to conduct a thorough investigation of the simulation results in comparison to real-world data. This analysis will reveal where the simulation model closely matches reality and where there are inconsistencies [12]. Based on this analysis, the study will make specific recommendations for increasing the simulation model's accuracy. It will also provide insights into the practical application of HaulSim for optimizing mining operations, highlighting the tool's strengths and limitations [7]. Finally, In hopes to improve decision-making in mining operations by demonstrating how a validated simulation model may be utilized to assist strategic decisions [4]. This involves demonstrating the ability of simulation models to identify bottlenecks, optimize equipment usage, and increase overall operational efficiency [2]. The study seeks to establish a comprehensive framework for designing and verifying simulation models for mining operations. This would ultimately enhance the efficiency and effectiveness of managing mining activities.

1.3. Scope and Limitations

This study aims to cover various important aspects, with a primary focus on creating and verifying an extensive simulation model for mining operations with HaulSim. The model will incorporate critical activities like loading and hauling, as well as the performance characteristics and operational limitations of various types of equipment such as trucks, loaders, and shovels [5, 9]. Various haulage routes, material types, and production schedules will be explored to mimic realistic operational situations [2]. The simulation model will be validated using real-life data acquired from an operational mining site. The data encompasses information regarding the performance of equipment, rates of production, times for hauling, and operational costs [10]. The validation method will include comparing simulation findings to real-world data to determine the model's correctness and reliability [6]. A detailed examination of the simulation results will be undertaken in comparison to real-world data, finding areas where the simulation model closely matches reality and regions where there are differences [3, 12]. The analysis will provide practical recommendations for enhancing the simulation model and increasing its accuracy. The project will provide valuable insights into the practical application of HaulSim for enhancing mining operations, emphasizing the advantages and constraints of the instrument [7]. Finally, the study intends to improve mining decision-making by demonstrating how a validated simulation model can help with strategic decisions. This involves demonstrating the ability of simulation models to identify bottlenecks, optimize equipment usage,

and increase overall operational efficiency [2, 4]. However, the report acknowledges several shortcomings. The accuracy of the simulation model is strongly reliant on the availability and quality of real-world data. Any omissions or inconsistencies in the data can undermine the model's validity [2, 11]. The investigation may be constrained by the scope and detail of the operational data available from the mining site. To manage complexity, the simulation model may make certain simplifications and assumptions, which can result in differences between the model and real-world operations [4]. According to Adams and Parker, the simulation model cannot properly reflect all operational nuances or unforeseen events [1]. The capabilities and limits of the HaulSim software will have an impact on the simulation model's breadth. Certain features or functionalities may not be supported or may necessitate workarounds [8]. Furthermore, the study is limited by the computer capacity and resources available to execute the simulations [25]. External elements such as market conditions, regulatory changes, and technical improvements are not included in the simulation model but can have an impact on mining operations in practice [13]. The model's projections are based on present operational conditions and may not reflect future changes in these external elements [26]. The validation process is limited to the mining operation and data set used in this investigation. The findings may not be directly transferable to other mining sites with distinct characteristics and conditions [27]. Furthermore, the validation focuses on operational measures, which may not adequately reflect mining operations' environmental, safety, and social elements [8]. By defining the scope and accepting these constraints, the study hopes to give a clear and realistic framework for building, implementing, and assessing a simulation model for mining operations using HaulSim [4].

1.4. Conceptualization

The conceptualization stage of mining operation simulation is critical for developing a complete framework for analysis. It begins with determining the simulation's scope and objectives. The primary focus is on the haulage system of a mining operation, which includes the movement of ore and waste materials from loading points to locations. This includes evaluating the performance of various equipment types, such as trucks and loaders, that are critical to the operation's efficiency. The goals include modeling the haulage system's performance, finding operational bottlenecks, and comparing simulated data to real-world data for validation and calibration. The haulage system's effectiveness and efficiency are measured using key performance indicators (KPIs). These KPIs include cycle time, which is the entire time it takes for a vehicle to complete a full cycle of loading, transporting, unloading, and returning empty. The conceptual model was created to describe the structure and processes of the haulage system. This includes details on trucks, loaders, routes, and control systems. Trucks are regarded as the primary equipment for transporting materials, with variations in type and capacity. Loaders, which include shovels and front-end loaders, are required to load goods into trucks. Routes are predefined itineraries with specified properties such as distance, gradient, and surface quality that influence trip durations [28]. Loading and dumping points are defined as essential places in the process, with control systems in charge of assigning and managing equipment. The haulage system's processes include loading, transporting, dumping, and returning. During the loading phase, loaders fill trucks with materials, and the time required varies based on the material type, loader capacity and efficiency. The hauling phase entails moving items to the dumping site, which is influenced by factors such as road conditions, road gradient, truck load and truck speed. The dumping time varies depending on the substance and unloading method employed. Finally, during the returning phase, trucks travel empty back to the loading point for the next cycle. To simplify the model, assumptions are used such as consistent equipment availability and reliability, uniform road conditions, and constant operator skill levels [29]. This extensive concept serves as a solid foundation for creating a detailed simulation model. The model will be used to evaluate the simulation against real-world data, identify operational inefficiencies, and analyze various optimization strategies for the haulage system, ultimately enhancing the overall performance and cost-effectiveness of the mining operation.

2. Methodology

2.1. Data Collection and Preparation

The CNRL data of their horizon mine site, which is saved in a SQL file, is a large dataset that contains critical information on a mining operation's fleet activities, such as source and destination points, cycle periods, and other operational parameters. This data serves as the foundation for analyzing and optimizing the mining fleet's performance, which is critical for effective resource management and operational planning. To assure the data's precision, I made sure the sources and destinations were precisely mapped into the road network using SQL code. This mapping method entailed linking the fleet's movements to the actual road network, which improved data accuracy. Specifically, actions on November 1, 2016, during the day shift were tracked and plotted, providing a precise picture of operations under normal circumstances. The SQL query used in this procedure was critical in matching source and destination data to the road network and determining the precise locations of fleet activities like loading and unloading stations. This amount of data collecting enables simulation models that closely resemble real-world operations. Precise information on the fleet's origins, destinations, cycle periods, and road network enables simulations to take into consideration a variety of factors influencing operational efficiency, including traffic patterns, road conditions, and equipment performance. Accurate data is critical for identifying potential bottlenecks or inefficiencies and implementing targeted solutions. Furthermore, this rigorous data gathering and mapping process ensures that the dataset is full, which is required for reliable analysis. Incomplete or erroneous data may result in flawed models and suboptimal decision-making. The painstaking approach to data accuracy, achieved through extensive SQL mapping and validation, aids in the development of robust simulation frameworks and successful mining optimization methods. In conclusion, the CNRL data provides a thorough foundation for analyzing and optimizing mining fleet operations. The dataset covers critical variables such as source and destination points, as well as cycle periods, allowing for the development of reliable simulation models that influence strategic decisions and improve operational efficiency.

2.2. Model Development

2.2.1. Features

The simulation model's features were derived from the CNRL topography, which was imported as a Digital Terrain Model (DTM) file. This file contained topographic data for the area, including dump locations. The DTM served as the fundamental surface for mapping the road network and conducting simulations. The accurate terrain representation was critical for realistic simulation of mining operations, notably in terms of vehicle mobility and topography's impact on haulage.

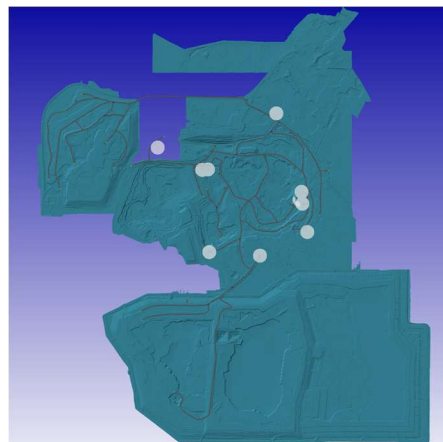


Figure 1. Topography of the mine site.

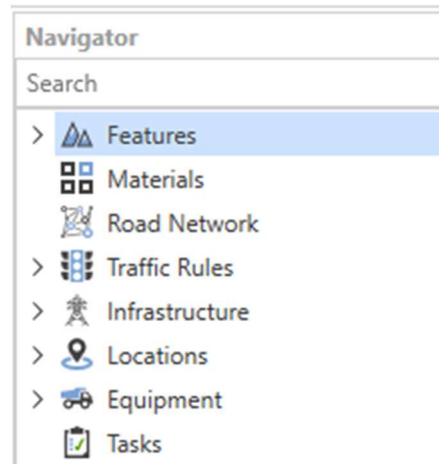


Figure 2. Feature button on the Navigator bar.

2.2.2. Materials

The type of material carried is critical for model analysis and simulation. According to the data, there are several types of materials. However, the most interesting item is ore and waste. Because it is oil sands, the material is loose sand, and material properties such as in-situ bank density, ability to be excavated, swell factors and loose density, loader bucket fill factor, and load and haul or load carry times should be considered. The values of the material's attributes will be entered by right-clicking on the material tab in the navigation pane shown in figure 3, selecting configure, and making the following changes to material attributes in the material pop-up panel. You click on the plus sign at the top left corner shown in figure 4 to add material, select any material, and then study the information on the material dialog box. This information will provide you with the material's numerous properties, such as the swell factor, in-situ density, struck and heaped capacity. You close the window and save the project. In the simulation, the materials that were selected were "Mud-Wet Compactly Dry" and "Sand-Dry". This material was chosen because it resembles the oil sands material used in CNRL operations. The in-situ bank density was 3.25 t/m³ and 1.9 t/m³ respectively, indicating modest compactness. The material has a swell factor of 1.2 t/m³ and 1.1 t/m³ and a loose density of 2.71 t/m³ and 1.73 t/m³ respectively. These features were critical for precisely modeling the handling and movement of material throughout the mining operation, including factors such as load capacity, transit efficiency, and material handling during dumping.

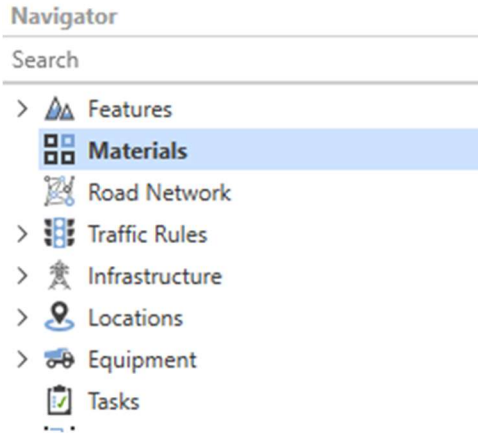


Figure 3. Materials button on the Navigator bar.

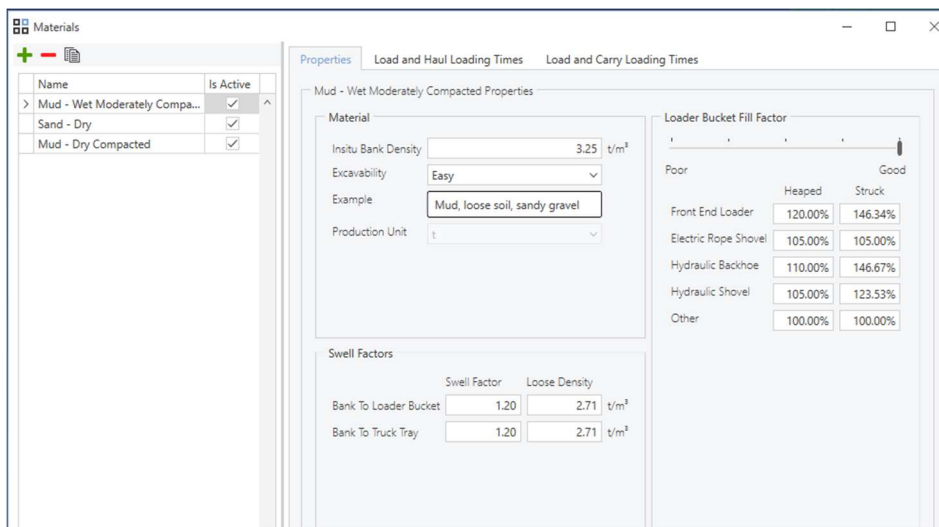


Figure 4. Materials menu dialog box.

2.2.3. Road network

The road network in HaulSim is imported via a string file named `deswik_road`, which specifies the paths for equipment movement in the simulation. This road network is critical for correct modeling since it influences the speed and efficiency of equipment travel. The file, which is part of the CNRL dataset and topography, must have a String ID that represents the grouping of nodes on the same road, as well as the X, Y and Z coordinates for each X, Y, and Z node, each listed on its own line. The road network representation employs several colors to represent distinct features: gray for waypoints, blue for intersections, and yellow for termination points. These indicators are critical for route analysis and equipment simulation. To import the road network, left-click the road network option in the navigation panel, then import the file and save your changes. You can also display road grades using the legend button on the toolbar and configure cutting planes by modifying the elevation in the Build toolbar, which allows you to see the road's measurements from top down.

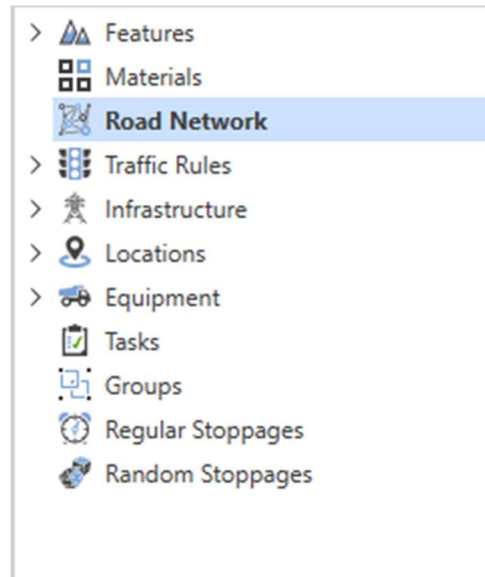


Figure 5. Road Network button on the Navigator bar,

2.2.4. Location

The CNRL data is an SQL file containing information about the mining fleet's sources, destinations, cycle time, and various other details. The sources and destination were mapped on the road for accuracy by using an SQL code to map the sources and destination on a day on a particular shift (day shift) on the road for accuracy. The day that was chosen was the 1st day of the 11th month of the year 2016 during the day shift of the two tables *[Shell_Productivity].[dbo].[EFHtable]* and *[Shell_Productivity].[dbo].[road_network]* were used in extracting the data we need for the sources as well as the destinations for that particular shift.

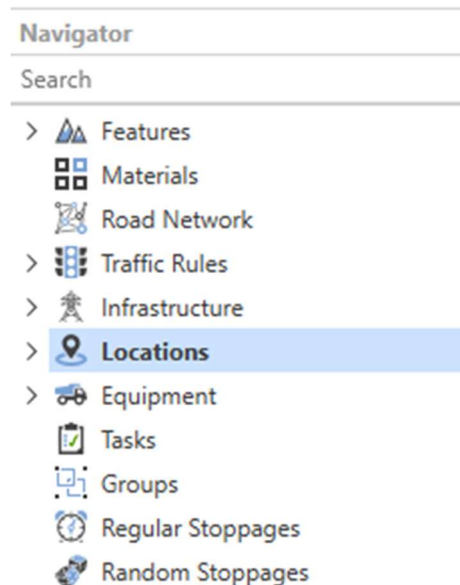


Figure 6. Location button on the Navigator bar.

2.2.5. Sources

In haulage simulation modeling, material is moved from the source (Load and Carry or Load and Haul) to the destination (dump, stockpile, crusher, Haul Load point, or Ore Pass In). In this situation, the material is carried from the digging site and stockpiled at the destination. The material is taken from the Load and Haul unit and either dumped or stockpiled at the oil sand mine. To import the source file, click on the location in the navigation pane, then choose sources, open the file, and import. The next step is to customize and modify the methodology to single or double-sided, then save the file. The next step is to move about the grids. To accomplish this, click in the navigation pane, expand the location tab, and pick source, then right-click on the source tab and select configure. Click the filter button to pick and filter your desired source. Close the pop-up window and save the project. The data's pit sites served as their sources. The data was collected for the year 2016, the 1st day of the eleventh month. Consider looking at the simulation for a day to ensure accuracy. We extracted pit areas for one day during the day shift. The pit sites during that period are listed below: PIT-300-S007, PIT-265-S009, PIT-305-S2503, PIT-BORROW3-S2504, PIT-310-S806, PIT-301-S807, PRJ-CLN-IPD2-2889, ST_SAND_EAST_CR, ST_REJECTS_JPM, PRJ-CLN-IPD2-2900, and ST_SAND_EAST_CR.

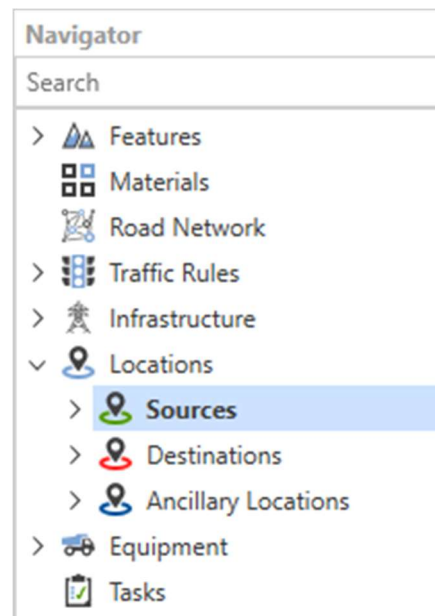


Figure 7. Source button under the Location Menu.

2.2.6. Destination

The destination in HAULSIM is the location where the truck will deposit the material collected from the source. It marks the end of the road network. The data shows the following destinations: dump, crusher, and stockpile. The destination file is either imported or manually added, just like the source file. In this model, we will deal with three different destinations: dump, stockpile, and crusher. To import the destination file, click on the location in the navigation pane, then select the destination, click on import, and finally select the file to import. The details about the file will appear in the import destination pop-up window; click next to import. The details about the file will appear in the import destination pop-up window; click next to import. The next step is to customize and make changes to the destination pop-up window, which allows the user to adjust the layout, crush rate, initial quantity, material, and capacity of the three destinations indicated above, before saving the

project. The destinations are the various dumps and stockpile locations found in the data. The destinations were extracted just like the sources for one day during the day shift. These were the various destinations: CR2_JPM_REJ, DY_INPIT_D2_SHELL_553, DY_INPIT_D2_SANDCHIMNEY, IN_ROADS_JPM, DU_WODA_N_SHELL, DU_WODA_NORTH_SLOP, CR2_JPM, DY_INPIT_D2_SHELL_539, DY_INPIT_D2_CORE and DU_WODA_N_OVB.

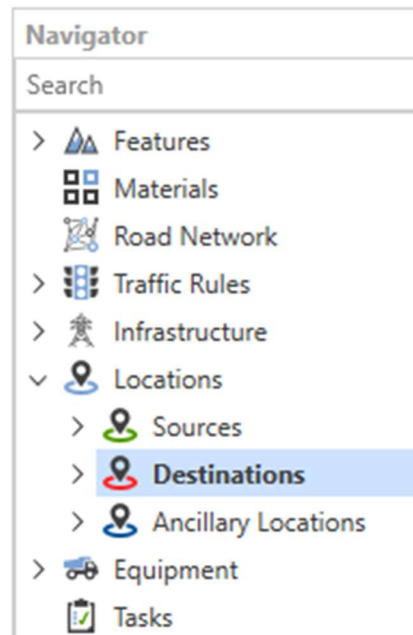


Figure 8. Destination button under the Location Menu.

2.2.7. Ancillary locations

The ancillary location is where the trucks will come from before they move to the assigned locations. The ancillary location was created on the southeast side of the CNRL topography. These are the list of the ancillary locations: 1) Fuel bay; equipment move to this location to refill their tank with fuel, 2) Lunch room; where the operators take a break for their lunch, 3) Truck Bay; the location where the trucks travel from, and 4) Workshop; where the equipment move to if there is a breakdown. These locations were added to mimic the real-life situation in a mining operation. There was no data provided for this, so it was randomly added at locations close to the pit.

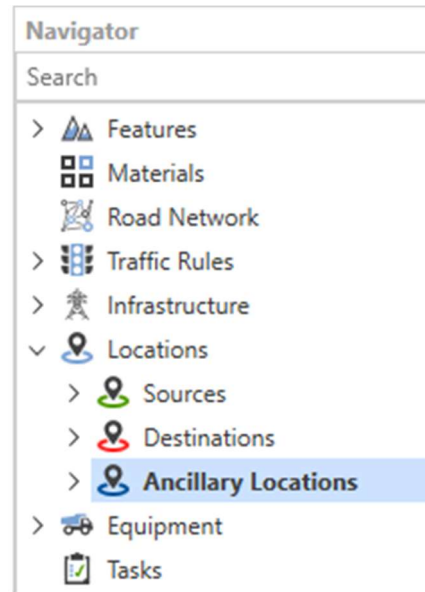


Figure 9. Ancillary Locations button under the Location Menu.

2.2.8. Equipment

After establishing the material, road, sources, and destinations, adding equipment is a critical step in finishing and validating the simulation model. The simulation uses a variety of equipment to accurately mimic the mining operation. Loading units, such as shovels, are stationed at source locations to haul trucks, which transport material to dumps, stockpiles, or facilities. Load and carry units are utilized for material transport, while ancillary units, such as graders and dozers, ease the loading and hauling operation. For the simulation, the equipment consisted of haul trucks and shovels. The shovels used were nine in total, from five different brands: Bucyrus-495B (BE 495B2), Hitachi-EX 2500-6(HIT 2500), Hitachi-EX 8000-6(HIT 8000), Hitachi- EX850-3 (Hit ZX850), and Hitachi-ZX 870LC-5A (Hit ZX870). The truck fleet included 23 trucks of two types: Caterpillar-797B (CAT 797B) and Caterpillar-797B (CAT 797). The CAT 797B has a payload capacity of 349.02t with a maximum speed of 66.22km/h and the CAT 785 has a payload of 99.67t with a speed of 55.68km/h. Both the shovels and trucks were extracted for a single day during the day shift. The table below shows the name of the loaders, the loader type and the start location. Among the 22 haulers 16 were Caterpillar-797B and 8 were Caterpillar-785.

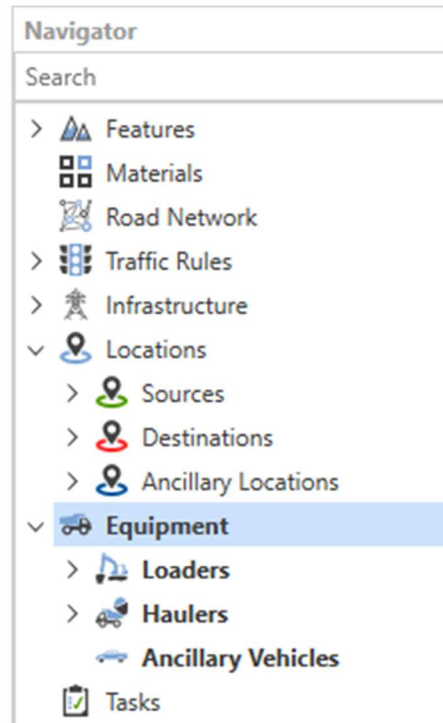


Figure 10. Location button on the Navigator bar.

Table 1. Name, loader type and location of the Loaders.

Name	Loader Type	Start Location
S007	Bucyrus-495B	PIT-265-S009
S009	Bucyrus-495B	PIT-300-S007
S2504	Hitachi-EX 2500-6	PIT-305-S2503
S2504	Hitachi-EX 2500-6	PIT-305-S806
S806	Hitachi-EX 8000-6	PIT-305-S807
S807	Hitachi-EX 8000-6	PIT-BORROW3-S2504
S2889	Hitachi- EX850-3	ST_SAND_EAST_CR
S2899	Hitachi-ZX 870LC-5A	PRJ_CLN_IPD2_2900
S2900	Hitachi-ZX 870LC-5A	ST_REJECTS_JPM

2.2.9. Tasks

The tasks panel is used to assign the loaders to the destination. Right-click on the task button and select configure, and a pop-up window opens where it contains a table. In the table, add load and haul groups. The load and haul groups should contain the number of loaders that are used for the simulation. The load and haul groups are created, each loader is assigned to it, the pit locations of the loader, and the various destinations to which the truck will move from the source to the destination. There are other columns such as the material, task cycle, and tonnages, but those are optional.

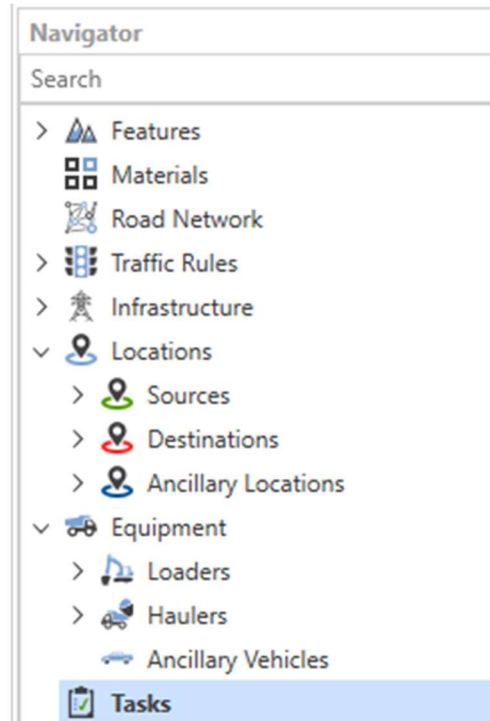


Figure 11. Tasks button on the Navigator bar.

Tasks

Task Group + - [Icons] Task + - [Icons]

Use Duration

Group						Task						
Group Id	Group Type	Loader	Edit	Dispatcher Target Rate (t/h)	Duration	Source	Destination	Material	Quantity (t)	Haulers	Task Cycles	Id
> 1	Load & Haul	S009	<input type="checkbox"/>	859,950.00	07:30:00	> PIT-265-S0	DU_WODA_N	Mud -...	100,000.00	T126,T136,T13	∞ ^	1 ^
2	Load & Haul	S007	<input type="checkbox"/>	859,950.00	08:15:00	> PIT-300-S0	CR2_JPM	Mud -...	100,000.00	T126,T136,T13	∞ ^	2
3	Load & Haul	S807	<input type="checkbox"/>	614,250.00	08:30:00	> PIT-301-S8	CR2_JPM	Mud -...	100,000.00	T126,T136,T13	∞ ^	3
4	Load & Haul	S2503	<input type="checkbox"/>	230,343.75	09:00:00	> PIT-305-S2	DU_WODA_N	Mud -...	100,000.00	T136,T138,T16	∞ ^	4
5	Load & Haul	S806	<input type="checkbox"/>	614,250.00	07:30:00	> PIT-310-S8	CR2_JPM	Mud -...	100,000.00	T126,T136,T13	∞ ^	5
6	Load & Haul	S2504	<input type="checkbox"/>	2,448.41	05:00:00	> PIT-BORRC	DY_INPIT_D2	Sand -...	100,000.00	T154,T156,T15	∞ ^	6
7	Load & Haul	S2889	<input type="checkbox"/>	61,425.00	08:00:00	> PRJ-CLN-IF	DU_WODA_N	Mud -...	100,000.00	T456,T458,T46	∞ ^	7
8	Load & Haul	S2900	<input type="checkbox"/>	46,653.75	08:00:00	> PRJ-CLN-IF	DU_WODA_N	Mud -...	100,000.00	T456,T458,T46	∞ ^	8
9	Load & Haul	S2899	<input type="checkbox"/>	46,653.75	08:00:00	> ST_REJECT	CR2_JPM_REJ	Mud -...	100,000.00	T471,T473,T47	∞ ^	9
10	Load & Haul	S2889	<input type="checkbox"/>	39,174.55	08:00:00	> ST_SAND_f	IN_ROADS_JPI	Sand -...	100,000.00	T467,T474	∞ ^	10
11	Load & Haul	S2900	<input type="checkbox"/>	29,754.00	09:00:00	> ST_SAND_f	DU_WODA_N	Sand -...	100,000.00	T467,T474	∞ ^	11

Close

Figure 12. Pop-up window of the tasks button.

2.2.10. Verification

After all, the necessary information has been added to the model. We will verify whether the simulation can run by checking whether any parameters are highlighted in red, as a sign of any errors or inconsistency. If any of the parameters are highlighted in red, we will make the necessary changes to make the model work.

2.2.11. Run simulation

On the Run menu, under the toolbar select the run button to finally run the simulation. The simulation was run for 11 hours, taking account of the 12-hour shift of a mine with 1 hour for the operational and non-operational delays that could reduce the operating hours of the equipment. After the simulation is run, the results from the reports button are obtained on the Run menu bar and imported in an excel format for further analysis.

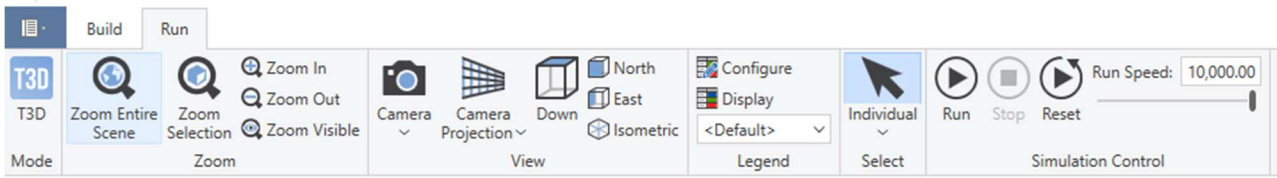


Figure 13. Run button under the Run Menu bar.

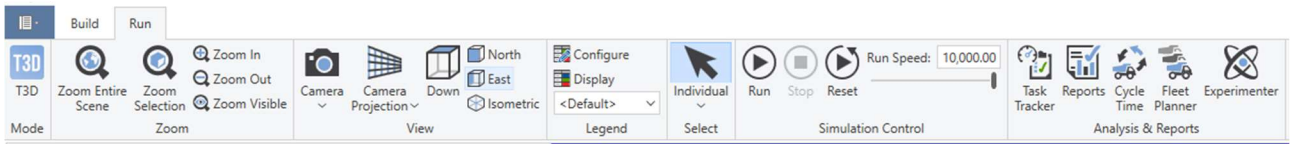


Figure 14. Reports button under the Run Menu bar.

2.3. Validation

After the model was built, it should be analyzed for accuracy and validated by checking how the simulated values are close to historically recorded values. The real-life data was extracted and imported as an excel file taking into consideration a particular shift in a specific day to mimic real world mining operation. The simulation data was extracted in a table form for the comparison. The tonnage from each location was extracted from the simulation results; and the real-life data, the total tonnages for each pit was extracted using SQL. These are the following results obtained after the data was analyzed with python:

3. Results

Once the simulation data was compared to the real-life data, these were the following results that were obtained through tables and graphs. The total tonnages of the pit locations and the dump locations were collected. The simulation data and the real life data are summarized in the tables below:

Table 2. Comparison of the tonnages for pit locations, Simulation vs. Real values.

Pit Locations	Simulation Data (tonne)	Real-Life data (tonne)
PIT-265-S009	34354.70	33631.52
PIT-300-S007	44698.97	45715.32
PIT-301-S807	34037.22	31202.52

PIT-305-S2503	14787.06	11868.55
PIT-310-S806	28839.61	26848.68
PIT-BORROW3-S2504	7403.92	3314.43
PRJ-CLN-IPD2-2889	3584.26	1489.80
PRJ-CLN-IPD2-2900	3584.26	1411.70
ST_REJECTS_JPM	5926.79	9871.80
ST_SAND_EAST_CR	797.89	266

From the table below that is from Table 2, we can spot some differences between the simulation data and the real-life data, the pit locations where there is a significant amount of difference is the “PIT-BORROW3-S2504”, “PRJ-CLN-IPD2-2889”, “PRJ-CLN-IPD2-2900” and “ST_REJECTS_JPM”, “ST_REJECTS_JPM”. The percentage difference of the total tonnages between the simulation values and the Real-life values is 7%. This small difference between the total tonnages between both data indicates the closeness of the simulation data to the real-life data. Even though individual pits showed vast differences due to the inflexibility of assigning information to the software, these are some of the limitations of the HaulSim software and the difficulties in getting accurate results for simulations. The most important thing is to work on the simulation and get close or similar results.

Table 3. Comparisson of the tonnages for dump locations, Simulation vs. Real values.

Dump Locations	Simulation Data (tonne)	Real-Life data (tonne)
CR2_JPM	107575.80	103403.70
CR2_JPM_REJ	5926.79	9871.80
DU_WODA_N_OVB	53306.97	33038.88
DY_INPIT_D2_CORE	3801.21	10235.68
DY_INPIT_D2_SANDCHIMNEY	7403.92	3176.33
IN_ROADS_JPM	0	3677.49
DU_WODA_NORTH_SLOP	0	1122.50
DY_INPIT_D2_SHELL_553	0	365.56

We can also see from Table 3, that there is some empty data for the simulation data, this is for the same reason above due to the inflexibility of assigning information to the software. From table 3, we can see from the last three pits that the simulation values are empty, so I represented it with zero, even though the real-life values show that the material was sent to the sump. From the CNRL data, the major places where the ore material was taken to be the “CR2_JPM” and “CR2_JPM_REJ”. These are the major crushers where the ore was taken to, the rest are dump locations. Most of the values from the simulation were significantly higher than the real-life data. The percentage difference for the total tonnage at the dumps between the simulation data and real-life data is 8%. This indicates the closeness of the simulation to real life scenario.

We will examine some graphs and make some analysis on the data for the tonnages for the pit locations and the dump locations respectively.

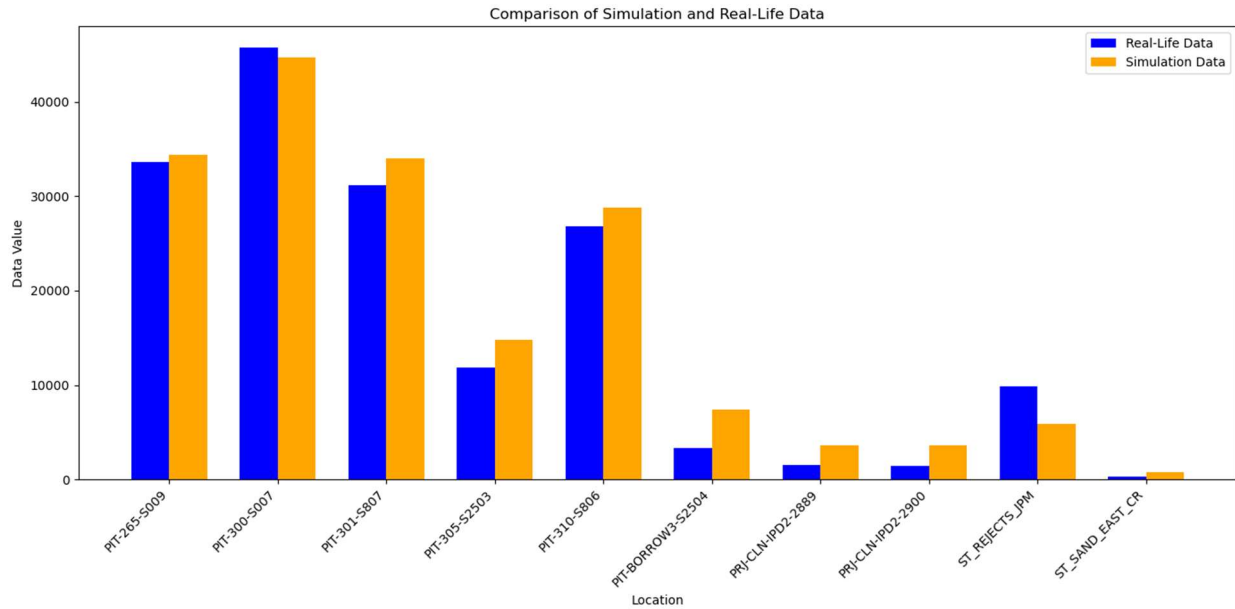


Figure 15. Bar plots representation of tonnages for each pit.

This is a bar graph for the tonnages for each of the pit locations; the blue indicates the real-life data and the yellow the simulation data. We can see from most of the bars that the simulation values for most pits were higher than the real-life data. This is just the graphical representation of Table 2.

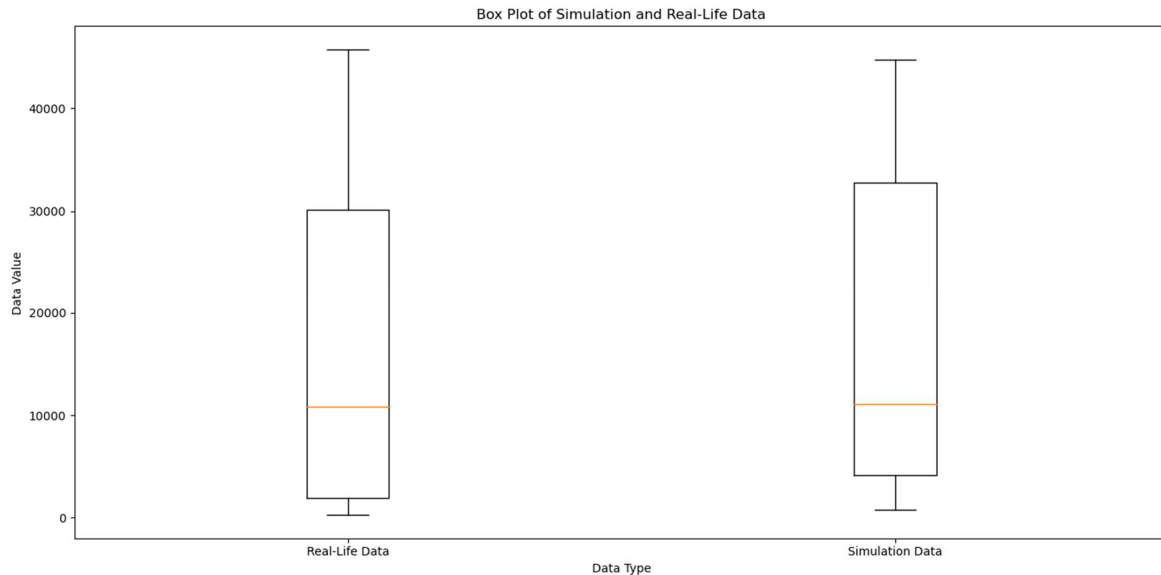


Figure 16. Box plot of Simulation and Real-life Data for the pit locations.

The box plot provides a comparison of the distribution of values between simulated data and real-life data, highlighting significant disparities in their dispersion and central tendency. Both datasets exhibit a comparable median, situated slightly below 10,000, suggesting similar center values. Nevertheless, the real-life data demonstrates reduced variability with a narrower interquartile range (IQR) in comparison to the simulated data, indicating more uniform outcomes. The simulation data, on the other hand, has a larger IQR, indicating more unpredictability and a broader range of probable outcomes. Both datasets exhibit some right skewness, with longer whiskers on the upper end, ranging from near zero to slightly more than 40,000. This comparison indicates that, while the core tendencies

are consistent, the simulation data is less exact or more varied, likely simulating a broader range of scenarios, necessitating additional research to refine the model or identify the source of this variability.

The Pearson Correlation Coefficient is 0.99, which is very near to one. This demonstrates a strong positive linear relationship between simulated values and real-life values. Essentially, when real-life values grow, so do the anticipated values. This substantial correlation suggests that the model is quite good at detecting the underlying patterns in the data.

Moreover, the other measures were used such as the Root Mean Square error and the Mean Absolute Error was calculated to better understand the relationship between both data, and these were the results:

The Mean Absolute Error (MAE) is 2231.71, indicating that the model's predictions depart from actual data by around 2232 units. This metric provides insight into the average magnitude of the errors without considering their direction, offering an overall idea of how inaccurate the predictions are. The Root Mean Square Error (RMSE) is reported at 2524.87, which is slightly greater than the MAE. RMSE is more sensitive to larger mistakes because it squares the differences before average, giving greater weight to significant discrepancies. The fact that the RMSE is not much bigger than the MAE shows that the forecasts contain minimal extreme errors, indicating that the model's performance is rather consistent.

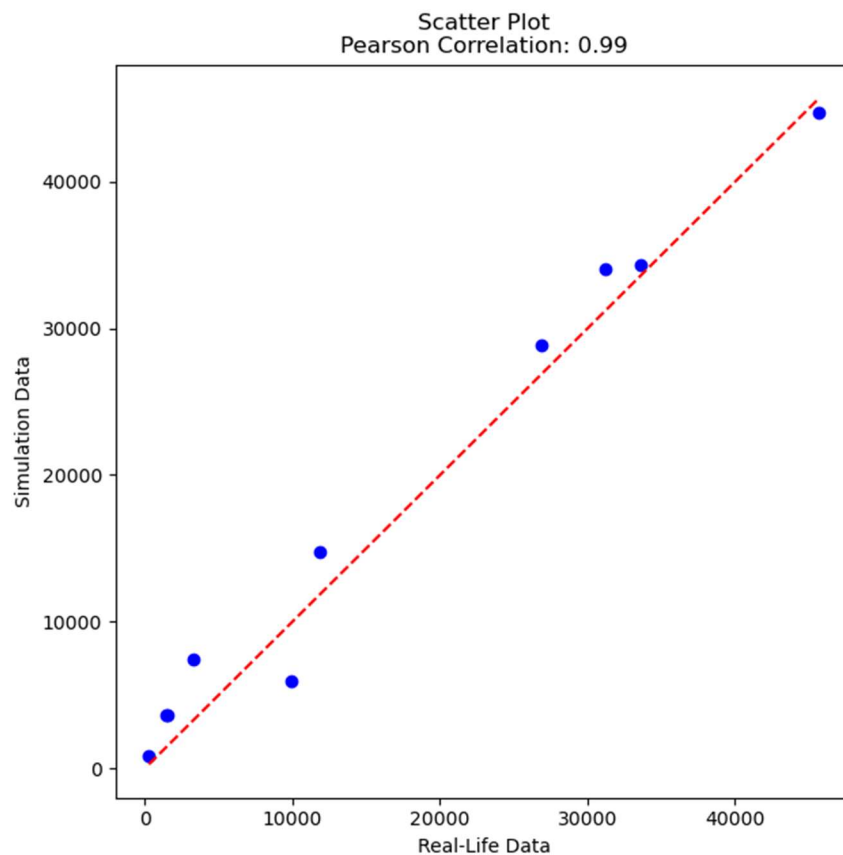


Figure 17. Scatter plot of Simulation and Real-life Data for the extracted tonnage at pit locations.

We will now examine the charts for the dump locations and make some analyses on them:

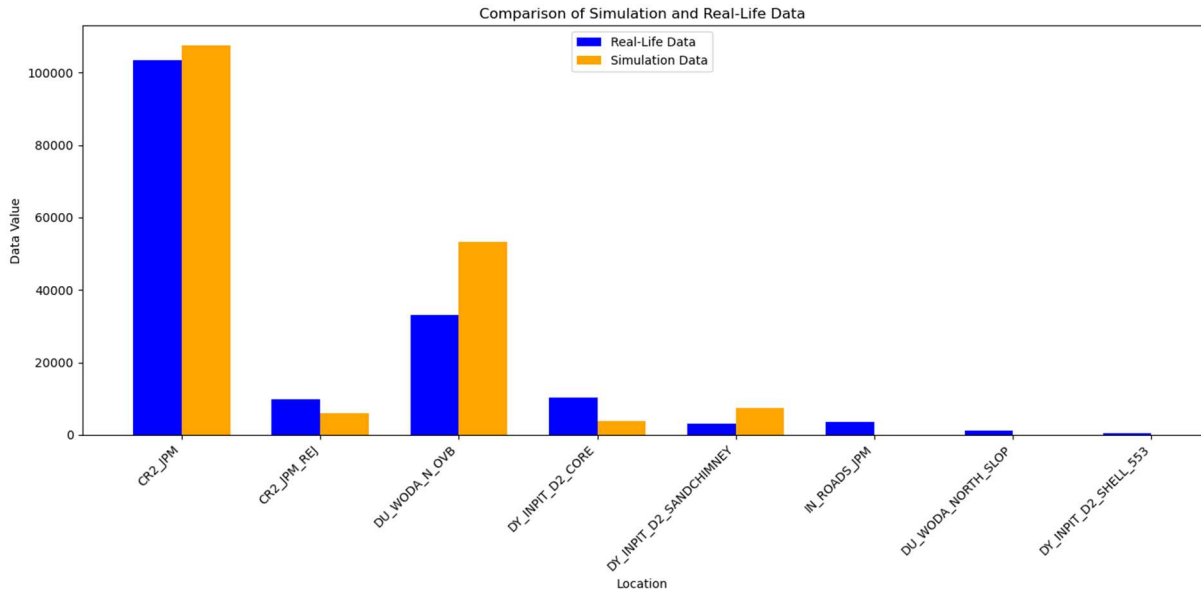


Figure 18. Bar plots representation of tonnages for each dump location.

This is a bar graph for the tonnages for each of the dump locations; the blue indicates the real-life data and the yellow the simulation data. We can see from most of the bars that the simulation values for most pits were higher than the real-life data. This is just the graphical representation of Table 3.

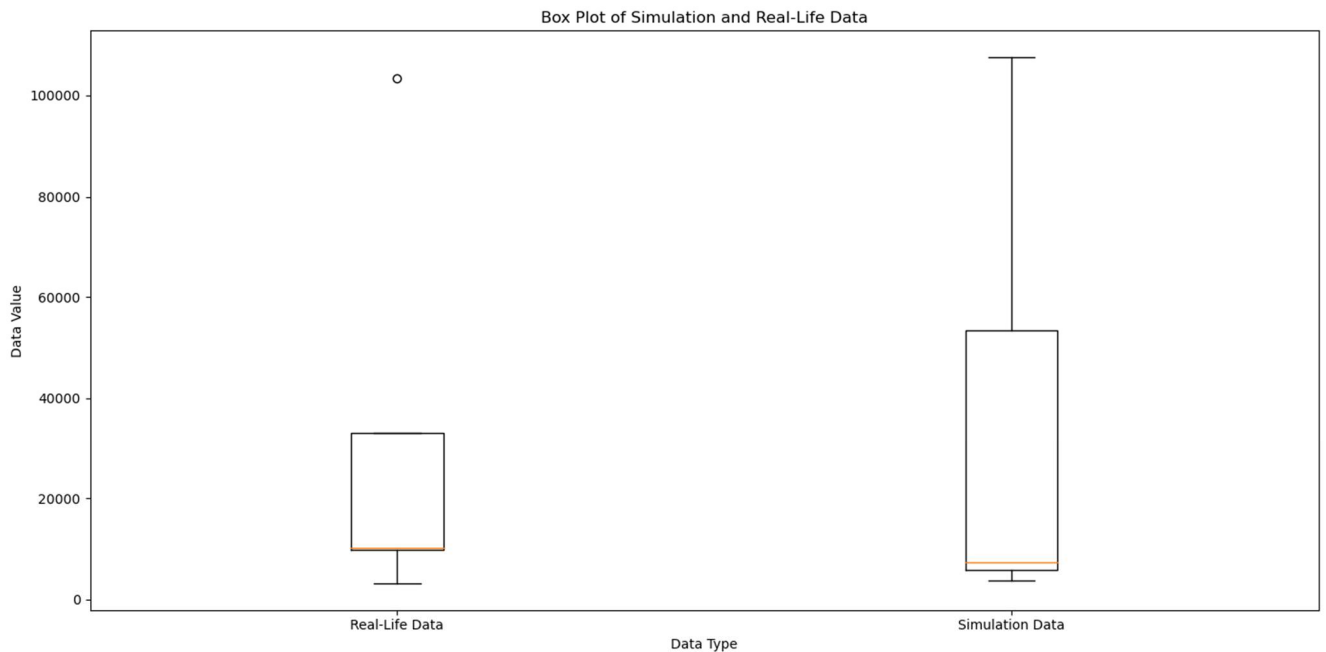


Figure 19. Box plot of Simulation and Real-life Data for the dumped tonnage at dump locations.

The real-life data has a shorter interquartile range compared to the simulation data; this shows reduced variability compared to the real-life data. The simulation data, on the other hand, has a larger IQR, indicating more unpredictability and a broader range of probable outcomes. The simulation data exhibits right skewness, from 0 to 100,000. the real-life data has just a lower tailed whiskers, meaning there is less or almost no variability of the real-life data as compared to the simulation data,

there is an outlier that is visible on the real-life data on the 100000 unit, the same level that the right whiskers of the simulation data extend to, from table 3 we can see the first dump location has more 100000 tonnes of material for each data. The median is on the same level as the interquartile range; this suggests that a larger portion of the data is concentrated in the upper range, with a tail extending towards lower values. This indicates that there are relatively smaller values in the dataset compared to larger values.

The Figure 18 shows a strong correlation between the real-life data and the simulated values. The Pearson Correlation Coefficient of 0.975 shows a very strong positive linear relationship between predicted and actual dump locations, showing that the model adequately reflects the data's accuracy.

The performance metrics for the dump locations provide a complex picture of the model's success. With a Mean Absolute Error (MAE) of 7809.45, the model's predictions are around 7809.45 units off. This represents the average magnitude of prediction mistakes, without regard for their direction. However, the Root Mean Square Error (RMSE) is substantially greater at 10030.35, indicating that there are some significant inconsistencies in the forecasts, since RMSE is more sensitive to outliers.

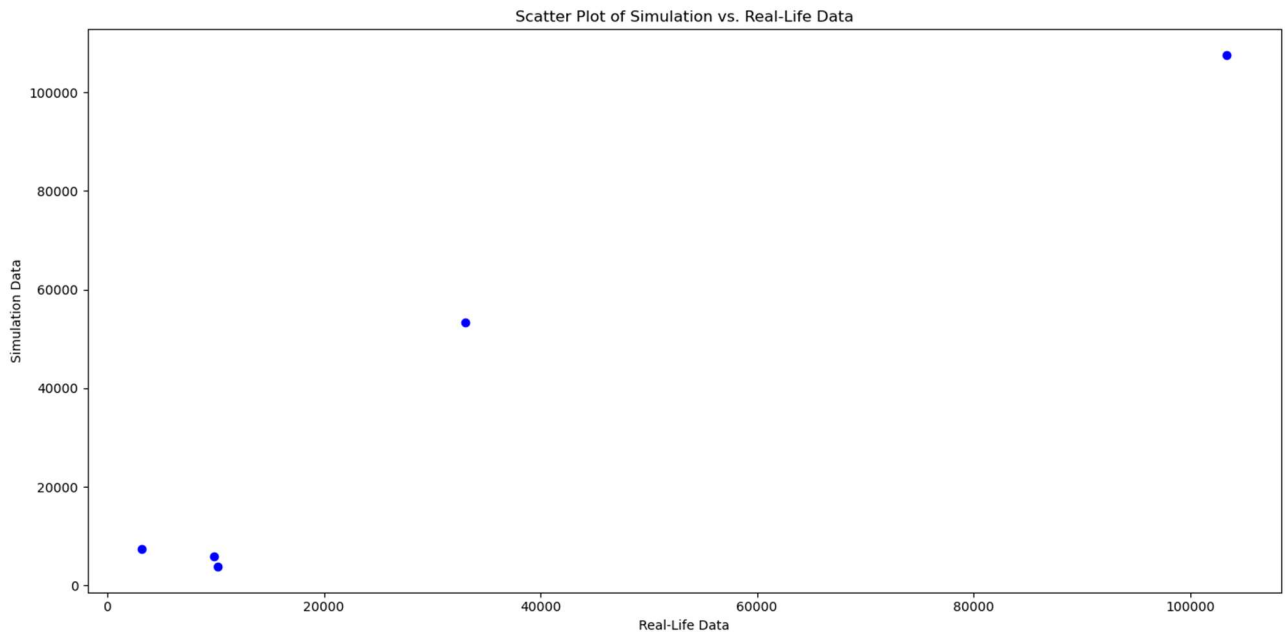


Figure 20. Scatter plot of Simulation and Real-life Data of the dump locations.

4. Discussion

Using comprehensive data on material properties, road networks, equipment, and operational factors, a simulation model of the mining operation was created to mimic the real-life system. The main goal was to evaluate the correctness of the model by contrasting the simulation output with real operational data from the CNRL operations. This comparison helps pinpoint areas for improvement by illuminating the model's advantages and disadvantages.

The simulation considered crucial aspects such as material qualities (e.g., in-situ bank density, swell factor, loose density), road network characteristics, and equipment requirements. The road network, which is critical for calculating equipment movement and speed, was meticulously mapped using a precise string file, assuring accuracy in depicting the mine's design. Equipment data, such as the types and number of shovels and trucks, were retrieved for a single day to provide a snapshot of the operation's capacity and workflow. The simulation model was analyzed by comparing total material

tonnage from simulation and real-life operations. The histogram and box plot representations demonstrated substantial differences between the two data sets. The tables below show the total tonnages that were gathered from collecting data from a single day in a single shift to depict a real-life scenario of the mine. As described in the former chapter the values between both data were not similar because of the limitations of Haulsim and its inflexibility to adjust information to depict real life data. The tables and the bar graphs showed the representation of both data and their discrepancies. Despite all this the total tonnage from the pit and dump as compared to the simulation data showed a percentage difference of 7% and 8%, which is a laudable and acceptable difference between both data. The box plot for the pit and dump location describes the data for each of them respectively. The box plots of the pit location show similarities between the real-life data and the simulation data. It showed that both data were similar with the simulation data having a slightly higher variability. The dump locations were slightly different; this could be attributed to the missing values in the simulation data. However, the simulation data for the dump locations shows variability in both lower and upper values. The real-life data also showed more variability in the lower values but not as much with the higher values as compared to the simulation values. The Pearson correlation matrix between the pit locations and the dump locations were 0.99 and 0.97 respectively. This shows a stronger correlation for the pit locations, though the dump locations showed a lower correlation compared to the pit locations. This as I stated earlier could be due to the missing values of the dump locations. The MAE and RMSE further indicated that the simulation values and the real-life values were similar and the simulation was able to replicate the real-life data really well. Furthermore, the calibration of the model's parameters may require adjustment. Fine-tuning parameters such as equipment cycle durations, haul road conditions, and loading efficiencies may increase the model's accuracy. Incorporating a broader range of real-world data from different days and operational settings would give a more solid foundation for testing the model.

5. Conclusion

The simulation model is a useful tool for analyzing and projecting mining operations, as it provides insights into prospective improvements and efficiencies. However, the current validation procedure indicates considerable disparities between the simulated and actual data, identifying areas for improvement in the model's accuracy. By resolving these constraints and fine-tuning the model's parameters and assumptions, the simulation can become a more trustworthy predictor of real-world performance, enabling more effective decision-making in mining operations. The findings highlight the significance of continual model validation and calibration against actual operating data to ensure simulation relevance and accuracy. The software HaulSim can be further used for comparing different scenarios and selecting the best one. There are also some features for optimizing distances between roads there by enhancing the operations. Short term schedules can be imported from XPAC; a scheduling software to HaulSim and we can create a simulation model from that schedule. I believe HaulSim can be more exploited and used effectively especially with the conjunction of other softwares.

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