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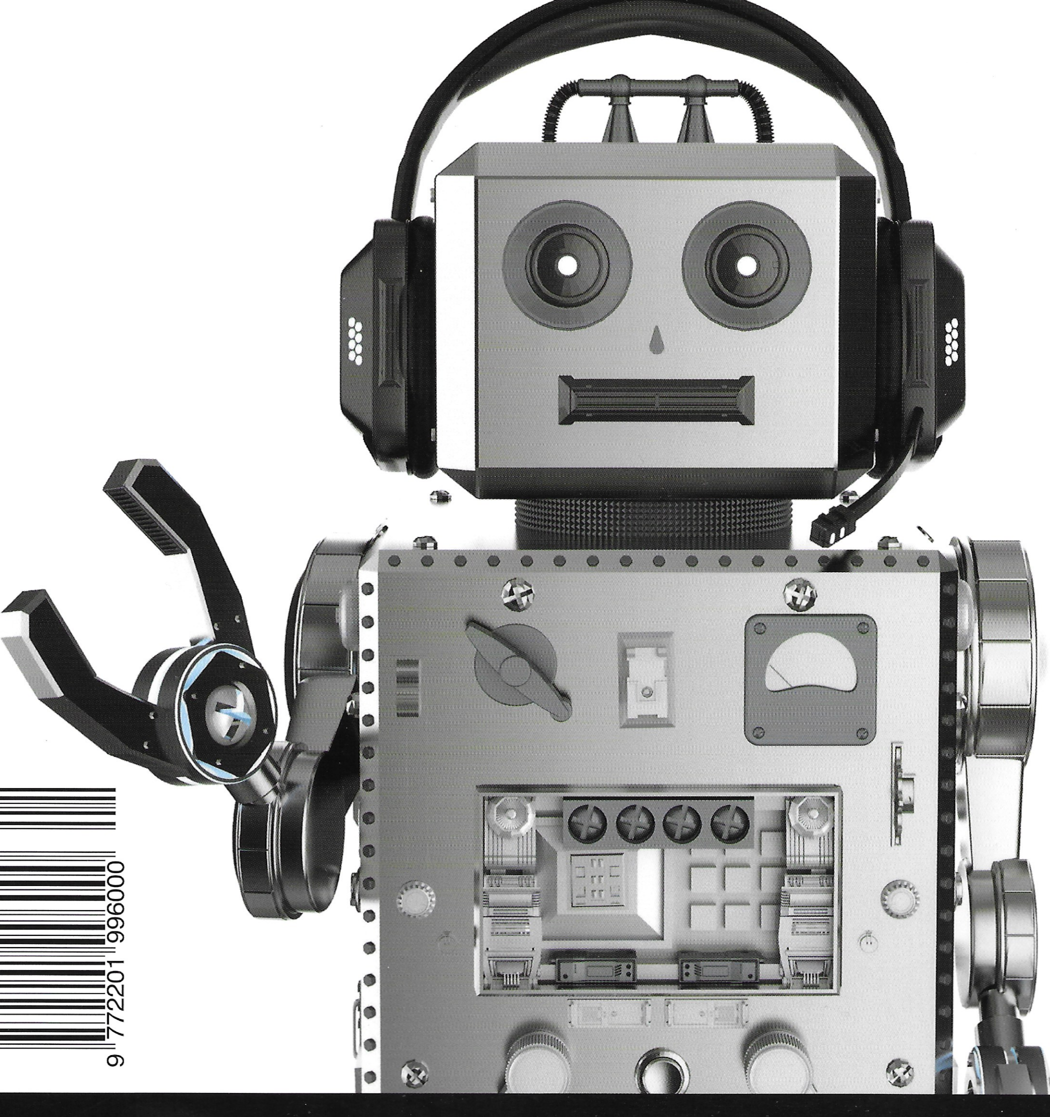

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Haul trucks queuing prediction in open pit mines

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Improving the efficiency of haulage systems is one of the more significant challenges in mining engineering, and is the subject of many research projects undertaken in both academia and industry. For mining, haulage systems must be designed to be as efficient as possible to minimise haulage costs, improve profitability, and increase the total mine value.

Haulage system inefficiency is typically derived from inadequate engineering, which results in poor haul road design, machinery stand-by and downtime, and circuit traffic. Haulage costs can be some of the largest in the mining system. In various case studies, it was found that material transportation represents 50 per cent of the operating costs of a surface mine.

One of the most effective components of haulage system efficiency is the movement of trucks, where these machines consume a significant amount of fuel and play a central role in mine productivity and efficiency. Many factors affect the efficiency of haul trucks, such as the accuracy of dispatching systems, payload, truck speed, haul road condition, road design, traffic layout, fuel quality, weather conditions and drivers' skill.

A review of the literature indicates that the understanding of the energy efficiency of a haul truck is not limited to the analysis of vehicle-specific parameters. Mining companies can often find a more significant increase in productivity, energy-saving opportunities and efficiency improvement by expanding the analysis to include other practical factors, such as payload distribution and variance.

Hauling operations in surface mines consist of different kinds of components. These components are loading, hauling, manoeuvring, dumping, returning and spotting (Figure 1).

In the standard hauling operation, loading time is the time taken to load the truck, and returning time is travelling time for each truck between the loading zone and dumping area. Spotting time is the time during which the loading unit has the bucket in place to dump but is waiting for the truck to move into position. Spotting time will depend on the truck driver's ability and the loading system. Double-side loading should almost eliminate spot time. Dumping time is the time taken for the truck to manoeuvre and dump its payload either at a crusher or dump.

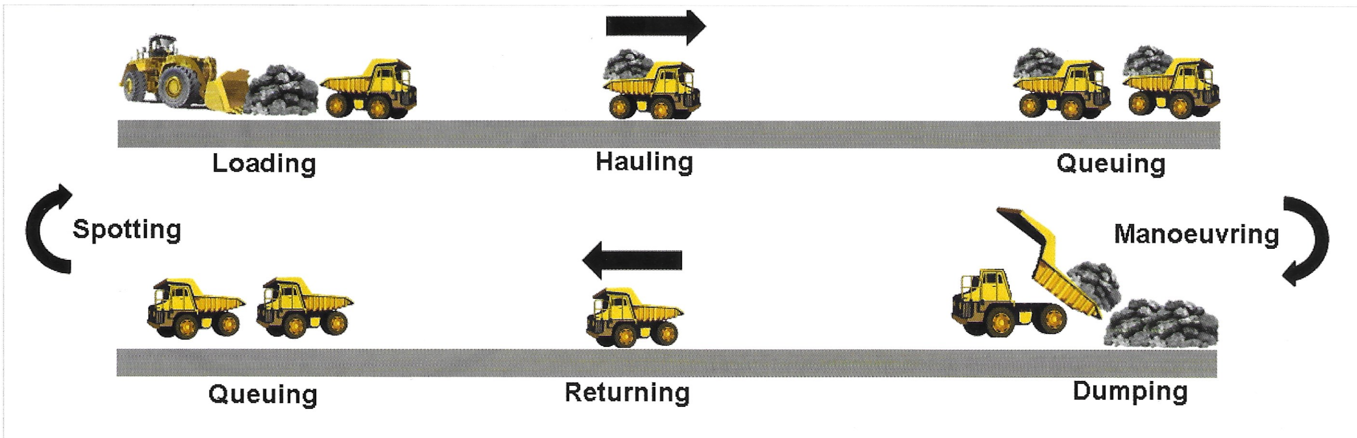

Figure 1. Schematic of a hauling operation in surface mines

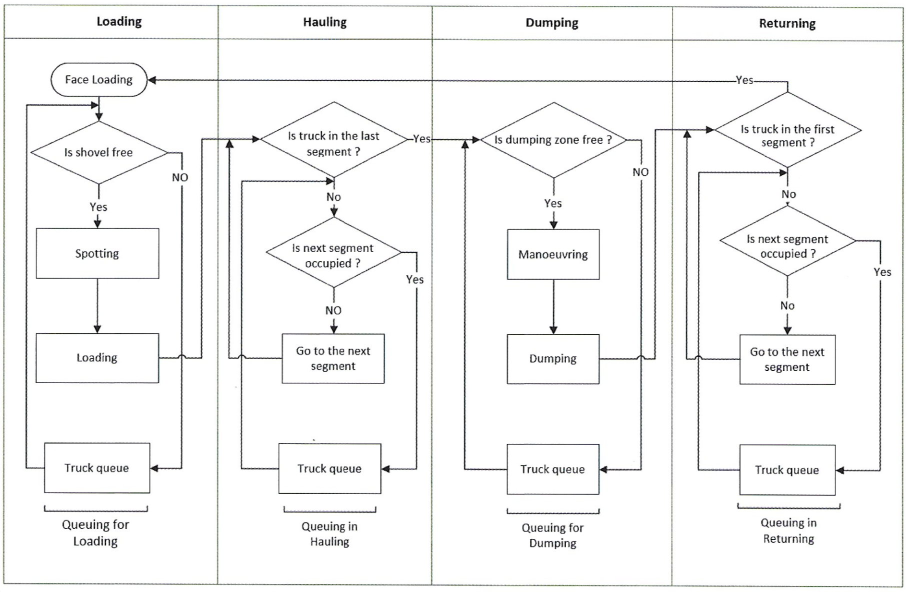

Figure 2. Truck queuing in a surface mine fleet

Based on these hauling operation components, four main times can be defined: fixed time, travel time, wait time and cycle time. The fixed time is a summation of the loading, manoeuvring, dumping and spotting time. It is called 'fixed' because it is substantially invariable for a truck and loading unit combination. Travel time is the time taken to haul and return the payload. Wait time is the time the truck must wait before being served by the loading unit, waiting in a queue for dumping and the waiting time in line behind the overloaded trucks in large surface mines (truck bunching). Cycle time is the round-trip time for the truck. It is the sum of the fixed, travel and waits times. Figure 2 illustrates the four types of truck queuing in a surface mine hauling operation.

Excessive haul-truck queuing at loading and dumping areas results in lower productivity and higher fuel consumption.

On the other hand, every minute a shovel is not loading trucks, or the crasher doesn't have enough mine material, is wasted time and money. Generally, the dispatch system provides industry-proven optimisation of truck assignments in real time, minimising truck queuing in loading and dumping areas to reduce the shovel hang time and crasher idle time. The current dispatch technologies, including the application and related algorithms, however, are not good enough to avoid unnecessary queuing in an open pit mine fleet, especially in loading and dumping areas.

This article summarises a successful advanced analytics application used in a couple of iron ore mine sites in South America to predict the truck queuing in the fleet. The aim of developing the mentioned application was to predict a surge of queues on dumping areas of open pit mines, along with the presumed reasons for those problems. The explanations provided empower the action of final users aiming at avoiding or minimising those scenarios before they happen.

DATA MINING

This project is part of a broader initiative at the advanced analytic centre in a big mining company in South America. It was started in early 2018 when the first stages of the cross-industry standard process for data mining (CRISP-DM) was applied to complete the project. CRISP-DM is an industry-proven way to guide data mining efforts (Figure 3).

As a methodology, CRISP-DM includes descriptions of the typical phases of a project, the tasks involved with each step, and an explanation of the relationships between these tasks. As a process model, CRISP-DM provides an overview of the data mining life cycle.

The life cycle model consists of six phases, with arrows indicating the most important and frequent dependencies between steps. The sequence of the steps is not strict. Most projects move back and forth between stages as necessary. The CRISP-DM model is flexible and can be customised easily. In such a situation, the modelling, evaluation and deployment phases might be less relevant than understanding the data and preparation phases. It is still essential, however, to consider some of the questions raised during these later phases for long-term planning and future data mining goals.

The developed model in this project is being used in the six different dumping locations in the north of Brazil, simultaneously providing a 24/7 set of hourly predictions for each crushing area. The benefit collected by the usage of this tool so far has been accounted for in a total of 10 per cent reduction of queue time on each dumping area it is being used. Following is a summary of each CRISP-DM methodology, and steps in this project – including an exact time frame – are explained.

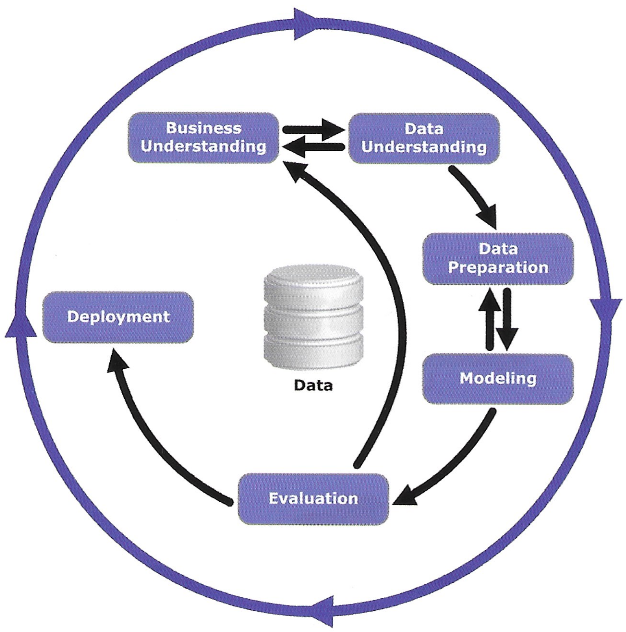

Figure 3. Cross-industry standard process for data mining

Business and data understanding

(Four months)

During these two phases, a series of statistical analyses were conducted to identify which abnormal behaviour had a more significant impact on the productivity cycle of haul trucks. The result of this analysis identified surges of queues on the dumping area as the most counterproductive scenario for the hauling operation cycle. The results were presented and validated in a series of workshops and individual presentations with stakeholders.

Data preparation

(Two months)

During this step, a data mining process was conducted to identify possible reasons for the surge of queue time. This process was performed along with the mine site productivity supervisors throughout a series of discussions, visits to the mine site in question, and in collaboration with the information technology (IT) department. A considerable amount of time was spent to understand all the different variables that somehow impacted the system and where to retrieve them from available datasets.

It was identified that four different data sources contained relevant information for the problem addressed. There was no previous primary key in the four databases (e.g., A, B, C and D), which could be used to join all this information on the same grain of analysis. Nonetheless, all of them were discrete events associated with a start time and end time of that specific event. For example, the central database – referred to here as A – contained the productivity cycle information, such as loading time, dumping time, queue time and the amount of material carried by the truck along with its lithology, and all those events were associated with a specific time in seconds of a day shift. To tackle this challenge, a set of time intervals was selected (i.e., every two hours) to aggregate all features of interest in each database separately, thus resulting in a primary key, making possible the joining of information in a time interval of analysis. The loss of information while aggregating the features was inevitable and necessary to build a primary key to join all the relevant information from the different data sources. A strategy applied to minimise this loss of information was done by taking the average and standard deviation from each continuous feature aggregated on the desired time interval.

Modelling

(Four months)

With the prepared data, and after treating some inconsistencies found, the modelling step started aiming at devising a system capable of predicting surges of queues and stratifying its main contributors. The final designed method is composed of three modules:

1. a predictor module consisting of a nonlinear autoregressive exogenous model (NARX) based on an artificial neural network (ANN) capable of predicting the average queue time faced by haul trucks at dumping areas with performance of 12 per cent of relative root mean square error (RRMSE) on the test set
2. a decision-maker module responsible for producing alarms of surge of queue events performing an F1 score of 0.71 on the test set
3. an explainer module based on the local interpretable model-agnostic explanations (LIME) algorithm, which is capable of stratifying the main contributors for the alarms generated, providing a leaver of action to avoid or minimise such counterproductive scenarios before they occur.

All information generated by the system is displayed on a web user interface.

Evaluation

(One month)

Besides the statistical tests applied during the modelling phase, a more in-depth assessment into the final users' reality was performed. This step consisted of an assisted pilot in which the usage and performance of the system were tested in the real world. Insightful feedback was collected and used to enhance the system.

The user interface that displays the system predictions was the part of the solution that was most benefited by this stage. One example was the creation of a field on the webpage in which the user could write down feedback for each prediction. This feedback is stored in a Structured Query Language (SQL) database for later analysis.

Deployment

(Two months)

During this step, all the integration and automatisation tasks were addressed to establish a full autonomous routine of the application.

Furthermore, it was defined as a crucial entity of the advanced analytics centre projects – the control group. This group is formed by a data scientist and a subject matter expert who meet with the final user every week to collect feedback regarding the performance and usability of the system. Those meetings, which often happen face to face, are essential to keep the users engaged and provide a sense of continuous improvement. This proximity helps to overcome fears in the usage of artificial intelligence–based solutions, which are primarily linked to the replacement of the human workforce.

All possible enhancements regarding user experience and performance of the machine learning models are addressed by the team of the advanced analytics centre led by the control group, which undertakes this essential task as long as the product lives.

SCALABILITY STRATEGY

The code, data, model, packages and metrics achieved during the experimentation cycles were stored to facilitate the rollout of the solution and to guarantee reproducibility of the results obtained in the production environment.

Additionally, to facilitate scaling the project, a maturity scale matrix regarding all topics (i.e., people, data, systems and processes) necessary was developed to apply this solution for different locations.

This scale matrix is presented at workshops of the overall advanced analytic centre solutions' portfolio in events about innovation in many different mine sites. Once the business area shows interest in the solutions, the scale matrix is shared and filled. Based on the result of the as-is scenario, the adaption of the product is started, and it usually takes two to three months to have the product running in an assisted production environment. AR&I