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Procedia Computer Science 6 (2011) 118–123

Procedia
Computer Science

Complex Adaptive Systems, Volume 1
Cihan H. Dagli, Editor in Chief
Conference Organized by Missouri University of Science and Technology
2011- Chicago, IL

An interactive simulation model of human drivers to study autonomous haulage trucks

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Abstract

Driverless haulage trucks have recently been developed for open pit mines. To predict the benefits of an Autonomous Haulage System (AHS), a deterministic/stochastic model has been created to compare AHS to a manual system by estimating bench-marked Key Performance Indicators (KPIs) such as productivity, safety, breakdown frequencies, maintenance and labor costs, fuel consumption, tire wear, and cycle times. The goal of this paper is to describe the driver/autonomous sub-models that function within a virtual 24/7 open pit mine operating with 9 trucks and 2 shovels to move ore to a crusher and waste rock to a dump.

Keywords: Autonomous mine haulage trucks; simulation; ; driver behaviour ; vehicle motion; fuel consumption; tire wear

1. Introduction

How a person drives a vehicle will differ according to individual skills, stress level, training, motivation, concentration, chemical influences, etc. Differences in these parameters may lead to a decline in work performance and an increase in costs as well as creating significant interactions between vehicles that may compromise safety. In order to compare the performance of manually-operated and autonomous systems, it is necessary to build a driver sub-model to simulate different types of drivers operating over a 12-hour shift for 14 work-day periods. Much has been written about factors that influence driving performance, however, little of this literature relates to mine haulage activities. Detailed information about open pit truck drivers is not widely available, so the driver model in this research has been based on a general profile that can be assembled and calibrated with relative ease.

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1877–0509 © 2011 Published by Elsevier Ltd.
doi:10.1016/j.procs.2011.08.023

The hostile and ever-changing environment of a mine site greatly affects driver behaviour. Drory (1985) studied heavy-haul truck drivers in a large open pit mine for 8-hour shifts. Drivers and supervisors described the task as boring and monotonous suggesting that the length, intensity, and repetitive nature of this work with its lack of mental variation lead to this characterization. According to Modular Mining (2011), up to 65% of all haulage truck accidents are caused by operator fatigue.

Driver individuality has a unique impact on driving skills in which health and lifestyle issues such as fitness, poor diet, poor sleep habits and disorders have a strong positive effect on the correlation between performance and fatigue (Mabbott and Lloyd, 2005). According to Hanowski et al. (2003), the worst drivers (up to 25 per cent) are responsible for over 85 percent of haul road accidents. Compounding this problem is the fact that many mines have annual turnover rates of 40% necessitating expensive training programs and leading to poor-quality drivers during the training period - quality being measured both in terms of production and safety.

Thompson (2010) claims that interactions involving driver error and road design are responsible for about 25% of haul truck accidents and he argues that driver performance should be considered when designing haulage roads. As a pit develops, the haul road evolves and undergoes constant redesign with new sections and adaptation of existing sections to pit development and slope stability issues.

Table 1. General factors that affect truck haulage accidents [after Thompson (2010)].

Factors	Percent
Road Design Factors alone	18
Road Design plus Human Error	25
Human error and non-standard acts	19
Human error and Mechanical issues	3
Mechanical Factors alone	1.5
Other Factors	32.5

2. Driver Sub-Model

The number of factors that may influence driver behaviours are extensive and interactions and correlations are difficult to assess directly. Some mines prefer female drivers, for example, claiming that gender issues affect the need for additional maintenance. The suggestion is that women are less aggressive and more respectful of their truck. Whether such anecdotal concepts are accurate or uniform across the industry is speculative and without proper study; one would be remiss in accepting such ideas verbatim. Certain individual traits may also play a role such as energy level, age, health, family and personal issues, as well as tiredness. These are all likely candidate attributes for a model on driver behaviour, but issues of provability diminish this approach. Initially, our model consisted of human attributes such as skill level, time since training, personality, gender, fatigue, time in shift, and time in work period in order to establish a “style" of driving. Although there may be a logical way to relate these inputs to velocity, acceleration, and reaction time behaviours, the method was set aside due to the difficulty in validation. Instead the model was changed to consider only two attributes – Aggressiveness and Stability.

It is evident that how a vehicle is driven with respect to desired velocity and acceleration will affect the KPI elements within an overall haulage system. Some drivers are aggressive while some are passive. The majority operate the vehicle within a close tolerance to the desired levels. As such we can define a global parameter called Aggressiveness that ranges from -1.0 to +1.0 to characterize how a particular human drives a particular truck. The normal behaviour will be 0.0 while the two extremes represent undesired behaviours that exist within the crew.

The best drivers are experienced (more than a year of driving background) and generally have recently completed a retraining program (within the past two months). On the other hand, the worst drivers are novices with less than several months of experience and only preliminary training. Such a driver exhibits either a degree of aggressiveness or a degree of passivity. Average drivers will be somewhere between these two extremes

The objective of the driver sub-model is to generate controlled differences in driver behaviour to obtain valid output ranges for fuel consumption, tire wear, cycle times, production levels, and CO_2 emissions. These ranges can then be compared to those achieved by a simulated Autonomous System in which the variances and deviations from acceptable results are significantly reduced. The model is being created using a discrete-event simulation program called EXTENDSIM that allows the inclusion of a deterministic model of truck movement (ExtendSim, 2007).

Each driver is assigned an Aggressiveness Factor with fuzzy descriptions of Passive, Normal, and Aggressive respectively (see Fig. 1). A second factor called the Stability Factor characterizes the degree to which these fuzzy terms may change during a model test run from the supremum positions of -1.0, 0.0, or +1.0. (The supremum value in Fuzzy Set theory represents values with full membership in the set). Variations from the supremum position describe the "support" range of the fuzzy set which can be relatively large or small depending on the Stability Factor. For each time increment (0.1 seconds) in the truck movement model, the Aggressiveness Factor is allowed to trend on a random basis between the limits established for each support range and at a rate related to the Stability Factor. The Random Trending Algorithm is as follows:

$$AF(t) = AF(t\text{-}1) + \Delta af \qquad \text{Eq. 1.}$$

$$\text{subject to: } AF(t) \leq AF_{max}$$
$$\text{and: } AF(t) \geq AF_{min}$$

where:

AF_{max} = Maximum Aggressiveness Factor of the driver in question
AF_{min} = Minimum Agressiveness Factor of the driver in question
Δaf = Random number between ± 0.005 * AF_{max}

The Aggressiveness Factor determines how each driver chooses to select the steady state velocity on any particular road segment as well as the acceleration. Each segment is assigned a designed maximum velocity and a maximum acceleration. However drivers will deviate from these ranges depending on inter-vehicular interactions as well as their Aggressiveness Factor (see Fig. 2). For example, an Aggressive Driver (+1.0) may choose a steady-state velocity 20% higher than the maximum designed velocity and an acceleration level 20% higher than the maximum designed acceleration. In such a case, this latter variation may result in tires spinning or trucks skidding which can be calculated from truck Rimpull-Speed equations (Parreira and Meech, 2011). These negative behaviours significantly affect tire wear and fuel consumption and are characterized in the model.

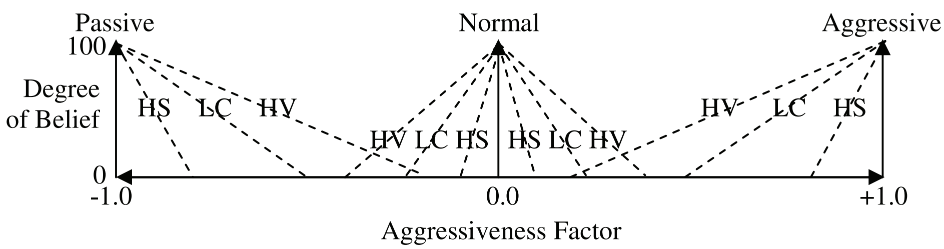

Fig. 1- Aggressiveness Factor and Stability Factor to characterize fuzzy sets: Passive, Normal, and Aggressive. The Stability Factor sets the support range. HS = Highly Stable; LC = Little Change; HV = Highly Variable.

A Passive Driver, on the other hand, will drive much slower than the minimum designed velocity and will accelerate much slower than the minimum. The model uses -15% to characterize this behaviour at the moment. The range of designed velocities and accelerations allow a stochastic Monte Carlo simulation of any particular haulage system and truck-fleet/driver-crew combination. The Aggressiveness Factor allows the impact of individual driver variations on this stochastic simulation to be studied. The model can calibrate the overall distribution range of outputs derived from any test run against the overall distribution range of real data if the simulation uses the real road network and truck-scheduling scheme. Fig. 2 shows data for a CAT 793D truck operating at the Mt. Keith mine between January and June 2011 to illustrate the influence of driver behaviour and truck payload on the velocity selected by each driver. Note that the velocity decisions overlap for each of the three driver types. Aggressive behaviour does not seem to decline with payload suggesting maintenance needs and tire wear will increase. Fuel consumption is not as clear since distance travelled is the dominant factor which is independent of driver behaviour.

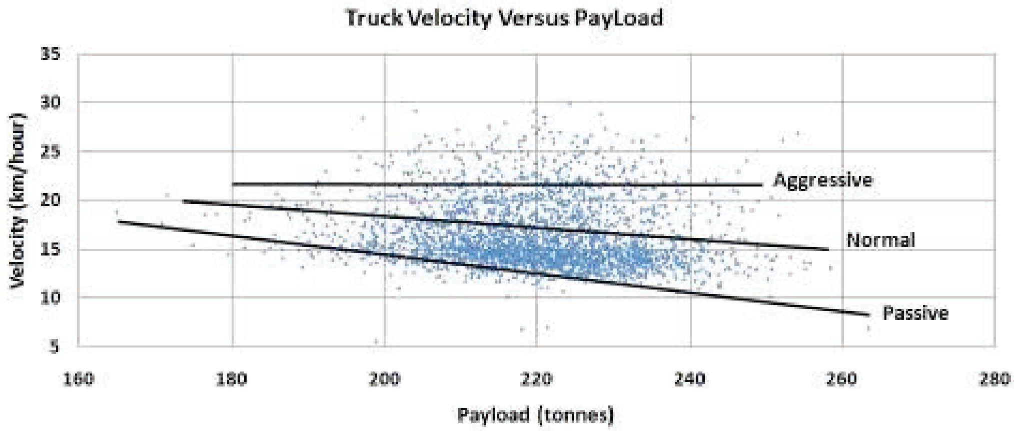

Fig. 2. Truck Velocity as a function of Payload for Truck RD 2020 at Mt. Keith Mine. The trend lines shown for different driver behaviours are for illustrative purposes only to represent approximate supremum positions.

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Table 2. Individual Driver Characterizations.

Aggressiveness Factor		**Stability**		
		Very Stable	Limited Change	Variable
Aggressiveness	Passive	-1.00 to -0.80	-1.00 to -0.50	-1.00 to -0.20
	Normal	-0.10 to +0.10	-0.25 to +0.25	-0.40 to +0.40
	Aggressive	+0.80 to +1.00	+0.50 to +1.00	+0.20 to +1.00

The benefits of Autonomous Haulage are clearly related to higher truck utilization from gains in having no lunches, breaks, and shift-changes - the sum of which can be as much as to 5 hours or more per day. The simulation model allows us to characterize how more consistent driving behaviour results in changes in KPIs such as production, productivity, maintenance schedules and costs, tire wear, and fuel consumption. The same Aggressiveness-Stability Factor analysis can be used to characterize an Autonomous System in which the Aggressiveness Factor is held close to 0.0 (Normal), with a very small deviation reflecting changes in speed and acceleration due to tolerances of the on-board Obstacle Detection and Navigation systems. The set points for velocity and acceleration in an Autonomous System can be chosen to be equal to that of the Manually-Controlled trucks or reduced to a level that is considered safer.

2.2 Reaction Time

The driver model also considers the reaction time that a driver takes to react to a change need with respect to acceleration or braking. The reaction time depends on many factors such as weather, stress level, working conditions, etc. A stochastic set is used to define this reaction:

Table 3. Reaction Times

Type	**Reaction Lag (0.1 s/step)**	
	Time Step	**Variation**
Passive	4	± 1
Normal	3	± 1
Aggressive	2	+ 1
Autonomous	1	0

The model includes stochastic events such as rocks or workers on the road and pick-up vehicles operating within the haulage route. The reaction events and outcomes are as follows:

Table 4. Reaction Event

Rock on the haulage routes	
Manual reaction	**Outcome**
Drive over Rock	higher tire wear
Drive around rock	added distance and time
AHS Reaction	**Outcome**
Always drives around rock	added distance and time
Safety (Human or human in pick-up truck)	
Manual reaction	**Outcome**
Stop	Added time
Failure to see human	Accident (blind spot)
AHS	**Outcome**
Stop	Added time
Stop all trucks until human has left the road network	Zero accidents

A truck can avoid a large rock thus impacting cycle time or it can run over the rock and increase tire wear through cutting the tread. On the other hand, the AHS truck will always drive around a detected rock avoiding any tire failure. Note that if a manual truck is set in the model to run over rocks it may show a better cycle time, however the manual truck tires will deteriorate faster. Looking at safety, a manual truck may stop for a light vehicle or may run over it due to blind spots or driver states such as fatigue or stress. The AHS shuts down its entire system until the worker is at a safe distance. The goal of attempting to define safety KPIs in the model involves studying delays caused by AHS shutdowns compared to the impact of accidents caused by human failures. A series of rules about human behaviour and location are used to study these impacts. The model stochastically varies human presence in the road network every 3 hours (± 2 hours) for durations of 1 hour (± 0.5 hour).

2.2 Navigation

Steering variations in the model are accounted for by stochastically changing travelled distance for each road segment which is affected by driver type and road conditions. A person can drive in a straight line, i.e., with only small deviations; or he/she can travel a longer distance due to rutted conditions, driver behaviours, and the presence of objects (or humans) on the road. Distance variations up to 5% for a short distance of 50 meters, 3% for distances of 500 meters and 2% for distances of 2,000 m or more are assumed. The AHS has a very small distance variation.

3. Output

Based on the value for AF, the velocity and acceleration limits for each driver are set at the start of a 14-day work period. During the simulation, data are stored and managed in an internal ExtendSim database and the relevant run results are exported to an Excel template spreadsheet when the simulation completes. Table 5 shows a comparison of cycle times, productivity, and fuel consumption among different driver types. When completed, the model will be able to compare maintenance and tire wear as well. The tire wear model consists of a fuzzy rule-base that reflects wear in mm/km as a function of Gross Machine Weight (GMW), travel velocity, and temperature. Tire temperature rises at a rate related to GMW and velocity; and then falls back during idle time according to the atmospheric temperature obtained from the Weather sub-model. The maximum wear rate in mm/10,000km can be calibrated according to frequency of tire replacement at the mine.

Table 5. Driver Output (simulated results)

<table>
<tr><th colspan="2"></th><th>Passive</th><th>Normal</th><th>Aggressive</th></tr>
<tr><td colspan="2">Velocity Travel Empty (kph)</td><td>20.0</td><td>26.5</td><td>40.0</td></tr>
<tr><td colspan="2">Velocity Travel Loaded (kph)</td><td>13.0</td><td>16.5</td><td>20.0</td></tr>
<tr><td colspan="2">Cycle Time Empty (min)</td><td>22.50</td><td>16.98</td><td>11.25</td></tr>
<tr><td colspan="2">Cycle Time Loaded (min)</td><td>34.62</td><td>27.27</td><td>22.25</td></tr>
<tr><td colspan="2">Idle Time (min)</td><td>6.00</td><td>6.00</td><td>13.25</td></tr>
<tr><td rowspan="4">Fuel Consumption (L/hr)</td><td>Idling</td><td>20</td><td>20</td><td>20</td></tr>
<tr><td>Loaded</td><td>295</td><td>300</td><td>330</td></tr>
<tr><td>Empty</td><td>170</td><td>186</td><td>210</td></tr>
<tr><td>Total</td><td>236</td><td>189</td><td>168</td></tr>
<tr><th colspan="2">Overall Results</th><th colspan="2">Manual</th><th>Autonomous</th></tr>
<tr><td colspan="2">Number of Cycles / day</td><td colspan="2">20.0</td><td>23.2</td></tr>
<tr><td colspan="2">Average Cycle Time (min)</td><td colspan="2">52.0</td><td>54.0</td></tr>
<tr><td colspan="2">Total Driving Time (hours)</td><td colspan="2">17.3</td><td>20.9</td></tr>
<tr><td colspan="2">Breaks / Lunches (min)</td><td colspan="2">180.0</td><td>0.0</td></tr>
</table>

4. Conclusion

In order to build a driver model, this research has focused on defining Aggressiveness and Stability Factors that can be assigned by mine engineers to characterize particular members of their fleet crew. A key factor in this sub-model is the variation in how different driver behaviours influence truck speed and acceleration. The main objective of the driver sub-model is to obtain output ranges for fuel consumption, tire wear, cycle times, production levels and CO_2 emissions for comparison with a less variable AHS. When the model described in this paper is completed, an accurate comparison of Autonomous Haulage with a human-driver system can be done using benchmarked Key Performance Indicators such as tire wear, fuel consumption, productivity, maintenance, etc.

5. Acknowledgment

The authors wish to thank BHP-Billiton Nickel West Division for supporting this research.

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