Development of an Advanced Data Analytics Model to Improve the Energy Efficiency of Haul Trucks in Surface Mines



Research Team:

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Dr Saiied Aminossadati
Professor Peter Knights
Associate Professor Mehmet Kizil
Professor Paul Lever







Ali Soofastaei BSc, MSc, PhD, MIEAus, PMP

12 years Work Experience in Mining, Oil and Gas Industry

7 years Work Experience in Academia (Mechanical, Industrial and Mining Engineering)

- **38** Published Journal Paper
- **19** Conference Paper
- 3 Patents
- 2 Developed Software

More Information:

www.soofastaei.net



- 103 years old (founded in 1910)
- Over 43,000 students
- ❖ 10,500 international students from 130 countries
- Ranked 48th in the world by time higher education (2015)
 The best research university in Australia by ERA (2014)
- ❖ Over 500 PhDs awarded annually
- ❖ Budget of \$1.2 billion, research income \$500 million



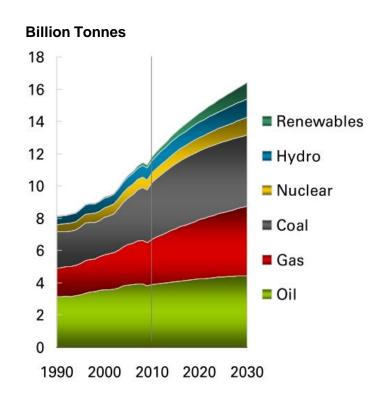


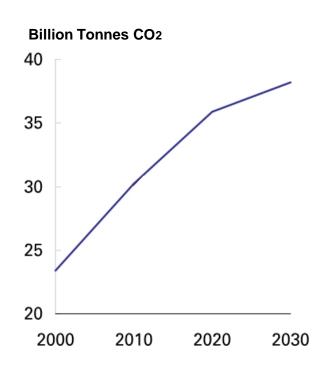
- ❖ Home to 1.9 million residents
- Inner-city beach, cultural centres, museums, art galleries, mall and world-class international airport
- Gateway to the gold and sunshine coasts, tropical islands, theme parks, great barrier reef, outback, golden beaches, and endless tourist attractions
- 243 days of sunshine throughout the year
- **❖** Multicultural, international city

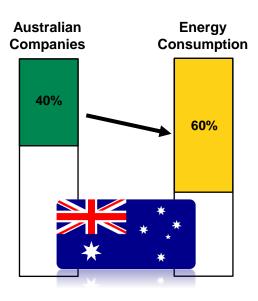




Introduction







The international energy agency, estimates that by 2030 global energy needs will be **50%** higher than today and this will be **60%** in Australia. (IEA, 2015)

It is estimated that **60%** of energy use in Australia is consumed by **40%** of businesses with about **30%** Saving opportunity. (EEO, 2014)



Aim and Objectives

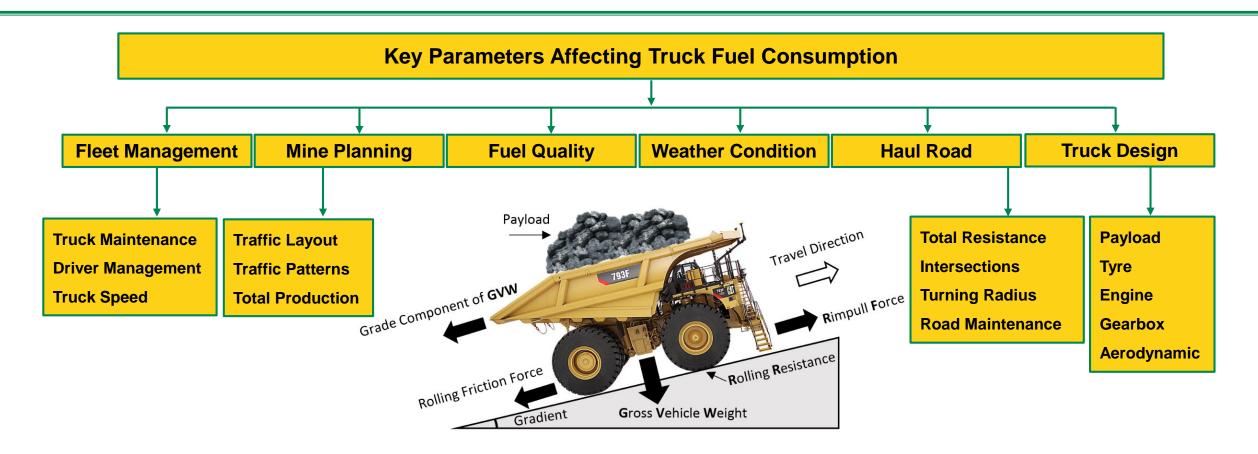
Aim:

To develop an advanced data analytics model for analyzing the complex interactions that influence the energy efficiency of haul trucks in surface mining.

Objectives		Method
Identify key factors driving haul truck energy efficiency;	-	Literature Review
Select the most important controllable parameters;	\rightarrow	Survey
Quantify the impact of the selected parameters;	\rightarrow	Data Analysing (Non-linear Regressions)
Simulate the combined interaction of the parameters;	\rightarrow	Artificial Neural Network (ANN)
Maximise resultant energy efficiency gains; and	\rightarrow	Genetic Algorithm (GA)
Validate the resultant models.	\rightarrow	Analysing Mine Site Real Data Sets



Identify key factors driving haul truck energy efficiency

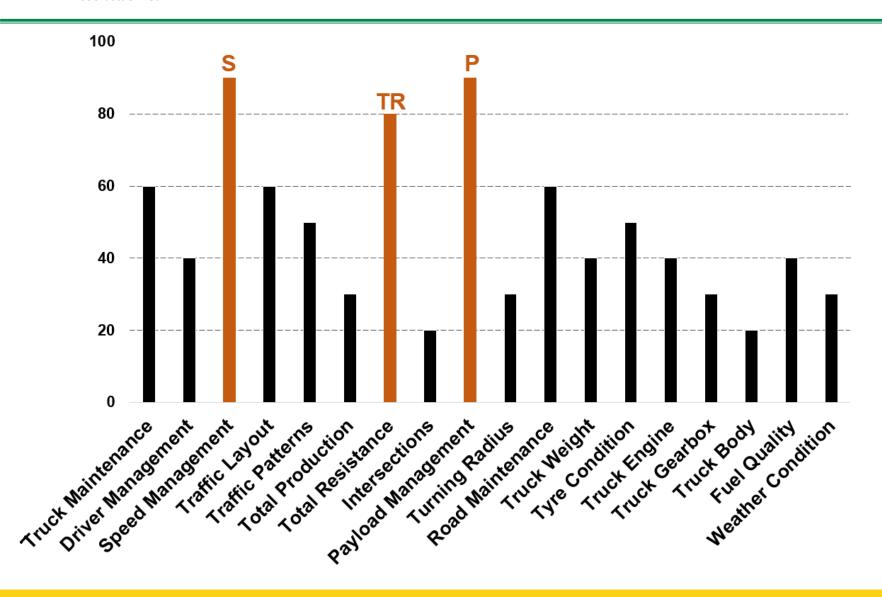


References:

(Beatty and Arthur, 2009), (Peck and Lee, 2011), (Clark and Cox, 2008), (Masic, et al, 2011), (Li and Liu, 2012), (Bascetin, et al, 2010), (Kesimal, 2004), (Roobin and Wilson, 2008), (Satterthwait, 2013), (Lowery, 2010), (Carter, 2011), (Choi and Nieto, 2012), (E.E.O, 2012), (Wayne and Brus, 2001), (Holman, et al, 2006), (Peake and Septian, 2010), (Redich, 2012), (Wang, et al, 2013), (Caterpillar, 2011), (Anzabi, et al, 2012), (Kecojeric, et al, 2011), (Komatsu, 2012), (Mitsubishi, 2012), (Lee, 2010).



Select the most important controllable parameters



Criteria

Can we collect data?

Are they controllable?

Are they achievable?

Can we model them?

Are they important for industry?

Selected Parameters

Payload

Total Resistance

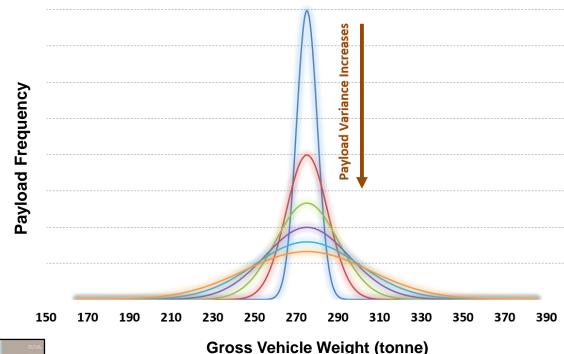
Truck Speed



A Comprehensive Investigation of Loading Variance Influence on Fuel Consumption and Gas Emissions in Mine Haulage Operation

Effective Parameters on Loading Variance:

- Material density
- Truck-loader Matching
- Particle size distribution
- Number of shovel passes
- Swell factor



Normal Payload Distribution for Difference Standard Deviation (CAT 793D)



Soofastaei, A., Aminossadati, S.M., Kizil, M.S. and Knights, P.,

A Investigation of Loading Variance Influence on Fuel Consumption
and Gas Emissions in Mine Haulage Operation. International Journal
of Mining Science and Technology, (2016). 22(1): P. 245-258





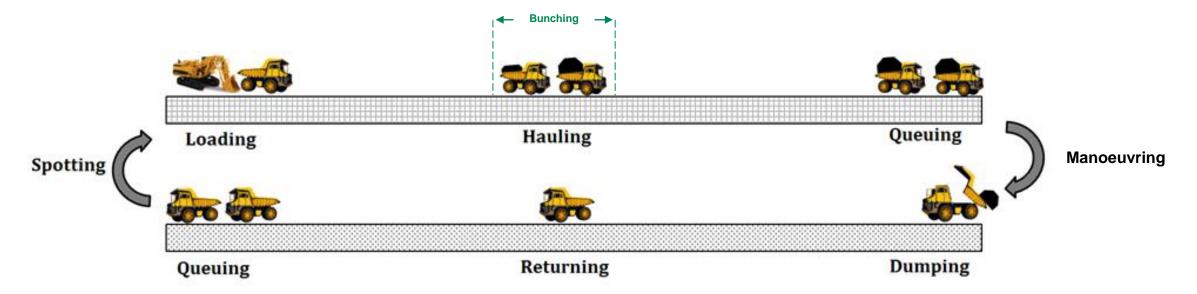
Calculated Indexes for CAT 793D with average Total Resistance 15% (Sample)

σ	FC_{Index} L/(tonne.hr)	Fuel Cost _{Index} \$/(tonne.hr)	CO ₂ -e _{Index} kg/(tonne.hr)	CO ₂ -e Cost _{Index} \$/(tonne.hr)	Total Cost _{Index} \$/(tonne.hr)
0	0.38	0.37	1.02	0.05	0.42
5	0.45	0.44	1.22	0.07	0.51
10	0.53	0.52	1.44	0.08	0.60
15	0.63	0.61	1.69	0.09	0.70
20	0.73	0.72	1.97	0.11	0.83
25	0.85	0.83	2.29	0.12	0.95
30	0.98	0.96	2.65	0.14	1.10

Data collected from company (2015-2016)



Truck Congestion (Bunching) in Deep Surface Mining Operations





Soofastaei, A., Aminossadati, S.M., Kizil, M.S. and Knights, P.,

A Discrete-Event Model to Simulate the Effect of Payload Variance on Truck Bunching, Cycle Time and Hauled Mine Materials.

International Journal of Mining Technology, (2016). 18(1): P. 161-179

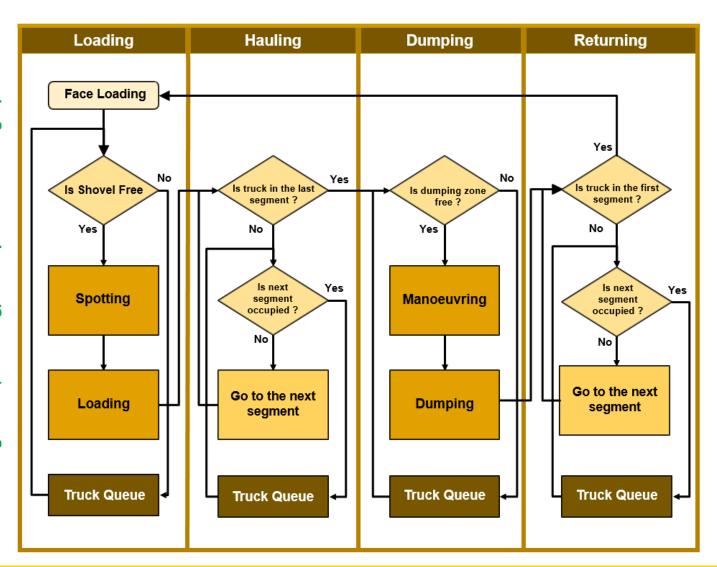


Bunching

Heavily loaded trucks travel slower up ramps than lightly loaded trucks. Faster trucks are slowed by the presence of slower trucks, resulting in 'bunching' and production losses.



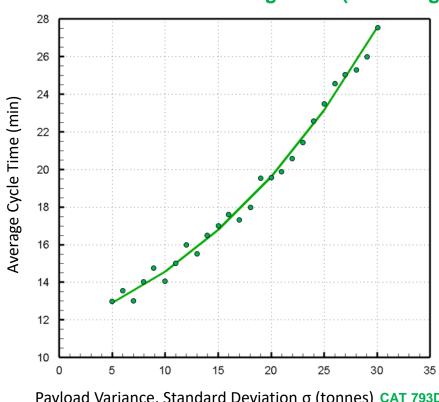
Operations Truck Congestion (Bunching) in Deep Surface Mining



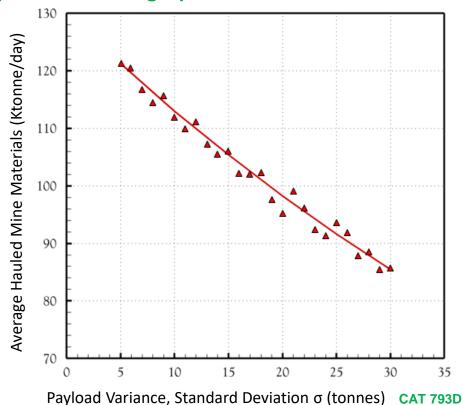




Truck Congestion (Bunching) in Deep Surface Mining Operations



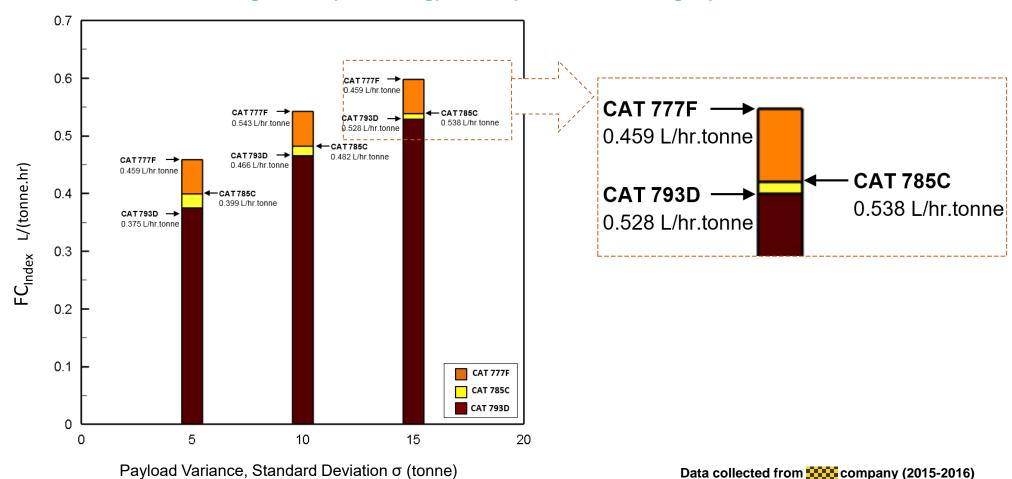
Payload Variance, Standard Deviation σ (tonnes) CAT 793D



Data collected from company (2015-2016)



Truck Congestion (Bunching) in Deep Surface Mining Operations





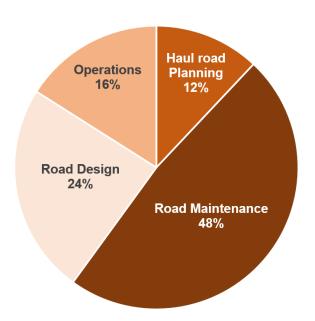
Quantify the impact of the selected parameters (Total Resistance)

The Influence of Rolling Resistance on Haul Truck Fuel Consumption in Surface Mines

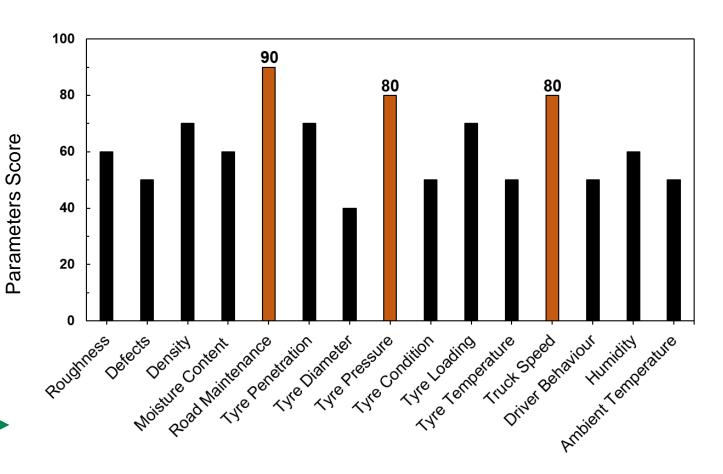
Online Survey

Participants: 50 Industry Personnel

Response Rate: 76%



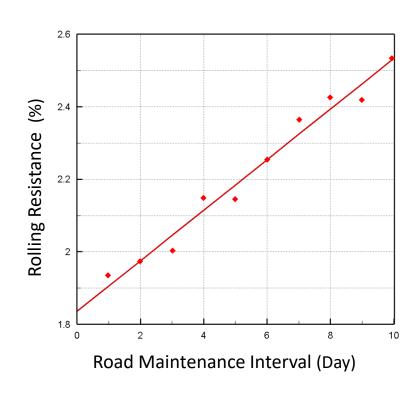
Influential Parameters on Rolling Resistance

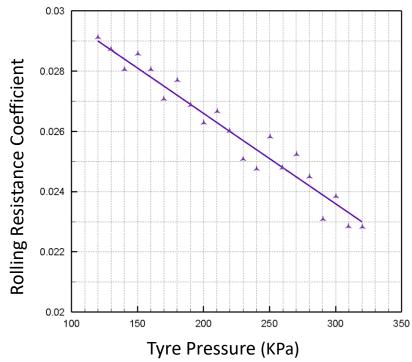


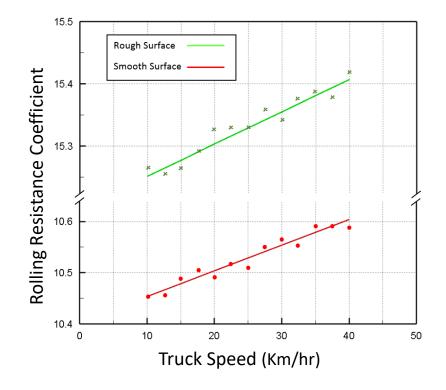


Quantify the impact of the selected parameters (Total Resistance)

The Influence of Rolling Resistance on Haul Truck Fuel Consumption in Surface Mines



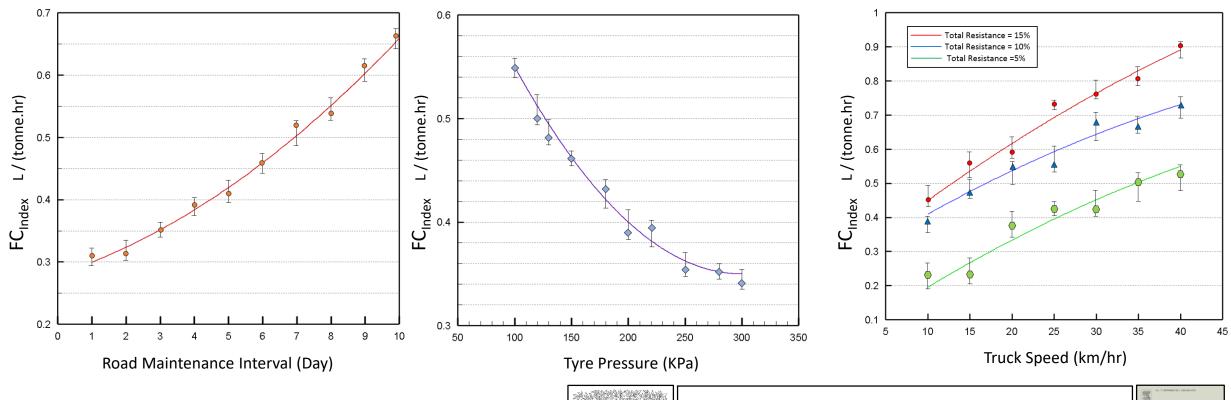






Quantify the impact of the selected parameters (Total Resistance)

The Influence of Rolling Resistance on Haul Truck Fuel Consumption in Surface Mines



Data collected from company (2015-2016)



Soofastaei, A., Aminossadati, S.M., Kizil, M.S. and Knights, P.,

The Influence of Rolling Resistance on Haul Truck Fuel Consumption in

Surface Mines. Tribology International Journal, (2016). 15(1): P. 185-191





Quantify the impact of the selected parameters (Truck Speed)



Hauling Operation





On-line Data Processing



Collecting Data (On-Board Computer Device)





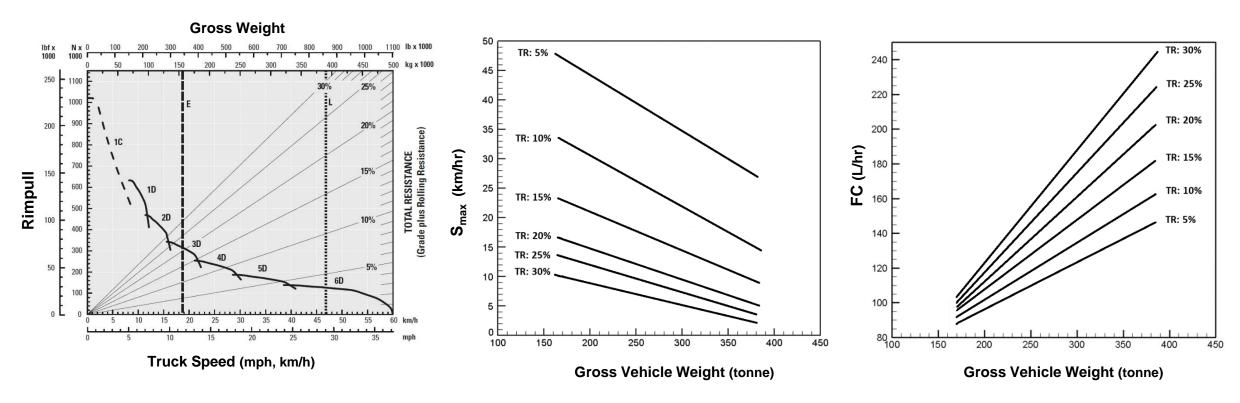
On-Board Monitoring





Quantify the impact of the selected parameters (Truck Speed)

The Effect of Average Truck Speed on Fuel Consumption in Surface Mines





Completed based on the Caterpillar Performance Handbook (2015)

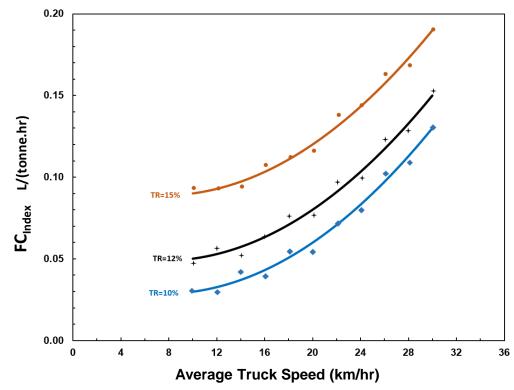


Quantify the impact of the selected parameters (Truck Speed)

The Effect of Average Truck Speed on Fuel Consumption in Surface Mines



The mine is a large iron mine located in western Australia in represents one of the largest iron ore reserves in Australia and in the world having estimated reserves of 2 billion tonnes of ore grading 35.5% iron metal.





Soofastaei, A., Aminossadati, S.M., Kizil, M.S. and Knights, P.,

AppliedEnerg

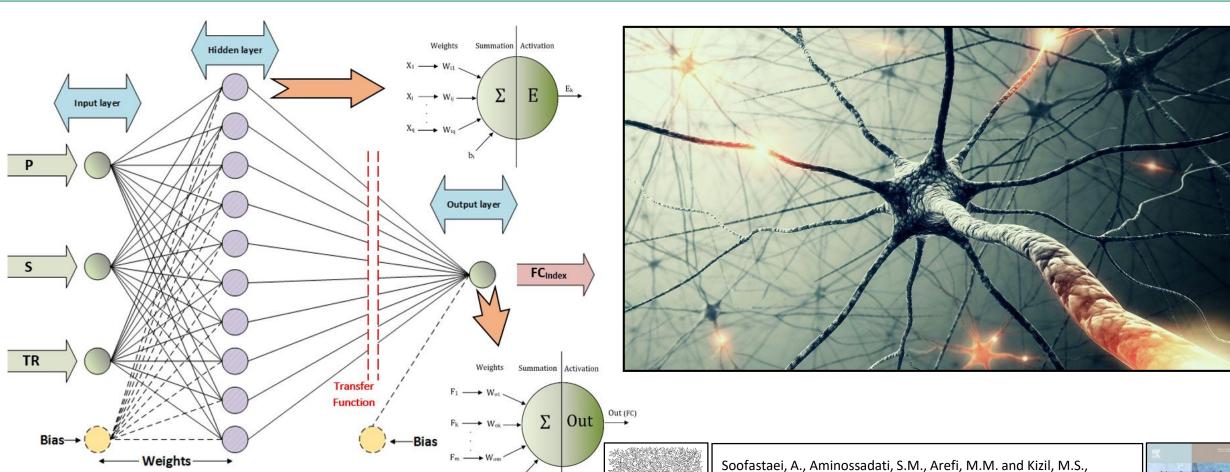
The Influence of Truck Speed on Energy Consumption.

Tribology International Journal, (2016). 12(2): P. 352-231





Artificial Neural Network (ANN)



P: Payload (tonne), S: Truck Speed (Km/hr), TR: Total Resistance (%)

FC_{Index}: Fuel Consumption (L/(tonne.hr))

Development of a multi-layer perceptron artificial neural network
model to determine haul trucks energy consumption. International

Journal of Mining Science and Technology, (2016). 26(2): P. 285-293





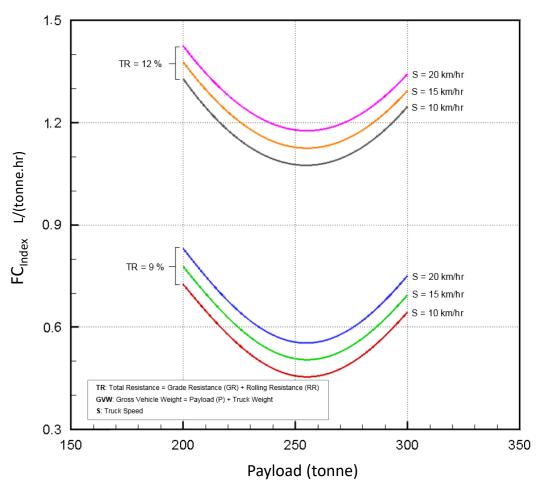
Artificial Neural Network (ANN)



Mine

mine is a coal mine located in the Central Queensland south of the town of the town of the mine has coal reserves amounting to 877 million tonnes of coking coal, one of the largest coal reserves in Asia and the world. It has an annual production capacity of 13 million tonnes of coal.





Correlation between P, S, TR and FC_{Index} based on the developed ANN model for CAT 793D.

Data collected from company (2015-2016)



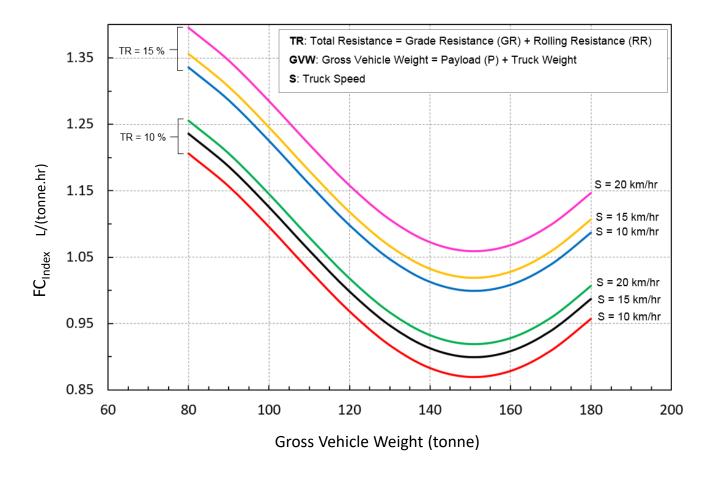
Artificial Neural Network (ANN)



Mine

The mine is a large copper mine located in Arizona. represents one of the largest copper reserves in the United States and in the world, having estimated reserves of 3.2 billion tonnes of ore grading 0.16% copper.





Correlation between P, S, TR and FC_{Index} based on the developed ANN model for CAT 777D.



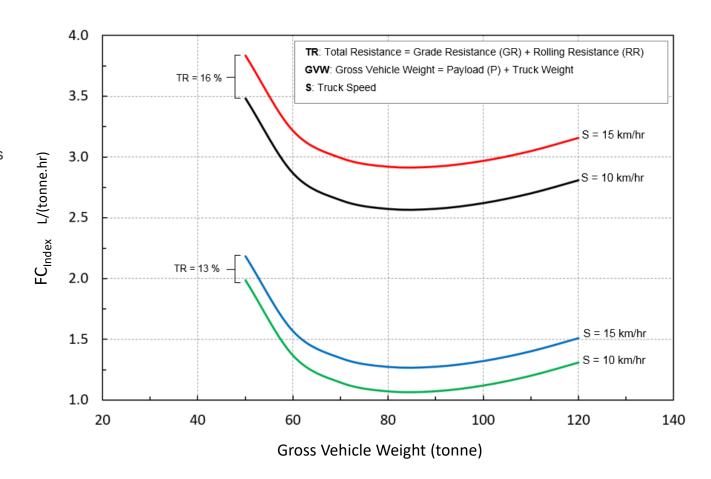
Artificial Neural Network (ANN)



Mine

The Mine is a large copper mine located in the Mountains of Arizona. The deposit had estimated reserves (in 2013) of 907 million tonnes of ore grading 0.26% copper and 0.03% molybdenum. The mine is located in southern Pima County, southwest of Tucson.





Data collected from company (2015-2016)

Correlation between P, S, TR and FC_{Index} based on the developed ANN model for CAT 775G.



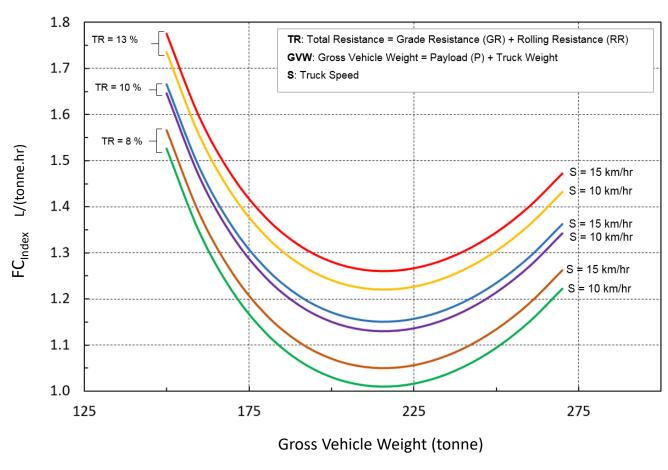
Artificial Neural Network (ANN)



Mine

The mine is a surface coal mine operated by Energy on the Navajo Indian Reservation in northern Arizona. About 400 acres are mined and reclaimed each year, providing about 8 million tonnes of coal annually.

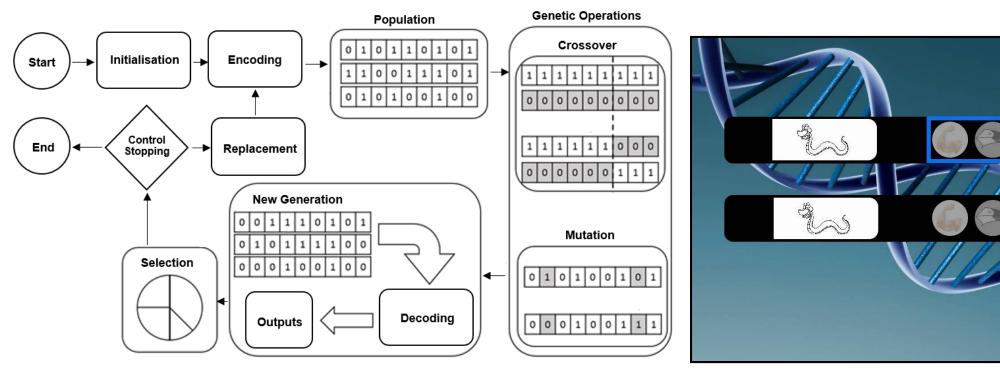


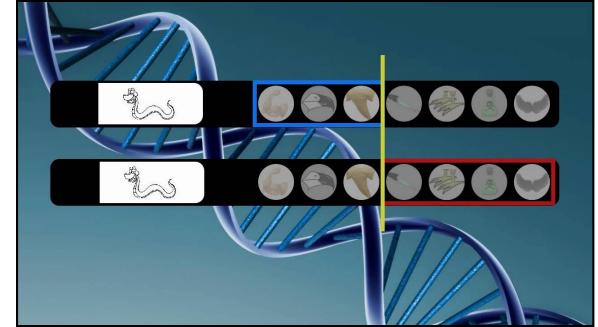


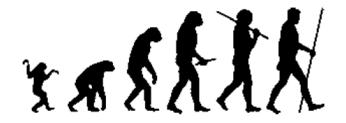
Correlation between P, S, TR and FC_{Index} based on the developed ANN model for CAT 785D.



Genetic Algorithm (GA)







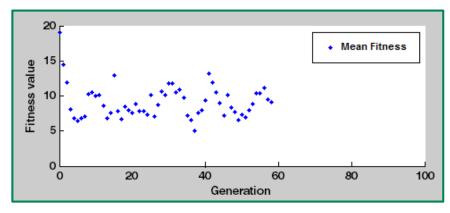


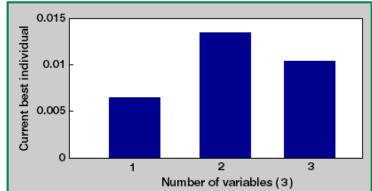
Soofastaei, A., Aminossadati, S.M., Kizil, M.S. and Knights, P., Reducing **Fuel Consumption of Haul Trucks in Surface Mines Using Genetic Algorithm.** Applied Soft Computing, (2016). 38(2): P. 264-298

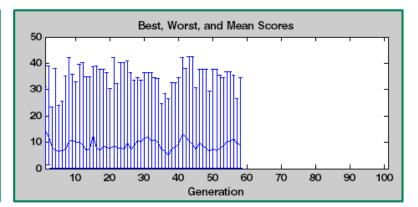


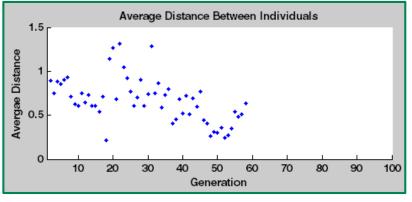


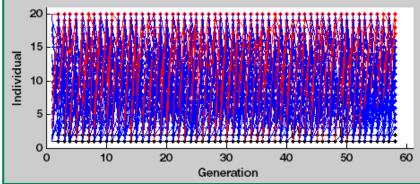
Genetic Algorithm (GA)

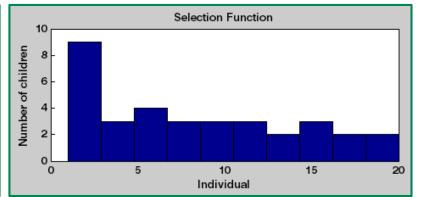






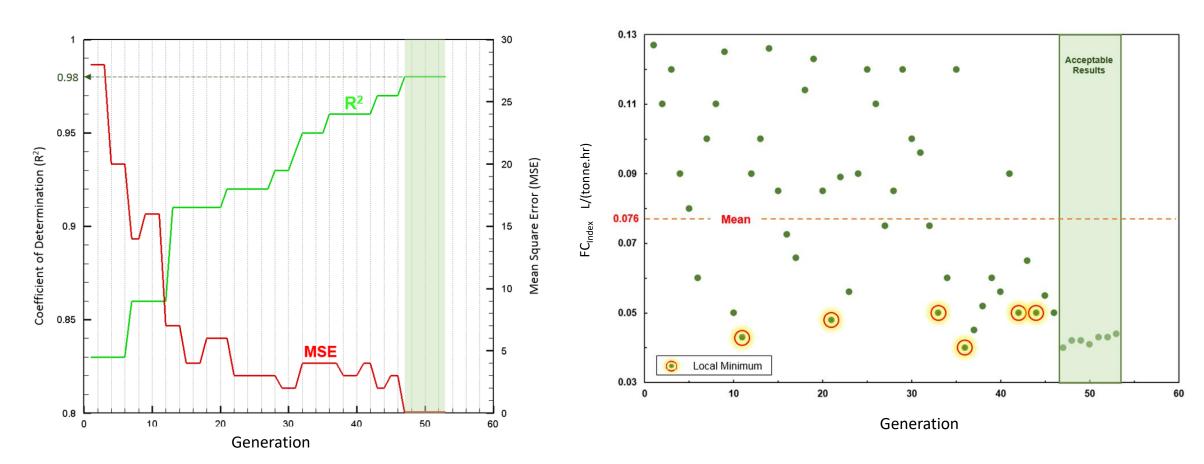








Genetic Algorithm (GA)



The coefficient of determination and mean square error for all generation

Fuel consumption (Fitness Value) in all generations



Genetic Algorithm (GA)

The range of normal values for variables in developed model

Variables	Minimum	Maximum
Gross Vehicle Weight (tonne)	150	380
Total Resistance (%)	8	20
Truck Speed (Km/hr)	5	25



Optimum	range of variables to minimise fuel consumption
	by haul trucks finalised by GA Model

Variables	Minimum	Maximum
Gross Vehicle Weight (tonne)	330	370
Total Resistance (%)	8	9
Truck Speed (Km/hr)	10	15

Variables	Minimum	Maximum
Gross Vehicle Weight (tonne)	65	150
Total Resistance (%)	9	25
Truck Speed (Km/hr)	10	45



Variables	Minimum	Maximum
Gross Vehicle Weight (tonne)	145	155
Total Resistance (%)	9	11
Truck Speed (Km/hr)	10	12



Genetic Algorithm (GA)

The range of normal values for variables in developed model

Variables	Minimum	Maximum
Gross Vehicle Weight (tonne)	45	85
Total Resistance (%)	13	20
Truck Speed (Km/hr)	5	55



Optimum range of variables to minimise fuel consumption by haul trucks finalised by GA Model

Variables	Minimum	Maximum
Gross Vehicle Weight (tonne)	75	90
Total Resistance (%)	13	14
Truck Speed (Km/hr)	9	13

Variables	Minimum	Maximum
Gross Vehicle Weight (tonne)	125	215
Total Resistance (%)	8	15
Truck Speed (Km/hr)	5	45

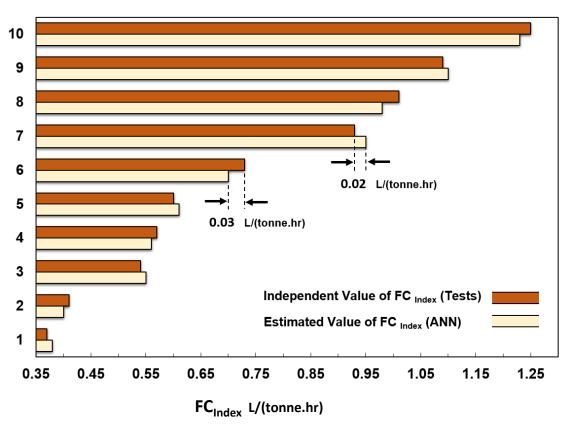


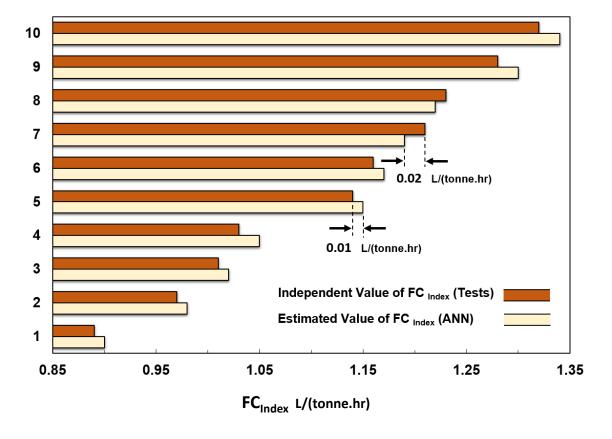
Variables	Minimum	Maximum
Gross Vehicle Weight (tonne)	200	225
Total Resistance (%)	8	9
Truck Speed (Km/hr)	10	15



Validate the developed ANN computer model

Sample values for estimated (ANN) and independent (Tests) fuel consumption





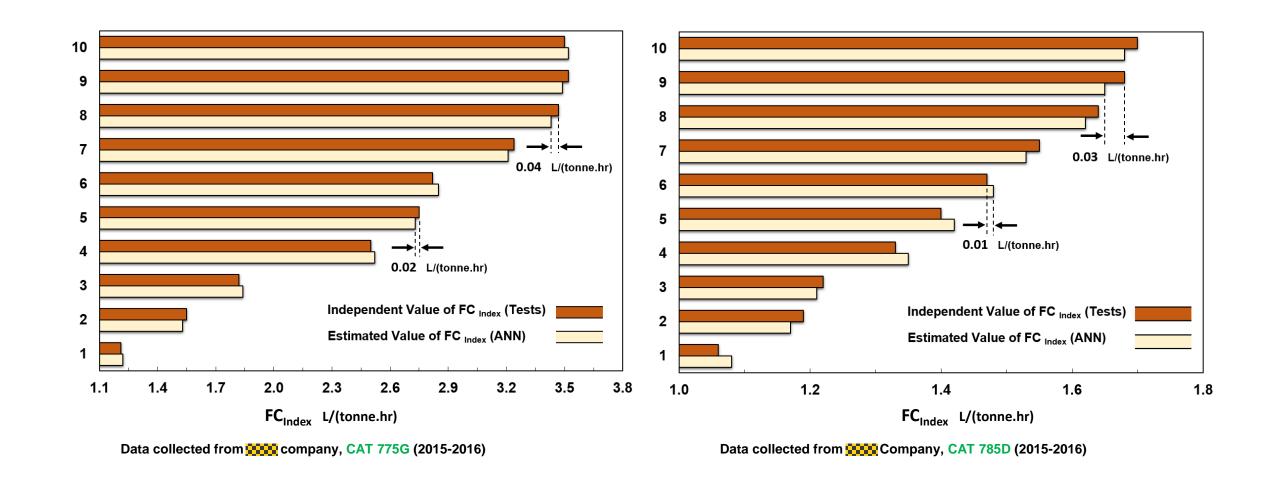
Data collected from company, CAT 793D (2015-2016)

Data collected from Company, CAT 777D (2015-2016)



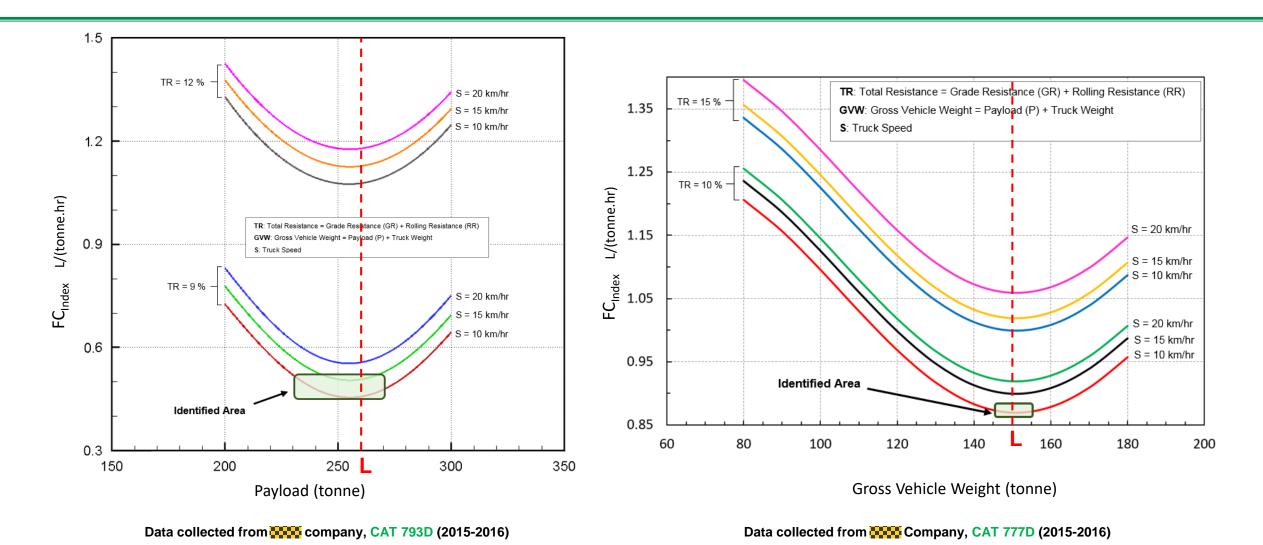
Validate the developed ANN computer model

Sample values for estimated (ANN) and independent (Tests) fuel consumption



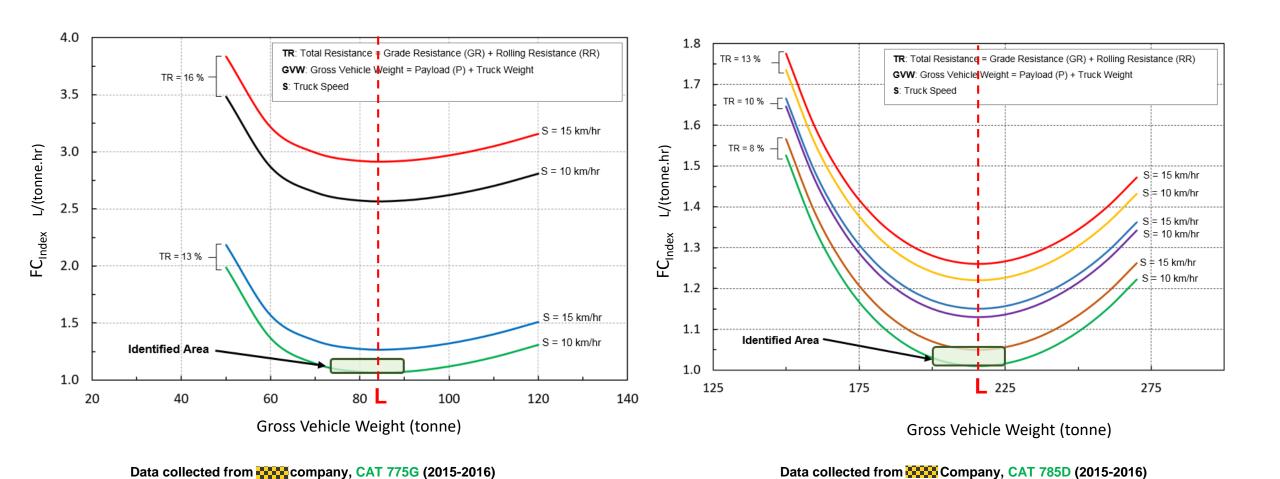


Validate the developed GA computer model





Validate the developed GA computer model





Conclusions

- ✓ This study has advanced a structured methodology involving ANNs and GAs to predict fuel consumption of mining haul trucks and to optimise set points for key controllable parameters.
- ✓ In this application, the results of the ANN and GA algorithms applied to coal and coper mine case studies demonstrate that control parameters (payload, speed and total resistance) should be maintained between tight control limits.
- √ This methodology is applicable to a range of data analytics problem.



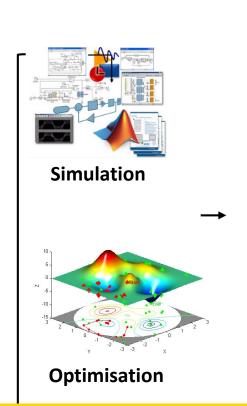






Current research projects







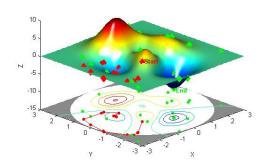




Current research projects



Simulation



Optimisation

Haul Truck Advanced Data Analytics Model

VIMS ® Simulation & Prediction MineStarTM Model Optimization



Current research projects



Maintenance



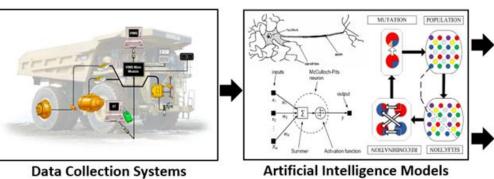
Breaking System

ACARP

Australian Coal Association Research Program

ACARP Accepted Proposal

Project Title: Advanced Predictive Analytics for Haul Trucks Braking System





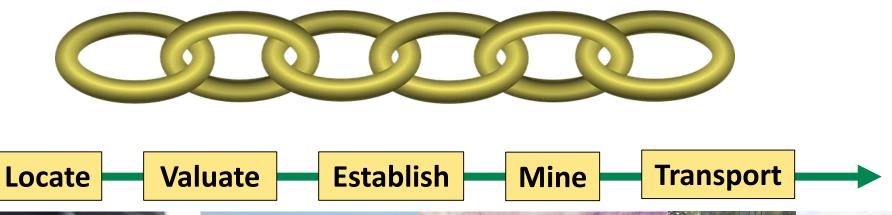
Advanced Predictive Analytics



Future research plan

Development of a Comprehensive Advanced Data Analytics Model to Improve Energy

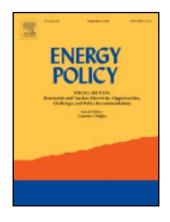
Efficiency and Productivity through the Mining Value Chain

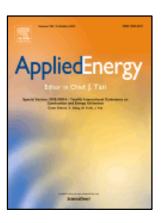




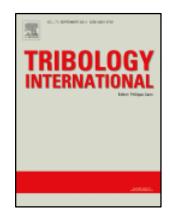


Publications

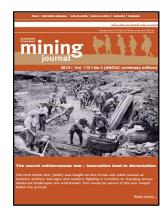


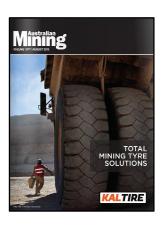




















Collaborations

Academia

The University of Arizona – Tucson

West Virginia University

The Pennsylvania State University

The University of California Berkeley

The University of California Los Angeles

The Massachusetts Institute of Technology – Cambridge

Harvard University – Boston

Columbia University – New York

Microsoft Research Centre – Washington DC

















Collaborations

Academia

The University of Western Australia – Perth

The University of Queensland

Mining Education Australia

The University of Adelaide

University of Wollongong

The University of New South Wales















Collaborations

Industry

Downer EDI Mining Company – Brisbane Office

BHP Billiton Mitsubishi Alliance Company

Fortescue Mining Company – Perth Office

Leighton Mining Company

Rio Tinto Mining Company

Caterpillar

Freeport-McMoRan, Peabody Energy

CONSOL Energy – Pittsburgh, Pennsylvania Office

Computer Science Corporation

Australia Mining Cooperative Research Centre

Mining 3 Australia

























