

# Why autonomous assets are good for reliability – the impact of ‘operator-related component’ failures on heavy mobile equipment reliability

Melinda R. Hodkiewicz<sup>1</sup>, Zac Batsioudis<sup>1</sup>, Tyler Radomiljac<sup>1</sup>, Mark T.W. Ho<sup>1</sup>

<sup>1</sup>University of Western Australia, Perth, WA, 6009, Australia

[Melinda.hodkiewicz@uwa.edu.au](mailto:Melinda.hodkiewicz@uwa.edu.au)

## ABSTRACT

This study examines the maintenance records for components necessary for the comfort and safety of the operators of heavy mobile equipment. The results show that air conditioners, ladders, driver’s seats and mirrors and other required operator-related components can have a significant impact on an asset’s reliability. Analysis was conducted on 10 years of work orders for five identical 1400HP shovels and three identical 1470HP shovels. The results suggest that removing operator-related components contribute to a 15% decrease in the number of work orders and an 8% increase in reliability. In an autonomous asset these components would not be required. The key to this analysis is a rule-based expert system used to clean more than ten thousand work orders and allocate events to specific sub-systems with associated failure modes. While the mining industry has moved to autonomous haul trucks and drills, there are as yet no autonomous shovels. For manufacturers looking at the business case for these units, the availability of data on the reliability increase from removing the operator-related components will be valuable information.

## 1. INTRODUCTION

The mining sector has and continues to be a significant factor in many national economies such as in Australia, Chile, South Africa and other countries. In the decade to 2012 the bulk commodity mining sector such as iron ore and coal experienced a boom. As a result mining companies expanded production and management focus was on moving tons rather than an emphasis on cost saving and efficiency. However starting in 2011/2012, prices for these commodities more than halved and cost cutting and capital efficiency are major concerns for mining leaders. As a result there is considerable emphasis on innovation. One focus area is the reduction of

people on site through automation of mobile equipment. This has potential benefits in both health and safety, through reduced exposure of workers to site conditions and in cost savings by reduction in payroll costs (Hodkiewicz, 2015, Durrant-Whyte et al., 2015). As a result the mining sector has been a leader in the development of unmanned or autonomous haul trucks and more recently drill rigs.

A mining operation can generally be broken down into five processes – drilling, blasting, loading, hauling, and processing. Once the ore is drilled and blasted into small fragmentations, it is loaded (typically using excavators and shovels) onto haul trucks where it is taken away for processing or to the waste dump. A shovel is a mobile mining machine used predominantly for extracting ore from the ore body using a ‘digging’ mechanism. A typical open pit mine site will have a small number, usually one to five, shovels. The purchasing costs of these heavy duty shovels is typically millions of dollars (approximately 3 million USD for the shovel used in this study). Shovels are primary production units and operate continuously unless they are taken down for planned or unplanned maintenance. Any downtime on the shovel means that production is halted and the trucks assigned to that shovel have to be rerouted or are idle.

The automation of a shovel is a more complex task than haul trucks and drill rigs. The expertise of the shovel operator is believed to play a key role in terms of identifying ore and waste, and in managing the digging action of the shovel bucket to maximize material movement, achieve ore/waste separation and minimize wear and tear on the equipment. However there are a number of research projects aimed at monitoring and improving the performance of the operator. As these develop, it is conceivable that the concept of an autonomous shovel will be realistic.

It is therefore appropriate to ask ourselves “what is the reliability cost of having an operator on a shovel?” A number of components are only installed on the shovel because we have an operator. These include operator-related components such as the seat, radio, air conditioning/ heating, mirrors,

Melinda Hodkiewicz et al. This is an open-access article distributed under the terms of the Creative Commons Attribution 3.0 United States License, which permits unrestricted use, distribution, and reproduction in any medium, provided the original author and source are credited.

ladders and so on. These would not necessarily be required on an autonomous unit. This work sets out to examine how the reliability of the shovel is affected by the reliability of the operator-related components.

## 2. LITERATURE REVIEW

Reliability block diagram models (RBD) are a tried and tested approach to modelling mobile equipment. In today's mining sector both mining companies and original equipment manufacturers have developed RBDs however their structure and the values used in the individual reliability blocks are commercially sensitive. They are usually maintained by a reliability engineering group internal to the company using commercial software packages. One of the few peer-reviewed publications on RBD for mobile mining assets is by (Kumar et al., 1989). This 1989 study examined the reliability of a load haul dump (LHD) truck used in a Swedish underground mine. Five major systems, the engine, transmission, hydraulics, brakes, and other, were considered. Operation and maintenance data was collected over one year on 19 LHD units; 3 sets of data are presented in the paper. The paper presents detailed analysis of the data including tests for trend and serial correlations, and maximum likelihood estimates of the Weibull parameters for the different sub-systems. Only a few recent studies in last 10 years have been found that look at the reliability of open-pit shovels or their parts (Delghandi et al., 2014), and none on the reliability of the operator-related components of mobile mining equipment. That is not to say that these studies do not exist, it is plausible they have been conducted by mining companies and original equipment manufacturers (OEMs), but they have not been made public.

Having said this, conducting studies based on failure data has been fraught with challenges due to the way maintenance and failure data has historically been collected in the mining sector (Ho et al., 2013, Hall and Daneshmend, 2003). Operational data, collected by the OEM's proprietary may be available to the mining operator, depending on their agreement with the OEM. If the mining company does their own maintenance then they will know what failed and when from data in the computerized maintenance management system (CMMS). The mining company may or may not share this information with the OEM. The OEM will be able to infer failures have happened through the ordering of spare parts and requests for warranty but will not necessarily have this information for units that are out of warranty or if 3<sup>rd</sup> party spares are used. The mining company is best placed to determine inputs to an RBD from the data stored in their CMMS. Historically the CMMS data has been used reluctantly by reliability engineers. It is widely viewed as "dirty" data requiring considerable expertise to clean and analyze it.

Every maintenance action on a shovel is initiated and tracked using a record, called a work order, in the CMMS. These

records provide insight into what work was done and why, when, who did the work, how long it took, and what parts were used. Records are kept by mining companies detailing an individual assets maintenance work orders and costs. The detail and consistency in how this data is recorded varies from company to company. Some of the data is structured but much of the potentially useful data is in unstructured fields, these are time consuming for engineers to analyze. Mobile equipment engineers have traditionally kept track of failure events on bespoke systems such as Excel spreadsheets but these often do not survive turnover of personnel making development of a whole of life view over a decade of operation difficult to accumulate. One solution is to relook at the CMMS and bring modern data analytics methods to examine the data within. Ontological and expert systems are now making access to insights from these fields possible.

The aim of this paper is to understand the impact of operator-related components on the reliability of a mining shovel over the life of the shovel. The motivation is driven by the need to understand if automation of the shovel might improve the reliability of a shovel unit through elimination of the need to maintain operator-related components.

## 3. APPROACH

The process of determining the influence operator-related components have on the overall reliability of a shovel system follows a number of steps. Two sets of shovel assets with failure data are identified for the case study. Maintenance records on several shovels were available through the Mobile Mining Equipment Reliability Database (Ho, 2015). Five 1400 HP units (Shovel Set A) and three 1470 HP units (Shovel Set B) were selected. The data are cleaned using the DEST, Data Extraction and Cleaning tool, the process is described in Hodkiewicz and Ho (2016). This is a customizable MATLAB script for a rule file containing conditions and actions to be performed based on keywords in the database. Cleaning results in allocation of work orders to the correct functional location, categorizing what failed and/ or the work done, identifying the date the work commenced, and if the event qualifies as a failure or suspension. Both the raw and cleaned data files are being made available, see Section 6 for details.

Data is compiled for each functional location and where possible by failure mode into data sets. The main functional location groups such as Engine, Hydraulics, Transmission, Miscellaneous and Operator Related Equipment (ORE). In the ORE subsystem, the components are sorted by Air Conditioner, Radio, Cabin, Ladder, Lights, Controls and Superstructure. Only maintenance events that result in the repair or replacement of components are considered, inspections and condition based maintenance are not included. As far as this study goes whether maintenance work was planned or unplanned is not relevant to the analysis.

All data sets are manually checked for misleading or erroneous data that has not been detected by the DEST tool. Maintenance work orders are entered using calendar days. In order to calculate time between events for each functional location, the days between maintenance events were determined and converted to hours based on a 24 hour day. The actual utilization time is less than 100% and varies by machine; the conversion of the calendar hours to operating hours is discussed in the results section.

Failure data is examined graphically and statistically for outliers or evidence of a trend before fitting data to different distributions and evaluating goodness of fit (O'Connor, 2012). Graphical methods included cumulative failures vs. total time plots and scatter plots of successive service lives. The potential presence of a trend is also assessed using the Laplace test (Ansell and Phillips, 1990) and Military Handbook Trend test (Caroni, 2010). We followed the process presented by Louit et al. (2009). Testing for departure from trend is important as a number of components and sub-systems on the shovels are repairable items. There is sufficient evidence from the tests performed that there are no trends present in each failure time data set.

The resulting data sets are fitted to Weibull distributions using Isograph's Availability Work Bench (AWB) software, a widely used industry reliability software package. Parameters from these distributions inform the development of the reliability block diagram (RBD). The RBD is essentially a series system of all of the main components. Simulation is also conducted using the AWB package. A 720 hour period is selected for analysis. At 100,000 simulations the results for the system reliability converge.

At the conclusion of the simulation the results of the shovel system reliability with and without the operator related components are compared and the failure probability of the main systems considered. The overall system availability results are compared with information provided by industry contacts to assess their validity.

#### 4. RESULTS

The results for shovels in Set A and B are described below. The shovel set A data set had five identical 1400 HP units and shovel set B had 3 identical 1470 HP units. Shovel set A had 8,264 work orders and shovel set B 6,430 work orders originally available at the top functional location level. Data is available over a 10 year period from 2002. Shovels A and B are from different original equipment manufacturers. They perform primary production digging duties at the same organization. The work orders for the two data sets were cleaned and sorted by two individuals working independently but using the same process as described earlier.

#### 4.1. Distribution parameter estimation

Table 1 shows the results of the data cleaning, sorting and distribution fitting. 4515 of the 8264 work orders (55%) were used in the analysis for shovel set A and 54% for shovel set B. Work orders were discarded due to issues such as incorrect functional location allocation, duplication, an absence of hours or costs logged and if the work order did not result in the repair or replacement. This high number of non-included work orders is not unusual and illustrates the scale of the data quality challenge and the necessity of some sort of expert system assistance.

Table 1. Results of analysis of cleaned and sorted data for Shovel set A showing number of work orders (N), failures (F), and suspensions (S), Weibull distribution location parameter ( $\eta$ ) in calendar hours and shape parameter ( $\beta$ ).

Sub-system	N	F	S	$\eta$	$\beta$
Engine	858	829	29	276	0.99
Hydraulics	693	672	21	340	1.01
Transmission	106	91	15	1995	0.85
Grease system	514	512	2	408	0.96
Mounts/seals	475	468	7	450	0.94
Bucket system	580	574	6	376	0.98
Superstructure	59	56	3	3484	0.79
Miscellaneous	586	578	8	157	1.25
<i>Sub-total non-operator related</i>	<i>3871</i>	<i>3780</i>	<i>91</i>		
Air conditioner	247	243	4	988	0.86
Ladder	86	84	2	1845	0.85
Radio	69	67	2	2304	0.74
Controls	32	30	2	6457	0.70
Driver's Cabin	210	209	1	968	0.92
<i>Sub-total operator-related</i>	<i>644</i>	<i>633</i>	<i>11</i>		
<i>Total</i>	<i>4515</i>	<i>689</i>	<i>102</i>		
<i>% operator-related events</i>	<i>14.3%</i>				

Of the 4515 work orders processed 14.3% are associated with operator-related components for shovel set A and 15.9% for shovel set B. The main contributions to unreliability are the

engine and hydraulic systems and the bucket system. There is a planned maintenance strategy in place for the engine with fixed interval repairs, replacements and inspections. The hydraulic system has fixed interval inspections and preventative work such as checking/ changing filters. However leaks are common leading to unplanned work. The bucket system includes work orders on ground engaging tools, these are a replaceable wear element with a relatively short and unpredictable life.

Table 2. Results of analysis of cleaned and sorted data for Shovel set B showing number of work orders (N), failures (F), and suspensions (S), Weibull distribution location parameter ( $\eta$ ) in calendar hours and shape parameter ( $\beta$ ).

Sub-system	N	F	S	$\eta$	$\beta$
Engine	280	203	77	768	0.99
Hydraulics	787	687	100	222	0.88
Transmission	153	143	10	968	0.67
Induction & Exhaust	128	116	12	1063	0.65
Bucket system	945	897	48	219	0.96
Superstructure	181	172	9	798	0.70
Track	79	56	23	2374	0.91
Miscellaneous	344	266	78	572	0.81
Operator-related	546	492	54	421	0.91
<i>Total</i>	<i>3443</i>	<i>3032</i>	<i>411</i>		
<i>% operator-related events</i>	<i>15.9%</i>				

Estimated values for the Weibull shape parameters show values close to or less than 1 for almost all data sets. This is not an uncommon result when data sets containing multiple components are pooled together. Please note the location parameter ( $\eta$ ) for the Weibull distribution is reported in calendar hours. Generally the mining industry will report in operating or utilized hours; converting from one time scale to the other is covered in the discussion section.

#### 4.2. System reliability modelling

Two approaches to estimating system reliability are used. The first is a traditional RBD as described in (O'Connor, 2012). The second is to use the Monte-Carlo simulation in the AWB commercial software package. As mentioned earlier, it is a series system with a reliability block for each subsystem as shown in Tables 1 and 2. A summary of the results is shown in Table 3 based on 100,000 simulations over a 24 hour

period. The Reliability Block Diagram for the results shown in the Tables 3 and 4 is shown in Figure 1.

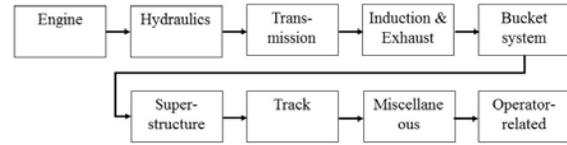


Figure 1. Reliability Block Diagram for the Shovel.

Table 3. System reliability using Monte-Carlo simulation over a 24hr period.

	Shovel set A	Shovel set B
System reliability with operator-related components	0.569	0.487
Reliability of operator related components	0.866	0.829
System reliability <i>without</i> operator-related components	0.657	0.557
Difference in reliability due to operator-related components	0.088	0.070

Table 4. Traditional system reliability approach over a 24hr period.

	Shovel set A	Shovel set B
System reliability with operator-related components	0.524	0.489
Reliability of operator related components	0.858	0.929
System reliability <i>without</i> operator-related components	0.611	0.526
Difference in reliability due to operator-related components	0.087	0.037

The results for the simulation show that there is a difference in system reliability due to operator-related components of 0.070 – 0.088. This reliability loss translates into impact on the availability of this high capital primary production unit.

The results for estimating the difference in reliability due to operator-related components using the traditional approach (0.088) and the simulated approach (0.087) compare well for shovel set A. There is a wider difference for the estimated difference for shovel set B. We suspect this is due to the high number of suspensions in the operator-related data set for set B, these influence the simulated estimate for the operator-related reliability block.

**4.3. Mean time between events**

As mentioned earlier the shovels do not operate for 24 hours a day. The mining industry uses standard time definitions to calculate metrics such as availability, utilized time and mean time between failures (MTBF). A typical example is shown in Figure 2.

Calendar Time (CT)					
Available Time (AT)				Down Time (DT)	
Utilized Time (AT)		Operating Standby (OS)	No scheduled production (NSP)	Unscheduled Loss Failures (ULF)	Unscheduled Loss Other (ULO)
Operating Time (OT)	Operating Delay (OD)				

Figure 2. Standard time definitions for mobile mining equipment.

A commonly tracked metric of shovel performance is MTBF/ utilized hour. MTBF is usually determined as a point estimate based on the ratio of utilized time to the number of breakdowns based on a count of unscheduled loss events. Back in 2012, when the data collection used in our study ended, the industry average mean point estimate for hydraulic shovels is 20 utilized hours. However the range is large with some shovels having MTBF values as high as 70 and others as low as 10 utilized hours.

Determining how the reliability calculated by our analysis compares to the industry ranges given above is problematic as we do not have the actual utilized hours for the shovels in our example, just the maintenance records. For the industry values we only have the MTBF for a utilized hour but not a value for the number of utilized hours in a 24 hour period. Another issue is that our study is interested in all work done on the shovel not just unscheduled loss events. The aim of our work is to examine all work done on the operator related components, not just the unscheduled loss events. We are not developing an accurate simulation of the reliability of the shovels rather we are interested in the difference in two reliability estimates.

**4.4. Contribution to operator-related events**

Table 1 shows the number of failures and suspensions in the data set and Table 5 shows the reliability calculation for a calendar month (720 hours) for the operator-related components for shovel set A. The main contributors to maintenance work are the air conditioner and driver’s cabin. There is a 0.53 probability that you will work on an air conditioner during a calendar month, the same for the driver’s cabin. Collectively these units, the air conditioner, ladder, radio, operator controls, and driver’s cabin are not required if the unit is autonomous.

These operator related components are not optional in current shovel models. Work, safety and health rules mandate that they are installed and functional. Malfunctioning air conditioners and damaged seats mean that the shovel cannot be used until they are repaired.

Table 5. Proportion of operator-related events and probability of failure by location.

Operator-related component	% of total events in the data set	Probability of failure in a calendar month
Air conditioner	38%	0.53
Ladder	13%	0.36
Radio	11%	0.34
Operator Controls	5%	0.19
Driver’s Cabin	33%	0.53
Operator-related components		0.93

**5. DISCUSSION**

This study used 7958 cleaned and sorted maintenance work orders collected over 10 years on eight hydraulic shovels (Set A and Set B). We found that operator-related components accounted for 0.070-0.088 of the system reliability. These components are only on the shovel to provide control capability, comfort, and safety of the operator. In an autonomous unit they would not be necessary. This data contributes to studies on the business value of autonomous shovels.

Work orders for operator-related components are usually generated as unplanned work orders, less than 1% are planned. As they relate to the health, safety and comfort they need to be dealt with as soon as possible. This generally means they must managed outside of the weekly scheduled work plan. This requires taking the shovel down specifically or doing opportunistic repairs. In both these situations the

need to manage unplanned work draws supervisors, planner and their teams away from scheduled work. The cost of this is difficult to value although it can be seen in maintenance metrics such as % scheduled work and % scheduled work completed. These interruptions impact planned work such as inspections and condition monitoring and contribute to a reactive maintenance culture.

To examine the business value of the increased shovel reliability we use a loose coal density (in bucket) of 1.2 tonne/m<sup>3</sup>. The heaped capacity of a 15.4 m<sup>3</sup> bucket is 20 tonnes and typical cycle time is around 50 sec delivering 70 cycles per hour. We assume an availability of 85% and utilization of that availability of 70%. Based on this a single shovel unit works ~ 5200 hours per year moving 7.28 million tonnes. Assume a sales price for coal at the mine of A\$40 / tonne. If we could increase the availability by 1% by not having to stop for work on operator-related components, this would translate to an additional A\$3.4m of income per annum per shovel. Each unplanned maintenance event associated with operator-related components impacts availability. For the eight shovels in this study there were 1,190 unplanned maintenance events over a 10 year period, or 15 per year per shovel.

Further savings would be realized from reduced labor costs. Each shovel requires a team of four operators to cover the rotating shift roster, wage, travel, and accommodation costs for fly-in-fly-out shovel operators exceed A\$200,000/yr. From a health perspective, removing operators from the shovel also reduces exposure to heat, noise, dust and vibration.

There is considerable work ongoing on the technology to support automation of shovels. Much has been learned from the automation of haul trucks and drills that is on-going but the shovel is a more complex operation. The unit needs to be moved and positioned appropriately with respect to the digging surface. The bucket needs to be lifted, oriented appropriately and driven into the digging surface, material loaded at the right payload, the bucket swung away from the surface to above the haul truck, emptied and returned to the face. Lidar, hyper-spectral imaging, haptic sensing are all playing a part in this automation journey. The mining industry is working towards moving people away from the front-line of the mining industry. It is only a matter of time before shovel automation becomes an engineering reality.

## 6. DATA SHARING

A major factor in enabling this work has been the ability to semi-automate cleaning the ~5000 raw maintenance work orders with our DEST tool. In order to promote the developments of other data cleaning tools, we are making our raw and cleaned data sets for Excavator Set A available through the Prognostics Data Library <https://prognosticsdl.ecm.uwa.edu.au/>. Each data set (raw and cleaned) has an associated metadata file describing the

fields. We have also included cost data, although it is not used in this paper. We hope that this encourages others to develop cleaning tools and compare their results for reliability with what we have presented here. This will enable conversation about the decisions made in data cleaning and how the influence resulting reliability distributions.

## ACKNOWLEDGEMENTS

The authors would like to acknowledge the support of ARMS Reliability for providing an AWB license to the students to conduct this analysis, CRC Mining (now Mining3) who funded development of the Data Extraction and Sorting Tool (DEST), and Dr. Ross Marriott who prepared the data sets and metadata files for upload to the Prognostics Data Library. Finally to Professor Peter Knights for providing estimates of shovel tonnage capacity.

## REFERENCES

- Ansell, J. I. & Phillips, M. J. (1990). Practical reliability data analysis. *Reliability Engineering & System Safety*, vol. 28, pp. 337-356.
- Caroni, C. (2010). "Failure limited" data and TTT-based trend tests in multiple repairable systems. *Reliability Engineering & System Safety*, vol. 95, pp. 704-706.
- Delghandi, S. H., Sayadi, A. R. & Hoseinie, S. H. (2014). Reliability analysis of loading system of hydraulic excavator. *International Conference on Reliability Engineering*, Godkand:
- Durrant-Whyte, H., Geraghty, R., Pujol, F. & Sellschop, R. (2015). How digital innovation can improve mining productivity. *Metals and Mining*, vol. November, pp.
- Hall, R. A. & Daneshmend, L. K. (2003). Reliability modelling of surface mining equipment: data gathering and analysis methodologies. *International Journal of Surface Mining, Reclamation and Environment*, vol. 17, pp. 139-155.
- Ho, M. T., Hodkiewicz, M. R., Pun, C., Petchey, J. & Li, Z. (2013). Asset Data Quality - A case study on mobile mining assets. *8th World Congress on Engineering Asset Management* October, Hong Kong:
- Ho, M. T. W. (2015). *A shared reliability database for mobile mining equipment*. Doctoral dissertation. University of Western Australia, Perth, Australia
- Hodkiewicz, M. & Ho, M. T. W. (2016). Cleaning historical maintenance work order data for reliability analysis. *Journal of Quality in Maintenance Engineering*, vol. 22, pp. 146-163.
- Hodkiewicz, M. R. (2015). Maintainer of the future. *Australian Journal of Multi-Disciplinary Engineering*, vol. 11, pp. 135-146.
- Kumar, U., Klefsjo, B. & Granholm, S. (1989). Reliability investigation for a fleet of load haul dump machines in a Swedish Mine. *Reliability Engineering & System Safety*, vol. 26, pp. 341-361.

Louit, D. M., Pascual, R. & Jardine, A. K. (2009). A practical procedure for the selection of time-to-failure models based on the assessment of trends in maintenance data. *Reliability Engineering & System Safety*, vol. 94, pp. 1618-1628.

O'Connor, P. D. T. (2012). *Practical Reliability Engineering*, John Wiley & Sons Ltd.



Mark Tien-Wei Ho has a Bachelor of Electrical and Electronic Engineering (1998) and Doctor of Philosophy in 2016 from the University of Western Australia. He has worked developing software for the semiconductor and transportation industry, and worked in asset management for the mining industry. He currently works as an asset manager in the hospital sector with a focus on business improvement via data analytics.

## BIOGRAPHIES



Melinda R. Hodkiewicz is the BHP Billiton Fellow for Engineering for Remote Operations at the University of Western Australia (UWA). She has a BA(Hons) in Metallurgy and Science of Materials from Oxford University in 1985, and a Ph.D. in Mechanical Engineering from the University of

Western Australia in 2004. Prior to her Ph.D she worked in industry in Operations and Maintenance roles. She now leads the System Health Laboratory at UWA and works in the areas of Asset Health, Maintenance and Safety. She is a Chartered Engineer, a Member of the Institute of Materials, Minerals and Mining (IOM3) and the Asset Management Council. In 2016 she was awarded the MESA Medal for services to Asset Management.



Zac Batsioudis is a graduate of the University of Western Australia. He graduated in 2015 with a Bachelors of Engineering/Commerce majoring in Mechanical Engineering and Finance. During his degree, he gained experience in the field of Reliability Engineering working for Rio Tinto in 2013 and 2015.

Upon completing his degree, he has taken up the position of Mechanical Reliability Engineer for Alcoa at their Wagerup operations.



Tyler Radomiljac graduated from the University of Western Australia with a double degree, Bachelor of Engineering (Mechanical) and a Bachelor of Commerce (Finance) in 2016. During his time at The University of Western Australia, he also gained work experience with the

Perth Metropolitan Redevelopment Authority and Cossill & Webley Consulting Engineers.