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Haul Truck Automation: Beyond Reductionism to Avoid Seeing Turtles as Rifles

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ABSTRACT

Artificial intelligence offers a promising route to a sustainable future for the Western Australian (WA) Mining Industry, in which haul truck automation will play a pivotal role. The argument of this article is that the success of driverless technology hinges on the ability of artificial intelligence to embody the complexity of the world around it. The epistemology of automation is one of reduction. Reductionism has already applied practical constraints on the ability of intelligent machines to recognise dark faces, classify reptiles correctly, determine appropriate areas for policing and the likelihood of a criminal recidivism. The value position of artificial intelligence is one of prediction, and the machines' predictive capacity generally puts non-designed situations outside of its parameters, making its narrow and very bias view of the world appear to be more intelligent. This article argues that technology that is applied in a mining environment must embrace its intricacies, otherwise the Western Australian (WA) Mining Industry may miss the mark and witness similar examples of turtles being classified as rifles.

1. INTRODUCTION

In a recent study of neural networks, researchers found that existence of adversarial imagery in real-world systems. The study manipulated patterns on a turtle to fool image classifiers into identifying the reptile as a rifle (Athalye et al., 2018). Neural network classifiers are vulnerable to conflicts in the physical world and remain open to varying perspectives. What this highlights is how artificial intelligent systems are operating in a pre- programmed view of the world re-arranged by the designer. Designers engineer artefacts by reducing them to their most basic parts. For example, the body, pattern, head and tail of a turtle are all stereotyped and fixed. Secondly, if it is process that we are trying to engineer, then the techniques are often analysed through time and motion studies. A great deal of 'science' is performed, determining what efficiency techniques should be standardised. Standardised methods provide the platform for automation, which attempt to lock-in the relentless repetition of that one best method.

Haul truck operations can be considered complex, where the constituent parts do not represent the function of the whole. In order to understand a haulage system, the process cycle is divided into component tasks: travelling empty, queuing at source, loading at source, travelling loaded and tipping at destination (Hamada & Saito, 2018). With technology becoming increasingly popular, researchers are raising doubts about the future of work in open- cut mining as technology is now capable of

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completing a large portion of truck driving tasks. For example, a driverless truck can drive from source to destination with what appears to be with limited interruption. What is not always known, however, is the localised adaptions that make driverless haulage possible. There are multiple supervisory roles working in the background to join the dots (Caterpillar, 2013). Connections are being made between what has been designed and what occurs in practice. That is because driverless systems are only as good as the designer's imagination of how each mining system functions. If we only allow engineers to develop this technology on a reductionist view of the world, driverless trucks will be less adaptive and restricted to innovative ways of working.

When technology systems are designed as expert systems, they run the risk of operating way out-of-context. While they were designed specifically for a workload or optimisation problem, their success has led to them being applied more generally. This has resulted in the product facing situations that are beyond its design parameters (McKinnon, 2019). Strict parameters may even lock in the biases and inefficiencies that steered the Western Australian (WA) Mining Industry to automation in the first place (Bellamy & Pravica, 2011). Industries are often drawn to automation to release latent capacity and to fix supply chain inefficiencies. However, more often than not, the algorithms simply compound existing methods and inefficiencies. The technology transforms the aspects that it was designed to substitute or replace. What was imagined to be a simple substitution of a driver for a machine, turned out to be rather complex. Users find that there are residual activities that cannot be completed by automated systems. Therefore, human supervisors are given a number of residual tasks to help the truck fleet navigate around a mine site (Caterpillar Global Mining, 2019). Moreover, despite the designed activities, there are also unspecified tasks with highly cognitive problem-solving aspects that automated systems are unable to resolve. As a consequence, what was once imagined as a like-for-like replacement, while reducing cycle delays and removing human exposure, ensued the creation of new strengths and weaknesses (Department of Mines and Petroleum, 2015a).

Haul truck automation has been adopted to respond to the increasing operating costs and for a reduction of human exposure to danger. However, this paper argues that engineering haulage cycle needs to go further to resist reduction and embody the complexity of physical mining. The design in application needs to revisit the many ways of transparency and explainability. If such focus is not given, then both safety and productivity will be compromised. There are numerous safety proposals that highlight the removal of people from danger. While others explain how the inattentional, fatigue and attitude-related aspects can be eliminated. However, before engineering a haulage system, the consequences and trade-offs need to be considered. In this research, the approach to reductionism, functional allocation and reconstruction of haulage systems will be explained, while offering empirical evidence of the impacts of truck automation within the WA Mining Industry-to date.

2. THE REDUCTION OF A HAULAGE SYSTEM

2.1. Simplifying the haulage cycle

A simplified haulage system represents a number of components that work seamlessly together to load, haul and dump. Reductionism distinguishes between what the system has and what it does, achieving simplicity through what it excludes. The practice also distinguishes between what humans and machines undertake as well (Dekker, 2014). The simplification of haulage systems rests on the belief that components operate independently, without non-linear interactions disrupting the flow of the cycle. This is achieved by breaking down the system into its most basic parts, re-allocating tasks to either human or machine (Pritchett et al., 2013). The system is then put back together again, with isolated components that operate independently. This enables engineering to contain incidents and serious breakdowns in the design of the haulage cycle.

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The reductionist approach aims to understand each components of the cycle individually within the system (Hamada & Saito, 2018). A simplified system improves upon knowing the behaviours of the constituent parts and being able to lock-in the productive methodologies for automation. It removes the variability and increases the predictability in what the system will perform. Haul trucks in a simplified system will therefore appear to be foreseeable and controlled in the way they execute the tasks. Therefore, trucks working within the design parameters will ultimately improve workplace safety and haul truck productivity. This constitutes the set of appearances that sit behind a much simpler haulage system.

2.2. Understanding truck driver contributions

Now that the system has been simplified to its most basic steps, haul truck activities within the system are analysed to determine the contributions of a truck driver. For example, a driver may enter the intersection, indicate left, turn left and then accelerate away. This is where the components, in isolation, unfold as expected without interruption. What is not always clear, however, is the types of interactions that are likely to occur on that intersection. There are various situations that could emerge, such as trucks entering the intersection, graders maintaining road conditions, or broken-down machines being recovered. A truck driver has various means of adapting to any of those situations. Firstly, the truck driver can follow priority rules and either proceed or allow other trucks to enter the intersection. Secondly, a driver is capable of communicating with grader operators via a two-way radio and requesting to make a pass around the machine. Thirdly, the driver can request permission via two-way radio to Mine Control to pass broken-down machines. Consequently, the ability of a human to analyse and adapt to a single example, such as this, makes reverse engineering truck driver contributions very difficult.

Despite the high levels of confidence in manufacturing how the brain and mind work, people learn and think by acquiring knowledge from one instance, not tens of thousands of examples (Lake et al., 2016). The ability of human to adapt, particularly in novel situations, is unprecedented. If a crusher is unavailable, a truck driver will call Mine Control to ask what is happening. Furthermore, a driver will ask to dump their load at a stockpile in order to keep the trucks cycling. Oncoming trucks observing the queue at the crusher, radio ahead and request to drive to another crushing location. On route, truck drivers may observe rock spillages and windrows that impede their travel path. The ability to classify objects and avoid them can often be taken for granted. Even in wet conditions, truck drivers have the capacity to observe wet roads and adjust to impeding conditions (Jamasmie, 2019). There are also experiences and lessons that have been learned and retained. For example, knowing that a ramp is made out of clay material and is widely understood to be slippery in wet weather. An automated truck cannot remember this information. Despite having driven over that particular part of the road numerous times before, driverless trucks will not retain the data for future reference. Trucks may even slide out of their lane on the same road multiple times. Therefore, without humans injecting smooth layers of adaptive performance, such as traction controls and avoidance zones (Caterpillar, n.d.), driverless trucks would continue to operate on haul roads as they would previously. By truly understanding the truck drivers' contributions, it can be observed how far technological advancement has come, and where it still needs to evolve.

3. ENGINEERING A HAULAGE SYSTEM

3.1. Technological advancement

Engineering a haulage system attempts to reverse engineer what activities manual haul trucks perform. It combines the understanding of the haulage cycle in loading, haul and dumping, with what we know

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about the human mind and brain. Without that intricate knowledge, the technology will just be making trucks available without optimising the circuit. Nonetheless, whenever automated systems are deployed, there is always a specific safety or optimisation problem that the user is trying to solve. For example, reducing driver delays, increasing truck availability or removing human exposure. Therefore, automated systems, at this stage, are all 'expert' systems. Expert systems require specific training data in order to program the execution of activities to be undertaken. Quite often, the training data came from the users themselves, with the technology simply replicating the knowledge that was contained within those facts and statistics. Earley (2016) explains how there cannot be artificial intelligent systems without high-quality sources of data. For that reason, driverless trucks are limited to the data sources that are collected, coupled with the intricate knowledge of the activities undertaken by truck drivers.

Data sources are now considered a key enabler for becoming an incumbent disruptor in industry (Araujo, 2018). However, data is not always free from biases, discrimination and may simply reinforce the problems of the past. Recidivism rates, for example, were based on how many arrests occurred in a particular area. Therefore, the technology simply redirected police to 'crime' where they were already policing (Lum & Isaac, 2016). Technology is recognising the patterns in a data set and compounding the information that is contained. With enough data, designers are able to recognise recurring themes and the common types of ideologies. Whether it is language processing (Hermjakob et al., 2018), computer vision (Brandt, 2017), robotics (Frohm et al., 2006) or self-driving vehicles (Goel, 2016), they all contain basic visual scene understanding, pattern recognition and the ability to recognise objects. That aside, there are other aspects, like the ability to communicate over the radio to pass another machine. Equally important, the ability to recognise the physical artefacts that surround the truck. LiDAR and Radar are capable of representing physical objects by bouncing light and radio signals, though it does not truly 'understand' those objects. Understanding dates back to the thought experiment of the Chinese Room. The experiment highlighted that if someone was given a set of questions in Chinese, followed those instructions to look up the required responses, they could appear to outsiders that they understood Chinese (Hermjakob et al., 2018). While this may be the case, this situation is very different to navigating real-world aspects that have never been confronted before.

Narrow-minded expert systems can be exposed when faced with non-designed situations. When automated systems are developed and tested against the data they were trained upon, automated systems can appear to achieve human level performance (Firmin, 2019). However, when faced with a novel situation or adversarial images, machines can operate beyond their context (Athalye et al., 2018). This may result in unintended interactions, misclassifying the object or not identifying the objects at all (Department of Mines and Petroluem, 2015b). Although technological advancements have made object detection possible, it is not there yet (Teichman et al., 2011). There are attempts to reverse engineer more human-like reasoning systems in machines, allowing them to become more adaptive outside their design parameters (Lake et al., 2016). Bridging the gap between science and engineering intends to increase our understanding of human intelligence, while figuring out the techniques to build human capabilities in a machine. The important part of this, is teaching the WA Mining Industry how driverless technology works, not just how to work it. To enable worker to better understand the computerised systems they work with, this can equip them with the inside knowledge to observe situations beyond the design and identify potential areas of overfitting.

3.2. Supporting roles, functions and tasks

The supporting roles of a driverless system are never conceived with humans in mind. Roles, functions and their tasks are leftovers from what engineers are yet to automate. The residual is based on technical limitations and the premise that human-machine capabilities are fixed (de Winter & Dodou, 2011).

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However, the strengths and weaknesses are never static; their abilities will co-evolve as people learn and technological systems are upgraded (Woods & Hollnagel, 2006). At the beginning, supporting roles are residual tasks that are allocated to human supervisors. The arrangements of the system are studied for what is contained (i.e. a truck driving from A to B), which excludes how the driver is deeply connected in how the system functions. For example, calling another machine to clarify whether a load unit is down for maintenance. Therefore, although supporting roles are given specified functions by design, the inability of a truck to think outside the box requires more human intervention than was once thought.

Functions are areas of responsibility that are found along the fringes of the role. Although a truck driver is expected to travel from load source to destination, they are also expected to communicate via two-way radio, identify hazardous road conditions and respond to emergency situations. The literalism of a machine agent, however, does not provide the same levels of insight to supervisors (Billings, 2018). The explainability for what a driverless truck performs can be quite low, which forces supporting roles to learn truck functions through observation. This can be observed in driverless trucks that perform a U-turn while waiting in queue to be loaded. While Mine Control may analyse the assignment engine to work out the reason for its actions, ancillary equipment operators can be left confused as to why the truck did not wait in line to be loaded. Where radio communications were used to advise others of truck movements, is now hidden among computerised interfaces and systems. Depending on access, roles and functions have different levels of access. It can also be difficult to determine the right level of information for the role, without inundating them with information they do not need or know how to interpret.

There are a residual set of tasks that have been developed by design. Uploading surveys, calling trucks to be loaded and verifying dump locations are examples of tasks created for support roles (Caterpillar, 2013). Human support roles play a critical role in ensuring the safety of driverless operations. The tasks support the verification of the virtual world to the physical world, a task that has failed to be verified correctly in the past (Department of Mines and Petroleum, 2014). This is where the processes between humans and machines become so important. Even though the process does not unfold in a predictable manner, support roles must have the foresight to prevent trucks from falling into sticky situations. A driverless truck, for example, may be attempting to achieve a reverse point that is located behind a windrow. Despite the dump being verified correctly, Mine Control may have simply corrected the face in order to become a straight line. Local adaptions are continuously evolving, adjusting and manoeuvring around danger that continuously emerges. The supporting roles, in effect, are now the eyes and ears of the operation.

3.3. Processes for supervisors and team members

Processes are instructions that enable people to work with driverless haul trucks. Those instructions are the tasks that provide the driverless operating environment or supply chain interfaces. Moreover, instructions are underpinned by the designers' imagination of operational practices. For instance, to mode change a truck, there is a sequence of steps to follow when executing the task (Glover, 2016). However, it is dependent on whether the task proceeds along predicable lines. The engineered component of that task theorises the truck responding to a person's requests. Its simplicity comes with the exclusion of the complexities that arise in real world applications. Designers are unable to plan for every contingency; therefore, they call upon humans to solve problems. Consequently, when a conflict between the design and the real world emerges, it is human adaption thinking outside the box that is required to close the gaps.

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Conflicts emerge when a person identifies truck function that is beyond the parameters. Despite the design allocating tasks to be undertaken by either human or machine, there will undoubtedly be unique situations. The paradox, however, is intervening to prevent a truck failure or intervening to cause a failure. This is the distinct situation that occurs in supervising automated systems. If a driverless truck is unable to achieve the reverse location at the crusher, supervisors would be expected to resolve the situation. Although the truck has been assigned that process by design, the unspecific creativity necessary to recover the situation will be novel and complex. Operational practices are a collection of individual experiences and external information. Nonetheless, automated systems offer little opportunities for people to practice their marginalised skills. Therefore, when those skills are called upon, people can perform dreadfully. Rather than debating deviations from design processes, leveraging the problem-solving aspect of human intelligence can enable supervisors to assist automated system navigate operational complexities.

3.4. Protecting the system from negative outcomes

Layers of protection are controls that are designed to prevent the system from failure (Willey, 2014). On the surface, the linear causal chain gives the appearance that the system is well protected (Glover, 2016). The assumption, however, is that the trajectories of workplace incidents are linear. The indirect sequence may not even commence at the top of the theoretical walls of protection. When the interactions are non-linear, interactions can arise from various angles, and those linear protections can become ineffective. Despite the layers of defense being engineered, automated systems are not known for their response to isolated failures. Rigorous fail-safe systems and test structures designed to insulate driverless technology, manufactured their own causal pathways that have mystified the WA Mining Industry (Department of Mines and Petroleum, 2014). No one would have imagined that a driverless truck would be unresponsive towards an impending truck collision (Department of Mines and Petroluem, 2015b). The consequences of engineering a complex system is that the outcomes are generated from complex interactions, not the failure of the individual components themselves.

Engineering more layers of defense only adds to the complexity of the system. Therefore, controls need to be applied diligently to not impose further opacity on the system. Protection may even need to be applied in areas where the gaps do not appear. The introduction of a new barrier simply creates a new opportunity for interaction. For instance, with the introduction of predictive path capability, even though manual equipment may not be heading for a truck's intended path, its potential direction and speed can project a collision. This can lead to the trucks engaging the emergency stop device, which can result in the travel lane breaches where they did not exist before. Although the diligence of high levels of protection, success depends on whether the system can withstand disruption and bounce back from novel situations. Control systems must move beyond literalism, becoming agile when compressed and stretched to their operating limits. The protection systems (i.e. LiDAR, Radar, emergency stops) designed to insulate people from human limitations (i.e. fatigue, concentration), appears to have introduced its own level of complexity through the reconstruction of the haulage system.

4. RECONSTRUCTING A 'SIMPLIFIED' HAULAGE SYSTEM

4.1. Team dynamics

When the system is eventually reconstructed, humans find themselves feeling out the trucks' operating parameters. The reactions attempt to figure out what the truck is capable of and when it will stop. For example, grader operators work closely to the truck's boundary to observe how the machine will respond. It is a game play often observe in teams, feeling out how far another player can pass or kick the ball. It is often known then, how far players should be placed in order to receive the ball. When it

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comes to machine agents, the approaches to replacing human work are rarely human-centric methodologies. Therefore, despite the specific training people undertake for their functional role, supervisors find themselves working out how machine functions in the workplace. This is due to the machine logic being hidden from the user, which claim to protect the vendors' intellectual property and stop the system from being overridden.

The storming phase is where the trade-offs and the frustrations occur since the replacement of truck drivers. Where manual machines could previously communicate directly with a truck, now requires a different line of communication. Communication involves selecting boxes, updating settings and typing instructions to inform the truck on what needs to be performed next. Moreover, it can also be difficult to get a machine to register what the human is trying to tell it. This is not just supervisors; it is the operators who have to work with the driverless trucks on regular basis. Excavators, for example, need to set a loading point with their bucket to enable trucks to identify where they need to reverse to. Operators are also required to press a button on their joystick to authorise awaiting trucks to enter the loading area. Where a truck driver previously self-spotted into the loading bay, now require the excavator operator to authorise their entry through a computerised system. Through practice, manual equipment operators working with driverless trucks learn what the functions the machine can and cannot perform. Often, it can be frustrating for users, who now need to complete tasks that were previously handled by truck drivers. On the other hand, the transfer of agency can be quite positive, allowing excavator operators to choose when a truck comes into the loading area. Overtime, mobile equipment operators learn driverless capability through their interactions with the system, identifying limitations and reactions to various situations. Although a screen interface helps with equipment separation, operators of manual equipment can activate a driverless trucks' proximity alarm. Until operators learn safe distances, manual equipment can frequently stop trucks by not knowing how to interact with them. In addition, a manned haul truck would remain outside another piece of equipment's 50 metre exclusion zone, making contact over the radio and asking for permission prior to entering their work area. As a consequence, manual operators interacting with driverless trucks go through a phase of working out driverless capability before they can begin to perform under these new circumstances.

The benefit of working with machine agents is the relentless repetition. Although there are complexities, the predictive path capability assists people to monitor the trucks' intended haul route. This also increases their level of trust towards driverless trucks. In a manual environment, it can be difficult to determine whether a truck driver will turn left or right. At times, truck drivers do not indicate or leave their indicator engaged, reducing the level of trust towards manually operated equipment. Contrastingly, human operators are given a level of security and control over driverless trucks. Each operator is given an emergency stop device that can stop all driverless trucks within several hundred metres. Once people identify recurring patterns and operating parameters of the trucks, they begin to perform more efficiently. Despite the positive performances observed with driverless trucks, the language and information outputs transform, resulting in a much more complex by-product to learn.

4.2. Learning what driverless trucks perform

Driverless technology is developed with the designer's best imagination of the system. What was previously controlled locally by truck drivers is now managed by a centralised control system. Where pre-shift briefings, radio announcements, safety meetings and return to works could articulate site-related matters to truck drivers, no longer exist. Alternatively, users are equipped with a standardised fleet management system that operates within specific operating parameters. The benefit of those parameters is that every truck performs each aspect of the cycle the same, yet the downside is they

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perform nothing else. Whether it is turning a corner, indicating or changing gears, the entire fleet will perform tasks the same way. Consequently, the same areas of the road are targeted, which results in corners and ramps deteriorating much faster. Since human supervisors have limited control over the driverless trucks' performance, they begin to adapt local practices within the operating parameters. This can be seen in installation of speed zones, which prevent trucks from changing gears on ramps and ultimately preserving road conditions for longer. As more capabilities and limitations are learnt, the more supervisors find creative methods of closing the gaps.

If engineers are the only architects of driverless technology, automation may only lock-in systemic ways of mining. Moreover, with multiple customers operating on the same parameters, the impact could be observed more broadly. If the designer is yet to figure out how to automate parts of the cycle, the system leans on ancillary equipment operators, supervisors and manual truck operations to cover the rest. Figuring out when a truck should leave a loading area is complex, therefore excavator operators are required to inform trucks by pressing a button. In addition, narrow work areas, such as stockyards, can require haul trucks to be operated manually. When it comes to supporting roles, trucks are unable to distinguish the difference in road objects. Therefore, the system relies heavily on humans to verify that the truck's travel path is clear before proceeding. A truck may have identified a windrow, tumble weed or even cattle. Supervisors have learned that reverse objects should be approached with caution, given that driverless trucks have reversed over waste dumps after being cleared to proceed (Department of Mines and Petroleum, 2014). Virtual and physical distinctions can result in trucks attempting to achieve dump locations regardless of context. Therefore, driverless trucks are unable to free themselves of machine literalism, executing specific instructions that are pre-programmed into the machine.

The difficult part about learning what a driverless truck can do, is that the logic behind a decision remains hidden. As a result, supervisors of driverless trucks learn by observing and doing. A supervisor can learn the patterns of a driverless truck by watching the reactions to machine interactions. In addition, people also monitor the assignment engine to compare with the trucks' instructions. Other than observations, the language and labels that are used must be learned in order to understand what the truck is trying to explain. The methods of communications are chosen by the designers of driverless systems, not the users themselves. Whether it is through alarms, beeps, lights and information boxes, they are all structured in unconventional methods that were previously experienced in a manual truck operation. Therefore, the learning process for users is evolutionary, as software systems are upgraded, and new product capabilities are developed. Supervisors will always compare driverless technology to human level performance, leveraging their domain expertise in how mining operations should function. Despite this, artificial intelligence systems like AlphaGo, may even find other methods of hauling that are worth exploring (Etherington, 2017).

4.3. Supervising and working with driverless trucks

The problem with working with a pre-programmed machine, is that they are not necessarily team players (Christoffersen & Woods, 2002). However, the WA Mining Industry has so far found driverless technology relatively good 'team players'. Driverless trucks run hard, play their role and do not complain. Moreover, supervisors feel empowered over the truck fleet, responsible for task allocation and capable of stopping the fleet at any time. The trucks will literally follow every instruction, re-assignment and take longer routes to achieve their objectives. However, it depends on the perspective. Although the trucks play their specified role, they also need a lot more support. There are residual tasks that are often unspecified, unpredictable and imbalanced. Supervisors can be completing monitoring tasks and simultaneously be confronted with network outages, truck slides and broken-down machines. This can quickly lead to fault-finding exercises in determining what has occurred and why. Monitoring

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the fleet can be long periods of inactivity, quickly followed up by highly cognitive tasks. Therefore, human improvisations rapidly materialise on the frontline; adapting, testing and playing in order to keep the trucks moving.

Supervisors of driverless equipment are often held accountable for the performance of the machine. If the machine did was it was programmed to do, there is only ever the supervisor who is to blame (McKinnon, 2019). In particular, if the situation was considered foreseeable, supervisors are expected to intervene to avoid negative events (National Transportation Safety Board, 2018). It is an interesting perspective when machines are not held to the same standard of accountability as supervisors. For example, if a truck's action resulted in an incident, yet the machine did what it was programmed, then the supervisor is held accountable. Supervisors are expected to monitor and detect failures that are unspecified and unpredictable. Available data is analysed retrospectively to highlight whether a supervisor could have intervened. However, with operating parameters rarely known by the supervisor, they can be left surprised when the machine simply hands back control. Automation surprises have been a phenomenon for quite some time (Sarter et al., 1997). Driverless trucks, for example, can be found driving the longest haul route to the crusher. To human supervisors, the action can be leave them amazed as to why the truck chose a further travel path. What is always not explained, is that if multiple network outages or obstacle stoppages occur along the direct route, the system eventually calculates that route to take longer. Therefore, a faster route is selected in order to get the trucks to their destination sooner. This prioritisation and decision-making process is not always explained without a prolonged analysis of the system. Supervisors are rarely afforded the time to reflect on the actions and insights that justify their marginalised roles in optimising the system.

4.4. Navigating beyond design situations

Situations that emerge beyond the design requires supervisors to think outside the box. The benefit of driverless haul trucks over self-driving cars is their ability to stop when faced with novel situations. For example, if a survey has not been uploaded for the area, the truck will not enter the area. Moreover, if the communication network is lost, the truck will stop. Self-driving cars, on the other hand, are not afforded the same luxury. The vehicle will hand back control to the driver regardless if the person is prepared for it (SlashGear, 2017). Navigating these situations in a mining environment is a little different, given that the landscape of the mine is always changing. Therefore, it is usually in the truck restart where the problems arise. For example, a truck detects an object while reversing to a tip edge, however it may not be an object at all. The object could simply be the windrow, with the reverse point being placed behind the windrow (Department of Mines and Petroleum, 2014). The truck would be unaware that the object is a windrow and should be the alternative dump location. Therefore, truck supervisor navigates this situation by physically verifying the location of the windrow and uploading a new survey. Without this type of adjustment, the trucks would attempt to achieve the location if the machine was cleared to proceed.

Since novel situations are infrequent, it is not often that recovery skills can be practiced. Monitoring automated systems has been argued to conflict with human cognition (Reason, 1990). Therefore, when humans are needed to intervene, they can react negatively. Despite this, the ability of a human to apply a level of unconstrained thinking to draw from external sources and experiences, reinforces why they remain. Operating parameters will continue to hamstring driverless trucks by design, given that a machine has pre-determined views of the world. While some simulations and games have multiple possible outcomes, all of the physical world's scenarios are unlikely to be computed. This is dependent, of course, on whether someone believes that the physical world is simply a simulation. If that were the case, simulation could simply learn to represent the artefacts of the world, making non-designed situations a thing of the past. However, as previously explained, this is a reductionist view of the world.

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Therefore, if human-machine systems are going to navigate complexity, many argue that they will have to work better together (Woods & Hollnagel, 2006). A more collaborative approach will have to allow information to flow freely between humans and machines. Currently, the focus appears to be more on replacing drivers to realise an economic value. This approach will ultimately lead to independent systems, which are ignorant of human-centered perspectives (Fridman, 2018). However, if engineers are to overcome complexity, driverless systems will need to become more open sourced and start working with other branches of science. Otherwise, driverless technology could end up in similar situations as other pieces of extended intelligence, becoming solutionist, opaque and bias in light of the customers' needs (Bleicher, 2017; Bolukbasi et al., 2016; Dressel & Farid, 2018).

5. CONCLUSION

Evaluating the approach to haul truck automation highlights limitations of reverse engineering a complex system. If driverless technology is to move beyond reductionism, it needs more than a collection of engineers to be included in its development. Otherwise, its deployment could experience similar practical constraints as other technologies, with an inability to recognise certain objects, incorrectly classify artefacts and predict outcomes based on stereotypes. What appears to be a truck functioning a particular way on the surface, could simply be a reinforcement of wider industry norms. Despite the industry buying this technology, they are not the custodian of the algorithms; they are merely the users. Therefore, mining companies have effectively handed over agency and their ability to innovate to vendors. Although the technology has reached enough engineering maturity to be deployed in a mining environment, there is far more to human intelligence. Drivers are able to recognise the physical elements and learn from the interactions that are had with them. Where operations were in directly controlled through truck drivers, is now managed by a centralised control system. The consequences can be observed in variety of settings where products target correlations and not causations. Therefore, to shift the industry paradigm, a diverse range of domain experts and product users need to assist design engineers to think beyond narrow and bias views of a mining operation.

The research highlighted various examples of reductionism in practice. Simplifying the prediction of criminal recidivism, foreseeing areas of crime and recognising objects. The predictive capacity and level of accuracy has been achieved by validating performances against data that is held out for testing. Therefore, as this study explained, when specialised technology faces non-designed situations, it relies heavily on human supervisors to overcome them. Although the technology can appear more intelligent than humans, this capability is achieved from what it excludes. As a result, haul truck automation has been no different, with the technology presented as a predictable and more accurate substitution for truck drivers. However, as significant incidents demonstrate, driverless technology has its own set of novel situations to resolve. If the industry is to truly work towards becoming safer and more productive, the underlying causes of incidents and inefficiencies need to be addressed, rather than simply running the system efficiently more unproductive. The industry must push for more open collaboration to enable users to establish new methods, ideas and products. More collaboration will enable the industry to move beyond the technological advancements of today and embrace complexity. As a result, the approach can avoid systemic tendencies, opacities and exploitations of inefficiencies that come with truck automation.

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