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Impact of Autonomous Solutions on Electric Earthmoving Design Using Machine Learning: Case Study

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Abstract

The increased development in automated driving systems (ADS) has opened up significant opportunities to revolutionize mobility and to set the path for technologies, such as electrification. The proposed methodology is a simulation model backed by a multi-objective optimization algorithm. This research investigates the adoption of future technologies in earthmoving application and explores its implications on the design of future machine concepts in terms of equipment size. The shift from "elephant to ants" in the machine selection, resulted in improved feasibility.

Keywords: conceptual design, product development, autonomous vehicles, electromobility, machine learning

1. Introduction

The construction industry is faced with challenges such as the shortage of manpower, increased labor costs, unsafe work environment, and rising consciousness towards reduced carbon footprint. Several researches reported a poor performance in the construction industry stating that the industry has been lagging behind other industries in terms of innovation and technology implementation (Barbosa et al., 2017). AI has been a key factor and enabler for many technologies. It imposes itself as a vital tool to revolutionize the automotive industry, whether passenger cars, commercial vehicles or heavy construction equipment (Ertel, 2017). Remarkable advantages in terms of user experience, efficiency, safety, mobility, productivity, energy, environment, and economy have been reported with ADS (Ghandriz et al., 2020). Wadud (2017) reported that the user objectives and motivations differ for passenger cars, commercial vehicles transport, and construction equipment. For passenger cars, the major motivations are user experience and environment, whereas in freight transport and construction equipment, the subject of this study, the driving forces are productivity and profitability.

The Covid-19 pandemic provided an opportunity for organizations to change "business as usual" and engage in innovation and transformation (Elfsberg et al., 2021), and underlined the importance of ADS in keeping human safe and avoiding production interruptions.

Along the construction and mining value chain, AI is predicted to trigger significant changes, and the disruption potential is highest in areas that are characterized by repetitive, known tasks with limited uncertainty (Schober, 2020). The use of automated and autonomous machines in earthmoving applications serves primarily to increase the productivity and the safety at the site (Frank et al., 2019), through higher utilization and reduced operating costs (Barbosa et al., 2017). Having said that, ADS could be seen as a key driver for many technologies, primarily electrification.

Over recent years, society has come to realize the need to reduce carbon footprint by looking into alternative solutions away from oil-fueled combustion engines. "Electric mobility is truly a disruptive technology that does not just change the powertrain of the automobile, but may also influence the conditions of its use" as per the European Commission (European Commission, 2017). Emerging technologies have an opportunity to address carbon neutral construction goals by enabling principles like resource utilization and electromobility (Melenbrink et al., 2020). As the performance and availability of batteries, motor and control systems is rapidly increasing, electric solutions could now cater one of the most demanding automotive application – namely, construction (Guyot, 2020).

Several studies have investigated the impact of integrating autonomous and electrification solutions on passenger and commercial vehicles. In terms of the total cost of ownership (TCO), Ghandriz et al. (2020) demonstrates that ADS allows to lower TCO for BEHV (battery electric heavy vehicles) by removing cab heating, and relaxing shift constraints allowing the reduction of the optimum speed, and the use of smaller battery sizes. Whether ADS or HD (human-driven), BEHV is not always more competitive than CHV. In cases where the driving ranges are long and hilly, and when the BEHV is large, CHV is more competitive, due to batteries weight and cost. Lebeau et al. (2019) concluded that the heavier the electric vehicle, the less competitive it is compared to its conventional diesel versions, in terms of TCO. The difference in TCO was underlined by a higher purchase price of the electrical vehicles since bigger batteries are needed. This discrepancy is subject to improvements with economies of scale, battery technology and/or machine conceptual design. From here, Wu et al. (2015) predicted a shift towards smaller vehicles, as smaller EV are more cost-efficient than larger ones, and a resistance from end-users towards EV because of their initial higher cost, which is easier to evaluate by end-user rather than looking at the TCO.

Construction machinery is very different from typical vehicles, particularly in terms of application, structure, load, weight range, transmission and energy consumption, etc. The weight of the machine is a decisive factor for the design of electric systems, where "a small tonnage can adopt pure battery electric system, and a large tonnage can adopt the HES based on an ICE" (He and Jiang, 2018). Börjesson et al. (2021) reported that "issues in an EV scenario are not only the battery cost but also the size and weight of the batteries, and the frequent recharging". According to Earl et al. (2018), the battery sizing for BEHV could be optimized using a driving cycle with lower speeds and a higher utilisation rate among other factors. Historically, the effectiveness of construction machinery has been limited by its size; larger machines meant that a single worker could be more productive, creating an economic incentive for "mechanical gigantism" (Abdelmassih et al., 2021a; Melenbrink et al., 2020). According to Melenbrink et al. (2020), one advantage of autonomy is the ability to disregard this economic incentive and reconceptualize the scale and scope of construction tasks from fundamentals. This came in line with Müller (2019) who considers that "automation is an enabler for electrification", and brought forward the concept of "moving from elephant to ants" in earthmoving. Müller (2019) investigates the electrification of a fleet of haulers for material transportation, as opposed to a stationary loading unit that can be connected continuously to a grid network. Unlike an on-road commercial vehicle, the haul path is cyclic and pre-defined within a closed site, making it possible to recharge the battery on the queues of every cycle. The challenge for the haulers is to design a 100% battery electric heavy vehicle taking into consideration an optimal sizing of the battery cell, by keeping the weight of the battery to a minimum, avoiding power peaks during charging, and maintaining a feasible cost for commercializing the product. Müller (2019) predicts that smaller capacity EVs are more efficient than bigger machines, especially in mining application where not only the cost of the batteries increases the TCO, but also the dead weight of the batteries renders the operation less efficient. He argued that smaller haulers will impose a larger number of units to sustain a specific operation and production. From here, ADS can be seen as a key driver in optimizing the battery sizing in EV, by reducing the operator cost, lowering driving cycle speeds, and increasing utilization.

Designing future concepts of construction and earthmoving equipment does not follow similar guidelines as the passenger and commercial truck industry where technology is more mature. From here, delivering an efficient development process has been a hot topic in recent years. Bertoni et al. (2017) demonstrated the use of operational data to complement experience-based decisions in engineering design. Thus, data-driven design automation from an operational data viewpoint in the concept development stage is largely unexplored and present major design opportunities. Although the empirical data collection being performed is from the construction machinery industry, literature shows that the

underlying challenges are not unique to such industry but are shared in other industrial sectors as well, giving promising insights for the future generalization of the findings in different industrial contexts (Machchhar and Bertoni, 2021). Schockenhoff et al. (2021) offered an exhaustive assessment of conventional design approaches such as the Six sigma, Munich procedure model, design thinking among others, and presented an autonomous vehicle concept development process that addresses design challenges in a user need-oriented way. Vidner et al. (2021) proposed an optimisation framework to simulate excavation rates and to optimize the design of the boring head cutter in tunnelling and mining applications. The optimization approach is based on a multi-objective evolutionary algorithm. Göhlich et al. (2019) presented a simulation-based methodology for the conceptual design of electric bus systems while investigating charging systems, battery technology and aging. The study concludes that different battery types and charging systems are suitable for different operating scenarios and stresses the need for a detailed analysis of the TCO for more accurate results.
The presented research investigates the impact of the adoption of autonomous solution on BEHVs taking into account vehicle size/weight. The research adopts a simulation-based optimization approach. The study challenges the question of whether automation is an enabler for electrification, and explores the economic feasibility of going "from elephant to ants" in the conceptual design of an autonomous electric articulated hauler.

2. Methodology

The proposed methodology examines the impact of ADS on the design of EV earthmoving machinery in terms of project completion costs, productivity, equipment utilization, and total cost of ownership (TCO), using a simulation-based optimization approach. The methodological approach minimizes the objective functions (TCO and total project cost) by optimizing the fleet selection, in other words the fleet and the equipment size. The presented research benchmarks conventional and future technologies scenarios in an earthmoving application. Given that little techno-commercial information is available for EV, ADS and EV-ADS solutions in earthmoving applications, the methodology considers specific parameters based on related literature review. These parameters dictate the ownership and operating costs of EV, ADS and EV-ADS equipment simulated. The conventional CHV machine types are selected from a pool of current commercialized equipment. Simulation-based optimization has been widely used in construction applications. This research adopts a multi-objective unsupervised machine learning approach based on a simulation model depicting a quarry operation. All input parameters for the model are based on real data collected from actual construction sites and from manufacturers specifications. That was possible thanks to the hands-on experience of one of the authors in the field. Volvo CE’s “Electric Site” at Vikan Kross is presented as a case study. Figure 1 depicts the optimization model adopted in the proposed methodology.

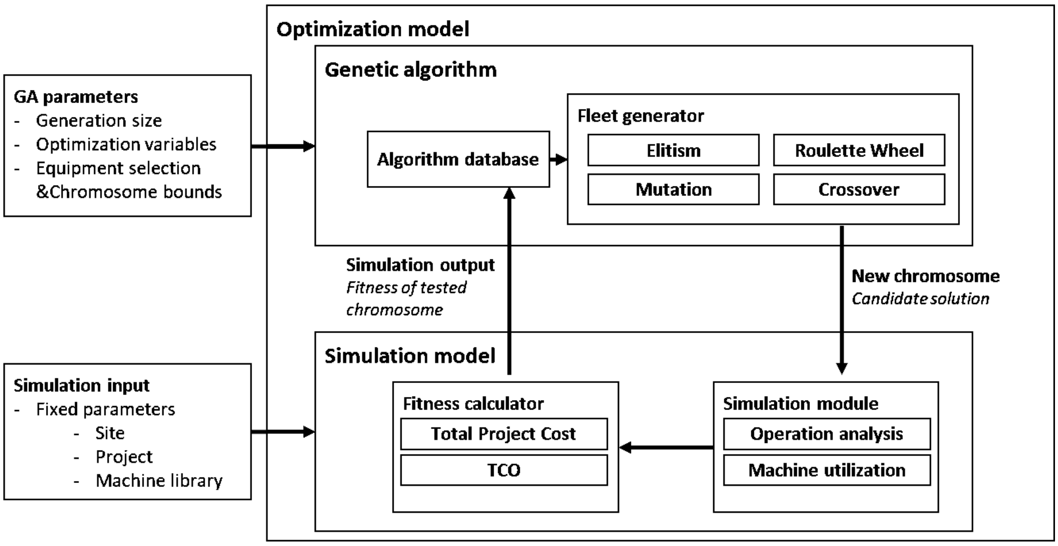

Figure 1. Optimization model

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On one hand, the simulation model depicts the actual earthmoving project given a specified set of input parameters, and returns the objective functions calculated or the fitness. The optimization model, on the other hand, is needed to improve the fitness value by finding the optimal set of parameters.
The presented approach is a research topic widely investigated and has shown improved optimization performance (Marzouk and Moselhi, 2002; RazaviAlavi and AbouRizk, 2017).

2.1. Simulation model

The proposed simulation models the load and carry operation from the quarry to the crusher based on "Vikan Kross" site. Earthmoving works, are complex systems during which the uncertain availability of several resources must coincide in time and space to carry out particular tasks. This renders construction operations even more complex and simulation-demanding where traditional and conventional optimization strategies become useless. The simulation model is based on a discrete event simulation (DES) approach. A series of blocks is used to define the transitions within the load and carry applications. The hauling units are defined as agents, while the loading units are seized from the resource pool as resources. As such as, discrete event modelling can be seen as a sequence of operations that agents perform. The flow chart starts with the source blocks that generate agents and inject them into the process. A set of parameters, variables and functions define the aspects of the site and equipment, allowing the model to calculate the objective function to be optimized by the machine learning algorithm. The objective function presented in section 2.3 define the cost aspect of each fleet configuration. Specific parameters for each of the CHV machines simulated such as the cycle time, fuel consumption, bucket capacities and the haulers' speed are based on Volvo Performance Manual (Volvo Construction Equipment, 2015). The maintenance, repair and ownership costs are based on market values. The model presented allows to test CHV, EV, ADS and EV-ADS solutions. As the proposed simulation model accepts parameters such as the initial cost, depreciation, maintenance and repair costs, fuel and operator costs, related assumptions and numerical justifications are offered to support the simulation of EV, ADS and EV-ADS based on the common CHV type.
A machine initial cost increase is applied for each of the EV and ADS solutions, based on the standard CHV model. According to Wu et al. (2015), there is a higher initial cost of EV and/or ADS compared to CHV, as a result of battery cost, and weaker economy of scale, even if EV saves the cost of the conventional CHV driveline, and ADS saves on the cost of cab, on-board human-machine interface and related accessories. It should be mentioned that the initial cost for EV and ADS is based on assumptions. As of the date this paper was written, no manufacturer of mining equipment revealed a possible retail price for such equipment. The current available solutions are being tested on pilot projects based on "Transport as a Service" business model. It should be mentioned that manufacturers such as Volvo Construction Equipment (VCE) are already retailing electric versions of compact wheel loaders and excavators.
The depreciation (per year) on EV is slower than diesel machines (15% on EV as opposed to 20% for diesel) (Lebeau et al., 2019). The battery cell's first lifetime for EV is 8-10 years, as per Guyot (2020). The battery life depends on the battery technology, the number of charge/discharge cycles, the equipment types and sizes, and the average equipment utilization. Werber et al. (2009) argued that the maintenance and repair cost for EV and for ADS is lower compared to that of CHV, having fewer moving parts, lower temperature stress and not requiring oil and filters. In addition, Lebeau et al. (2019) justified that the extra cost of batteries on electric vehicles are balanced by lower insurance, maintenance, and fuel costs of electric vehicles compared to their diesel versions. It should also be added that Emission After Treatment Systems (EATS) on CHV models (in particular in regulated countries), are raising the maintenance cost considerably, to the advantage of electromobility.
The model assumes that EV machines are charged during each cycle (Müller, 2019), and considers that the cost of electricity for charging follows the non-household rate in Sweden is 0.0645 €/kWh (European Union, 2020). The cost of electricity used to charge the electric machines is based on the amount of diesel consumed by each machine, using a value of 9.95 kWh/L to convert from equivalent liters to electrical energy (Kotz et al., 2020). On a further note, having zero tailpipe emissions is a major benefit of electric vehicles, however, when looking at the holistic impact of vehicle electrification it is necessary to also consider the emissions produced to generate electricity (Kotz et al., 2020). The proposed model

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takes into account the cost of carbon emissions in the objective function for CHV machine types (Abdelmassih et al., 2021b), however assumes that the electricity used for charging EVs is generated by renewable sources, and thus does not have carbon footprint. The operator hourly rate is an average of that rate taken from Sweden. The model does not take into account neither the cost of infrastructures, nor any government incentives for using clean technologies. Table 1 summarizes the input parameter justifications that will be applied to the simulation model.

Table 1. Factors for input parameters

Machine cost increase for EV / ADS	1.7
Machine cost increase for EV	1.45
Machine cost increase for ADS (less cab)	1.35
Depreciation year - CHV / ADS	7
Depreciation year - EV	8
Maintenance cost decrease for EV / ADS	0.85
Repair Mean cost decrease for EV/ ADS	0.85
Repair Sigma cost decrease for EV/ADS	0.75
Diesel Cost ($/L)	1.6
Cost of electricity for charging (non household) ($/kWh)	0.075
Operator cost for EV / CHV ($/hr)	20
Operator cost for ADS ($/hr)	0

2.2. Machine Learning algorithm

The proposed methodology seeks the optimal solution for the load and carry application, using an evolutionary programming approach based on the genetic optimization. Genetic algorithm (GA), originally introduced by John Holland in the 1960s and inspired by natural selection, is one of the earliest metaheuristic approaches, and has been widely used in the optimization of civil engineering application (Marzouk and Moselhi, 2002). It is an optimization tool that is not computationally demanding and can find good solutions without getting stuck at local optimum. GA is an optimization method that allows the evolution from one population to a new population using two genetic operators; crossover and mutation according to Mitchell (1999). The proposed model can be considered as an unsupervised machine learning approach which learns from simulated datasets. While simulations can model specific scenarios or operations given a specified set of input parameters, GAs are needed for finding the optimal set of parameters given a specified "fitness" function. Parameters sets are denoted "Chromosomes" in the GA paradigm. Each chromosome corresponds to a potential solution, representing a specific fleet composition. A chromosome consists of a one-dimensional array of genes. The genes in each chromosome represent the number of a specific predefined machine type, whether a wheel loader, excavator, or articulated hauler. Each gene of the chromosome is associated with a random integer within a pre-defined range representing the number of units of specified machine type. The GA uses a single point crossover operator. The mutation operator of the GA (with a probability of 15%) consists of randomly choosing a gene in the chromosome and assigning a random integer (within the specified range) to that gene. The GA uses the "roulette wheel" selection procedure to choose the chromosomes that will reproduce to generate the population of the next generation. The GA model collects data by adopting twenty generations, each generation constituted of 20 chromosomes (i.e. candidate solution), meaning a total of 400 iterations in one run. The earth moving simulation model returns the cost function and the total cost of ownership (TCO) used as the fitness required by the GA. It should be mentioned that even though elitism is used in the optimization method, and thus the fittest chromosomes are saved to the next generation, it is not possible to record an identical fitness value for two similar chromosomes, due to the stochastic nature of the simulation model. This approach was tested by Abdelmassih et al. (2021b, 2021a), and proved to yield improved and robust solutions to the earthmoving application in question.

2.3. Output variables

The presented methodology analyses and optimizes two output variables namely: total cost of ownership and total project cost.

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The total cost of ownership is formulated as

$$TCO\ (\$/\text{cbm}) = \frac{C_{own} + C_{op}\ (\$)}{Production\ (\text{cbm})} \quad (1)$$

where C_{own} is the ownership cost covering the initial purchase cost, cost of money, depreciation, taxes on equipment, insurance cost and storage expenses and C_{op} is the operating cost covering maintenance and repair, operator cost and fuel and lubricants. The recorded TCO will be calculated separately for each of the hauling and loading equipment type.
The cost function for loading and hauling of material from the quarry to the crusher is defined as

$$Cost = \text{EqCost} + \text{EmiCost} + \text{PenCost} \quad (2)$$

$$EqCost = \sum_{i=1}^{n} EqOpHr_i \times (MaintCost_i + OpCost_i + FuelCost_i) + \text{RpCost}_i + \text{OwnCost}_i \quad (3)$$

$$EmiCost = (\sum_{i=1}^{n} EqOpHr_i \times FuelCons_i) \times 2.68/1000 \times 41.64 \quad (4)$$

where Cost is the total cost function (\$), EqCost is the cost of all equipment (ownership and operating cost) (\$), EmiCost is the cost of emission (\$), PenCost is the penalty cost if production levels are not met (\$), i is the equipment number representing wheel loaders, excavators and articulated haulers, MaintCost is the maintenance cost of each machine per hour of machine operation (\$/hr), OpCost is the operator cost per hour of machine operation(\$/hr), FuelCost is the fuel cost per hour of machine operation (\$/hr), RpCost is the repair cost per hour (\$), OwnCost is the ownership cost combining both a fixed cost and an hourly rate of ownership (\$), and FuelCons is the fuel consumption per hour of every machine type. The ownership cost imposes a fixed cost for every equipment mobilized to the project in addition to an hourly rate based on the machine operating hours. The fixed cost is derived from the initial price of the equipment normalized to this project, based on the total simulation time (\$). The emission cost is calculated based on the total volume of fuel consumed. It is considered that 1L of fuel generates 2.68kg of CO2, and the price per ton of CO2 is 41.64\$ (Luckow et al., 2015).

2.4. Case Study - Vikan Kross "The Electric Site"

The presented methodology uses Volvo CE's "Electric Site" as a case study. The hauling units are loaded at the quarry using wheel loaders and/or excavators. The haulers travel a distance of 1km to dump the earth onto the crusher. An average of 1.25 million tons is mined each year with a daily rate of 6,000 tons (Volvo CE, 2018). The simulation model considers a density of 1.5ton/cbm and run until 1 million cbm of earth is transported to the crusher. The crusher is assumed to have a maximum output rate of 400 cbm/hr, which will act as a constraint if capacity is reached. In that case, trucks will queue to empty the load. Volvo "Electric Site" features VCE's prototypes of an electric hybrid wheel loader and excavator, and an autonomous fully electric 15 tons hauler.

3. Results

The impact of the integration of automation in earthmoving electrification is presented while assessing the implication of equipment-specific design parameters, namely machine size/weight. The results are presented under two headlines (i) Enabling electrification (ii) "from Elephant to Ants".

3.1. Is automation an enabler for electrification?

The presented methodology compares the optimized objective function of machine types based on different machine technology: the conventional CHV model, EV, ADS and EV-ADS. The EV, ADS and EV-ADS machines are based on the CHV conventional models, however are subject to the factors defined and justified. Figure 2 shows the optimized total cost curve to complete a similar task for each of the four simulation scenarios. The x-axis shows the number of generations (20), each generation consists of 20 chromosomes (simulation), while the y-axis shows the fitness. The chart presents the minimum value of a chromosome in each generation.
As can be noted in figure 2, the GA allows the simulation model to converge towards the fittest fleet configuration, offering the lowest cost. As the generation evolves, the fitness optimizes until the curve

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reaches a flat where the best fitness is reached. It can be seen that the scenario, where both EV-ADS solutions are implemented, converges to the lowest total cost compared to the CHV, ADS and EV.

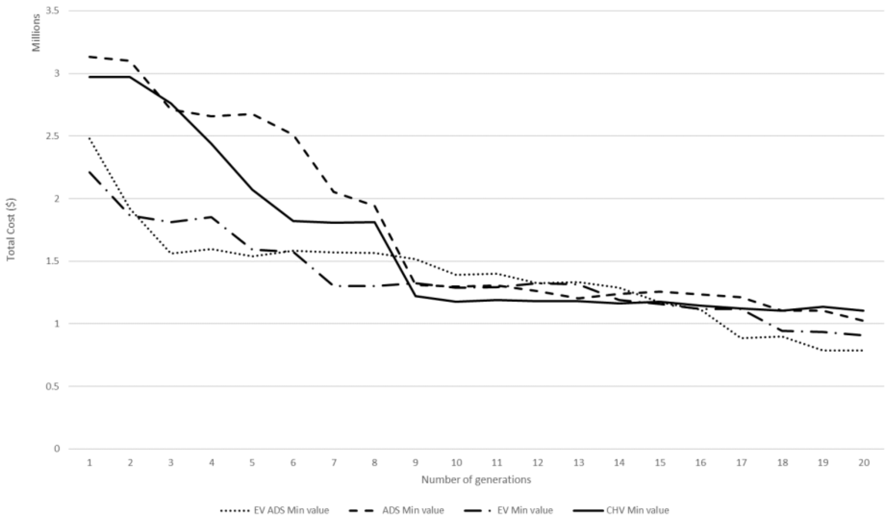

Figure 2. Cost curve for each scenario

Table 2 presents the optimal fleet chromosome from each machine type scenario. For the scenarios of CHV and EV, the optimal fleet configuration is composed of one EC750D and two A60Hs, while the configuration for scenarios ADS and EV-ADS contains one EC750D and four A25Fs. It should be noted that different fleet configurations can yield comparable near optimal solutions, however it is important to highlight the trend that the hauler size follows. As opposed to CHV, the integration of ADS in EV, induced a machine size shift from larger to smaller, reported by the fact that the 25-tons hauler replaced the 60-tons hauler in the optimal fleet configuration. The impact of the equipment size on the integration of future technologies is investigated in the following section.

Table 2. Optimal fleet configuration of each technology type

Scenario	Fleet						
Machine type	L350F	L180H	EC750D	EC380D	A60H	A40F	A25F
CHV	0	0	1	0	2	0	0
ADS	0	0	1	0	0	0	4
EV	0	0	1	0	2	0	0
EV ADS	0	0	1	0	0	0	4

Table 3 summarizes the results recorded in figure 2, by comparing the total cost and the TCO of the optimal chromosome, in each of the four scenarios of CHV, ADS, EV and EV-ADS machines.
The result shows that EV-ADS not only offers an improvement to the CHV scenario, but also offers a bigger improvement to the CHV compared to each of the ADS and EV alone. When ADS is combined with EV solutions, and even though EV-ADS solution has the highest initial cost, it is noted that the lowest total cost and TCO are recorded. It should be noted that electric machines are modelled in such a way that when machines are idle or in a queue, they neither consume energy, nor clock maintenance hours, unlike the conventional CHV or ADS (CHV) type.

Table 3. Numerical comparison of output parameters

Machine technology	TCO hauler ($/cbm)	TCO loader ($/cbm)	Total Cost ($)
CHV	0.79	0.29	1,104,000
ADS	0.71	0.28	1,023,304
EV	0.65	0.25	909,520
EV ADS	0.55	0.23	787,315

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The recorded results are based on the "Vikan Kross" site in Sweden, where specific country parameters, external to the site, such as the diesel cost, electricity cost and operator hourly rates apply. The climate factor is ignored.

3.2. From Elephant to Ants

In order to investigate the impact of ADS on the design of EV haulers compared to CHV in relation to the equipment size, the proposed methodology simulates the quarry operation using different articulated hauler models. The genetic optimization supports a convergence from larger to smaller hauler capacity, as ADS integrates with EV, recorded in table 2. Based on these results, the model compares the earthmoving operation, in terms of the cost function and the TCO, by selecting separately each of the articulated hauler sizes (A60H, A40F, A25F), while maintaining comparable daily production rates among the three scenarios. Table 4 presents the results collected from each scenario.

In the case of CHV, the results show that the configuration containing the largest hauler "A60", having a capacity of approximately 60-tons, offers the lowest cost outputs, compared to the smaller hauler sizes (A40 and A25). On the other hand, in the case of EV-ADS, the impact of the hauler size is reversed in terms of the total cost function and TCO. The results show that the largest hauler offers a higher TCO and total cost function, compared to the smaller hauler sizes. The smallest of the three articulated haulers (A25) offers the lowest costs. The 25-tons articulated hauler recorded a hauler TCO of 0.55$/cbm compared to 0.64$/cbm and 0.62$/cbm for the 60- and 40-tons haulers, respectively. The smaller the hauler size is, the lower the TCO and total cost are.

Table 4. Output parameters based on hauler size

Scenario	Fleet				CHV		EV ADS	
Hauler size	EC750D	A60H	A40F	A25F	TCO hauler ($/cbm)	Total Cost ($)	TCO hauler ($/cbm)	Total Cost ($)
A60	1	2	0	0	0.78	1,104,000	0.64	884,216
A40	1	0	3	0	0.80	1,124,760	0.62	858,216
A25	1	0	0	4	0.80	1,144,366	0.55	787,315

It should be noted that the number of the hauling units increases as the hauler size is reduced. This is to maintain a comparable production level between the three scenarios, a production level indicated in the case study of Vikan Kross. It is worth nothing that increasing the number of haulers resulted in additional queues and idle times at the loading and dumping blocks of each cycle in the simulation runs, and thus recorded reduced machine utilization. Conventional practice seeks to minimize idle time while ensuring maximum machine utilization. A CHV type equipment consumes diesel and clocks maintenance hours at idle, unlike an EV which on the other hand could benefit from a queue to optimize the charging cycle, and reduce the battery size needed to a minimum. For instance, a downsizing of the crusher production capacity not only reduces crusher operating costs, but also induces additional idle/charging time to the EVs.

4. Discussion

The results obtained justifies that automation is an enabler for electrification. A 30% and 28% decrease in the hauler TCO and the cost objective function, respectively, compared to the CHV is noted when EV-ADS is applied. This decrease in the cost is greatest compared to each of the EV and ADS solutions alone. Also, in line with previous research results (Ghandriz et al., 2020), we conclude that the adoption of ADS in EV, improved TCO by more than 25%.

This study also explores equipment-specific design parameters. The obtained results validate and support the approach of going from "Elephant to ants", in accordance with Wu el al. (2015) and Müller (2019)'s rationale behind the development of the smaller HX2 (EV-ADS) 15-tons hauler. The heavier the electric vehicles, the less competitive it is in terms of TCO. In the case of on-road applications, increasing the driving range or the vehicle size render EV less competitive compared to CHV, as per Werber et al. (2009) and Lebeau et al. (2019). Equally, the haul range and the machine size are important factors affecting the competitiveness of EV in construction applications. This conclusion can be

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explained in two folds. First, ADS solutions allow to increase the number of the smaller electric capacity haulers, without incurring operator costs. Second, designing smaller capacity haulers, not only reduces the number of battery cells needed and the dead weight of the batteries, but also optimizes the initial cost (i.e. ownership cost) of the unit. It is worth mentioning that the adoption of smaller machines, more modular solutions, facilitates adequate resource allocation between projects, quarries and mines. It is important to re-state that since little techno-commercial information from future technologies adaption in the off-highway segment is available, the presented methodology is based on substantiated assumptions that could possibly be argued. The methodology adopts consistent criteria to support the assumptions and provide a fair benchmark between the different simulation scenarios considered. Further findings from the industry's pilot projects adds robustness to the present model.

5. Conclusion

This research investigates the integration of ADS in the electrification of earthmoving operations, and delivers a deeper understanding behind design considerations in terms of equipment size/weight. The adoption of future technologies in earthmoving and mining applications brings major transformation in terms of productivity, efficiency, safety and environment. The study validates the positive economic impact of "going from elephant to ants" driven by the adoption of ADS in the electrification of earthmoving operations. Further studies shall explore the benefits that connectivity could bring to the EV-ADS combination. Connected autonomous equipment could optimize the battery sizing and energy consumption, by monitoring an adequate travel speed, benefiting from coasting and rolling, avoiding unnecessary stops and demanding accelerations, cancelling non-ideal operator behaviour, and designing an optimal battery charging cycle.

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