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Merging agent-based simulation and vehicle dynamics: a hybrid approach for value exploration in the mining industry

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Abstract

Innovation plays a vital role in ensuring sustainable mining operations. Electrification and autonomy are two significant trends, but their implementation brings complexity at vehicle and site levels. Therefore, it is crucial to understand how these technologies impact the overall site value creation. This paper suggests a hybrid approach that combines Agent-Based Simulation and vehicle dynamics modeling to explore site configurations. By regarding a mining site as a System-of-Systems, designers can concurrently test different designs to find the optimal combination for a specific scenario.

Keywords: simulation-based design, autonomous vehicles, system of systems, electromobility

1. Introduction

Innovation plays a critical role in the development of more effective products and systems operations and in meeting the increasing demands of sustainability. Operations in the mining industry are no exception. Mining is typically a sector categorized by low margins and returns, in which the innovation effort is generally focused on higher production efficiency while reducing environmental impact (Humphreys, 2001). Challenges like decreasing ore grades, deeper deposits, and increased environmental and social awareness are currently central to the research initiatives in the industry (Sánchez and Hartlieb, 2020). This stresses mining organizations and mining equipment manufacturers to innovate where productivity and sustainability are accounted for.

In such a context, electrification is an increasingly recognized approach for improving sustainability metrics, both in the mining industry (Ertugrul et al., 2020) and in the transportation sector as a whole (Ranjbar and Sharifzadeh, 2022). Ertugrul et al. (2020) raise several challenges or potentials that must be addressed in the electrification, such as understanding the effect of regeneration of energy when breaking, understanding how to combine best and select between different technologies (e.g., fast-charging versus battery swap), and understanding the interplay between vehicles, infrastructure, and context (e.g., a mining site and its support infrastructure).

In such a context, introducing new concepts of electric vehicles and machines makes modifying site and fleet setup a cumbersome and exhaustive task and is, hence, not a viable option for testing and identifying the optimal site setup. Yet the site and fleet configuration can substantially impact the system's value, e.g., productivity, efficiency, and sustainability. A more feasible approach is then to use simulation modeling. At a theoretical level, a site can be considered as a Systems-of-Systems (SoS) construct. A SoS can be defined as an assembly of individual systems where each system possesses operational and managerial independence in relation to the other systems (Maier, 1998). An example of this is a quarry site where each machine, e.g., wheel loader, hauler, crusher, etc., can operate by itself, but the site, which is the SoS, relies on the successful integration and interaction between these systems to function. This

means that the mining site can be seen as a multi-objective optimization problem where an optimal balance between each system and SoS operations is sought. However, the high level of complexity and uncertainty, in combination with limited resources, makes the search for an optimal solution practically impossible (Keating et al., 2003). Instead, the focus should reside on finding working solutions and exploring the value of those solutions, i.e., finding the optimal solution among found working solutions. Exploring design options in SoS is about understanding the impact of different systems' behavior and configuration on the overall SoS level, something that is typically done through simulation and modeling. Kinder et al. (2014) raise multiple modeling and simulation approaches for SoS, e.g., Discrete-Event Simulation, Agent-Based Simulation (ABS), and System Dynamics. Out of these, ABS is the most robust and versatile approach (Hester and Tolk, 2010). Specifically, in SoS, ABS is raised as a suitable approach thanks to its bottom-up approach that allows for autonomous agent behavior (as characterized by an SoS), natural interactions between systems, and modeling of dynamic environments (Hester and Tolk, 2010; Kinder et al., 2014; Silva and Braga, 2020). ABS is a modeling approach that uses agents that operate autonomously and interact with the given context and other agents (Kinder et al., 2014). From an engineering perspective, ABS can model complex behaviors and have agents dynamically adapt to changing contexts to reflect real-world scenarios better and achieve a close representation of the intended SoS (Silva and Braga, 2020). However, trying to program behavior that represents complex systems, such as electric vehicles with advanced dynamics, could lead to an impossible task. Here, a hybrid approach that combines analytic models and simulations is beneficial. This approach is good when the problem cannot (within reason) be analytically modeled, but a part of the system (or SoS in this context) can be (Shanthikumar and Sargent, 1983).
Based on such rationale, this paper describes a hybrid approach for simulation-driven configuration of System-of-Systems developed with the aim of assessing the joint impact of sub-system and system designs on the overall SoS value creation. The research objective can thus be summarized as follows:

> *How can a System-of-Systems, with its inter-layer dependencies, be simulated for the mining industry?*

The approach is exemplified in the context of mining and quarrying in a design case consisting of electric-autonomous vehicles and related infrastructure. A core aspect of the approach is capturing the linkage between the vehicle (system) and site (SoS) to be able to manage both infrastructural, contextual, and operational design parameters. This could include site, vehicle specifications, charging policies, and operational strategies, among others.
Finally, the paper is structured as follows. Section 2 goes through the methodology deployed in the research efforts. Section 3 raises the challenges faced by the mining industry and the challenges of simulation and modeling in this sector. Section 4 presents the hybrid simulation approach developed as well as its connected process, and Section 5 provides a case study where the approach has been tested as a Proof of Concept. Finally, Section 6 presents general reflections, and Section 7 concludes the paper and raises proposals for future research.

2. Research method

This paper is based on Action Research, which can be explained as a combination of theory and practice where problems, interventions, and learning are iterated among researchers and practitioners (Avison et al., 1999). AR is a suitable approach when the active involvement of practitioners, integration between descriptive and prescriptive actions, and its direct link to the studied context are sought (Bradbury, 2015). At a more granular level, this paper builds on the cumulative learnings from researchers and practitioners and presents a loop of problem identification, action interventions, and learnings. The problem identification is based on a collection of data through unstructured interviews, workshops, and debriefs that happened in three research projects run in parallel with different stakeholders of the same partner company in a 2-year timeframe. Potential action interventions have been discussed during periodical bi-weekly debriefs and by-monthly co-located workshops where the overall purpose of a site-vehicle simulation has been addressed. The proposed framework was implemented and tested in a design case as a Proof of Concept to evaluate the proposed support to a level of validation that likens the "support evaluation" stage of the Design Research Methodology as described by (Blessing and Chakrabarti, 2009).

3. Challenges in System-of-Systems modeling in the mining and quarry industry

The mining and quarry industry is undergoing a transformative innovation process that suggests the emergence of disruptive technologies related to autonomy and electrification in the near future. The digital transformation is shaping the mining industry and the transition from man-operated sites to autonomous and remote-controlled sites (Sánchez and Hartlieb, 2020). This is also reflected in the equipment providers as more and more are deploying autonomy as a next step in mining and hauling innovation. Some of the stated benefits of going autonomous are better safety, reduced wear on components, more accurate life predictions, increased efficiency, cost reductions, lowered emissions, and the ability for 24-hour uptime (Caterpillar, 2021; Komatsu, 2023; Volvo Autonomous Solutions, 2023). Further, this innovation goes hand in hand with the general industrial trend of moving from buying products to performance and total care solutions (Kumar and Kumar, 2004) and emerging business models such as Transport as a Service (TaaS) (Volvo Autonomous Solutions, 2023). However, this also poses challenges for OEM manufacturers in finding the trade-offs between different customers' needs and ensuring contractual fulfillment, i.e., managing the risks connected to being in charge of both the product and its operations (Kumar and Kumar, 2004).

One method for exploring these trade-offs and better understanding the impact of design decisions at the systems level on the overall SoS value creation is through process simulations, an approach used when prototyping or experimenting in the real world is expensive or impossible (Borshchev and Filippov, 2004). Modeling and simulation are key areas in SoS engineering (Kinder et al., 2014) and are important approaches for understanding the behavior of SoS and its internal interactions (Silva and Braga, 2020). Especially in the earlier design stages, simulations can provide vital input and the ability to explore alternatives without extensive investments.

In the field of simulating mining processes, there are examples of demonstrators using tabular data values or probabilistic functions for hauling times based on sample data, e.g. (Ghaziania et al., 2021; Huayanca et al., 2023; Salama et al., 2014) as well as an example of electric hauler simulation at system level (Lindgren et al., 2022). However, research on evaluating electric haulers at a SoS level is missing. Mining sites can generally be considered as SoS and thus cannot be modeled as large, complex systems, but they require appropriate modeling and simulation approaches (Kinder et al., 2014). For example, when transitioning to autonomous drive, the speed can be optimized at a much granular level, significantly affecting travel time duration. In electric vehicles, the selected speed at a given point tremendously impacts energy consumption. This impacts the vehicle's performance to a greater extent than combustion-powered vehicles, as the energy density of a battery is much lower than that of diesel. A simulation model must henceforth be capable of simulating these aspects to provide a reliable result, and hence, a tabular and probabilistic simulation approach is not appropriate. A SoS simulation approach would allow design teams to, through simulations, test and fine-tune the site and vehicle setup to be tailored for the specific context early in the design process. However, it demands a simulation approach that can combine site simulation with vehicle dynamics.

4. A hybrid approach for simulation-driven configuration of System-of-Systems

The approach proposed is illustrated in Figure 1 and is based on the classification of hybrid simulations posed by Shanthikumar and Sargent (1983), where the simulation and analytic model run in parallel (Class II). This is because of the time dependency that exists between the two models, and as the vehicle agents in a mining site require advanced dynamics, a well-explored field, it is more effective to outsource this part and run it through an external analytical model that integrates with the ABS. The core of the approach is thus a site model that is used for modeling the site environment, the operating vehicles, boundary objects, and internal interactions. The site model has two main inputs: site data (a database with environmental data regarding the site) and operational scenario (site setup, operational strategy, operational data, hauler specifications, etc.). The site model utilizes ABS as a method due to its previously mentioned advantages. ABS allows the behavior of the site to be developed and then automatically adapt to a given context without the need for user interventions.

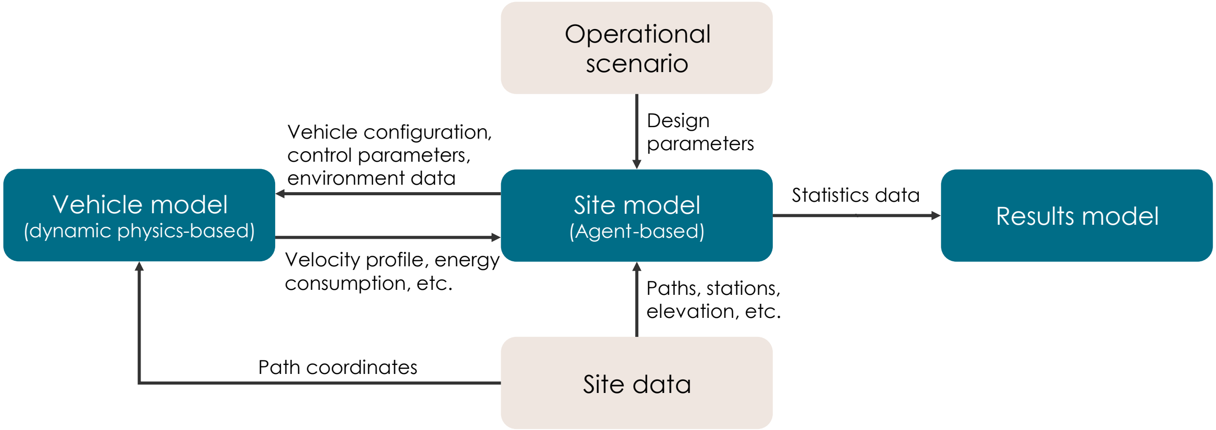

Figure 1. The architecture of the hybrid approach for simulation-driven configuration of Systems-of-Systems

The site model then interacts with a dedicated vehicle model that is aimed at calculating the most optimal movement through a given path based on input and control data from the site model. This model is an analytical model of the vehicle dynamics, solved using a quasistatic approach (Guzzella and Sciarretta, 2013) for electric haulers. Finding the optimal control policy for the hauler is based on the minimization of a cost function using dynamic programming. This cost function is particularly tuned to predict different optimal control policies based on the different prioritizations of saving time and energy. The optimal control policy is then executed in the vehicle model for the corresponding vehicle as it transitions in state (moves between stations). Throughout the simulation, statistical data is collected (e.g., hauled material, queueing, energy consumption) and stored. Once the simulation is completed, the collected statistical data is transmitted to a result model, which aggregates the data to value metrics.

The main aspect of this approach is the simultaneous interaction between the site and vehicle model, i.e., the hybrid simulation-modeling approach. The architecture is constructed so that whenever the site model assigns a new target location for a vehicle, it identifies the correct path or paths that lead to that target from its current location. Afterward, it calls the vehicle model to calculate the most optimal velocity profile based on a predetermined optimization goal. The input for the vehicle model (transmitted by each hauler agent in the simulation environment) can be divided into three categories: vehicle data (specifications about the specific hauler), control data (control policy, fill factor, state of charge, and speed limits), and environment data (ambient temperature, paths, road frictions). The vehicle model returns the coordinates for each incremental step, step velocity, and energy consumption. The individual vehicle can then execute its movement according to the vehicle model output. In connection with the development of the approach, a process for execution has been defined. In summary, it can be explained in five steps:

1. Experiment setup
   The first step is to decide the design parameters that should be used in the simulation. The amount of design parameters is dependent on the simulation model capabilities, but it could, for instance, include the number of vehicles, vehicle capacity, site location, operational strategy, etc. Setting up multiple simulations to perform parameter variation experiments is also possible.
2. Simulation startup
   Once the design parameters have been selected and imported into the simulation model, the model will set up the site model with correct paths, stations, and vehicles. It will also start the vehicle model with the correct settings and prepare it for later execution.
3. Simulation execution and vehicle model
   The heart of the framework is the third step when the decided simulation/-s are executed in the site and vehicle models. Based on the predetermined modeling time, the site model will execute the hauling process according to the operational strategy. The simulated vehicle agents in the site model call the vehicle model as they are assigned new movement tasks.

4. Post-processing
   Once the model time is reached, the collected statistics data, e.g., hauled material, energy consumptions, queueing times, etc., is exported to the results model for post-processing, where the data is aggregated to predetermined value metrics.
5. Visualizations
   The value metrics for each simulation are accumulated into charts to create a better overview and support for decision-making.

5. Case from the mining industry

A case study has been conducted as a Proof of Concept (PoC) as well as an initial demonstration of the capabilities of the approach. For this, an operational scenario was elaborated in collaboration with research partners. The data used in the case study is anonymized, and results are normalized to avoid exposing sensitive company data. Figure 2 shows a hypothetical open pit mining site layout where the positioning of the dumping point, loading point, and charging station are marked. Although hypothetical, it does maintain some realism compared to real short-hauling cycle sites and the positioning of various stations. The paths were extracted based on an existing mining site using user mapping on Google Earth. The paths were further discretized into 1-2 meter segments that will be used in the dynamic programming algorithm in the vehicle model to find the optimal control policy. The paths, in this case, are assumed to be bi-directional. Some assumptions and constraints were also determined, e.g., loading and dumping times, one hauler at a time for loading, dumping, charging, fixed environmental conditions (temperature, weather, etc.), no gating or path restrictions, queuing was done at stations, no limitations on material extraction/deposit at load station nor dump station. Despite probabilistic functions being available, a fixed value for fill rate was used to remove natural variation and allow for easier reliability assessment of the results and replicability.

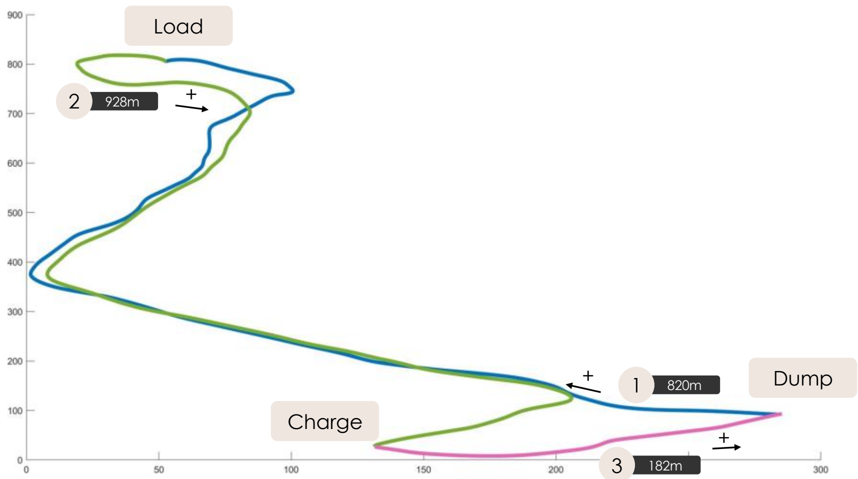

Figure 2. Site layout of the case study (x-y coordinates in meters)

Moreover, an IDEF0 diagram was created to show the process as previously explained at a more granular level, see Figure 3. The IDEF0 diagram highlights the five steps, their input and output, mechanisms, and controls. From a more practical viewpoint, the implementation of the approach was supported by the simulation tool AnyLogic® as the site model and main architecture due to its ability to perform ABS and ease of external integration. This tool was also utilized to perform the graphical visualization of the simulation. The vehicle model was developed using MATLAB® as it functions well for optimization and advanced analytical modeling. This model was validated with vehicle models and vehicle data existing at the partner companies. This includes synchronization between developed vehicle dynamics models and partner companies' existing simulation models as well as compared to measured field data. The simulation model has not been validated with existing site operation data, as the intention was primarily to obtain a Proof of Concept at an initial stage. However, each agent (e.g., wheel loader loading cycle, charging station, tilting cycles, etc.) has been calibrated using expert knowledge from partner companies. The results model uses Excel as it is a good tool for statistical computation and data visualization. The remainder of this section goes through the five process steps.

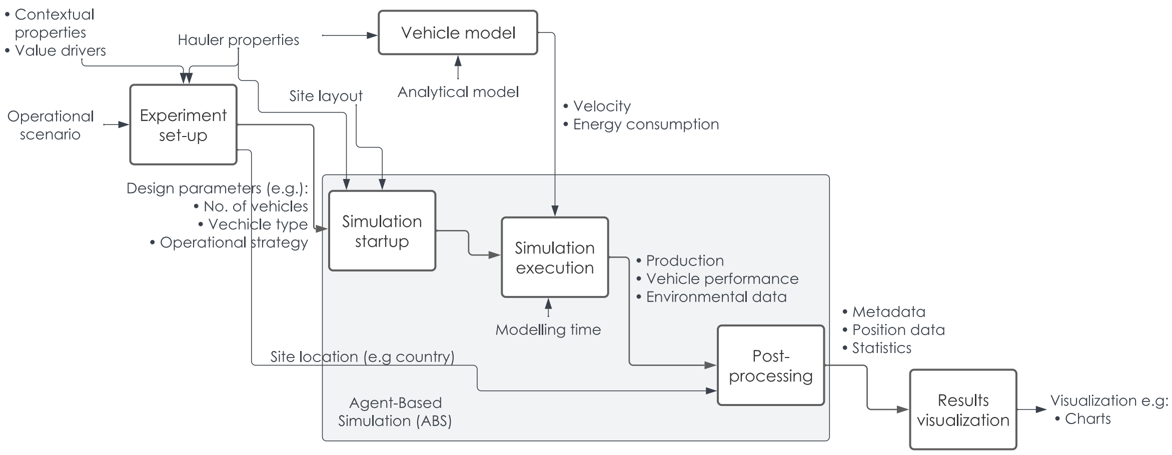

Figure 3. IDEF0 diagram for case study

5.1. Experiment setup

Firstly, the value metrics of interest were identified as productivity, efficiency, and sustainability. These were selected as they represent the key indicators of a mine and key drivers for the electric-autonomous transition. The operational cycle was determined to be load-dump-charge/load (depending on charging policy). The selection of design parameters was limited to vehicle configurations, charging infrastructure, and operational strategies, as these significantly impact the behavior of an electric-autonomous site. More precisely, design parameters were limited to vehicle type (X tons or 4X tons electric-autonomous haulers), number of haulers (2, 4, or 6 haulers), charging power (slow or fast charger), charging policy (at threshold or each cycle), and velocity optimization goal (energy or time). This resulted in a total of 48 different scenarios, which were all tested by the simulation environment using a model run time of 24 hours. A snippet of the experiment setup is displayed in Table 1. The table presents the simulation runs in sets of three where, for each simulation in the set, the number of haulers is changed from 2 to 4 to 6 haulers.

Table 1. Experiment setup for case study

ID	Hauling capacity [tons]	No. of haulers	Charging power	Charging policy	Velocity opt.
SIM-1, 2, 3	X	2, 4, 6	Slow	At threshold	Energy
SIM-4, 5, 6	4X	2, 4, 6	Slow	At threshold	Energy
SIM-7, 8, 9	X	2, 4, 6	Slow	Each cycle	Energy
…	…	…	…	…	…
SIM-46, 47, 48	4X	2, 4, 6	Fast	Each cycle	Time

5.2. Simulation startup

The next step was to load the experiment setup into the architecture and start the model. The experiment manager then executes one simulation for each design parameter combination for the given model run time. For the site model, the paths, stations, and haulers are loaded and positioned. For the PoC, the start position of the haulers is assumed to be the charging station. Depending on the experiment run, the corresponding design parameters are assigned. The site model, in turn, also starts a MATLAB engine that holds the functions of the vehicle model. Once everything has been initiated, the simulator starts the site model.

5.3. Simulation execution

For the PoC, a simple operational process control was executed where the haulers repeatedly go from load to dump. Depending on the charge policy, the haulers go to charge either when the state of charge goes below a set threshold (in this case, 50%) or after each dumping cycle. Further, no pre-heat is applied to the simulation, but the statistics are collected from the start. This is to reflect the operational context of a site where the haulers are co-located at the beginning of a shift. A vehicle model was called for every movement action to obtain the speed and energy consumption at each incremental step along the path that the vehicle should travel. Statistics were continuously captured and stored.

5.4. Post-processing and visualization

Once all simulations were completed, the meta- and statistical data was exported and stored in a CSV file. The CSV file was then imported into Excel for data visualization. The results were aggregated into the three predetermined value metrics and sorted based on the design parameters. Finally, the results were visually presented using the chart tool in Excel.

5.5. Case simulation results

Parts of the results, only the “at threshold” charging policy, are displayed in Table 2 (normalized due to confidentiality). Noteworthy, productivity and efficiency are maximization objectives, while sustainability is a minimization objective as it is a measure of CO2-equivalent emissions. Looking at the three value metrics used in the case demonstrator, it is possible to see that the best option for achieving high productivity is through SIM-42 (6 haulers, 4X-tons capacity, fast charger, “at threshold” charging policy) while SIM-6 (6 haulers, 4X-tons capacity, slow charger, “at threshold” charging policy) is the best performer in efficiency and sustainability, this holds true also looking at all charging policies.

Table 2. Case study results (normalized) of the “at threshold” charging policy

<table>
<tr><th colspan="4" rowspan="2"></th><th colspan="3">Energy</th><th colspan="3">Time</th></tr>
<tr><th>2</th><th>4</th><th>6</th><th>2</th><th>4</th><th>6</th></tr>
<tr><td rowspan="12">At threshold</td><td rowspan="6">Slow charger</td><td rowspan="3">X tons</td><td>Productivity</td><td>0,047</td><td>0,094</td><td>0,130</td><td>0,067</td><td>0,094</td><td>0,095</td></tr>
<tr><td>Efficiency</td><td>0,439</td><td>0,439</td><td>0,438</td><td>0,298</td><td>0,300</td><td>0,300</td></tr>
<tr><td>Sustainability</td><td>0,678</td><td>0,678</td><td>0,678</td><td>1,000</td><td>0,994</td><td>0,994</td></tr>
<tr><td rowspan="3">4X tons</td><td>Productivity</td><td>0,218</td><td>0,433</td><td>0,483</td><td>0,249</td><td>0,275</td><td>0,284</td></tr>
<tr><td>Efficiency</td><td>0,927</td><td>0,966</td><td>1,000</td><td>0,521</td><td>0,538</td><td>0,555</td></tr>
<tr><td>Sustainability</td><td>0,321</td><td>0,309</td><td>0,298</td><td>0,571</td><td>0,553</td><td>0,536</td></tr>
<tr><td rowspan="6">Fast charger</td><td rowspan="3">X tons</td><td>Productivity</td><td>0,047</td><td>0,094</td><td>0,130</td><td>0,067</td><td>0,094</td><td>0,095</td></tr>
<tr><td>Efficiency</td><td>0,439</td><td>0,439</td><td>0,438</td><td>0,298</td><td>0,300</td><td>0,300</td></tr>
<tr><td>Sustainability</td><td>0,678</td><td>0,678</td><td>0,678</td><td>1,000</td><td>0,994</td><td>0,994</td></tr>
<tr><td rowspan="3">4X tons</td><td>Productivity</td><td>0,271</td><td>0,547</td><td>0,797</td><td>0,435</td><td>0,881</td><td>1,000</td></tr>
<tr><td>Efficiency</td><td>0,941</td><td>0,914</td><td>0,925</td><td>0,493</td><td>0,496</td><td>0,496</td></tr>
<tr><td>Sustainability</td><td>0,315</td><td>0,327</td><td>0,321</td><td>0,601</td><td>0,601</td><td>0,601</td></tr>
</table>

Based on this, it can be stated that six 4X tons haulers charged when needed seem to be the best option for the simulated site. The selection of charging power is, on the other hand, dependent on which value metric is most important: slow charger for efficiency and sustainability and fast charger for productivity. Naturally, the applied velocity optimization goal dictates whether the solution is more efficient or productive. Noteworthy, this simulation does not regard the target production rate. Typically, a given site will have a target production rate that is requested, which leads to some of the design options being over-designed. Moreover, this simulation only varied five design parameters, which is only a subset of all possible. It is, however, deemed sufficient for a PoC.

As previously said, the gold path seems to be six 4X-ton haulers. Taking a more visual approach and looking at these specific simulations, it is possible to explore the value metrics more easily. This selection of the results has been plotted in a chart, see Figure 4. The chart shows how different infrastructure selection and operational strategies impact the value metrics. It is evident that a fast charger boosts productivity while the efficiency and sustainability impact does not change that drastically. It is also possible to see that the charging policy has a higher impact on time optimization than energy with the fast charger, while for the slow charger, the impact is more or less the same. Furthermore, the slow charger leads to higher productivity for energy optimization, opposite of what should be expected, possibly due to the increased duration for charging caused by the time optimization, resulting in the charger being a larger bottleneck. For the fast charger, this phenomenon does not occur. In conclusion, it is possible to see that the different design parameters in conjunction impact the SoS value creation differently.

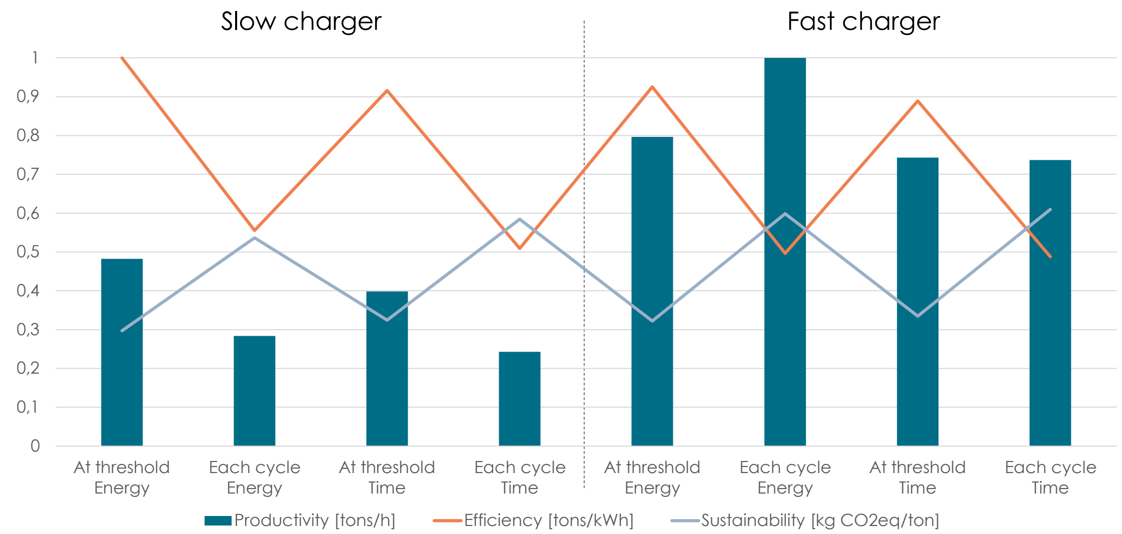

Figure 4. Case study results (normalized) of the 4X-ton haulers showing productivity, efficiency, and sustainability

6. Discussion

The aim of the paper was to propose a hybrid approach for simulation-driven configuration of System-of-Systems for exploring system configuration decisions and their impact on the overall SoS value creation in the mining sector. The major target has been to allow for optimization at both a vehicle and site level using a hybrid approach, not focusing on changing the design of a specific vehicle but rather choosing between a vehicle selection based on manufacturers' product families. Based on this effort, some reflections can be made.

Firstly, the simulation approach has been demonstrated, proving that it works and provides reliable results as a PoC for mining operations. The authors see that there is still potential for increasing the reliability of the simulations, e.g., loading times dependent on the loading method, incorporation of failure modes, and integration with the entire mining production process. With this said, the hybrid simulation allows a design team to explore multiple scenarios and design choices in mine hauling in a rather short time. This is applicable for design options at both vehicle and site levels, thus equipping the design team with a larger toolbox and design parameters in their pursuit of finding good SoS mining configurations. By testing multiple design scenarios, the design team can evaluate different setups early in the design process without investing significant resources. For SoS, the ability to simulate and explore scenarios helps mitigate risks of operational bottlenecks, unwanted behaviors, and uncertainties.

However, the approach has some limitations. The first one is the exponential growth of complexity as the degree of freedom increases. Managing this phenomenon effectively and using strategies such as Design of Experiments is important. An important aspect of SoS engineering is the ability to create value-robust or resilient designs. The resilience of an SoS will depend on both the reliability of its constituent systems and their interaction with the operational context (Uday and Marais, 2015). The PoC has not included any disturbances such as temperature variation, weather conditions, etc. The authors believe that aspects such as these are beneficial to include in the simulation to better understand the mining site's resilience and take design actions towards value robustness.

Another limitation is the reliance on computing power. The simulations consume lots of computing power, especially as a dynamic vehicle model is used to make state transitions at each step in ABS. One approach to mitigate this is through pre-processing the vehicle model and interpolating the results. However, this will reduce the accuracy of the results. Depending on the requirements of the hybrid simulation, an appropriate approach can be selected.

7. Conclusion and future work

The introduction of electricity and autonomy in the mining industry provides great potential and opens new design strategies. At the same time, it adds more complexity and intralayer dependencies that must be acknowledged. The hybrid approach posed in this paper has been conceptualized to support the design and configuration at both the vehicle and site level through the active integration of a site simulation and vehicle dynamics model. The approach enables designers to concurrently try out different designs at both levels to explore value and find the optimal combination of vehicle design and site setup for a specific context and scenario.

The research presented in this paper is at a support evaluation stage and has potential for further development. For instance, the design parameters only consider the core characteristics of the Systems-of-Systems. More perspectives can be added to better reflect reality, e.g., failure modes, dynamic operational strategies, the introduction of contextual disturbances, and the resilience and value robustness of the different design options. Also, the experimental setup is currently manual. The future scope includes the formulation of an optimization problem for an exhaustive search of viable solutions. Finally, research investigating how the visualization can be improved by creating a more immersive environment to view and experience the design scenarios as well as better communicating the exhaustive data that is connected to the expansion of input parameters and value metrics, e.g., (Machchhar et al., 2023), is something that could be incorporated into this paper's research looking forward.

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