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Supporting the Transition Towards Electromobility in the Construction and Mining Sector: Optimization Framework and Demonstration on an Electrical Hauler

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Abstract

The paper presents a framework for the integration of the system's design variables, state variables, control strategies, and contextual variables into a design optimization problem to assist early-stage design decisions. The framework is based on a global optimizer incorporating Dynamic Programming, and its applicability is demonstrated by the conceptual design of an electrical hauler. Pareto front of optimal design solutions, in terms of time and cost, together with optimal velocity profiles and battery state-of-charge is visualized for the given mining scenario.

Keywords: *systems engineering (SE), decision making, design optimisation, dynamic programming, early design phase*

1. Introduction

Transition into electromobility and autonomy in vehicle design calls for the development of solutions requiring, on one hand, the integration of many novel technologies (e.g. batteries, motors, and control) in an established platform and, on the other hand, the increased consideration of the influence of contextual factors such as infrastructure, environment, and human-machine interaction in a vehicle operation (Grunditz, 2016; Wang et al., 2018). The novelty of the rapidly emerging technologies and the uncertain contextual aspects pose a significant challenge to industries dealing with systems having a long lifecycle and high capital investment. Such challenge is stressed in the early design phase when consistent capital commitment is done on systems concepts with a high degree of uncertainty concerning the future operational context, with the inferred system needing to be designed to account for contextual uncertainties along the operational phase.

One of the industries highly influenced by the electromobility transition is the construction machinery industry that has embarked on a journey into autonomy and electrification (Frank, 2019). Here, cross-disciplinary knowledge needs to complement the established approach for mechanical simulations, considering, for instance, increased attention on external conditions (e.g. topography, ambient temperature), or the human experience when using new machines (Bertoni et al., 2017); variables that can have a significant impact on the energy consumption of Electric Vehicles (EVs) (Fiori et al., 2016). In previous studies related to the development of vehicle components for electromobility (including Hybrid EVs), several approaches have been proposed, including multi-objective design optimization (DO) using evolutionary algorithms (Fries et al., 2017), nonlinear integer programming, (Ostadi and Kazerani, 2014), data-driven decision support (Bertoni et al., 2017), etc. However, such approaches have often been developed "ad-hoc" to solve pre-defined design problems and are difficult to be generalized in different contexts. In this light, this paper presents the preliminary results of a research effort focusing on the development of a generalizable model-driven approach to support the transition towards electromobility and autonomy by deploying multi-disciplinary simulation models to support engineering decisions in the early stages of design. In detail, the paper has the following two objectives:

- Firstly, to present a generic framework that enables seamless integration of the system's design variables, state variables, control strategies, and contextual variables into an optimization problem to assist early design decisions. The design variables influence the configuration of the system, the control strategies govern the different conceivable states of the system while performing a task, and the context variables influence the ability of the system to perform a task.
- Secondly, to demonstrate the applicability of the proposed framework through electric-driven construction equipment (i.e., a Hauler) operating in a mining scenario.

The paper is structured as follows: Section 2 describes the research approach briefly, and section 3 describes the proposed framework. Section 4 elaborates on the various disciplinary models to be used, and section 5 demonstrates the application of the proposed framework on a hauler case. Finally, section 6 describes the key findings, critiques the proposed framework, and concludes the paper.

2. Research approach

The research was pursued via participatory action research (Baum et al., 2006). Multiple data collection strategies were applied, including unstructured and semi-structured interviews with company partners to define the state-of-the-art, needs and expectations of the future electrical mining scenario. To demonstrate the proposed framework, data were further collected through accessing construction machinery technical data available on manufacturer websites and complemented with state-of-the-art data about the development of batteries and electromobility solutions obtained through literature review and freely available vendors data. The development of the framework followed an iterative process of theorization and demonstration of incrementally improved steps. Initially, the system was considered to be fixed, and a demonstrator was developed just to analyze the different states of the system under different control strategies, and their eventual impact on the objective. Contextual variables were gradually added as the models become more mature. Parallelly, another demonstrator was developed to understand how different design variables can affect the configuration of the overall system under the applied constraints. These two demonstrators were then merged to propose a unified framework that addresses the first objective of the paper. To address the second objective of the paper, a battery-electric hauler having a single-motor-clutch system was chosen. To avoid the exposure of sensitive information, readily available online catalogue data were used for this case as elucidated in the succeeding sections, and the drive cycle was suitably modified to represent a fake mining site while conserving a certain degree of realism to the actual scenario.

3. Proposed framework

Systems engineering (SE) literature points out that as systems become more complex, the definition of system boundary (a boundary that distinguishes the system of interest and the context), and what constitutes within this frame of reference becomes blurrier. To have a consistent viewpoint in this work, the distinction of the system and the context is based on the system "*boundary*" definition (Kossiakoff and Sweet, 2003), where all the variables beyond the development control of the engineering team, but still influencing the functioning of the system, are regarded as contextual variables. The frame of reference, i.e., the "*operational scenario*" consists of the system, all its form, along with all the possible contexts (Machchhar and Bertoni, 2021; Yannou et al., 2013). The system comprises of design variables and state variables, where the design variables define the configuration of the system while the state variables are the "*responses*" (Martins and Lambe, 2013) of the system during its operation. The state variables consist of lower and upper bounds like the design variables, but whether they are controlled by the system optimizer depends on the problem formulation.

Figure 1 shows the overview of the proposed framework where the design problem is solved via a dual-layer optimization framework. Although dual-layer purports the aspect of optimization problem partitioning, the execution is sequential, and not simultaneous or iterative amongst disciplinary models. The essence of multidisciplinary DO is solving a coupled system rather than having a system of many disciplines solved sequentially (Martins and Lambe, 2013). In this regard, the proposed framework is multi-objective and involves multiple disciplines but is not multidisciplinary as no strategy or architecture to solve coupling has been discussed. The outer layer of the framework comprises of the overall objective functions and the applicable constraints formulated in the standard way (equality and inequality constraints). In case the function derivative is noisy or unreliable, if the design variables are well-bounded, then a gradient-free algorithm is a suitable choice of solver despite them being less efficient (Kokkolaras, 2019). Rios and Sahinidis (2013) provide a comprehensive overview of various gradient-free optimization algorithms that exhibit different characteristics. One such subset includes evolutionary algorithms characterized by global search properties, proposed as global optimizer in Figure 1. Despite the name, the convergence established by these algorithms is likely optimal, and it may not be (truly) optimal as it is based on heuristics rather than mathematical principles. The disciplinary analyses of the models confined by design constraints typically configure a viable system. This system along with the respective conceivable states is fed to the inner layer. Conceivable states are the different states the system can transition while operating, and they may be internally constrained, or externally constrained. To illustrate, the max velocity that the vehicle can achieve (one of the conceivable states) can be limited by the engine/motor capacity or speed limits on the trajectory. The inner layer aims to find the optimal control strategy that directs the operation of the system for the intended task. Sequential linear/quadratic programming is one of the known methods to solve control problems. However, these methods have implementation difficulties for mixed-integer problems (Ghandriz et al., 2021). The logic is intuitive; mixed-integer problems are characterized by discontinuous functions making the computation of gradients unreliable. To make the proposed framework more generic and applicable for different use-cases, Dynamic Programming (DP) has been proposed to solve the control problem. Based on Bellman's "*Principle of Optimality*" (Bellman, 1966), it is widely used in optimal control problems across disciplines, especially for automotive applications (Guzzella and Sciarretta, 2007; He et al., 2013; Ke and Song, 2018), and is one of the useful methods for performance benchmarking of systems executing a task in non-real-time applications. In a DP formulation, the state variables are discretized into a "grid" that allows the system to switch between conceivable states. These states may be continuous (such as vehicle velocity) or discrete (such as gear selection). The act of operating can either be discretized in the spatial or time domain, and there have been several studies in time (Luin et al., 2019) as well as spatial (Ghandriz et al., 2021; Ye et al., 2019) domains, respectively. Usually, a finer discretization achieves better results at the cost of computational time (Ye et al., 2019). The result of solving the DP layer is the vector of optimal control strategy along with costs incurred during the system's operation under the control constraints. These results are utilized by the global optimizer to calculate objective values, and the process is iterated until convergence.

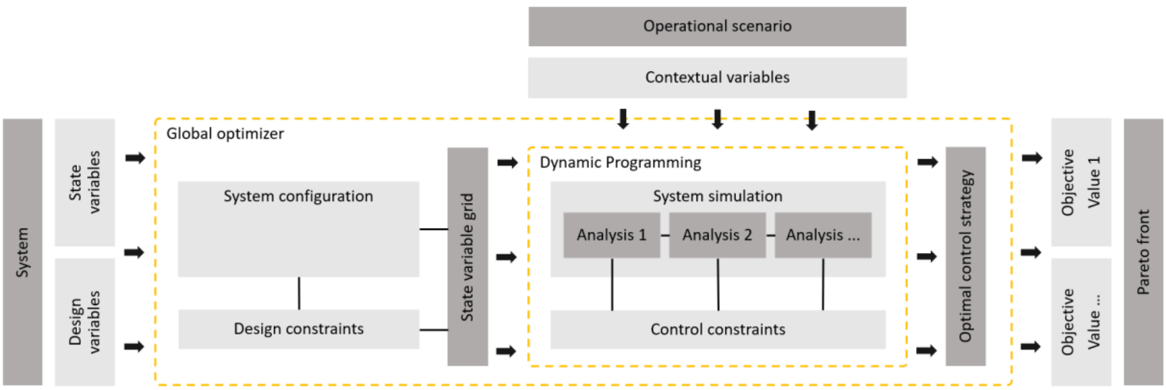

Figure 1. The proposed dual-layer optimization framework to find pareto fronts based on system design variables, state variables, control strategies, and applicable contexts.

4. Vehicle simulation models

Vehicle simulation models can be broadly classified into two categories: forward and backward models. As the name suggests, backward models run backward, essentially calculating the cumulative force

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required at the wheels, propagating it back towards the engine while the forward models calculate the cumulative force produced at the engine and propagate it towards the wheel (Pettersson et al., 2020). Forward models are especially useful when the system needs to be analyzed based on the driver's input, while backward models have their strength in calculating the energy consumption based on system and contextual parameters effectively, i.e. calculating reliable energy consumption profile over the given instances with quicker execution time (Fiori et al., 2016). Once these models are established, there are three possible ways to analyze them depending on the required level of accuracy (Guzzella and Sciarretta, 2007). The first one is the "*average operating point*" approach where all the operating points of the propulsion system are averaged to represent a single operating point, and the corresponding efficiencies are chosen. The next is the "*quasistatic*" approach where the drive cycle is discretized into small instances and entities such as acceleration, gradient, total vehicle weight, etc. are assumed to be constant over a single instance. The last is the "*dynamic*" approach where the models are formulated using ordinary differential equations rather than only algebraic to represent the dynamic effects within the propulsion system and calculate a highly accurate energy consumption profile. The challenge, however, is the required analysis time (Fiori et al., 2016).

4.1. Energy consumption

There are a plethora of examples in the literature on models for calculating the energy consumption of the vehicle as this can be one of the critical aspects for evaluating the performance of the vehicle, regardless of the vehicle being conventional (fuel-driven) or non-conventional (hybrid, electric, fuel cell, etc.). Vehicle energy consumption is affected by many factors, broadly classified into six categories, such as, vehicle-, weather-, traffic-, roadway-, travel- and driver-related factors (Liu et al., 2016). Essentially, the vehicle must overcome the inertial resistance, gradient resistance, rolling resistance, and aero resistance during its operation, and based on Newton's second law, the force required at the wheel can be calculated.

4.2. Transmission and motors

A gearbox is typically used to scale the output torque or speed, but due to the intrinsic nature of electric motors, i.e., their torque and speed characteristics and high overall efficiency contour, EVs are usually equipped with a single- or dual-speed gearbox (Sorniotti et al., 2011). But for battery EVs, there are many options for motors, such as induction motors, switched reluctance motors, and permanent magnet synchronous motors (PMSM) that all belong to the category of AC motors (Gundabattini et al., 2021). A typical PMSM has a constant torque and a constant power operating region, and the power delivered at any given instance by the motor is a function of motor torque and motor speed that is derived from the gearbox, and the motor efficiency that is based on the efficiency maps of the motor. Efficiency maps are the contour plots under the max achievable torque and power curves of the motor that indicate the power loss in its operation. For the vehicle to be as efficient as possible, the operational point (in terms of torque and speed) should be chosen such that these losses are minimized, but a single gear leaves no choice but to take relevant efficiency values as the vehicle operates (Guzzella and Sciarretta, 2007).

4.3. Battery

Battery packs are usually expressed in terms of capacity (kWh) or specific energy density (Wh/kg), and the two dimensionless parameters that describe the condition of the battery are SoC and SoH. SoC describes the charge remaining in the battery and SoH describes the remaining useful life of the battery, usually in percentages. Also, lithium-ion battery packs have a min and max allowed current (called C-rating) that describes how much current can be drawn from the battery at the given instance. A rating of 1C means drawing current from the battery that will discharge it within an hour (Grunditz, 2016).

5. Context-based design and optimization of an electric hauler

A hauler is an automotive vehicle, typically used for hauling material from one point to another in a mining site. In this demonstrative case, the aim is to dimension the payload capacity and the battery capacity of an electrical hauler, along with the selection of an appropriate motor from the catalogue.

Also, a variable termed "time penalty" was introduced, allowing the exploration of different optimal control strategies. All these constitute the design variables $\bar{x}$. The overall optimization problem is represented in Equation 1, where the two competing objective functions used were the total time required to complete the intended operation and the total operational cost. The total time required was a function of cycle time and battery charging time, whereas the total operational cost was the sum of fixed cost for each subsystem, and operational costs were simplified into energy consumption. The time penalty essentially directs the weightage on energy and time minimization during the control simulation via DP. Two state variables $\bar{y}$ considered were hauler velocity and battery state of charge (SoC). Hauler velocity was discretized into several instances between zero and max limit, where the max limit was arbitrarily defined while SoC was confined to operate between 20% to 80%. The hauler was constricted to a single gear transmission system and thus gear selection was not an optimization problem. Also, battery state of health (SoH) was neglected in this case. The control inputs $\bar{u}$ comprised of propelling and braking force at the motor shaft. Contextual variables mainly influenced the disciplinary analysis, such as ambient temperature affecting the battery (Choi and Chang, 2020) or rolling resistance and air density (Wang et al., 2018), while elevation profile affecting the regenerative capability and so on. Also, the operational scenario was assumed to consist of a wheel loader having a 5-ton capacity. This constrains the payload capacity to be a multiple of 5 as no optimal will be found intermediately.

A vehicle typically contains many design constraints g_d and control constraints g_c, many of those were deliberatively ignored since it doesn't influence the demonstration of the proposed framework. One of the applied inequality design constraints was that the volume of the battery pack cannot exceed the base volume available beneath the hauler. The design constraints also included gradeability and acceleration requirements. The control constraints mainly comprised of acceleration limits based on motor torque and battery discharge capacity.

$$
\begin{array}{lrl}
 & \min f(\bar{x},\bar{y}) & \mathit{Total\ time\ required, Total\ operational\ cost} \\
\text{with respect to} & \bar{x} & \mathit{Payload, Battery\ capacity, Motor\ type, Time\ penalty} \\
 & \bar{y} & \mathit{Velocity\ grid, Battery\ state\ of\ charge\ grid} \\
\text{subjected to} & g_d(\bar{x}) & \mathit{Design\ constraints} \\
 & g_c(\bar{x},\bar{y}) & \mathit{Control\ constraints}
\end{array}
\tag{1}
$$

To simulate the operation of the hauler, deterministic DP was implemented that is based on the procedure explained by Guzzella and Sciarretta (2007) in their Appendix-III. This work also uses their pseudo-code as a skin for finding the optimal control strategy of the hauler. A similar procedure can also be found in He et al. (2013), however, their purpose was optimal energy management, whereas the purpose in this work is to find the optimal velocity for the hauler. As explained previously, the operation needs to be discretized into several instances in spatial or time domain, and for each instance in deterministic DP problems, the successive state of the system $y(k+1)$ is a function of the initial state $y(k)$ and the control inputs $u(k)$ as shown in Equation 2:

$$y(k+1) = f(y(k), u(k)) \tag{2}$$

The end step calculation is given by Equation 3:

$$J_N(y(N)) = L(y(N)) \tag{3}$$

And the intermediate step calculation is given by Equation 4:

$$J_k^o(y(k)) = \min_{u(k)}\{L(y(k), u(k)) + J_{k+1}^o(y(k+1))\} \tag{4}$$

Where $J_k^o(y(k))$ represents the min cost to reach the state $y(k)$ from the end of the operational cycle as the algorithm commences from the targeted end goal and solves the problem recursively to reach the point k, L represents the instantaneous step cost and $y(k+1)$ represents the state achieved on the application of control $u(k)$. The $u(k)$ that minimizes Equation 4 is the optimal control policy C^o for the inferred system from the point of interest k to the end of the cycle, as shown in Equation 5:

$$C^o = \{u^o(k), u^o(k+1), \dots, u^o(N-1)\} \tag{5}$$

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In this work, a spatial discretization was used as the drive cycle was available in terms of latitude, longitude, and altitude. The segment length for the discretized path was calculated as smooth splines and the altitude was used to calculate the segment gradient. The instantaneous step cost comprised of energy cost, time cost, and speed deviation cost, as shown in Equation 6:

$$L = (1 - \beta)\left(\frac{e}{e_{norm}}\right) + \beta\left(\frac{t}{t_{norm}}\right) + (\phi * |v - v_{set}|) \tag{6}$$

Where, e is the step energy consumption, t is the step time, and e_{norm} and t_{norm} are the normalization factors, respectively. β is the time penalty, referred from $\bar{x}$, adapted from the work of (Ye et al., 2019). Also, for the given drive cycle, there can be several stops along the path such as extraction, crusher, charging station, etc. Thus, v_{set} represents the set velocity at various instances along the drive cycle and it can also take zero as a value. ϕ is a conditionally activated speed deviation penalty which is zero unless a velocity is set for the given instance. Then, the speed deviation penalty takes a very high value, forcing the hauler velocity to be exactly equal to the set velocity. Finally, the inconceivable states of the hauler were handled by assigning an infinite cost, and no auxiliary power requirement was assumed.

5.1. Implementation of disciplinary models

In this work, a quasistatic approach was adopted to calculate reasonably accurate energy consumption profiles within a shorter timeframe. Especially, this choice was made as they enable a certain level of flexibility in the simulation architecture, allowing easier swapping of models, integration into more complex frameworks, and simulation of different drive cycles (Fiori et al., 2016).

The total hauler mass was calculated as a sum of the curb weight, battery weight, and payload. The design bounds of the battery capacity varied the weight of the battery to a notable extent. Thus, the battery weight was considered separately. The curb weight and payload are interdependent, i.e., if the value of one of the entities increases, the other increases accordingly. To capture this relation, a regression model was built based on the previous experiences of the company partners and the available data of past designs. This model predicts the curb weight as a function of payload. Also, since the path followed by the hauler in the mining site is fixed for this case, the instances when the hauler is loaded or unloaded can be easily distinguished for each instance. This change in total hauler mass is reflected in all the disciplinary analyses below.

The modeling of the vehicle energy consumption was analogous to the VT-CPEM (Virginia Tech Comprehensive Power-Based EV Energy Consumption Model) (Fiori et al., 2016) which needs inputs of instantaneous velocity along with vehicle parameters and contextual variables. Equation 7 shows the formulation used:

$$P_w = \left(C_i m a + m g \sin(\theta) + C_r m g \cos(\theta) + \frac{C_d \rho_a A_f v^2}{2}\right) v \tag{7}$$

Where, P_w = power at wheel, C_i = mass correction factor to account for inertial forces, m = total hauler mass (including payload), a = acceleration, g = gravitational acceleration, θ = road gradient, C_r = coefficient of rolling resistance, C_d = coefficient of aerodynamic resistance, ρ_a = density of air, A_f = vehicle frontal area, v = velocity. The rationale for choosing VT-CPEM against, for example, the VSP (Vehicle-Specific Power) model (Luin et al., 2019) is that the mass of the vehicle is a conditional parameter (loaded and unloaded) in this study, and vehicle drag is independent of mass. Thus, scaling the specific power with mass can endure incorrect results (Luin et al., 2019). Also, C_r modelled as a function of velocity can increase the accuracy (Fiori et al., 2016), however, it was assumed to be a constant for this demonstrative case.

The gearbox efficiency was assumed to be constant, adopted from Ostadi and Kazerani (2014), and thus, the power at the gearbox can be scaled proportionately. For motor, two different PMSMs, available at "HVH Series Electric Motor - BorgWarner" (n.d.) were chosen, and their peak torque and power characteristics were utilized. Also, a regression model of the efficiency map was built. With all this information, the power at the motor can be calculated using Equations 8, 9, and 10:

$$\omega_m = \omega_w g_r \tag{8}$$

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$$T_m = \frac{P_g}{\omega_m} \tag{9}$$

$$P_m = P_g + \begin{cases} \frac{(1-\eta_m)P_g}{\eta_m}, & P_g > 0 \\ (\eta_m - 1)P_g, & P_g < 0 \end{cases} \tag{10}$$

Where, ω_w = wheel speed, ω_m = motor shaft speed g_r = gear ratio, P_g = power at gearbox, T_m = torque at motor, η_m = motor efficiency, and P_m = power at motor, respectively. Max torque limit was a control constraint, and the unreachable states were assigned an infinite cost. Furthermore, inertial flywheels were not modeled in the powertrain, and thus no energy was stored in the powertrain, allowing end-to-end energy balance (Ghandriz et al., 2021). The functioning of the motor in the regeneration mode was assumed to be the same as the propulsion mode. Also, the regenerative braking efficiencies can be a function of deceleration (Fiori et al., 2016) or ambient temperature (Luin et al., 2019), but it was assumed to be independent of these entities due to lack of data for the case.

The data for the lithium-ion battery pack, available at "Lithium Ion Batteries (Li-Ion) - Panasonic" (n.d.) was used, where battery cells were combined and scaled to represent a battery pack. Although, the properties of the pack can be considerably different from the cell (Huria et al., 2012). The max charge/discharge current at the battery is often limited by the DC-AC converter (Grunditz, 2016). As there was no DC-AC converter modeled for this demonstrative case, two assumptions were made. Firstly, the max current was assumed to be limited to 2C, and secondly, there were no converter losses. Thus, the power at the battery is equal to the power at the motor, and the current at the battery can be calculated using Equation 11:

$$I_b = \frac{V_{oc} - \sqrt{V_{oc}^2 - 4R_bP_b}}{2R_b} \tag{11}$$

Where, P_b = power at battery, I_b = current at battery needed to achieve P_b, V_{oc} = open-circuit voltage, R_b= internal resistance, respectively. Internal resistance during charging and discharging was assumed to be the same. To make the model more accurate, however, dynamic effects due to varying SoC and temperature were modeled. While there are several methods proposed in the literature, this work adopted the methodology proposed by Huria et al. (2012) that produces accurate results when experimental data is available. Using the catalogue data instead, and referring to their steps, V_{oc} was modelled as a function of SoC while R_b was modeled as a function of SoC and temperature. Also, the working region of the battery was assumed to be between 20% and 80% over the drive cycle, a region where the voltage drop is quite linear. Based on the current withdrawn, coulomb counting method can be used to determine the successive state of charge, as shown in Equation 12:

$$SoC(k+1) = \mathrm{SoC}(k) - \left(\frac{I_b \Delta t}{3600 Q_b}\right) \tag{12}$$

Where, Q_b = battery capacity, Δt = step time, I_b = current at battery, SoC = battery state of charge, respectively. Furthermore, a good margin from breakdown voltage is necessary (Grunditz, 2016), and thus 500V was chosen as the max voltage in the system and was not varied in this study. Given the assumed voltage, based on catalogue data, the number of cells in series can be calculated, and the design variables associated with the battery capacity essentially drive the ampere-hours of the battery, and hence the number of cells in parallel. Based on the number of cells in series and parallel, the battery parameters such as weight, volume, cost, etc. can be calculated.

5.2. Exemplary results from the demonstrator

The Pareto-optimal solutions have been presented in Figure 2, where all the dominated solutions have been removed for improved decision-making. The hauler payload capacity is in the multiples of 5 tons since the wheel loader capacity was assumed to be 5 tons, and thus there are no intermediate optimal solutions. The Pareto front not only enables decision-making between different hauler configurations but also the control strategy. Each grey bar in Figure 2 represents the same configuration, but a different control strategy. To illustrate, designs B and C have the same configuration, but different objective values are achieved by adjusting the time penalty, and hence the control inputs of forces. Figure 3

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illustrates this distinction, where different optimal velocity profiles incur different operational costs by depleting SoC differently. The usefulness of the control strategy becomes more apparent when jointly view w.r.t different configurations. For example, instead of increasing the time penalty for design A further, a better choice would be to use design B. Basically, design configuration and control strategy can be compared head-to-head for making a utility choice for the given operational scenario. Figure 3 also shows a notable regeneration of energy based on the SoC curve. The loading of the hauler happens at a higher altitude and then it rides downhill. This is one of the favorable conditions where the overall SoC depletion is lesser, often not the case in actual mining sites.

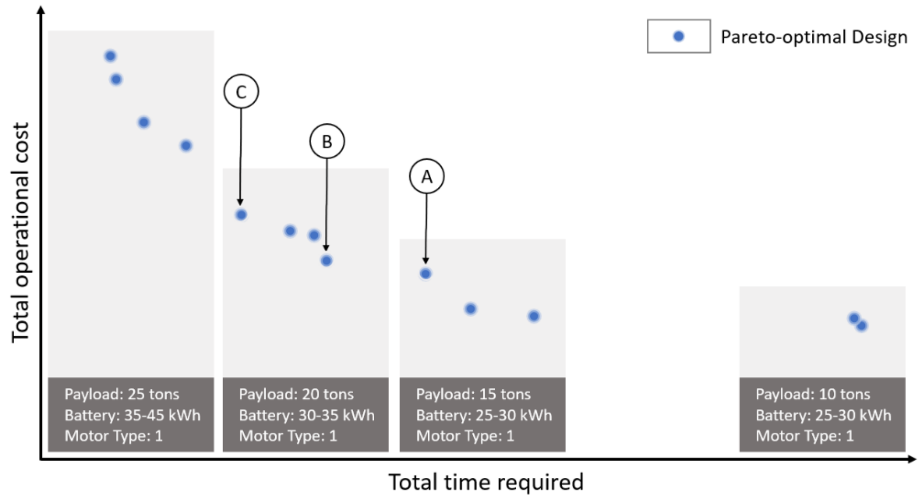

Figure 2. Scatter plot showing the pareto optimal designs of the hauler. Each design within a grey square box has the same design configuration but a different control strategy.

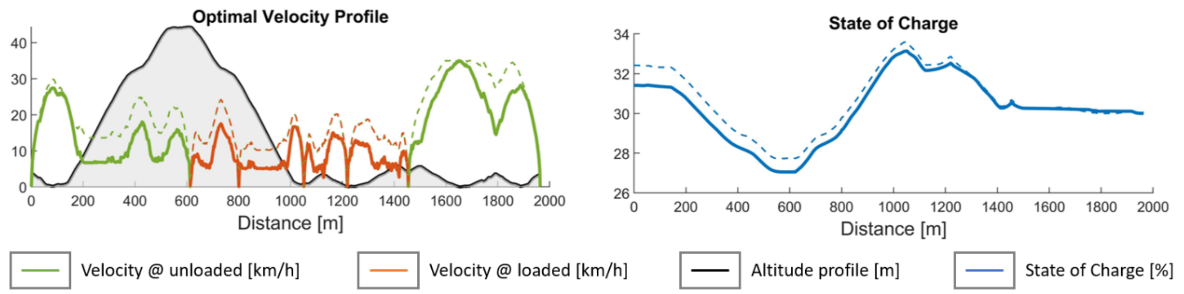

Figure 3. Optimal hauler velocity and SoC for design point B (shown by solid lines) and C (shown by dashed lines) in Figure 2

6. Discussion and Conclusion

In this paper, a framework was proposed to make early design decisions based on contextual factors and how the system will perform in the given context. A practical implementation on a demonstrator of an electrical hauler was presented. The work presented in the paper shall be regarded as preliminary results of a wider research effort focusing on the development of a generalizable model-driven simulation approach to support the transition towards electromobility and autonomy. The aim is to be able to deploy multi-disciplinary simulation models to support engineering decisions in the early stages of design. The validation of the framework is limited to its preliminary implementation in a single case of a hauler in a mining context. Research is currently taking place in several parallel case studies related to autonomy and electromobility to investigate further improvement and seek additional validation of the presented findings.

The approach builds on established DO and optimal control techniques in SE. Having system states as responses is common practice in DO (Martins and Lambe, 2013), but usually these states are a function of nominal or averaged system control. Control problems often consider the system to be well-

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established, and the goal becomes turning the right knobs to achieve the desired performance output, see, for example, (Ghandriz et al., 2021; He et al., 2013; Ke and Song, 2018). The proposed framework attempts the confluence of these two domains, enabling making decisions about the configuration and the control of the system simultaneously, especially early in the design phase for relatively mature systems. Typically, design decisions are not taken in real-time, and thus, the real-time performance of the algorithm was not critical for this study. Regarding changing contexts, the ambient temperature was assumed to be fixed throughout the demonstrative case. To simulate proper temperature effects, an approximate thermodynamic model and a coolant model needs to be built, and this has been subjected to future studies. Considering the time required for convergence, improvement can be made at the global optimizer level and DP level. Teaching-learning-based optimization is argued to be quicker when the problem is highly nonlinear with many constraints for each sampling interval (Ostadi and Kazerani, 2014). Also, for DP, there are techniques such as coarse discretization, elimination of unreachable states (Ke and Song, 2018), varying step-size DP (Ye et al., 2019), approximate DP (Powell, 2007), to reduce computational time. While some of these techniques can be argued to be a niche in a specific domain, more studies in different disciplines are needed to make a decisive supposition. Nonetheless, in the wake of autonomous vehicle technology enabling rigid path definition and typical shorter drive cycles of haulers in a mining scenario, combining DO and DP seems to be an approachable technique.

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