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A tradespace exploration approach for changeability assessment from a system-of-systems perspective: application from the construction machinery industry

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Abstract

The rapid development of new technologies such as electrification, autonomy, and other contextual factors pose significant challenges to development teams in balancing competing aspects while developing value-robust solutions. One approach for achieving value robustness is designing for changeability. This paper presents a tradespace exploration from a Systems-of-Systems perspective to facilitate changeability assessment during early design stages. The approach is further demonstrated on a fleet of haulers operating in a mining site.

Keywords: systems engineering (SE), design optimisation, dynamic programming, process modelling, early design phase

1. Introduction

The construction machinery industry is rapidly progressing towards electrification and autonomy (Frank, 2019). However, integrating electromobility and autonomy presents inherent challenges during the transitional phase. Firstly, developing new solutions requires the integration of novel technologies (e.g., electric power train including batteries, motors, etc.) in an established vehicle architecture. Secondly, contextual factors, including infrastructure, legislation, and human-machine interaction in the operational phase, become increasingly important from a decision-making standpoint (Ertugrul et al., 2020; Ghandriz et al., 2020). The uncertainties stemming from these rapidly emerging technologies and contextual factors pose a substantial challenge to the development team concerning the trade-offs between competing aspects for achieving higher value, especially when the system under development has a longer lifecycle and increased investment cost. The challenges during the early design stage are often stressed since many future alternatives exist in the wake of traditional mining challenges like extreme environmental conditions and lower grades of extracted ore (Sánchez and Hartlieb, 2020), and modern mining challenges like deeper ore deposits and processing harder rock mass that consumes higher energy (Sánchez and Hartlieb, 2020).

One of the common strategies to deal with future uncertainties is incorporating "changeability" (Ross et al., 2008), where an internal change counters the effects of external changes to maintain operational value. Such systems are called "value robust" (Ross et al., 2009), and incorporating changeability implies incorporating means and mechanisms in the system to resist value depreciation. Consideration of changeability and its quantification has been argued to be a relevant dimension in different design contexts, including systems engineering (SE) (Rehn et al., 2019) and Product-service Systems (PSS) (Machchhar et al., 2023). The basis can be traced to the Responsive Systems Comparison (RSC) method that combines Multi-Attribute Tradespace Exploration and Epoch-Era Analysis (Ross et al., 2009). RSC is a seven-step process that enables the assessment of changeability in complex systems. One of the steps in this process is the formulation of value-driven design (VDD) (Collopy and Hollingsworth, 2011), which plays a central role in changeability assessment. VDD enables Tradespace exploration, which is fundamental for the evaluation of changeability. If this exploration maps operational strategies, configuration variables, and control policies, changeability can be assessed with increased precision and specificity. To this end, this paper aims to present the initial research outcomes of an effort to develop a flexible architecture that supports the transition towards electromobility and autonomy during early design stages. Specifically, the paper has the following research objective:

- Introduce an approach that facilitates the incorporation of a system's design variables, state variables, control policies, and contextual variables into an optimization problem to cater to different operational strategies from a SoS perspective.

The design variables configure a viable system, and control policies regulate the conceivable system states from an enormous array. The contextual variables affect system performance, and operational strategies govern the overall goal of the SoS. The proposed approach is further demonstrated for a fleet of haulers operating at a mining site. The paper is outlined as follows: Section 2 describes the applied research method, and Section 3 describes the relevant theoretical domains. Section 4 illustrates the proposed tradespace exploration approach, and Section 5 demonstrates the proposed approach for a case of a fleet of haulers. Finally, Section 6 discusses the findings and concludes the paper with future scope.

2. Research method

The work presented in this paper stems from Participatory Action Research (PAR) (Avison et al., 1999). In the frame of PAR, various data collection strategies were employed in collaboration with industry partners from the construction equipment manufacturing sector. The authors have harnessed real-time and retrospective data collection methods, following the principles presented in Blessing and Chakrabarti (2009). Concerning retrospective data, existing literature has been one of the primary sources for understanding the state-of-the-art. A narrative-styled literature review was performed in the domain of PSS and SE, specifically focused on design decisions concerning changeability in early design stages. Snowballing from selected sources has been instrumental in navigating through the extensive literature landscape. Apart from the literature review, qualitative data were collected from industrial partners via semi-structured and unstructured interviews. These data were supplemented with data from regular weekly and bi-weekly virtual or physical meetings at the company partner's facilities and mining sites; this includes a few co-located workshops with partners and stakeholders. These meetings were avenues for understanding the core problem, lifting the challenges faced, and obtaining valuable feedback. Besides, focused meetings were held to present preliminary findings and evaluate the consistency of the results. Based on the diagnosis of the problem, a "support" (Blessing and Chakrabarti, 2009) was developed in collaboration with the industry partners, thus completing the "think-look-act" (Stringer, 2013) cycle typical in PAR.

3. Changeability in System-of-Systems

As per (Maier, 1998), a system can be referred to as an SoS if the cluster can be broken down into constitutive systems, and these systems continue to operate and fulfill some purpose as independent systems. Thus, an SoS exists to achieve a broader purpose that an individual system cannot accomplish. This taxonomic distinction is preserved in this study. Further, they pose five distinguishing characteristics that differentiate them from traditional large-scale systems: operational autonomy, managerial autonomy, geographic dispersion, emergent behavior, and evolutionary development (Maier, 1998). The development of such SoS inherits many complexities, typically distinguished as internal and external complexity. Internal complexity refers to aspects within the system boundary. In contrast, external complexity refers to factors beyond the system boundary. Both these complexities go hand-in-hand to avoid under/over-engineering a solution (Heydari and Herder, 2020). To address the complexity aspects, McManus and Hastings (2005) proposed an approach to translating the complexities into uncertainties, and the attributes incorporated in the system to exploit or mitigate the effects of these uncertainties lead to systems having certain characteristics. Changeability is one such characteristic that enables any system to achieve value robustness by changing its form, function, or operation (Ross et al., 2008). A metric that quantifies the changeability level of systems is "Filtered Outdegree" (Ross et al., 2008), representing the number of change paths the system can execute within specified constraints like time, cost, etc. Many different forms of such a metric and their applications have been proposed in the literature (Rehn et al., 2019; Ross et al., 2009) in the prospect of developing a cost-effectively changeable system. However, for quantifying system changeability, change options need to be identified. A recent literature review details several methods and tools to identify appropriate change candidates because the effect of change propagate (Brahma and Wynn, 2023). In early design stages, however, a detailed system representation is often missing, making an explicit evaluation of design variables a viable choice for change option identification (Cardin, 2013). In explicit evaluation, the design variables are tested for their potential impact on value if changed, where tradespaces serve as an effective means. Valuation of these options is the next step based on these tradespaces using procedures like lattice analysis, decision analysis, stochastic programming, etc. Thus, it is evident that incorporating changeability in a system is an interplay of identification, quantification, and valuation, where a practical exploration of tradespace is crucial. From an SoS perspective, the tradespace is a combinatorial representation of several systems, including their configuration and control variables, in an operational context (Machchhar and Bertoni, 2022; Papageorgiou et al., 2020).

To enable the tradespace exploration, a number of tools and methods have been developed, spanning from scenario simulations (Rondini et al., 2017), including agent-based simulation (ABS) or discrete event-based simulations (DES) to detailed finite element simulation. When evaluating the lifecycle-oriented value, it can be argued that ABS, DES, or a combination of both methods, known as hybrid simulations, is a viable choice (Rondini et al., 2017). In DES, simulation proceeds as a sequence of events or a sequence in time, and the system can change its state only at discrete points. In ABS, independent agents have the intelligence to make decisions during their operational phase. Hybrid simulations combine the strength of both methods, which is referred to as DES-ABS in this work.

4. A tradespace exploration approach for changeability assessment

SE often stresses the need to define the boundary for the development team to maintain consistency in synthesizing internal and external factors for the "system of interest" (SoS in this case) (INCOSE, 2015). This boundary is often defined based on the factors the development can influence within a project. Thus, the factors lying beyond this SoS boundary are called context. Within this context, considerations extend beyond environmental parameters to encompass "enabling systems" (INCOSE, 2015), such as infrastructure, including humans, that can affect the performance of a system of interest. For consistency in nomenclature, any system part of an SoS will be referred to as a constitutive system (CS). Thus, in this study, the operational scenario comprises SoS and influencing context interacting to deliver value to the stakeholders. The SoS includes many CS, which have many subsystems (SS).

Figure 1 shows the overall layout of the proposed tradespace exploration approach to support changeability assessment, especially during the early design stages. This approach extends the dual-layer optimization approach (Machchhar and Bertoni, 2022), where a multi-objective problem is solved to obtain tradespaces. This dual-layer optimization approach has two limitations: Firstly, it does not consider a SoS perspective, and secondly, it does not involve tools potentially more effective in calculating lifecycle-oriented value, such as ABS, DES, or hybrid. The dual-optimization layers from Machchhar and Bertoni (2022) can be seen in Figure 1, marked with a dashed blue box. The outer layer comprises a standard design optimization (DO) problem with objective maximization/minimization and equality/inequality constraints (Martins and Ning, 2021). No disciplinary coupling (Papageorgiou et al., 2020) between CS and SS levels is modeled to reduce computational time. Also, the existence and computability of gradients is not guaranteed. Thus, heuristic gradient-free algorithms (Martins and Ning, 2021), such as evolutionary algorithms, are proposed to be used. These algorithms are different mathematical gradient-free algorithms (or derivative-free algorithms) that rely on mathematical optimality criteria for convergence. By using heuristics, the trade-off is that optimality cannot be guaranteed. However, a better solution is often desirable than a strictly optimal solution. The inner layer comprises an optimal control problem (Bertsekas, 2019) that allows finding an optimal control policy for a given objective. Several methods exist for deriving optimal policies for control problems. However, Dynamic Programming (DP) is used as it is one of the most versatile methods for different use cases (Bertsekas, 2019). DP is based on the Principle of Optimality, where control problems are broken down into smaller subproblems, and an optimal solution is found for those subproblems. These subproblems are then used to construct the optimal solution. Overall, the proposed approach comprises three modules: configuration, control policy, and DES-ABS module, respectively. As a first step, the development team starts by defining the problem. In this case, the design space consists of the SoS, and the context includes all aspects that can affect the value of the SoS, such as the environment, enabling systems, and humans. The configuration module assembles a viable SoS, the control policy modules evaluate various control policies using DP, and the DES-ABS module tests the SoS in the desired operational scenario. Figure 2 elaborates on each module highlighted in Figure 1 in detail:

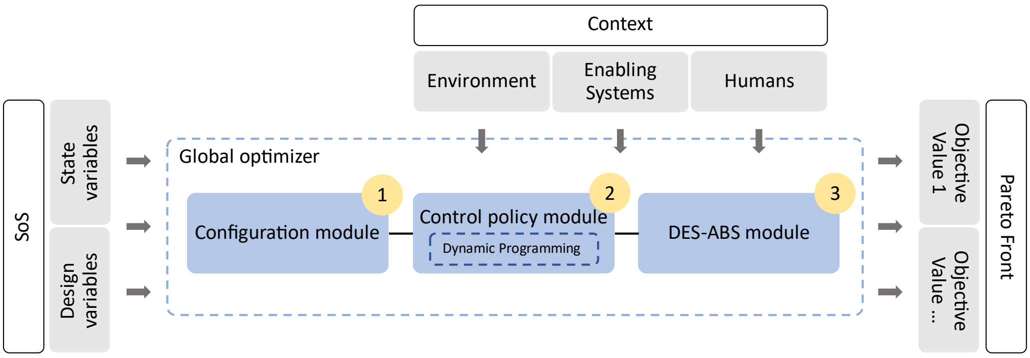

Figure 1. The layout of the proposed tradespace exploration approach

- Configuration module: In this module, the defined SoS design space results in p possible SoS combinations under combination constraints. Not all CS can be combined practically for reasons, such as compatibility, interoperability, etc. The hierarchy logic in SE projects is adopted, and hence, each unique combination of SoS comprises q CS, and each CS, in turn, comprises r SS, and so on. For brevity, Figure 2 shows the k^{th} SoS denoted as SoS^k. CS^k is one of the members of SoS^k comprising many SS. This CS is also configured under configuration constraints, as all SS may not be compatible with each other. Once a viable SoS is configured with q CS, each CS is assigned a set of tasks by the global optimizer or the DES-ABS environment, corresponding to the overall objective.
- Control policy module: In this module, DP is used to find the optimal control policy for all the CS iteratively, and the assigned task serves as the boundary condition. For example, a task for a vehicle to go from point A to B would imply that the vehicle is at a complete standstill at points A and B. DP then finds a control law to travel from point A to B that achieves specific optimality criteria. Since DP is a numerical algorithm used to solve continuous control problems, the problem must be discretized. This discretization includes the state and control variables in a discrete-time or discrete-space problem. The states a CS can reach are governed by its configuration and the control inputs. A sequence of these control inputs results in an optimal control policy if it minimizes a cost function (Bertsekas, 2019). Thus, the discretization allows the construction of the so-called subproblems in the principle of optimality, where the resolution of this discretization can be decided based on fidelity requirements (Bertsekas, 2019). As shown in Figure 2, the discretization serves as an input to the DP algorithm. Disciplinary analyses under control constraints compute an optimal control policy based on minimizing the cost function. This policy represents a specific way of fulfilling a task in the operational context.
- DES-ABS module: The DES-ABS module represents the operational scenario comprising the SoS interacting with the context to achieve the expected value. The DES-ABS simulation implies a process-centric simulation in the form of a sequence of activities combined with agents that operate and interact with the given context and other agents. Each CS is represented by one such agent in a DES-ABS simulation. From an engineering perspective, it reflects real-world operational scenarios, and specific rules set by the user govern the processes and the agents. For an agent (i.e., the CS) to perform a task, the time aggregated result of adopting an optimal control

policy is fed to a DES-ABS simulation. In DES-ABS simulations, a system can change its state at discrete events or timesteps. Connecting these transitions with the control policies gives the user dynamic control of system behavior (Dehghanimohammadabadi and Keyser, 2017). In Figure 2, a DES-ABS simulation represents the operational scenario and CS^k is in process of transitioning from i^{th} to j^{th} state, represented as CS_i^k transition to CS_j^k. This transition is a function of the control policy used. Many such transitions regulated by different control policies happen parallelly or sequentially in the DES-ABS simulation. The results from the DES-ABS simulation are fed back to the global optimizer to calculate objective values.

Iteratively, the global optimizer varies the design variables, including the configuration and control variables, to calculate the desired objective values. Thus, the tradespace contains design points that may differ solely in control policy. Upon reaching the stopping criteria, tradespaces comprising the Pareto Front for each varied context are presented to the user.

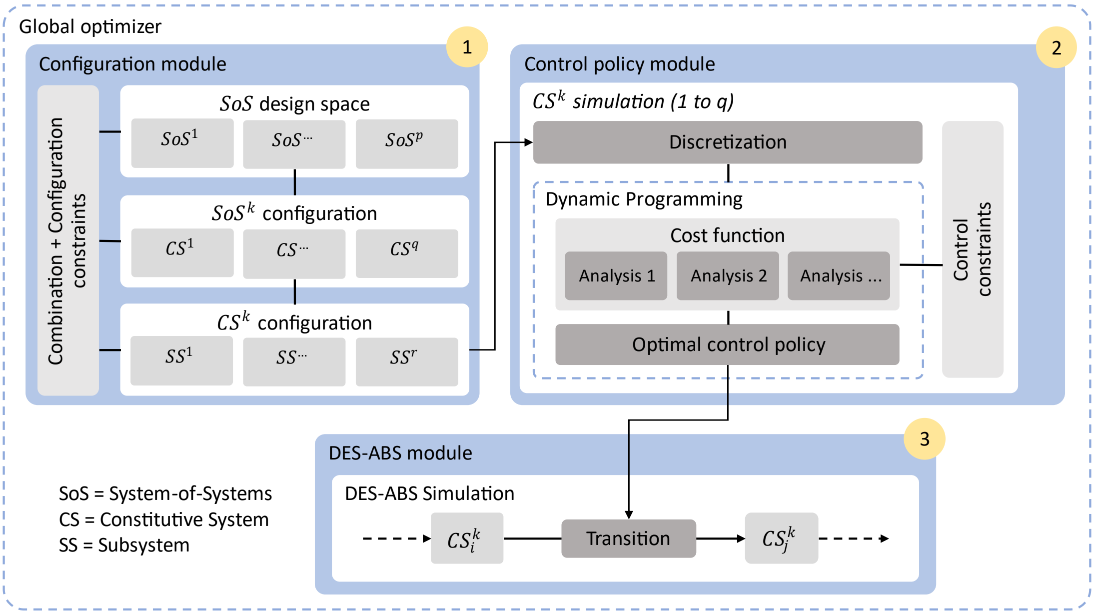

Figure 2. The proposed tradespace exploration approach for changeability assessment from a System-of-Systems perspective

5. Case: a fleet of haulers in a mining site

A hauler is an automotive vehicle predominantly used for hauling ore in mining sites. The design of a fleet of haulers poses a significant challenge to the development team in the contemporary shift towards autonomy and electromobility. The established hauler architecture needs to be radically innovated to fit the new requirements along with consideration of a multitude of dynamic contexts. This challenge is further stressed in newer business models like B2B sales and servitization. An entire spectrum of contexts is bound to change in such business models, as the hauler can be commissioned to several different operational scenarios during its lifecycle, leading to design uncertainties. Arguing that changeability in the SoS can be a valuable property to deal with future uncertainties, the assessment of changeability requires a thorough mapping of operational strategies, configuration variables, and control policies under influencing contexts, such that the synthesis of this tradespace allows changeability assessment by modification at SS and CS levels along with combinatorics at SoS level.

5.1. Experimental setup

To enable a tradespace exploration, the operational scenario was modeled in a DES environment that resembled the mining site. This model was built using the rules and logics prevalent in a mining site and further supported identifying the relevant contextual variables. In this case study, the fleet of haulers is the SoS under development; one hauler corresponds to CS, and the motors, batteries, gearboxes, etc., correspond to SS for this demonstrative case. These haulers were modeled as agents, specifically utilizing ABS modeling techniques within the DES environment that allowed implementing certain behavioral characteries for each hauler. Thus, the process simulation of the mine is a hybrid simulation, combining DES-ABS modeling techniques. Contextual factors were aspects like environment, enabling systems, and humans, which can affect the value of the SoS. Together, infrastructure systems like crushers, screeners, charging stations, etc., and mobile systems like wheel loaders, excavators, etc. are enabling systems. The distinction of enabling systems was based on the system boundary definition. Factors such as weather, ambient temperature, ore properties, route properties, etc., were the environmental factors. Notably, all these factors are strongly coupled to the SoS for value creation. A change in any single factor can instigate a cascading series of alterations within the operational scenario, resulting in fluctuation in expected value. This study considers only one operational scenario with many contextual changes for demonstration. Each contextual change will require a new tradespace to be explored. The global optimizer in Figure 1 aimed to solve Equation 1.

$$
\begin{array}{lll}
 & \min f(\bar{x},\bar{y}) & \textit{Ore Rate, Fixed cost, Operational cost} \\
\text{with respect to} & \bar{x} & \{n, x_1, \dots, x_k, \dots, x_n\} \\
 & \bar{y} & grid\{n, y_1, \dots, y_k, \dots, y_n\} \\
\text{subjected to} & g_1(\bar{x}) & \textit{Combination constraints} \\
 & g_2(\bar{x}) & \textit{Configuration constraints} \\
 & g_3(\bar{x},\bar{y}) & \textit{Control constraints}
\end{array}
\tag{1}
$$

Where, the problem formulation comprises solving three competing objectives f, i.e., ore rate (ore transported per year), fixed costs, and operational costs. The design variables' vector $\bar{x}$ is an array of $n+1$ entities, where n represents the number of CS in the SoS. Following, each x_k represents a CS configuration from a list of possible configurations. This list is compiled by exhaustively enumerating all feasible combinations derived from the SS. To practically generate this list, a cartesian product of available options within each SS was used. The combination constraint g_1 regulates how many unique SoS options exist. Similarly, configuration constraint g_2 regulates how many unique CS options exist. The configuration variables used in this case were different payload capacities, motors, battery packs, and c-ratings. A vehicle can have many design variables, but many were deliberately converted to dependent variables to reduce the design complexity. For example, the gearbox was a function of the selected motor, wheel radius and tire stiffness were a function of payload capacity, and so on. The state variables vector $\bar{y}$ has the same size $\bar{x}$, where n represents the number of CS in the SoS. Following, each y_k represents a discretized grid of each state and control input that the DP algorithm shall use to find an optimal velocity profile for a CS. The control variables regulated the exploration of different control policies. Control constraint g_3 governs the determination of optimal control policy and is a function of configuration and control variables. In this work, a single control variable, referred to as the time penalty, was used, which struck a balance between energy and time to explore different operating ways. The state variables primarily used in DP were velocity, current gear, and battery SoC, while the control inputs were torque and selected gear. A finite horizon deterministic DP was used to support a quicker global convergence, and the formulation was based on the pseudo-DP code presented in Guzzella and Sciarretta (2007). In a horizon of N steps, it starts with Equation 2 for all y_N:

$$J_N^o(y_N) = L(y_N) \tag{2}$$

and for steps $k = 0, \dots\dots, N-1$, Equation 3 represents the min cost J_k^o to reach the state y_N from y_k:

$$J_k^o(y_k) = \min_{u_k \in U_k(y_k)} [L(y_k, u_k) + J_{k+1}^o(y_{k+1})] \tag{3}$$

Where, $y_{k+1} = f(y_k, u_k)$ describe the mechanism used for updating the CS states. The control inputs $u_k, \dots\dots, u_N,$ that minimize Equation 3 together constitute to be the optimal control policy. The mechanism for updating the states is a vehicle dynamics model of the CS, selected by balancing the trade-offs between simulation time and accuracy. A 3DOF bicycle model (Berntorp et al., 2013) with appropriate tire properties was used. It considers longitudinal, lateral, and yaw motions, allowing the dynamic optimization for a route considering the instantaneous coeff. of friction, elevation, and curvature. The step cost, denoted by L in Equation 3, is represented in Equation 4:

$$L = (1 - \beta)\left(\frac{e}{e_{norm}}\right) + \beta\left(\frac{t}{t_{norm}}\right) + (\psi_1 * |v - v_{set}|) + (\psi_2 * |g - g_{set}|) + (\psi_3 * |SoC - SoC_{set}|) \quad (4)$$

Where, β is the time penalty, that balances time t and energy expenditure e. Intuitively, as β increases, DP will aim at achieving instantaneous velocities for the CS. Furthermore, v_{set}, g_{set} and SoC_{set} represent instantaneous constraints on the three states of the CS set by g_3 from Equation 1. Violating these constraints is penalized by pre-defined factors ψ_1, ψ_2 and ψ_3. Concerning operational strategies, the implications can be manifested at various hierarchical levels. At the SoS level, an operational strategy may dictate overall goals, such as maximizing productivity, minimizing wear, minimizing power loss, etc. At the CS level, strategies may include charging policies for a CS, such as charging when the battery reaches a threshold, charging at each cycle, or a dynamic charging policy. At the SS level, an operational strategy may govern input-outputs in specific SS, for instance, dedicated rest periods after using peak motor power for a specified time. It is argued that the implication of operational strategies at SoS levels can be dealt with objective function formulation for the global optimizer. The impact at CS or SS levels can be included in control policies via modification in the cost function or additions of newer control variables.

5.2. Simulation results

Figure 3 shows the tradespaces generated by applying the proposed approach, where the objective values are normalized. Each tradespace is plotted for the last 50 generations of the global optimizer. Given the development team's focus on optimal design points, an exclusive selection of non-dominant designs is not advisable due to the limited model reliability in the early design stages. Also, a non-dominant design in a specific context may be dominated in a different context. Thus, a fuzzy Pareto front is extracted from these tradespaces that enables a reduction in the design space yet enhances the selection of "passively value-robust" (Ross et al., 2008) designs and supports developing "actively value-robust" (Ross et al., 2008) design by highlighting possible change option. Since the problem formulation comprised three competition objectives, the fuzzy Pareto front is extracted by creating a regression surface on the Pareto front and using an "offset" value (Machchhar et al., 2023). This surface is highlighted in grey in all the tradespaces in Figure 3. Blue points then denote the fuzzy Pareto front.

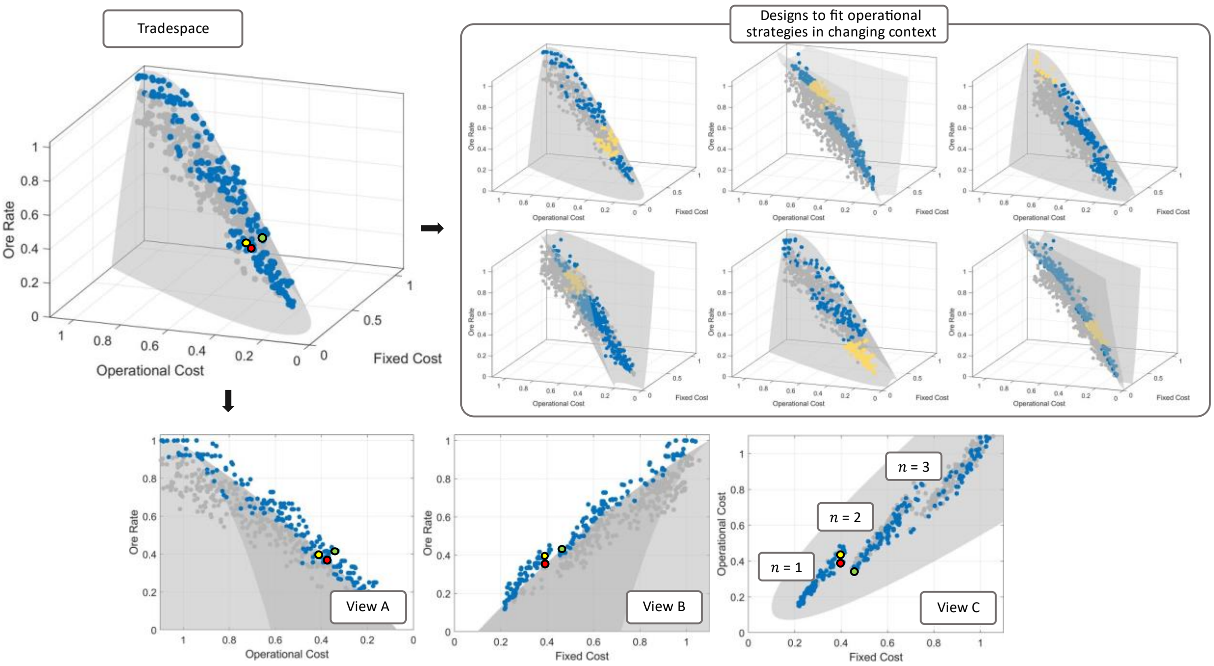

Figure 3. Tradespaces explored using the proposed approach

The tradespace at the top left corner of Figure 3 resembles a typical tradespace for a fleet of haulers as SoS. This tradespace is a combined mapping of configuration and control variables. Views A, B, and C have been presented in Figure 3 to compare two objectives at a time. In view C, n represents the number of CS in an SoS. Evidently, the fixed cost rapidly increases as n increases; however, the same correlation does not hold for operational cost. Three exemplary points have been highlighted in red, yellow, and green to emphasize decision-making concerning the value of an SoS. Design Red is a single hauler with a 30-ton payload capacity and a 50kWh battery capped at a 2C rating. Design Green is a fleet of two haulers with a 10-ton payload capacity each and with 50kWh and 20kWh batteries, respectively, both capped at a 3C rating. Despite Design Green having a higher investment cost, it outperforms Design Red in ore rate and operational cost. Also, design yellow is the same design as design red, although with a higher time penalty. While productivity increases, design green is still a better choice, given the investment costs. Such a simultaneous view of configurations and control policies supports a thorough investigation of design options. Several such tradespaces can be generated for different requirements and contexts. To cater to changing operational strategy along the contextual shift, a clustering algorithm, as shown in Machchhar et al. (2023), can be iteratively used on these tradespaces to highlight a cluster of designs that best suit the operational strategy. Figure 3 shows six such tradespaces where the operational strategy is arbitrarily changed. The clusters, marked in yellow, signify designs that align effectively with the operational strategy.

The mapping of configuration and control variables in the tradespaces above was based on state transition in DES-ABS simulations governed by control variables. Time penalty β enabled a different formulation of the cost function in DP. The effect of using different β values is shown in Figure 4, where a short hauling route dump-to-load is considered. The dashed lines show β biased towards energy, while solid lines show a bias towards time. Once an optimal control policy is calculated, aggregated results of applying this policy, such as average velocity and ΔSoC, are fed to the DES-ABS environment. In this environment, the state of the CS^k changes from i to j.

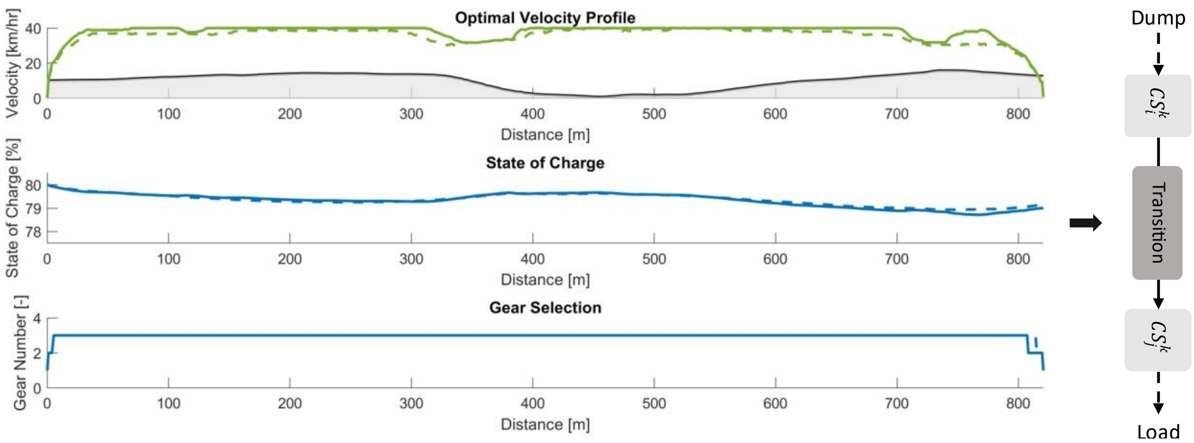

Figure 4. Different time penalty values affecting the optimal velocity profile

6. Discussion and conclusion

Changeability assessment entails atleast three challenges from an engineering design perspective (Cardin, 2013; Rehn et al., 2019; Ross et al., 2008). The first challenge concerns the identification of feasible change options that confer advantages on incorporating into the system. The second challenge involves quantifying the system's changeability level based on the identified change options. The third challenge concerns valuing the change options in the system's lifecycle. While these challenges are cyclic, all these challenges revolve around a focal point of change options. Explicit evaluation of design variables in tradespaces is usually preferred over change propagation techniques (Brahma and Wynn, 2023) to identify a feasible change option, as a detailed system representation is missing in the early design stages. For such explicit tradespace exploration, hybrid simulations utilizing DES-ABS are usually adopted for process simulation from an SoS perspective (Papageorgiou et al., 2020). However, these approaches are limited to using fixed average operating points for analyzing a CS. On the other

hand, approaches that consider the dynamic behavior of CS during operation often lack considering the SoS and the implications of enabling systems (Machchhar and Bertoni, 2022).
In this light, the proposed tradespace exploration approach combines system configuration and control policies, including their enumerative combinatorics in changing contexts. It can be seen as a flexible model-driven simulation approach that integrates established methods, such as DO, DP, and DES-ABS, from an SoS perspective. It can be positioned as a semi-quantitative value modeling effort based on the iterative definition of value models (Bertoni and Bertoni, 2019) that allows better design trade-offs in the early design stages at the expense of modeling and computational costs. The presented approach is further demonstrated for a fleet of haulers operating in a mining context, showing how a control policy change can replace a configurational change to alleviate value depreciation during disruptions, rendering some configurations less valuable. While examining these tradespaces in evolving contexts, it is further shown how a cluster of designs can be selected from each tradespace to represent an operational strategy in that context. Such an analysis allows decisions, such as investing in cutting-edge infrastructural technology versus opting for an aggressive yet suboptimal operational strategy. These tradespaces shall be seen as a stepping stone for supporting changeability assessment during early design stages because a characterization in terms of investment and change costs (Ross et al., 2008) was not performed. However, both the “top-down” and “bottom-up” approaches for quantifying changeability, based on Rehn et al. (2019) are plausible. The contention is that the proposed approach introduces a heightened precision and specificity to tradespaces, facilitating a more robust changeability assessment.
Several limitations and avenues for further exploration can be highlighted for the proposed approach, most importantly, investigating its generalizability in other industrial sectors. In this case study, the CS (i.e., the vehicle) was a model-based system, and various SS efficiencies were assumed. Next, DP is already scrutinized for its computational complexity (Guzzella and Sciarretta, 2007). Here, the complexity is scaled by n times, for all CS in an SoS. Reinforcement learning can support in addressing this aspect by value space or policy space approximations (Bertsekas, 2019). Besides, adding probabilistic noise to the currently used deterministic DP can be worthwhile for estimating the impact of uncertainty in control optimization. The global optimizer is based on heuristics; hence, optimality cannot be guaranteed. Additionally, the fixed costs were speculated based on feedback from industrial partners, and the operational costs did not include maintenance and labor costs. Thus, the objective functions relating to cost have a higher level of uncertainty in their mappings. Using historical data for a more robust quantification is worth investigating. Currently, operational strategies do not impose any constraints at the CS and SS levels. Future studies shall aim to understand the impact of operational strategies along the hierarchy. Finally, after exploring the tradespace, a fuzzy Pareto front is defined to reduce the design space while keeping the superiorly performing design points. The current design space reduction process is based on a surface regressed from the Pareto front. Thus, the spread of the Pareto front plays a vital role in how well the design space is reduced. An alternative for design space reduction is seen as a future step for enhancing the proposed approach.

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