

MITIGATING UNCERTAINTY IN CONCEPTUAL DESIGN USING OPERATIONAL SCENARIO SIMULATIONS: A DATA- DRIVEN EXTENSION OF THE EVOKE APPROACH

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ABSTRACT

The paper presents an approach where the iterative replication of Discrete Event Simulations on future operational scenarios is used to derive data-driven design merit functions. The presented contribution proposes an extension of the EVOKE (Early Value Oriented Design Exploration with Knowledge Maturity) approach determining when and how the experience-based judgment about maximization, minimization, optimization, and avoidance functions, correlating value drivers and quantified objectives, can be substituted by data-driven mathematical functions obtained by scenarios simulations. The approach is described through a simplified case concerning the development of autonomous electric vehicles to complement the public transport system in the city of Karlskrona in Sweden. The consideration of value drivers and quantified objectives presented is meant to support a preliminary screening of potential design configurations to support the definition of high-level product and system-related functional requirements, to be run before a more detailed conceptual design analysis.

Keywords: Conceptual design, EVOKE, Decision making, Discrete Event Simulation, Systems Engineering (SE)

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Cite this article: Bertoni, A. (2023) 'Mitigating Uncertainty in Conceptual Design Using Operational Scenario Simulations: A Data-Driven Extension of the Evoke Approach', in *Proceedings of the International Conference on Engineering Design (ICED23)*, Bordeaux, France, 24-28 July 2023. DOI:10.1017/pds.2023.267

1 INTRODUCTION

During conceptual design, decisions are made about a future product or system while having limited knowledge about the future products and systems configuration (Ullman, 1992). The methods supporting conceptual design decision-making acknowledge the presence of uncertainty and manage it by supporting intuition and subjective qualitative assessment. Decision-making matrixes, such as Quality Functional Deployment (QFD), Pugh Matrix (PM) (Frey et al., 2009), and Analytic Hierarchy Processes (Saaty 1988) are among the most common methods utilized in industrial practices. The minimum common denominator of such methods is the request for input from decision-makers based on a qualitative assessment of priorities and/or correlations existing between different criteria, such as needs, requirements, or engineering characteristics. QFD often expresses such correlations with a numerical scale (e.g., 0.9, 0.3, 0.1), PM uses the logic of "+" and "-", while AHP assigns numerical values to a hierarchy of criteria using decimals that sum up relevancy to the total of 1 (or 100%). More recently, in the field of Value Driven Design (VDD), a semi-quantitative approach named EVOKE (Early Value Oriented Design Exploration with Knowledge Maturity) (Bertoni et al., 2018) has been proposed to support engineers to design complex systems to 1) relate the "value" at a system - or even 'use of system' level - to the existing sub-system descriptions, 2) benchmark alternative sub-system solutions using 'value' as a metrics, and 3) conduct rapid WHAT-IF analysis of alternative scenarios, where different strategies for value creation are considered. EVOKE is presented as an extension of QFD, still using numerical scales to correlate criteria, namely "value drivers" (VDs) and "quantified objectives" (QOs), and introduces a quantification of such correlations by using non-linear merit functions derived from utility theory (Khamuknin et al. 2015). In EVOKE, decision-makers are asked not only to indicate if a correlation exists but also to select if a QO shall be maximized, minimized, optimized, or shall avoid, a specific value, to render higher design merit. Minimization, maximization, optimization, and avoidance functions assign design merits for each QO numerical value. This is determined by the shape of such functions, defined by on neutral point, indicating the 50% of design merit (thus determining the curve inclination) and eventually by optimal or avoidance points. Those points are defined by the decision makers' own experience and knowledge about the product or system under consideration. Despite EVOKE being applied in a number of industrial cases (Bertoni and Bertoni, 2019; Bertoni, 2019), the approach does not deal with the ingrained uncertainties introduced by the need to select a proper design merit function with its inclination and optimal or avoidance points.

Inspired by the research on scenario simulations for product-service systems design (Rondini et al., 2017), the paper presents an approach where the iterative replication of Discrete Event Simulations (DES) on future operational scenarios is used to derive data-driven design merit functions, quantifying how a change in a QO impacts the design merit for each value driver. In EVOKE, this means determining when and how the subjective selection of maximization, minimization, optimization, and avoidance functions can be substituted by data-driven mathematical functions obtained by scenarios simulations. The outputs of iterative DES are analyzed through regression analysis to establish the most suitable shape of the design merit function to be used in EVOKE. Therefore, the paper aims to present an approach to integrate DES results as a substitute for experience-based judgment when defining the type of correlation between VDs and QOs in EVOKE.

Overall, the work presented in the paper contributes to answering the research question:

RQ. How can the uncertainty ingrained in the subjective assessment of decision matrixes during early design be mitigated using simulations built on data from the future operational scenario?

The concepts of VDD and EVOKE are presented in section 3. The rationale and the logic of the proposed approach are firstly theoretically described (section 4) and then exemplified for the conceptual design of an autonomous electric vehicle to be used as part of a fleet of public transport vehicles serving the city of Karlskrona in the south of Sweden (section 4.1). The proposed approach features some limitations in its applicability based on the existence of a baseline reference solution, and the case example has been simplified for a demonstrative purpose. Those aspects are discussed in section 5, together with a description of the impact on engineering design practices of such a proposed extension of EVOKE.

2 RESEARCH APPROACH

The research presented in this paper is based on the further development of the EVOKE approach that was initially proposed through action research within the EU FP7 CRESCENDO project (Bertoni et al., 2018). The proposal of integration with DES emerges as a prescriptive approach from the needs collected during several tests with industrial practitioners and engineering students framed as the support evaluation and the application evaluation stage of the descriptive study II in the Design Research Methodology (Blessing and Chakrabarti, 2009). The need to reduce uncertainties in the selection and quantification of design merit functions, and the desire to increase data-driven automation of the EVOKE matrixes for more extensive design space exploration activities, led to the prescriptive proposal of the integration of DES described in this paper. Workshops with company partners and semi-structured interviews served as data collection methods to identify stakeholders' needs and challenges, while the presented application case is primarily based on the development of computer-based simulations.

3 VALUE-DRIVEN DESIGN AND EVOKE

As George Hazelrigg (1998) stated, decisions made during design should always add value to the solution space. VDD methods aim to cope with this issue by turning 'value' into a driver for the system design activity, as opposed to requirements and/or cost-related characteristics. Value-centered methodologies (e.g. de Weck et al., 2003; Ross and Rhodes, 2008) consider customer value embedded in the customer process context and the concept of 'ilities' has been used both in systems engineering and in product-service systems literature to evaluate the system robustness under changing process conditions (Ross et al., 2004; McManus et al., 2007; Bertoni and Bertoni, 2019). VDD (Collopy and Hollingsworth, 2011) is one of such value-centric approach for the design of complex systems. VDD aims at moving the target of the modeling activity from identifying a favorite performance point to creating a space where there can be a discussion of product performances, trade-off benefits, and drawbacks of different solutions (Dahlgren, 2006).

Within the VDD community, authors claimed that deterministic models limit communication among the decision-makers and negatively affect early design decision-making activities. Soban et al. 2012, initially support the hypothesis that a qualitative assessment of the 'goodness' of a design is preferable against a monetary-based encoding of preferences when qualitative data, assumptions, and forecasts prevail. Isaksson et al. (2013) further observed that exact quantitative functions are typically missing when performing a preliminary screening of new product technologies. This eventually suggests practitioners look at different constructs to share information about a design's intent and overcome intellectual property rights barriers (Lindquist et al. 2008). Monceaux et al. (2014) concluded that while deterministic models for value are relevant in the detailed design phase of a new system, in the conceptual phase, different constructs are needed to establish the necessary links between system attributes and the overall 'value' of the system. These considerations brought to the development of a VDD process that links high-level customer expectations to product features at the sub-system level, and that communicates back to the system integrator the results of specific value analysis (Isaksson et al., 2013). Such a process is based on an initial definition of a Value Creation Strategy (VCS) as a shared document, iteratively reworks in the supply chain, to translate and jointly analyze the needs emerging from the different levels of the supply chain. Once VCS loops are initiated, engineers are left with the problem of choosing the most suitable value modeling approach to benchmark design concepts and support decision-making at each stage. In such a context, more recent research showed the need for the value models to create a shared understanding among business stakeholders and technology-focused design teams (Panarotto et al., 2020), and methods have been proposed to trade off parameters such as flexibility and changeability against traditional engineering attributes (Panarotto et al., 2020b; Machchhar and Bertoni, 2022b). Among such approaches, EVOKE is a concept scoring method proposed as a complementary approach to the VCS for the semi-quantitative assessment of different design concepts.

3.1 Early Value Oriented design exploration with Knowledge maturity - EVOKE

The EVOKE approach translates the VCS information shared by the upper layers of the supply chain into meaningful sub-system value drivers (VDs). These sub-system VDs are then used to calculate a

'merit score' for alternative design options to identify the most value-adding solution candidate to be communicated back to the system integrator. The EVOKE approach for concept selection features the use of three matrixes, namely:

- a Weighting Matrix, which correlates the system-level VCS to the sub-system VDs;
- an Input Matrix, which gathers information about the characteristics of each design alternative under consideration;
- a Customer Oriented Design Analysis (CODA) matrix, which produces a merit score for each design alternative.

In CODA, as in mainstream QFD, VDs, and QOs are linked by numeric values to express strong, weak, minimal, or no correlation between them. CODA further adds minimization (Min), maximization (Max), optimization (Opt), and avoidance (Avo) type functions to compute a score representing the 'merit' of a design. Min and Max functions are shaped along an exponential curve, which is considered a reasonable approximation of the customers' response to changes in a product attribute. The shape of Opt and Avo functions mirrors that of a Gaussian distribution anchored on a preferred target value. This value indicates a customer satisfaction of 1 for optimization, and 0 for avoidance. Their shape is further regulated by a so-called tolerance point (τ), which works similarly to the neutral point η . By varying neutral and optimum points it is possible to draw different customer responses to changing product attributes: an ideal design solution shall obtain a 100% design merit score at each QO/VD intersection.

Target merit value expresses the desirable outcome of the design task aggregating the merit score of each value driver. Such a target can reflect a vision emerging from long-term forecasts or can be calculated, for instance, as 110% of the baseline value score. If the Target is met, the design is considered to be satisfactory. If not, QOs have to be fine-tuned to trade excellent capabilities in some areas (i.e., concerning a set of VDs) and deficiencies in others.

4 THE PROPOSED APPROACH

As described in the previous sections, to populate the matrixes of EVOKE, subjective evaluations from decision-makers are required, both concerning the degree of correlation between VDs and QOs and to determine which type of design merit function best fits each identified correlation. Additionally, subjective assessment is employed when deciding tolerances, optimal points, neutral points, and optimization and avoidance points for each function. Such a subjective assessment generates ingrained uncertainties in the decision-making matrixes. The approach proposed in this paper uses operational scenario simulations to substitute the minimization, maximization, optimization, and avoidance functions with mathematical functions obtained by applying regression analysis to the output of multiple DES. The approach relies on a baseline reference solution operating in an existing and known scenario to simulate design concept variations. The introduction of DES prescribes additional steps in the EVOKE approach (as shown by the light blue boxes in Figure 2). Those consist initially in creating a baseline scenario simulation setup after the definition of the weighting matrix and the input matrix. Based on the reference scenario, DES are iteratively run for each QO featuring as input a range of values falling in between the lower limit and upper limit defined in the Input matrix (such step is defined as DES experiment). For instance, as shown in the example in section 4.1, if the seating capacity of a vehicle can be defined between 3 and 20 people, each DES experiment will feature an increasing vehicle capacity between 3 and 20, with the output depicting a response surface of simulation results based on such changing parameter. In case of large variations, the granularity of input variations can be manually decided or defined by applying Design of Experiment (DoE) strategies (Giunta et al, 2003). In the case of DES experiments providing results possible to be represented in meaningful mathematical terms (e.g., through regression functions), such representations substitute the design merit functions in the CODA. If no clear correlation emerges from DES simulation, the choice falls back to the subjective assessment of the decision makers as in the original CODA matrix definition. The approach represented in figure 1 is exemplified in the following subsection describing the conceptual design stage of an autonomous electrical vehicle for public transportation.

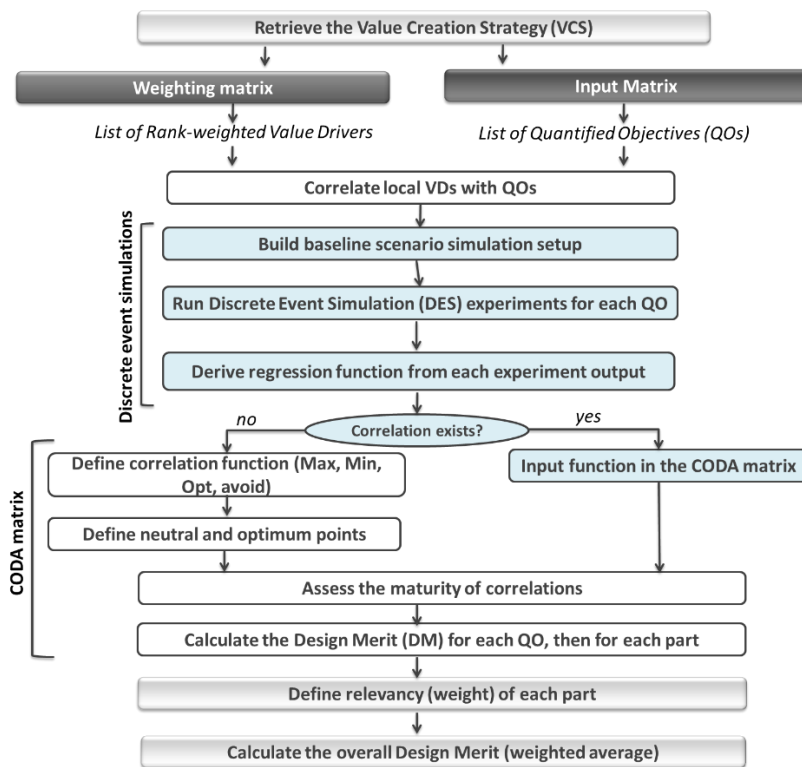


Figure 1. The process followed in the EVOKE approach complemented by the discrete event simulations steps (in the light blue boxes)

4.1 Application case: concept selection of autonomous vehicle for public transportation

The approach described in figure 1 has been applied to the demonstrative case of the concept selection of alternative design configurations for autonomous electrical vehicles complementing the public transportation system of the city of Karlskrona in the south of Sweden. The case is described here with several simplifications to demonstrate the approach rather than presenting accurate results. The reference scenario features six autonomous electrical vehicles circulating on fixed routes connecting the central train station with three stops located respectively 1) in the city center, near shops and restaurants, 2) near major companies and public offices, and 3) near the university. The charging station for electric vehicles is located beside the central station, which serves as "source" of passengers for the DES. The number of potential customers of the autonomous vehicles is shaped based on trains scheduled arrival time to model the average presence of passengers in peak and "non-peak" hours during the day. The pre-defined route for the vehicles mirrors real distances and the real topography of the city. The distribution of passenger destinations among work, restaurants, and university is statistically determined, with the typical behavior of the passenger modeled as the one of a commuter reaching the city for leisure, work, or studies and leaving the city when such activity has been completed.

4.1.1 Value drivers and quantified objectives

Four value drivers have been selected in the conceptual design stage to represent the potential value creation of the new autonomous transportation system. Those have been defined as follows:

- Mobility, i.e., the capability to provide transportation solutions to passengers. This is quantified in the model as the number of people utilizing the system both when arriving in the city and returning to the train station to leave the city at the end of their activities.
- Waiting time, i.e., how long a passenger shall wait for an autonomous electric vehicle to pick him/her up at the train station when arriving in the city. This is quantified in the model as the average minutes waited at the station by the passengers. Too long waiting time will drive passengers' decisions to seek an alternative transportation solution.

- Cost, i.e., how much is the operating cost of the fleet of vehicles. This is modeled by determining a cost per minute of the utilization of the vehicle when carrying one or more passengers and an idle cost per vehicle when not carrying any passenger. In this specific case, the vehicle's capital cost was not included in the simulation since it was deemed to be marginally impacted by the variation of the selected quantified objectives.
- Utilization, i.e., how much passengers use a vehicle during an operating day. This is modeled in the DES by quantifying the percentage of the total time the vehicle carries one or more passengers. The time in the vehicle has no passengers on board, the charging time of the battery, the repair time, and the safety control time accounts for the percentage of non-utilization of the vehicle.

Such VDs should not be seen as comprehensive but rather as functional to demonstrate the approach. As an initial conceptual design activity, the relevancy of QOs was studied to investigate the potential design configurations of the new vehicle design. In this example, three quantified objectives were initially explored, namely:

- Speed. Defined as the average cruising speed of the vehicles circulating in the city. This has been modeled in meters per second, defining a lower limit of 4 meters per second (as acceptable minimum speed) and 12 meters per second as the upper limit for safety reasons.
- Seat capacity. It was defined as the maximum number of passengers to be carried simultaneously by each vehicle. In this case, the lower limit is set to 3 passengers and the upper limit to 20.
- Time to Check. Defined as the time operators need to regularly check the vehicle's status and conditions to avoid any malfunctioning or safety issue. This is modeled in the DES in hours with a lower limit of 0.2 hours and an upper limit of 3 hours. Simultaneously, the mean time between checks is modelled in DES as a normal distribution based on a predefined estimated mean time between failures.

It must be noted that those QOs only partially represent the QOs impacting the design of the final electrical vehicle. Considering these three QOs is meant to support a preliminary screening of potential design configurations to support the definition of high-level functional requirements. More specific QOs, (e.g., battery type, engine, gearbox) are planned to be considered in the following stage of conceptual design, not described in this paper.

4.1.2 Simplified Input matrix, simulation scenario and DES experiments

Four different design concepts were compared in terms of value delivery in relation to the previously described VDs, namely a baseline and three alternative design options #1, #2, and #3. Their features are summarized in table 1. DES experiments were run iteratively for each QO to derive a function representing the design merit of the different VDs. For instance, given the scenario simulation setup, DES was run while changing the speed of one unit between 4 and 12 meters per second for each experiment iteration, generating different outputs for each VD in each iteration.

Table 1. Input matrix used in the EVOKE approach.

Quantified objectives	Units	Baseline	Option #1	Option #2	Option #3	Lower limit	Upper limit
Speed	m/s	5	5	7	10	4	12
Seat capacity	(# people)	6	4	8	16	3	20
Time to check vehicle	hours	0,4	0,2	2	2,3	0,2	3

The DES setup consisted of one source of entities (the passengers), four servers managing the time spent by passengers in the different locations of the city, and also representing the location of the stops for the vehicles, a sink counting the number of people leaving the city, a node corresponding to the charging station where the vehicles park while charging, a fleet of vehicles working as transporters of passengers in the simulations, and a network of paths based on the topography of the city connecting servers, nodes, source, and sink representing the possible roads to be taken by the transporting vehicles.

Figure 2 shows a screenshot of the DES experiment results as obtained in the DES software environment. The figure shows one DES experiment for each row, changing one unit of the vehicle's speed and replicating the simulation three times for each row for statistical reasons. The figure shows replicated three DES control variables in light blue and DES output in the light brown cells.

Scenario	Name	Status	Replications	Completed	Controls	ElectricVehicle_Ini...	ElectricVehicle_InitialRideCapacity	TimeToRepair_El...	ElectricVehicle_Speed...	Responses	AvgWaitingTimeParking (Minutes)	ScheduleUtilization	No_Leaving_city	VehicleCost
Scenario 1	Idle	3	3 of 3	6	6	0.4	4	437,172	76,1529	1226	18549			
Scenario 2	Idle	3	3 of 3	6	6	0.4	5	427,921	78,1945	1379,67	16357,7			
Scenario 3	Idle	3	3 of 3	6	6	0.4	6	396,887	72,4747	1566	15930,2			
Scenario 4	Idle	3	3 of 3	6	6	0.4	7	378,554	74,5482	1743,67	14740,3			
Scenario 5	Idle	3	3 of 3	6	6	0.4	8	371,129	74,6455	1800,33	13430			
Scenario 6	Idle	3	3 of 3	6	6	0.4	9	332,233	69,2846	1950,33	13076,9			
Scenario 7	Idle	3	3 of 3	6	6	0.4	10	300,743	69,5425	2057,33	12593			
Scenario 8	Idle	3	3 of 3	6	6	0.4	11	299,218	64,9537	2139	11573,8			
Scenario 9	Idle	3	3 of 3	6	6	0.4	12	291,728	66,1693	2196,33	11022			

Figure 2. Screenshot of the DES experiment for vehicle speed variation between 4 and 12 meters per second. The figure shows one DES replicated three times for each row, with input in light blue and output in light brown cells.

4.1.3 Output from the CODA matrix

Each DES experiment allowed determining a function representative of the correlation between the QO and its design merit for each VD. This means that, for instance, for the speed variation shown in Figure 3 four functions expressing the design merit variation in terms of mobility, waiting time, cost, and utilization were calculated. Similarly, this has been calculated for the seating capacity and the time-to-check. The correlations between QOs and VDs were quantified by selecting the regression function best fitting the output of the simulations. The choice was done by selecting the R2 value closest to one among linear regression, logarithmic regression, exponential regression, power regression, and polynomial regressions up to the order of four. Once the functions were determined, they were used for each option evaluation in the CODA matrix. Figure 3 shows the functions defined for the variation of the seating capacity of the vehicles between 3 and 20 people.

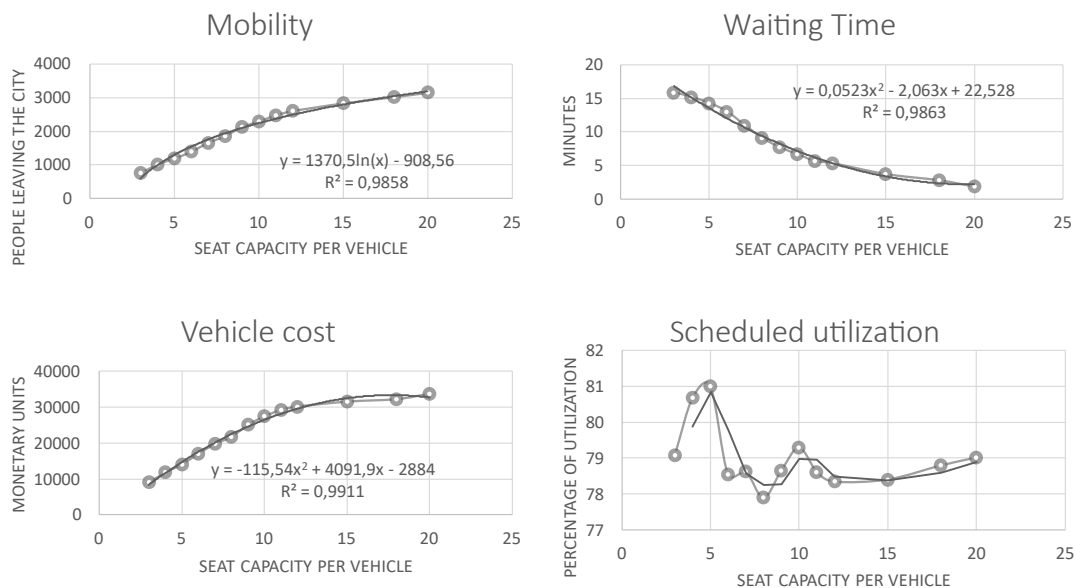


Figure 3. Correlation between seat capacity (between 3 and 20 passengers on x-axis) and the four value drivers (mobility, waiting time, vehicle cost, vehicle scheduled utilization) as derived from DES experiments.

The points in Figure 4 show the output of the DES experiments, while the lines indicate the potential regression functions approximating the output. The equation in each graph shows the regression function that best approximated the results obtained in DES and that it was utilized in CODA. In the case of the bottom right graph in Figure 4, no regression functions could represent the correlation between seat capacity and vehicle scheduled utilization with a low margin of error (defined for this case as a minimum R2 of 0.95). In other words the average percentage of utilization, did not show a clear trend. In such a case, the selection of the design merit function was left to the qualitative assessment of decision makers as in the original version of CODA. With the obtained functions used as input in the CODA matrix, it was then possible to calculate the design merit for each VD. Those were further aggregated for each of the four design options in the input matrix.

Figure 4 shows the final output of the EVOKE assessment aggregating each QO and VD correlation., On the right-hand side the overall design merit for each option, calculated as the weighted sum of the design merit of each VD is visualized, and, on the right-hand side, a spider diagram of the design merit for each value driver is presented. As shown in Figure 4 option 3 renders the highest design merit at 55,85%, having a relatively high score for mobility and waiting time compared with other options, although trading off a lower performance in terms of utilization and higher operating costs.

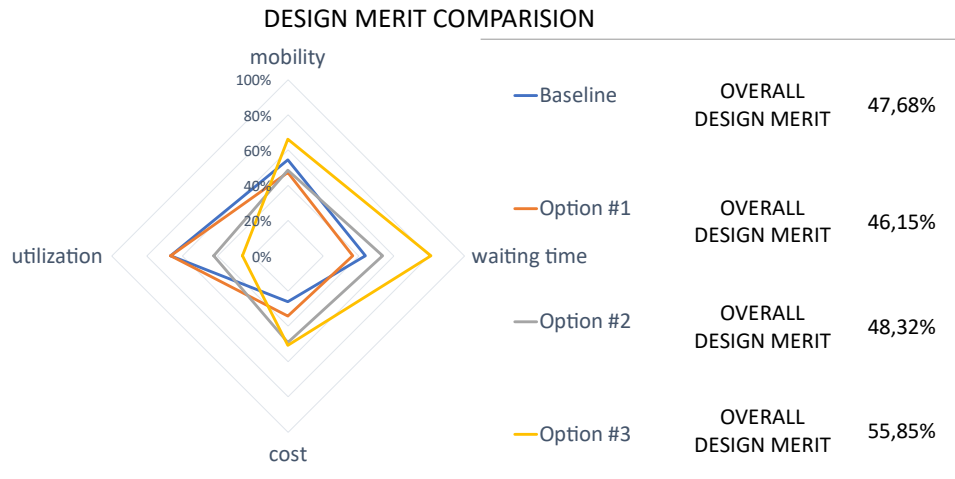


Figure 4. Output of the EVOKE calculation for the electrical autonomous vehicle concepts in terms of overall design merit (on the left) and in terms of value contribution for each value driver (on the right).

5 DISCUSSION

In recent years, scientific literature has repetitively highlighted the potential of simulations, data-driven decisions, and digital twins for moving into a new way of approaching engineering design and product development. Nevertheless, when dealing with the early conceptualization of products or services, many decisions are still made based on experience, intuition, and forward-thinking of engineers, managers, and decision-makers. The approach presented in this paper is a step toward a more extensive integration of data-driven decision support into the early conceptual design to reduce the uncertainty and mitigate the subjectivity of early design concept assessment. The approach focuses on increasing decision-makers' awareness about the impact that a change in a product parameter can have on the overall value delivered by the final product or by the system into which this product will be integrated. Using discrete event modeling and simulation forces decision-makers to recreate a model of the future product's context. This pushes toward identifying the known unknown or questioning existing assumptions about potential correlations between design variables and context that might be intuitively true but not later emerge from the data.

For the proposed approach to be applicable and successful two main conditions need to be met: the flowless integration in the current practice, and the existence of a baseline reference solution. Firstly, the analysis needs to integrate with the right level of accuracy in the current practice of concept assessment in early design. Precision and accuracy of the scenario simulations need to be good enough to be trusted more than experienced-based assumptions, but also not too precise to become irrelevant for generalization or excessively time-consuming. This is particularly true for the integration in the concept assessment phase, while, in a later stage, increasingly detailed and trustworthy simulations would be needed for a more limited and better-defined set of concepts under evaluation. Secondly, the approach is applicable to the development of a product that will be used in a well know existing operational scenario. This was the case of the electrical vehicle presented, which was conceptualized for being integrated into an already existing public transportation system. Such a characteristic also limits the application of the approach for radically innovative systems, since a clear reference baseline is often unavailable, making it challenging to create simulation scenarios based on discrete events. Another limitation is that the design merit functions derived through regression from the DES experiments are obtained by varying one QO at a time in the baseline DES configuration. Doing so,

the QOs are treated under the assumption of linear independence, while in many cases, such a condition might not be true. This limits the identification of emerging behaviors in the simulations given by the concurrent changes of multiple QOs. The case of autonomous electric vehicles for public transportation in the city of Karlskrona deliberately includes several simplifications. First of all, no calculation optimizing the route of the electric vehicle in the city is included. Routes and stations have been instead pre-defined. Secondly, the selection of the regression functions best fitting the output of the DES experiments was done through the simple comparison of the R2 coefficient between linear, exponential, logarithmic, power, or polynomial functions. More appropriate modeling could have been done by applying data science algorithms to increase the accuracy of predictions. However, given the ingrained uncertainty already present in the scenario definition, this step was deemed irrelevant for demonstration purposes.

6 CONCLUSION

The paper has presented an extension of the EVOKE approach for early design concept assessment integrating the use of DES to support a more reliable selection of suitable design merit functions in the concept assessment matrix. The approach relies on the established definition of value drivers and quantified objectives, such as already proposed in the literature, and introduces operational scenario simulation in discrete events to define the shape and quantify the design merit of each value driver. The approach has been described through the case of the development of autonomous electric vehicles to complement the public transport system in the city of Karlskrona in Sweden. The proposed approach is currently under further development in industrial contexts rapidly facing the transition toward electromobility and autonomy, such as mining and quarrying. Here new paradigms for machine and site design are emerging as an answer to the need to increase productivity while preserving human safety and reducing the environmental impact.

The future development of the approach will feature EVOKE's automation to evaluate hundreds of design cases in a DoE setting. The proposed integration of DES would happen, as a one-time activity, before the automatic execution of each design case in the CODA matrix. The accuracy of the simulation will also increase as far as iterative value modelling in EVOKE will be performed. This includes increasingly detailed simulations that consider more specific quantified objectives, which value will be obtained through mathematical simulations in CAE environment (on the line of what was proposed in [Machchhar and Bertoni, 2022](#) and [Bertoni et al., 2022](#)).

ACKNOWLEDGEMENT

The work was performed partially in the frame of the TRUST-SOS project funded by the Swedish Innovation Agency (VINNOVA) through the FFI Fossil-free mobile work machine initiative. The work has also been partially performed in the frame of the Strategic Innovation Program Swedish Mining Innovation, concurrently funded by the Swedish Innovation Agency (VINNOVA), the Swedish Research Council for Sustainable Development, (FORMAS) and the Swedish Energy Agency (Energimyndigheten).

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