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Optimization-based design support for engineer-to-order product quotation

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Abstract

Quotation of engineer-to-order products provides substantial challenges in effectively managing engineering resources. This paper describes an approach that rationalizes this process by integrating multi-disciplinary design analysis and optimization with a new open-source library for managing engineering knowledge before and after optimization. The approach is applied and evaluated on mechanical rock excavation machines. Adapting the approach and considering the user feedback gathered can lead to an enhanced design space overview during quotation and thus more competitive product offerings.

Keywords: mass customisation, multi-/cross-/trans-disciplinary approaches, design optimisation, computational design methods, knowledge management

1. Background and framing

Manufacturers of physical products are increasingly recognizing the significance of product customization. Quick and accurate responses to unique customer requirements can provide a substantial competitive advantage in certain industries. However, the customization of complex products is usually more complicated, as it can require extensive engineering effort before the manufacturing of the product or even providing a quotation for its cost. Such products are commonly referred to as engineer-to-order (ETO) products. Although the level of engineering required varies for different product offerings, the significant factor is that engineering work cannot commence until certain details about the business case in question are made available as part of the customer request (Gosling et al., 2017).

The design process paradox suggests that a large proportion of the product development costs are committed during the sales and conceptual design stages (Verhagen et al., 2012). For ETO products, this regularly amounts to as much as 80% of the total costs committed in this early stage (Hicks et al., 2000). At the same time, the success rate of ETO offerings is around 30% (Konijnendijk, 1994) – some claim it is even lower (Hicks et al., 2000). This implies a large risk for ETO offerings since large investments in engineering efforts might be needed, while their return is not guaranteed. In this context, there is a trade-off to be made. The detail level of the quote must be high enough to enable business decisions that are valuable for both supplier and customer, but also low enough to not waste engineering resources on business cases that might not make it. If higher fidelity of quotes can be achieved with less engineer time committed, profitability and resource efficiency can both gain considerably.

Previous work, e.g., Elgh (2012) points to structuring knowledge in reusable containers as a fruitful way of supporting ETO quotation processes. Another way of supporting complex product development is through the use of multidisciplinary design analysis and optimization (MDAO), a technique for optimizing products while considering multiple inter-dependent models (see e.g., Papageorgiou and

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Ölvander, 2017; Simpson and Martins, 2011). Van Gent et al. (2020) have argued that the promises of MDAO have yet not been fulfilled for complex products. While also proposing a solution for an aerospace application, its effects are yet to be proven in a wider perspective. Thus, MDAO seems to show more potential than utility for many industries.

While Johansson and Elgh (2019) propose a way to combine optimization information with structured engineering knowledge, the exact data that should be recorded is not made clear, and the proposed solution framework does not consider multi-disciplinary optimization where mutual interactions between models need to be considered. Furthermore, no open implementation of the framework is provided. Still, combining structured engineering knowledge with MDAO techniques seems to be an interesting way forward for supporting ETO quotation processes.

Against this background, this work explores the opportunities with incorporation of reusable MDAO support for ETO quotations. Using an interactive research approach focusing on quotation of mechanical rock excavation machines, the work contributes with a demonstration of an MDAO-based design tool. The tool utilizes the OpenMDAO framework (originally devised by Gray et al., 2019) but complements existing work with new concepts on how to handle engineering knowledge and multidimensional data, developed in open-source packages. Furthermore, it showcases how a GUI with visualization tools can aid decision-making in the ETO process for a specific type of excavation machines, Mobile Miners.

The paper is divided into six sections, where section two covers the approach used, including framework development and user feedback collection. Section three presents the Mobile Miner application and its challenges. Section four describes the implementation of an MDAO-based design support tool. Section five evaluates the technical and user-facing aspects of the tool. Section six discusses the results, lessons learned, and future work, and concludes by summarizing the contributions.

2. Approach

An industry-based case study was conducted to address the gap between state-of-art and state-of-practice in MDAO applications, using the *industry-as-laboratory* approach (Potts, 1993). Here an industrial context is used for two main purposes: as a source of relevant problems, and as an experimental environment onto which research outcomes can be evaluated (as shown by e.g., Muller and Heemels, 2007). In this work, an industrial problem, in the form of design and implementation of design support for ETO quotation of Mobile Miners, was solved in parallel with performing research on how to solve that kind of problem from a more generic perspective. The process was therefore interactive, where solutions were proposed and demonstrated on the industry problem, and at the same time, data was collected by observations and interviews with the industry partner. Based on the feedback received, the industrial needs for the solution were collected and documented.

A design support framework and a software library were implemented in a graphical design support system. The system was evaluated by a group of experts on Mobile Miner development and quotation, who provided feedback through a group workshop and individual interviews. User statements were independently recorded separately by two of the authors to capture all feedback and later merged. The user group consisted of three senior engineers from the partner company, each with a unique background and focus in their work. They were selected to provide diverse perspectives on the developed design support system, with backgrounds in design, simulation, optimization, and business development.

The statements were analyzed and sorted into groups based on their content, and any duplicates were removed. These groups of user statements were then translated into the needs of the developed application. The approach taken was inspired by the process of identifying customer needs in product development (as presented by Ulrich, 2003). Sometimes, a single statement was divided into multiple needs and other times, several statements were combined into a single need. Although the identified needs are stated specifically to the design support system developed in this project, there is a large potential to translate them into generic needs for optimization-based design support systems.

3. Application

Excavation of rock for mining and construction has been conducted in multiple ways over the years. Since the invention of dynamite and the hydraulic drill, most mining operations of hard rock have been

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dominated by the drill-and-blast (D&B) technique (Vogt, 2016). In the 1950s, mechanical excavation became a viable alternative to D&B (Maidl et al., 2008). About twenty years later, Mobile Miners emerged as a family of mechanical excavation machines (Sugden and Boyd, 1988), originating as a hybrid between tunnel-boring machines (TBMs) and roadheaders, but adapted for hard-rock excavation applications (Vogt, 2016). The Mobile Miner works by thrusting its cutter wheel, equipped with hard disc cutters, against the rock wall and simultaneously turning the wheel, consequently crushing the rock (Hartwig and Delabbio, 2010). An example of a modern Mobile Miner with its cutter wheel and individual cutter discs is depicted in Figure 1.

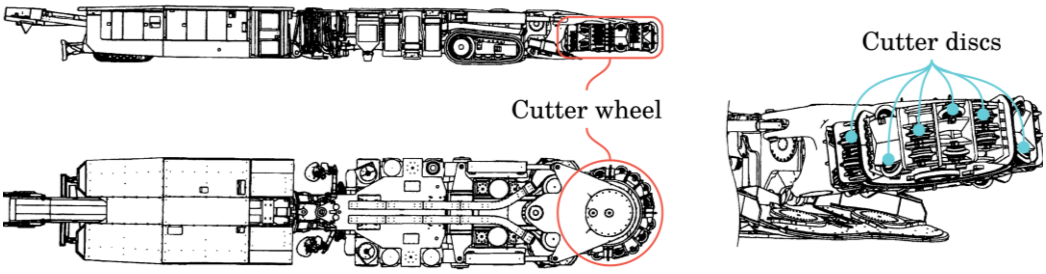

Figure 1. Top and side view of a Mobile Miner, and close-up view of the cutter wheel; The total length of the machine is in the order of 20 meters, and the cutter wheel diameter is in the order of 4 meters; Adapted from Bergling et al. (2020)

Skawina et al. (2014) have shown that the Mobile Miner concept can outperform D&B in certain scenarios, in terms of excavation rate (volume or mass per time unit) or advance rate (distance per time unit). Additionally, it has been considered for tunneling repositories for spent nuclear fuel, due to its high wall surface smoothness and low vibration emission (Lislerud, 1997).

Determining whether a Mobile Miner provides a viable excavation method for a specific mining environment is a clear example of an ETO development process – it requires the supplier to have customer-specific data available to perform the extensive engineering work needed to design and conclude the product's suitability to the customer's needs. An especially important engineering effort lies in establishing the dimensions of the cutter wheel for achieving the desired tunnel dimensions. Then, the placement of individual cutters on the wheel must be determined. The placement of cutters is dependent on rock properties at the customer's mining site and has substantial implications on excavation and advance rates, cutter lifetime as well as the static and dynamic loads exerted on the machine – all heavily impacting the machine's financial outlook.

Using design optimization for designing mechanical excavation machines has been partially covered in the literature. Roadheaders have been subject to optimization for a long time (see e.g., Jin et al., 2022; Rostami et al., 1994). TBMs have also undergone MDAO (see e.g. Sun et al., 2018), including reliability-based optimization to assure that they can handle the varying operating conditions that are part of their lifecycle (Wang et al., 2018). Authors of this paper have previously considered an MDAO approach for a Mobile Miner, highlighting the potential of an optimization-based quotation process, but also the need for decision-supporting tooling (Vidner et al., 2021a).

4. Design support

The design support framework developed in this paper extends upon a basic framework presented in (Vidner et al., 2021b), where an optimization problem is automatically built and solved using the product description data given by the user, as outlined in Figure 2. Here, the aim is for the user to only interact with a GUI, which should provide the tools needed to enter the product description in a specified format, and present design concept specifications in a way that is actionable for the user.

As a part of the pre-processing routine, an optimization problem is automatically built, and the product description is transformed into a design space ($\mathbb{X}$) and a set of design parameters ($\boldsymbol{p}$) for the computational models to use. After letting the optimizer solve the problem, the model and optimizer outputs ($\boldsymbol{x}, \boldsymbol{y}, \boldsymbol{f}, \boldsymbol{g}, \boldsymbol{h}$) are gathered into a dataset and then post-processed into design specifications. The human user thus interacts with the system only to supply their desired product properties and to examine the proposed design specifications, while the other steps of the process are automated.

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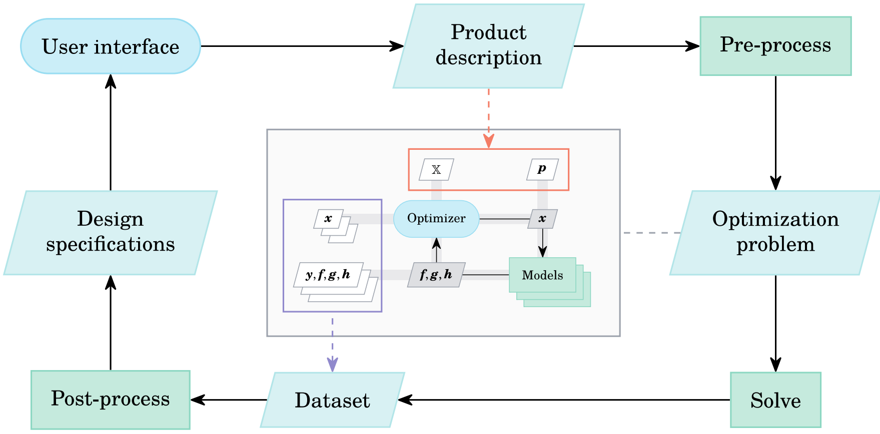

Figure 2. Conceptual overview of optimization-based design support framework, and its connection to a generic MDAO formulation

Realizing the design support constitutes mainly of defining a pre-processing routine for converting the abstract product description into an optimization problem, and a post-processing routine for converting the raw optimization result data set into comprehensible design specifications. One of the challenges in defining these routines lies in managing the metadata of models and parameters in the pre-processing and managing the resulting dataset in the post-processing routines. General utilities for facilitating this are motivated and described below.

4.1. Knowledge management in MDAO

MDAO formulations commonly consist of multiple models that are interconnected, meaning that the output of one model should be fed on as an input of another model (Sobieszczanski-Sobieski et al., 2015). As the number of models increases, so does the number of input and output parameters. It may also be the case that certain quantities will occur multiple times throughout the formulation, as multiple models may use one particular quantity as an input. For complex products, many models are commonly needed to account for the multiple engineering disciplines involved, thus also resulting in a large number of parameters. Another source of complexity stems from the fact that parameter *values* may be multi-dimensional arrays e.g., for indexing performance metrics by time and location.

As will be developed below, the example optimization problem considered in this paper manifests this complexity. For instance, an array within the Mobile Miner application has five dimensions, with the fifth dimension indexing the cutter for which a value (such as a force) is applicable. Here, the index "5" conveys no information on what the dimension represents, while a name like "cutter" can encode at least some information for a human actor and a computer to act upon. It is therefore plausible that data structures supporting named dimensions can carry more information about its data's *meaning* and thus improve program comprehension (Lawrie et al., 2007) and maintainability. Named dimensions are however rarely used explicitly in the MDAO field.

To describe a model's inputs and outputs sufficiently to assemble an MDAO formulation and to adequately understand the data in post-processing, multiple aspects of semantic *metadata* might be needed to be associated with it, e.g.: units, descriptions, typical values, allowed ranges, and dimension names. Typically, this parameter metadata is defined every time it occurs as an input/output, even though it might represent the *very same* parameter. In simple cases, the cost of repetition might be justifiable, but in more complex scenarios with tens or hundreds of parameters (such as the Mobile Miner problem), defining and maintaining duplicated parameter metadata might pose a considerable inefficiency, consuming engineering time that is not value-adding. Devising MDAO formulations for complex products thus implies repetitive and non-creative tasks, which is what design automation systems often strive to eliminate (Cederfeldt and Elgh, 2005; Verhagen et al., 2012).

Some solutions for structuring and referencing engineering knowledge, encoded as model and parameter metadata, include the approaches applied in Heeds MDO (Siemens PLM, 2018), version 3 of the FMI specification (Modelica Association, 2022) and the CMDOWS format (van Gent et al., 2018). However, these approaches lack support for multi-dimensional arrays or named dimensions; or they are focused

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on working in other environments, not suited for the context of MDAO, such as dynamic modeling. Thus, a software library has been developed as part of this work, to support the following activities:

- Structuring the engineering knowledge captured in computational models and their (potentially multi-dimensional) parameters, as metadata describing the semantic meaning of models and parameters, in the end enabling rapid reuse of existing engineering knowledge
- Assembling multiple models and connecting their parameters to formulate MDAO problems
- Storing and structuring parameter values into a unified data structure alongside semantic model and parameter metadata for post-processing and visualization

An open-source, reusable software library in Python is available as the *Facit* package (Vidner, 2023a). The Facit library integrates with the OpenMDAO platform for realizing model connections and solving the MDAO problem. The central part of the software library is the class structure outlined in Figure 3.

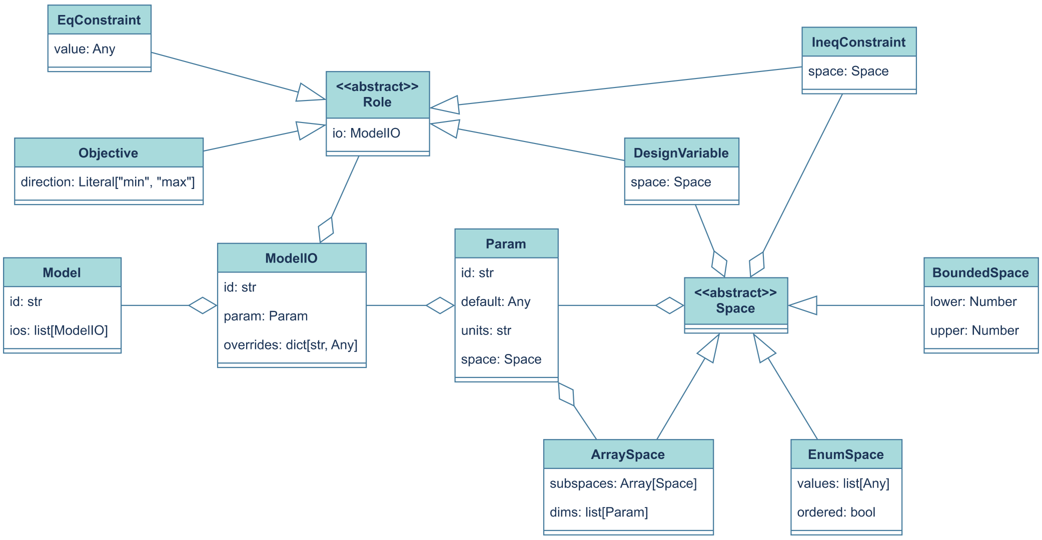

Figure 3. Class diagram of the Facit software library, using a notation adapted from UML (Object Management Group, 2017)

Engineering knowledge is structured into *models* and *parameters*, where a parameter stands for any given engineering quantity that can be shared between multiple models. To track the parameters used in each model, the model's inputs/outputs are represented by *model I/O* entities that can also override the properties of the parameter object. Typical or allowed parameter values are represented by *spaces* that can represent bounded (e.g. [1–23.4]) or enumerated values (e.g. {"a", 2, 6.1}). Spaces can also be defined as multi-dimensional arrays of bounded or enumerated values. Variables of interest for optimization (e.g., design variables, objectives, and constraints), are modeled as distinct *role* objects, associating a specific model I/O with one or multiple specific roles in an optimization formulation. Thus, the definition of an optimization problem is decoupled from the definition of models and parameters, allowing reuse. Instances of the classes can be created statically and kept as-is in a codebase or a database; or, created on-demand to create another level of flexibility in the possible formulations.

Parameter values given by every iteration are stored in the *xarray* dataset format (described by Hoyer and Hamman, 2017). To facilitate post-processing activities and enhance traceability of design data, the dataset is also enriched with the metadata and engineering knowledge captured in the object instances described above. The metadata and data management utilities can thus provide reusable primitives for supporting the definition of both the pre-processing and post-processing routines mentioned in section 4. By utilizing pre-made and reusable primitives, development and maintenance efforts can focus on application-specific aspects rather than generic aspects.

4.2. Optimization formulation

Using the outlined software library together with OpenMDAO, an MDAO model representation is devised, to enable automatic evaluation and improvement of the conceptual Mobile Miner design

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within the design support system. The utilized formulation is outlined in Figure 4. Derived from the product description supplied by the user through a GUI, important application parameters from the user (such as rock properties, operational planning properties, and desired tunnel dimensions) are fed together with the design variable bounds, into applicable models. Then the NSGA-2 system optimizer (originally devised by Deb et al., 2002; implementation from Vidner, 2023b), automatically supplies the computational models with sets of design variable values, based on the product performance given by previous values. After using a non-linear Broyden solver from OpenMDAO for converging two models that both stipulate the width of the cutter wheel, the cutter wheel design is then finalized by placing the cutters in a way that minimizes the fatigue loads. Next, the cutter positions are translated and rotated in multiple copies to accommodate calculations of system loads in multiple time steps. An *fzero* solver from Matlab then finds the penetration depth of the cutters into the rock wall which yields the maximum allowed loads. Now, the excavation process can be simulated, to calculate the advance and excavation rates, passing this information on to the cutter lifing model which estimates the lifetime of individual cutters. Finally, important metrics for making a total cost of ownership (TCO) analysis are gathered. The total number of known and unknown parameters in this setup amounts to approximately 200, including several multi-dimensional parameters in up to 6 dimensions.

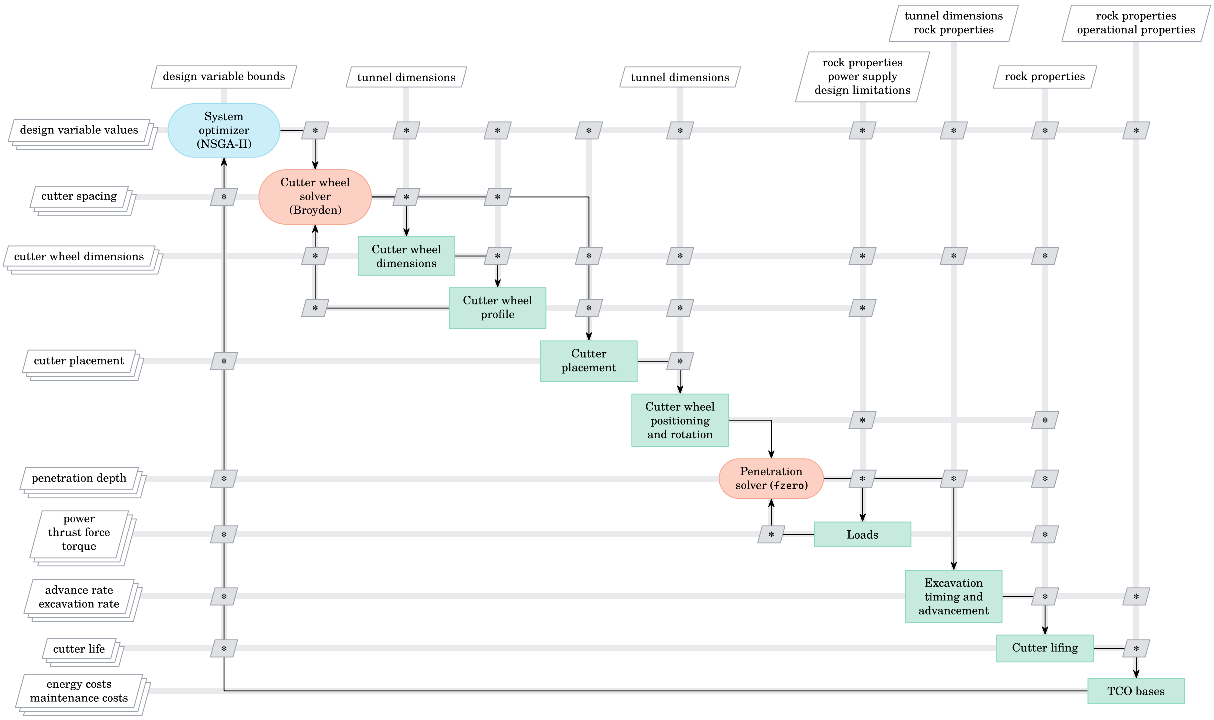

Figure 4. Schematic XDSM diagram of optimization formulation embedded in the design support system, including input (top row) and output (leftmost column) presented in the GUI; For brevity, intermediate parameters are omitted and indicated with *

During the analysis and optimization procedure, model data is accumulated and saved for post-optimization analysis (that is, for presentation in the design support GUI). As indicated in Figure 4, the data used for the automatic decision-making of the optimizer is not precisely the same as that used for the manual decision-making by the user.

The formulation presented here is an extended version of the MDAO formulations presented by Melbro and Jersenius (2018) and Vidner et al. (2021a). Improvements from the previous versions include the addition of a model for calculating the bases for a TCO analysis; an improved cutter placement algorithm, minimizing fatigue loads; verification of the computational results; and corrections to the penetration solver, ensuring that the machine concept satisfies given power and design limitations.

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4.3. Graphical design support system

To support the decision-making in Mobile Miner quotation and to realize the full framework presented, an optimization-based design support system has been developed. A GUI is defined, to aid the capturing of customer requirements and the presentation of design data. It is divided into three main areas, as depicted in Figure 5: a problem definition area, an overview of the dataset, and a design detail area.

The problem definition area enables the user to supply case-specific design parameters and variable limits for the underlying optimization problem. After solving the optimization problem (or loading a pre-existing dataset), the dataset gathered is represented with a scatter plot to give the user an overview of all solutions in objective space (here excavation rate vs. cutter lifetime). This representation can be filtered to display only feasible or Pareto-optimal designs. From here, the filtered or full dataset can be exported to an internal format and Excel format. Also, one or multiple designs can be selected in the scatter plot, to enable a detailed view of each design. In the design detail area, some key metrics for the engineer's decision-making are represented in different ways to give a deeper insight into the cause of a design's objective values:

- Individual cutters' placement is represented in a 3D view.
- Performance metrics such as torque and thrust are represented using violin plots to show their distribution over time, as well as their minimum and maximum values.
- Scalar design variables and responses are displayed in numeric form.

Figure 5. GUI for the design support system

The GUI has been realized using the open-source libraries *HoloViews* for plotting and *Panel* for GUI elements. To ensure reproducibility in the industrial deployment of the design support system, it is packaged into a self-contained system, using PyInstaller.

5. Evaluation

To verify the accuracy of the computational model's results, they are compared with measured data gathered from three different manufactured Mobile Miner machines working in two different mining environments. The computational models have been fed with the corresponding machine and environmental properties and evaluated using the presented formulation, with the results summarized in Table 1. It should be noted that the measured data, especially the measured environmental properties,

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are known to exert substantial variations. Using *face validation* and *historical data validation* techniques (Sargent, 2013), a domain expert has examined the results. Despite design A in environment 2 exhibiting large deviations, the domain expert deemed the results as accurate enough for the model's given purpose: supplying fast approximations in a very early phase of development.

From the full list of needs on the design support system, five key requirements were identified. The most basic aspect is the tool's reliability and consistency in addressing the problem at hand. This involves presenting a precise and well-defined explanation of the problem to be solved, along with a comprehensive overview of the inputs and outputs of the system. Additionally, the system should allow the user to modify the problem definition by adjusting input values and models. In terms of the system's responses, the tool should communicate both the uncertainties in the responses and which responses have the greatest impact on product performance.

The optimization process must fulfill fundamental criteria, including the delivery of accurate outcomes and the absence of errors. Nonetheless, user inputs have highlighted the need for supplementary functionalities, such as enhanced user feedback, estimated optimization duration, and the option to halt an ongoing optimization once the user is content with the results.

The users expressed interest in the presentation of results and decision support, with a strong desire to export results in a format that provides transparency and traceability of the computational results. Additionally, users emphasized the importance of inspecting uncertainties and identifying limiting factors in a given design. The possibility of effortlessly conducting additional simulations for selected designs based on minor adjustments was also suggested.

Table 1. Comparison of measured versus calculated product performance metrics for three designs (A-C) in two environments (1-2); values are proportionally scaled per metric to ensure confidentiality while maintaining the same order of magnitude as the original data

		Thrust [kN]		Torque [kNm]		Penetration [mm]	
Design	Env.	Meas.	Calc.	Meas.	Calc.	Meas.	Calc.
A	1	1228	1251	256	230	2.2	3.2
A	2	950	1248	701	406	7.8	10.0
B	1	968	1250	234	316	6.1	6.0
C	2	1126	1247	286	397	9.3	9.9

6. Discussion

The need for flexible optimization formulations for use in ETO quotation has been highlighted in the literature, yet not clearly mapped. From the gathered responses, we can however start to crystallize what can constitute this desired flexibility. In the quotation process considered in this case study, we see a need to solve the problem of having product knowledge put into models and variable metadata before a request for quote is received. Then that knowledge must be leveraged as part of the quotation process. Within the process, computer models can be used as-is or combined to solve optimization problems. The resulting dataset can then be used for follow-up analyses. Manual engineering work may also be carried out before handing the quote to the customer or sales representative. Additionally, new product models may be created during the quotation process and made available to other parties working with the same product or product family.

The gathered statements suggest that the developed graphical design support system only covers a part of this kind of quotation process as it does not answer every single question at once. Instead, an optimization-supported quotation workflow is envisioned, where multiple MDAO workflows and manual engineering processes are consecutively and concurrently carried out. The data outcome from one workflow or engineering process can be reused and transparently fed into another, using different models than those used in the previous. In this way, the gradually defined product specification, characteristic of ETO development, can be captured and supported in a way that exploits both a computer and human engineering judgment and creativity. Yet, the process must be able to reuse the engineering knowledge gathered over time, embedded in the product models.

While the GUI does not fully cater to this need for emergent analyses, the presented framework and software library provide important enablers for such a process, in that the dataset provides enough

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semantical information about the output parameters for them to be used as inputs to compatible models used in another workflow. However, to provide greater design support, the library should furthermore facilitate automatic matching of these parameters, using a forward-chaining or backward-chaining solver. Another layer of metadata that can provide value is model fidelity and runtime information, allowing a solver to identify the optimal fidelity-to-runtime ratio for a given problem formulation.

The contributions outlined can provide means to support an optimization-based configuration system (as described by e.g., Wehlin, 2021). In the user input phase, traditional configuration systems allow the user to configure a product by guiding the user while they combine alternatives. An optimization-based system could instead propose solutions based on high-level inputs. The graphical design support system presented in this work could be viewed as a technical configurator, but more work is needed to investigate the necessary adaptations needed to realize customer-facing, optimization-based sales configurators that automatically find optimal design solutions to customer-unique problems.

7. Conclusions

This paper presents a significant advancement in the field of product customization and the quotation of ETO products. By combining product customization methodologies with MDAO, the paper demonstrates an improved and accelerated quotation process for complex products, here exemplified by a Mobile Miner. Users can input essential design-specific metrics, such as desired tunnel dimensions and rock characteristics, and the MDAO framework is dynamically tailored to these specifications and subsequently solved by integrating computational models. This approach allows the evaluation of a broader range of design alternatives than traditional manual quotation processes. Moreover, this automated method can refine the accuracy of quotation processes and foster better design alternatives.

Using the OpenMDAO framework, this study defines the problem and improves it by creating reusable open-source components to manage knowledge within the MDAO context. This innovation enables the comprehensive handling of multidimensional parameters and data, from their setup and utilization to their storage and presentation. The research also explains how this data management system can be seamlessly integrated into an MDAO framework, contextualizing it within a product customization setting. Additionally, the study introduces a GUI that captures user inputs and visualizes results through various plots, making it easy to compare design alternatives.

The framework's effectiveness is evaluated by comparing its outputs with real-world measurements from an operational Mobile Miner. The framework's usability is also assessed through evaluations by three domain-specific experts, whose insights provide valuable feedback. Based on this, the study proposes strategic directions to enhance the utility of similar frameworks, highlighting specific requirements and recommendations for the next generation of adaptive MDAO frameworks tailored for product customization.

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