Full length article

Product design-optimization integration via associative optimization feature modeling

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Abstract
This paper addresses an important problem of integrating structural optimization into a traditional CAx system and therefore, realizes an integrated product design-optimization system. Specifically, structural optimization has been embedded as an independent module of most commercial CAx systems. It mainly communicates with CAD but can only have the STL-based CAD geometry as input. The knowledge-level information transfer is not supported which causes the optimization intent not fully captured. The consequence could be quite negative that the optimization process generates unsatisfactory or even useless design solutions and tedious manual efforts are required to modify or even redesign the immature solutions, which reduces the overall design efficiency and quality. To fix this issue, this paper proposes an integrated product design-optimization system by enabling the complete information transfer between CAD and structural optimization modules. Interfacing rules have been defined to enable the complete information transfer and the associative optimization feature concept is proposed to manage the transferred information for the structural optimization module. Furthermore, knowledge based reasoning is performed to capture the full optimization intent in order to create a fit-for-purpose optimization model, including both the optimization problem formulation and the solution strategy. For technical merits, this integrated product design-optimization system robustly ensures the timely and high-quality product design delivery which is superior to the existing commercial systems. Effectiveness of this proposed system has been proven through a few case studies.

1. Introduction

Industrial products are embedded of increasingly rigorous and complex design requirements which make the product design process difficult and time-consuming. To meet the challenge, increasingly more design tasks are solved through structural optimization algorithms and the structural optimization tools are gaining the popularity. Generally speaking, structural optimization algorithm performs the finite element analysis to evaluate the structural performance and accordingly, calculates the sensitivity result to decide design changes. This process is repeated till convergence and the derived design solution is at least close to the global optimum which can hardly be achieved through the traditional trial-and-error approach.

A flow chart of the feature-based product design process involving structural optimization is demonstrated in Fig. 1. We can see that structural optimization plays a major role during the embodiment design phase which effectively generates the design solution from a conceptual idea or an existing product model.

After introducing the background, this paragraph will disclose the remaining research issue that structural optimization is not fully embedded into the feature-based product design process; in other words, the structural optimization module is not a well-integrated part of the CAx-based product design system. As indicated in Fig. 1, structural optimization starts by extracting geometry from a conceptual CAD model or an existing product model. All the attached semantic information is just removed and their importance is ignored. The semantic information is generally a reflection of design intent which supports the product related high-level reasoning, e.g. functionality and manufacturability evaluations. Conventionally, a major principle of feature-based design is to keep the information consistency in order to avoid design intent violations. However, the geometry extraction procedure definitely violates this principle, which in fact isolates the structural optimization module and makes it a standalone tool. The impact of ignoring the attached semantic information is quite negative that, the optimization process would generate less optimal or even
useless design solutions and afterwards, tedious manual efforts are required to modify or even regenerate the solutions.

An example is demonstrated in Fig. 2. External profile of the pipe gripper is generated as a conceptual idea and the internal ribs are to be designed through structural optimization. The semantic information attached indicates the injection molding manufacturing method. Then, if only the geometry is imported into the structural optimization module, it will generate the solution as presented in Fig. 1b; in contrast, if the attached manufacturing information is also received and properly interpreted, the optimal solution will satisfy the constant rib thickness requirement as demonstrated in Fig. 1c which employs much better manufacturability. In summary, embedment of the structural optimization module into the CAX-based product design system is not well realized because of the incomplete information transfer.

To fix this issue, the paper proposes an integrated product design-optimization system which supports the complete information transfer between the internal modules. The framework is presented in Fig. 3.

This system consists of four main components: associative feature modeling, information transfer, associative optimization feature modeling, and optimization intent capture. The associative feature concept was proposed earlier by the authors (see Fig. 4) [26,28]. It effectively supports the semantic information creation and management, and therefore, is adopted as the core part of the information management mechanism in CAD module.

Fig. 1. Feature-based product design process involving structural optimization.
Information transfer is mandatory and the main requirement is to ensure the completeness. Since both the geometry and the attached semantic information are represented in different forms between the internal modules, a set of interfacing rules has been established to support the information transformation. The associative optimization feature is a newly proposed concept which follows the associative feature concept and realizes the equivalent information management in structural optimization module. The last but the most important component: optimization intent capture, interprets the semantic information contained by the associative optimization feature model and serves the role of creating a fit-for-purpose optimization model. Details about these components will be introduced in the later sections.

For the technical merits of this proposed system, product design-optimization integration is realized through the complete information transfer between the internal modules; more importantly, the semantic information can be properly interpreted from the perspective of structural optimization through knowledge based reasoning to create a fit-for-purpose optimization model. Both design efficiency and quality could be greatly enhanced.

To highlight the technical merits, a brief survey about the commercial software systems is conducted. So far, structural optimization has been embedded as a module of most commercial CAx systems, e.g. the OptiStruct from Altair HyperWorks, and the SIMULIA Tosca Structure applied in Abaqus, ANSYS, and MSC Nastran. However, these systems commonly share the limitation that the CAD and structural optimization modules are only integrated at the geometry level, i.e. the structural optimization module reads in the STL-based CAD geometry. At the knowledge level, majority of the design intent is lost and the optimization intent is restored based on the designer’s intuition which is tedious and lacks of completeness. On the other hand, the structural optimization module supports few options about the optimization intent restoration, such as design domain selection, symmetric and repetitive patterns, and minimum length scale, which are far from enough. Therefore, the integrated design-optimization system proposed in this work shows superior characteristics in optimization intent capture and optimization model creation.

It is also worth noticing that, scope of this paper is to demonstrate how this proposed system works by emphasizing the consisting components and their inter-relationship. A few prototypes will be programmed for demonstration, instead of developing a rigorously working platform based on commercial software tools.

The following contents will be organized as: Section 2 presents a literature survey about the associative feature modeling and the level set structural optimization. Section 3 introduces the associative optimization feature concept and the interfacing rules for complete information transfer. Section 4 introduces the optimization intent concept and its capture through the knowledge based reasoning. Section 5 presents two 3D design examples to demonstrate the effectiveness of feature based product design-optimization integration. A conclusion is given in Section 6.

2. Literature survey and motivations

2.1. Associative feature modeling

Feature technology plays a dominating role in today’s product design process. Specifically, geometric feature serves as the basis for product modeling; functional feature associates the
functionality to the geometry; engineering features, including manufacturing feature and assembly feature, etc., attach certain engineering meanings to the geometry to address downstream engineering concerns during the early design stage. In summary, feature-based design unifies the geometry and the semantic information to build the product model, which supports the high-level reasoning from different engineering aspects, e.g. functionality and manufacturability evaluations, etc. [25,8].

Because of the diversified feature definitions, numerous semantic information could be attached to a product model. It has been a long-lasting issue about how to effectively manage the design consistency during the entire product design process, spanning from the conceptual design, the embodiment design, to the detail design. Quite a few management mechanisms have been proposed [26,28,35,46,5], among which the associative feature concept, proposed by [26,28], works effectively and shows outstanding characteristics. Associative feature was introduced in the form of self-contained design object group with a set of geometric and non-geometric design associations (DAs) built on the product geometry entities [26,27,28]. Here, geometric DAs indicate the spatial relationships among the geometric entities and non-geometric DAs mean the attributes attached to the geometric entities. Therefore, associative feature offers a mechanism of tightly bonding the semantic information to the geometric entities through DAs, and it has been proven that associative feature could deal with the intricacy of DAs across the multiple design stages and effectively maintain the design consistency subject to the numerous design changes [26,27,28,29]. The first implementation of associative feature was found in the area of mold design which made extensive use of the “smart objects” [26,27]. The cooling channels was abstracted into smart guiding lines associated with attributes describing the cooling channel diameter, depth, and end type, etc. Geometrically, the smart guiding lines were mutually associated to form the cooling system. With such well-organized DAs, designers could be released from the tedious geometry reconstruction subject to any design change, which significantly shortens the mold design process [26,27,29]. The associative feature concept later was extended to the assembly design domain by defining the associative assembly feature, which realized the DA management between components [28].

A few requirements of associative feature modeling have been identified and summarized as below [28]:

- All DAs related to geometric entities must be collected to form a complete associative feature model.
- A self-validation mechanism must be defined to check the consistency of the associative feature instances.
- Necessary methods for construction, storing, indexing, editing, and destroying the associative feature instances must be provided.

![Fig. 4. Partial relations defined in the associative feature/associative assembly feature class [28].](image-url)
The associative feature must be query-able and executable for high level knowledge process.

The associate feature must be able to interact with other engineering applications.

In fact, some commercial CAx systems have implemented similar concepts as of associative feature. CATIA has the knowledge module to capture engineering knowledge. Geometric DAs can be established through building formulas on the geometric parameters and there is the check function to ensure the formulated relationship not violated. Basic geometric entities can be grouped to form user defined features or part templates. The powercopy function greatly facilitates the product design and knowledge reuse. More importantly, rules can be established for high-level engineering reasoning and the rules can be automatically checked to prevent violation. NX has a similar module named Knowledge Fusion, which provides the similar functionalities.

Even though the effectiveness of the associative feature modeling has been proven by many research works and commercial software tools, the concept is never extended to the structural optimization domain, especially for shape and topology optimization. As discussed earlier, the semantic information attached to the CAD geometry get stripped off during model transfer, or in other words, all the attached DAs are removed. Therefore, it is critical to develop the associative optimization feature concept to inherit and manage the complete information for the structural optimization module.

2.2. Level set structural optimization

Normally, structural optimization can be classified into three levels: sizing optimization, shape optimization, and topology optimization. For many problems, the different levels of optimization are concurrently involved. Therefore, structural optimization in this work will be based on the level set method [36,38,1], because it well supports the concurrent sizing, shape, and topology optimization, as well as the geometric feature manipulations [9,10,11,30,50,4,18,23].

In addition, feature-based product design may be performed under different physical disciplines, e.g. solid mechanics, fluid dynamics, thermodynamics, etc. Therefore, to be part of the design process, structural optimization should be able to work under any of these physical disciplines, where level set method has demonstrated the capability. In solid mechanics domain, Wang et al. [38] and Allaire et al. [1] solved the compliance-minimization problems; and later, the stress-minimization and stress-constrained problems were also solved [2,17,45,41,17,15]; in [39,40,43], the structural design problems with multiple materials/functionally graded materials were addressed through level set method. About fluid mechanics, the flow channel design problems have been addressed through level set method given different flow types, e.g. Darcy flow, Stokes flow, and Navier-Stokes flow [51,1,13,14]. Similarly, heat conduction problems were also solved through level set method [19,52]. For more details, a comprehensive review could be found in [37].

Apart from the superior problem solving capability, another reason of employing the level set method for structural optimization is that level set itself is a powerful geometry modeling method.

Osher and Sethian [33] proposed the level set function as a natural way of closed boundary representation. Let $D \in \mathbb{R}^n$ ($n = 2$ or 3) be the initial design domain, $\Omega \in \mathbb{R}^n$ ($n = 2$ or 3) represent the area filled with materials and $\partial \Omega$ be the boundary of the material domain. $\Phi(X): \mathbb{R}^n \rightarrow \mathbb{R}$ is the level set function that

\[
\begin{align*}
\Phi(X) > 0, & \quad X \in \Omega / \partial \Omega \\
\Phi(X) = 0, & \quad X \in \partial \Omega \\
\Phi(X) < 0, & \quad X \in D / \Omega
\end{align*}
\]

(1)

Because of the implicit nature, level set function could trivially define any freeform geometry, as well as the form features [9,10,30]. For instance, a circle can be represented by

\[
\Phi(X) = R - \sqrt{(X^2 + Y^2)}
\]

(2)

and a square by

\[
\Phi(X) = \min \left[ \frac{L}{2} - (X - x_0), \frac{L}{2} + (X - x_0), \frac{L}{2} - (Y - y_0), \frac{L}{2} + (Y - y_0) \right]
\]

(3)

Then, complex geometry can be formed by Boolean operations on the individual level set functions [9,10,30] as,

\[
\begin{align*}
\Phi_1 \cup \Phi_2 &= \max(\Phi_1, \Phi_2) \\
\Phi_1 \cap \Phi_2 &= \min(\Phi_1, \Phi_2) \\
\Phi_1 \setminus \Phi_2 &= \min(\Phi_1, -\Phi_2)
\end{align*}
\]

(4)

Therefore, level set geometry modeling conforms to the conventional CSG (constructive solid geometry) format. The geometry transfer from CAD into structural optimization module is simplified into the format transformation from B-rep to CSG. This is a superior advantage compared to other structural optimization methods.

For the high-level attempts to embedding structural optimization into feature-based product design process, Cugini et al. [12] used the PROSIT approach to integrate CAI (Computer-Aided Innovation) and PLM (Product Lifecycle Management) via the topology optimization method. Later, Cardillo et al. [6] expresses a similar idea of using topology optimization as the main body of embodiment design, to connect CAI and PLM. Muzzupappa et al. [31] defined the roles, activities, data to be exchanged, and software tools to be used to integrate topology optimization into product development process; special attentions have been paid to knowledge transfer. However, these attempts are all based on density based topology optimization method. It employs the voxel-based geometry representation, with which the geometric constraints and the other semantic information are nearly impossible to be maintained. Additionally, sizing optimization cannot be supported which severely limits the optimization flexibility. Therefore, we conclude that level set method is the most appropriate for structural optimization for the integration purpose.

Hence, in this work, level set structural optimization is adopted as the core method by the structural optimization module.

3. Associative optimization feature modeling

3.1. Definition of the associative optimization feature

Associative optimization feature is an extension of the associative feature concept into the structural optimization domain. As shown in Fig. 5, it groups form and freeform features represented by implicit level set functions, and manages the in-group DAs, which has the similar definition as compared to associative feature concept. On the other hand, clear distinctions exist between these two concepts: (1) They are both domain-specific concepts, as associative feature functions in the CAD module and associative optimization feature is adopted by the structural optimization module. They express the feature group and in-group DAs in different formats, and information communication and inheritance associates these two concepts to collaboratively support the feature based product design. (2) From the perspective of design flow,
associative feature modeling and associative optimization feature modeling employ the sequential relationship. As illustrated in Fig. 1, associative feature functions at the conceptual and detail design phases to manage the conceptual design and refine the optimized solution; instead, associative optimization feature plays the role in the embodiment design phase which calculates the material distribution to form the embodied shape and topology.

3.2. Information transfer

To generate the associative optimization feature model, it requires the complete information transfer, including both the geometry and the attached DAs. Clear interfacing rules have been defined to support the transfer, as follows:

(1) Geometry transfer

In CAD systems, B-rep (Boundary representation) is the widely used geometry representation, which stores the explicit boundary entities and the in-between topological relationship; however, CSG (Constructive solid geometry) is more appropriate to be used by optimization activities [9,10], because CSG employs the implicit representation which is not sensitive to topological changes. Therefore, the primary step of the information transfer is to transform the geometry representation from B-rep to CSG.

(2) DA transfer

DAs widely exist in the feature based product model, which can be both geometric and non-geometric, including “constraints, dependencies, equations, memberships, part-whole relations, coupling, patterns, etc.” [28]. A specific categorization is plotted in Fig. 6. It is worth noticing that, Fig. 6 covers some frequently applied DA types; however, it cannot cover all in a single image. This categorization is extendable according to the specific needs, i.e. there could be more manufacturing methods involved other than the listed three.

About details of the DA transfer, non-geometric DAs remain to be semantically stored, while the imposed objects switch from explicit boundary/body entities to implicit level set contours/fields; geometric DAs would be directly written into constraints, which later will form part of the optimization problem formulation if necessary.

An instance is presented in Fig. 7. The B-rep model is composed of two explicitly represented block features, as well as a group of geometric and non-geometric DAs. When transformed into the optimization model, the block features are switched into level set descriptions and combined by union operations as: $\Phi_1 \cup \Phi_2$. The geometric DA: $d_1 > 5$ is transformed into $z_1 + d_2/2 - (z_2 + d_3/2) > 5$, where $(x_1, y_1, z_1)$ and $(x_2, y_2, z_2)$ are the center points of feature 1 and feature 2, respectively. For non-geometric DA, we assume a coating layer is designed to faces $f_1, f_2, f_3, f_4,$ and $f_5$, and after transformation, it is re-attached to the surface: $(\partial \Omega_{f_1} \cup \partial \Omega_{f_2})$.

So far, all required information transfer has been completed, including both the geometry and the attached DAs. In other words, the associative feature model has been switched into the associative optimization feature model. Again, it reveals that these two concepts are equivalent in information representation while they serve for different engineering modules.

Fig. 5. Partial relations defined in the associative optimization feature class.
4. Optimization intent

4.1. Introduction to optimization intent

In [49], design knowledge is subdivided into three categories: process history, design intent, and domain specific knowledge. For product modeling, modeling history and design intent support the associative feature modeling, and assembly specific knowledge supports the associative assembly feature modeling. For simulation, Nolan et al. [32] proposed the concept of simulation intent, which was defined to “include all of the analysis, modeling and idealization decisions, and all the parameters required to create an efficient and fit-for-purpose analysis model from an input CAD geometry”. In fact, simulation intent is the simulation specific knowledge captured from both the designer’s input and the interpretation of the CAD geometry. For instance, loading and boundary conditions are defined by designer input, and detail and dimension reduction is performed by the system by analyzing the geometry.

In this paper, we proposed the new concept, named optimization intent. As indicted by the name, optimization intent belongs to the structural optimization specific knowledge and it includes all decisions in formulating and solving the optimization problem. It is obtained by reasoning the associative optimization feature model and also receiving some supplemental user input. Properly and completely capturing the optimization intent is extremely important because it will facilitate the effective and efficient
optimization model creation. To fulfill this job, knowledge based reasoning is mandatory and a list of possible optimization intent attributes should be summarized; see Table 1.

It is worth noticing that this table covers majority of the attributes within the authors’ knowledge scope. It is general in application and could cover a large variety of optimization problems. However, this table may be extended in the near future as the structural optimization technique is currently under rapid development and accordingly, new optimization intent attributes may appear.

4.2. Optimization intent capture

4.2.1. Define the optimization variables/optimization domains

After model transformation, the feature based CSG model contains numerous implicitly-represented feature primitives, as well as their parameter sets. Generally, they would not all be employed as designable optimization variables/domains and user input is required to make the selection.

One situation is that the feature primitive is only allowed with parametric changes, which means design freedoms of scaling, rotation and movement. The designer needs to pick up the active sizing and mounting parameters to be the designable optimization variables. For the other situation, the feature primitive is allowed of shape and topological changes and this type of feature primitive would be defined as designable optimization domain of the level set structural optimization. However, because of the shape and topological changes, parameters related to the feature primitive will disappear and so will the related geometric DAs. To fix this problem, a bounding feature is virtually added which is geometrically identical to the initial feature primitive. It inherits the sizing and mounting parameters; see Fig. 8, and the main function is to maintain the related geometric DAs.

Structural optimization is a simulation based reverse process. Therefore, the simulation intent should be manually defined as well. It specifically includes the attributes of dimensionality, boundary condition, mesh type, model clean-up, and solution type, etc.

4.2.2. Define the basic optimization intent

The basic optimization intent includes the objective function, physical constraints, solution method, sensitivity analysis technique, and design update. Definition of the basic optimization intent relies on user input, and it is already commercialized in most structural optimization tools.

### Table 1: Optimization intent attributes.

<table>
<thead>
<tr>
<th>Optimization intent attribute</th>
<th>Potential decisions</th>
</tr>
</thead>
<tbody>
<tr>
<td>Objective function</td>
<td>Compliance minimization/ Stress minimization/ Energy dissipation minimization/</td>
</tr>
<tr>
<td>Extra control functional</td>
<td>Thickness control/ Boundary smoothing/ Graduate change of material mixture/ …</td>
</tr>
<tr>
<td>Physical constraint</td>
<td>Stress constraint/ Material volume constraint/ Component/ void size constraints/ Boundary curvature constraint/</td>
</tr>
<tr>
<td>Geometric constraint</td>
<td>Angle/ Parallel/ Perpendicular/ Distance/ …</td>
</tr>
<tr>
<td>Optimization variable</td>
<td>Level set function/ Geometric parameters/ Local material parameter/</td>
</tr>
<tr>
<td>Optimization domain</td>
<td>Optimization domain/ Multi-material optimization domain/ Non-optimization domain</td>
</tr>
<tr>
<td>Solution method</td>
<td>Lagrange multiplier method/ …</td>
</tr>
<tr>
<td>Sensitivity analysis technique</td>
<td>Regular sensitivity analysis on the level set function or other parameters/ Repetitive or symmetric sensitivity analysis/</td>
</tr>
<tr>
<td>Design update</td>
<td>Solving the Hamilton-Jacobi equation/ Parametric update/ Adjustment of boundary velocities</td>
</tr>
</tbody>
</table>

The general level set structural optimization formulation is,

\[
\min J(u, \Phi) = \int_D F(u) H(\Phi) d\Omega \quad \text{(objective function)}
\]

subject to \(a(u, v, \Phi) = \{v, \Phi\} \quad \text{(weak form of the governing equation)}\)

\[
V(\Phi) = \int_D H(\Phi) d\Omega \leq V_{\text{max}} \quad \text{(material volume constraint)}
\]

(5)

Through adjoint sensitivity analysis, the sensitivity result can be derived as,

\[
L'(u, w, \Phi) = \int_D \beta(u, w, \Phi) \delta(\Phi) d\Omega
\]

where \(L(u, w, \Phi)\) is the Lagrange function and \(\beta(u, w, \Phi)\) is the shape sensitivity density; \(u\) is the status variable such as deformation or temperature and \(v\) is the test variable; \(w\) is the adjoint variable. It should be emphasized that the sensitivity result has to be in the boundary integration form because of the boundary velocity based design update, and the shape sensitivity density determines the rate of local boundary evolvement.

Based on the sensitivity result, the regular approach for design update is to solve the Hamilton-Jacobi equation through upwind difference. For more details, interested readers can refer to [34].

4.2.3. Analysis of the associative optimization feature model

Other than the basic optimization intent, the main contribution of this paper is to capture the optimization intent through reasoning the DAs managed by the associative optimization feature model.

As mentioned earlier, knowledge based reasoning is mandatory and a list of rules should be established. These rules support the decision making in mapping the DAs contained by the associative optimization feature model into specific optimization intent attribute selections. Specifically in implementation, an inference agent goes through the DA list and creates the related mappings. There could be different situations that: some DAs are clearly mapped into optimization intent attribute selections; some DAs are irrelevant to any optimization intent, e.g. geometric DA defined on non-designable parameters; some DAs would lead to conflicting options of an optimization intent attribute which requires user intervention to resolve the conflict; and some DAs lead to incomplete optimization intent attribute which requires additional user input to supplement information, e.g. targeted thickness value of the uniform thickness requirement. All these situations should be predicted in advance and resolvable by the inference agent.

So far, we have accumulated the following rules to support the knowledge based reasoning.

(1) Geometric DAs: The geometric DAs are already in the form of equivalent or inequivalent equations, and therefore, they can be directly applied as geometric constraints in the optimization problem formulation.

(2) Non-geometric DAs: It is non-trivial to deal with the non-geometric DAs, because of the diversity as shown in Fig. 6. Each of the sub-categories may be mapped to quite different optimization intent attributes.

(2.1) Material: Homogeneous material is the most common case in structural optimization and the underlying optimization intent is just the fixed material properties. Comparatively, it is worth a deep investigation about the heterogeneous material, especially for its complexity and the increasing popularity.

- Multi-material: Multi-material means that the component is composed of multiple materials and there is a macro material/material interface.
the underlying optimization intent, the optimization domain should be defined by the multi-material level set model. Currently, there are mainly two multi-material level set models: the “color” level set [39,40] and the “multi-material” level set [42]. They could achieve equivalent optimization effects.

- Functionally graded material (FGM): FGM means the material mixture gradually varies within the component following linear or other low-order profiles. About the underlying optimization intent, the local material parameter is needed to reflect the local material mixture. A material mixture function is required [21] or an extra control functional is adopted to realize the gradually-varying material mixture in the optimization result [43].

- Highly nonlinear: Highly nonlinear means the material mixture varies arbitrarily in highly nonlinear pattern. The underlying optimization intent is simple that, only local material parameter is required to reflect the local material mixture and there is not gradual-change requirement. Besides, there could be local micro-geometry involved other than the simple material mixture, for which extra effort is required to calculate the local material properties, e.g. by applying homogenization and/or surrogate modeling [16].

A mold insert design case study is presented below to demonstrate the structural optimization with heterogeneous materials. About the basic optimization intent, the objective is to maximize the thermal compliance under the material volume ratio constraints of 0.35 for the copper and 0.65 for the steel. Heat conductivity of the cooper is 380 W/(m·°C) and that of the steel is 20 W/(m·°C). Concerning the simulation intent, boundary conditions attached to the optimization domain are presented in Fig. 9a and the static heat conduction simulation is employed.

For multi-material scheme, the optimization result is shown in Fig. 9b, in which the yellow color represents copper and the grey color represents steel. For highly nonlinear scheme, the local micro-geometry as presented in Fig. 9c is applied and the optimization results are shown in Fig. 9d and e. We can see that both parameter a and the orientation of the local micro-geometry can be effectively optimized.

(2.2) Manufacture: The adopted manufacture method has a major influence in configuring and solving the optimization problem. The underlying optimization intent is separately summarized below for the different manufacture methods [24].

- Machining: There are several special requirements in structural optimization because of the employment of the machining method. First, very small hole features should be avoided because they are non-manufacturable [53] and this can be satisfied by adding component/void size constraints [18,24]. Second, the maximum local curvature of the boundary contour is determined by the minimum cutting tool radius and this can be satisfied by adding boundary curvature constraints. Third, no undercut and interior holes should appear, also because they are non-manufacturable [44,3]. This requirement can be satisfied by adjusting the boundary velocity directions.

- Injection molding: An important rule for injection molding parts is the uniform rib thickness distribution, because it could improve the cooling balance and therefore reduce the defects. To satisfy this rule, both adding component size constraints [18,4] and using extra thickness control functional [11,22] are feasible solutions. In addition, the third requirement of no undercut and interior holes, as mentioned in the last paragraph, should also be satisfied, because they are also non-manufacturable features for injection molding.

Here, we present a case study to demonstrate the structural optimization of injection molding parts. About the basic optimization intent, the objective is to minimize the structural compliance and different solid material volume constraints will be imposed. The solid material employs Young’s modulus of 1.3 and the Poisson ratio of 0.4. Concerning the simulation intent, boundary condition attached to the optimization domain is presented in Fig. 10a and the static elastic simulation is employed.

The optimization results with different targeted rib thickness values are demonstrated in Fig. 10b–d. This case is cited from [22] in which the uniform rib thickness is realized through adding extra thickness control functional.
5. 3D Examples

In this section, the authors intend to study two 3D examples to demonstrate the effectiveness of the proposed method.

5.1. A wheel structure problem

First, internal structure of a plastic wheel of size 100 mm × 15 mm is to be innovatively designed. The conceptual CAD model is presented in Fig. 12a and the attached semantic information indicates the injection molding manufacturing method and the 4 × 1 circular repetition and symmetry requirement for the spoke area.
After model transformation, the simulation intent is attached to the optimization model as shown in Fig. 12b.

Clearly, the spoke area is adopted as the optimization domain, and no optimization variable is employed in this case. The basic optimization intent is to minimize the structural compliance under the material volume constraint of 50%.

Conventionally, the optimization process would start immediately once the simulation intent and the basic optimization intent have been defined. Consequently, the optimization result is shown in Fig. 13a. It’s clear that the design quality is poor because the semantically attached design requirements are not addressed. Warpage will appear in the large plane because of the injection molding manufacturing method, and the wheel can only bear tangential load located at certain points of the outer frame because of the non-repetitive internal structure.

In contrast, if the associative optimization feature model is constructed through complete information transfer and properly interpreted through the knowledge based reasoning, the full optimization intent could be captured and a very different optimization result could be derived as presented in Fig. 13b. All the
(a) CAD geometry
(b) Optimization geometry with simulation intent

Fig. 12. Conceptual models.

(a) Optimization result without full optimization intent
(b) Optimization result with full optimization intent

(c) Output CAD geometry

Fig. 13. Optimization results for an example wheel component.
Semantically defined design requirements have been addressed including the closely-satisfied uniform rib thickness and the tightly-satisfied circular repetition and symmetry. So far, only a minor post-treatment is required to derive the final CAD model. Owing to the employed level set method, the skeletons of the internal rib structure can be trivially extracted. The skeletons are approximated into piecewise straight lines and a double-sided offset is performed to derive the strictly satisfied constant rib thickness. These are trivial CAD operations to quickly derive the final CAD model; see Fig. 13c.

5.2. Rib-enhanced thin plate design

For this case, the milk tray design is retrieved from the database as shown in Fig. 14a, and is intentionally to be enhanced about its working stiffness.

During the conceptual design phase, the wall structure (400 mm × 300 mm) is recognized into four design regions as shown in Fig. 14b which will be separately enhanced. A few manual modifications have been made that, region 1 and 3 are deployed of two groups of symmetric ribs and the geometric DAs of repetition and symmetry are created; region 4 is filled of solid materials which is intended to be topologically optimized in the embodiment design phase; the non-geometric DA of injection molding manufacturing is attached to the whole structure.

After model transformation, user input is required to define the optimization variables and optimization domains. In region 1 and 3, the rib orientations are employed as optimization variables within the allowable range [−60°, 60°]. In region 2, vertical distance of the handle $x_2$ is to be optimized within the range of [27 mm, 37 mm]. More importantly, region 4 is employed as the optimization domain for the structural topology optimization.

In addition, two groups of boundary conditions are attached to the optimization model as shown in Fig. 15. The basic optimization intent is to maximize the structural stiffness.

Then, by reasoning the included DAs, the repetitive and symmetric pattern of the ribs in region 1 and 3 makes all the ribs share a unified optimization variable $x_1$, and the related injection molding manufacturing leads to the uniform rib thickness requirement for the structural topology optimization in region 4. Once the optimization intent is fully captured, two separate optimization processes are conducted which derives two distinctive optimization results as demonstrated in Fig. 16. It can be seen that both results have been effectively enhanced by adding ribs; more importantly, the optimization intent is well reflected in the optimization results.

6. Conclusion

This paper proposed an integrated product design-optimization system by making structural optimization tools seamlessly integrated into the traditional CAx system. A few prototypes have been developed and implemented. It has been observed from the implementations that the fit-for-purpose optimization model could be effectively and efficiently created and the optimized design solutions well conform to the original design intent; in other words, design quality is greatly improved while little post-treatment is required. Therefore, the effectiveness of the proposed system has been proven.

Characteristics of the proposed system are summarized below:

1. Design intent included in the original CAD model is well sustained and reflected in the optimization result; see Figs. 13 and 16 for the satisfied uniform thickness distribution and the repetitive and symmetric structural patterns. This again confirms that an important motivation of realizing the product design-optimization integration is to maintain the design consistency throughout the entire product design process. The proposed associative optimization feature modeling and optimization intent capture serve the purpose of sustaining the design intent throughout the structural optimization process.

2. Design intent violation is no longer a major problem associated with structural optimization. The benefit would be the greatly saved post-treatment effort. In practice, it has always been a headache to designers to manually post-treat the structural optimization result.

3. The concurrent sizing, shape, and topology optimization is realized in a single structural optimization process; see Fig. 16, while in existing structural optimization tools, these processes are generally conducted procedurally which sacrifices of the overall optimality.

About limitations of the proposed system, the fully captured optimization intent complicates the optimization model and many control parameters are involved. This reduces the stability of the optimization model and a fine tuning process is required to find the fit values of the control parameters. This issue reduces the
implementation efficiency and is currently under active exploration.

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